Scientific Annals of Economics and Business

Alexandru Ioan Cuza University of Iasi

Volume 73 (LXXIII), Issue 3, 2026

Editura Universității „Alexandru Ioan Cuza” din Iași
2026

Editor-in-Chief:
Ovidiu STOICA, *Alexandru Ioan Cuza University of Iasi, Romania*

Editors:
Iulia GEORGESCU, *Alexandru Ioan Cuza University of Iasi, Romania;* **Ștefan-Cristian GHERGHINA**, *Bucharest University of Economic Studies, Romania;* **Carmen PINTILESCU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Cristian POPESCU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Cristina Teodora ROMAN**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Alexandru ȚUGUI**, *Alexandru Ioan Cuza University of Iasi, Romania,* **Adriana ZAIȚ**, *Alexandru Ioan Cuza University of Iasi, Romania*

Editorial Board:
Daniela-Tatiana AGHEORGHIESEI (CORODEANU), *Alexandru Ioan Cuza University of Iasi, Romania;* **Richard AJAYI**, *University of Central Florida, USA*; **Claudiu Tiberiu ALBULESCU**, *Politehnica University of Timisoara, Romania*, **Paola BERTOLINI**, *University of Modena, Italy;* **Franziska CECON**, *Upper Austria University of Applied Sciences, Linz, Austria;* **Andrea CILLONI**, *University of Parma, Italy;* **Laura Mariana CISMAȘ**, *West University, Timisoara, Romania;* **Kıymet ÇALIYURT**, *Trakya University, Merkez, Turkey*; **Luminița ENACHE**, *University of Calgary, Canada;* **Francisco FLORES MUÑOZ**, *University of La Laguna, Spain;* **Konstantin GLUSCHENKO**, *Siberian Branch of the Russian Academy of Sciences, Russia*; **Jesús HEREDIA CARROZA**, *University of Seville, Spain*; **Luminița HURBEAN**, *West University, Timisoara, Romania;* **Jürgen JERGER**, *University of Regensburg, Germany;* **Ali M. KUTAN**, *Southern Illinois University Edwardsville, USA;* **Ion LAPTEACRU**, *Université de Bordeaux, France,* **Jana MARASOVA**, *Matej Bel University, Banska-Bystrica, Slovakia;* **Seyed MEHDIAN**, *University of Michigan-Flint, USA;* **William MENVIELLE**, *University of Québec, Canada*; **Antonio MINGUEZ VERA**, *University of Murcia, Spain;* **Gareth MYLES**, *University of Adelaide, Australia;* **Mihai Ioan MUTAȘCU**, *West University, Timisoara, Romania;* **Luis PALMA MARTOS**, *University of Seville, Spain;* **Bogdan NEGREA,** *Bucharest University of Economic Studies, Romania;* **Ion PÂRȚACHI**, Academy of Economic Studies, *Republic of Moldova;* **Yvon PESQUEUX**, *National Conservatory of Arts and Crafts, Paris, France;* **António Manuel PORTUGAL DUARTE**, *University of Coimbra, Portugal;* **Marius PROFIROIU**, *Bucharest University of Economic Studies, Romania;* **Rasoul REZVANIAN**, *University of Wisconsin-Green Bay, USA,* **Grażyna ŚMIGIELSKA**, *Cracow University of Economics, Poland;* **Daniel STAVÁREK**, *Silesian University, Karviná, Czech Republic;* **Satoshi SUGAHARA**, *Kwansei Gakuin University, Japan;* **Stanka TONKOVA**, *Sofia University, Bulgaria;* **Adriana TIRON TUDOR**, *Babes-Bolyai University, Cluj-Napoca, Romania;* **Eleftherios THALASSINOS**, *University of Piraeus, Greece;* **Sivaram VEMURI**, *Charles Darwin University, Australia;* **Davide VIAGGI**, *University of Bologna, Italy;* **Giacomo ZANNI**, *University of Foggia, Italy*; **Wei-Bin ZHANG**, *Ritsumeikan Asia Pacific University, Japan;* **Bogdan Gabriel ZUGRAVU**, *Alexandru Ioan Cuza University of Iasi, Romania.*

Editorial assistant in chief:
Bogdan CĂPRARU, *Alexandru Ioan Cuza University of Iasi, Romania*

Editorial Assistants:
Constantin-Marius APOSTOAIE, *Alexandru Ioan Cuza University of Iasi, Romania;* **Adina DORNEAN**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Bogdan-Narcis FÎRȚESCU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Alexandru-Napoleon SIRETEANU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Marinica Lilioara ARUȘTEI**, *Alexandru Ioan Cuza University of Iasi, Romania,* **Simona-Elena DINU (CIOBANU)**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Erika-Maria DOACĂ**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Mihaela NEACȘU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Adelina-Andreea SIRITEANU**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Nicoleta Raluca TELEMAN (GĂINĂ)**, *Alexandru Ioan Cuza University of Iasi, Romania;* **Mina Madalina TOMA**, *Alexandru Ioan Cuza University of Iasi, Romania.*

Language editor:
Sorina CHIPER, *Alexandru Ioan Cuza University of Iasi, Romania*

Scientific Annals of Economics and Business (continues *Analele ştiinţifice ale Universităţii „Al.I. Cuza" din Iaşi. Ştiinţe economice / Scientific Annals of the Alexandru Ioan Cuza University of Iasi. Economic Sciences*)
Founded in 1954
ISSN–L 2501-1960; ISSN (Print) 2501-1960; ISSN (Online) 2501-3165
Publisher: Editura Universității „Alexandru Ioan Cuza" din Iași (http://www.editura.uaic.ro/)
Frequency: Four issues a year (March, June, September and December)

Indexed and Abstracted:
Clarivate Analytics Web of Science – Emerging Sources Citation Index (ESCI), Scopus, EBSCO, EconLit (The American Economic Association's electronic bibliography), Directory of Open Access Journals (DOAJ), Research Papers in Economics (RePEc), ERIH PLUS, Central and Eastern European Online Library (CEEOL), Cabell's Directories, Scirus, IndexCopernicus, Online Catalogue of the ZBW - German National Library of Economics (ECONIS), Electronic Journals Library, The Knowledge Base Social Sciences in Eastern Europe, Scientific Commons, The ZDB, Intute: Social Science (SOSIG - Social Science Information Gateway), New Jour, GESIS SocioGuide, Genamics Journalseek, Catalogo Italiano dei Periodici (ACNP), ResearchGate.

Journal metrics:
Clarivate Analytics - Journal Citation Reports 2026: Impact Factor 2025: 1.3 (Quartile Q3); AIS 2025: 0.163
Scopus: CiteScore 2025: 2.2 (Quartile Q2); Scimago Journal Rank (SJR) 2025: 0.314

Digital preservation & permanent archiving:
All of SAEB's content is is digitally preserved through **Portico** (https://www.portico.org/), which provides independent permanent archiving service for electronic scholarly journals.

Contact
Alexandru Ioan Cuza University of Iasi
Faculty of Economics and Business Administration
Bd. Carol I no. 22, Iasi, 700505, Romania
Tel.: +40232201433, +40232201435, Fax: +40232217000
Email: saeb@uaic.ro, Website: http://saeb.feaa.uaic.ro

Table of contents

Does Financial Performance Shield Greenwashers? Evidence from European Firms..... 465
Seyfullah Selimefendigil

When ESG Meets Risk and Resilience: Quantile on Quantile Connectedness Across the G7, Volatility Index, and Gold Mining Sector..... 489
Halilibrahim Gökgöz, Aamir Aijaz Syed, Ahmed Jeribi, Azza Bejaoui

Corporate Social Responsibility through the Lens of CEO Sociodemographic: The Effects of Education and Gender..... 509
Mariem Bouzguenda, Dhouha Bouaziz, Anis Jarboui

Green Investment as a Buffer: Analyzing the Economic and Environmental Impacts of Non-Renewable Energy Consumption in G20 Countries..... 527
Muhammad Adil, Rana Yassir Hussain, Rashid Mehmood, Kai-Yin Woo

Financial Development, Financial Globalization, Energy Consumption, and Environmental Degradation as Long-Run Determinants of Economic Growth: Causal Dynamics, Cointegration, and Distributional Evidence from Panel Data..... 551
Thomas Panagiotou, Constantinos Katrakilidis

Profitability of US Small Banks pre-during-post 2008 Global Financial Crisis: Evidence from Ratio Analysis..... 577
Rasoul Rezvanian, Seyed Mehdian, Kevin Jaklin, Nafise Aalipour

Technical and Non-Technical Employees' Perceptions on How Low-Code and No-Code Development Platforms Impact the Democratization of Coding: A fsQCA Analysis..... 593
Emil Lucian Crișan, Diana Maria Chiș, Elias Appiah-Kubi, Eniko Elisabeta Bodea, Alin Mihăilă, Napoleon-Alexandru Sireteanu

Unveiling the Dynamics of Irregular Migration and Border Mission Expenditures at the Serbian - Romanian Frontier: A Wavelet-Based Approach..... 617
Iliuta Cumpanasu, Mihai Mutascu

Organisational Capacity and Membership: An Analysis of Professional Associations of Economists in Spain..... 641
Eduardo Infante Rejano, Asunción Rodríguez-Ramos, Maria Claudia Scurtu Tura

A Hybrid MCDM Approach Using Fuzzy AHP–TOPSIS to Evaluate Digital Logistics Market Performance in Selected Asian Economies..... 657
Thanh Tung Bui

You can access the full issue by scanning the QR code.

Scientific Annals of Economics and Business
73 (3), 2026, 465-487
DOI: 10.47743/saeb-2026-0019

Does Financial Performance Shield Greenwashers? Evidence from European Firms

Seyfullah Selimefendigil*

Abstract: This paper attempts to examine the impact of greenwashing on firms' risk and the shielding effect of financial performance across different sustainability conditions. Using a sample of 457 non-financial firms from European countries and a two-step generalized method of moments (GMM) model, this study assesses the moderating role of financial performance in the relationship between greenwashing and firm risk. In this study, we use both total risk and market risk to measure firms' risk. To address construct validity, we operationalize greenwashing as the industry-adjusted abnormal gap between a firm's self-reported environmental, social, and governance (ESG) score and its controversy-adjusted ESG combined score, thereby capturing intentional ESG decoupling. We have documented that greenwashing increases firms' risk when sustainability conditions are not enough developed. Furthermore, our results reveal that financial performance effectively mitigates the adverse impact of greenwashing on firm risk primarily under transitioning (medium) sustainability conditions. Overall, our findings indicate that the risk effects of greenwashing are context-dependent across different sustainability development levels.

Keywords: greenwashing; total risk; systematic risk; agency theory; legitimacy theory.

JEL classification: Q56; G32.

* Turkish- German University, Turkey; e-mail: *selimefendigil@tau.edu.tr*.

Article history: Received 3 January 2026 | Accepted 22 April 2026 | Published online 24 June 2026

To cite this article: Selimefendigil, S. (2026). Does Financial Performance Shield Greenwashers? Evidence from European Firms. *Scientific Annals of Economics and Business*, 73(3), 465-487. https://doi.org/10.47743/saeb-2026-0019.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

After the Paris Agreement in 2015 and Sustainable Development Goals set by the United Nations (UN), firms started to adopt sustainability goals in their agendas. Furthermore, public awareness has increased towards the environmental and social activities of firms as more funds flow into these activities (Matos, 2020) and investors start to pay more attention to sustainability activities (Amel-Zadeh and Serafeim, 2018). ESG-friendly investment strategies help investors to avoid high risk associated with companies that conduct undesirable business activities (Ahmed *et al.*, 2021). Whereas ESG activities are known for their risk-mitigating features, they may also be used opportunistically to divert investors' attention as noted by (Lueg *et al.*, 2019). The overstatement of ESG-related activities which are known as greenwashing is used strategically to attract more investors, to sell more products or to improve firm's image (Wolniak, 2016). Firms under pressure of regulatory environmental changes may mislead investors by overstating their sustainability-related performance (Marquis *et al.*, 2016). Holding that many countries are committed to meeting requirements of Green Deal, the firms operating in these countries may overstate their ESG-related activities and mislead their investors. However, greenwashing increases information asymmetry between firms and investors and has detrimental effects on the firms (Ledeboer and Kil, 2023). This lack of information transparency between firms and their investors has such detrimental consequences as underpricing of capital or inefficient allocation of it (Gregory, 2024). Firms with a great level of greenwashing have been found to be exposed to lower stock prices (Walker and Wan, 2012; Du, 2015; Testa *et al.*, 2018; Ghitti *et al.*, 2024). The main drivers of greenwashing are elusive as previous studies associated it with different firms characteristics such as; financial constraints (Zhang, 2022), profitability (Kim and Lyon, 2015), firm size (Marquis and Toffel, 2012) or high unsystematic risk (Gregory, 2024).

Since greenwashing has heterogeneous impacts on firms and the main motivation for it remains ambiguous, we aim to investigate the impact of greenwashing on firm risk (both total and market risk). Furthermore, many studies underscored the risk mitigating impact of profitability (Brown and Kapadia, 2007; Angel *et al.*, 2018; Ahmed *et al.*, 2024). We examine whether and how financial performance influences the impact of greenwashing on firm risk.

Prior studies allege that greenwashing is more severe in underdeveloped sustainability conditions, often at the expense of genuine green initiatives Lund-Thomsen *et al.* (2016) due to insufficient capacity Lim and Tsutsui (2012) and weak oversight (Yang *et al.*, 2020; Xu *et al.*, 2025). Conversely, in highly developed sustainability conditions, ESG is frequently used as a license to enter the market (Jamali *et al.*, 2017). Nevertheless, some studies defend the importance of sustainability for firms in underdeveloped sustainability conditions Zhang *et al.* (2018), arguing that firm-level sustainability initiatives can offset weak governmental Corporate Social Responsibility (CSR) oversight (Jauernig and Valentinov, 2019; Huang *et al.*, 2020). Therefore, we divide our sample based on the sustainability levels of country-year observations to observe the interaction between financial performance and greenwashing across low, medium, high, and very high sustainability environments. In doing so, we aim to examine whether and how greenwashing impacts firm risk in the shadow of financial performance under different institutional contexts. We empirically demonstrate that the risk of greenwashing and the risk-mitigating (shielding) effect of financial performance are not unified; rather, they are strictly contingent upon the country's sustainability conditions.

Section 2 of this study is devoted to literature review and main hypotheses development. In Section 3 and 4 we explain the theoretical framework, the main variables, and empirical strategy. We then present the results of main analysis in Section 5 and robustness tests in Section 6. Finally, in Sections 7 and 8 we present the conclusion, future research avenues and limitations of the study.

2. RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

Although there is a growing body of literature on greenwashing, there is a limited number of papers that examine the impacts of greenwashing on the financial metrics of firms (Testa *et al.*, 2018; Gregory, 2024). In this way, Ghitti *et al.* (2024) used a sample of the 500 largest U.S. public companies and found that greenwashing decreases firm value. Another study conducted by Walker and Wan (2012), using over 100 top-performing Canadian firms, showed that greenwashing decreases firm value and greenhighlighting (equivalent sustainability-disclosure and sustainability-performance) has no impact on firm value. However, Gallas *et al.* (2025) revealed that the impact of greenwashing varies depending on the type of profitability measurement among European-listed banks. Whereas greenwashing has a positive impact on return on assets, it has a negative impact on return on equity and Tobin's Q. Another study conducted by Testa *et al.* (2018) documented that greenwashing deteriorates firm value using a sample of 3,490 publicly traded companies from 58 countries and 19 industries.

There is a limited number of papers focused on the risk and greenwashing relationship. Notably, Gregory (2024) discovered that greenwashing increases firm total risk and has no effect on systematic risk using a sample of firms from 70 countries over the period 2012–2022. An Australian-based study conducted by Mirza *et al.* (2025) documented that firms' one-period-lag greenwashing is positively associated with risk reduction, while two-period-lag greenwashing is marginally associated with it. Furthermore, Liu *et al.* (2024) documented that greenwashing increases stock price crash risk using a dataset of Chinese A-share listed companies from 2014 to 2021. Based on these mixed findings, we develop our hypotheses (H1 and H2) as follows.

***H1**: Greenwashing increases firm risk.*

***H2**: Financial performance negatively moderates the relationship between greenwashing and firm risk.*

An emerging-country-based study conducted by Li *et al.* (2023), has shown that greenwashing contributes to the financial performance of Chinese companies. Whereas this relationship weakened with stringent environmental regulations, it was reversed with low media favourability. In a parallel vein, Purnamasari and Umiyati (2024) documented that greenwashing has a positive impact on financial performance and this impact is strengthened with internal audit quality. Another Chinese-based study conducted by Chen and Dagestani (2023) has shown that greenwashing increases firm value and this impact strengthens with local directors and political connections. Furthermore, they noted that polluting firms, firms audited by the Big 4, and firms with mandatory disclosure benefit from greenwashing more than their counterparts. On the other hand, Ali *et al.* (2025) used a dataset from Chinese enterprises and documented that greenwashing diminishes the positive impact of environmental innovation on firm performance. By focusing on Chinese A-share agribusinesses, Wang and Tian (2025)

documented that greenwashing has a negative impact on return on assets, and this impact is mediated by green innovation. Using a cross-national firm-level sample, Xu *et al.* (2025) found that greenwashing decreases stock market value. This negative impact is more pronounced for companies with higher ESG commitment and operating in emerging markets. However, country factors such as culture and institutions are beyond the economic development level in explaining sustainability development (Cai *et al.*, 2016).

Therefore, we examine whether greenwashing increases firm risk under different sustainability conditions by considering the Sustainable Development Index (SDI), rather than general country development levels. This index is obtained from the Sustainable Development Report created by the Sustainable Development Solutions Network (SDSN) (Sachs *et al.*, 2025). As profit is often prioritized over ethical behaviours and social welfare in underdeveloped sustainability conditions Vives (2008), companies in these environments are more likely to shield their greenwashing activities through financial performance. Therefore, we develop our third hypothesis (H3) as follows.

***H3**: The risk-enhancing effect of greenwashing is more strongly alleviated by financial performance when sustainability conditions are underdeveloped.*

Figure no. 1 depicts our research framework.

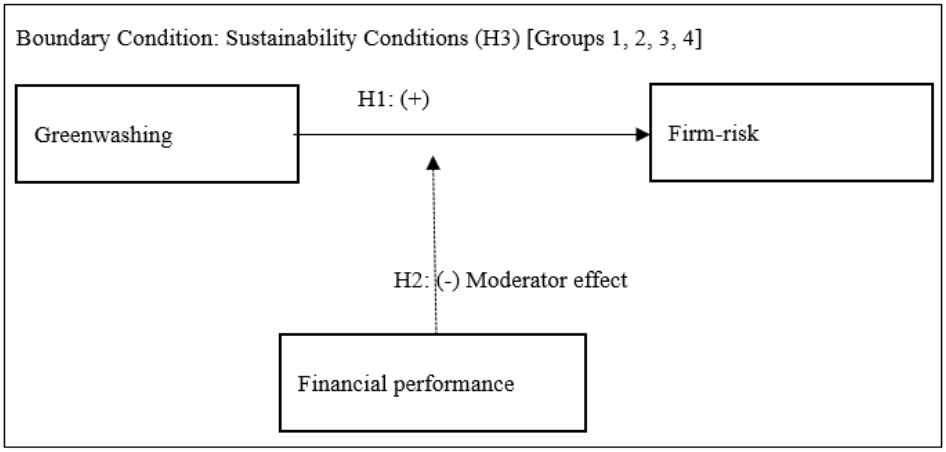


Figure no. 1 – Research framework

3. THEORETICAL FRAMEWORK

If firms adhere to the rules of the game (pressures) set by humans, society, the state, and institutions, they will succeed, remain stable, and remain competitive (La Porta *et al.*, 1998). Through the lens of *institutional isomorphism theory*, both formal and informal pressures exerted by external groups lead organizations to change their traditional business activities to more modern ones. Therefore, firms need to understand the norms, societal rules, and prestige pressures set by society (Saurabh *et al.*, 2024).

However, agency theory holds that managers follow their self-interest instead of improving firms' financial or social performance. In line with this theory, conflict of interest and information asymmetry between managers and stakeholders increase when firms greenwash (Mao, 2019). As investors cannot distinguish the difference between actual and disclosed social performance, it may result in stakeholders paying more attention to the positive tone (Donkor *et al.*, 2022). In line with this, unethical managers may prioritize short-term financial performance instead of considering all stakeholders' interests (Velte, 2025). Furthermore, *legitimacy theory* stipulates that managers choose various strategies to remain legitimate (Patten, 1992). According to this theory, an organization attempts to change bad perceptions into positive ones. As part of the legitimation process, an organization may conform to or change social perceptions and values (Dowling and Pfeffer, 1975). If companies change their activities or the perception of their activities, they should disclose them publicly (Cormier and Gordon, 2001). Kuruppu *et al.* (2019)argues that based on the different legitimation phases (i.e., gain, maintain, or repair), public disclosure differs. Therefore, it is worth noting that environmental and social disclosure has a legitimate motivation (O'Donovan, 2002).

Based on agency and legitimacy theories (Ross, 1973; Shocker and Sethi, 1973; Jensen and Meckling, 1976), we assume that greenwashing is related to higher firm risk. Furthermore, this risk is more pronounced in country-year observations with a lower sustainability level. Institutional voids, which can be described as the existence of weak and multiple informal institutions, have been associated with more opportunistic behaviour (Doh *et al.*, 2017). To clarify the conceptual mechanism of this relationship, we argue that high profitability creates a 'shielding effect' operating through the investors' pricing channel. Specifically, superior financial returns shield the firm and its management from investors' market penalties (i.e., adverse risk pricing) by inducing an economic tolerance for greenwashing. Moreover, this risk is alleviated by high profitability, especially in country-year observations with lower sustainability levels. Since country-year observations with a high sustainability level are associated with more intensive oversight and accountability for environmental and social activities (Xu *et al.*, 2025), observations in these categories are less likely to represent the risk mitigation impact of profitability.

4. DATA AND METHODOLOGY

4.1. Sample selection

This study uses a sample of firms from European countries between the years 2015 and 2024. Given that Europe is a unique continent committed to being the first carbon-neutral continent, and the firms operating in this region are pioneers in sustainable performance (Zahid *et al.*, 2022), CSR conditions have a major impact on European firms (Velte, 2025). We included the United Kingdom (UK) and Switzerland in our sample since they are also committed to net-zero emission goals and have strong trade integration with other European countries (Department for Business Energy & Industrial Strategy, 2022; Swiss Confederation, 2025). Primary data were obtained from the LSEG database (formerly known as Eikon with Datastream). Financial firms have been omitted due to their unique capital structure characteristics. Furthermore, continuous variables are winsorized at the 1% and 99% levels to

handle outliers. The final dataset of this study consists of 457 non-financial firms. Table no. 1 shows the distribution of firms across countries.

Table no. 1 – Sample distribution by country

Country	Number of firms	Percentage (%)
UK	90	19.7
France	63	13.8
Germany	50	10.9
Switzerland	39	8.5
Spain	28	6.1
Sweden	32	7.0
Finland	20	4.4
Netherlands	30	6.6
Denmark	16	3.5
Italy	16	3.5
Poland	13	2.8
Austria	10	2.2
Belgium	16	3.5
Portugal	6	1.3
Luxembourg	7	1.5
Ireland	13	2.8
Greece	8	1.8
Total	457	100

4.2. Independent variable

There are different categories of greenwashing prominent in empirical research. First, it can be measured as decoupling between the external ESG actions and internal ESG actions based on one ESG database (e.g., LSEG) Hawn and Ioannou (2016), which often reflects symbolic disclosure. Second, it can be measured as the divergence between different databases (e.g., Bloomberg and LSEG) (Hauch, 2026). Third, it can be measured through the divergence between raw disclosed ESG performance and verified combined ESG performance (Long *et al.*, 2025) which explicitly accounts for ESG incidents and controversy risk.

Prior research describes greenwashing as a form of decoupling strategy, through the use of such channels as green labels, social accreditation, codes of conduct, and policy claims (Roulet and Touboul, 2015). Building on this theoretical premise, we operationalize greenwashing as the industry-adjusted abnormal gap between a firm's self-reported ESG score and its controversy-adjusted ESG combined score. By isolating this abnormal variance, our measure effectively distinguishes routine sustainability frictions from intentional misrepresentation. Therefore, we use the difference between actual ESG performance and disclosed ESG performance from LSEG as a proxy for greenwashing, following previous studies (Chen and Dagestani, 2023; Long *et al.*, 2025; Zeng *et al.*, 2025). ESG scores from LSEG are adjusted through ESG controversies of firms and verified as the ESG combined score. The ESG combined score covers sustainability activities of firms regarding environmental, social, and governance metrics (Shakil *et al.*, 2025). Once we compute the divergence between disclosed and verified ESG scores, we standardize it for each industry to reveal the relative divergence as shown in Equation (1).

$$GW_{it} = \left[\frac{ESGdis_{i,t} - \overline{ESGdis}}{\sigma\text{dis}}\right] - \left[\frac{ESG\text{verif}_{i,t} - \overline{ESG\text{verif}}}{\sigma\text{verif}}\right] \quad (1)$$

In Equation (1); GW_{it} represents the standardized divergence of the greenwashing index for firm *i* in year *t* in its industry. $ESGdis_{i,t}$ stands for the earlier disclosed ESG score of company *i* at the time of *t,* while $\overline{ESGdis}$ and σdis stand for mean value of ex-ante disclosed ESG scores and standard deviation of disclosed ESG scores of companies operating in the same industry respectively. $ESGverif_{i,t}$ stands for *ex-post* verified ESG score of company *i* at time of *t,* while $\overline{ESGverif}$ and σverif stand for mean value of verified ESG scores and standard deviations of verified ESG scores of companies operating in the same industry respectively. Figure no. 2 shows the intensity of greenwashing across years and across countries.

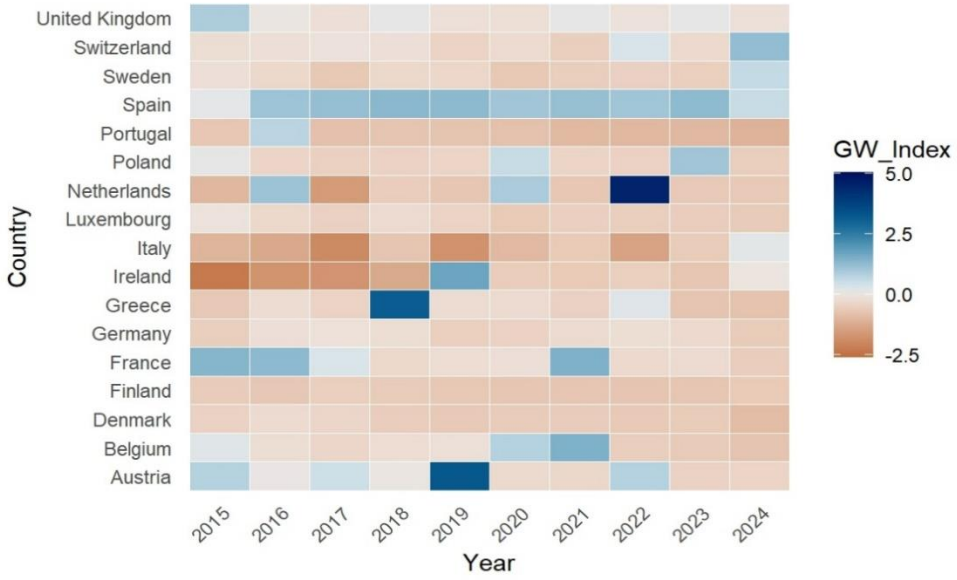


Figure no. 2 – Heatmap of Greenwashing (2015-2024)

4.3. Dependent variable

Various risk types have been used in the literature to measure firm risk. In this regard, some studies focus on the total and market risks of firms (Korinth and Lueg, 2022; Landi *et al.*, 2022; Khorilov and Kim, 2024) whereas others employ Altman (1968) Z-score (Cohen, 2023; Habermann and Fischer, 2023) Ohlson (1980) O-score (Truong *et al.*, 2025) or Zmijewski (1984) ZM-score (Meles *et al.*, 2023) based on key financial figures. On the other hand, some studies use market-based risk indicators such as Merton (1974) model (Shahrour *et al.*, 2021) or Bharath and Shumway (2008) model (Meles *et al.*, 2023).

In this study, we use both the total and market risks of firms to provide a broader perspective. Total risk is calculated as the standard deviation of stock returns for each month,

and the beta of the capital asset pricing model (CAPM) is used to measure the systematic risk. Since beta values are not available prior to 2015 in the LSEG database, we set 2015 as the starting period. We use Equation (2) to compute total risk.

$$Risk_{it} = std(r_{i,t}) \quad (2)$$

In Equation (2), $Risk_{it,}$ is the monthly total risk of firm i in year t, r represents monthly stock return, and *std* represents the standard deviation.

4.4. Moderator variable

As previously mentioned, we use profitability ratios as moderator variables. Firms that greenwash initially benefit from greenwashing, and it is not transformed into long-term sustainable profitability (Gallas *et al.*, 2025). In this way, we use the return on assets (ROA) to measure profitability. Based on agency and legitimacy theories, we assume that firms with operational efficiency decrease their risks at the expense of greenwashing. Similarly, we use return on equity (ROE) to measure the returns generated for shareholders and how effectively firms use shareholders' investments. Furthermore, we also use the earnings growth (EG) ratio to measure the effectiveness of sustainable profitability of firms.

4.5. Stratification by SDI

SDI is created by the SDSN, considering the conformity of countries to 17 different Sustainable Development Goals (SDGs) put forward by the UN across different years. This index ranges from 0 to 100, where 100 represents full conformity with the SDGs and 0 represents no commitment to the SDGs. Hence, in countries and during years with high sustainability commitments, greater oversight and accountability exist, and distinct social and environmental rules may curb the opportunistic behaviour of firms. We have divided our sample into four different classes based on the 25th, 50th, and 75th percentiles of SDI. In this way, we have labelled our four classes of observations as low, medium, high, and very high. Figure no. 3 depicts the SDI level across years and countries. As shown in this figure, countries with high income per capita levels lag behind other countries in terms of sustainability, suggesting that sustainability goes beyond economic development and is more closely related to cultural and institutional development (Cai *et al.*, 2016).

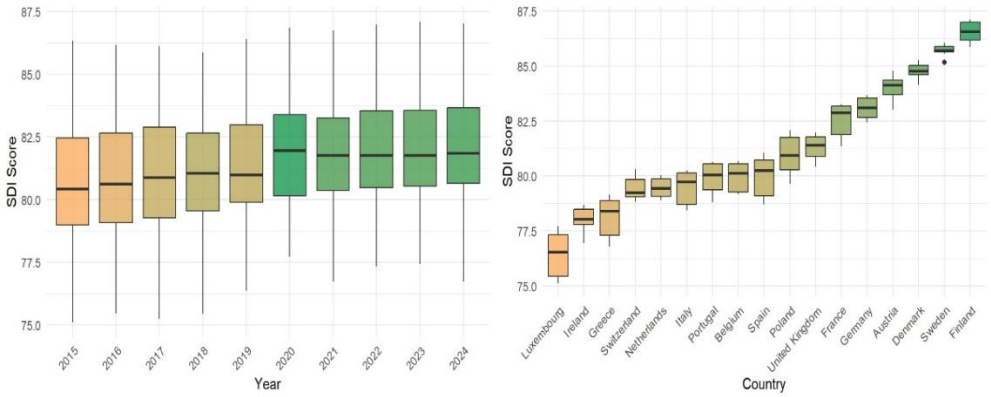


Figure no. 3 – Sustainability level across years and countries

4.6. Control variables

As for basic firm characteristics, prior research has included firm size, debt ratio, and market value as control variables (Gregory, 2024). We use several control variables to reveal basic firm characteristics and firm risk relationship. To measure debt ratio, we use total debt to total equity. Companies with higher debt ratios are more exposed to bankruptcy risk as noted by (Ben-Zion and Shalit, 1975). Additionally, we computed the market-to-book ratio as company market value divided by its book value of equity. In this sense, future growth expectations are associated with less risk (Philosophov and Philosophov, 2005). Additionally, we computed market to book ratio as company market value divided by its book value of equity. In this sense, future growth expectations are associated with less risk (Piotroski, 2007). Table no. 2 summarizes the variables used in this study.

Table no. 2 – Variable description

Abbreviation	Name	Description	Source
TR	Total risk	Standard deviation of the monthly stock returns for each year	LSEG
Beta	Systematic risk	Systematic risk of CAPM	LSEG
GW	Greenwashing index	Divergence between the ESG disclosed score and the ESG combined score	LSEG
ROA	Profitability ratio	Net income divided by average total assets	LSEG
SIZE	Firm size	Natural logarithm of firm's total assets	LSEG
LEV	Leverage ratio	Total debt divided by firms' total equity	LSEG
MTB	Market to book ratio	Firms market value divided by book value	LSEG
EG	Earnings Growth ratio	The difference in earnings between two consecutive years, divided by average total assets	LSEG
ROE	Return on equity	Net income divided by shareholders' equity	LSEG
SDI	Social Development Goals Index	Commitment level of countries to the Sustainable Development Goals set by the UN	SDSN

4.7. Empirical models

To examine the impact of greenwashing on firm risk, we use a system GMM model. Firm time-invariant factors may remain sticky and influence the association between firm risk and greenwashing. Therefore, we use this model to overcome biased estimates of our research results. The system GMM model introduced by Blundell and Bond (1998) is known for its endogeneity handling, which stems from time-invariant heterogeneity (Ali *et al.*, 2025). In our model, we treat GW, firm risk indicators (i.e., beta and total risk), and the interaction term as endogenous variables to account for reverse causality. All other control variables are treated as exogenous. Furthermore, we have conducted the Modified Wald test to check for the presence of heteroskedasticity. The Modified Wald test results confirmed the presence of heteroskedasticity in our model, and thus we used the robust option in our System GMM estimation. Equations (3) and (4) show the main models utilized in this study.

$$Risk_{it} = a_0 + a_1 GW_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

$$Risk_{it} = a_0 + a_1 GW_{it} + a_2 ROA_{it} + a_3 GW_{it}\#ROA_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

In Equations (3) and (4), $Risk_{it}$ stands for both total and systematic risk, GW_{it} for the greenwashing index, ROA_{it} for the profitability ratio, $Controls_{it}$ for control variables, μ for firm fixed effects, λ for year fixed effects, and ε for the error term respectively.

5. RESULTS

Table no. 3 shows the descriptive statistics of all variables used in this study. Our descriptive statistics show that both risk and greenwashing have higher values in the high SDI group. Furthermore, in terms of risk and greenwashing, the low SDI group has the lowest values compared to the other groups of observations. On the other hand, the profitability ratio, namely ROA, has its highest value in the very high SDI group and its lowest value in the low SDI group. In contrast, our alternative financial performance indicator, EG, attains its highest value in the low SDI group and its lowest value in the very high SDI group. Furthermore, another alternative financial performance indicator, ROE, has its highest value in the medium SDI group, whereas it has its lowest value in the low SDI group.

To provide a clearer context, we benchmarked our descriptive statistics against prior empirical studies. The mean value of our Greenwashing index (GW) in the high SDI group is 0.078, which aligns closely with the distribution reported by (Chen and Dagestani, 2023). Additionally, the mean GW in the very high SDI group is -0.0029, consistent with the findings of (Long *et al.*, 2025). Regarding firm risk, while our mean Beta values across all SDI categories are in line with those in Gregory (2024) our total risk averages are generally lower than his reported values. Furthermore, the average ROE documented by Gregory (2024) corresponds closely to the mean ROE of our low SDI group. Finally, while our average ROA is highly consistent with the study by Liu *et al.* (2024), it remains higher than the mean ROA reported by (Gregory, 2024).

Table no. 3 – Descriptive statistics

	Mean	Min	Max	Std Dev
Low SDI				
Total Risk	0.0836	0.0256	0.5389	0.0416
Beta	0.98761	0.0388	2.748	0.4529
GW	-0.0719	-2.596	4.584	0.9494
ROA	0.0247	-3.292	0.501	0.1881
SIZE	22.78	14.318	26.270	1.519
LEV	1.678	0.434	3.6828	5.117
MTB	2.649	0.5965	6.166	1.847
EG	0.0902	-3.317	79.292	0.0902
ROE	-0.0222	-107.39	4.982	3.2320
Medium SDI				
Total Risk	0.0983	0.02328	1.4986	0.0710
Beta	1.019	0.0388	2.748	0.48453
GW	-0.00510	-2.149	4.3494	0.9151
ROA	0.0424	-2.8960	2.518	0.2057
SIZE	22.588	15.523	26.742	1.681
LEV	1.748	0.43468	3.6828	1.1175
MTB	2.389	0.59659	6.1665	0.5965
EG	0.0104	-0.669	3.5714	0.1515
ROE	0.2145	-13.951	27	1.611
High SDI				
Total Risk	0.13768	0.0296	49.960	1.462
Beta	1.1056	0.0388	2.748	0.5561
GW	0.0778	-1.8854	4.004	0.9186
ROA	0.0444	-0.9421	1.922	0.1258
SIZE	23.051	17.40	27.027	1.61657
LEV	1.660	0.43468	3.6828	1.0518
MTB	2.2427	0.59659	6.16653	1.6545
EG	0.0043	-0.7380	2.1074	0.1022
ROE	0.1567	-56.459	179.76	5.671
Very High SDI				
Total Risk	0.0914	0.0264	0.6905	0.0448
Beta	1.0153	0.03884	2.748	0.4113
GW	-0.0029	-2.099	5.0433	0.96422
ROA	0.04824	-0.46723	0.3994	0.07084
SIZE	22.793	15.438	27.2198	1.4297
LEV	1.5778	0.4346	3.6828	0.91595
MTB	2.441	0.5965	6.1665	1.7139
EG	0.00084	-0.5935	0.47748	0.06105
ROE	0.0979	-9.9143	2.322	0.4060

Table no. 4 shows the correlation between selected variables. It can be stated that there is no high level of correlation among the selected variables. The highest level of correlation is observed between SIZE and GW (0.23) and it is below the acceptable threshold level of 0.80 (Porter, 2010).

Table no. 4 – Correlation Matrix

	GW	ROA	LEV	SIZE	MTB
GW					
ROA	0.0099				
LEV	0.0543	-0.0631			
SIZE	0.2299	0.0557	0.2204		
MTB	-0.0386	0.2363	0.1698	-0.0550	

Tables no. 5 and no. 6 show the relationship between GW and firm risk. According to our results, GW increases firm total risk only under medium sustainability conditions. Therefore, we can conclude that in country-year observations with low and medium sustainability levels, investors react more strongly than in other groups of observations. Once a greenwashing scandal is exposed, it continues to increase and triggers other scandals in the same market, and thus risk increases are stronger in these environments than in other ones (Xu *et al.*, 2025). In this way, our H1 hypothesis is partially accepted. Considering the main control variables, the profitability ratio is negatively associated with total risk in all groups except for the *low SDI* group, whereas it is negatively related to systematic risk in all groups. Whereas the leverage ratio has been found to be positively correlated with firm total risk only in the *medium SDI* group, it has not been found to be positively related to firm risk in other groups. Furthermore, SIZE has been found to be negatively related to firm total risk, and the MTB ratio is negatively related to total risk in all groups except for the *low SDI group.*

Furthermore, Table no. 7 and no. 8 show moderating role of financial performance measured by ROA. Our results suggest that operational performance shields the reverse effect of GW in the *medium and very high SDI* groups considering total risk. However, market risk measured by beta is only mitigated through ROA in the *medium SDI* group.

Table no. 5 – The nexus between GW and TR across SDI Groups (GMM Model)

SDI Groups	**1 (low)**	**2 (medium)**	**3 (high)**	**4 (very high)**
TR_{t-1}	0.1340*	0.1582***	0.1997**	0.1650**
	(0.079)	(0.0556)	(0.0857)	(0.073)
GW	0.0020*	0.0060***	0.0013	-0.0005
	(0.0013)	(0.0018)	(0.0011)	(0.00101)
ROA	-0.1382	-0.1679***	-0.1623**	-0.0815**
	(0.0342)	(0.0240)	(0.0381)	(0.0379)
LEV	0.00008	0.0018***	0.00066	0.0013
	(0.0013)	(0.00061)	(0.00098)	(0.0013)
SIZE	-0.0055***	-0.0085***	-0.0068**	-0.0045***
	(0.00155)	(0.00080)	(0.0015)	(0.0012)
MTB	0.00052	-0.0010**	-0.0015**	-0.0018***
	(0.00058)	(0.00047)	(0.00076)	(0.0006)
AR(1) Test (p-value	0.000	0.000	0.000	0.000
AR(2) Test (p-value	0.699	0.300	0.559	0.319
Hansen Test (p-value)	0.063	0.490	0.143	0.809
Number of Instruments	41	40	24	38
Number of Groups	155	286	216	190
Number of Observations	902	922	1080	991
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	1 to max	1 to max	1 to max	1 to max

Table no. 6 – The nexus between GW and Beta across SDI Groups (GMM Model)

SDI Groups	**1 (low)**	**2 (medium)**	**3 (high)**	**4 (very high)**
$Beta_{t-1}$	0.889***	0.946***	0.900***	0.874***
	(0.074)	(0.052)	(0.034)	(0.047)
GW	0.0039	-0.006	0.0212	-0.0240
	(0.0139)	(0.0141)	(0.0095)	(0.0406)
ROA	-0.5595***	-0.661***	-0.6008***	-0.6276**
	(0.1522)	(0.2835)	(0.2101)	(0.2064)
LEV	-0.0032	0.0100	-0.0051	0.0009

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
	(0.0051)	(0.0065)	(0.0037)	(0.00650)
SIZE	0.0029	0.0019	-0.0122	0.0027
	(0.0059)	(0.0058)	(0.0152)	(0.0089)
MTB	0.0032	0.0011	0.0018	-0.003
	(0.0038)	(0.0039)	(0.0034)	(0.0036)
AR(1) Test (p-value	0.000	0.000	0.000	0.000
AR(2) Test (p-value	0.681	0.472	0.237	0.600
Hansen Test (p-value)	0.285	0.522	0.729	0.647
Number of Instruments	40	29	23	35
Number of Groups	156	288	221	190
Number of Observations	878	915	1085	993
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	1 to max	1 to 3	3 to 4	2 to max

Table no. 7 – Moderating role of ROA in the GW-TR nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
TR_{t-1}	0.0677*	0.1381*	0.1490**	0.1226*
	(0.0819)	(0.0647)	(0.071)	(0.0705)
GW	0.00171	0.00760	0.0028	0.00043
	(0.0028)	(0.0023)	(0.0022)	(0.0016)
ROA	-0.1503***	-0.1769***	-0.1416	-0.0814**
	(0.0379)	(0.0294)	(0.0298)	(0.0355)
GW#ROA	-0.0282	-0.0531*	-0.0292	-0.0520**
	(0.0535)	(0.0313)	(0.0322)	(0.0232)
LEV	0.0003	0.0017***	0.00103	0.0013
	(0.0014)	(0.00064)	(0.00100)	(0.0013)
SIZE	-0.0059***	-0.0080***	-0.0075**	-0.0053***
	(0.0015)	(0.0008)	(0.0014)	(0.0012)
MTB	0.0004	-0.0010**	-0.0020**	-0.0025***
	(0.00058)	(0.00046)	(0.00084)	(0.00072)
AR(1) Test (p-value	0.000	0.000	0.000	0.000
AR(2) Test (p-value	0.986	0.287	0.405	0.220
Hansen Test (p-value)	0.065	0.390	0.149	0.882
Number of Instruments	50	50	42	47
Number of Groups	155	286	216	190
Number of Observations	902	922	1080	991
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	1 to max	1 to max	1 to max	1 to max

Table no. 8 – Moderating role of ROA in the GW-Beta nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
$Beta_{t-1}$	0.876***	0.937***	0.969***	0.755
	(0.077)	(0.0452)	(0.0317)	(0.064)
GW	-0.0026	0.0221	0.0535	-0.0094
	(0.0196)	(0.0207)	(0.0574)	(0.0513)
ROA	-0.6011***	-0.7854***	-0.5485***	-0.7705***
	(0.1609)	(0.2839)	(0.1973)	(0.2516)
GW#ROA	0.1132	-0.6475*	-0.2090	-0.3020
	(0.2682)	(0.3712)	(0.5875)	(0.5877)
LEV	-0.0025	0.0096	-0.0049	-0.0017
	(0.0045)	(0.0060)	(0.0040)	(0.0092)
SIZE	0.0043	-0.00114	-0.0107	0.0069

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
	(0.0060)	(0.0053)	(0.0094)	(0.0108)
MTB	0.0038	-0.00024	-0.0018	-0.0085
	(0.0037)	(0.0035)	(0.0045)	(0.0054)
AR(1) Test (p-value	0.000	0.000	0.000	0.000
AR(2) Test (p-value	0.762	0.746	0.314	0.060
Hansen Test (p-value)	0.243	0.263	0.253	0.464
Number of Instruments	50	33	43	41
Number of Groups	156	288	221	190
Number of Observations	878	915	1085	993
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	1 to max	1 to 3	2 to max	3 to max

6. ROBUSTNESS TESTS

To validate the robustness of our results, we reconduct our main regression models by substituting the profitability ratio with alternative financial performance ratios; earnings growth (EG) and return on equity (ROE).

$$Risk_{it} = a_0 + a_1 GW_{it} + a_2 EG_{it} + a_3 GW_{it}\#EG_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \qquad (5)$$

Equation (5) represents our robustness tests model. Where EGit represents earnings growth and other variables are defined previously.

Table no. 9 and no. 10 show the moderating role of EG in the GW-risk relationship. The robustness of our model is validated only for the medium SDI groups. Therefore, these results partially support our H2 and H3 hypotheses.

Table no. 9 – Moderating role of EG in the GW-TR nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
TR_{t-1}	-0.0071	0.1505**	0.1505**	0.2285*
	(0.211)	(0.0631)	(0.068)	(0.1322)
GW	0.0092	0.0044*	0.0018	0.0038
	(0.0080)	(0.0022)	(0.0015)	(0.0064)
EG	0.0003	-0.0033	-0.0153	-0.067**
	(0.0011)	(0.0025)	(0.0210)	(.0224)
GW#EG	0.0063	-0.0160*	-0.0262	-0.0589
	(0.0063)	(0.01606)	(0.0242)	(0.0721)
LEV	0.0011	0.0025***	0.0024**	0.0014
	(0.0011)	(0.0007)	(0.0010)	(0.0013)
SIZE	-0.0085**	-0.0093***	-0.0076***	-0.0045*
	(0.0023)	(0.0011)	(0.0013)	(0.0017)
MTB	-0.00038	-0.0028***	-0.0033***	-0.00247***
	(0.00051)	(0.0005)	(0.0007)	(0.00069)
AR(1) Test (p-value	0.039	0.000	0.000	0.000
AR(2) Test (p-value	0.648	0.340	0.191	0.400
Hansen Test (p-value)	0.081	0.463	0.873	0.460
Number of Instruments	46	49	41	43
Number of Groups	155	286	216	190
Number of Observations	902	922	1080	991
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	2 to max	1 to max	1 to max	2 to max

Table no. 10 – Moderating role of EG in the GW-Beta nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
$Beta_{t-1}$	0.8111***	0.7682***	0.9808***	0.8850***
	(0.074)	(0.0693)	(0.0240)	(0.0451)
GW	0.0945	-0.00994	0.0215	0.0081
	(0.0610)	(0.0350)	(0.0349)	(0.0440)
EG	0.00001	-0.0338***	-0.2138	-0.4750**
	(0.0036)	(0.0120)	(0.1928)	(0.1865)
GW#EG	0.0191	-0.1341*	0.1205	0.4182
	(0.0237)	(0.0751)	(0.3292)	(0.5761)
LEV	0.0026	0.0177***	-0.0038	0.0061
	(0.0059)	(0.0055)	(0.0034)	(0.0066)
SIZE	-0.0196*	0.0010	-0.0125*	-0.0011
	(0.0114)	(0.0090)	(0.0063)	(0.0110)
MTB	-0.0025	-0.0068*	-0.007**	-0.0091***
	(0.0039)	(0.0038)	(0.0034)	(0.0031)
AR(1) Test (p-value	0.000	0.000	0.000	0.000
AR(2) Test (p-value	0.865	0.245	0.268	0.102
Hansen Test (p-value)	0.280	0.522	0.333	0.338
Number of Instruments	46	46	42	43
Number of Groups	156	288	221	190
Number of Observations	878	915	1085	993
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	2 to max	2 to max	2 to max	2 to max

Furthermore, we replace our main financial performance indicator, ROA, with ROE. Unlike ROA, which focuses on asset efficiency, ROE captures the impact of the firm's financial leverage and capital structure. Equation (6) shows our alternative model used in this study.

$$Risk_{it} = a_0 + a_1 GW_{it} + a_2 ROE_{it} + a_3 GW_{it}\#ROE_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

In Equation (6), ROE_{it} represents return on equity and other variables were defined previously.

Tables no. 11 and no. 12 show the moderating role of ROE in the GW-risk relationship. Our results show that the risk-increasing effect of GW is mitigated through financial performance (ROE) under *medium sustainability* conditions in line with the findings presented in Tables no. 7 and no. 9.

However, regarding total risk, the results are different. Likely driven by the financial leverage component embedded in ROE, total risk is not decreased with GW. While ROE masks GW engagements against market risk, it fails to protect firms from total risk. In this way, as suggested by Wang and Tian (2025), a robust and optimized financial structure acts as an internal governance mechanism to curb greenwashing related risk.

Table no. 11 – Moderating role of ROE in the GW-TR nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
TR_{t-1}	0.043	0.1486**	0.1744***	0.0708
	(0.064)	(0.060)	(0.0644)	(0.1370)
GW	0.0016	0.0032*	0.0016	0.00081
	(0.0016)	(0.0018)	(0.0018)	(0.0073
ROE	-0.0305***	-0.0172**	-0.0081	-0.0206***
	(0.0067)	(0.0076)	(0.0118)	(0.0074)
GW#ROE	-0.0032	-0.00038	-0.0046	-0.0238
	(0.0108)	(0.0086)	(0.0119)	(0.0213)
LEV	0.0011	0.0030***	0.0016*	0.0008
	(0.0005)	(0.0006)	(0.0008)	(0 .0010)
SIZE	-0.0073***	-0.0079***	-0.006***	-0.0059***
	(0.0014)	(0.0010)	(0.0011)	(0.0017)
MTB	-0.00003	-0.0015***	-0.0028***	-0.0029***
	(0.00042)	(0.00049)	(0.0008)	(0.0008)
AR(1) Test (p-value	0.000	0.000	0.000	0.003
AR(2) Test (p-value	0.481	0.221	0.349	0.334
Hansen Test (p-value)	0.141	0.441	0.692	0.638
Number of Instruments	50	50	42	44
Number of Groups	155	286	216	190
Number of Observations	902	922	1080	991
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	1 to max	1 to max	1 to max	2 to max

Table no. 12 – Moderating role of ROE in the GW-Beta nexus (GMM)

SDI Groups	1 (low)	2 (medium)	3 (high)	4 (very high)
$Beta_{t-1}$	0.834***	0.929	0.9762***	0.8739***
	(0.0633)	(0.0565)	(0.029)	(0 .0492)
GW	0.04106	-0.0314	0.0557	-0.0169
	(0.0418)	(0.0525)	(0.0400)	(0.0353)
ROE	-0.135**	0.0284	-0.0393	-0.1019
	(0.060)	(0.081)	(0.0777)	(0.0570)
GW#ROE	0.08246	-0.2701*	-0.1006	0.0315
	(0.1059)	(0.1670)	(0.1549)	(0.1225)
LEV	0.00072	0.0063	-0.0023	0.0036
	(0.0053)	(0.0070)	(0.0033)	(0.0067)
SIZE	-0.00645	0.0095	-0.0145	-0.00077
	(0.0087)	(0.0104)	(0.0089)	(0.0075)
MTB	0.0015	-0.0021	-0.0049	-0.0087**
	(0.0043)	(0.0033)	(0.0059)	(0.00367)
AR(1) Test (p-value	0.000	0.001	0.000	0.000
AR(2) Test (p-value	0.790	0.142	0.290	0.242
Hansen Test (p-value)	0.507	0.206	0.570	0.582
Number of Instruments	47	44	43	44
Number of Groups	156	288	221	190
Number of Observations	878	915	1085	993
Instrument Collapse	YES	YES	YES	YES
Lag Depth (GMM)	2 to max	3 to max	2 to max	2 to max

7. DISCUSSION

Based on the agency and legitimacy theories, we have concluded that financial performance helps to offset the risk-increasing features of GW. Since financial performance is used by managers to send signals that they have specific business successes, it mitigates the overstatement impact of ESG performance. However, this situation is confirmed by our robustness test only in environments where the level of sustainable development is transitional. There are restricted but uncertain regulations on GW activities in developing markets (Yang *et al.*, 2020). According to Huang *et al.* (2020), weak governmental enforcement and unfair competition in developing markets lead to more greenwashing activities. However, investors in these markets react more strongly and may express heightened concern about the company's ESG activities, which leads to more adverse market reactions (Xu *et al.*, 2025).

On the other hand, in countries with a lower development level, unethical behaviours are more common (Na *et al.*, 2018). Poor governance and lack of transparency in these countries lead executives to adopt more opportunistic practices (Viana *et al.*, 2022). Additionally, the information asymmetry that is associated with opportunistic behaviours is more severe in these countries (Christopher *et al.*, 2012). Nevertheless, firms' characteristics become more important with the development level. Yet, it does not mean that there is always a linear relationship between countries' development status and firm characteristics; rather, it could well be that there is a threshold development effect (Doidge *et al.*, 2007) . In this way, we found that the negative impact of greenwashing matters more in the low and medium SDI group and can be alleviated with good financial performance in transitional sustainable environment.

Our results corroborate the findings of Liu *et al.* (2024) and Mirza *et al.* (2025), which used Chinese and Australian companies, respectively. Based on the SDI classification, these countries' commitment levels to sustainability are close to the countries in our sample in the low category. However, our study extends this existing empirical evidence by revealing that the risk-enhancing effect of greenwashing is highly context-dependent. While prior studies such as Gregory (2024) documented no impact of greenwashing on systematic risk, we also did not find any impact of greenwashing on it. Nevertheless, we found that in some cases, financial performance mitigates the adverse impact of greenwashing on systematic risk.

8. SUMMARY

8.1. Conclusion

This study examined the impact of greenwashing on firm risk under different sustainability conditions using both total and market risk. Our main regression results show that engagement in greenwashing activities increases firm risk specifically in environments with medium sustainability performance. Through the lens of *agency theory,* the information asymmetry between principals and agents stemming from greenwashing activities elevates firm risk. Since ESG reporting suffers from restricted comparability, it intensifies agency problems. To remain legitimate, firms often overstate their ESG activities. Our results indicate that investors penalize greenwashing by increasing firm risk in both low and medium sustainability environments. However, critical divergence emerges in the moderating role of

financial performance. While high profitability fails to mitigate this risk in severely underdeveloped (low SDI) markets—likely due to deep institutional voids and lack of trust in financial reporting, it effectively acts as a shield in transitioning (medium SDI) conditions. A decent financial performance covers up the opportunistic behaviour, as investors in these regions prioritize financial returns over ethical concerns.

8.2. Theoretical implications

Regarding theoretical implications, this study's core contribution to the literature is uncovering the non-linear, macro-institutional boundaries of the shielding effect. We extend the traditional firm-level ESG discussions by demonstrating an institutional threshold effect. The risk-mitigating power of financial performance does not operate universally; it is inactive in severely underdeveloped economies due to market apathy and dissipates in highly developed regimes due to investor complacency and reliance on strict state enforcement. The performance-induced tolerance strictly peaks at the inflection point of transitioning economies, providing a novel macro-level perspective to agency and legitimacy theories.

8.3. Managerial and policy implications

For managerial and policy implications, our findings offer specific warnings. Rather than relying on symbolic green communication in transitioning environments, managers should prioritize operational benefits for investors. Since our findings indicate that financial performance acts as a shield, firms in these regions should focus on genuine operational efficiency (as reflected by ROA) rather than leverage-driven financial engineering (i.e., ROE), which fails to mitigate risk entirely. For stakeholders and policymakers, it is highly risky to focus solely on stated sustainability activities in these transitioning regions without strict verification. Policymakers must realize that standard ESG disclosures are easily masked by high profitability; therefore, they should evaluate such activities with stricter, independent audits that look beyond the firm's financial health.

8.4. Research implications

The main motivation for greenwashing remains ambiguous, and previous studies have documented heterogeneous impacts on firm performance. In this study, we used 457 non-financial firms from European countries and concluded that the impact of greenwashing on firms' risk varies depending on the sustainability conditions and firms' financial performance. Further studies are recommended to investigate this relationship in more detail. Furthermore, we compared the firms based on the country-year sustainability development levels; other studies may come across different results when considering different benchmarking criteria (i.e., civil law vs. common law countries or market-based vs. bank-based countries). We used the divergence between the initially disclosed ESG performance and validated ESG performance as a proxy for greenwashing. Future studies are recommended to use different greenwashing indicators such as the divergence between different databases – e.g., the divergence between Bloomberg and LSEG (Ghitti *et al.*, 2024) –, or residuals obtained from the regression models – e.g., regressing relative CSR strategy against ESG performance; (Gregory, 2024). While we focused on the divergence of composite ESG scores, analysing

the divergence of individual pillars (i.e., environmental, social, and governance) may yield different conclusions regarding firm performance.

This study has several limitations. First, we have used the LSEG database to determine the greenwashing index, but this database may not fully reflect the total ESG performance of firms. Furthermore, we used both total risk and market risk to measure firm risk. Future studies are recommended to use different idiosyncratic risk indicators to capture firm risk more precisely. In this study, we used *institutional theory, legitimacy theory and agency theory,* to explain the impact of greenwashing on firms' risk. Future studies are encouraged to focus on alternative theoretical frameworks to explain the impact of greenwashing on firms' performance.

ORCID

Seyfullah Selimefendigil https://orcid.org/0000-0001-7017-9673

References

Ahmed, A., Neel, M., & Safdar, I. (2024). Why does operating profitability predict returns? New evidence on risk versus mispricing explanations. *Accounting and Finance, 64*(2), 1243–1276. http://dx.doi.org/10.1111/acfi.13178

Ahmed, M. F., Gao, Y., & Satchell, S. (2021). Modeling demand for ESG. *European Journal of Finance, 27*(16), 1669–1683. http://dx.doi.org/10.1080/1351847X.2021.1924216

Ali, S., Zahid, R. M. A., Battisti, E., & Vincurova, Z. (2025). Environmental innovation and corporate financial performance: the moderating role of greenwashing. *International Journal of Emerging Markets, 21*(2), 535–557. http://dx.doi.org/10.1108/IJOEM-09-2024-1611

Altman, E. I. (1968). The Prediction of Corporate Bankruptcy: A Discriminant Analysis. *The Journal of Finance, 23*(1), 193–194. http://dx.doi.org/10.2307/2325319

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal, 74*(3), 87–103. http://dx.doi.org/10.2469/faj.v74.n3.2

Angel, K., Menéndez-Plans, C., & Orgaz-Guerrero, N. (2018). Risk management: Comparative analysis of systematic risk and effect of the financial crisis on US tourism industry: Panel data research. *International Journal of Contemporary Hospitality Management, 30*(3), 1920–1938. http://dx.doi.org/10.1108/IJCHM-03-2016-0173

Ben-Zion, U., & Shalit, S. S. (1975). Size, leverage, and dividend record as determinants of equity risk. *The Journal of Finance, 30*(4), 1015–1026. http://dx.doi.org/10.1111/j.1540-6261.1975.tb01018.x

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies, 21*(3), 1339–1369. http://dx.doi.org/10.1093/rfs/hhn044

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115–143. http://dx.doi.org/10.1016/S0304-4076(98)00009-8

Brown, G., & Kapadia, N. (2007). Firm-specific risk and equity market development. *Journal of Financial Economics, 84*(2), 358–388. http://dx.doi.org/10.1016/j.jfineco.2006.03.003

Cai, Y., Pan, C. H., & Statman, M. (2016). Why do countries matter so much in corporate social performance? *Journal of Corporate Finance, 41*, 591–609. http://dx.doi.org/10.1016/j.jcorpfin.2016.09.004

Chen, P., & Dagestani, A. A. (2023). Greenwashing behavior and firm value–From the perspective of board characteristics. *Corporate Social Responsibility and Environmental Management, 30*(5), 2330–2343. http://dx.doi.org/10.1002/csr.2488

Christopher, R., Kim, S. J., & Wu, E. (2012). Do sovereign credit ratings influence regional stock and bond market interdependencies in emerging countries? *Journal of International Financial*

Markets, Institutions and Money, 22(4), 1070–1089. http://dx.doi.org/10.1016/j.intfin.2012.01.003

Cohen, G. (2023). ESG risks and corporate survival. *Environment Systems & Decisions, 43*(1), 16–21. http://dx.doi.org/10.1007/s10669-022-09886-8

Cormier, D., & Gordon, I. M. (2001). An examination of social and environmental reporting strategies. *Accounting, Auditing & Accountability Journal, 14*(5), 587–617. http://dx.doi.org/10.1108/EUM0000000006264

Department for Business Energy & Industrial Strategy. (2022). *Why Net Zero*. Retrieved from London: https://www.gov.uk/government/publications/net-zero-strategy/1-why-net-zero

Doh, J., Rodrigues, S., Saka-Helmhout, A., & Makhija, M. (2017). International business responses to institutional voids. *Journal of International Business Studies, 48*(3), 293–307. http://dx.doi.org/10.1057/s41267-017-0074-z

Doidge, C., Karolyi, G. A., & Stulz, R. M. (2007). Why do countries matter so much for corporate governance? *Journal of Financial Economics, 86*(1), 1–39. http://dx.doi.org/10.1016/j.jfineco.2006.09.002

Donkor, A., Djajadikerta, H. G., Mat Roni, S., & Trireksani, T. (2022). Integrated reporting quality and corporate tax avoidance practices in South Africa's listed companies. *Sustainability Accounting, Management and Policy Journal, 13*(4), 899–928. http://dx.doi.org/10.1108/SAMPJ-03-2021-0116

Dowling, J., & Pfeffer, J. (1975). Organizational legitimacy: Social values and organizational behavior. *Pacific Sociological Review, 18*(1), 122–136. http://dx.doi.org/10.2307/1388226

Du, X. (2015). How the market values greenwashing? Evidence from China. *Journal of Business Ethics, 128*(3), 547–574. http://dx.doi.org/10.1007/s10551-014-2122-y

Gallas, S., Chouchene, M. R., & Bouzgarrou, H. (2025). Greenwashing Illusion and Financial Performance: The Moderating Role of Environmental Practices. *Business Strategy & Development, 8*(4), 1–20. http://dx.doi.org/10.1002/bsd2.70234

Ghitti, M., Gianfrate, G., & Palma, L. (2024). The agency of greenwashing. *The Journal of Management and Governance, 28*(3), 905–941. http://dx.doi.org/10.1007/s10997-023-09683-8

Gregory, R. P. (2024). How greenwashing affects firm risk: An international perspective. *Journal of Risk and Financial Management, 17*(11), 1–30. http://dx.doi.org/10.3390/jrfm17110526

Habermann, F., & Fischer, F. B. (2023). Corporate Social Performance and the Likelihood of Bankruptcy: Evidence from a Period of Economic Upswing. *Journal of Business Ethics, 182*(1), 243–259. http://dx.doi.org/10.1007/s10551-021-04956-4

Hauch, S. (2026). ESG rating divergence and corporate credit risk. *The Journal of Risk Finance, 27*(1), 132–157. http://dx.doi.org/10.1108/JRF-05-2025-0236

Hawn, O., & Ioannou, I. (2016). Mind the gap: The interplay between external and internal actions in the case of corporate social responsibility. *Strategic Management Journal, 37*(13), 2569–2588. http://dx.doi.org/10.1002/smj.2464

Huang, H., Xing, X., He, Y., & Gu, X. (2020). Combating greenwashers in emerging markets: A game-theoretical exploration of firms, customers and government regulations. *Transportation Research Part E, Logistics and Transportation Review, 140*. http://dx.doi.org/10.1016/j.tre.2020.101976

Jamali, D., Lund-Thomsen, P., & Khara, N. (2017). CSR institutionalized myths in developing countries: An imminent threat of selective decoupling. *Business & Society, 56*(3), 454–486. http://dx.doi.org/10.1177/0007650315584303

Jauernig, J., & Valentinov, V. (2019). CSR as hypocrisy avoidance: A conceptual framework. *Sustainability Accounting, Management and Policy Journal, 10*(1), 2–25. http://dx.doi.org/10.1108/SAMPJ-05-2018-0141

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics, 3*(4), 305–360. http://dx.doi.org/10.1016/0304-405X(76)90026-X

Khorilov, T. G., & Kim, J. (2024). ESG and firm risk: Evidence in Korea. *Sustainability (Basel), 16*(13). http://dx.doi.org/10.3390/su16135388

Kim, E. H., & Lyon, T. P. (2015). Greenwash vs. brownwash: Exaggeration and undue modesty in corporate sustainability disclosure. *Organization Science, 26*(3), 705–723. http://dx.doi.org/10.1287/orsc.2014.0949

Korinth, F., & Lueg, R. (2022). Corporate Sustainability and Risk Management—The U-Shaped Relationships of Disaggregated ESG Rating Scores and Risk in the German Capital Market. *Sustainability (Basel), 14*(9). http://dx.doi.org/10.3390/su14095735

Kuruppu, S. C., Milne, M. J., & Tilt, C. A. (2019). Gaining, maintaining and repairing organisational legitimacy: When to report and when not to report. *Accounting, Auditing & Accountability Journal, 32*(7), 2062–2087.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. *Journal of Political Economy, 106*(6), 1113–1155. http://dx.doi.org/10.1086/250042

Landi, G. C., Iandolo, F., Renzi, A., & Rey, A. (2022). Embedding sustainability in risk management: The impact of environmental, social, and governance ratings on corporate financial risk. *Corporate Social Responsibility and Environmental Management, 29*(4), 1096–1107. http://dx.doi.org/10.1002/csr.2256

Ledeboer, P., & Kil, J. (2023). *The effects of a company's greenwashing practices on stock liquidity & stock price volatility: Evidence from the S*: Erasmus University, Erasmus School of Economics.

Li, W., Li, W., Seppänen, V., & Koivumäki, T. (2023). Effects of greenwashing on financial performance: Moderation through local environmental regulation and media coverage. *Business Strategy and the Environment, 32*(1), 820–841. http://dx.doi.org/10.1002/bse.3177

Lim, A., & Tsutsui, K. (2012). Globalization and commitment in corporate social responsibility: Cross-national analyses of institutional and political-economy effects. *American Sociological Review, 77*(1), 69–98. http://dx.doi.org/10.1177/0003122411432701

Liu, G., Qian, H., Shi, Y., Zhang, Y., & Wu, F. (2024). Does ESG report greenwashing increase stock price crash risk? *China Journal of Accounting Studies, 12*(3), 615–639. http://dx.doi.org/10.1080/21697213.2024.2303070

Long, L., Wang, C., & Zhang, M. (2025). Does social media pressure induce corporate hypocrisy? Evidence of ESG greenwashing from China. *Journal of Business Ethics, 197*(2), 311–338. http://dx.doi.org/10.1007/s10551-024-05747-3

Lueg, K., Krastev, B., & Lueg, R. (2019). Bidirectional effects between organizational sustainability disclosure and risk. *Journal of Cleaner Production, 229*, 268–277. http://dx.doi.org/10.1016/j.jclepro.2019.04.379

Lund-Thomsen, P., Lindgreen, A., & Vanhamme, J. (2016). Industrial clusters and corporate social responsibility in developing countries: What we know, what we do not know, and what we need to know. *Journal of Business Ethics, 133*(1), 9–24. http://dx.doi.org/10.1007/s10551-014-2372-8

Mao, C. W. (2019). Effect of corporate social responsibility on corporate tax avoidance: Evidence from a matching approach. *Quality & Quantity, 53*(1), 49–67. http://dx.doi.org/10.1007/s11135-018-0722-9

Marquis, C., & Toffel, M. W. (2012). *When do firms greenwash?: Corporate visibility, civil society scrutiny, and environmental disclosure*: Harvard Business School Boston.

Marquis, C., Toffel, M. W., & Zhou, Y. (2016). Scrutiny, norms, and selective disclosure: A global study of greenwashing. *Organization Science, 27*(2), 483–504. http://dx.doi.org/10.1287/orsc.2015.1039

Matos, P. (2020). *ESG and responsible institutional investing around the world: A critical review*: John Wiley & Sons.

Meles, A., Salerno, D., Sampagnaro, G., Verdoliva, V., & Zhang, J. (2023). The influence of green innovation on default risk: Evidence from Europe. *International Review of Economics & Finance, 84*, 6922–6710. http://dx.doi.org/10.1016/j.iref.2022.11.036

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470.

Mirza, R., Bhuiyan, T., & Hoque, A. (2025). False Stability? How Greenwashing Shapes Firm Risk in the Short and Long Run. *Journal of Risk and Financial Management, 18*(12). http://dx.doi.org/10.3390/jrfm18120691

Na, K., Kang, Y. H., & Kim, Y. S. (2018). The effect of corporate governance on the corruption of firms in BRICs (Brazil, Russia, India & China). *Social Sciences (Basel, Switzerland), 7*(6), 1–16. http://dx.doi.org/10.3390/socsci7060085

O'Donovan, G. (2002). Environmental disclosures in the annual report: Extending the applicability and predictive power of legitimacy theory. *Accounting, Auditing & Accountability Journal, 15*(3), 344–371. http://dx.doi.org/10.1108/09513570210435870

Ohlson, J. A. (1980). Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research, 18*(1), 109–131. http://dx.doi.org/10.2307/2490395

Patten, D. M. (1992). Intra-industry environmental disclosures in response to the Alaskan oil spill: A note on legitimacy theory. *Accounting, Organizations and Society, 17*(5), 471–475. http://dx.doi.org/10.1016/0361-3682(92)90042-Q

Philosophov, L. V., & Philosophov, V. L. (2005). Optimization of a firm's capital structure: A quantitative approach based on a probabilistic prognosis of risk and time of bankruptcy. *International Review of Financial Analysis, 14*(2), 191–209. http://dx.doi.org/10.1016/j.irfa.2004.06.010

Piotroski, J. D. (2007). Discussion of the book-to-price effect in stock returns: Accounting for leverage. *Journal of Accounting Research, 45*(2), 469–479. http://dx.doi.org/10.1111/j.1475-679X.2007.00241.x

Porter, D. C. (2010). *Essentials of econometrics*: McGraw-Hill/Irwin.

Purnamasari, P., & Umiyati, I. (2024). Greenwashing and financial performance of firms: The moderating role of internal audit quality and digital technologies. *Cogent Business & Management, 11*(1), 2404236. http://dx.doi.org/10.1080/23311975.2024.2404236

Ross, S. A. (1973). The economic theory of agency: The principal's problem. *The American Economic Review, 63*(2), 134–139.

Roulet, T. J., & Touboul, S. (2015). The intentions with which the road is paved: Attitudes to liberalism as determinants of greenwashing. *Journal of Business Ethics, 128*(2), 305–320. http://dx.doi.org/10.1007/s10551-014-2097-8

Sachs, J. D., Lafortune, G., Fuller, G., & Iablonovski, G. (2025). *Financing Sustainable Development to 2030 and Mid-Century. Sustainable Development Report 2025*. Retrieved from Paris:

Saurabh, K., Rani, N., & Upadhyay, P. (2024). Towards novel blockchain decentralised autonomous organisation (DAO) led corporate governance framework. *Technological Forecasting and Social Change, 204*. http://dx.doi.org/10.1016/j.techfore.2024.123417

Shahrour, M. H., Girerd-Potin, I., & Taramasco, O. (2021). Corporate social responsibility and firm default risk in the Eurozone: A market-based approach. *Managerial Finance, 47*(7), 975–997. http://dx.doi.org/10.1108/MF-02-2020-0063

Shakil, M. H., Pollestad, A. J., & Kyaw, K. (2025). Environmental, social and governance controversies and systematic risk: A machine learning approach. *Finance Research Letters, 75*. http://dx.doi.org/10.1016/j.frl.2025.106894

Shocker, A. D., & Sethi, S. P. (1973). An approach to incorporating societal preferences in developing corporate action strategies. *California Management Review, 15*(4), 97–105. http://dx.doi.org/10.2307/41164466

Swiss Confederation. (2025). *Supplement to Switzerland's Long-Term Climate Strategy – NDC 2031–2035*. Retrieved from https://unfccc.int/sites/default/files/resource/Supplement_Switzerland_Long_Term_Climate_Strategy_for_NDC_2031-2035_en.pdf

Testa, F., Miroshnychenko, I., Barontini, R., & Frey, M. (2018). Does it pay to be a greenwasher or a brownwasher? *Business Strategy and the Environment, 27*(7), 1104–1116. http://dx.doi.org/10.1002/bse.2058

Truong, Q. T., Tran, Q. N., Srivuttichan, T., & Chen, R. (2025). The significance of ESG performance for financial distress: New evidence. *Applied Economics Letters*, 1–7. http://dx.doi.org/10.1080/13504851.2025.2471553

Velte, P. (2025). Corporate Social Responsibility (CSR) Decoupling and Tax Avoidance: Symbolic Use of Sustainable Boards in the European Union? *Corporate Social Responsibility and Environmental Management, 32*(3), 4179–4193. http://dx.doi.org/10.1002/csr.3172

Viana, D. B. C., Lourenço, I. M. E. C., & Paulo, E. (2022). The effect of IFRS adoption on accrual-based and real earnings management: emerging markets' perspective. *Journal of Accounting in Emerging Economies, 13*(3), 485–508. http://dx.doi.org/10.1108/jaee-05-2021-0172

Vives, A. (2008). Corporate Social Responsibility: The role of law and markets and the case of developing countries. *Chicago-Kent Law Review, 83*(1).

Walker, K., & Wan, F. (2012). The harm of symbolic actions and green-washing: Corporate actions and communications on environmental performance and their financial implications. *Journal of Business Ethics, 109*(2), 227–242. http://dx.doi.org/10.1007/s10551-011-1122-4

Wang, Z., & Tian, X. (2025). From Greenwashing to Sustainability: The Mediating Effect of Green Innovation in the Agribusiness Sector on Financial Performance. *Agriculture, 15*(12). http://dx.doi.org/10.3390/agriculture15121316

Wolniak, R. (2016). *Relations between corporate social responsibility reporting and the concept of greenwashing*: Zeszyty Naukowe. Organizacja i Zarządzanie/Politechnika Śląska.

Xu, M., Tse, Y. K., Geng, R., Liu, Z., & Potter, A. (2025). Greenwashing and market value of firms: An empirical study. *International Journal of Production Economics, 284*. http://dx.doi.org/10.1016/j.ijpe.2025.109606

Yang, Z., Nguyen, T. T. H., Nguyen, H. N., Nguyen, T. T. N., & Cao, T. T. (2020). Greenwashing behaviours: Causes, taxonomy and consequences based on a systematic literature review. *Journal of Business Economics and Management, 21*(5), 1486–1507. http://dx.doi.org/10.3846/jbem.2020.13225

Zahid, R. M. A., Khan, M. K., Anwar, W., & Maqsood, U. S. (2022). The role of audit quality in the ESG-corporate financial performance nexus: Empirical evidence from Western European companies. *Borsa Istanbul Review, 22*, S200–S212. http://dx.doi.org/10.1016/j.bir.2022.08.011

Zeng, F., Wang, J., & Zeng, C. (2025). An optimized machine learning framework for predicting and interpreting corporate ESG greenwashing behavior. *PLoS One, 20*(3). http://dx.doi.org/10.1371/journal.pone.0316287

Zhang, D. (2022). Are firms motivated to greenwash by financial constraints? Evidence from global firms' data. *Journal of International Financial Management & Accounting, 33*(3), 459–479. http://dx.doi.org/10.1111/jifm.12153

Zhang, L., Li, D., Cao, C., & Huang, S. (2018). The influence of greenwashing perception on green purchasing intentions: The mediating role of green word-of-mouth and moderating role of green concern. *Journal of Cleaner Production, 187*, 740–750. http://dx.doi.org/10.1016/j.jclepro.2018.03.201

Zmijewski, M. E. (1984). Methodological Issues Related to the Estimation of Financial Distress Prediction Models. *Journal of Accounting Research, 22*, 59–82. http://dx.doi.org/10.2307/2490859

Scientific Annals of Economics and Business
73 (3), 2026, 489-507
DOI: 10.47743/saeb-2026-0036

When ESG Meets Risk and Resilience: Quantile on Quantile Connectedness Across the G7, Volatility Index, and Gold Mining Sector

Halilibrahim Gökgöz*, Aamir Aijaz Syed, Ahmed Jeribi***, Azza Bejaoui§**

Abstract: This study examines the connectedness between the G7 countries' ESG Leader indices, the CBOE Volatility Index (VIX) an indicator of market stress and the NYSE Arca Gold Miners Index (GDM), representing the gold-mining sector, using the Quantile-on-Quantile Connectedness approach. The analysis employs daily return data covering the period from January 2, 2019, to May 12, 2025. The findings reveal significant differences in the connectedness of G7 ESG Leader indices with VIX and GDM, varying according to market conditions and quantile levels. Results demonstrate that, under normal market conditions, ESG indices exhibit stronger connectedness with VIX. However, during periods of heightened market volatility, connectedness with GDM intensifies. Additionally, the notably high connectedness at reverse quantile levels emphasises the importance of monitoring the gold sector under varying market scenarios when assessing ESG investment performance. Furthermore, global economic and political events during the studied period, such as the COVID-19 pandemic, the Ukraine-Russia conflict, the SVB collapse, the Israel-Palestine conflict, and Trump's tariff implementations, significantly impact these connectedness measures, with the nature of the impact varying according to event type. Consequently, for ESG investors, adopting a dynamic, quantile-based monitoring strategy sensitive to market conditions is crucial. The study suggests that tracking VIX during normal market conditions and focusing on GDM during crisis periods would be more effective for portfolio diversification and risk management. The study is an original work; inclusion of GDM offers a more nuanced insight into the equity performance of gold mining companies, which frequently exhibit varying behaviours, particularly in times of financial distress. Furthermore, the integration of VIX as an indicator

* Afyon Kocatepe University, Faculty of Economics and Administrative Sciences, Turkey; e-mail: *hgokgoz@aku.edu.tr* (corresponding author).
** School of Business, Chandigarh University, Uttar Pradesh, Unnao Campus, India; e-mail: *aamir.l100960@culko.in*.
*** Faculty of Economics and Management of Sfax, University of Sfax, Tunisia; e-mail: *ahmedjeribi07@yahoo.fr*.
§ Higher School of Commerce of Tunis, University of Manouba, Tunisia; e-mail: *bjaouiazza@gmail.com*.

Article history: Received 23 September 2025 | Accepted 17 September 2026 | Published online 29 September 2026

To cite this article: Gökgöz, H., Syed, A. A., Jeribi, A., Bejaoui, A. (2026). When ESG Meets Risk and Resilience: Quantile on Quantile Connectedness Across the G7, Volatility Index, and Gold Mining Sector. *Scientific Annals of Economics and Business*, 73(3), 489-507. https://doi.org/10.47743/saeb-2026-0036.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

for market uncertainty enable the paper to effectively reflect the transmission of financial shocks emanating from the U.S. market.

Keywords: ESG Leader Indices; VIX; GDM; Quantile on Quantile Connectedness.

JEL classification: C32; G11; G15; Q02; Q56.

1. INTRODUCTION

Recently, various catastrophic events, including the COVID-19 pandemic, the Russia-Ukraine War, the Israel-Palestine Conflict, and the U.S.-China trade war, have led to significant uncertainties and unpredictability within the global financial markets (Sheikh *et al.*, 2024). The influence of these uncertainties and unpredictability on the financial market has become more pronounced due to growing financial and economic integration. Existing literature indicates that due to increasing financial integration, the effects of uncertainties and unpredictability can be readily observed across a wide range of financial assets, including traditional stock markets, commodities markets, and digital assets, among others (Vo and Ellis, 2018). In the quest to mitigate the adverse implications of raising volatility and uncertainties among the financial assets, as well as to explore alternative safe haven assets, numerous studies have been conducted to evaluate the level of financial interconnectedness within the traditional and evolving financial instruments. For instance, Mensi *et al.* (2021) investigated the volatility and stock market connectedness among 16 international equity markets; Bahloul and Khemakhem (2021) explored the return and volatility connectedness between commodities and the Islamic stock market; Khalfaoui *et al.* (2022) examined the connectedness and spillover effects between digital assets, green assets and the traditional equity market; Wang *et al.* (2023) explore the interconnection and risk transmission between the foreign exchange market and global stock indexes, etc. In addition to the aforementioned studies, numerous other scholars have also explored market interconnectedness and spillover effects among a range of financial assets (please see (Khalfaoui *et al.*, 2023; Hanif *et al.*, 2024; Ben Salem and El Aoun, 2025)). Most of the aforementioned studies concluded that strong market interconnectedness and spillover effects exist between several financial assets. Some studies projected that developed countries' stock markets are the net transmitter of risk, whereas some studies indicate that developing countries' stock markets are the net transmitter of risk (Mensi *et al.*, 2021). Additionally, a few studies also conclude that under specific economic conditions some commodities are immune to traditional equity market volatility and serve as potential safe haven assets (de Boyrie and Pavlova, 2024). However, some existing literature challenges this viewpoint by discounting the safe-haven potential of specific commodities in relation to traditional equity market volatility. These inconclusive outcomes and the potential to choose alternative asset classes motivated investors to explore alternative options that could boost portfolio diversification and provide a hedge against risk transmission stemming from market interconnectedness amid fluctuating economic conditions.

The quest for alternative financial assets has recently drawn investors' attention toward sustainable investment options. Among the widely available sustainable investment alternatives, Environmental, Social, and Governance (ESG) investing has surfaced as a crucial component in global financial markets, garnering increasing interest among investors, policymakers, and scholars alike. Existing literature indicates that investor interest toward environmental sustainability compelled stakeholders in financial markets to inculcate ESG

dimensions in their decision-making (Alharbi *et al.*, 2025). The integration of ESG factors into investment strategies has experienced notable expansion, especially following the post-pandemic period. Moreover, the inclusion of ESG in one of the 17 United Nations' sustainable development goals (SDGs) has significantly contributed to the substantial growth of ESG investments. This is evidenced by the current valuation of the ESG investing market at USD 27,480 billion in 2023, with projections indicating it will reach USD 130,880 billion by 2032, exhibiting a compound annual growth rate of 17.31% from 2024 to 2032. The recent expansions in the ESG investing market can also be correlated with the growth in ESG-focused indices across developed and emerging economies. Existing literature claims that investment decisions that include ESG dimensions are characterised by higher returns, lower risk during market uncertainty, foster reputation management, and have a healthy environmental and social impact (Alharbi *et al.*, 2025). Globally, ESG indices have witnessed a significant increase in sustainable investment flows. However, existing literature indicates that these indices may perform similarly to conventional investments and might be susceptible to financial shocks and economic uncertainties (Alda, 2021). The recent growing global uncertainties stemming from events like the Russia-Ukraine War, the Israel-Palestine conflict, the U.S.-China trade war and the India-Pakistan border conflict and the concern about the effect of risk transmission due to financial integration both within and from other financial markets on ESG investments warrant an investigation on the market interconnectedness of ESG investments with key financial indicators in response to the evolving global landscape.

Recently, due to the raising trend toward ESG investments, numerous scholars have examined the interconnectedness of ESG investments with prominent conventional markets (de Boyrie and Pavlova, 2024; Naeem *et al.*, 2024; Sharma and Rani, 2025). Most of the aforementioned studies explained that ESG investment alternatives are sensitive to broader market sentiment and risk factors. However, studies exploring the dynamic connectedness of ESG indices against exclusive market volatility indices and commodity-linked assets are still in a developing state. The present study offers a novel perspective to the existing body of literature by integrating both the GDM and the VIX into the analysis of financial contagion and market linkages. While existing studies have predominantly focused on broad market indices or commodity prices such as spot gold, the inclusion of GDM offers a more detailed insight into the equity performance of gold mining companies, which frequently exhibit distinct behaviours compared to physical gold, particularly in diverse market conditions. Moreover, the integration of VIX as an indicator for market uncertainty allows the paper to effectively capture the transmission of financial shocks that stem from the U.S. market. By examining the role of VIX, this study is able to assess how investor fear and volatility in American markets potentially spill over to other asset classes and international financial systems, thereby enhancing the understanding of global risk transmission mechanisms. The incorporation of both GDM and VIX adds originality and unique dimensions, setting it apart from existing literature that often overlooks these critical elements. Additionally, most of the studies on the interconnectedness of ESG investments and conventional financial assets focus on specific market conditions (Alda, 2021). Nonetheless, with the exception of a limited number of studies, there is no existing literature that has explored the dynamic interconnectedness of ESG indices across varying market conditions. Motivated by these research gaps, this study investigates the connectedness of G7 ESG Leader indices with market stress indicators – namely, the VIX and the GDM – using the Quantile-on-Quantile Connectedness (QQC) approach.

The study contributes to the existing literature in several ways. First, unlike the existing literature, which focuses on specific ESG indices, the present study contributes by exploring the dynamic interconnectedness of G7 ESG leader indices. G7 ESG leader indices are included because the G7 countries, i.e., the U.K., the USA, Canada, France, Germany, and Italy, represent the world's largest and most advanced economies. These economies account for more than 40 percent of the global GDP and contribute around 25 percent of global greenhouse gas emissions. Their considerable economic footprints highlight their essential role in the development of a global ESG standard. Moreover, existing literature also indicates the G7 nations are the major investors in renewable and sustainable infrastructure (Erdogan *et al.*, 2023). Notably, the United States, France, Germany, the United Kingdom, and Japan rank among the top contributors to global renewable energy investment. Their contribution toward clean and sustainable infrastructure not only adds to their own goals of carbon neutrality but also serves as a model for other nations to follow. Furthermore, investigating G7 nations is crucial because the ESG market structure, investor sentiments, and market conditions differ significantly among these economies. As such, the empirical estimation of the dynamic interconnectedness in context with the G7 economies will contribute by capturing asymmetries and heterogeneous responses to hedging effectiveness and provide valuable insights for globally diversified ESG portfolios. Second, the study contributes not only by exploring the dynamic connectedness within G7 ESG leader indices but also by examining how these indices connect with VIX and GDM indices across varying market conditions. Investigating the dynamic connectedness between G7 ESG and VIX indices will offer critical insight to comprehend how sustainable investments react to global uncertainty, especially during financial distress. The VIX index, commonly referred to as the fear index, explains investor sentiments and market volatility. Investigating the time-varying nature of interconnectedness between ESG investments and VIX will contribute to unveil how ESG investments react asymmetrically to evolving volatility regimes, stable during normal periods but vulnerable under stress, which is critical for investors looking to manage risk and for policymakers attempting to construct robust sustainable finance systems. Additionally, including GDM in our empirical analysis further contributes to the existing literature, which mostly concentrates on gold as a safe haven asset. The gold mining sector exhibits sensitivity to commodity fluctuations and follows a cyclical pattern. Unlike physical gold, its performance is closely linked to operational factors, geopolitical influences, and ESG considerations, particularly given the significant environmental externalities associated with mining activities. These characteristics make GDM a relevant proxy for examining the interaction between ESG-related equity markets and commodity-linked equity exposure under different market conditions. Moreover, existing literature indicates that GDM acts as a substitute for safe havens and commodity exposure, frequently moving in a countercyclical manner relative to equities. Therefore, exploring the dynamic connectedness with G7 ESG and GDM will contribute to understand shock transmission within sustainability-focused and commodity-orientated markets, which will assist in risk management and portfolio diversification. Finally, it methodologically contributes by applying the QQC approach to assess connectedness across different market quantiles, unlike conventional VAR or TVP-VAR models, thus offering regime-specific insights into ESG market connectedness. Specifically, we applied the concept of reverse total connectedness in the context of stress conditions and direct total connectedness during normal market conditions, along with their

differential, to measure regime-sensitive spillover effects, which will assist to offer a novel insight on market connectedness under varying market conditions and quantiles.

The paper is further summarised as follows. Section 2 provides the detailed overview of existing literature. Section 3 discusses the methodology employed. Section 4 presents in detail the result and analysis, and finally, the last section encompasses the concluding remarks.

2. LITERATURE REVIEW

Due to growing financial integration, numerous studies have been conducted to model volatility, dynamic interconnectedness, spillover effects, and co-movements among traditional assets and commodity markets. However, recently, the excessive volatility of conventional assets and the rising environmental concerns have also attracted investors' interest toward ESG investment alternatives. The following sections provide a detailed overview of existing literature, focussing on dynamic interconnectedness and spillover involving traditional assets, commodities, and alternative investments, such as ESG investments.

Emphasising the significance of dynamic market interconnectedness, Syllignakis and Kouretas (2011) conducted one of the pioneering studies by investigating the dynamic conditional correlation between weekly returns of seven emerging stock markets of Central and Eastern Europe and concluded that during the financial crisis, Central European markets are closely connected with the U.S. and the German markets. However, post-crisis, there was a regime shift in the connectedness among these markets, i.e., the usual pattern of movement between markets was varied during the crisis compared to the normal period. In a similar context, Ahmad *et al.* (2013) investigated the market interdependency among the financial markets of BRICS and GIPSI countries during the Eurozone crisis period. The empirical outcome of the multivariate DCC–GARCH model indicates that the financial markets of BRICS countries are strongly influenced by the GIPSI countries during the Eurozone crisis period. Alongside the aforementioned pioneering studies on financial market interconnectedness, numerous other scholars also attempted to explore the interconnectedness among the financial markets through several dimensions and methodologies. However, the literature on financial market interconnectedness rose significantly due to the significant contribution from new models like the Diebold and Yilmaz (2014) model, which was best suited to measure how shocks spillover among different markets, indicating their direction and magnitude of interconnectedness. Using the aforementioned model, Zhang (2017) revisited the market connectedness between oil and stock market returns from the global perspective. The author concluded that the interconnectedness between the oil and stock markets is limited. However, large shocks in the oil prices have a significant influence on the global stock market's returns. Rehman *et al.* (2018), by extending the Diebold and Yilmaz (2014) framework, investigated the time-varying connectedness between oil prices and precious metals returns and concluded that during the financial crisis there was a notable increase in the time-varying effect of oil shocks on the precious metals except for gold. The author also highlighted the hedging potential of palladium against oil price shocks. Connectedness applications have also extended to energy markets. Arifoğlu *et al.* (2023), using a connectedness approach for Türkiye electricity markets, show that the relationship between intraday electricity prices, day-ahead prices, and electricity generation sources changes over time and is affected by global events. Existing literature indicates that the studies employing the Diebold and Yilmaz (2014) model, although providing intriguing outcomes, fail to capture nonlinearities or asymmetric responses under different

market conditions. Recently, this limitation has prompted the exploration of quantile-based methods, which facilitate the representation of dependence between two variables throughout their entire conditional distribution and address extreme tail behaviours that are often neglected in linear or average-based analyses.

In this context, several studies have recently applied the QQR approach to ascertain the dynamic market connectedness between a wide array of financial assets. For instance, Dong *et al.* (2022) investigated the time-varying connectedness and asymmetric effect of the Covid-19 pandemic on global stock sectors. The empirical estimate indicated that during COVID-19, there was a sharp increase in the time-varying connectedness of the global stock sector. However, this effect was not uniform across all sectors, and the daily volatility in stock returns exhibited variations corresponding to the daily fluctuations in Covid-19 cases and fatalities. In a similar vein, Shang and Hamori (2024) examined the quantile time frequency connectedness between crude oil, gold, financial markets, and macroeconomic indicators within the United States and the European Union. The empirical outcome reveals that oil is the primary source of shocks within both regions, whereas gold sends only long-term shocks. The study also indicates that the U.S. market volatility varies as per the bullish and bearish trends, whereas the EU markets exhibit greater balance and stability. Similarly, Chen *et al.* (2024) examined the dynamic connectedness between commodity and financial markets and also explored how various forms of uncertainties like EPU, VIX and GPR interact with this connectedness. The findings indicate that a strong time-varying connectedness exists between commodities and the conventional financial markets. Additionally, the selected uncertainties, i.e., EPU, VIX, and GPR, alter this connectivity depending on market conditions and investment horizons. In addition to the aforementioned studies, several other authors also attempted to examine the dynamic connectedness between various forms of financial assets across diverse market conditions (Afşar *et al.*, 2025; Singh *et al.*, 2025). Recent quantile-based network methods have extended connectedness analysis toward directionality, simultaneity, and network heterogeneity. Quantile Granger causality is useful for examining predictive links across distributional tails (Karpman *et al.*, 2022), whereas DNQR and TGNQ-type models are more suitable for predetermined or high-dimensional network structures (Liu *et al.*, 2024; Xu *et al.*, 2024). The approaches mentioned are complementary to the current study; however, our objective extends beyond simply estimating a high-dimensional ESG network or testing formal quantile causality. Instead, this research focuses on the pairwise cross-quantile connectedness between each G7 ESG Leader index and VIX/GDM. Therefore, QQC is better suited to distinguish between direct and reverse quantile spillovers in this study.

Conclusively, the aforementioned literature review indicates that from time to time numerous studies have investigated the nature and dynamics of financial market connectedness under varying market conditions using a diverse range of methodologies and financial assets. Nevertheless, the review of existing literature indicates that most of the aforementioned studies are centred around conventional stock markets, mostly oil prices, digital assets, and a few selected precious metals. Most of the above studies concluded strong market interconnectedness and spillover among the conventional stock indices. Additionally, the studies reported that market connectedness among the conventional stock indices is volatile and subject to variations in market conditions, such as bullish and bearish trends. A few studies also suggested strong market interconnectedness and risk transmission from the conventional stock indices to commodities markets and vice versa. A strand of literature exhibits strong risk transmission from the commodities to the conventional stock market

returns, whereas few studies reported contradictory outcomes. Recently, in pursuit of improved investment alternatives that can offer enhanced hedging and risk diversification compared to conventional assets across fluctuating market conditions and in light of increasing environmental concerns, researchers have also started to explore the potential of ESG investments relative to traditional assets. For instance, Ferrer *et al.* (2018) investigated the time-varying interconnectedness between ESG stocks and oil prices and suggested that oil price is not the significant driver for ESG stocks. On the contrary, Saeed *et al.* (2021) indicated that energy stocks are the net transmitters of shocks to the oil markets. Cagli *et al.* (2023) examined the dynamic connectedness between ESG investing and commodity markets and concluded the ESG investment alternatives are the net transmitters of shocks, whereas all the selected commodities except crude oil are the net shock receivers. Also, Celik *et al.* (2025) examine asymmetric interconnectedness among green, sustainable, and environmental markets and show that connectedness varies according to the direction of shocks, with negative shocks during turbulent periods increasing dynamic connectedness among these markets. Additionally, scholars also attempted to explore the performance of ESG investments against conventional stock indices; for instance, Wang *et al.* (2023) employed a TVP-VAR model to examine the return and volatility transmission between ESG leader indices and G7 traditional equity markets. In a related sustainable-finance setting, Demir (2024) examines the dynamic connectedness between investor sentiment indicators and U.S. conventional and green bond markets using a Q-VAR framework and reports that VIX and MOVE act as volatility transmitters, while the bond market indices are positioned as volatility receivers. The empirical estimates indicate a significant level of connectedness between ESG and traditional equity markets, and ESG leader indices are the net transmitters of return and volatility spillover to the conventional equity markets. However, there are few authors who have contradicted the above outcome (de Boyrie and Pavlova, 2024; Alharbi *et al.*, 2025).

The aforementioned literature review indicates that the literature on ESG investment alternatives is in a developing phase, and most of the existing literature focuses on exploring the dynamic connectedness of ESG investments in context to conventional stock indices and selected commodities. As per the author's knowledge, there is no specific study that has examined the dynamic connectedness of ESG investments against systemic risk indicators such as the VIX. Additionally, although a limited number of studies have examined the interconnectedness of ESG investments with commodities, including gold, there is no specific study that has examined the interconnectedness and risk spillover of ESG investments with real, financial, and commodity-linked assets, such as GDM under extreme market conditions. The inclusion of GDM adds a novel dimension to the existing literature, as it exhibits the performance of gold mining equities, which are influenced not only by fluctuations in gold prices but also by macroeconomic and geopolitical risks, thus providing a sector-specific perspective on investor sentiment during times of stress. Additionally, the inclusion of VIX as a measure of U.S. financial stress and uncertainty permits us to analyse how disturbances in the American market influence ESG-related assets on a global scale. The incorporation of both the aforementioned measures facilitates a more detailed exploration of tail-risk dependencies and asymmetric spillover effects across varying market conditions, an area that continues to be inadequately addressed in the existing research. Moreover, the literature also indicates that most of the existing literature on ESG investments focuses on specific ESG-related stocks or country-specific ESG indices; there is a dearth of literature on ESG investments, which evaluate a comprehensive and a well-diversified and developed ESG market. Therefore, against this

backdrop, the present study attempts to investigate the dynamic connectedness of G7 ESG leader indices with VIX and GDM indices under varying market conditions. The study adds to the existing literature on ESG investment by bridging two different but similar risk alternatives, that is, volatility shocks and safe-haven dynamics. Furthermore, unlike most of the existing literature on ESG investments, which employs linear and mean-based techniques, the present study also adds to it by employing non-linear and distribution-sensitive methods to capture the behaviour of the aforementioned assets under varying market conditions. The applications of QVAR and the reverse and direct total connectedness approach will assist to comprehend how connectedness varies across different distributions and market conditions, which will have direct implications on asset allocation, hedging and policy formulation within the realm of sustainable finance and risk management. The subsequent section provides a detailed explanation of the data description and methodology employed.

3. METHODOLOGY AND DATA

3.1. Quantile on Quantile Connectedness

This study investigates the relationship between the ESG Leader indices of the G7 countries, the VIX – a market uncertainty and stress indicator – and the GDM – an indicator for the gold mining sector. The methodology applied in this research is the Quantile-on-Quantile Connectedness approach developed by Gabauer and Stenfors (2024), an extended version of the Quantile Connectedness method proposed initially by Chatziantoniou *et al.* (2021), which allows connectedness to vary simultaneously across different quantiles. This method enables a dynamic analysis of G7 ESG Leader indices, VIX, and GDM relationships across varying market conditions and quantile levels. Thus, interactions can be comprehensively captured not only in normal market states but also during periods characterized by high volatility – such as when ESG indices, VIX, and GDM are increasing or decreasing simultaneously or moving inversely to each other (e.g., ESG indices rising/falling while VIX and GDM are falling/rising).

$$Q_t = \mu(\tau) + \sum_{l=1}^{p} B_l(\tau) x_{t-j} + u_t(\tau) \tag{1}$$

The vector and its lagged form are defined as endogenous variable vectors of dimension. The symbol represents quantile levels within the interval [0,1], whereas p indicates the selected lag order for the QVAR model. Additionally, is the conditional mean vector of dimension , and is a coefficient matrix of dimension associated with the QVAR framework. Furthermore, refers to the error vector with dimension , possessing an accompanying variance-covariance matrix, , also of dimension .

To facilitate the calculation of the generalized forecast error variance decomposition (GFEVD), as introduced by Koop *et al.* (1996), we convert the QVAR model into a QVMA representation by employing the Wold decomposition theorem. This yields the following transformation:

$$Q_t = \mu(\tau) + \sum_{l=1}^{p} B_j(\tau) Q_{t-l} + u_t(\tau) = \mu(\tau) + \sum_{k=0}^{\infty} A_i(\tau) u_{t-k}(\tau) \quad (2)$$

The H-step ahead GFEVD subsequently captures the influence of shocks originating from variable on variable . This relationship is formally expressed using an indicator vector, defined as an vector of zeros except for a single unit at the “”th position:

$$\phi^{g}_{k\leftarrow l,\tau}(H) = \frac{\sum_{h=0}^{H-1} \left(\boldsymbol{e}_i' \boldsymbol{A}_f(\boldsymbol{\tau}) \boldsymbol{F}(\boldsymbol{\tau}) \boldsymbol{e}_j\right)^2}{\boldsymbol{F}_{kk}(\boldsymbol{\tau}) \sum_{h=0}^{H-1} \left(\boldsymbol{e}_i' \boldsymbol{A}_f(\boldsymbol{\tau}) \boldsymbol{F}(\boldsymbol{\tau}) \boldsymbol{A}_f(\boldsymbol{\tau})' \boldsymbol{e}_k\right)} \; g\mathrm{SOT}_{k\leftarrow l,\tau}(H) = \frac{\phi^{g}_{i\leftarrow l,\tau}(H)}{\sum_{l=1}^{n} \phi^{g}_{k\leftarrow l,\tau}(H)} \quad (3)$$

Since the rows of the GFEVD, denoted , do not sum to one, Diebold and Yilmaz (2014) propose normalization by dividing each element by its respective row sum. The resulting normalized measure is termed the scaled GFEVD, symbolized as .

This scaled GFEVD constitutes the core of the connectedness analysis. It is employed in calculating directional connectedness measures, specifically the total directional connectedness TO (FROM) other variables. The TO measure indicates the aggregate impact exerted by series on all other series in the system, whereas the FROM measure captures the cumulative effect of all series on series . Formally, these measures can be defined accordingly.

$$C^{\text{gen,to}}_{k\rightarrow,\tau} = \sum_{n=1,k\neq l}^{N} gSOT_{n\leftarrow k,\tau} \quad (4)$$

$$C^{\text{gen,from}}_{k\leftarrow,\tau} = \sum_{n=1,k\neq l}^{N} gSOT_{k\leftarrow n,\tau} \quad (5)$$

The difference between total directional connectedness TO and FROM yields the NET directional connectedness for series.

$$C^{\text{gen,net}}_{k,\tau} = C^{\text{gen,to}}_{k\rightarrow,\tau} - C^{\text{gen,from}}_{k\leftarrow,\tau} \quad (6)$$

A positive net directional connectedness, implies that series k acts predominantly as a transmitter of shocks to other variables, while a negative net directional connectedness, indicates that series k is predominantly a recipient of shocks from others.

Ultimately, an adjusted total connectedness index (TCI), ranged within [0,1], is computed. This index provides a succinct measure of the extent of interconnectedness within the network. A higher TCI indicates greater market risk, reflecting elevated systemic interconnectedness (Gabauer and Stenfors, 2024):

$$TCI_{\tau}(H) = \frac{N}{N-1}\sum_{n=1}^{N} C_{n\leftarrow,\tau}^{\text{gen,from}} \equiv \frac{N}{N-1}\sum_{n=1}^{N} C_{n\leftarrow,\tau}^{\text{gen,to}} \quad (7)$$

In the empirical implementation, separate country-specific bivariate QQC-QVAR systems are estimated. For each G7 country c, two systems are considered: (ESG_c, VIX) and (ESG_c, GDM), and the reported TCI values should be interpreted as pairwise connectedness measures. The lag length is selected automatically according to the Bayesian Information Criterion, and the baseline specification uses a 200-day rolling window and a 20-step-ahead forecast horizon.

3.2. Data

In this study, we use daily return data covering the period from January 2, 2019, to May 12, 2025, for the G7 countries' ESG Leader indices (USA, CAN, UK, FRA, GER, ITA, JAP), the VIX, and the GDM. VIX is also expressed as a return series to focus on changes in implied-volatility conditions and to maintain consistency with the return-based ESG and GDM series. The G7 ESG Leader indices data are obtained from msci.com, while VIX and GDM data are sourced from investing.com. Table no. 1 presents the descriptive statistics for the dataset.

Table no. 1 – Descriptive Statistics

	USA	CAN	UK	FRA	GER	ITA	JAP	VIX	GDM
Mean.	0.0006	0.0004	0.0003	0.0003	0.0004	0.0005	0.0003	0.0031	0.0007
Med.	0.0005	0.0005	0.0005	0.0007	0.0007	0.0010	0.0002	-0.0071	0.0003
Max.	0.0992	0.1226	0.0932	0.0898	0.1018	0.0833	0.0895	0.7404	0.1452
Min.	-0.1212	-0.1302	-0.1241	-0.1389	-0.1325	-0.1825	-0.0955	-0.3575	-0.1057
Std. Dev.	0.0131	0.0127	0.0121	0.0135	0.0138	0.0147	0.0126	0.0839	0.0199
Skew.	-0.2851	-0.8498	-0.6820	-0.6175	-0.3481	-1.4475	-0.0111	2.1390	0.1634
Kur.	16.3744	25.6566	15.7490	13.9696	13.4977	21.1149	11.2584	15.1900	7.1384
JB	12148.33*	34994.82*	11144.74*	8260.92*	7503.553*	22814.05*	4623.504*	11314.28*	1168.274*
LB Q^2 (5)	1149.57*	978.531*	278.409*	214.838*	166.007*	144.924*	417.698*	62.5841*	518.292*
LB Q^2 (10)	1840.94*	1501.31*	717.532*	443.187*	410.765*	190.492*	459.326*	69.2038*	722.357*
LB Q^2 (20)	2157.37*	1697.66*	800.689*	514.328*	478.923*	209.922*	464.09*	74.4247*	941.016*
ADF	-12.4303*	-13.9185*	-14.8294*	-40.0081*	-14.6981*	-26.5253*	-44.3234*	-42.8816*	-34.892*
Correlations	**USA**	**CAN**	**UK**	**FRA**	**GER**	**ITA**	**JAP**		
VIX	-0.7143	-0.5522	-0.3247	-0.3655	-0.3694	-0.3823	-0.0770		
GDM	0.2788	0.4058	0.3000	0.2818	0.2993	0.2718	0.2035		

All series display positive average returns. The series with the highest standard deviation is VIX, followed by GDM. JB (Jarque-Bera) test statistics indicate non-normality for all series, while ADF (Augmented Dickey-Fuller) tests confirm stationarity across all variables. LB (Ljung-Box) test results on squared residuals also reveal autocorrelation, implying heteroskedasticity within the return series. Furthermore, Pearson correlation coefficients illustrate a negative correlation between the G7 ESG Leader indices and VIX, whereas correlations with GDM are positive. Given that the observation period of this study encompasses significant global economic, health-related, and political events such as COVID-19 (March 2020), the Ukraine-Russia conflict (February 2022), the Silicon Valley Bank (SVB) collapse (March 2023), the Israel-Palestine conflict (October 2023), and Trump's tariff implementations (April 2025), interactions among these series are expected to be influenced by these events and may exhibit temporal variability. Consequently, employing a dynamic modelling approach becomes crucial.

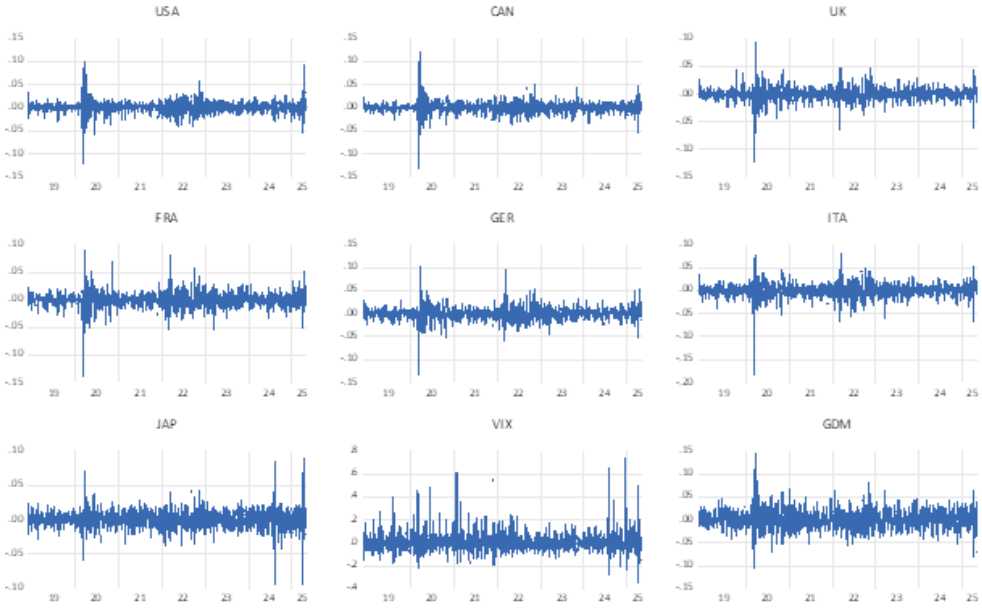


Figure no. 1 – Time Series Graphs of Return Series

Figure no. 1 displays the time-series plots of the analyzed series, highlighting their variability and volatility over time. Notably, periods of increased volatility in the series align closely with the aforementioned global events. The onset of COVID-19 (March 2020) and Trump's tariff implementations (April 2025) demonstrate notably pronounced common impacts across all series. Furthermore, the initiation of the Ukraine-Russia conflict (February 2022) has significantly affected the UK, FRA, GER, and ITA series, while the 7.6-magnitude earthquake in Japan in August 2024 distinctly impacted the JAP and VIX series.

4. EMPIRICAL RESULTS

This part of the study presents empirical findings related to Quantile-on-Quantile Connectedness measures. We illustrate static and dynamic pairwise connectedness between the G7 ESG Leader indices, GDM, and VIX across various market conditions and cross-quantiles to achieve this. Table no. 2 provides the average total connectedness between the G7 ESG Leader indices and GDM and VIX at different quantile levels.

The total connectedness results show that overall pairwise connectedness between G7 ESG Leader indices, GDM, and VIX is generally higher in extreme same-quantile states (0.05-0.05 or 0.95-0.95) and reverse-tail states (0.05-0.95 or 0.95-0.05) compared to normal market conditions (0.5-0.5). The intermediate quantiles (0.25 and 0.75) further indicate that connectedness is not uniformly distributed across the quantile grid, with stronger spillover patterns remaining concentrated in tail and reverse-tail combinations. However, total connectedness varies according to both VIX and GDM, as well as by individual ESG Leader indices.

Table no. 2 – Averaged pairwise dynamic quantile-on-quantile total connectedness

		0.05		0.25		0.5		0.75		0.95	
		VIX	GDM	VIX	GDM	VIX	GDM	VIX	GDM	VIX	GDM
0.95	USA	47.69	77.14	38.86	54.04	62.62	47.32	42.33	55.45	56.54	76.02
	CAN	51.65	82.68	34.49	64.38	54.9	58.06	38.44	65.49	57.3	81.7
	UK	57.19	78.23	34.48	55.34	44.84	47.77	35.2	56.88	61.26	77.43
	FRA	53.38	76.99	32.88	54.81	45.68	46.71	35.2	55.93	59.07	76.78
	GER	55.37	77.72	34.28	54.99	47.33	47.39	36.22	56.5	59.16	76.73
	ITA	54.94	75.83	34.5	53.62	48.03	45.13	37.4	54.6	60.7	75.02
	JAP	68.24	75.8	44.89	50.78	42.06	42.17	45.12	52.13	74.22	74.66
0.75	USA	35.27	57.05	26.44	33.95	50.2	27.23	29.9	35.36	44.12	55.93
	CAN	32.55	66.31	15.4	48.01	35.81	41.69	19.36	49.13	38.2	65.32
	UK	31.61	57.72	8.9	34.83	19.27	27.26	9.62	36.37	35.68	56.92
	FRA	30.45	55.57	9.96	33.39	22.76	25.29	12.28	34.51	36.15	55.36
	GER	31.3	57.43	10.2	34.7	23.25	27.09	12.14	36.21	35.08	56.43
	ITA	29.5	24.78	9.06	33.27	22.59	24.78	8.19	32.55	35.26	54.68
	JAP	47.65	53.85	24.53	30.18	21.47	20.23	24.53	30.19	53.63	52.72
0.5	USA	56.42	48.34	47.59	25.24	71.35	18.52	51.06	26.65	65.27	47.22
	CAN	49.45	58.57	32.29	40.27	52.7	33.95	36.24	41.38	55.09	57.59
	UK	40.38	50.07	17.67	27.18	28.04	19.62	18.39	28.72	44.45	49.27
	FRA	40.14	47.01	19.65	25	32.44	16.73	21.97	25.95	45.84	46.8
	GER	41.8	48.95	20.7	26.22	33.75	18.61	22.64	27.73	45.58	47.95
	ITA	40.38	46.29	19.95	24.08	33.48	15.59	22.85	25.06	46.15	45.49
	JAP	45.91	44.62	22.56	19.6	19.73	10.99	22.79	20.95	51.9	43.48
0.25	USA	32.69	55.36	23.86	32.26	47.62	25.54	27.33	33.67	41.54	54.24
	CAN	30.76	65	13.61	46.7	34.02	40.38	17.56	47.81	36.41	64.01
	UK	34.99	57.32	12.28	34.42	22.05	26.86	13	35.97	39.06	56.52
	FRA	30.79	54.8	10.3	32.62	23.1	24.52	12.62	33.74	36.49	54.59
	GER	33.31	55.88	12.22	33.15	25.26	25.54	27.11	33.15	37.09	54.88
	ITA	28.62	54.75	8.19	32.55	21.71	24.05	11.08	33.52	34.38	53.95
	JAP	49.82	52.68	26.47	27.66	23.64	19.06	26.7	29.01	55.8	51.55
0.05	USA	42.02	78.22	33.19	55.12	56.95	48.4	36.66	54.82	50.87	77.1
	CAN	46.18	83.41	28.93	65.11	49.44	58.79	32.98	66.22	51.83	82.42
	UK	52.67	79.07	29.97	56.19	40.33	48.62	30.69	57.73	56.74	78.27
	FRA	49.15	76.88	28.66	54.69	41.45	46.59	30.98	55.81	54.85	76.66
	GER	49.1	77.98	28.01	55.25	41.06	47.64	29.95	56.76	52.89	76.98
	ITA	47.32	76.54	26.89	54.34	40.41	45.85	29.79	55.32	53.08	75.74
	JAP	64.2	76.97	40.85	51.95	38.02	43.34	41.08	53.3	70.19	75.83

Note: The results are based on separate country-specific bivariate QQC-QVAR systems. For each country, two pairwise systems are estimated: (ESG_c, VIX) and (ESG_c, GDM). The row quantile refers to the ESG Leader index, while the column quantile refers to VIX or GDM. The baseline specification uses a 200-day rolling window, an automatically selected lag length based on BIC, and a 20-step-ahead forecast horizon. The quantile grid is (0.05,0.25,0.50,0.75,0.95). The magnitude of the TCI values increases progressively from light blue to dark blue. All TCI values are reported in percentage terms.

Connectedness values with GDM are generally higher compared to those with VIX, particularly in tail and reverse-tail quantile states. However, the median same-quantile state (0.5-0.5) displays a different pattern: VIX-related connectedness is higher than GDM-related connectedness across the G7 ESG Leader indices, with particularly high values for the USA and Canada. Thus, while G7 ESG Leader indices exhibit stronger connectedness with VIX under normal market conditions, connectedness with GDM is higher in extreme and reverse-tail market conditions. This suggests that, under stress-related and reverse-tail scenarios, G7 ESG Leader indices have closer relationships with the gold mining sector, whereas VIX remains more informative under normal market conditions. This finding implies that ESG

investors in G7 countries should adjust their performance-tracking strategies based on market conditions. Specifically, while monitoring market stress indicators might be more effective under normal conditions, focusing on GDM during extreme rises or falls in the gold sector may offer better insights for ESG market tracking. Furthermore, the weaker connectedness with GDM under normal conditions indicates that gold-mining equities may offer diversification potential for ESG-inclusive portfolios in calmer market states. However, these benefits may diminish during periods of significant market volatility.

Connectedness between the G7 ESG Leader indices and GDM is especially pronounced at extreme same-quantile states (0.05,0.05 and 0.95,0.95) and reverse-tail states (0.05,0.95 and 0.95,0.05), while intermediate quantile combinations generally display more moderate spillovers. Hence, monitoring GDM during extreme market conditions and periods when ESG indices and GDM move in opposite directions could serve as an effective ESG Leader index performance evaluation risk-assessment strategy. Conversely, lower connectedness with VIX during extreme or cross-market conditions implies that, under regular market circumstances, VIX might provide a more effective benchmark for ESG Leader index tracking. Nevertheless, excluding the USA and CAN ESG Leader indices, connectedness with VIX in non-normal market conditions and opposite quantile levels tends to be higher compared to normal market conditions. Thus, although focusing on GDM may generally be more beneficial during changing market conditions, tracking VIX can also offer valuable contributions in monitoring the movements of G7 ESG Leader indices.

It is crucial to demonstrate connectedness dynamically to understand the impact of global economic events on connectedness and examine how these connectedness measures evolve. For this purpose, we dynamically illustrate the total connectedness between the G7 ESG Leader indices and VIX and GDM under normal market conditions, the total connectedness in reverse quantiles, and the differences between these two measures. Examining connectedness at opposite quantile levels is particularly significant, as total connectedness at opposite quantiles becomes higher during periods when series are negatively correlated. Hence, investigating reverse quantile connectedness reveals the influence of market risks on connectedness measures (Gabauer and Stenfors, 2024; Lin *et al.*, 2024). Figure no. 2 shows the time-varying graphs of direct connectedness, reverse TCI and the differences between these two measures for the G7 ESG Leader indices and VIX.

The direct, reverse, and reverse-direct TCI measures between the G7 ESG Leader indices and VIX display notable variation over time. Generally, for ESG Leader indices other than the USA, the total connectedness at the reverse quantile level is higher. The reverse-direct TCI is predominantly negative for the USA and CAN indices but positive for the remaining G7 ESG Leader indices. Thus, for ESG Leader indices excluding USA and CAN, higher reverse connectedness than direct connectedness implies stronger linkages when ESG Leader indices are in the lower-tail state while VIX is in the upper-tail state. Conversely, focusing on direct TCI appears more effective for USA and CAN. Despite Pearson correlation results in Table no. 1 indicating the highest negative correlation with VIX for the USA and CAN series, the observation of higher reverse connectedness values in other ESG indices emphasizes the importance of evaluating different quantile levels – and especially reverse quantiles – when analyzing connectedness to capture maximum interactions between variables.

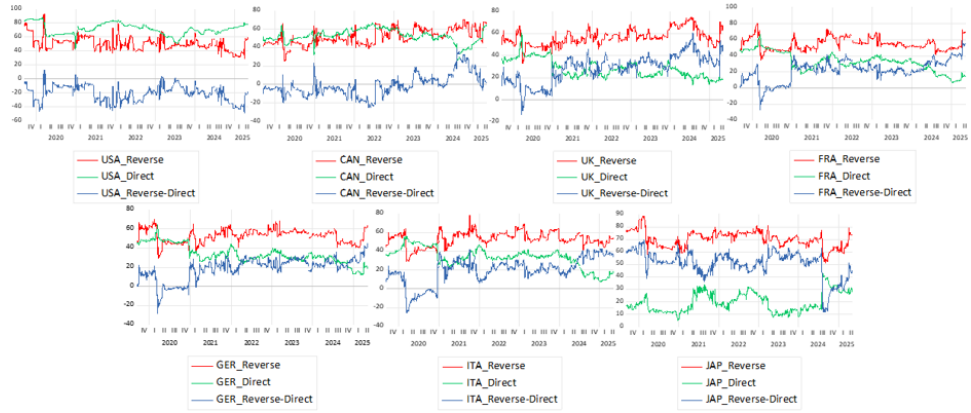


Figure no. 2 – Dynamic Reversely-Related and Directly-Related Quantiles Total Connectedness between G7 ESG Leaders Indices and VIX

Note: The Reverse TCI captures periods when the G7 ESG Leaders indices are in decline (at the 0.05 quantile level) and the VIX is exhibiting an upward trend (at the 0.95 quantile level). The Direct TCI reflects conditions where both the G7 ESG Leaders indices and the VIX are under normal market conditions (at the 0.5 quantile level), while the Reverse-Direct TCI represents the differential between the two.

Extreme fluctuations in direct, reverse, and reverse-direct TCI values generally coincide with global economic events. Specifically, direct and reverse TCI between VIX and nearly all G7 ESG Leader indices reach their peak during the onset of COVID-19 (March 2020). Additionally, early 2021, marked by high volatility in VIX (as observed in Figure no. 1), coincides with increased fluctuations in TCI due to announcements and concerns over COVID-19's delta and other variants. The rise in direct TCI for USA, CAN, UK, FRA, GER, and ITA, along with declines for JAP, aligns closely with the initiation period of the Ukraine-Russia conflict. Other events, such as the SVB collapse in March 2023, the earthquake in Japan in August 2024, and Trump's tariff adjustments in April 2025, also visibly impact total connectedness. Consequently, these globally significant events substantially influence TCI measures, highlighting that ESG investors would benefit from incorporating direct and reverse connectedness into their strategic positioning decisions during these periods. Figure no. 3 illustrates the dynamic evolution of direct connectedness, reverse TCI and the differences between the G7 ESG Leader indices and GDM.

The direct TCI, reverse TCI, and their differences between the G7 ESG Leader indices and GDM vary over time; however, reverse TCI values are consistently higher throughout the entire period than direct TCI values. This finding indicates that total connectedness is stronger when ESG Leader indices decline and GDM trends upward, suggesting reverse connectedness should be monitored together with direct connectedness when assessing ESG–GDM linkages, especially under stress-related market conditions. Additionally, while the Pearson correlation findings in Table no. 1 indicate positive correlations between GDM and the ESG Leader indices, the reverse connectedness values remain higher. This result aligns with previous findings and highlights the importance of considering multiple quantile levels, especially reverse quantiles, for more effective market forecasting.

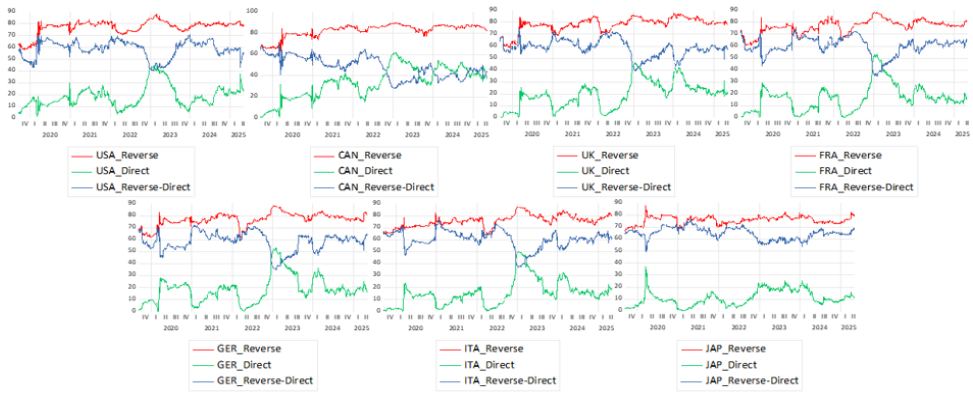


Figure no. 3 – Dynamic Reversely-Related and Directly-Related Quantiles Total Connectedness between G7 ESG Leaders Indices and GDM

Note: The Reverse TCI captures periods when the G7 ESG Leaders indices are in decline (at the 0.05 quantile level) and the GDM is exhibiting an upward trend (at the 0.95 quantile level). The Direct TCI reflects conditions where both the G7 ESG Leaders indices and the GDM are under normal market conditions (at the 0.5 quantile level), while the Reverse-Direct TCI represents the differential between the two.

Changes (increases and decreases) in direct TCI and reverse TCI and the differences between G7 ESG Leader indices and GDM over time are consistent and coincide closely with global economic events. However, the impact of global economic events on total connectedness differs depending on the nature of the event. For example, at the onset of COVID-19 and during the Silicon Valley Bank (SVB) collapse, significant increases in direct (more prominently) and reverse TCI are observed. In contrast, a clear decrease occurs during the initial phase of the Ukraine-Russia conflict. This finding illustrates that while global economic events significantly influence TCI measures, the direction and magnitude of this impact differ according to the type of event. While increased asset interconnectedness is generally expected during periods of rising risk, one of the primary uncertainties triggered by the Ukraine-Russia conflict was related to energy supply. Concerns about meeting fossil fuel energy demands heightened awareness of renewable energy sources and underscored the importance of ESG investments. Thus, energy supply risks at the onset of the Ukraine-Russia conflict had distinct implications for energy prices and the ESG sector beyond general economic uncertainty, potentially explaining the reduced connectedness observed between ESG and GDM during this period.

The findings demonstrate that VIX and GDM provide different information across market regimes. VIX appears more informative under normal market conditions, while GDM-related connectedness becomes more pronounced in tail and reverse-tail states. This suggests that ESG-related risk monitoring should be regime-sensitive rather than based on a single indicator. In particular, VIX may be useful for tracking central-market volatility conditions, whereas GDM may provide additional information during stress-related or cross-quantile states.

Additionally, reverse and direct TCI values are more positively pronounced for GDM compared to VIX. Although correlations between ESG Leader indices and VIX are negative, they are positive with GDM. This indicates that while correlations reflect the strength of co-movements among assets, connectedness measures may not always align with correlation results. Therefore, examining connectedness across different quantiles, particularly reverse connectedness, offers greater potential effectiveness for market monitoring. This finding aligns with those of Gabauer and Stenfors (2024); Lin *et al.* (2024).

5. CONCLUSION AND POLICY RECOMMENDATIONS

Recently, due to the raising trend toward ESG investments, numerous scholars have examined the interconnectedness of ESG investments with prominent conventional markets. However, studies exploring the dynamic connectedness of ESG indices against exclusive market volatility indices and commodity-linked assets are still in a developing state. In view of the aforementioned literature void, the study examines the G7 ESG Leader indices in connection with two significant systemic indicators, the VIX and GDM, employing a comprehensive quantile-on-quantile connectedness analysis. The inclusion of GDM provides a nuanced understanding of the equity performance of gold mining companies, which demonstrate unique behaviours in contrast to physical gold, particularly across varying market conditions. Moreover, the integration of VIX as an indicator for market uncertainty enables the study to accurately reflect the propagation of financial shocks originating from the U.S. market. The inclusion of VIX assists to assess how investor fear and volatility in American markets potentially spill over to other asset classes and international financial systems, thereby enhancing the understanding of global risk transmission mechanisms. The results demonstrate that connectivity patterns are markedly affected by the state, showing substantial differences across quantile levels and economic regimes. The VIX exhibits a stronger connectedness with ESG indices during periods of market stability, particularly within the North American context, encompassing both the USA and Canada. Conversely, the GDM exhibits a stronger connectedness with ESG indices during periods of significant market downturns, particularly when ESG indices demonstrate movements that are contrary to market risk indicators. The data indicates that connectivity increases during global crises such as the COVID-19 pandemic and the SVB collapse. This phenomenon can be attributed to an increase in systemic risk coupled with a reduction in the advantages typically associated with diversification. Conversely, specific geopolitical occurrences such as the Ukraine-Russia conflict yield distinct repercussions, illustrating the intricate ways in which energy dynamics and ESG consciousness influence asset interdependence. Furthermore, it is observed that reverse quantile connectedness consistently surpasses direct connection, particularly in the context of GDM. This indicates that gold and associated sectors are increasingly significant for ESG portfolio hedging in periods of market volatility. These findings enhance our comprehension of asset movement in ways that traditional correlation or linear VAR frameworks fail to reveal. The findings underscore the significance of utilising quantile-based and time-varying connectivity models to accurately depict interconnections within financial markets, particularly in relation to investments centred on ESG considerations.

In light of the aforementioned conclusion, the study proposes the following policy recommendations. In context with ESG portfolio managers, it is recommended that investment plans incorporate quantile-on-quantile connectivity to assess tail risk and portfolio sensitivity across varying market conditions. Given the persistent correlation between GDM and ESG indices during extreme market conditions, GDM may serve as a useful monitoring indicator for ESG-related risk during stress-related market states. Managers may monitor GDM more closely under tail and reverse-tail states, while VIX remains informative under normal market conditions. From the perspective of the regulators, it is recommended that regulators must advocate for enhanced risk disclosures that account for the interplay between tail risk and systemic indicators such as VIX and GDM. Moreover, supervisory frameworks should integrate scenario-based stress testing that includes quantile-based connectivity. This technique holds

particular significance for identifying vulnerabilities during systemic events. The ramifications of the Ukraine-Russia conflict demonstrate the urgent need to align energy security policies with emerging trends in ESG investments. Such alignment will contribute to maintaining investor confidence and stability within ESG markets. Although the present study shares a comprehensive and intriguing insight into the quantile connectedness between G7 ESG Leader indices in connection with two significant systemic indicators, the VIX and GDM, the study has certain limitations, which serve as a potential avenue for future research. Since the present study focuses on connectedness measurement rather than formal portfolio optimization, the portfolio implications should be interpreted as risk-monitoring implications. Future research may extend the analysis by incorporating hedge ratios, hedging effectiveness, or minimum-connectedness portfolio strategies. Another limitation is that daily data may not fully eliminate non-synchronous trading effects across markets, particularly for Japan relative to US-based VIX; future research may address this issue using market-close-adjusted or intraday data. Additionally, examining the interactions between various sectors or regions may provide valuable insights into the behaviour of ESG assets across diverse economic conditions.

ORCID

Halilibrahim Gökgöz https://orcid.org/0000-0001-8000-9993
Aamir Aijaz Syed https://orcid.org/0000-0002-5510-7644
Ahmed Jeribi https://orcid.org/0000-0003-3029-1585
Azza Bejaoui https://orcid.org/0000-0001-7813-0014

AI Use Declaration

AI-assisted tools, including GPT and Grammarly, were used solely for language editing and grammatical correction. These tools were not used for data analysis, interpretation of results, or the generation of the study's scientific content.

References

Afşar, M., Polat, O., Afşar, A., & Kahraman, G. Ö. (2025). Dynamic interlinkages between oil price shocks and stock markets: A quantile-on-quantile connectedness analysis in emerging economies. *Applied Economics*, 1–17. http://dx.doi.org/10.1080/00036846.2025.2473121

Ahmad, W., Sehgal, S., & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling, 33*, 209–225. http://dx.doi.org/10.1016/j.econmod.2013.04.009

Alda, M. (2021). The environmental, social, and governance (ESG) dimension of firms in which social responsible investment (SRI) and conventional pension funds invest: The mainstream SRI and the ESG inclusion. *Journal of Cleaner Production, 298*, 126812. http://dx.doi.org/10.1016/j.jclepro.2021.126812

Alharbi, S. S., Naveed, M., Ali, S., & Moussa, F. (2025). Sailing towards sustainability: Connectedness between ESG stocks and green cryptocurrencies. *International Review of Economics & Finance, 98*, 103848. http://dx.doi.org/10.1016/j.iref.2025.103848

Arifoğlu, A., Gökgöz, H., & Kandemir, T. (2023). Testing the factors affecting intraday market electricity prices by connectedness approach. *Sosyoekonomi, 31*(57), 179–194. http://dx.doi.org/10.17233/sosyoekonomi.2023.03.09

Bahloul, S., & Khemakhem, I. (2021). Dynamic return and volatility connectedness between commodities and Islamic stock market indices. *Resources Policy, 71*, 101993. http://dx.doi.org/10.1016/j.resourpol.2021.101993

Ben Salem, S., & El Aoun, O. (2025). Banking index volatility and spillover effects in G7 and BRICS economies: A quantile connectedness approach. *Studies in Economics and Finance, 42*, 836–864. http://dx.doi.org/10.1108/SEF-01-2025-0046

Cagli, E. C. C., Mandaci, P. E., & Taşkın, D. (2023). Environmental, social, and governance (ESG) investing and commodities: Dynamic connectedness and risk management strategies. Sustainability Accounting. *Management and Policy Journal, 14*(5), 1052–1074. http://dx.doi.org/10.1108/SAMPJ-01-2022-0014

Celik, I., Demir, S., Ozdemir Hol, A., & Celik, M. (2025). Asymmetric interconnectedness and investing strategies of green, sustainable and environmental markets. *The Investment Analysts Journal*. *55 (2),* 219-245. http://dx.doi.org/10.1080/10293523.2025.2530857

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2021). Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Economics Letters, 204*, 109891. http://dx.doi.org/10.1016/j.econlet.2021.109891

Chen, X., Yao, Y., Wang, L., & Huang, S. (2024). How EPU, VIX, and GPR interact with the dynamic connectedness among commodity and financial markets: Evidence from wavelet analysis. *The North American Journal of Economics and Finance, 74*, 102217. http://dx.doi.org/10.1016/j.najef.2024.102217

de Boyrie, M. E., & Pavlova, I. (2024). Connectedness with commodities in emerging markets: ESG leaders vs. conventional indexes. *Research in International Business and Finance, 71*, 102456. http://dx.doi.org/10.1016/j.ribaf.2024.102456

Demir, S. (2024). Yatırımcı duyarlılığı ile ABD geleneksel ve yeşil tahvil piyasaları arasındaki bağlantılılık analizi. *Afyon Kocatepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 26*(2), 264–275. http://dx.doi.org/10.33707/akuiibfd.1451827

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134. http://dx.doi.org/10.1016/j.jeconom.2014.04.012

Dong, Z., Li, Y., Zhuang, X., & Wang, J. (2022). Impacts of COVID-19 on global stock sectors: Evidence from time-varying connectedness and asymmetric nexus analysis. *The North American Journal of Economics and Finance, 62*, 101753. http://dx.doi.org/10.1016/j.najef.2022.101753

Erdogan, S., Pata, U. K., & Solarin, S. A. (2023). Towards carbon-neutral world: The effect of renewable energy investments and technologies in G7 countries. *Renewable & Sustainable Energy Reviews, 186*, 113683. http://dx.doi.org/10.1016/j.rser.2023.113683

Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics, 76*, 1–20. http://dx.doi.org/10.1016/j.eneco.2018.09.022

Gabauer, D., & Stenfors, A. (2024). Quantile-on-quantile connectedness measures: Evidence from the US treasury yield curve. *Finance Research Letters, 60*, 104852. http://dx.doi.org/10.1016/j.frl.2023.104852

Hanif, W., Hadhri, S., & El Khoury, R. (2024). Quantile spillovers and connectedness between oil shocks and stock markets of the largest oil producers and consumers. *Journal of Commodity Markets, 34*, 100404. http://dx.doi.org/10.1016/j.jcomm.2024.100404

Karpman, K., Lahiry, S., Mukherjee, D., & Basu, S. (2022). Exploring Financial Networks Using Quantile Regression and Granger Causality. Retrieved from http://dx.doi.org/10.48550/arXiv.2207.10705

Khalfaoui, R., Ben Jabeur, S., & Dogan, B. (2022). The spillover effects and connectedness among green commodities, Bitcoins, and US stock markets: Evidence from the quantile VAR network. *Journal of Environmental Management, 306*, 114493. http://dx.doi.org/10.1016/j.jenvman.2022.114493

Khalfaoui, R., Mefteh-Wali, S., Dogan, B., & Ghosh, S. (2023). Extreme spillover effect of COVID-19 pandemic-related news and cryptocurrencies on green bond markets: A quantile connectedness analysis. *International Review of Financial Analysis, 86*, 102496. http://dx.doi.org/10.1016/j.irfa.2023.102496

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*(1), 119–147. http://dx.doi.org/https://doi.org/10.1016/0304-4076(95)01753-4

Lin, X., Meng, Y., & Zhu, H. (2024). Exploring hedging potentials of green bonds against oil price shocks: Evidence from quantile-on-quantile connectedness measures. *Finance Research Letters, 65*, 105640. http://dx.doi.org/10.1016/j.frl.2024.105640

Liu, W., Xu, G., Fan, J., & Zhu, X. (2024). Two-way Homogeneity Pursuit for Quantile Network Vector Autoregression. Retrieved from http://dx.doi.org/10.48550/arXiv.2404.18732

Mensi, W., Nekhili, R., Vo, X. V., Suleman, T., & Kang, S. H. (2021). Asymmetric volatility connectedness among US stock sectors. *The North American Journal of Economics and Finance, 56*, 101327. http://dx.doi.org/10.1016/j.najef.2020.101327

Naeem, M. A., Anwer, Z., Khan, A., & Paltrinieri, A. (2024). Do market conditions affect interconnectedness pattern of socially responsible equities? *International Review of Economics & Finance, 93*, 611–630. http://dx.doi.org/10.1016/j.iref.2024.03.031

Rehman, M. U., Shahzad, S. J. H., Uddin, G. S., & Hedström, A. (2018). Precious metal returns and oil shocks: A time varying connectedness approach. *Resources Policy, 58*, 77–89. http://dx.doi.org/10.1016/j.resourpol.2018.03.014

Saeed, T., Bouri, E., & Alsulami, H. (2021). Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Economics, 96*, 105017. http://dx.doi.org/10.1016/j.eneco.2020.105017

Shang, J., & Hamori, S. (2024). Quantile time-frequency connectedness analysis between crude oil, gold, financial markets, and macroeconomic indicators: Evidence from the US and EU. *Energy Economics, 132*, 107473. http://dx.doi.org/10.1016/j.eneco.2024.107473

Sharma, C., & Rani, P. (2025). Dynamic Interconnectedness of ESG Indices and Crude Oil Prices: A Wavelet Coherence Approach in Asia-Pacific Markets. *Australian Economic Papers, 64*, 289–298. http://dx.doi.org/10.1111/1467-8454.12392

Sheikh, U. A., Asadi, M., Roubaud, D., & Hammoudeh, S. (2024). Global uncertainties and Australian financial markets: Quantile time-frequency connectedness. *International Review of Financial Analysis, 92*, 103098. http://dx.doi.org/10.1016/j.irfa.2024.103098

Singh, S., Singh, M., & Attri, S. (2025). Dynamic volatility linkages among crude oil, exchange rate, interest rate, gold and equity markets: An empirical Asian perspective. *Managerial Finance*. http://dx.doi.org/10.1108/MF-01-2025-0016

Syllignakis, M. N., & Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance, 20*(4), 717–732. http://dx.doi.org/10.1016/j.iref.2011.01.006

Vo, X. V., & Ellis, C. (2018). International financial integration: Stock return linkages and volatility transmission between Vietnam and advanced countries. *Emerging Markets Review, 36*, 19–27. http://dx.doi.org/10.1016/j.ememar.2018.03.007

Wang, G. J., Wan, L., Feng, Y., Xie, C., Uddin, G. S., & Zhu, Y. (2023). Interconnected multilayer networks: Quantifying connectedness among global stock and foreign exchange markets. *International Review of Financial Analysis, 86*, 102518. http://dx.doi.org/10.1016/j.irfa.2023.102518

Xu, X., Wang, W., Shin, Y., & Zheng, C. (2024). Dynamic Network Quantile Regression Model. *Journal of Business & Economic Statistics, 42*(2), 407–421. http://dx.doi.org/10.1080/07350015.2022.2093882

Zhang, D. (2017). Oil shocks and stock markets revisited: Measuring connectedness from a global perspective. *Energy Economics, 62*, 323–333. http://dx.doi.org/10.1016/j.eneco.2017.01.009

Scientific Annals of Economics and Business
73 (3), 2026, 509-525
DOI: 10.47743/saeb-2026-0035

Corporate Social Responsibility through the Lens of CEO Sociodemographic: The Effects of Education and Gender

Mariem Bouzguenda[*], Dhouha Bouaziz[**], Anis Jarboui[***]

Abstract: This study investigates the impact of two key sociodemographic variables, CEO education level and gender, on Corporate Social Responsibility (CSR) performance. The research aims to examine how these characteristics influence companies' commitment to different CSR dimensions, including environmental, social, and governance aspects. Using a sample of firms listed on the CAC All Share index from 2015 to 2023, this study employs panel data regression analysis to assess the effects of CEO education and gender on CSR performance. Data on CSR performance were obtained from the Thomson Reuters ASSET4 database, while CEO demographic information was collected from company reports and Bloomberg. The results indicate that both CEO education level and CEO gender have a positive and significant impact on CSR performance. Highly educated CEOs appear better equipped to integrate sustainable practices, while female CEOs tend to foster more impactful CSR initiatives. This study contributes to the existing literature by focusing on the intersection of CEO sociodemographic factors and CSR performance. It highlights the importance of considering both education and gender to better understand how executive characteristics shape corporate approaches to social responsibility.

Keywords: CEO education; CEO gender; CAC All Share index; Corporate Social Responsibility.

JEL classification: M12; M14; G34; Q01.

[*] University of Economic Science and Management of Sfax, Tunisia; e-mail: *mariembouzguenda@hotmail.fr* (corresponding author).
[**] Tunisia; e-mail: *dhouha.fsegs@gmail.com*.
[***] Tunisia; e-mail: *anisjarboui@yahoo.fr*.

Article history: Received 30 November 2025 | Accepted 10 March 2025 | Published online 9 April 2025

To cite this article: Bouzguenda, M., Bouaziz, D., Jarboui, A. (2026). Corporate Social Responsibility through the Lens of CEO Sociodemographic: The Effects of Education and Gender. *Scientific Annals of Economics and Business*, 73(3), 509-525. https://doi.org/10.47743/saeb-2026-0035.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

Corporate Social Responsibility (CSR) has become a critical issue in today's economic landscape, with companies striving to meet the growing expectations of diverse stakeholders. In this context, the role of the CEO is central, as they shape the organization's CSR strategies and practices (Schwoy *et al.*, 2023; Wang *et al.*, 2023). The CEO has the ability to influence CSR strategies and practices because he/she holds an important and privileged position within the firm (Amore *et al.*, 2019; Zhou *et al.*, 2021; Bhaskar, 2023). Numerous studies have examined how CSR decisions are influenced by various CEO characteristics, including demographic factors, professional experience, and personal values (Manner, 2010; McCarthy *et al.*, 2017; Liu *et al.*, 2020; Schwoy *et al.*, 2023; Rahman *et al.*, 2024; Chulkova and Kim, 2025). Among the many factors shaping CEOs' decisions, education and gender are two sociodemographic dimensions that warrant particular attention. Thus, examining CEO education and gender through the lens of the Upper Echelons Theory provides a relevant framework to understand how top executives' sociodemographic attributes shape CSR performance and contribute to variations in firms' social and environmental engagement.

The education of the CEO plays a pivotal role in shaping their approach to Corporate Social Responsibility (CSR) and their ability to embed these values into the company's strategic operations. CEOs with a strong academic background, particularly in disciplines such as management, business, economics, sustainability, or social sciences, are more likely to possess a nuanced understanding of societal and environmental issues. This comprehensive perspective enables them to evaluate the long-term implications of their decisions, foresee potential risks, and prioritize strategies that align business objectives with the expectations of society.

A well-educated CEO is often equipped with critical analytical skills and an awareness of global challenges such as climate change, resource scarcity, and social inequality. This knowledge drives them to adopt and implement robust CSR practices that address these issues effectively. They are more likely to establish sustainable development goals, invest in eco-friendly technologies, and promote ethical labor practices (Wen *et al.*, 2024).

On the other hand, CEOs with limited formal education may lack exposure to these complex issues and their potential impact on the business landscape. Consequently, they might undervalue the strategic importance of CSR or view it primarily as a compliance requirement rather than a core aspect of the company's mission. This could lead to reactive or superficial CSR strategies that fail to capitalize on the long-term benefits of sustainability and ethical business practices.

Overall, the educational background of a CEO significantly influences the depth, scope, and effectiveness of a company's CSR initiatives, emphasizing the importance of leadership education in fostering responsible and sustainable business operations.

Gender plays an essential role in shaping a company's CSR strategies, with female CEOs bringing unique leadership qualities that significantly advance corporate social responsibility. Research shows that women in leadership positions are more likely to adopt inclusive and ethical management approaches, deeply rooted in personal and social values. They often prioritize long-term sustainability, focusing on the well-being of parties perennates and the wider societal impacts of corporate decisions (Braun and Zenker, 2022; Choi *et al.*, 2023; Liang *et al.*, 2024; Chulkova and Kim, 2025).

This strong commitment to CSR stems from their heightened awareness of social and environmental issues, enabling them to align business practices with sustainable development

goals. Moreover, women leaders tend to emphasize transparency, collaboration, and fairness, fostering an environment where ethical practices can thrive (Velte, 2025; Yahya, 2025). By championing these principles, female CEOs not only enhance a company's reputation but also build stronger trust with stakeholders, underscoring their critical role in promoting socially responsible and sustainable business practices.

In contrast, male CEOs often focus on maximizing short-term profits and improving operational efficiency. While this strategy can deliver immediate financial gains, it may sometimes overlook the broader social and environmental consequences of business decisions.

Thus, the relationship between the education and gender of the CEO and their effects on CSR constitutes a pertinent field of investigation. Understanding how these two factors interact can provide valuable insights into how companies can better address contemporary societal challenges.

This study contributes to the literature on CSR by illuminating the combined influences of CEO education and gender on corporate CSR practices. By focusing on these sociodemographic dimensions, our research highlights the importance of diversity in leadership and its impact on CSR strategies. Furthermore, by addressing CSR as a multidimensional concept, we provide a more nuanced understanding of the mechanisms through which CEO characteristics affect various CSR dimensions, such as environmental, governance, and social engagement.

Previous research has documented that personal characteristics of CEOs, such as age, experience, and personality, influence CSR decisions (Manner, 2010; McCarthy *et al.*, 2017; Liu *et al.*, 2020). However, few studies have specifically explored the effects of education and gender in this context. Our work addresses this gap by emphasizing how education can shape CEOs' values and behaviors, while gender can influence their management style and approach to CSR.

Finally, the findings of this research can serve as a foundation for practical recommendations for companies seeking to strengthen their CSR engagement, taking into account the varied leadership profiles.

The remainder of this paper is structured as follows. Section 2 provides a comprehensive literature review. Section 3 describes the methodology and the variables used in the analysis. Section 4 presents the empirical results and their discussion. Section 5 concludes the study, and Section 6 highlights the limitations and proposes avenues for future research.

2. LITERATURE REVIEW

The role of CEOs in shaping Corporate Social Responsibility (CSR) practices has been widely studied, as their decisions significantly influence how firms approach social and environmental responsibility. Among the various factors affecting CSR, CEO characteristics, particularly education and gender, have emerged as key determinants of how CSR is prioritized and executed within organizations. The literature suggests that a CEO's background, values, and leadership style can strongly impact a company's strategic direction regarding its CSR commitments and initiatives. This review explores how these two specific CEO characteristics education and gender affect CSR practices, focusing on their direct and indirect influence on corporate policies and behaviors (Shahzadi *et al.*, 2024; Wen *et al.*, 2024; Susilo *et al.*, 2025).

To better understand the relationship between CEO characteristics and CSR practices, this review incorporates the Upper Echelons Theory (Hambrick and Mason, 1984), a widely

recognized framework in organizational behavior. According to this theory, the experiences, values, and personalities of top executives play a significant role in shaping organizational outcomes, including strategic decisions. CEOs' individual characteristics such as their educational background and gender are thought to influence their cognitive frames, values, and preferences, which, in turn, guide their decisions regarding CSR. The Upper Echelons Theory thus provides a useful lens for examining how CEO education and gender directly impact their strategic behaviors and the CSR strategies adopted by the firms they lead (Zhou *et al.*, 2021; Bhaskar, 2023; Bouzguenda and Jarboui, 2024a; Velte, 2025).

By integrating these perspectives, this review highlights the important role that both education and gender play in shaping CSR practices. It shows how these characteristics influence CEOs' leadership styles and decision-making processes, ultimately affecting how CSR is conceptualized, implemented, and integrated into corporate strategy. The review underscores the significance of understanding these CEO attributes to better predict and explain CSR outcomes across different organizational contexts.

2.1. CEO Education and CSR

Of the demographic characteristics of CEOs, education is recognized as a crucial determinant of CSR strategies (Borghesi *et al.*, 2014; Lewis *et al.*, 2014; Tang *et al.*, 2015; Yuan *et al.*, 2017; Velte, 2019; Huang *et al.*, 2024). Education shapes individuals' moral and ethical values (Hambrick and Mason, 1984; Frank, 1993; Manner, 2010) and fosters open-mindedness (Wei *et al.*, 2018). Previous research has shown that individuals' education level, defined as "formal qualification in the form of degrees obtained from higher education institutions" (Shahzadi *et al.*, 2024), influences their way of thinking and increases their sensitivity to social and [2]environmental issues (Jani *et al.*, 2020; Garrido-Ruso and Aibar-Guzmán, 2022; Hewa Heenipellage and McCall, 2022). In this sense, a higher education level among CEOs appears to be associated with a greater concern for sustainability challenges, as well as an increased awareness of the importance of communicating the company's social and environmental actions (Malik *et al.*, 2020).

Several studies examine the direct relationship between the CEO's education level and CSR. Smith *et al.* (2021) show that CEOs with a higher education level have a global vision of management, making them more sensitive to the expectations of different stakeholders and social issues, and more aware of the importance and significance of CSR disclosure (Malik *et al.*, 2020). Schaper (2002) and Gadenne *et al.* (2009) state that a higher education level would be associated with a more developed level of sensitivity to CSR issues. CSR activities are diverse and require significant research and development, as well as innovation, which in turn requires CEOs who are generally associated with new technologies and tend to have a higher cognitive density to assimilate these various CSR activities (Malik *et al.*, 2020; Garrido-Ruso *et al.*, 2023).

Furthermore, the type of education pursued, i.e., the discipline studied, also influences the cognitive models' individuals use to make decisions (Hambrick and Mason, 1984). Some authors argue that economic studies may reduce individuals' ethical and social concerns (Frank, 1993), while studies in the humanities tend to have the opposite effect (Davis *et al.*, 2018). Since most business schools include ethics in their curricula (Huang *et al.*, 2024), CEOs with an MBA tend to adopt a proactive approach to CSR, promoting CSR initiatives within their companies (Finkelstein *et al.*, 2008; Lewis *et al.*, 2014; Huang *et al.*, 2024).

Moreover, training in CSR can enhance a CEO's awareness and commitment to the SDGs (Manes-Rossi and Nicolo, 2022). For example, Villalba-Ríos *et al.* (2022) found that CEOs with both engineering and MBA degrees are associated with companies having high CSR performance.

Numerous studies establish a positive relationship between CEOs' education level and their CSR performance and disclosure (Lewis *et al.*, 2014; Huang *et al.*, 2024), suggesting that education makes CEOs more sensitive to disclosure needs (Malik *et al.*, 2020). We argue that the CEO's education level significantly influences their CSR decisions. Therefore, the following hypothesis is proposed:

H1*: CEOs with a higher education level have higher CSR performance.*

2.2. CEO Gender and CSR

The gender of CEOs plays a significant role in shaping the direction and effectiveness of Corporate Social Responsibility (CSR) strategies. Female leaders are often perceived as more ethical and responsible, largely due to their heightened empathy and risk aversion (Bear *et al.*, 2010). These traits enable female CEOs to more effectively integrate social and environmental considerations into corporate strategy, thereby fostering the adoption of sustainable practices within organizations (Chulkova and Kim, 2025).

Empirical evidence suggests that companies led by women tend to outperform those led by men in terms of CSR performance and are more likely to align closely with the Sustainable Development Goals (SDGs) (García-Sánchez and Rodríguez-Ariza, 2019; Braun and Zenker, 2022; Choi *et al.*, 2023; Liang *et al.*, 2024). This is attributed to the fact that women, as leaders, place greater emphasis on sustainability and corporate social and environmental responsibility. According to Chu *et al.* (2022), female CEOs are more attuned to social and environmental issues, which aligns with their psychological traits and leadership competencies, such as conflict resolution, adaptability to change, and the ability to inspire and motivate others. These qualities not only help foster a positive organizational culture but also contribute to improving employee well-being, reducing stress and turnover, and enhancing organizational stability Huang *et al.* (2024).

In fact, female CEOs diverge from their male counterparts in leadership styles in several ways. They are more likely to promote sustainability (Glass and Cook, 2018), prioritize CSR and ethical practices (Choi *et al.*, 2023; Liang *et al.*, 2024), and invest in social capital (Zhang *et al.*, 2014). Furthermore, research has shown that women leaders are generally more inclined to embrace long-term value creation over short-term gains, which leads to more sustainable decision-making (Nielsen and Huse, 2010). Female CEOs are more likely to focus on creating value for a wider range of stakeholders, including employees, local communities, and the environment. This approach results in a more holistic and socially responsible corporate strategy, where CSR activities are embedded into the company's overall vision and mission (Velte, 2025; Yahya, 2025).

Additionally, gender diversity in top management teams has been linked to better decision-making and more balanced risk management practices (Adams and Ferreira, 2009). A higher representation of women in leadership roles enhances corporate governance by bringing diverse perspectives to the table, ultimately leading to better CSR performance (Manner, 2010; Marquis and Lee, 2013; García-Sánchez *et al.*, 2022; Garrido-Ruso *et al.*, 2023; Yin *et al.*, 2024).

Recent studies also provide additional empirical support for the positive relationship between female CEOs and CSR performance. Gala *et al.* (2024) and Chulkova and Kim (2025) both show that female CEOs are positively associated with higher CSR performance, reinforcing the notion that female leadership fosters more sustainable and socially responsible corporate strategies. Given these considerations, the following hypothesis is proposed:

H2*: Female CEOs are more likely to achieve superior CSR performance.*

3. METHODOLOGY

This section is dedicated to outlining the study's sample, tools, data collection procedures, variable measurements, empirical model, and research design.

3.1. Sampling and data collection

Our sample includes French firms listed on the CAC All Share index between 2015 and 2023. Initially, we had data on 335 publicly listed companies. However, we excluded 65 financial institutions due to their unique financial reporting practices, 90 companies with incomplete annual reports, and 60 companies with insufficient data on their CEOs. The study focuses on the French context, which is marked by weak legal institutions, a high prevalence of family-owned businesses, and a tendency for leaders to come from dominant families. In this environment, many large publicly traded companies are controlled by families or concentrated groups of shareholders, which can influence the selection of CEOs and their decision-making processes. The final sample consists of 120 companies over a 9-year period, yielding 1,080 firm-year observations. CEO data were manually extracted from annual reports available on www.boursier.com/indices and Zone Bourse, while financial data were sourced from Datastream.

The sample encompasses companies from a range of sectors. Table no. 1 presents a breakdown of the number of companies by sector.

Table no. 1A – Sample selection procedure

Description	No. of companies
Initial sample listed on the CAC ALL Shares index	335
Financial firms	(65)
Firms with insufficient annual report	(90)
Firms within sufficient data	(60)
Final sample	120
Duration study	9
Total firm-observations	**1080**

Table no. 1B – Distribution of the sample according to sectors' type

Sector	Number	Percentage
Industrial sector		
Construction material	9	7.5%
Various industries	40	33.33%
Total industrial firms	49	40.83%
Commercial sector		
Total commercial firms	17	14.17%

Sector	Number	Percentage
Service sector		
Computer service and consulting	8	6.67%
Construction and Mining	4	3.33%
Transport, communication, gas	12	10%
Various service	30	25%
Total service firms	54	45%
Total firms	**120**	**100%**

3.2. Measures variables

3.2.1. Dependent Variables: CSR performance

In line with the studies by Marquis and Lee (2013) and Wang *et al.* (2023), this research utilizes ESG scores to evaluate Corporate Social Responsibility (CSR). The ESG score provides a comprehensive assessment of a company based on three key pillars: environmental, social, and governance factors. Sourced from the ASSET4 database within Thomson Reuters DataStream, the CSR score is derived from a set of weighted data points assigned to each dimension (environmental, social, and governance), reflecting their respective significance. CSR performance is expressed as a percentage, ranging from 0 to 100, with higher scores indicating superior performance in CSR (Ahn, 2020; Bhaskar *et al.*, 2023; Wang *et al.*, 2023; Yin *et al.*, 2024).

3.2.2. Independent Variables

- CEO Education Level (EDUC): This is a dichotomous variable coded as 1 if the CEO holds an MBA (Master of Business Administration), and 0 otherwise (Aier *et al.*, 2005; Kouaib and Jarboui, 2016).
- CEO Gender (GENDER): A binary variable where 1 represents a male CEO, and 0 represents a female CEO (Manner, 2010; Marquis and Lee, 2013).

3.2.3. Control Variables

- Firm Size (FS): This variable is measured as the natural logarithm of the book value of total assets at the beginning of the year (McWilliams and Siegel, 2001; Puchakayala *et al.*, 2023; Bouzguenda and Jarboui, 2024a).
- Return on assets (ROA): is calculated as profit before extraordinary items, based on the book value of total assets at the beginning of the year (Tang *et al.*, 2015; Biju *et al.*, 2023).
- Firm Age (AGEFIRM): The number of years of existence of the company since its creation (Muttakin *et al.*, 2018; Erdiaw-Kwasie *et al.*, 2023; Bouzguenda and Jarboui, 2024b).
- Firm leverage (LEV): The debt ratio is equal to total debt/total assets (McCarthy *et al.*, 2017; Bagh *et al.*, 2024; Bouzguenda and Jarboui, 2024a).

Table no. 2 – Summary of variables definitions

Variable	Definition	Measure	Source of Data	Authors
Dependent variable				
CSR	The ESG score is an aggregate score.		Asset 4	Ahn (2020); Bhaskar *et al.* (2023); Yin *et al.* (2024)
Independent variable				
GENDER	1 when the CEO is male, and 0 otherwise.		Annual reports	Furlotti *et al.* (2019); Choi Choi *et al.* (2023)
EDUC	1 if the CEO holds an MBA (Master of Business Administration) and 0 otherwise.		Annual reports	Velte (2019); Hewa Heenipellage and McCall (2022)
Control variables				
ROA	Return on assets	Net income / Total assets.	Worldscope	Fujianti and Satria (2020); Oh *et al.* (2016); Suwardi and Saragih (2023)
FS	Firm size	Ln (Total assets)	Worldscope	Oh *et al.* (2016) Shahab and Ye (2018); Marwa *et al.* (2020); Suwardi and Saragih (2023)
AGEFIRM	Firm age	The number of years of existence of the company since its creation	Hand collected Annual reports 2015-2023	Omer *et al.* (2020)
LEV	Firm leverage	Total liabilities / Total assets	Worldscope	Abba *et al.* (2018); Marwa *et al.* (2020)

3.3. Research methodology

A panel regression using Feasible Generalized Least Squares (FGLS) was conducted on a sample of 120 firms listed on the French CAC All Share index over ten years (2015–2023). This approach was chosen to address potential heteroskedasticity and autocorrelation in the panel data, ensuring efficient and consistent estimates. The model tested the research hypotheses as follows:

$$CSR = \beta 0+\beta 1\ (EDUC) + \beta 2(GENDER) + \beta 3\ (FS) +\beta 4(ROA) + \beta 5(AGEFIRM) + \beta 6(LEV) + \varepsilon_{it} \quad (1)$$

with: CSR is corporate social responsibility measured by ESG score, EDUC is CEO education, GENDER is CEO gender, FS is firm size, ROA is return on assets, AGEFIRM is firm age, LEV is firm leverage. These variables are defined in Table no. 2.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Descriptive statistics

Tables no. 3A and 3B present the summary statistics for the test variables used in our regression analysis. Table no. 3A provides descriptive statistics for the continuous variables, including the mean, median, standard deviation, maximum, and minimum values. Table no. 3B presents the descriptive statistics for the dichotomous and continuous variables for the firms in our sample. The minimum firm ESG is -11.27, and the maximum is 95.87, with a

mean of 65.046. The median value is 66.345, and the standard deviation is 15.057. Regarding the control variables, from Table no. 3A, the results show that the average ROA is 7.962 with minimum of -25.95 and maximum of 69.32. The average firm size is 16.207, with a minimum of 10.328, a maximum of 19.862, and a standard deviation of 1.499. The average age of the sampled firms is 3.882 years, with a minimum of 1 year and a maximum of 187 years. The firms' financial leverage averages 25.613% of total assets, indicating that, on average, firms rely slightly more on equity than on debt.

Table no. 3A – Summary statistics for continuous variables

Variable	N	Mean	SD	Minimum	Maximum	Median
RSE	1080	65.046	15.057	11.27	95.87	66.345
ROA	1080	7.962	8.484	-25.95	69.32	5.975
FS	1080	16.207	1.499	10.328	19.862	16.120
AGEFIRM	1080	3.882	0.947	1	187	30
LEV	1080	25.613	16.027	1.1	92.74	24.59

The descriptive statistics for the dichotomous variables in Table no. 3B reveal that the mean value of gender diversity is 16.67%, indicating that the vast majority of firms have female CEOs. Regarding CEO education, 78.70% of the CEO holds an MBA.

Table no. 3B – Summary statistics for dichotomous variables

Variables	Modality	Frequences	Percentage
GENDER	0	180	16.67%
	1	900	83.33%
EDUC	0	230	21.30%
	1	850	78.70%

where**:** CEO gender is GENDER, CEO education is EDUC.

4.2. Correlation analysis

The correlation matrices in Table no. 4 display the correlation coefficients among the independent variables. Pearson correlation is used to assess the relationship between two continuous variables, point-biserial correlation for a continuous and a binary variable, and Phi correlation for two binary variables (Welkowitz *et al.*, 2012). The matrices reveal that all correlation coefficients are below 0.7 and above -0.7, suggesting a minimal risk of multicollinearity. According to Tabachnick and Fidell (2013), a Pearson correlation coefficient of 0.80 or higher may indicate potential multicollinearity. As shown in Table no. 5, the highest correlation is between firm size and firm leverage, with a coefficient of 0.1149. This confirms that multicollinearity is not a concern in this model, as no correlation exceeds the 0.8 threshold.

Table no. 4 – Correlation matrix

	GENDER	EDUC	ROA	FS	AGEFIRM	LEV	VIF
GENDER	1.0000						1.01
EDUC	-0.0275 (0.2584)	1.0000					1.01
ROA	-0.0181 (0.4577)	-0.0119 (0.6239)	1.0000				1.05
FS	-0.0784 (0.0013)	-0.0055 (0.8204)	-0.2104 (0.0000)	1.0000			1.06
AGEFIRM	0.0097 (0.6890)	-0.0092 (0.7040)	0.0345 (0.1561)	0.0959 (0.0001)	1.0000		1.05
LEV	0.0185 (0.4471)	0.0712 (0.0034)	-0.2072 (0.0000)	0.1149 (0.0000)	-0.1697 (0.0000)	1.0000	1.08

4.3. Regression results

Table no. 5 reports the results of the CSR performance regression on the explanatory variables. Testing H1, Table no. 5presents that the relationship between the CEO gender and CSR performance is positive and significant at the level of 1 per cent. This result is consistent with the work of Gala *et al.* (2024); Chulkova and Kim (2025), which show that CEO gender positively influences corporate social responsibility (CSR) performance. Indeed, women tend to be more inclined to integrate the interests of stakeholders (such as local communities, employees, the environment, etc.) into their strategic decisions. This management style promotes more transparent and responsible stakeholder engagement practices, leading to stronger CSR initiatives that are better aligned with the company's overall strategy. Female leaders often take a more invested approach to creating long-term value, beyond immediate financial gains, by including benefits for employees, communities, and the environment. A well-defined CSR strategy can enhance the company's reputation, attract diverse talent, and strengthen customer loyalty, particularly among those who are concerned with ethics and sustainability. A female CEO could implement CSR initiatives that better address current social and environmental concerns, thus enhancing the overall impact of the company's CSR strategy.

Testing H2, the results in Table no. 5 display that CEO education has a positive and statistically significant effect on CSR performance at the 1% level. A higher level of education equips CEOs with broader cognitive abilities and a deeper understanding of social, environmental, and economic issues, enabling them to adopt more responsible and forward-looking managerial decisions. Well-educated CEOs are generally better prepared to integrate CSR into corporate strategy, to mobilize the necessary resources, and to align organizational practices with societal expectations.

This finding is consistent with prior research showing that education enhances managers' analytical capacity and strengthens their sensitivity to sustainability considerations, thereby improving CSR outcomes (Khan *et al.*, 2021; Choi *et al.*, 2023; Garrido-Ruso *et al.*, 2023). For example, Malik *et al.* (2020) argue that higher educational attainment increases CEOs' awareness of the importance and strategic value of CSR disclosure, and Bouzguenda and Jarboui (2024a) highlight that educated CEOs are better equipped to integrate CSR into corporate strategy and respond effectively to ESG challenges. By better grasping the implications of ESG-related decisions, highly educated CEOs are more

capable of anticipating reputational risks, regulatory pressures, and stakeholder demands, which leads to more effective CSR initiatives and enhanced CSR performance. Therefore, the significant effect observed supports the hypothesis that CEO education plays a crucial role in shaping corporate sustainability behaviors.

We also observe from the reading of this table that the size of the company has a positive and significant impact on CSR performance. This shows that an increase in the size of the company is often correlated with an improvement in its corporate social responsibility (CSR) performance. Additionally, the age of the company has a positive effect on CSR performance. The experience accumulated over time allows the company to better understand social, environmental, and economic issues, and to adopt more suitable and sustainable strategies (Wen *et al.*, 2024). This table also shows that debt has a positive impact on CSR performance. However, ROA does not appear to have any significant effect on CSR performance.

Table no. 5 – Multivariate regressions of CEO's gender, CEO's education, CSR performance and other control variables

Variable	Model		
	Predicted sign	**Coefficient**	**P-value**
GENDER	+	3.14***	0.002
EDUC	+	5.03***	0.000
ROA	+	-0.26	0.793
FS	+	15.96***	0.000
AGEFIRM	+	9.73***	0.000
LEV	-/+	4.26***	0.000
R-square		0.1788	
Prob>F		0.0000	
Wald khi-2		407.05	
Number of observations		1080	

5. CONCLUSION

This study explored the influence of CEO characteristics, specifically education level and gender, on Corporate Social Responsibility (CSR) performance, providing important insights into how these traits shape corporate sustainability efforts (Susilo *et al.*, 2025). The findings highlight that CEOs with higher education levels possess enhanced cognitive abilities and strategic foresight, allowing them to effectively address the complexities of social and environmental challenges. CEOs with advanced educational backgrounds are more likely to engage with innovative solutions, integrate sustainability into the company's long-term strategy, and make decisions that align with broader societal goals. In addition, female CEOs were found to demonstrate empathetic leadership styles and a strong ethical orientation, which positively influences CSR initiatives. Their inclusive and ethical approach to decision-making not only enhances CSR practices but also fosters a corporate culture that values sustainability, social equity, and transparency (Zhou *et al.*, 2021; Bhaskar, 2023; Yahya, 2025).

These results underscore the critical role of leadership traits in shaping CSR practices, particularly in driving sustainability and fostering responsible corporate behavior. CEO characteristics such as education and gender influence how organizations address environmental, social, and governance (ESG) issues, ultimately determining the scope and effectiveness of their CSR initiatives. By emphasizing the need for a well-rounded and diverse

leadership team, organizations can better navigate the complex challenges associated with sustainability and social responsibility (Wen *et al.*, 2024; Velte, 2025).

From a theoretical standpoint, the results of this study provide direct support for the Upper Echelons Theory, which argues that organizational outcomes are shaped by the demographic and cognitive characteristics of top executives. In this context, the evidence delves that two key sociodemographic attributes CEO education level and gender significantly impact CSR performance among French listed firms. These findings give proof that CSR performance is not solely driven by corporate policies or external pressures but also reflects the profile of the CEO. By indicating that higher education levels and female leadership are associated with stronger CSR engagement, this study extends the Upper Echelons framework and confirms its relevance for understanding sustainability-oriented managerial behavior.

On a practical level, the findings suggest that organizations should prioritize diversity in their executive teams, not only focusing on gender inclusivity but also emphasizing varied educational backgrounds to ensure well-rounded strategic decision-making. A more diverse executive team can provide a broader range of perspectives, leading to more comprehensive and effective CSR strategies. Additionally, policymakers could consider developing guidelines or incentives aimed at increasing female representation in senior leadership roles. Encouraging a greater presence of female CEOs could contribute to the advancement of CSR initiatives and positively influence corporate behavior on a larger scale.

Furthermore, integrating ethical training and sustainability-focused education into leadership development programs can better equip future executives to meet the growing demands of stakeholders who expect companies to demonstrate a commitment to social responsibility and environmental stewardship. By fostering these competencies, organizations can prepare leaders who are capable of navigating the complexities of the modern business environment and responding to the evolving expectations of both investors and consumers.

For investors and stakeholders, understanding the influence of CEO characteristics on CSR can provide valuable insights when evaluating a company's sustainability trajectory and ethical commitments. Companies with leaders who prioritize education, ethics, and diversity are more likely to adopt forward-thinking CSR strategies that align with long-term value creation and sustainability goals. As such, these insights can guide investment decisions and influence stakeholder engagement strategies.

Finally, organizations can use the findings of this study to refine their recruitment and leadership development strategies, ensuring that the competencies of their executive teams align with long-term sustainability objectives. By promoting diversity in leadership and providing executives with the tools and knowledge to lead with integrity, companies can enhance their CSR performance and contribute to the broader goal of sustainable development.

6. LIMITATIONS AND FUTURE RESEARCH

While this study provides valuable insights, it has certain limitations that warrant further investigation. First, the reliance on Essi G scores from the ASSET4 database of Thomson Reuters may not comprehensively capture the multidimensional nature of CSR, particularly in varying industry or regional contexts. Future studies could incorporate alternative CSR measures or conduct comparative analyses across different databases to validate the findings.

Second, the sample focuses on publicly listed companies, potentially limiting the applicability of results to private firms or small and medium-sized enterprises (SMEs). Expanding the scope to include diverse organizational structures could provide a more holistic understanding of the relationship between CEO characteristics and CSR.

Finally, this study primarily considered education level and gender, leaving other potentially significant attributes, such as international experience, leadership styles, or psychological traits, unexplored. Future research could investigate these factors, as well as the moderating effects of cultural, regulatory, and industry-specific variables, to offer deeper insights into how leadership influences CSR across varying contexts.

By addressing these limitations and broadening the scope of investigation, future studies can enrich the understanding of how leadership characteristics shape sustainable corporate practices, ultimately supporting the global transition towards more responsible business strategies.

References

Abba, M., Said, R. M., Abdullah, A., & Mahat, F. (2018). The Relationship Between Environment Operational Performance and Environmental Disclosure of Nigerian Listed Companies. *Journal of Environmental Accounting and Management, 6*(1), 1–15. http://dx.doi.org/10.5890/JEAM.2018.03.001

Adams, R. B., & Ferreira, D. (2009). Women in the Boardroom and Their Impact on Governance and Performance. *Journal of Financial Economics, 94*(2), 291–309. http://dx.doi.org/10.1016/j.jfineco.2008.10.007

Ahn, J. (2020). Exploring ESG Ratings and Corporate Sustainability. *Journal of Sustainable Finance & Investment, 10*(2), 345–361. http://dx.doi.org/10.1080/20430795.2020.1719826

Aier, J. K., Comprix, J., Gunlock, M. T., & Lee, D. (2005). The Financial Expertise of CFOs and Accounting Restatements. *Accounting Horizons, 19*(3), 123–135. http://dx.doi.org/10.2308/acch.2005.19.3.123

Amore, M. D., Garofalo, O., & Minichilli, A. (2019). CEO Characteristics and Corporate Social Responsibility in the Manufacturing Sector. *Journal of Business Ethics, 155*(3), 501–516. http://dx.doi.org/10.1007/s10551-017-3475-2

Bagh, T., Fuwei, J., & Khan, M. A. (2024). From Risk to Resilience: Climate Change Risk, ESG Investments Engagement and Firm's Value. *Heliyon, 10*(5), e26757. http://dx.doi.org/10.1016/j.heliyon.2024.e26757

Bear, J., Rahman, H., & Post, C. (2010). The Influence of CEO Gender on Corporate Social Responsibility. *Journal of Business Ethics, 94*(2), 201–215. http://dx.doi.org/10.1007/s10551-009-0260-3

Bhaskar, R. (2023). The Role of Leadership Traits in Promoting Sustainable Corporate Practices. *Corporate Governance Review, 18*(2), 123–135. http://dx.doi.org/10.1007/s10551-022-3547-1

Bhaskar, S., Mittal, V., & Agrawal, R. (2023). ESG Scores and Their Impact on Corporate Financial Performance: Evidence from Emerging Markets. *Emerging Markets Review, 27*, 134–150. http://dx.doi.org/10.1016/j.ememar.2023.134150

Biju, A. V. N., Kodiyatt, S. J., Krishna, P. P. N., Sreelekshmi, G., & al. (2023). ESG Sentiments and Divergent ESG Scores: Suggesting a Framework for ESG Rating. *SN Business & Economics, 3*(12), 209. http://dx.doi.org/10.1007/s43546-023-00592-4

Borghesi, R., Houston, M. B., & Nitzsche, D. (2014). The Effect of CEO Characteristics on Corporate Social Responsibility. *Journal of Business Ethics, 119*(4), 595–615. http://dx.doi.org/10.1007/s10551-013-1862-5

Bouzguenda, M., & Jarboui, A. (2024a). The Multidimensional Nature of CSR: The Role of the CEO Socio-Demographic Profile. *Scientific Annals of Economics and Business, 71*(4), 449–472. http://dx.doi.org/10.47743/saeb-2024-0025

Bouzguenda, M., & Jarboui, A. (2024b). The Role of the Psychological and Behavioral Profile of the CEO in Assessing the Dimensions of the Corporate Social Responsibility. *SN Business & Economics, 4*(10), 117. http://dx.doi.org/10.1007/s43546-024-00712-8

Braun, E., & Zenker, S. (2022). In GovernmentsWwe Trust: A Two-Country Brexit Field Experiment on Perceived Uncertainty as Mediator for Consumer Decisions. *Journal of Business Research, 138*(C), 335–346. http://dx.doi.org/10.1016/j.jbusres.2021.09.014

Choi, B., Lee, J., & Lee, S. (2023). Gender and Sustainability: The Influence of Female Leadership on CSR and SDG Alignment. *Sustainable Development (Bradford), 31*(1), 87–101. http://dx.doi.org/10.1002/sd.2323

Chu, Y., Liu, P., & Zhang, R. (2022). Gender and CSR: How Female CEOs Influence Corporate Sustainability. *Sustainable Business Journal, 12*(3), 34–46. http://dx.doi.org/10.1080/20421338.2022.1823417

Chulkova, A., & Kim, Y. (2025). Female Leadership and CSR: The Influence of Empathy and Risk Aversion. *Journal of Corporate Responsibility, 21*(1), 45–59.

Davis, K., Ghorashi, H., & Smets, P. (2018). *Contested Belonging: Spaces, Practices, Biographies*: Emerald Group Publishing. http://dx.doi.org/10.1108/9781787432062

Erdiaw-Kwasie, M. O., Abunyewah, M., & Baah, C. (2023). Corporate Social Responsibility (CSR) and Cognitive Bias: A Systematic Review and Research Direction. *Resources Policy, 86*(2023), 104201. http://dx.doi.org/10.1016/j.resourpol.2023.104201

Finkelstein, S., Hambrick, D. C., & Cannella, A. A. (2008). *Strategic Leadership: Theory and Research on Executives, Top Management Teams, and Boards* (1st ed.): Oxford University Press. http://dx.doi.org/10.1093/acprof:oso/9780195162073.003.0005

Frank, M. S. (1993). The Essence of Leadership. *Public Personnel Management, 22*(3), 381–389. http://dx.doi.org/10.1177/009102609302200303

Fujianti, L., & Satria, I. (2020). Firm Size, Profitability, Leverage as Determinants of Audit Report Lag: Evidence From Indonesia. *International Journal of Financial Research, 11*(2), 61–67. http://dx.doi.org/10.5430/ijfr.v11n2p61

Furlotti, K., Mazza, T., Tibiletti, V., & Triani, S. (2019). Women in top positions on boards of directors: Gender policies disclosed in Italian sustainability reporting. *Corporate Social Responsibility and Environmental Management, 26*(1), 57–70. http://dx.doi.org/10.1002/csr.1657

Gadenne, D. L., Kennedy, J., & McKeiver, C. (2009). An Empirical Study of Environmental Awareness and Practices in SMEs. *Journal of Business Ethics, 84*(1), 45–63. http://dx.doi.org/10.1007/s10551-008-9672-9

Gala, P., Kashmiri, S., & Nicol, C. D. (2024). Female CEOs and Corporate Social Responsibility: Effect of CEO Gender on Relational and Rational CSR. *European Journal of Marketing, 58*(10), 2129–2168. http://dx.doi.org/10.1108/EJM-06-2023-0448

García-Sánchez, I. M., Gómez-Miranda, M.-E., David, F., & Rodríguez-Ariza, L. (2019). Analyst Coverage and Forecast Accuracy When CSR Reports Improve Stakeholder Engagement: The Global Reporting Initiative-International Finance Corporation disclosure strategy. *Corporate Social Responsibility and Environmental Management, 26*(5), 1139–1151. http://dx.doi.org/10.1002/csr.1755

García-Sánchez, I. M., Hussain, N., Khan, S. A., & Martínez-Ferrero, J. (2022). Assurance of Corporate Social Responsibility Reports: Examining the Role of Internal and External Corporate Governance Mechanisms. *Corporate Social Responsibility and Environmental Management, 29*(1), 89–106. http://dx.doi.org/10.1002/csr.2186

Garrido-Ruso, J., & Aibar-Guzmán, C. (2022). CEO education and the rise of sustainability in corporate decisions. *Sustainability, 14*(7), 2080. http://dx.doi.org/10.3390/su14072080

Garrido-Ruso, M., Aibar-Guzmán, B., & Suárez-Fernández, Ó. (2023). What Kind of Leaders Can Promote the Disclosure of Information on the Sustainable Development Goals? *Sustainable Development (Bradford), 31*(4), 2694–2710. http://dx.doi.org/10.1002/sd.2539

Glass, C., & Cook, A. (2018). Female CEOs and Sustainability: Do Women Lead Differently? *Leadership and Organization Development Journal, 39*(6), 712–728. http://dx.doi.org/10.1108/LODJ-03-2017-0111

Hambrick, D. C., & Mason, P. A. (1984). Upper Echelons: The Organization as a Reflection of Its Top Managers. *Academy of Management Review, 9*(2), 193–206. http://dx.doi.org/10.2307/258434

Hewa Heenipellage, R., & McCall, R. (2022). Higher Education and CSR Adoption: How CEOs' Educational Backgrounds Affect Sustainability Strategies. *Journal of Business Ethics, 171*(3), 551–565. http://dx.doi.org/10.1007/s10551-019-04348-7

Huang, X., Sun, S., & Zhao, Y. (2024). The Psychological Traits of Female CEOs and Their Impact on Organizational Culture. *The Journal of Applied Psychology, 109*(1), 115–130. http://dx.doi.org/10.1037/apl0000672

Jani, R., Byrne, R., Love, P., Agarwal, C., Peng, F., Yew, Y. W., . . . Naumovski, N. (2020). The Environmental and Bitter Taste Endophenotype Determinants of Picky Eating in Australian School-Aged Children 7–12 years—A Cross-Sectional Pilot Study Protocol. *International Journal of Environmental Research and Public Health, 17*(5), 1573. http://dx.doi.org/10.3390/ijerph17051573

Khan, T. M., Bai, G., Fareed, Z., Quresh, S., Khalid, Z., & Khan, W. A. (2021). CEO Tenure, CEO Compensation, Corporate Social and Environmental Performance in China: The Moderating Role of Coastal and Non-Coastal Areas. *Frontiers in Psychology, 11*(2020), 574062. http://dx.doi.org/10.3389/fpsyg.2020.574062

Kouaib, A., & Jarboui, A. (2016). Real Rarnings Management in Innovative Firms: Does CEO Profile Make a Difference? *Journal of Behavioral and Experimental Finance, 12*(C), 40–54. http://dx.doi.org/10.1016/j.jbef.2016.09.002

Lewis, B. W., Walls, J. L., & Dowell, G. W. (2014). Difference in Degrees: CEO Characteristics and Firm Environmental Disclosure. *Strategic Management Journal, 35*(5), 712–722. http://dx.doi.org/10.1002/smj.2127

Liang, J., Luo, H., & Li, Z. (2024). The Gendered Approach to CSR: Exploring Leadership Styles and Decision-Making Processes. *International Journal of Corporate Social Responsibility, 9*(1), 21–37. http://dx.doi.org/10.1186/s40991-024-00119-2

Liu, Y., Li, W., & Li, Y. (2020). Ambidexterity between Low Cost Strategy and CSR Strategy: Contingencies of Competition and Regulation. *Asia Pacific Journal of Management, 37*(3), 633–660. http://dx.doi.org/10.1007/s10490-019-09647-3

Malik, F., Wang, F., Naseem, M. A., Ikram, A., & Ali, S. (2020). Determinants of Corporate Social Responsibility Related to CEO Attributes: An Empirical Study. *SAGE Open, 10*(1), 1–12. http://dx.doi.org/10.1177/2158244019899093

Manes-Rossi, F., & Nicolo, G. (2022). Exploring Sustainable Development Goals Reporting Practices: From Symbolic to Substantive Approaches—Evidence from the Energy Sector. *Corporate Social Responsibility and Environmental Management, 29*(3), 504–517. http://dx.doi.org/10.1002/csr.2328

Manner, M. H. (2010). The Impact of CEO Characteristics on Corporate Social Performance. *Journal of Business Ethics, 93*(Suppl 1), 53–72. http://dx.doi.org/10.1007/s10551-010-0626-7

Marquis, C., & Lee, M. (2013). Corporate Social Responsibility and Gender: The Influence of CEO Gender on CSR Performance. *Business & Society, 52*(3), 422–451. http://dx.doi.org/10.1177/0007650312460185

Marwa, M., Salhi, B., & Jarboui, A. (2020). Environmental Audit and Environmental Disclosure Quality. *Scientific Annals of Economics and Business, 67*(1), 93–115. http://dx.doi.org/10.47743/saeb-2020-0007

McCarthy, S., Oliver, B., & Song, S. (2017). Corporate Social Responsibility and CEO Confidence. *Journal of Banking & Finance, 75*(February), 280–291. http://dx.doi.org/10.1016/j.jbankfin.2016.11.024

McWilliams, A., & Siegel, D. (2001). Corporate Social Responsibility: A Theory of the Firm Perspective. *Academy of Management Review, 26*(1), 117–127. http://dx.doi.org/10.2307/259398

Muttakin, M. B., Khan, A., & Mihret, D. G. (2018). The Effect of Board Capital and CEO Power on Corporate Social Responsibility Disclosures. *Journal of Business Ethics, 150*(1), 41–56. http://dx.doi.org/10.1007/s10551-016-3105-y

Nielsen, S., & Huse, M. (2010). Women Directors and CSR. *Journal of Business Ethics, 91*(3), 297–312. http://dx.doi.org/10.1007/s10551-009-0151-4

Oh, W. Y., Chang, Y. K., & Cheng, Z. (2016). When CEO Career Horizon Problems Matter for Corporate Social Responsibility: The Moderating Roles of Industry-Level Discretion and Blockholder Ownership. *Journal of Business Ethics, 133*(2), 279–291. http://dx.doi.org/10.1007/s10551-014-2397-z

Omer, W. K. H., Aljaaidi, K. S., & Habtoor, O. S. (2020). The Associations of Corporate Social Responsibility and Management Characteristics with Performance in Saudi Arabia. *Polish Journal of Management Studies, 21*(1), 251–264.

Puchakayala, N. V. V. S., Nallamalli, U. B., & Narapareddi, V. (2023). Corporate Social Responsibility: A Way of Enhancing Financial Performance—Evidence from Select NSE Listed Companies. *SN Business & Economics, 3*(2023), 118. http://dx.doi.org/10.1007/s43546-023-00492-7

Rahman, M. H., Tanchangya, T., Rahman, J., Aktar, M. A., & Majumder, S. C. (2024). Corporate Social Responsibility and Green Financing Behavior in Bangladesh: Towards Sustainable Tourism. *Innovation and Green Development, 3*(3), 1–14. http://dx.doi.org/10.1016/j.igd.2024.100133

Schaper, M. (2002). Higher Education and Its Influence on CSR: A Comparison between Business and Technical Disciplines. *Business and Society Review, 107*(1), 39–58. http://dx.doi.org/10.1111/1467-8594.00014

Schwoy, S., Dutzi, A., Corten, M., & Steijvers, T. (2023). Staging or Real Commitment? CEO Reputation Management as a Moderator of the Influence of Firm Size on Corporate Social Responsibility Performance and Controversies. *Journal of Cleaner Production, 410*(1), 137325. http://dx.doi.org/10.1016/j.jclepro.2023.137325

Shahab, Y., & Ye, C. (2018). Corporate social responsibility disclosure and corporate governance: empirical insights on neo-institutional framework from China. *International Journal of Disclosure and Governance, 15*(2), 87–103. http://dx.doi.org/10.1057/s41310-018-0038-y

Shahzadi, G., John, A., Qadeer, F., Jia, F., & Yan, J. (2024). CSR beyond Symbolism: The Importance of Substantive Attributions for Employee CSR Engagement. *Journal of Cleaner Production, 436*(6), 14044. http://dx.doi.org/10.1016/j.jclepro.2023.140440

Smith, N., Eriksson, T., & Smith, V. (2021). Gender Stereotyping and Self-Stereotyping among Danish Managers. *Gender in Management, 36*(5), 622–639. http://dx.doi.org/10.1108/GM-01-2020-0018

Susilo, B., Usman, B., & Lestari, H. S. (2025). The Influence of CEO Characteristics, Risk Management, Financial Digitalization and Exchange Rate on Bank Performance Moderated By Interest Rate. Asian Journal of Management. *Asian Journal of Management Entrepreneurship and Social Science, 5*(01), 329–353. http://dx.doi.org/10.63922/ajmesc.v5i01.1235

Suwardi, E., & Saragih, A. H. (2023). The effect of tax risk on audit report delay: Empirical evidence from Indonesia. *Cogent Business & Management, 10*(1), 2192315. http://dx.doi.org/10.1080/23311975.2023.2192315

Tabachnick, B. G., & Fidell, L. L. S. (2013). *Using Multivariat Statistics* (6th ed.) New York: Pearson Education.

Tang, Z., Hull, C. E., & Zhang, Y. (2015). The Impact of Education on CEO's Ethical Decision-Making. *Journal of Business Ethics, 128*(1), 143–160. http://dx.doi.org/10.1007/s10551-014-2064-7

Velte, P. (2019). How Education Influences CEOs' Commitment to Corporate Social Responsibility. *Journal of Applied Accounting Research, 20*(3), 492–514. http://dx.doi.org/10.1108/JAAR-03-2018-0062

Velte, P. (2025). Female Chief Financial Officers (CFOs) and Environmental Decoupling. The Moderating Impact of Sustainability Board Committees. *Corporate Social Responsibility and Environmental Management, 32*(1), 1147–1160. http://dx.doi.org/10.1002/csr.3003

Villalba-Ríos, P., Barroso-Castro, C., & Vecino-Gravel, J. D. (2022). The Influence of CEO Profile on Corporate Social Responsibility Companies. A Qualitative Comparative Analysis. *Corporate Social Responsibility and Environmental Management, 29*(2), 356–366. http://dx.doi.org/10.1002/csr.2205

Wang, L., Lin, Y., Jiang, W., Yang, H., & Zhao, H. (2023). Does CEO Emotion Matter? CEO Affectivity and Corporate Social Responsibility. *Strategic Management Journal, 44*(7), 1820–1835. http://dx.doi.org/10.1002/smj.3474

Wei, Z., Tang, S., & Zhang, Z. (2018). The role of education in CSR decision-making processes. *Corporate Governance (Bradford), 18*(6), 1032–1051. http://dx.doi.org/10.1108/CG-12-2017-0270

Welkowitz, J., Cohen, B. H., & Lea, R. B. (2012). *Introductory Statistics for the Behavioral Sciences* (Seventh ed.). United States of America: John Wiley & Sons.

Wen, R., Xue, C., & Zhang, J. (2024). The Relationship Between CEO Characteristics and Corporate Social Responsibility: Evidence from China. In W. A. Barnett & B. S. Sergi (Eds.), *The Finance-Innovation Nexus: Implications for Socio-Economic Development* (1st ed., Vol. 34, pp. 1–13): Emerald Publishing Limited. http://dx.doi.org/10.1108/S1571-038620240000034001

Yahya, H. (2025). Female Leadership and ESG Performance of Firms: Nordic Evidence. *Corporate Governance (Bradford), 25*(1), 109–127. http://dx.doi.org/10.1108/CG-03-2023-0129

Yin, J., Li, J., & Ma, J. (2024). The Effects of CEO Awards on Corporate Social Responsibility Focus. *Journal of Business Ethics, 190*(4), 897–916. http://dx.doi.org/10.1007/s10551-023-05411-2

Yuan, L., Li, S., & Wang, Z. (2017). CEO Education and the Implementation of Corporate Social Responsibility: Evidence from China. *Asian Business & Management, 16*(2), 125–142. http://dx.doi.org/10.1057/s41291-017-0035-7

Zhang, F., Cantwell, J., & Jiang, G. (2014). The Competence Creation of Recently-Formed Subsidiaries in Networked Multinational Corporations: Comparing Subsidiaries in China and Subsidiaries in Industrialized Countries. *Asian Business & Management, 13*(1), 5–41. http://dx.doi.org/10.1057/abm.2013.12

Zhou, M., Chen, F., & Chen, Z. (2021). Can CEO Education Promote Environmental Innovation: Evidence from Chinese Enterprises. *Journal of Cleaner Production, 297*(2021), 126725. http://dx.doi.org/10.1016/j.jclepro.2021.126725

Scientific Annals of Economics and Business
73 (3), 2026, 527-549
DOI: 10.47743/saeb-2026-0034

Green Investment as a Buffer: Analyzing the Economic and Environmental Impacts of Non-Renewable Energy Consumption in G20 Countries

Muhammad Adil[*], Rana Yassir Hussain[**], Rashid Mehmood[***], Kai-Yin Woo[§]

Abstract: The G20 countries are among the world's fastest-growing economies. However, they are also major contributors to environmental degradation, as most of them rely heavily on non-renewable energy sources to support economic growth. This study investigates the moderating role of green investment in the relationships between non-renewable energy consumption, economic growth and environmental degradation in G20 countries. A panel data approach was used to analyze data from G20 countries for the period 2010 to 2023. The study employed the panel-corrected standard error (PCSE) method as the main estimator, supplemented by a feasible generalized least squares (FGLS) model for robustness checks. Additionally, to address endogeneity in panel data, a one-step system generalized method of moments (GMM) regression was used, which provides consistent estimates in dynamic panels. The findings indicate that non-renewable energy consumption has a significant positive effect on economic growth but also significantly increases environmental degradation. Furthermore, the moderation results show that green investment strengthens the positive effect of non-renewable energy consumption on economic growth and reduces its negative environmental effects. Hence, policymakers in G20 countries should promote green investment initiatives to mitigate the environmental challenges associated with the consumption of non-renewable energy resources.

Keywords: environmental degradation; economic growth; non-renewable energy consumption; green investment.

JEL classification: C10; C50; Q56.

[*] University of Education, Lahore, Pakistan; e-mail: *msf23005553@ue.edu.pk*.
[**] University of Education, Lahore, Pakistan; e-mail: *yassir.hussain@ue.edu.pk* (corresponding author).
[***] University of Education, Lahore, Pakistan; e-mail: *rashid.mehmood@ue.edu.pk*.
[§] Hong Kong Shue Yan University, Hong Kong; e-mail: *kywoo@hksyu.edu*.

Article history: Received 24 July 2025 | Accepted 17 September 2026 | Published online 29 September 2026

To cite this article: Adil, M., Hussain, R.Y., Mehmood, R., Woo, K.-Y. (2026). Green Investment as a Buffer: Analyzing the Economic and Environmental Impacts of Non-Renewable Energy Consumption in G20 Countries. *Scientific Annals of Economics and Business*, 73(3), 527-549. https://doi.org/10.47743/saeb-2026-0034.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

Consumption of non-renewable energy has long been linked to the pursuit of economic growth. In the context of national development strategies, economic development is the primary goal of every country (Adanma and Ogunbiyi, 2024). Due to the rising need for energy, researchers in energy economics have extensively examined the link between energy consumption and economic growth (Pegkas, 2020; Asiedu *et al.*, 2021; Cevik *et al.*, 2021; Ivanovski *et al.*, 2021). Yet research outcomes on both variables have generally been ambiguous, suggesting a lack of consensus among scholars. The primary factors contributing to this uncertainty are geographical differences, econometric methods, and the diverse characteristics of different countries. Besides being effective catalysts for economic growth, non-renewable energy sources also contribute to ecological deterioration (Amin *et al.*, 2022). Economic growth is linked to energy consumption, and energy usage contributes to environmental degradation (Wen *et al.*, 2021; Usman *et al.*, 2023). Currently, almost every country meets the bulk of its energy requirements through non-renewable energy resources. Therefore, as countries' energy consumption increases, environmental degradation also grows (Islami *et al.*, 2022). The main challenge today is to maintain equilibrium between sustainable economic expansion and environmental concerns.

The world is currently confronted with escalating environmental degradation, which is destructive to human life (Shivanna, 2022). Several countries have failed to implement energy-efficient technologies in manufacturing processes. That is why their economic activities continue to rely on energy-inefficient methods, contributing to global environmental degradation (Yang *et al.*, 2021; Chin *et al.*, 2022). Growing consumption of non-renewable energy is accelerating environmental degradation, leading to significant CO_2 emissions worldwide (Asif *et al.*, 2021). Energy-related CO_2 emissions worldwide rose by 1.1% in 2023, climbing 410 million tonnes to achieve an unprecedented total of 37.4 billion tonnes (IEA, 2024). This statistic highlights the ongoing degradation of the environment and underscores the urgent need for more sustainable economic development. Indeed, the world is experiencing a significant degradation of environmental conditions. This environmental degradation is primarily driven by the extensive consumption of non-renewable resources in the pursuit of economic development (Pegkas, 2020; Cevik *et al.*, 2021). Consequently, green investment has become imperative, particularly for countries that remain heavily dependent on non-renewable energy sources (Güney, 2019). Such environmentally sustainable investments not only support economic growth but also contribute to environmental preservation. Against this backdrop, the present study seeks to examine whether green investment can mitigate the environmental and economic consequences of non-renewable energy consumption.

The G20 countries have considerable influence on global economic, environmental and energy dynamics. The G20 nations collectively account for about 85% of global GDP, 75% of international trade and two-thirds of the world's population (Munyati, 2023). Consequently, their energy and environmental policies exert a significant influence on the global environment. Notably, like many other countries around the world, G20 nations continue to meet the majority of their energy demands through non-renewable energy sources (Ajide and Mesagan, 2022; Shah *et al.*, 2024). Fossil fuel consumption of most G20 countries has been rising. The overall consumption of fossil fuels by G20 countries was 92,804 TWh in 2010, and this increased to 107,585 TWh by 2023, representing an increase of approximately 15.93% (Our World in Data, 2025). Figure no. 1 presents the fossil fuel

consumption tendencies in G20 countries, with India having the highest growth in consumption (+67%) and the United Kingdom having the lowest (-36%).

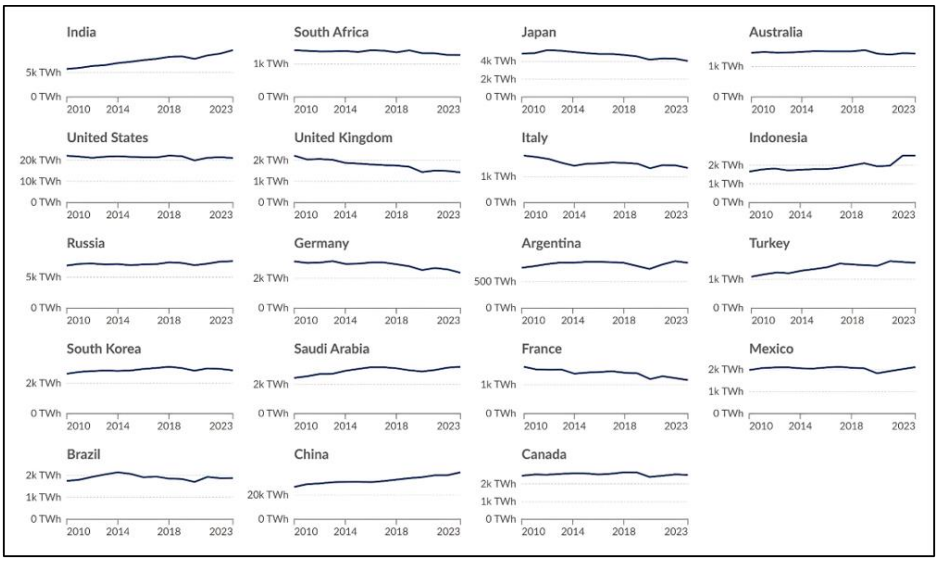


Figure no. 1 – Trends in fossil fuel consumption across G20 countries, 2010 to 2023

This 15.93% increase in fossil fuel consumption is one reason behind the upsurge in CO_2 emissions to the environment worldwide. The CO_2 emanating from non-renewable sources is giving rise to various environmental consequences. These outcomes include global warming, an increase in sea levels, and threats to ecosystem balance. The total CO_2 emissions by G20 countries increased by 15% from 2010 to 2023 (Ritchie *et al.*, 2023). Figure no. 2 shows the trend of CO_2 emissions by G20 countries from 2010 to 2023. India had the highest increase in emissions, at +83%, and the United Kingdom had the lowest, at -40%.

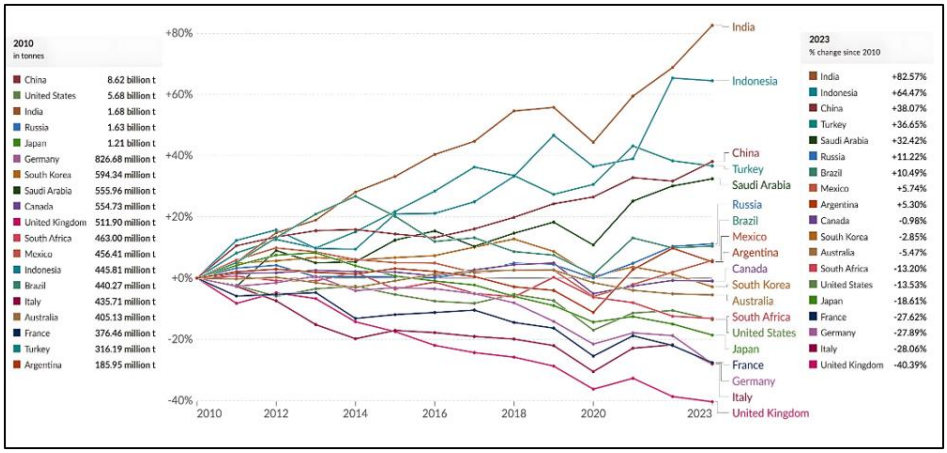


Figure no. 2 – The trend of relative changes in CO_2 emission among G20 members from 2010 to 2023

Statistics show that G20 countries with high consumption of non-renewable resources also contribute extensively to the degradation of the world environment. Their heavy dependence on non-renewable energy resources significantly contributes to the worsening of global environmental challenges. Fossil fuel dependence and carbon emissions remain substantial across the G20, though patterns differ among individual economies. G20 members at the 2023 summit emphasized the need to expand green finance to address environmental degradation concerns. The G20 leaders further emphasized their conviction that financial flows should be aligned with the climate goals established under the Paris Agreement (Citil, 2024). The emphasis on green investment is increasing worldwide due to the growing concerns about environmental degradation. These commitments raise an important empirical question: does greater green investment weaken the environmental cost of non-renewable energy while improving its contribution to economic growth?

Recent research has broadened the literature regarding the association among energy use, environmental policies, and economic results. Ozcan *et al.* (2020) analyze the 35 OECD member countries and conclude that higher levels of economic development, combined with improved energy efficiency, lead to better environmental outcomes. Likewise, Chien (2022) indicates that excessive consumption of fossil energy fuels economic growth of the N-11 economies but also exacerbates the environmental situation. Wang *et al.* (2023) further show that non-renewable energy promotes long-run economic growth in selected Northeast Asian nations. However, it also intensifies long-run CO_2 emissions. The results indicate that non-renewable energy provides economic benefits; however, it is also a significant factor in environmental problems. These studies provide important evidence regarding the associations among non-renewable energy consumption, environmental degradation and economic growth, but they primarily focus on direct associations, individual environmental outcomes, and countries with different characteristics. However, there are several gaps in the literature related to these relationships. Firstly, previous studies focus on either environmental or economic impacts of non-renewable energy consumption. This represents an incomplete measure of the benefits and costs of fossil fuel dependence. Second, these studies considered green investment as only a direct determinant of growth and environmental quality. These studies do not fully establish whether green investment changes both the economic and environmental effects of non-renewable energy consumption in G20 economies. There is limited evidence on whether green investment moderates the relationship between non-renewable energy consumption and the study outcomes. Third, the net impacts of different levels of green investment on the G20 economies when using non-renewable energy have not been studied. The novelty of the present study lies not in re-examining the direct relationship among energy consumption, economic growth, and environmental quality. Rather, it investigates the conditional role of green investment within an integrated economy-environment framework. Further, it analyzes the net effects of non-renewable energy consumption at different levels of green investment. This study seeks to fill the research gap by examining the extent to which green investment can mitigate the environmental consequences of non-renewable energy consumption while sustaining economic progress.

Green investment can alter these relationships through several channels. It may weaken environmental damage by supporting energy efficiency, cleaner production, and low-carbon technologies (Umar and Safi, 2023; Cheng and Zhu, 2024). It may also influence the growth effect of non-renewable energy by improving resource efficiency and technological

productivity (Hussain *et al.*, 2025; Adil *et al.*, 2026). However, its moderating effect on economic growth is not automatically positive. Green investment may complement conventional energy during the transition toward cleaner production. Furthermore, it may encourage substitution away from fossil fuel-based activities (Doğan *et al.*, 2026). The direction and magnitude of this moderating effect therefore require empirical examination. Accordingly, this study pursues three main objectives. First, it analyzes the impact of non-renewable energy consumption on economic growth in G20 economies. Secondly, it examines the impact of non-renewable energy consumption on environmental degradation. Third, it investigates how green investments influence the relationship between non-renewable energy consumption, economic growth, and environmental degradation. Along with estimating the interaction coefficients, the study computes the corresponding net effects to explain the moderating relationships in an economically meaningful way.

This study makes four contributions to the existing literature. First, it explores the economic and environmental implications of non-renewable consumption within a single empirical framework. Second, in addition to examining the direct impact, it extends the literature on environment-focused investments by analyzing green investment as a moderating mechanism. Third, it estimates and interprets the net consequences of non-renewable energy consumption at varying levels of green investment, providing greater clarity regarding the practical implications of the interaction terms. Fourth, it presents evidence from the G20 economies, which are globally significant yet economically and institutionally diverse. Moreover, it examines the robustness of the findings using multiple panel estimation methods. The study comprehensively investigates these relationships using data from G20 countries, which account for a substantial share of global economic activity, energy consumption, and carbon emissions. Hence, to achieve the objectives, the study estimates the relationships through two econometric approaches, panel-corrected standard errors (PCSE) and feasible generalized least squares (FGLS). Both approaches yield reliable estimates in the presence of cross-sectional dependence, serial correlation, and heteroskedasticity. In addition, the one-step system generalized method of moments (GMM) estimator is employed to address potential endogeneity concerns associated with the main findings. The interaction terms are interpreted through net effect calculations and marginal effect plots. The remainder of the paper reviews the relevant literature, explains the research methodology, and presents the main and robustness results. Consequently, the policy recommendations derived from the study's primary findings will help promote sustainable economic development in these countries and enhance the quality of the global ecosystem.

2. LITERATURE REVIEW

2.1. Non-Renewable Energy Consumption and Economic Growth

Ivanovski *et al.* (2021) examined how the effects of non-renewable energy consumption on economic growth change over time in both OECD and non-OECD nations from 1990 until 2015. The study applied a local linear dummy variable estimation technique, and it argued that this approach does not require any assumptions about functional form and is more effective in capturing non-linear relations. Hence, their analysis suggested that non-renewable energy consumption significantly influences economic growth in both OECD and non-OECD countries. Furthermore, Asif *et al.* (2021) reported that the

use of non-renewable energy resources significantly promotes economic growth. Their study examined panel data from 99 countries spanning the period 1995 to 2017, employing dynamic OLS (DOLS), fully modified OLS (FMOLS), and fixed-effects estimation techniques. Moreover, Pegkas (2020) found that the use of non-renewable energy fostered long-run economic growth in Greece. However, Cevik *et al.* (2021) found a bidirectional link between energy usage and economic development in the USA. They identified that the use of non-renewable energy is crucial for the USA's economic progress. Rahman and Velayutham (2020) analyzed the data from five South Asian nations using panel FMOLS and DOLS assessment approaches. Their study found that non-renewable energy consumption contributes to a 0.10% increase in economic growth. Moreover, Mohammadi *et al.* (2023) analyzed the selected advanced and underdeveloped countries from 1993 to 2019 through an OLS approach. Their study results highlighted the constructive role of non-renewable energy consumption on the economic progress of both categories of countries. Consequently, by considering the discussion outlined above, we propose that:

H1*: Non-renewable energy consumption significantly positively influences economic growth.*

2.2. Non-Renewable Energy Consumption and Environmental Degradation

Chien (2022) analyzed panel data from the N-11 economies covering the period 1990-2020 using the MMQR approach to examine the relationship between non-renewable energy consumption and environmental degradation. The study's findings demonstrated that using non-renewable resources positively impacts ecological settings; however, this impact is only at minor quantiles (0.10–0.40). Moreover, in response to Australia's growing environmental challenges in recent years, Rahman and Alam (2022) investigated the roles of several environment-related factors. Employing the ARDL model and Granger causality tests, their study found that non-renewable energy consumption exerts a positive effect on environmental degradation. Furthermore, Randhawa *et al.* (2026) found that technological innovation plays an important role in shaping environmental stress in Pakistan. Their study further supports the need to consider complementary factors beyond energy consumption when examining environmental outcomes. Moreover, Adekoya *et al.* (2024) examined the relationship between energy consumption and ecological degradation by distinguishing between oil-importing and oil-exporting countries. Using the AMG regression technique, their study found that the use of non-renewable resources in both groups of countries plays a substantial role in environmental deterioration. However, their study further revealed that this effect is more pronounced in oil-exporting countries. This is because of their substantial reliance on crude oil and energy inefficiencies. In addition, combating climate change has become a central objective of policy initiatives across Sub-Saharan African countries in recent years. Therefore, Ahmad Khan *et al.* (2024)investigated Sub-Saharan African nations because of their strong commitment to achieving sustainable targets. According to their two-step system GMM regression findings, the use of non-renewable energy positively impacts the environment. Additionally, Zhang *et al.* (2024) analyzed Chinese data from 1991 to 2020 to examine the impact of non-renewable energy consumption on CO_2 emissions. Using the QARDL approach, the study revealed that the consumption of non-renewable energy is positively associated with CO_2 emissions. Thus, by considering the discussion outlined above, we hypothesize that:

H2*: Non-renewable energy consumption contributes to environmental degradation.*

2.3. Moderating Role of Green Investment

Dong *et al.* (2024) found that carbon emissions are greatly curtailed in an economy that values green investment. Beşer *et al.* (2025) examined the annual data of 20 African nations from 2000 to 2019 by employing the GMM estimator and found that green investments can positively tackle the environmental degradation issues. More recently, Solangi and Magazzino (2025) examined the relationship between natural resource management and green energy investment in Gulf Cooperation Council countries. Their study suggests that investment in cleaner energy sources can play an important role in improving environmental outcomes. Similarly, Solangi *et al.* (2025) investigated the role of green finance in sustainable development across 16 emerging market economies during 2014 to 2022. Their findings showed that green finance has a positive effect on sustainable development. Their study highlighted the importance of increasing green investment to tackle the environmental challenges. In contrast, Onifade *et al.* (2025) argued that green investments promote sustainable economic development rather than hinder it. Wan and Sheng (2022) analyzed panel data from 30 Chinese provinces and cities covering the period from 2003 to 2017. Their findings confirmed the significant positive contribution of green investment to economic development. Furthermore, the study suggested that green investment is an effective means of stimulating economic growth. In light of the debate above, we hypothesize that:

H3a: *Green investment significantly moderates the association between non-renewable energy consumption and economic growth.*

H3b: *Green investment significantly moderates the association between non-renewable energy consumption and environmental degradation.*

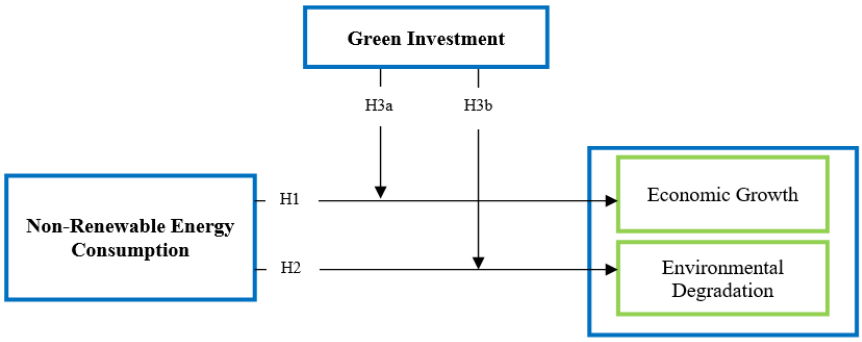


Figure no. 3 – Conceptual framework of the current study

3. DATA AND METHODOLOGY

3.1. Database and Variables

We have chosen a panel dataset of G20 countries covering the years 2010 to 2023. The sample includes 19 countries, each with 14 years of data. Consequently, our dataset has a

large number of cross-sections *(N)* as compared to time periods *(T)*. Our independent variable is non-renewable energy consumption *(lnNREC)*, measured as per capita fossil fuel consumption in kWh. Furthermore, we have employed two dependent variables, namely economic growth *(lnEG)* and environmental degradation *(lnED)*. We gauged economic growth by the annual percent change in real GDP. Environmental degradation is assessed by CO_2 emissions from fossil fuels and industry in billion tonnes. Moreover, we incorporated green investment *(lnGI)* as a moderator variable, measured by government funds allocated for environmental protection as a percentage of GDP. We also included trade openness *(lnTO)*, foreign direct investment *(lnFDI)* and COVID19 as control variables.

The measurements of all variables were in different units. Therefore, we transformed them into logarithmic form following Appiah-Otoo *et al.* (2023) and Sun *et al.* (2022) to obtain more accurate estimates. The data for non-renewable energy consumption and environmental degradation were obtained from the Our World in Data database. Furthermore, the statistics regarding economic growth and green investment were gathered from the International Monetary Fund. We fetched the data on trade openness and foreign direct investment from the World Development Indicators database. Thus, we created a sample panel dataset that integrates both cross-sectional and time-series data characteristics. Also, it provides better information, greater efficiency, lower collinearity, and higher degrees of freedom (Baltagi, 2008; Hsiao, 2022). Table no. 1 provides a separate description of each variable along with the source.

Table no. 1 – Description of Variables

Variable	Acronym	Description	Source
Non-Renewable Energy Consumption	lnNREC	Fossil fuels per capita (kWh)	Our World in Data
Economic Growth	lnEG	Real GDP growth (annual percent change)	IMF
Environmental Degradation	lnED	CO_2 emissions from fossil fuels and industries, measured in billion tonnes	Our World in Data
Green Investment	lnGI	Funds allocated by the government for environmental protection as a percentage of GDP	IMF
Trade Openness	lnTO	Trade (% of GDP)	WDI
Foreign Direct Investment	lnFDI	The net value of foreign direct investment (FDI) equity flows into a country, quantified in terms of current U.S. dollars	WDI
COVID19 Pandemic	COVID19	It indicates the presence (1) or absence (0) of COVID-19 epidemic influence	Binary Variable

Note: authors' compilation

3.2. Model Specification and Methodology

The empirical models are developed to examine both the direct effects of lnNREC and the moderating role of lnGI. The underlying intuition is that lnNREC can support economic activity by providing the energy required for production, transportation and other economic activities. However, greater dependence on non-renewable energy can also increase lnED through higher carbon emissions. Therefore, the effect of lnNREC cannot be evaluated only from an economic perspective (Tiba and Omri, 2017; Vincent and Ezaal, 2022).

lnGI is introduced as a moderating variable because it may change the effects of lnNREC. Khan *et al.* (2023) argued that higher lnGI can reduce the environmental damage associated with lnNREC by supporting energy efficiency and environmentally friendly production processes. Similarly, Kwilinski *et al.* (2023) suggested that lnGI can influence the economic effects associated with lnNREC by improving resource efficiency and supporting the transition toward cleaner production. Therefore, the interaction between lnNREC and lnGI is included in the empirical models to determine whether the level of lnGI changes the proposed relationships. Figure no. 3 presents the conceptual model of the current study.

Accordingly, the interaction term between lnNREC and lnGI captures the conditional effects of lnNREC. A statistically significant interaction coefficient indicates that the effect of lnNREC depends on the level of lnGI. The corresponding net effects are also calculated at different levels of lnGI to provide a clearer interpretation of the interaction effects. To examine the effect of lnNREC on lnEG and lnED, the following baseline regression models are estimated.

$$lnEG_{i,t} = \propto + \beta_1(lnNREC_{i,t}) + \beta_2(lnGI_{i,t}) + \left(\sum \beta_k\, Controls_{i,t}\right) + \varepsilon_{i,t} \quad (1)$$

$$lnEG_{i,t} = \propto + \beta_1(lnNREC_{i,t}) + \beta_2(lnNREC \times lnGI_{i,t}) + \beta_3(lnGI_{i,t}) + \left(\sum \beta_k\, Controls_{i,t}\right) + \varepsilon_{i,t} \quad (2)$$

$$lnED_{i,t} = \propto + \beta_1(lnNREC_{i,t}) + \beta_2(lnGI_{i,t}) + \left(\sum \beta_k\, Controls_{i,t}\right) + \varepsilon_{i,t} \quad (3)$$

$$lnED_{i,t} = \propto + \beta_1(lnNREC_{i,t}) + \beta_2(lnNREC \times lnGI_{i,t}) + \left(\sum \beta_k\, Controls_{i,t}\right) + \varepsilon_{i,t} \quad (4)$$

Table no. 2 – Model parameters and notation

Symbol	Definition
α	Constant term
β_1	Coefficient of lnNREC
β_2	Coefficient of lnGI
β_3	Coefficient of lnNREC × lnGI
β_k	Coefficients of control variables
i	Country
t	Year
N	Number of countries
T	Number of years
ε_{it}	Error term
lnNREC	Non renewable energy consumption
lnEG	Economic growth
lnED	Environmental degradation
lnGI	Green investment
lnNREC × lnGI	Interaction term

In Equations (1) to (4), α represents the constant term, while β_1, β_2, β_3 and β_k represent the coefficients of the explanatory, moderating, interaction and control variables, respectively. The subscripts i and t denote country and year, respectively, while N and T represent the number of countries and years. The term ε_{it} represents the error term for

country *i* in year *t*. The *lnNREC* denotes non-renewable energy consumption, *lnEG* denotes economic growth, *lnED* denotes environmental degradation and *lnGI* denotes green investment. Further, the interaction term *lnNREC* × *lnGI* is included to examine the moderating role of green investment. The notation and parameters used in the model specifications are summarized in Table no. 2.

In empirical models, we adopted environmental degradation *(carbon dioxide emissions in billion tonnes)* and economic growth *(annual percent change in real GDP)* as dependent variables, following Gür (2022) and Landefeld *et al.* (2008). The basic research framework of this study examines the direct impact of non-renewable energy consumption on economic growth and environmental deterioration, while also addressing the moderating role of green investment. The models include an interaction term between lnNREC and lnGI. Therefore, the coefficients cannot be interpreted separately. Therefore, we calculated the conditional effects of the variables included in the interaction terms by following Ullah *et al.* (2025). The conditional effect of lnNREC is calculated as:

$$\frac{\partial Y_{it}}{\partial \ln NREC_{it}} = \beta_1 + \beta_3 \ln GI_{it} \quad (5)$$

Here, Y_{it} represents either lnEG or lnED. The coefficient $\beta_1$represents the effect of lnNREC when lnGI equals zero. The coefficient β_3 shows how the effect of lnNREC changes with the level of lnGI. The conditional effects of lnNREC were calculated at low, mean, and high levels of lnGI. The low level was defined as one standard deviation below the mean. The high level was defined as one standard deviation above the mean. Further, we also constructed the interaction plots. These plots illustrate the predicted values of lnEG and lnED at low and high levels of lnNREC across low and high levels of lnGI. This procedure was conducted separately for each dependent variable model.

We used panel data in which N > T. As a result, the dataset exhibits both cross-sectional and time-series characteristics. During panel data analysis, issues such as heteroskedasticity, cross-sectional dependence, and autocorrelation may arise and must be addressed to ensure reliable estimation results. Therefore, this study employs the Feasible Generalized Least Squares (FGLS) and Panel-Corrected Standard Errors (PCSE) estimation techniques instead of panel OLS. The rationale is that the PCSE and FGLS regression methods are effective estimation techniques when the data exhibit heteroscedasticity, serial correlation, and cross-sectional dependence (Parks, 1967). First, we conducted heteroskedasticity, autocorrelation, and cross-sectional dependence analyses, and their outcomes provided the grounds in favor of the PCSE and FGLS estimators. We implemented the PCSE statistical technique as our primary regression due to its practicality for cross-section-dependent data. Beck and Katz (1995) highlighted that the FGLS statistical technique causes underestimated standard errors in the analysis that the PCSE estimator can correct. Nevertheless, Reed and Webb (2010) disagreed with these assertions and advocated for the advantages of the FGLS estimator. In line with this, we included the FGLS estimator in our investigation to increase the reliability of our findings.

4. EMPIRICAL RESULTS AND DISCUSSION

Empirical analysis involves the application of various statistical techniques to obtain a thorough understanding of the characteristics of the data. Selecting appropriate regression methods without a comprehensive analysis of the data is largely speculative, as the key regression estimates must align with the identified characteristics of the dataset. Therefore, this section employs several statistical tests to characterize the data, and the main empirical findings are presented to draw statistical conclusions regarding the proposed relationships. Table no. 3 presents the descriptive statistics of the study variables. The dataset consists of 266 observations for each variable, forming a balanced panel of data from 19 countries. The mean value of lnEG is 1.002, with values ranging from -1.600 to 2.434. The mean value of lnED is 20.325, while lnNREC has an average value of 7.979. The relatively wide ranges of lnED and lnNREC show substantial variation in environmental degradation and non-renewable energy consumption across the G20 economies. The mean value of lnGI is 0.5895 with a standard deviation of 0.2972. This variation supports the moderating role of green investment.

Table no. 3 – Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnEG	266	1.002	0.803	-1.609	2.434
lnED	266	20.325	1.114	17.886	23.2
lnNREC	266	7.979	0.94	6.603	10.563
lnGI	266	0.5895	0.2972	0.0357	1.2616
lnFDI	266	22.829	5.668	-1.273	26.96
lnTO	266	3.919	0.36	3.113	4.659
COVID19	266	0.286	0.453	0	1

Note: Calculated by authors. Descriptive statistics are based on the original variables before logarithmic transformation. The logarithmically transformed variables are used in the subsequent empirical estimations.

Figure no. 4 shows the findings of the pairwise correlation analysis along with the variance inflation factor (VIF). The degree and direction of the linear association among the study variables are evaluated through pairwise correlation analysis for all possible combinations of variables. High correlation coefficients among variables may indicate multicollinearity (Mansfield and Helms, 1982). Variables that introduce multicollinearity into the econometric model should be carefully examined because strong correlations among explanatory variables can distort regression estimates and compromise the reliability of the results. In our situation, the correlation values are well within acceptable limits. It indicates a low probability of significant multicollinearity among the variables.

In addition to pairwise correlation analysis, we have also employed the VIF test to allay apprehensions about multicollinearity. Studenmund (2000) noted that a VIF exceeding 10 may indicate multicollinearity. The results of the VIF test are encouraging, as the calculated VIF values for all variables are close to 1, suggesting the absence of multicollinearity in the model. Furthermore, Table no. 4 reports the results of the panel unit root tests. Significant Levin-Lin-Chu and Harris-Tzavalis test statistics lead to the rejection of the null hypothesis that all panels contain a unit root, thereby supporting the alternative hypothesis that all panel series are stationary. In contrast, significant Hadri LM test statistics lead to the rejection of the null hypothesis of stationarity, thereby supporting the alternative

hypothesis that at least some panel series contain a unit root. The results show that some variables are stationary at level, while others become stationary after first differencing. Consequently, these tests confirm the stationarity properties of the variables under study.

Table no. 5 reports the results of the cross-sectional dependence tests. We examined cross-sectional dependence using the Pesaran CD and Breusch-Pagan LM tests. Testing for cross-sectional dependence is essential in panel data analysis, as ignoring it may lead to unreliable results in panel estimation. In our analysis, the p-values for all models (Models 1-4) in both tests are below the 1% significance level, indicating cross-sectional dependence in the data. Therefore, we reject the null hypothesis of cross-sectional independence.

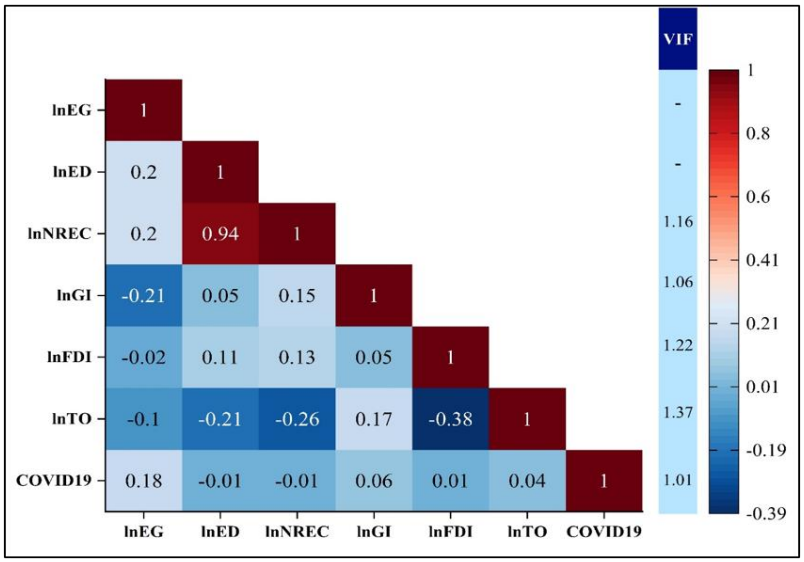


Figure no. 4 – Pairwise correlations and variance inflation factor (VIF) results for the study variables

Table no. 4 – Results of Panel Unit Root Tests

Variable	Levin–Lin–Chu		Harris-Tzavalis		Hadri LM	
	Level	First Difference	Level	First Difference	Level	First Difference
lnEG	-8.2802***	-12.1334***	-0.0775***	-0.5031***	0.2275	-3.5782
lnED	0.9823	-9.7932***	0.8669	-0.1966***	27.1350***	-1.5992
lnNREC	0.4294	-9.3889***	0.8472	-0.1277***	25.0253***	-1.5682
lnGI	-27.5156***	-25.5375***	0.6499***	-0.0648***	15.3404***	-2.0634
lnFDI	-4.6470***	-9.7897***	0.1469***	-0.3600***	0.7780	-2.8971
lnTO	-4.3380***	-13.3797***	0.6847***	-0.0759***	18.1759***	-2.1179
COVID19	2.1227	-6.5207***	0.9000	-0.0909***	21.3087***	-0.8939

Note: The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table no. 5 – Results of Cross-Sectional Dependence Tests

	Model 1	Model 2	Model 3	Model 4
Pesaran CD test	8.469***	8.721***	8.837***	7.962***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Breusch-Pagan LM test	565.386***	574.441***	533.367***	528.164***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Note: The figures in the parentheses are p-values. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table no. 6 presents the results of the Modified Wald and Wooldridge tests. The test statistics from the Modified Wald test are statistically significant at the 1% level for all models. Hence, the Modified Wald test rejects the null hypothesis of groupwise homoskedasticity in all models, confirming the presence of heteroskedasticity in the data. Furthermore, we employed the Wooldridge test to examine the presence of autocorrelation in the residuals of the panel regression models, following Zhou (2013). The results are statistically significant at the 5% level for Models 1 and 2 and at the 1% level for Models 3 and 4. Therefore, the Wooldridge test rejects the null hypothesis of no first-order autocorrelation, indicating the presence of autocorrelation in the panel data. Therefore, the results of these diagnostic tests justify the use of PCSE as the primary estimation technique and FGLS as a robustness estimator.

Table no. 6 – Results of Heteroskedasticity and Autocorrelation Tests

Modified Wald test for groupwise heteroskedasticity				
	Model 1	**Model 2**	**Model 3**	**Model 4**
χ^2	519.21***	470.53***	1830.14***	1529.49***
P-value	0.0000	0.0061	0.0000	0.0004
Accept/Reject	Reject	Reject	Reject	Reject
Wooldridge test for autocorrelation in panel data				
	Model 1	**Model 2**	**Model 3**	**Model 4**
F-statistic	5.870**	5.900**	33.731***	33.817***
P-value	0.0269	0.0265	0.0000	0.0000
Accept/Reject	Reject	Reject	Reject	Reject

Note: The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.1. Primary Regression Results

PCSE is the primary estimation technique employed in this study. Table no. 7 reports the results of the PCSE regression analysis. In Model 1, lnNREC has a positive and statistically significant effect on lnEG, with a coefficient of 0.1840***. This coefficient indicates that a 1% increase in lnNREC is associated with a 0.184% increase in lnEG. The finding suggests that lnNREC plays an important role in promoting lnEG in G20 countries. Therefore, the results support Hypothesis H1, which states that lnNREC has a significant positive effect on lnEG. Ivanovski *et al.* (2021) and Kahia *et al.* (2017) demonstrated that non-renewable energy sources are essential for economic expansion. The use of non-renewable energy sources remains high in G20 countries, many of which have experienced rapid population growth over the past few decades. Consequently, these economies continue to rely heavily on non-renewable energy sources to meet the growing energy demand (Aboueata *et al.*, 2021). In addition, we have

discovered a significant positive moderating role of lnGI (0.2231***) in the effects of lnNREC and lnEG in Model 2. The finding supports Hypothesis (H3a) that lnGI significantly moderates the relationship between non-renewable energy consumption and economic development. According to Onifade *et al.* (2025), lnGI promote sustainable economic development rather than hinder it. Similarly, Wan and Sheng (2022) confirmed the significant positive role of lnGI and suggested that it is an effective means of stimulating lnEG.

Table no. 7 – Results of PCSE Regression Analysis

Variable	Model 1		Model 2	
	Coefficient	p-value	Coefficient	p-value
lnNREC	0.1840*** (0.0317)	0.000	0.3327*** (0.0564)	0.000
lnGI	-0.2859*** (0.0570)	0.000	-2.0571*** (0.4776)	0.000
lnNREC × lnGI		-	0.2231*** (0.0560)	0.000
lnFDI	-0.0062 (0.0049)	0.204	-0.0026 (0.0043)	0.547
lnTO	-0.0464 (0.0863)	0.591	0.1235 (0.0796)	0.121
COVID19	0.4181 (0.2801)	0.136	0.3818 (0.2808)	0.174
_cons	-0.4306 (0.5617)	0.443	-2.3751*** (0.6550)	0.000
Wald chi²	65.05	0.0000	83.14	0.0000
N	228		228	
R-squared	0.1380		0.1633	

Note: The dependent variable is lnEG. The figures in parentheses are the standard errors. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table no. 8 – Results of PCSE Regression Analysis

Variables	Model 3		Model 4	
	Coefficient	p-value	Coefficient	p-value
lnNREC	1.1501*** (0.0088)	0.000	1.2838*** (0.0126)	0.000
lnGI	-0.1770*** (0.0198)	0.000	-1.6239*** (0.1216)	0.000
lnNREC × lnGI	-	-	-0.1836*** (0.0139)	0.000
lnFDI	0.0050*** (0.0010)	0.000	0.0082*** (0.0012)	0.000
lnTO	0.2262*** (0.0327)	0.000	0.3909*** (0.0400)	0.000
COVID19	0.0094 (0.0111)	0.399	-0.0134 (0.0082)	0.104
_cons	10.0174*** (0.2210)	0.000	8.2297*** (0.2724)	0.000
Wald chi²	132946.27	0.000	229563.88	0.000
N	260		260	
R-squared	0.8870		0.8967	

Note: The dependent variable is lnED. The figures in parentheses are the standard errors. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table no. 8 reports the results of the PCSE regression analysis, with lnED as the dependent variable. In Model 3, lnNREC has a positive and statistically significant effect on lnED, with a coefficient of 1.1501***. This coefficient indicates that a 1% increase in lnNREC is associated with a 1.150% increase in CO_2 emissions. The findings suggest that the use of non-renewable energy sources in G20 countries contributes significantly to lnED. Therefore, the results support Hypothesis H2, which posits that lnNREC exerts a significant positive effect on lnED. Our findings align with those of Chien (2022) and Adekoya *et al.* (2024), which highlighted the impact of using non-renewable energy on CO_2 emissions. The total CO_2 emissions by G20 countries increased by 15% from 2010 to 2023 (Ritchie *et al.*, 2023). Fossil fuel combustion generates substantial CO_2 emissions that are harmful to the environment and contribute to global warming (Zhang *et al.*, 2024). The 15.93% increase in fossil fuel consumption among G20 countries has contributed significantly to the rise in global CO_2 emissions (Our World in Data, 2025). Furthermore, our results indicate that lnGI mitigates the environmental impacts of lnNREC. In Model 4, the interaction term has a negative and statistically significant coefficient (-0.1836***), indicating that lnGI weakens the positive relationship between lnNREC and lnED. In other words, higher levels of lnGI mitigate the adverse environmental effects associated with lnNREC. Therefore, the finding supports Hypothesis H3b, which posits that lnGI significantly moderates the relationship between lnNREC and lnED. This result is consistent with Dong *et al.* (2024), who found that carbon emissions are significantly reduced in economies that prioritize lnGI (Shaukat *et al.*, 2026). Furthermore, lnGI can support research and development in cleaner technologies, thereby minimizing the environmental impact of lnNREC (Beşer *et al.*, 2025).

4.2. Conditional Net Effects and Interaction Plots

Table no. 9 presents the conditional effect of lnNREC at low, mean, and high levels of lnGI. The results show that the effect of lnNREC on lnEG increases with lnGI. At a low level of lnGI, the conditional effect is 0.0147. It increases to 0.1728 at the mean level and 0.3309 at the high level. This pattern indicates that lnGI strengthens the positive relationship between lnNREC and lnEG. The effect of lnNREC on lnED shows the opposite pattern. The conditional effect declines from 1.5455 at a low level of lnGI to 1.4154 at the mean level and 1.2853 at the high level. The effect remains positive at all three levels. However, its magnitude decreases as green investment rises. This result suggests that lnGI reduces the harmful environmental effect of lnNREC. Hence, the findings support the moderating role of lnGI in both models. Higher lnGI strengthens the economic effect of lnNREC and weakens its environmental effect.

Table no. 9 – Conditional net effects of lnNREC at different levels of lnGI

Level of lnGI	Value of lnGI	Effect on lnEG	Effect on lnED
Low	−1.4256	0.0147	1.5455
Mean	−0.7168	0.1728	1.4154
High	−0.0080	0.3309	1.2853

Note: Low and high levels represent one standard deviation below and above the mean of lnGI. The conditional effects are calculated from Models 2 and 4 of the PCSE analysis. The interaction terms are statistically significant at the 1% level in both models.

Further, the interaction plots present predicted lnEG and lnED at low and high levels of lnNREC under low and high levels of lnGI. This procedure is applied separately to models of both dependent variables. Figure no. 5 visually supports the net effect results for EG. The slope of lnNREC becomes steeper at a higher level of lnGI. This pattern shows that lnGI strengthens the positive relationship between lnNREC and lnEG. Figure no. 6 visually supports the net effect results for lnED. Although lnED increases with lnNREC at both levels of lnGI, the slope becomes less steep when lnGI is high. This suggests that lnGI mitigates the adverse environmental impact of lnNREC.

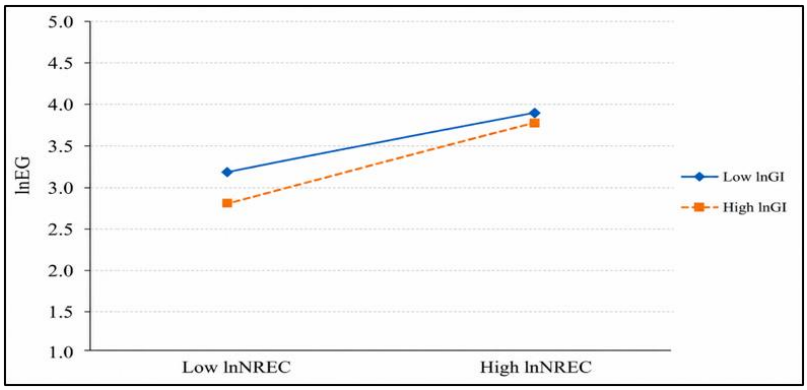


Figure no. 5 – Interaction between non-renewable energy consumption (lnNREC) and green investment (lnGI) on economic growth (lnEG)

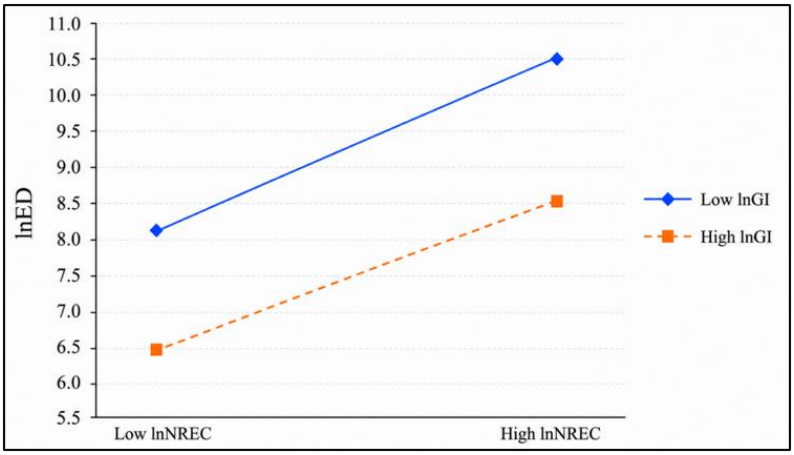


Figure no. 6 – Interaction between non-renewable energy consumption (lnNREC) and green investment (lnGI) on environmental degradation (lnED)

4.3. Endogeneity and Robustness Checks

Tables no. 10 and no. 11 report the findings of the FGLS estimator, which we have used for a robustness check. FGLS regression improves the effectiveness of estimates by

accounting for heteroscedasticity and autocorrelation. However, Lewis and Linzer (2005) highlighted that FGLS not only addresses heteroskedasticity, autocorrelation, and cross-section dependence, but also outperforms PCSE in terms of the precision and accuracy of the estimated parameters (Beck and Katz, 1995). Moreover, the FGLS findings indicate that the signs and significance levels of the coefficients of our study variables' relationships align with those of our primary estimator, PCSE. Therefore, our results are stable and robust across the various estimators used.

Table no. 10 – Results of FGLS Regression Analysis

Variables	Model 1		Model 2	
	Coefficient	p-value	Coefficient	p-value
lnNREC	0.1840*** (0.0548)	0.001	0.3327*** (0.0782)	0.000
lnGI	-0.2859*** (0.0755)	0.000	-2.0573*** 0.6777	0.002
lnNREC × lnGI	-	-	0.2231*** (0.0848)	0.009
lnFDI	-0.0062 (0.0092)	0.497	-0.0026 (0.0092)	0.776
lnTO	-0.0464 (0.1621)	0.775	0.1235 (0.1723)	0.474
COVID19	0.4181*** (0.1156)	0.000	0.3818*** (0.1147)	0.001
_cons	-0.4306 (0.9843)	0.662	-2.3751* (1.2195)	0.051
N	228		228	
Wald chi²	36.49	0.0000	44.51	0.0000

Note: The dependent variable is lnEG. The figures in parentheses are the standard errors. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table no. 11 – Findings of FGLS Regression Analysis

Variables	Model 3		Model 4	
	Coefficient	p-value	Coefficient	p-value
lnNREC	1.1501*** (0.0262)	0.000	1.2838*** (0.0368)	0.000
lnGI	-0.1770*** (0.0348)	0.000	-1.6239*** (0.2935)	0.000
lnNREC × lnGI	-	-	-0.1836*** (0.0370)	0.000
lnFDI	0.0050 (0.0045)	0.266	0.0082* 0.0043	0.057
lnTO	0.2262*** (0.0741)	0.002	0.3909*** (0.0782)	0.000
COVID19	0.0094 (0.0522)	0.857	-0.0134 (0.0501)	0.789
_cons	10.0174*** (0.4492)	0.000	8.2297*** (0.5605)	0.000
N	260		260	
Wald chi²	2039.94	0.0000	2145.71	0.0000

Note: The dependent variable is lnED. The figures in parentheses are the standard errors. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Another critical challenge is endogeneity, which arises when an independent variable is correlated with the error term in a model. Such a correlation can lead to biased estimation results and compromise the reliability of the study's conclusions (Ullah *et al.*, 2018; Barros *et al.*, 2020). To address this concern, we implemented a dynamic regression model referred to as the GMM. This strategy is better than alternative dynamic regression techniques when the dataset is contemporaneous (N > T). Instead of using the difference GMM estimator, this study employed the system GMM estimator, as it yields more robust results and offers superior treatment of endogeneity concerns (Zarra-Nezhad *et al.*, 2014). Table no. 12 reports the results of the one-step system GMM estimation. The estimated coefficients exhibit signs consistent with those obtained using the PCSE and FGLS estimators, thereby confirming the robustness of the main findings.

Table no. 12 – Results of One-Step System GMM Regression

Variables	Model 1	Model 2	Model 3	Model 4
L1. lnEG	0.3390*** (0.1113)	0.3377*** (0.1119)	-	-
L1. lnED	-	-	0.7086*** (0.1196)	0.6853*** (0.1173)
lnNREC	0.1843*** (0.0967)	0.2618** (0.1045)	0.3435*** (0.1250)	0.4115*** (0.1195)
lnGI	-0.2624 (0.1846)	-1.3655 (1.4210)	-0.0659 (0.0419)	-0.5235* (0.2820)
lnNREC × lnGI	-	0.1366*** 0.1689	-	-0.0579** (0.0328)
lnFDI	-0.0039*** (0.0067)	-0.0025*** (0.0070)	0.0017** (0.0011)	0.0027*** (0.0010)
lnTO	0.0125 (0.2205)	0.0733 (0.2445)	0.0751 (0.0615)	0.1296 (0.0826)
COVID19	0.0837 (0.0945)	0.0551 (0.0831)	-0.0012 (0.0064)	-0.0079 (0.0075)
Instruments	19	20	19	20
AR (1)	0.001	0.001	0.005	0.007
AR (2)	0.954	0.959	0.497	0.185
Sargan test	24.03	24.00	111.46	105.18
Prob > chi²	0.020	0.020	0.000	0.000

Note: The figures in parentheses are the standard errors. The asterisk symbols (*, **, and ***) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5. CONCLUSION AND POLICY IMPLICATIONS

G20 nations are among the world's most dynamic and rapidly developing economies. They face substantial environmental degradation as a result of using non-renewable energy resources to achieve economic growth. Therefore, we have examined the economic and environmental impacts of non-renewable energy consumption in G20 countries. This study examined panel data from G20 countries covering the period from 2010 to 2023. Using the PCSE and FGLS estimators, the results indicate that non-renewable energy consumption exerts a significant positive effect on the economic growth of G20 countries. The main reason is that most G20 nations still rely on non-renewable energy resources to support their economic expansion. A 15.93% increase in total fossil fuel consumption was recorded

across G20 countries between 2010 and 2023 (Our World in Data, 2025). Furthermore, we found a positive link between non-renewable energy and environmental deterioration. We noted that a 1% increase in non-renewable energy consumption is linked with a 1.150% increase in CO_2 emissions. Consequently, the total CO_2 emissions by G20 countries increased by 15% from 2010 to 2023 (Ritchie *et al.*, 2023). These CO_2 emissions are not only damaging the environment of G20 nations but also that of the entire world.

Further, we found that the moderating influence of green investment on the relationship between non-renewable energy consumption and economic development is positive. Green investment is an efficacious means of stimulating economic expansion in G20 nations. We found that integrating economic activities with green initiatives has generated positive outcomes in G20 economies. Secondly, we found that green investment negatively moderates the relationship between non-renewable energy consumption and environmental degradation. The G20 countries have always faced environmental issues for decades due to their excessive reliance on fossil fuels. Green investments have become imperative for G20 countries due to their heavy reliance on non-renewable energy sources. Such environmentally sustainable investments can promote economic growth while simultaneously contributing to environmental preservation. Given the substantial CO_2 emissions associated with the use of non-renewable energy sources, these countries should allocate a portion of their budgets to environmental conservation initiatives.

Therefore, policymakers in G20 nations must couple economic initiatives with green investments. Further, huge emissions of CO_2 can only be controlled by allocating a part of the country's budget to environmental conservation initiatives. Moreover, policymakers ought to allocate resources and support the adoption of green technologies for the production of goods and services. It is especially crucial for developing G20 nations and those that have massive population growth like India and China. Their economic growth initiatives through non-renewable sources must be supplemented by green investments. These investments in eco-friendly technologies can control the potential CO2 emissions from non-renewable energy resources and ultimately protect the environment.

Despite the robustness of the findings, this study has several limitations. First, the panel dataset covers a relatively short time span, which may not fully capture long-term structural trends or the gradual effects of policy interventions. Second, the study relies on aggregate panel data for G20 countries. The results could not account for country specific relationships among variables, as there are significant differences among member countries of the G20 in terms of geographical characteristics, economic structures, econometric conditions and energy consumption patterns. Finally, because the findings are based exclusively on G20 economies, their direct applicability to low- and middle-income countries with weaker institutional and financial capacities may be limited. Future research could address these limitations by examining individual G20 countries or groups of countries with similar economic and institutional characteristics.

References

Aboueata, W., Hijawi, U., Al-Kababji, A., Mohieddine, A., & Choe, P. (2021). Statistical Analysis of Renewable and Non-renewable Energy Consumption against Population Growth. *IOP Conference Series. Earth and Environmental Science, 726*(1), 012003. http://dx.doi.org/10.1088/1755-1315/726/1/012003

Adanma, U. M., & Ogunbiyi, E. O. (2024). A comparative review of global environmental policies for promoting sustainable development and economic growth. *International Journal of Applied Research in Social Sciences, 6*(5), 954–977. http://dx.doi.org/10.51594/ijarss.v6i5.1147

Adekoya, O. B., Oliyide, J. A., & Fasanya, I. O. (2024). Renewable and non-renewable energy consumption – Ecological footprint nexus in net-oil exporting and net-oil importing countries: Policy implications for a sustainable environment. *Renewable Energy, 189*, 524–534. http://dx.doi.org/10.1016/j.renene.2022.03.036

Adil, M., Hussain, R. Y., Al Rassas, A. H., Mehmood, R., & Woo, K. Y. (2026). Economic progress and FDI amid geopolitical risks: shielding role of government effectiveness. *Cogent Economics & Finance, 14*(1), 2635856. http://dx.doi.org/10.1080/23322039.2026.2635856

Ahmad Khan, K., Khalid Anser, M., Pala, F., Barut, A., & Wasif Zafar, M. (2024). Promoting sustainability in developing Countries: A Machine Learning-based approach to understanding the relationship between green investment and environmental degradation. *Gondwana Research, 132*, 136–149. http://dx.doi.org/10.1016/j.gr.2024.03.013

Ajide, K. B., & Mesagan, E. P. (2022). Heterogeneous analysis of pollution abatement via renewable and non-renewable energy: lessons from investment in G20 nations. *Environmental Science and Pollution Research International, 29*(24), 36533–36546. http://dx.doi.org/10.1007/s11356-022-18771-5

Amin, N., Song, H., & Shabbir, M. S. (2022). What factors contribute to environmental degradation in G11 economies? Emphasizing the importance of renewable and non-renewable energy sources. *International Journal of Sustainable Development & World Ecology, 29*(5), 472–482. http://dx.doi.org/10.1080/13504509.2022.2059720

Appiah-Otoo, I., Chen, X., & Ampah, J. D. (2023). Does financial structure affect renewable energy consumption? Evidence from G20 countries. *Energy, 272*, 127130. http://dx.doi.org/10.1016/j.energy.2023.127130

Asiedu, B. A., Hassan, A. A., & Bein, M. A. (2021). Renewable energy, non-renewable energy, and economic growth: evidence from 26 European countries. *Environmental Science and Pollution Research International, 28*, 11119–11128. http://dx.doi.org/10.1007/s11356-020-11186-0

Asif, M., Bashir, S., & Khan, S. (2021). Impact of non-renewable and renewable energy consumption on economic growth: evidence from income and regional groups of countries. *Environmental Science and Pollution Research International, 28*(29), 38764–38773. http://dx.doi.org/10.1007/s11356-021-13448-x

Baltagi, B. H. (2008). Econometric Analysis of Panel Data *Springer Texts in Business and Economics* (pp. 135–145): Springer International Publishing. http://dx.doi.org/10.1007/978-3-030-53953-5

Barros, L., Bergmann, D. R., Castro, F. H., & da Silveira, A. D. M. (2020). Endogeneity in panel data regressions: Methodological guidance for corporate finance researchers. *Revista Brasileira de Gestão de Negócios, 22*(Special Issue), 437–461. http://dx.doi.org/10.7819/rbgn.v22i0.4059

Beck, N., & Katz, J. N. (1995). What To Do (and Not to Do) with Time-Series Cross-Section Data. *The American Political Science Review, 89*(3), 634–647. http://dx.doi.org/10.2307/2082979

Beşer, N. Ö., Çabaş, M., Uğurlu, S., & Magazzino, C. (2025). The determinants of life quality in African countries: Moderating role of CO2 emissions and health expenditures. *Green Technologies and Sustainability, 3*(3), 100165. http://dx.doi.org/10.1016/j.grets.2024.100165

Cevik, E. I., Yıldırım, D. Ç., & Dibooglu, S. (2021). Renewable and non-renewable energy consumption and economic growth in the US: A Markov-Switching VAR analysis. *Energy & Environment, 32*(3), 519–541. http://dx.doi.org/10.1177/0958305X20944035

Cheng, Z., & Zhu, C. (2024). Positive impacts of green finance on environmental protection investment: Evidence from green finance reform and innovations pilot zone. *Heliyon, 10*(13), e33714. http://dx.doi.org/10.1016/j.heliyon.2024.e33714

Chien, F. (2022). How renewable energy and non-renewable energy affect environmental excellence in N-11 economies? *Renewable Energy, 196*, 526–534. http://dx.doi.org/10.1016/j.renene.2022.07.013

Chin, M. Y., Ong, S. L., Ooi, D. B. Y., & Puah, C. H. (2022). The impact of green finance on environmental degradation in BRI region. *Environment, Development and Sustainability, 26*(1), 303–318. http://dx.doi.org/10.1007/s10668-022-02709-5

Citil, M. (2024). Is green finance a prerequisite for green growth of G-20 economies. *Innovation and Green Development, 3*(4), 1–15. http://dx.doi.org/10.1016/j.igd.2024.100170

Doğan, B., Hossain, M. R., Khalfaoui, R., Nassani, A. A., & Ghosh, S. (2026). Navigating Chinese green deals through green investment, green technology, and green energy development: a race for sustainability or greenwashing? *Financial Innovation, 12*(67), 1–29. http://dx.doi.org/DOI:10.1186/s40854-025-00894-6

Dong, Z., Xin, Z., Liu, D., & Yu, F. (2024). The impact of artificial intelligence application on company environmental investment in Chinese manufacturing companies. *International Review of Financial Analysis, 95*(B), 103403. http://dx.doi.org/10.1016/j.irfa.2024.103403

Güney, T. (2019). Renewable energy, non-renewable energy and sustainable development. *International Journal of Sustainable Development & World Ecology, 26*(5), 389–397. http://dx.doi.org/10.1080/13504509.2019.1595214

Gür, T. M. (2022). Carbon Dioxide Emissions, Capture, Storage and Utilization: Review of Materials, Processes and Technologies. *Progress in Energy and Combustion Science, 89*, 100965. http://dx.doi.org/10.1016/j.pecs.2021.100965

Hsiao, C. (2022). Analysis of Panel Data *Google Books*: Cambridge University Press. http://dx.doi.org/10.1017/9781009057745

Hussain, R. Y., Adil, M., Tumwine, G. N., Hussain, H., & Irshad, H. (2025). Balancing green and growth: do innovation and contribution drive sales and environmental performance? *Discover Sustainability, 6*(1), 257. http://dx.doi.org/10.1007/s43621-025-01083-2

IEA. (2024). *CO2 Emissions in 2023 – Analysis*. Retrieved from https://www.iea.org/reports/co2-emissions-in-2023

Islami, F. S., Prasetyanto, P. K., & Kurniasari, F. (2022). The Effect of Population, GDP, Non-Renewable Energy Consumption and Renewable Energy Consumption on Carbon Dioxide Emissions in G-20 Member Countries. *International Journal of Energy Economics and Policy, 12*(2), 103–110. http://dx.doi.org/10.32479/ijeep.12548

Ivanovski, K., Hailemariam, A., & Smyth, R. (2021). The effect of renewable and non-renewable energy consumption on economic growth: Non-parametric evidence. *Journal of Cleaner Production, 286*, 124956. http://dx.doi.org/10.1016/j.jclepro.2020.124956

Kahia, M., Aïssa, M. S. B., & Lanouar, C. (2017). Renewable and non-renewable energy use - economic growth nexus: The case of MENA Net Oil Importing Countries. *Renewable and Sustainable Energy Reviews, 71*, 127–140. http://dx.doi.org/10.1016/j.rser.2017.01.010

Khan, S. A. R., Zia-Ul-Haq, H. M., Ponce, P., & Janjua, L. (2023). Re-investigating the impact of non-renewable and renewable energy on environmental quality: A roadmap towards sustainable development. *Resources Policy, 81*, 103411. http://dx.doi.org/10.1016/j.resourpol.2023.103411

Kwilinski, A., Lyulyov, O., & Pimonenko, T. (2023). Greenfield investment as a catalyst of green economic growth. *Energies, 16*(5), 2372. http://dx.doi.org/10.3390/en16052372

Landefeld, J. S., Seskin, E. P., & Fraumeni, B. M. (2008). Taking the Pulse of the Economy: Measuring GDP. *Journal of Economic Perspectives, 22*(2), 193–216. http://dx.doi.org/10.1257/jep.22.2.193

Lewis, J., & Linzer, D. (2005). Estimating Regression Models in Which the Dependent Variable Is Based on Estimates. *Political Analysis, 13*(4), 345–364. http://dx.doi.org/10.1093/pan/mpi026

Mansfield, E. R., & Helms, B. P. (1982). Detecting Multicollinearity. *The American Statistician, 36*, 158–160. http://dx.doi.org/10.1080/00031305.1982.10482818

Mohammadi, H., Saghaian, S., & Zandi Dareh Gharibi, B. (2023). Renewable and Non-Renewable Energy Consumption and Its Impact on Economic Growth. *Sustainability, 15*(4), 3822. http://dx.doi.org/10.3390/su15043822

Munyati, C. (2023). The African Union has joined the G20 – what does it mean? *World Economic Forum*.

Onifade, S. T., Musah, M., Gyamfi, B. A., & Agozie, D. Q. (2025). Quest for SDG-13: The Aptness of Green Investments and Information and Communications Technology (ICT) to Emission Mitigation Among Central-African States. *Sustainable Development, 33*(3), 3303–3330. http://dx.doi.org/10.1002/sd.3290

Our World in Data. (2025). Fossil fuel consumption. https://ourworldindata.org/grapher/fossil-fuel-primary-energy

Ozcan, B., Tzeremes, P. G., & Tzeremes, N. G. (2020). Energy consumption, economic growth and environmental degradation in OECD countries. *Economic Modelling, 84*, 203–213. http://dx.doi.org/10.1016/j.econmod.2019.04.010

Parks, R. W. (1967). Efficient Estimation of a System of Regression Equations when Disturbances are Both Serially and Contemporaneously Correlated. *Journal of the American Statistical Association, 62*(318), 500–509. http://dx.doi.org/10.1080/01621459.1967.10482923

Pegkas, P. (2020). The impact of renewable and non-renewable energy consumption on economic growth: the case of Greece. *International Journal of Sustainable Energy, 39*(4), 380–395. http://dx.doi.org/10.1080/14786451.2019.1700261

Rahman, M. M., & Alam, K. (2022). Impact of industrialization and non-renewable energy on environmental pollution in Australia: Do renewable energy and financial development play a mitigating role? *Renewable Energy, 195*, 203–213. http://dx.doi.org/10.1016/j.renene.2022.06.012

Rahman, M. M., & Velayutham, E. (2020). Renewable and non-renewable Energy consumption-economic Growth nexus: New Evidence from South Asia. *Renewable Energy, 147*(1), 399–408. http://dx.doi.org/10.1016/j.renene.2019.09.007

Randhawa, A. A., Ghafoor, A., Hussain, B., & Magazzino, C. (2026). Impact of Chinese foreign direct investment on environmental stress in Pakistan: Mediating role of technological innovation. *World Development Perspectives, 42*, 100776. http://dx.doi.org/10.1016/j.wdp.2026.100776

Reed, W. R., & Webb, R. (2010). The PCSE Estimator is Good — Just Not As Good As You Think. *Journal of Time Series Econometrics, 2*(1). http://dx.doi.org/10.2202/1941-1928.1032

Ritchie, H., Rosado, P., & Roser, M. (2023). CO_2 and Greenhouse Gas Emissions. *Our World in Data*.

Shah, W. U. H., Hao, G., Yan, H., Zhu, N., Yasmeen, R., & Dincă, G. (2024). Role of renewable, non-renewable energy consumption and carbon emission in energy efficiency and productivity change: Evidence from G20 economies. *Geoscience Frontiers, 15*(4), 101631. http://dx.doi.org/10.1016/j.gsf.2023.101631

Shaukat, S., Nawaz, M. S., & Adil, M. (2026). Eco-Innovation and Sustainable Growth in Manufacturing Sector: A Systematic Literature Review. *International Journal on Management of Innovation & Technology, 23*(02), 2650005. http://dx.doi.org/10.1142/S0219877026500057

Shivanna, K. R. (2022). Climate Change and Its Impact on Biodiversity and Human Welfare. *Proceedings of the Indian National Science Academy, 88*(2), 160–171. http://dx.doi.org/10.1007/s43538-022-00073-6

Solangi, Y. A., Alyamani, R., Asghar, M., Ali, S., & Magazzino, C. (2025). The impact of social investment and green finance on sustainable development: Evidence from emerging market economies. *Sustainable Development, 33*(3), 4366–4379. http://dx.doi.org/10.1002/sd.3353

Solangi, Y. A., & Magazzino, C. (2025). Building economic stability through effective natural resource management and renewable energy investment in GCC countries. *Empirical Economics, 68*(5), 2327–2355. http://dx.doi.org/10.1007/s00181-024-02706-9

Studenmund, A. H. (2000). *Using econometrics: a practical guide*. Harlow: Edinburgh Gate.

Sun, Y., Li, Y., Wang, Y., & Bao, Q. (2022). Financial Annexation, Green Innovation and Carbon Neutrality in China. *Frontiers in Environmental Science, 10*, 831853. http://dx.doi.org/10.3389/fenvs.2022.831853

Tiba, S., & Omri, A. (2017). Literature survey on the relationships between energy, environment and economic growth. *Renewable and Sustainable Energy Reviews, 69*, 1129–1146. http://dx.doi.org/10.1016/j.rser.2016.09.113

Ullah, S., Akhtar, P., & Zaefarian, G. (2018). Dealing with endogeneity bias: The generalized method of moments (GMM) for panel data. *Industrial Marketing Management, 71*, 69–78. http://dx.doi.org/10.1016/j.indmarman.2017.11.010

Ullah, S., Jianjun, Z., & Ali, S. (2025). Mitigating climate change in developing economies: Interactions between foreign capital inflows, governance, and renewable energy. *Energy & Environment*, 0958305X251354876. http://dx.doi.org/10.1177/0958305X251354876

Umar, M., & Safi, A. (2023). Do green finance and innovation matter for environmental protection? A case of OECD economies. *Energy Economics, 119*, 106560. http://dx.doi.org/10.1016/j.eneco.2023.106560

Usman, M., Kousar, R., Makhdum, M. S. A., Yaseen, M. R., & Nadeem, A. M. (2023). Do financial development, economic growth, energy consumption, and trade openness contribute to increase carbon emission in Pakistan? An insight based on ARDL bound testing approach. *Environment, Development and Sustainability, 25*(1), 444–473. http://dx.doi.org/10.1007/s10668-021-02062-z

Vincent, M., & Ezaal, O. (2022). Fossil fuel consumption, economic growth, and environmental degradation: Is the 'energy consumption-growth' nexus sustainable in Nigeria. *Journal of Economics and Finance, 13*(2), 51–68.

Wan, Y., & Sheng, N. (2022). Clarifying the relationship among green investment, clean energy consumption, carbon emissions, and economic growth: A provincial panel analysis of China. *Environmental Science and Pollution Research International, 29*(6), 9038–9052. http://dx.doi.org/10.1007/s11356-021-16170-w

Wang, Q., Ali, A., Chen, Y., & Xu, X. (2023). An empirical analysis of the impact of renewable and non-renewable energy consumption on economic growth and carbon dioxide emissions: evidence from seven Northeast Asian countries. *Environmental Science and Pollution Research, 30*(30), 75041–75057. http://dx.doi.org/10.1007/s11356-023-27583-0

Wen, J., Mughal, N., Zhao, J., Shabbir, M. S., Niedbała, G., Jain, V., & Anwar, A. (2021). Does globalization matter for environmental degradation? Nexus among energy consumption, economic growth, and carbon dioxide emission. *Energy Policy, 153*, 112230. http://dx.doi.org/10.1016/j.enpol.2021.112230

Yang, C., Li, T., & Albitar, K. (2021). Does Energy Efficiency Affect Ambient PM2.5? The Moderating Role of Energy Investment. *Frontiers in Environmental Science, 9*, 707751. http://dx.doi.org/10.3389/fenvs.2021.707751

Zarra-Nezhad, M., Hasanvand, M., & Hadi Akbarzadeh, M. (2014). The shadow economy and globalization: A comparison between difference GMM and system GMM approaches. *International Journal of Business and Development Studies, 6*(2), 41–57.

Zhang, Y., Li, L., Sadiq, M., & Chien, F. (2024). The impact of non-renewable energy production and energy usage on carbon emissions: Evidence from China. *Energy & Environment, 35*(4), 2248–2269. http://dx.doi.org/10.1177/0958305X221150432

Zhou, Z. (2013). Heteroscedasticity and Autocorrelation Robust Structural Change Detection. *Journal of the American Statistical Association, 108*(502), 726–740. http://dx.doi.org/10.1080/01621459.2013.787184

Scientific Annals of Economics and Business
73 (3), 2026, 551-575
DOI: 10.47743/saeb-2026-0028

Financial Development, Financial Globalization, Energy Consumption, and Environmental Degradation as Long-Run Determinants of Economic Growth: Causal Dynamics, Cointegration, and Distributional Evidence from Panel Data

Thomas Panagiotou*, Constantinos Katrakilidis**

Abstract: Using an annual panel of 142 economies over 1993–2020, we estimate long-run elasticities between real income per capita and financial development, financial globalisation, energy consumption, and ecological pressure. Under cross-sectional dependence and slope heterogeneity, CIPS unit-root tests confirm I(1) behaviour; Westerlund bootstrap cointegration tests establish a stable long-run equilibrium; and five heterogeneous panel estimators – MG-AUG, CCE-MG, CCE-GMM, DCCE-MG, and CS-ARDL – provide cross-estimator robustness. All four elasticities are positive: energy use and ecological pressure display the largest long-run associations with income, while finance and globalisation exhibit smaller positive elasticities once global common shocks are controlled for. Method-of-moments quantile regression reveals that finance and globalisation effects are stronger at lower income quantiles and attenuate upward, while energy remains positive throughout the distribution. Dumitrescu–Hurlin (2012) causality tests provide evidence of feedback linkages between GDP per capita and the four drivers, with the strongest bidirectional evidence for ecological pressure and weaker or marginal reverse-causality evidence for finance, energy, and financial globalisation. These results add directional information that cointegration tests alone cannot provide. Policy implications emphasise energy decarbonisation, cautious finance-led growth claims, and directing global capital toward sustainable investment.

Keywords: economic growth; financial development; financial globalization; energy consumption; environmental degradation.

JEL classification: C23; C32; F43; Q43; Q53.

* Department of Economics, Aristotle University of Thessaloniki Greece; e-mail: *thompana@econ.auth.gr* (corresponding author).
** Department of Economics, Aristotle University of Thessaloniki Greece; e-mail: *katrak@econ.auth.gr*.

Article history: Received 23 December 2024 | Accepted 1 August 2026 | Published online 15 September 2026

To cite this article: Panagiotou, T., Katrakilidis, C. (2026). Financial Development, Financial Globalization, Energy Consumption, and Environmental Degradation as Long-Run Determinants of Economic Growth: Causal Dynamics, Cointegration, and Distributional Evidence from Panel Data. *Scientific Annals of Economics and Business*, 73(3), 551-575. https://doi.org/10.47743/saeb-2026-0028.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

Long-run income differences across countries are shaped by a set of structural forces that operate simultaneously and interact in ways that single-nexus analyses are ill-equipped to capture. Financial intermediation mobilises savings and allocates capital toward productive uses; financial globalisation widens the frontier of risk sharing and external financing; energy use underpins industrial production and capital accumulation; and ecological pressure represents the environmental cost embedded in growth trajectories. Taken in isolation, each of these relationships has attracted an extensive empirical literature. Taken jointly – as they must be when informing policy in an integrated world economy – the evidence remains fragmented, often sensitive to sample coverage, proxy choice, and the treatment of global common shocks. This paper addresses that gap directly.

The finance-growth relationship is the most studied of the four. Theoretical work establishes that deeper financial systems reduce information and transaction costs, enhance screening and monitoring, and allocate capital more efficiently toward high-return investments (Levine, 1997; Beck *et al.*, 2000). Yet the empirical magnitude of this effect remains contested: it depends critically on what 'financial development' actually measures. Composite indices that capture depth, access, and efficiency of both institutions and markets produce different estimates than simple banking ratios, and the effect can exhibit diminishing returns or even reverse once financial systems become very large (Svirydzenka, 2016; Purewal and Haini, 2022).

Financial globalisation adds a cross-border dimension: it can supplement domestic savings, lower the cost of capital, and transmit technology and governance improvements through foreign direct investment and portfolio flows (Kose *et al.*, 2010; Obstfeld, 2020). However, premature or poorly sequenced integration also amplifies exposure to sudden stops and external financial cycles, so the growth payoff is conditional on domestic institutional quality and macroprudential capacity (Alfaro *et al.*, 2004; Gygli *et al.*, 2019). The KOF index distinguishes de jure openness from de facto integration, enabling separation of policy stance from its realised consequences.

Energy use underpins industrial production and capital accumulation, and a positive long-run association between energy and income is consistent with both the energy-led growth hypothesis and the growth-led energy demand hypothesis (Ozturk, 2010; Stern, 2011). The direction of causality is itself an open question, which is precisely why explicit panel causality testing adds value beyond cointegration analysis. Finally, ecological pressure—measured here by the consumption-based ecological footprint rather than territorial CO_2 emissions—reflects the full resource demand associated with a country's consumption pattern. A positive long-run association between income and ecological pressure is historically well-documented and reflects incomplete decoupling; it is an empirical observation, not a policy endorsement (Grossman and Krueger, 1995; Borucke *et al.*, 2013).

The existing literature presents mixed and inconclusive findings regarding the relationship between energy consumption, financial development, environmental degradation, and economic growth. Most studies have focused on the effects of energy, financial development, and economic growth on environmental degradation, with less emphasis on how financial development, energy use, and environmental degradation jointly influence economic growth, particularly in the long term. Recent contributions have begun to address parts of this gap. Odhiambo (2023) reviews international evidence on the finance-

growth relationship and highlights persistent sensitivity of findings to country selection and estimator choice. Singh *et al.* (2023) document asymmetric and regime-dependent finance-growth effects, suggesting that credit deepening supports growth up to a threshold before diminishing returns set in. He and You (2024) find that convergence in financial development across countries conditions the growth payoff from finance, implying that cross-country heterogeneity is a first-order empirical concern rather than a nuisance. On the environmental side, Zhou *et al.* (2024) show that environmental regulation moderates the finance-footprint link in regional panels, and Toumi (2025) documents quantile heterogeneity in ecological footprint responses across income levels. Notwithstanding these advances, no study in this strand has combined multi-dimensional finance, financial globalization, energy use, and ecological pressure in a single long-run framework that explicitly tests for both cointegration and causality under cross-sectional dependence and slope heterogeneity, leaving a clear gap this paper fills. Moreover, according to Obstfeld (2020, 2021), the significance of financial development depends on the degree of financial globalization within an economy. To our knowledge, there has been limited research on the role of financial globalization in the finance–energy–environmental degradation–economic growth nexus.

This paper makes four specific contributions to the existing literature. First, it is one of the few studies to simultaneously examine the joint long-run impact of financial development, financial globalization, energy consumption, and environmental degradation on economic growth in a unified global framework, rather than treating each nexus in isolation. Most existing studies focus on bilateral or partial relationships, leaving open the question of how these forces interact when modelled jointly. Second, the paper employs five complementary heterogeneous panel estimators – MG-AUG, CCE-MG, CCE-GMM, DCCE-MG, and CS-ARDL – that explicitly account for cross-sectional dependence and slope heterogeneity. Using multiple estimators simultaneously serves as an internal robustness strategy: consistent results across all five methods provide stronger evidence than any single estimator could on its own, particularly in panels subject to global common shocks. Third, it uses the ecological footprint per capita as the baseline environmental proxy rather than CO_2 emissions, providing a consumption-based measure of ecological pressure that captures resource use beyond territorial emissions and reflects total environmental demand associated with living standards. Fourth, and distinctively from most cointegration studies in this nexus, the paper provides explicit panel causality evidence via the Dumitrescu and Hurlin (2012) test, establishing the direction of causal linkages between each driver and economic growth. This allows us to determine not merely whether variables share a long-run relationship, but whether and how they drive each other, yielding actionable policy insights. Together, these contributions provide a more complete and methodologically robust assessment of the long-run growth nexus than prior studies.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and distils testable expectations. Section 3 describes the data. Section 4 presents the econometric strategy and results. Section 5 concludes with policy implications.

2. LITERATURE REVIEW

2.1. Financial development and economic growth nexus

The theoretical case for a positive finance–growth relationship rests on several complementary mechanisms. Deeper and more efficient financial systems reduce information and transaction costs, enabling effective mobilisation of savings (Stiglitz and Weiss, 1983; Diamond, 1984), more productive allocation of capital toward higher-return projects (Hicks, 1969; Greenwood and Jovanovic, 1990), and better monitoring of investments that alleviates agency problems and lowers corporate governance costs (Bencivenga and Smith, 1993). These mechanisms were first articulated systematically by Nasse (2016) and Schumpeter (1911); Schumpeter (1934), and formalised in the financial intermediation literature following McKinnon (1974) and Cole and Shaw (1974). The finance–growth relationship therefore has deep theoretical roots, even as its empirical magnitude remains contested.

Additionally, well-developed financial intermediaries support technological progress by rewarding entrepreneurs (King and Levine, 1993). Moreover, Levine (1997) suggests that financial institutions also facilitate trading, portfolio diversification, hedging, and risk reduction, alongside their traditional role in enabling transactions of goods and services (Levine, 2005; Beck *et al.*, 2010; Svirydzenka, 2016). These financial operations are rather important for influencing the behavior of savings and investments and defining how efficiently the available funds are distributed. Thus, financial development is vital in influencing the processes of the accumulation of human and physical capital as well as total productivity—all three key factors that stimulate the growth of an economy (Levine, 1997). Furthermore, the allocation of credit within the financial system creates a connection between the financial and real sectors. This channel supports firms by financing their working capital needs and investments in fixed capital, with the former enhancing production and the latter improving the productivity of the real sector (Das and Guha-Khasnobis, 2008). Finally, through the mitigation of information discrepancies and credit constraints, financial development promotes the efficiency with which financial systems can manage risks, minimize information costs, absorb, or cushion economic shocks and dampen the flanks of business cycles through the financial accelerator, as put forward by Bernanke *et al.* (1999). The financial sector has the potential to contribute to the stabilization of macroeconomic fluctuations and imbalances while also aiding in the reduction of inequality.

However, the widely accepted view of a positive relationship between financial development and economic growth has been questioned by some scholars. For instance, Robinson argued that finance has a relatively small influence on economic growth and is, instead, a consequence of the growth process itself. This notion was further supported by Van Wijnbergen (1983) and Buffie (1984), who suggested that the expansion of financial institutions could draw borrowers away from informal markets, ultimately reducing credit availability and impeding economic growth. Similarly, Lucas (1988) expressed a comparable sentiment, asserting that financial markets play only a modest role in fostering broader economic development.

In the literature, various measures of financial development have been employed, which can broadly be categorized into two groups: financial institutions and financial markets. Common proxies for financial institutions include the ratio of the banking sector's liquid liabilities to GDP (Levine, 1997; Adusei, 2013), the ratio of commercial bank assets to the

total assets of deposit money banks and central banks (Levine, 1997), the credit-to-deposit ratio (Adusei, 2013), and domestic credit to the private sector as a percentage of GDP (Levine, 1997; Levine and Zervos, 1998; Saci *et al.*, 2009; Adusei, 2013). For financial markets, widely used proxies include the total value of listed shares on the stock market as a percentage of GDP (Levine and Zervos, 1998), the total value of shares traded on a stock exchange as a percentage of GDP (Levine and Zervos, 1998; Saci *et al.*, 2009), and the ratio of the total value of shares traded to the average real market capitalization (Levine and Zervos, 1998; Levine *et al.*, 2000; Saci *et al.*, 2009). The majority of empirical studies indicate a positive relationship between financial development and economic growth. However, financial development is a multifaceted process, reflecting the evolution of financial sectors and the increasing complexity of financial systems (Čihák *et al.*, 2012). To address this complexity, Svirydzenka (2016) introduced a more comprehensive financial development proxy based on the functions of financial systems, institutions, and markets, considering their depth, access, and efficiency. This measure builds on the suggestions of Sahay *et al.* (2015) and the earlier work of Čihák (Čihák *et al.*, 2012; Sahay *et al.*, 2015; Svirydzenka, 2016).

2.2. Financial globalization and economic growth nexus

A significant theory regarding the influence of financial globalization on economic growth is the neoclassical growth model (Lucas, 1988). This model suggests that financial globalization facilitates the global allocation of capital flows from capital-abundant developed economies to capital-scarce economies, where the return on capital is higher. These inflows are expected to supplement the limited domestic savings in capital-deficient economies and, by reducing the cost of capital, promote increased investment. Certain types of financial inflows, such as foreign direct investments (Dunning, 1993; Borensztein *et al.*, 1998) and portfolio reallocations (Levine and Zervos, 1998) can foster technology spillovers and serve as channels for transferring managerial and organizational expertise from more advanced economies. Additionally, other studies emphasize the importance of indirect channels, suggesting that the positive impact of financial globalization on growth arises not only from direct financial flows but also from collateral benefits (Kose *et al.*, 2006a; Kose *et al.*, 2006b). These indirect channels include improvements in institutions – broadly defined to encompass aspects such as governance quality and the rule of law – and the enhancement of macroeconomic policy-making.

According to Mishkin (2009), the opening of financial markets to foreign participants fosters financial development and growth by expanding access to capital and reducing its cost for productive investments. However, studies suggest that premature exposure to international capital markets can heighten vulnerability to sudden stops in capital flows unless specific preconditions are met. These preconditions include a minimum threshold of institutional quality, financial market development, and macroeconomic stability (Eichengreen, 2001; Alfaro *et al.*, 2004; Klein and Olivei, 2008). Stulz (2005) finds that globalization can reduce agency problems by lowering the cost of external financing, incentivizing better corporate management. Gourinchas and Jeanne (2005) propose that financial globalization incentivizes better macroeconomic policies by emphasizing their benefits and encouraging reforms. Similarly, Bartolini and Drazen (1997) contend that increased financial openness signals a commitment to stronger macroeconomic policies. Paceskovski (2013) highlight that financial globalization provides substantial advantages for developing countries and emerging markets

by fostering financial sector development and supporting economic growth. However, it also brings risks, particularly the heightened potential for financial crises. Financial globalization enables capital-poor countries to diversify their economies beyond agriculture and natural resources, thereby reducing macroeconomic volatility. However, at more advanced stages, it may lead to increased specialization, making middle-income countries more vulnerable to industry-specific shocks and contributing to greater output volatility (Kose *et al.*, 2006a; Kose and Prasad, 2007; Prasad *et al.*, 2007; Kose *et al.*, 2010). Additionally, heavy reliance on external debt can further expose these countries to fluctuations in global interest rates, amplifying output volatility.

To investigate the features of financial globalization across countries, alternative proxies describing different characteristics of financial integration exist. Foreign direct investment (FDI), characterized by ongoing investments and extended business ties of foreign enterprises, is an important measurement and is recognized for its ability to stabilize the influence of international currency crises (Alfaro *et al.*, 2004; Broner *et al.*, 2013; Broner *et al.*, 2023). Integrating equity and debt securities into portfolio investments enhances financial openness but is often accompanied by increased volatility in capital flows, a characteristic feature of emerging markets (Bekaert *et al.*, 2014; Lane and Milesi-Ferretti, 2018). Obstfeld (Obstfeld, 2020, 2021; Obstfeld *et al.*, 2021) and Jeanne and Rancière (2011) observe that the objective behind central banks' domestic and foreign reserves is to safeguard against outside threats and regulate volatility during financial crises. A report by Avdjiev *et al.* (2021) indicates that gross foreign assets and liabilities depict the overall financial ties of a country, pointing to an increase in global banking networks. In 2009, Kose *et al.* (2006a) developed the financial globalization index (FGI). In line with limitations in cross-border transactional law, the KAOPEN index, which serves as a benchmark for assessing financial growth, is related to research findings that highlight a connection to financial growth (Chinn and Ito, 2008; Quinn *et al.*, 2011). More recently, the Financial Globalization KOF Index, introduced by the Swiss Economic Institute, is an extensive assessment tool that combines real economic activities, such as foreign assets and liabilities, with regulatory constructs, including capital account restrictions, and it summarizes both legal- *de jure* and functional – *de facto*, providing a thorough measurement of the degree of financial globalization (Gygli *et al.*, 2019). The literature primarily suggests that financial globalization plays a positive role in fostering economic growth.

2.3. Energy consumption and economic growth nexus

Energy is a crucial input in the production process, driving industrial activities and playing a key role in technological and economic development. The relationship between energy consumption and economic growth has sparked significant debate, particularly regarding the direction of causality. Specifically, there is ongoing discussion about whether energy consumption acts as a catalyst for economic growth or if it is merely a result of economic growth (Ozturk, 2010). Theoretical discussions around the energy–growth nexus are often framed around two main opposing hypotheses: the energy–led growth hypothesis, in which energy usage generates economic growth by supporting higher production and productivity levels (Cleveland *et al.*, 2004). This view is particularly relevant for industrialized and energy-dependent economies. In contrast, the growth-led energy hypothesis

posits that economic growth leads to increased energy consumption, implying that energy use is a byproduct rather than a driver of economic growth (Narayan and Smyth, 2008).

Empirical research provides inconsistent evidence because of differences in country sample selection, empirical techniques and the time span examined. For example, in the MENA region, Omri (2013) and Kahia *et al.* (2016) reported bi-directional causal relationship between energy consumption and economic growth, using a simultaneous system of equations and a panel VAR approach, respectively. In contrast, (Sadorsky, 2010) found that, in certain emerging markets, economic growth leads to increased energy consumption. Apergis and Payne (2010) reported evidence of both short-term and long-term interactions between energy consumption and economic growth. With respect to BRICS countries' growth and renewable energy use, Pao and Tsai (2010) observed a positive relationship between economic growth and renewable energy use, with unidirectional causality flowing from renewable energy use to economic growth, while also reducing CO2 emissions.

Given this evidence, total primary energy consumption per capita – which aggregates across all fuel types and end uses – is the most appropriate and widely used empirical proxy for the aggregate energy–income relationship in global macro panels, and it is the measure adopted here.

2.4. Environmental degradation and economic growth nexus

Environmental degradation resulting from pollution, such as carbon emissions and resource depletion, presents a complex and often contradictory relationship with economic growth. This connection has garnered significant attention from researchers, who have employed various methods to study the interaction between economic growth and environmental degradation in different countries and regions (Belloumi, 2009; Luzzati and Orsini, 2009; Apergis and Payne, 2010; Belke *et al.*, 2011; Tang and Tan, 2015; Dong *et al.*, 2017; Shuai *et al.*, 2017; Sarkodie and Strezov, 2018; Ma and Cai, 2019; Wang and Dong, 2019; Ike *et al.*, 2020; Sarkodie and Ozturk, 2020; Dong *et al.*, 2023).

There is strong evidence of a relationship between environmental degradation and economic growth; nevertheless, outcomes depend on the periods covered and the sample size as well as upon country selection. Many studies report a negative relationship, where environmental degradation hinders long-term economic growth, as seen in Azam (2016) and Padilla and Serrano (2006), who highlight the harmful effects of pollution and resource depletion on economic growth. In some cases, especially during early industrialization, degradation can have a positive impact, as economic expansion often involves higher emissions and resource use in developing economies (Kahia *et al.*, 2016; Balsalobre-Lorente *et al.*, 2018; Sarkodie and Ozturk, 2020).

Moreover, an increasing number of studies have explored the growth-environment relationship through the lens of the Environmental Kuznets Curve (EKC). The EKC suggests an inverted U-shaped relationship between environmental pollutants and economic growth (Kuznets, 1955). This hypothesis has been supported in various regions, including high-income countries such as those in the Organization for Economic Cooperation and Development (OECD) (Jaunky, 2011; Bilgili *et al.*, 2016), BRICS countries (Dong *et al.*, 2017), developing nations (Narayan and Narayan, 2010), the United States (Sencer Atasoy, 2017), and countries in the Asia-Pacific region.

3. DATA

The analysis uses an annual panel of 142 economies over 1993–2020, yielding 3,976 country–year observations. All variables enter the estimations in natural logarithms so that estimated coefficients are interpretable directly as long-run elasticities. Real income is measured by real GDP per capita in constant 2015 USD from the World Bank World Development Indicators (World Bank, 2021). Financial development is captured by the IMF Financial Development Index (Svirydzenka, 2016), a composite spanning the depth, access, and efficiency of both financial institutions and markets, avoiding the proxy sensitivity that plagues single banking-ratio measures such as private-credit-to-GDP. Financial globalisation is represented by the KOF de jure financial globalisation sub-index (Gygli *et al.*, 2019), which reflects the regulatory stance toward cross-border capital flows and separates openness from its realised magnitude. Energy consumption per capita is from the World Bank WDI (kg of oil equivalent), complemented by EIA data for a small number of missing country-years after unit harmonisation. Environmental pressure is proxied by the ecological footprint per capita (global hectares per person) from the National Ecological Footprint and Biocapacity Accounts (University of York, 2022), a consumption-based measure capturing total ecological demand – food, energy, built land, and waste absorption – broader than territorial CO_2 emissions. Table no. 1 summarises the variables and their sources.

Table no. 1 – Analysis Variables

Symbol	Variables	Unit of measurement	Source
y	Gross Domestic Product per capita	Constant 2015 USD	World Bank (2021)
fd	Financial Development Index	index	IMF (2022)
kof	Financial globalization index *de jure*	index	KOF Swiss Economic Institute
ec	Energy consumption per capita	kg of oil equivalent per capita	World Bank (2021); EIA
efc	Ecological footprint per capita	gha/person	University of York (2022)

Table no. 2 presents descriptive statistics. The wide cross-country dispersion in all variables – especially income, finance, and energy – confirms the appropriateness of heterogeneous-parameter estimation rather than pooled methods.

Table no. 2 – Descriptive statistics of the variables

Variable	Mean	Median	Std. Dev	Min	Max	Obs
y	8.490	8.452	1.456	5.248	11.630	3,976
fd	3.224	3.245	0.736	0.000	4.605	3,976
kof	3.959	4.027	0.408	1.920	4.580	3,976
ec	3.631	3.848	1.496	0.000	6.521	3,976
efc	1.193	1.148	0.566	0.000	3.233	3,976

The sample spans 142 countries over 1993–2020 (3,976 observations). A full list of countries is provided in the Annex.

4. RESULTS

The empirical analysis proceeds in five sequential steps, each motivated by the findings of the preceding one: cross-sectional dependence testing, unit-root testing under dependence, slope homogeneity testing, cointegration testing, and long-run estimation. The general long-run relationship of interest is:

$$y_{it} = f(fd_{it}, kof_{it}, ec_{it}, efc_{it}) \quad (1)$$

The long-term model under estimation is presented in equation (2):

$$y_{it} = \beta_0 + \beta_1 fd_{it} + \beta_2 kof_{it} + \beta_3 ec_{it} + \beta_4\, efc_{it} + \varepsilon_{it} \quad (2)$$

where β_0 is a constant term and the parameters β_1 to β_4 are the respective long-term elasticities for each variable and where ε_{it} is the disturbance term. By referring to the studies in Section 2, the respective long-term elasticities are expected to display positive signs.

In a globally integrated economy, national income, financial systems, energy markets, and environmental conditions are all exposed to common shocks – commodity price cycles, global financial conditions, and major crises – that induce co-movement across countries independently of bilateral linkages. In panel data, this manifests as cross-sectional dependence: residual correlation across units driven by unobserved common factors. Standard first-generation estimators that ignore such dependence produce inconsistent estimates and distorted inference (De Hoyos and Sarafidis, 2006; Pesaran, 2006). The first step of the empirical strategy therefore tests formally for cross-sectional dependence across all series.

We apply a series of tests to examine cross-sectional dependence, including the Breusch-Pagan LM test (1980), the Pesaran scaled LM test (2004, 2021), the Pesaran CD test (2004), the bias-corrected scaled LM test (Pesaran *et al.*, 2008), the Frees test (1995) and the Friedman test (1937). Additionally, we incorporate two advanced methods: the power-enhanced CD+ test (Fan *et al.*, 2015) and the Pesaran & Xie CD* test (Pesaran *et al.*, 2008), to evaluate the null hypothesis of weak cross-sectional dependence against the alternative of strong cross-sectional dependence. The results of these tests, summarized in Table no. 3, reveal statistically significant evidence of cross-sectional dependence across all variables. All test statistics reject the null hypothesis of no cross-sectional dependence at the 1% significance level.

Table no. 3 – Cross-sectional dependence test results

variable	Breusch–Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD	Power Enhanced CD+ test	Pesaran & Xie CD*	Frees	Friedman
ypc	186214.71***	1245.26***	1242.63***	349.92***	40543.8***	-1.72*	88.7***	2553***
fd	100191.02***	637.31***	634.69***	246.16***	27972.55***	-2.52***	41.5***	1719.7***
ec	93476.18***	589.86***	587.23***	82.96***	26130.98***	22.78***	40.2***	585.9***
efc	62301.54***	369.55***	366.92***	34.98***	20047.73***	9.67***	24.9***	267.9***
kof	65859.38***	394.69***	392.06***	34.54***	21383.02***	52.75***	24.2***	310.5***

Notes: p- values from the respective Tests, Null Hypothesis no cross sectional dependence,
* p<0.10; ** p<0.05; *** p<0.01

Given the pervasive cross-sectional dependence documented above, conventional first-generation unit-root tests are size-distorted and cannot be relied upon (O'Connell, 1998). The second step therefore employs Pesaran's (2007) CIPS test, a second-generation procedure that augments country-level ADF regressions with cross-sectional averages of the series and its lags, filtering out the common-factor component and yielding valid inference under dependence. The null hypothesis is a unit root for each series; results are reported for levels and first differences under both a constant and a constant-plus-trend specification.

The results from the CIPS unit root test (presented in Table no. 4) show that all the variables are non-stationary at their levels (i.e., they have a unit root, denoted as I(1)). However, after first differencing, the variables become stationary (i.e., I(0)), indicating that they are integrated of order one, or I(1). This finding suggests that the growth process and its key determinants exhibit persistent trends over time, consistent with studies that indicate macroeconomic variables often exhibit unit root properties, especially in the context of long-run data (Maddala and Wu, 1999).

Table no. 4 – 2nd generation unit root test results

CIPS Test Statistic	constant	constant &trend	constant	constant &trend
Variable	Levels		First Differences	
ypc	-1.87	-1.71	-3.45***	-3.38***
fd	-1.43	-2.23	-4.87***	-4.69***
ec	-1.56	-1.96	-4.97***	-4.58***
efc	-1.42	-2.43	-3.24***	-4.64***
kof	-1.84	-2.21	-4.77***	-4.91***

Notes: p- values from the respective Tests, Null hypothesis: unit root (non-stationarity).
* p<0.10; ** p<0.05; *** p<0.01

With cross-sectional dependence confirmed and I(1) behaviour established, the third step tests whether long-run slope coefficients are homogeneous across countries. Imposing slope homogeneity in a heterogeneous panel inflates type-I error and produces spurious average effects (Pesaran and Yamagata, 2008). The Pesaran–Yamagata (2008) Δ test and its bias-adjusted version provide the baseline inference; Blomquist and Westerlund (2013, 2016) extend the test to allow for autocorrelation and heteroscedasticity jointly via HAC correction and bootstrap critical values (Bersvendsen and Ditzen, 2021). Rejection of homogeneity motivates mean-group estimation rather than pooled methods.

Table no. 5 presents the results from the Pesaran and Yamagata (2008) and the Blomquist and Westerlund (2013, 2016) tests.

Table no. 5 – Slope homogeneity test results

Methodology	Pesaran -Yamagata				Blomqvist-Westerlund	
type of test	baseline test		Autocorr. Correction		hac Correction	
test statistic	Delta	p value	Delta	p value	Delta	p value
stat.	16.82	0.00	27.01	0.00	4.27	0.00
adj.stat	20.37	0.00	31.19	0.00	12.08	0.00

Note: Null Hypothesis: Homogeneous slope coefficients

Both the Pesaran–Yamagata test and the Blomqvist–Westerlund tests reject the null hypothesis of slope homogeneity, with p-values below 0.05 for all testing methods (baseline, autocorrelation correction, and HAC correction). This suggests that the long-term

relationships between GDP per capita and its determinants vary considerably across countries, reflecting differences in growth dynamics. This finding aligns with the empirical literature that supports heterogeneity in the growth–energy and environment relationship nexus (Stern, 2011) as well as the growth-financial development and financial integration nexus Westerlund (2005); (Ibrahim *et al.*, 2024; Wang *et al.*, 2024).

With all series confirmed as I(1) under dependence and slope heterogeneity established, the fourth step tests for long-run cointegration. We employ two complementary Westerlund procedures. Westerlund (2005) provides a variance-ratio statistic for the null that no panel is cointegrated. Westerlund (2007) generates four statistics: group-mean tests (Gτ, Ga) that allow heterogeneous adjustment speeds and are informative about the fraction of cointegrated units, and panel statistics (Pt, Pa) that pool information and gain power when the null is globally false. Both procedures are implemented with 1,500 bootstrap replications to obtain dependence-robust p-values.

The Westerlund (2005, 2007) cointegration tests presented in Table no. 6 provide strong evidence of a long-term cointegrating relationship between the variables. The null-hypothesis of no cointegration is rejected by the Ga, Pt, and Pa test statistics at a minimum confidence level of 95%, while the Westerlund (2005) test indicates that all panels are cointegrated at the 99% level. These results align with existing literature that identifies long-term equilibrium relationships between economic growth and energy consumption, as well as between economic growth and environmental degradation. The findings suggest that, despite short-term fluctuations, these variables are interconnected in the long run (Narayan and Narayan, 2010).

Table no. 6 – 2nd generation cointegration test results

Westerlund (2007) Bootstrap test for cointegration			
Statistic	Value	Z value	Rob. p value
Gt	-1.307	7.782	0.68
Ga	-0.079	16.422	0.05
Pt	-6.824	9.82	0
Pa	-0.611	8.969	0
Westerlund (2005) test for cointegration			
Alternative Hypothesis	Variance ratio	Statistic	Robust p value
Some panels not cointegrated		4.872	0.00
All panels cointegrated		3.161	0.00

Note: Null Hypothesis: No cointegration, model with constant & 2 lags, 1,500 simulations

With cointegration established, the fifth step estimates long-run elasticities across five heterogeneous panel estimators chosen to span a range of identifying assumptions and dynamic specifications. The Augmented Mean Group (MG-AUG) (Eberhardt and Teal, 2010, 2011) controls for cross-sectional dependence via an estimated common dynamic factor. The Common Correlated Effects Mean Group (CCE-MG) (Pesaran, 2006) proxies unobserved common factors with cross-sectional averages, allowing heterogeneous factor loadings. The CCE-GMM (Neal, 2015a; Neal, 2015b) introduces moment conditions to address potential regressor endogeneity within the CCE framework. Since the standard CCE estimator is consistent only in static specifications (Chudik and Pesaran, 2015b), we complement it with two dynamic variants: the Dynamic CCE Mean Group (DCCE-MG) (Chudik and Pesaran, 2015a) and the cross-sectionally augmented ARDL (CS-ARDL). Consistency of sign and significance across all five estimators – which differ in their treatment of dynamics, endogeneity, and common-

factor structure – constitutes a stringent internal robustness check. Table no. 7 reports the estimates.

Table no. 7 – Long-run estimates

(Dependent Variable *ypc*)

Equation	MG-AUG (long-run)		CCE-MG-OLS		CCE-MG-GMM		DCCE MG-OLS		CS-ARDL	
Variable	**coefficient**	**prob**	**coefficient**	**prob**	**coefficient**	**prob**	**coefficient**	**prob**	**coefficient**	**prob**
$ypc_{i,t-1}$							-0.442***	0.00	-0.459***	
$fd_{i,t-1}$	0.043**	0.02	0.035***	0.03	0.082***	0.03	0.019*	0.07	0.098**	0.04
$ec_{i,t-1}$	0.192***	0.00	0.140***	0.00	0.262***	0.00	0.084***	0.00	0.294***	0.00
$efc_{i,t-1}$	0.240***	0.00	0.154***	0.00	0.171***	0.00	0.165***	0.00	0.459***	0.00
$kofi_{i,t-1}$	0.052***	0.01	0.022*	0.10	0.076***	0.01	0.031***	0.01	0.093*	0.08
constant	6.838***	0.00	0.230	0.65	-0.453	0.43	-0.464945	0.23		

Notes: * p<0.10; ** p<0.05; *** p<0.01, *** significant at 1%

The MG-AUG method introduced by Eberhardt and Teal (2010), accounts for both heterogeneity and cross-sectional dependence across countries by incorporating a common dynamic factor affecting all countries, rather than treating the common factor as a nuisance term as in the CCE-MG approach. This methodology provides insights into the long-term relationships between economic growth and key variables. According to the MG-AUG estimates, the coefficients for financial development and globalization are 0.043 and 0.052, respectively, indicating a significant positive long-term relationship with economic growth. Additionally, energy consumption demonstrates a positive long-term effect with a coefficient of 0.192, while the ecological footprint (EF) has a coefficient of 0.240, indicating that environmental degradation also contributes positively to long-term economic growth.

The CCE-MG estimator (Pesaran, 2006) proxies unobserved common factors with cross-sectional averages of all variables, controlling for global shocks while allowing heterogeneous factor loadings. The CCE-MG long-run estimates are: fd = 0.035, kof = 0.022, ec = 0.140, efc = 0.154 – all positive and significant. Compared to MG-AUG (fd = 0.043; ec = 0.192), the CCE-MG coefficients for finance and energy are smaller, which is expected: MG-AUG absorbs the common factor as an explicit additional regressor, while CCE-MG uses cross-sectional averages; the two estimators apportion common versus idiosyncratic variation differently. Positive signs hold across both specifications (Pesaran, 2006).

The CCE-GMM estimation method (Neal, 2015a) addresses the potential endogeneity of independent variables by employing the generalized method of moments (GMM). This method produces higher coefficient estimates compared to the CCE-MG method. Specifically the long-run parameters are all positive and significant, with financial development having a coefficient of 0.082, financial globalization 0.076, energy consumption 0.262, and the ecological footprint 0.171. These estimates are notably larger than those obtained from the CCE-MG approach, underscoring the stronger influence of these factors on long-term economic growth when endogeneity is accounted for.

The CS-ARDL model (Chudik and Pesaran, 2015a; Ditzen, 2018) builds upon the pooled mean group (PMG) approach (Pesaran *et al.*, 1999) by incorporating cross-sectional averages to account for cross-sectional dependence. This method is particularly effective in capturing long-run equilibrium relationships within heterogeneous, cross-sectionally dependent panel data, while also accommodating dynamic specifications for both the dependent and independent variables. The CS-ARDL method provides the highest long-run coefficient estimates among the models analyzed. The coefficients are 0.098 for financial development, 0.093 for financial globalization, 0.294 for energy consumption, and a

particularly large 0.459 for the ecological footprint. The significant positive coefficient for the ecological footprint underscores its strong and enduring impact on economic growth. This finding aligns with studies suggesting that environmental exploitation can contribute to long-term growth, albeit often in an unsustainable manner (Grossman and Krueger, 1995). The CS-ARDL model's ability to account for the cumulative long-term effects of these factors likely explains why its parameter estimates are larger than those of other methods, providing a comprehensive understanding of their sustained impact on economic growth.

The Dynamic CCE Mean Group (DCCE-MG) estimator incorporates multiple lags of cross-sectional averages to absorb richer common-factor dynamics (Chudik and Pesaran, 2015b; Ditzen, 2018, 2019). As the most demanding specification in terms of factor absorption, it yields the smallest coefficients: fd = 0.019, kof = 0.031, ec = 0.084, efc = 0.165. This reflects the estimator partitioning out more of the global co-movement, leaving the idiosyncratic component – arguably the most relevant for country-level policy inference. All four remain positive and significant.

The long-term estimates indicate that the elasticity values for financial development and financial globalization are lower compared to those for energy consumption and environmental degradation. Interestingly, the relatively similar magnitudes for financial globalization and financial development suggest that policy-based financial openness and domestic financial deepening are comparably important long-run drivers of economic growth. Furthermore, the findings highlight that environmental degradation exerts a greater long-term impact on economic growth than energy consumption, reflecting the broad consumption-based nature of the ecological footprint proxy. These results are grounded in established theoretical channels. The positive finance coefficient is consistent with the savings mobilization and capital allocation role of financial intermediation posited by Levine (1997) and documented empirically by Beck *et al.* (2000). The positive globalization coefficient aligns with the neoclassical prediction that capital flows toward higher-return economies, supplementing domestic savings and lowering the cost of capital (Kose *et al.*, 2006b; Obstfeld, 2021). The positive energy coefficient reflects the energy-as-input view of production advanced by Stern (2011), whereby energy services underpin industrial productivity especially in energy-intensive economies. The positive ecological footprint coefficient reflects a scale effect: historically, higher income has been associated with higher resource consumption, consistent with incomplete decoupling documented across the 1993–2020 period (Grossman and Krueger, 1995; Borucke *et al.*, 2013). Comparing our results to prior literature, the positive finance-growth coefficient (0.019–0.098 across estimators) is consistent with the meta-analytic range reported by Levine (2005) and the cross-country evidence of King and Levine (1993), while the relatively modest magnitudes align with more recent evidence suggesting diminishing returns to finance in already-developed financial systems (Purewal and Haini, 2022). The energy elasticity (0.084–0.294) is broadly consistent with Apergis and Payne (2010), who document a long-run positive relationship across OECD panels, and with Stern (2011), though our global sample yields somewhat lower average magnitudes due to cross-country heterogeneity. The financial globalization coefficient (0.022–0.093) is positive and modest, consistent with the conditional nature of globalization's growth payoff documented by Kose *et al.* (2010), who find that benefits depend on absorptive capacity and institutional quality. The ecological footprint coefficient (0.154–0.459) is larger than typical CO_2 emission coefficients in the literature, partly reflecting the broader resource-demand coverage of the footprint and partly the sample composition, consistent with

footprint-based evidence in Charfeddine and Mrabet (2017). The key additional insight this study provides is that these positive long-run relationships hold robustly across all five complementary estimators, and that explicit causality testing reveals the directions of these linkages rather than merely their existence.

In the sixth step of the analysis, the causal relationships between GDP and the independent variables are examined using the Dumitrescu and Hurlin (2012) noncausality test, following the framework outlined by Lopez and Weber (2017). To address cross-sectional dependence, a block bootstrap procedure, as detailed in Section 6.2 of Dumitrescu and Hurlin (2012), is used to derive the critical values for the test statistics. The results, summarized in Table no. 8, reveal evidence of bidirectionality: strong bidirectional causality for ecological pressure, while financial globalisation, finance, and energy show asymmetric evidence, with one direction significant at conventional levels and the reverse direction marginal at the 10% level. These results indicate that each driver both influences and is influenced by economic growth, though with varying statistical strength. This finding indicates that these factors not only drive long-term GDP growth but are also influenced by economic growth, underscoring the dynamic interplay between growth and its key determinants.

Table no. 8 – Dumitrescu–Hurlin test results

Null Hypothesis:	W-bar	Z-bar	Z-bar tilde	Prob.
fd does not homogeneously cause *ypc*	2.966	16.572	13.511	0.06
ypc does not homogeneously cause *fd*	3.920	24.606	20.378	0.00
ec does not homogeneously cause *ypc*	2.672	14.090	11.389	0.08
ypc does not homogeneously cause *ec*	4.043	25.637	21.259	0.02
efc does not homogeneously cause *ypc*	2.550	13.060	10.509	0.02
ypc does not homogeneously cause *efc*	5.004	33.737	28.184	0.00
kof does not homogeneously cause *ypc*	2.861	15.681	12.749	0.00
ypc does not homogeneously cause *kof*	2.617	13.627	10.993	0.06

Note: bootstrap probabilities after 800 simulations

The causality evidence warrants careful interpretation given the significance levels. For financial development and GDP (p = 0.06 and 0.00 respectively), there is strong evidence that growth drives financial development, and weaker evidence (10% level) of the reverse direction. For energy, growth significantly drives energy demand (p = 0.02), while the energy→GDP direction is marginal (p = 0.08). Together these suggest a feedback dynamic between income and both finance and energy, consistent with the supply-side and demand-side channels discussed in Section 2 (Levine, 2005; Stern, 2011), though not all directions are significant at the conventional 5% threshold.

Ecological pressure and GDP show robust bidirectional causality at the 1–5% level: higher income is associated with greater ecological footprint (consistent with scale effects and incomplete decoupling), while footprint also Granger-causes income, possibly through resource-use channels that sustain production (Grossman and Krueger, 1995). Financial globalisation shows the clearest bidirectionality: kof→ypc is significant at the 1% level (p = 0.00) and ypc→kof is marginal at 10% (p = 0.06), consistent with the view that growing economies attract greater international financial integration (Kose *et al.*, 2006a; Prasad *et al.*, 2007). Taken together, the causality evidence supports an interpretation of mutual

reinforcement between income and its four structural drivers, with the strength and direction varying by variable.

To complement the long-run mean elasticities with distributional evidence, we estimate the long-run relationship across income deciles using the Method of Moments Quantile Regression (MMQR) approach of Machado and Santos Silva (2019). Unlike standard quantile regression, MMQR uses moment conditions that model heteroscedasticity through covariates, enabling conditional quantile estimation without distributional assumptions (Aziz *et al.*, 2021). To address cross-sectional dependence, variables are demeaned following Sarafidis *et al.* (2009). The MMQR estimates are presented in Table no. 9, with quantile coefficient plots in Figure no. 1.

Table no. 9 – Estimated quantile parameters

Panel Quantile Method of Moments (MMQR) Estimates

Variables	Location	Scale	0.1	0.2	0.3	0.4
fd	0.152***	-0.003	0.158***	0.15***	0.154***	0.153***
eci	0.239***	0.004	0.231***	0.235***	0.236***	0.238***
efc	0.277***	-0.050	0.354***	0.324***	0.304***	0.292***
kof	0.111***	-0.020	0.141***	0.129***	0.121***	0.116***
const	-6.362***	0.393	-6.970***	-6.729***	-6.573***	-6.473***

Variables	0.5	0.6	0.7	0.8	0.9
fd	0.152***	0.152***	0.150***	0.149***	0.147***
eci	0.238***	0.240***	0.241***	0.243***	0.246***
efc	0.278***	0.266***	0.250***	0.231***	0.197***
kof	0.110***	0.106***	0.100***	0.092***	0.078***
const	-6.371***	-6.273***	-6.148***	-5.998***	-5.729***

Notes: * p<0.10; ** p<0.05; *** p<0.01, *** significant at 1%

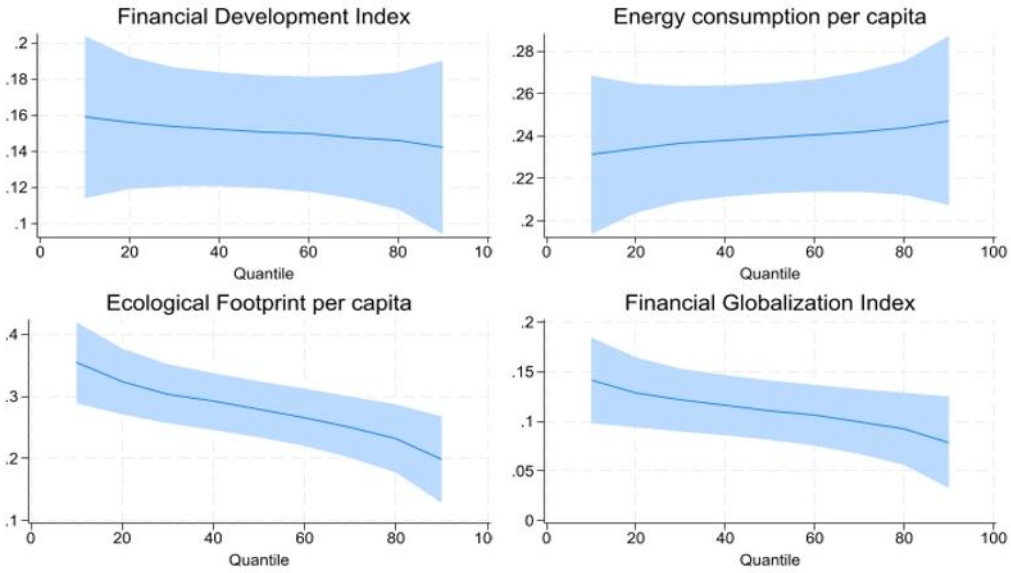


Figure no. 1 – Quantile coefficient graphs

The long-run elasticity estimates across different deciles (ranging from 0.1 to 0.9) reveal how the impacts of various factors differ across the GDP distribution. Financial development consistently demonstrates a positive and significant effect on GDP per capita across all deciles, with coefficients ranging from 0.158 at the lower deciles to 0.147 at the upper decile. This suggests that financial development promotes economic growth, particularly in lower- and middle-income economies, which aligns with previous empirical findings (Nguyen, 2023). The effect appears to diminish in higher-income countries. Likewise, financial globalization demonstrates a positive and significant impact on GDP per capita, but its effect decreases across quantiles – from 0.141 at the 0.1 decile to 0.078 at the 0.9 decile. This implies that financial globalization has a greater impact on lower-income countries, facilitating capital flows and access to international financial markets. However, in higher-income countries, domestic factors may play a more prominent role, reducing the relative importance of financial globalization.

Energy consumption per capita also exhibits a positive and significant impact on GDP across all deciles, with coefficients rising from 0.231 at the first decile to 0.246 at the highest decile. This underscores the critical role of energy consumption in driving economic growth, supporting the literature on the essential role of energy in powering industries and services. Notably, the increasing effect across income levels highlights energy's persistent and growing contribution to economic performance at various stages of development.

The ecological footprint per capita shows a significant yet diminishing impact on GDP across quantiles, with coefficients declining from 0.354 at the 0.1 decile to 0.197 at the 0.9 decile. This pattern suggests that while environmental degradation may contribute to economic growth in lower-income countries, its influence weakens as income levels rise. These findings align with the trade-offs between environmental degradation and economic growth, particularly in resource-intensive economies. However, the results also underscore the increasing awareness and prioritization of environmental costs as economies progress and develop.

Overall, the findings indicate that financial development, energy consumption, and financial globalization are critical drivers of economic growth across all income levels. Nevertheless, the ecological footprint has a positive impact in lower-income countries but becomes less beneficial as countries reach higher income levels, reflecting the increasing awareness of environmental sustainability. These results align with broader literature acknowledging the complex relationship between environmental sustainability and economic growth as economies evolve.

5. CONCLUSIONS AND POLICY IMPLICATIONS

This paper has examined the joint long-run determinants of real income per capita across 142 economies over 1993–2020, providing four distinct contributions: a unified framework for four drivers rarely modelled together, five complementary estimators as an internal robustness strategy, the ecological footprint as a consumption-based environmental proxy, and explicit panel causality evidence via the Dumitrescu–Hurlin test. Three substantive findings emerge consistently across all estimators. First, energy use and ecological pressure are the largest and most robustly estimated long-run correlates of income, reflecting the energy and resource intensity of historical development paths. Second, financial globalisation is positively and consistently associated with long-run income, with the effect stronger in lower-income quantiles. Third, financial development is positive across specifications but

more sensitive to proxy measurement and to common-factor absorption, consistent with recent evidence on diminishing returns and proxy sensitivity in the finance–growth literature.

Across the five estimators, financial development and financial globalisation remain positively associated with long-run income, but their elasticities are smaller than those for energy use and ecological pressure. This pattern suggests that finance and openness operate more as enabling conditions for growth than as stand-alone engines of long-run income expansion. The positive finance coefficient is consistent with the savings mobilisation and capital-allocation channel emphasised in the finance–growth literature (Levine, 1997; Beck *et al.*, 2000), while the positive financial-globalisation coefficient is consistent with the view that cross-border capital integration can supplement domestic savings and ease financing constraints, conditional on institutional and macroeconomic capacity (Kose *et al.*, 2006b; Obstfeld, 2021).

The ecological footprint remains positively associated with income across all estimators, reflecting the energy and resource intensity of observed development paths over 1993–2020. The MMQR results show that this positive association weakens at higher income quantiles – the coefficient declines from 0.354 at the 10th percentile to 0.197 at the 90th – consistent with partial decoupling as countries become richer, but not with reversal: ecological pressure does not become detrimental in the estimated quantiles. Finance and financial globalisation also display stronger conditional associations at lower quantiles, indicating that their marginal growth payoffs are larger where intermediation and integration constraints are more binding (Obstfeld, 2020).

Two limitations should be kept in view. First, although the Dumitrescu–Hurlin results provide useful directional evidence, they should be interpreted as Granger-causal rather than as evidence of structural causal identification. Second, the use of composite indices for financial development and financial globalisation improves conceptual coverage but also makes the results sensitive to index construction. Future research could examine subgroup heterogeneity across development stages, alternative environmental proxies such as material footprint or CO_2-based measures, and richer distributional frameworks that combine multifactor long-run controls with quantile inference.

Financial globalisation is positively associated with long-run income in our estimates, but the evidence also underscores that its payoff is conditional on regulatory quality, supervisory capacity, and macroprudential resilience. Reforms that increase the quality of integration – transparent regulatory frameworks, resilient financial supervision, and instruments that limit excessive risk-taking – matter as much as the level of integration itself. Gradual capital account liberalisation, paired with adequate macroprudential safeguards, can allow developing economies to access global capital without amplifying vulnerability to sudden stops. For sustainable globalisation strategies, policymakers should encourage foreign direct investment in renewable energy, green infrastructure, and low-emission technologies. Integrating environmental standards into trade agreements and FDI frameworks can better align global capital flows with environmental objectives, and cross-border climate finance collaborations can channel international capital toward sustainable investment.

The availability of energy is crucial for driving economic growth and enhancing productivity across industries, transportation, and households. However, to ensure sustainability, policymakers must prioritize energy efficiency by encouraging investments in energy-saving technologies and infrastructure that lower overall energy consumption without hindering economic progress. Expanding the use of renewable energy sources such as solar,

wind, and hydropower is another essential approach to diversifying energy systems, reducing dependence on fossil fuels, and minimizing environmental impacts. Governments can further support this transition by implementing favourable policies, including green bonds, subsidies, and feed-in tariffs, to attract private investment in renewable energy projects. Scaling up clean energy production not only reduces environmental footprints but also creates employment opportunities and stimulates economic activity. Additionally, carbon pricing mechanisms, such as carbon taxes or emissions trading systems, should be introduced to internalize the environmental costs of energy use, incentivizing businesses to lower their carbon emissions. Investing in local energy production and storage technologies can enhance energy security by ensuring stable supply chains amidst fluctuating global energy prices. By integrating these sustainability-focused measures into energy policies, countries can achieve economic growth while preserving environmental health, reducing carbon emissions, and mitigating long-term environmental degradation.

ORCID

Thomas Panagiotou https://orcid.org/0000-0002-3631-9676
Constantinos Katrakilidis https://orcid.org/0009-0004-9521-9204

References

Adusei, M. (2013). Financial Development and Economic Growth: Evidence from Ghana. *The International Journal of Business and Finance Research, 7*(5), 61–76.

Alfaro, L., Chanda, A., Kalemli-Ozcan, S., & Sayek, S. (2004). FDI and Economic Growth: The Role of Local Financial Markets. *Journal of International Economics, 64*(1), 89–112. http://dx.doi.org/10.1016/S0022-1996(03)00081-3

Apergis, N., & Payne, J. E. (2010). Coal Consumption and Economic Growth: Evidence from a Panel of OECD Countries. *Energy Policy, 38*(3), 1353–1359. http://dx.doi.org/10.1016/j.enpol.2009.11.016

Avdjiev, S., Hardy, B., McGuire, P., & von Peter, G. (2021). Home Sweet Host: A Cross-Country Perspective on Prudential and Monetary Policy Spillovers Through Global Banks. *Review of International Economics, 29*(1), 20–36. http://dx.doi.org/10.1111/roie.12504

Azam, M. (2016). Does Environmental Degradation Shackle Economic Growth? A Panel Data Investigation on 11 Asian Countries. *Renewable and Sustainable Energy Reviews, 65*(C), 175–182. http://dx.doi.org/10.1016/j.rser.2016.06.087

Aziz, N., Sharif, A., Raza, A., & Jermsittiparsert, K. (2021). The Role of Natural Resources, Globalization, and Renewable Energy in Testing the EKC Hypothesis in MINT Countries: New Evidence from Method of Moments Quantile Regression Approach. *Environmental Science and Pollution Research International, 28*(11), 13454–13468. http://dx.doi.org/10.1007/s11356-020-11540-2

Balsalobre-Lorente, D., Shahbaz, M., Roubaud, D., & Farhani, S. (2018). How Economic Growth, Renewable Electricity and Natural Resources Contribute to CO2 Emissions? *Energy Policy, 113*(C), 356–367. http://dx.doi.org/10.1016/j.enpol.2017.10.050

Bartolini, L., & Drazen, A. (1997). Capital-Account Liberalization as a Signal. *The American Economic Review, 87*(1), 138–154.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2010). Financial Institutions and Markets Across Countries and over Time: The updated Financial Development and Structure Database. *The World Bank Economic Review, 24*(1), 77–92. http://dx.doi.org/10.1093/wber/lhp016

Beck, T., Levine, R., & Loayza, N. (2000). Finance and the Sources of Growth. *Journal of Financial Economics, 58*(1–2), 261–300. http://dx.doi.org/10.1016/S0304-405X(00)00072-6

Bekaert, G., Ehrmann, M., Fratzscher, M., & Mehl, A. (2014). The Global Crisis and Equity Market Contagion. *The Journal of Finance, 69*(6), 2597–2649. http://dx.doi.org/10.1111/jofi.12203

Belke, A., Dobnik, F., & Dreger, C. (2011). Energy Consumption and Economic Growth: New Insights into the Cointegration Relationship. *Energy Economics, 33*(5), 782–789. http://dx.doi.org/10.1016/j.eneco.2011.02.005

Belloumi, M. (2009). Energy Consumption and GDP in Tunisia: Cointegration and Causality Analysis. *Energy Policy, 37*(7), 2745–2753. http://dx.doi.org/10.1016/j.enpol.2009.03.027

Bencivenga, V. R., & Smith, B. D. (1993). Some Consequences of Credit Rationing in an Endogenous Growth Model. *Journal of Economic Dynamics & Control, 17*(1–2), 97–122. http://dx.doi.org/10.1016/S0165-1889(06)80006-0

Bernanke, B. S., Gertler, M., & Gilchrist, S. (1999). The Financial Accelerator in a Quantitative Business Cycle Framework. In J. B. Taylor & M. Woodford (Eds.), *Handbook of Macroeconomics* (Vol. 1, Part C, pp. 1341–1393): Elsevier Science B.V. http://dx.doi.org/10.1016/S1574-0048(99)10034-X

Bersvendsen, T., & Ditzen, J. (2021). Testing for Slope Heterogeneity in Stata. *The Stata Journal, 21*(1), 51–80. http://dx.doi.org/10.1177/1536867X211000004

Bilgili, F., Koçak, E., & Bulut, Ü. (2016). The Dynamic Impact of Renewable Energy Consumption on CO2 Emissions: A Revisited Environmental Kuznets Curve Approach. *Renewable and Sustainable Energy Reviews, 54*(C), 838–845. http://dx.doi.org/10.1016/j.rser.2015.10.080

Blomquist, J., & Westerlund, J. (2013). Testing Slope Homogeneity in Large Panels with Serial Correlation. *Economics Letters, 121*(3), 374–378. http://dx.doi.org/10.1016/j.econlet.2013.09.012

Blomquist, J., & Westerlund, J. (2016). Panel Bootstrap Tests of Slope Homogeneity. *Empirical Economics, 50*(4), 1359–1381. http://dx.doi.org/10.1007/s00181-015-0978-z

Borensztein, E., De Gregorio, J., & Lee, J. W. (1998). How Does Foreign Direct Investment Affect Economic Growth? *Journal of International Economics, 45*(1), 115–135. http://dx.doi.org/10.1016/S0022-1996(97)00033-0

Borucke, M., Moore, D., Cranston, G., Gracey, K., Iha, K., Larson, J., . . . Galli, A. (2013). Accounting for Demand and Supply of the Biosphere's Regenerative Capacity: The National Footprint Accounts' Underlying Methodology and Framework. *Ecological Indicators, 24*(January), 518–533. http://dx.doi.org/10.1016/j.ecolind.2012.08.005

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. *The Review of Economic Studies, 47*(1), 239–253. http://dx.doi.org/10.2307/2297111

Broner, F., Didier, T., Erce, A., & Schmukler, S. L. (2013). Gross Capital Flows: Dynamics and Crises. *Journal of Monetary Economics, 60*(1), 113–133. http://dx.doi.org/10.1016/j.jmoneco.2012.12.004

Broner, F., Didier, T., Schmukler, S. L., & von Peter, G. (2023). Bilateral International Investments: The Big Sur? *Journal of International Economics, 145*(2024), 103795. http://dx.doi.org/10.1016/j.jinteco.2023.103795

Buffie, E. F. (1984). Financial Repression, the New Structuralists, and Stabilization Policy in Semi-Industrialized Economies. *Journal of Development Economics, 14*(3), 305–322. http://dx.doi.org/10.1016/0304-3878(84)90061-0

Charfeddine, L., & Mrabet, Z. (2017). The Impact of Economic Development and Social-Political Factors on Ecological Footprint: A Panel Data Analysis for 15 MENA Countries. *Renewable and Sustainable Energy Reviews, 76*(C), 138–154. http://dx.doi.org/10.1016/j.rser.2017.03.031

Chinn, M. D., & Ito, H. (2008). A New Measure of Financial Openness. *Journal of Comparative Policy Analysis, 10*(3), 309–322. http://dx.doi.org/10.1080/13876980802231123

Chudik, A., & Pesaran, H. (2015a). Large Panel Data Models with Cross-Sectional Dependence: A Survey. In B. H. Baltagi (Ed.), *The Oxford Handbook of Panel Data* (pp. 3–45): Oxford University Press. http://dx.doi.org/10.1093/oxfordhb/9780199940042.013.0001

Chudik, A., & Pesaran, M. H. (2015b). Common Correlated Effects Estimation of Heterogeneous Dynamic Panel Data Models with Weakly Exogenous Regressors. *Journal of Econometrics, 188*(2), 393–420. http://dx.doi.org/10.1016/j.jeconom.2015.03.007

Čihák, M., Demirgüç-Kunt, A., Feyen, E., & Levine, R. (2012). Benchmarking Financial Systems around the World *Global Financial Development Report 2013 : Rethinking the Role of the State in Finance* (pp. 15–43): World Bank Group. http://dx.doi.org/10.1596/9780821395035_ch01

Cleveland, C. J., Kaufmann, R. K., & Stern, D. I. (2004). Aggregation of Energy. In C. J. Cleveland (Ed.), *Encyclopedia of Energy* (1st ed., Vol. 1, pp. 17–28): ScienceDirect. http://dx.doi.org/10.1016/b0-12-176480-x/00231-x

Cole, D. C., & Shaw, E. S. (1974). Financial Deepening in Economic Development. *Oxford University Press, 29*(2), 1345–1348. http://dx.doi.org/10.2307/2978421

Das, P. K., & Guha-Khasnobis, B. (2008). Finance and Growth: An Empirical Assessment of the Indian Economy. In B. Guha-Khasnobis & G. Mavrotas (Eds.), *Financial Development, Institutions, Growth and Poverty Reduction* (pp. 120–140). London: Palgrave Macmillan UK. http://dx.doi.org/10.1057/9780230594029_6

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for Cross-Sectional Dependence in Panel-Data Models. *The Stata Journal, 6*(4), 482–496. http://dx.doi.org/10.1177/1536867X0600600403

Diamond, D. W. (1984). Financial Intermediation and Delegated Monitoring. *The Review of Economic Studies, 51*(3), 393–414. http://dx.doi.org/10.2307/2297430

Ditzen, J. (2018). Estimating Dynamic Common-Correlated Effects in Stata. *The Stata Journal, 18*(3), 585–617. http://dx.doi.org/10.1177/1536867x1801800306

Ditzen, J. (2019). *Estimating Long-Run Effects and the Exponent of Cross-Sectional Dependence: An Update to xtdcce2*. Centre for Energy Economics Research and Policy (CEERP) CEERP Working Paper No. 7. Heriot-Watt University

Edinburgh. Retrieved from https://journals.sagepub.com/doi/abs/10.1177/1536867X211045560

Dong, K., Sun, R., & Hochman, G. (2017). Do Natural Gas and Renewable Energy Consumption Lead to Less CO2 Emission? Empirical Evidence from a Panel of BRICS Countries. *Energy, 141*(C), 1466–1478. http://dx.doi.org/10.1016/j.energy.2017.11.092

Dong, K., Wang, S., Hu, H., Guan, N., Shi, X., & Song, Y. (2023). Financial Development, Carbon Dioxide Emissions, and Sustainable Development. *Sustainable Development (Bradford), 32*(1). http://dx.doi.org/10.1002/SD.2649

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger Non-Causality in Heterogeneous Panels. *Economic Modelling, 29*(4), 1450–1460. http://dx.doi.org/10.1016/j.econmod.2012.02.014

Dunning, J. H. (1993). *International Direct Investment Patterns*. Paper presented at the The Global Race for Foreign Direct Investment, Berlin, Heidelberg.

Eberhardt, M., & Teal, F. (2010). Productivity Analysis *Global Manufacturing Production* (Vol. Discussion Paper 515, pp. 1–32): University of Oxford

Eberhardt, M., & Teal, F. (2011). Econometrics for Grumblers: A New Look at the Literature on Cross-Country Growth Empirics. *Journal of Economic Surveys, 25*(1), 109–155. http://dx.doi.org/10.1111/j.1467-6419.2010.00624.x

Eichengreen, B. (2001). Capital Account Liberalization: What Do Cross-Country Studies Tell Us? *The World Bank Economic Review, 15*(3), 341–365. http://dx.doi.org/10.1093/wber/15.3.341

Fan, J., Liao, Y., & Yao, J. (2015). Power Enhancement in High Dimensional Cross-Sectional Tests. *Econometrica, 83*(4), 1497–1541. http://dx.doi.org/10.3982/ECTA12749

Frees, E. W. (1995). Assessing Cross-Sectional Correlation in Panel Data. *Journal of Econometrics, 69*(2), 393–414. http://dx.doi.org/10.1016/0304-4076(94)01658-M

Friedman, M. (1937). The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance. *Journal of the American Statistical Association, 32*(200), 675–701. http://dx.doi.org/10.1080/01621459.1937.10503522

Gourinchas, P., & Jeanne, O. (2005). *Capital Mobility and Reform.* . Retrieved from https://www.academia.edu/download/30738140/arcpaperoct2505.pdf

Greenwood, J., & Jovanovic, B. (1990). Financial Development, Growth, and the Distribution of Income. *Journal of Political Economy, 98*(5, Part 1), 1076–1107. http://dx.doi.org/10.1086/261720

Grossman, G. M., & Krueger, A. B. (1995). Economic Growth and the Environment. *The Quarterly Journal of Economics, 110*(2), 353–377. http://dx.doi.org/10.2307/2118443

Gygli, S., Haelg, F., Potrafke, N., & Sturm, J. E. (2019). The KOF Globalisation Index – revisited. *The Review of International Organizations, 14*(3), 543–574. http://dx.doi.org/10.1007/s11558-019-09344-2

He, Z., & You, Y. (2024). Convergence in Financial Development and Growth. *Open Economies Review, 35*(4), 779–799. http://dx.doi.org/10.1007/s11079-024-09767-4

Hicks, J. R. (1969). *A Theory of Economic History* (Vol. 163): Oxford University Press.

Ibrahim, R. L., Alomair, A., & Al Naim, A. S. (2024). How Financial Development Is Driving the Growth and Environmental Dimensions of Sustainable Development in Africa: Heterogeneous Analyses. *Sustainability (Basel), 16*(21), 9284. http://dx.doi.org/10.3390/su16219284

Ike, G. N., Usman, O., & Sarkodie, S. A. (2020). Testing the Role of Oil Production in the Environmental Kuznets Curve of Oil Producing Countries: New Insights from Method of Moments Quantile Regression. *The Science of the Total Environment, 711*(10), 135208. http://dx.doi.org/10.1016/j.scitotenv.2019.135208

IMF. (2022). IMF Data, Access to Microeconomic Financial Data. from IMF https://data.imf.org/?sk=388DFA60-1D26-4ADE-B505-A05A558D9A42sId=1479329132316

Jaunky, V. C. (2011). The CO2 Emissions-Income Nexus: Evidence from Rich Countries. *Energy Policy, 39*(3), 1228–1240. http://dx.doi.org/10.1016/j.enpol.2010.11.050

Jeanne, O., & Rancière, R. (2011). The Optimal Level of International Reserves for Emerging Market Countries: A New Formula and Some Applications. *Economic Journal (London), 121*(555), 905–930. http://dx.doi.org/10.1111/j.1468-0297.2011.02435.x

Kahia, M., Ben Aïssa, M. S., & Charfeddine, L. (2016). Impact of Renewable and Non-Renewable Energy Consumption on Economic Growth: New Evidence from the MENA Net Oil Exporting Countries (NOECs). *Energy, 116*(P1), 102–115. http://dx.doi.org/10.1016/j.energy.2016.07.126

King, R. G., & Levine, R. (1993). Finance, Entrepreneurship and Growth. *Journal of Monetary Economics, 32*(3), 513–542. http://dx.doi.org/10.1016/0304-3932(93)90028-E

Klein, M. W., & Olivei, G. (2008). Capital Account Liberalization, Financial Depth, and Economic Growth. *Journal of International Money and Finance, 27*(6), 861–875. http://dx.doi.org/10.1016/j.jimonfin.2008.05.002

Kose, M., & Prasad, E. (2007). Liberalizing Capital Account Restrictions. In E. Diehl & J. Clift (Eds.), *Finance globalization: The impact on trade, policy, labor, and capital flows* (pp. 90): IMF.

Kose, M. A., Prasad, E., Rogoff, K., & Wei, S. J. (2006a). Financial Globalization: A Reappraisal. *IMF Working Paper, 2006*(189), 94. http://dx.doi.org/10.5089/9781451864496.001

Kose, M. A., Prasad, E., Rogoff, K., & Wei, S. J. (2010). Financial Globalization and Economic Policies. In D. Rodrik & M. Rosenzweig (Eds.), *Handbook of Development Economics* (Vol. 5, pp. 4283–4359): Elsevier. http://dx.doi.org/10.1016/B978-0-444-52944-2.00003-3

Kose, M. A., Prasad, E. S., & Terrones, M. E. (2006b). How Do Trade and Financial Integration Affect the Relationship Between Growth and Volatility? *Journal of International Economics, 69*(1 (SPEC ISS)), 176–202. http://dx.doi.org/10.1016/j.jinteco.2005.05.009

Kuznets, S. (1955). Economic Growth and Income Inequality. In M. A. Seligson (Ed.), *The Gap Between Rich and Poor: Contending Perspectives On The Political Economy of Development* (Vol. 45, pp. 25–38). New York: Routledge. http://dx.doi.org/10.4324/9780429311208-4

Lane, P. R., & Milesi-Ferretti, G. M. (2018). The External Wealth of Nations Revisited: International Financial Integration in the Aftermath of the Global Financial Crisis. *IMF Economic Review, 66*(1), 189–222. http://dx.doi.org/10.1057/s41308-017-0048-y

Levine, R. (1997). Financial Development and Economic Growth: Views and Agenda. *Journal of Economic Literature, 35*(2), 688–726.

Levine, R. (2005). Finance and Growth: Theory and Evidence. In P. Aghion & S. Durlauf (Eds.), *Handbook of Economic Growth* (1st ed., Vol. 1, No. 1, pp. 865–934): Elsevier. http://dx.doi.org/10.1016/S1574-0684(05)01012-9

Levine, R., Loayza, N., & Beck, T. (2000). Financial intermediation and Growth: Causality and Causes. *Journal of Monetary Economics, 46*(1), 31–77. http://dx.doi.org/10.1016/S0304-3932(00)00017-9

Levine, R., & Zervos, S. (1998). Capital Control Liberalization and Stock Market Development. *World Development, 26*(7), 1169–1183. http://dx.doi.org/10.1016/S0305-750X(98)00046-1

Lopez, L., & Weber, S. (2017). Testing for Granger Causality in Panel Data. *The Stata Journal, 17*(4), 972–984. http://dx.doi.org/10.1177/1536867x1801700412

Lucas, R. E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics, 22*(1), 3–42. http://dx.doi.org/10.1016/0304-3932(88)90168-7

Luzzati, T., & Orsini, M. (2009). Investigating the Energy-Environmental Kuznets Curve. *Energy, 34*(3), 291–300. http://dx.doi.org/10.1016/j.energy.2008.07.006

Ma, M., & Cai, W. (2019). Do Commercial Building Sector-Derived Carbon Emissions Decouple from the Economic Growth in Tertiary Industry? A Case Study of four Municipalities in China. *The Science of the Total Environment, 650*(P1), 822–834. http://dx.doi.org/10.1016/j.scitotenv.2018.08.078

Machado, J. A. F., & Santos Silva, J. M. C. (2019). Quantiles Via Moments. *Journal of Econometrics, 213*(1), 145–173. http://dx.doi.org/10.1016/j.jeconom.2019.04.009

Maddala, G. S., & Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test. *Oxford Bulletin of Economics and Statistics, 61*(S1), 631–652. http://dx.doi.org/10.1111/1468-0084.0610s1631

McKinnon, R. I. (1974). Money and Capital in Economic Development. *International Journal, 29*(4), 200. http://dx.doi.org/10.2307/40201473

Mishkin, F. S. (2009). The Next Great Globalization: How Disadvantaged Nations Can Harness their Financial Systems to Get Rich. In F. S. Mishkin (Ed.), *The Next Great Globalization*: How Disadvantaged Nations Can Harness Their Financial Systems to Get Rich. http://dx.doi.org/10.2307/j.ctt7t55r

Narayan, P. K., & Narayan, S. (2010). Carbon Dioxide Emissions and Economic Growth: Panel Data Evidence from Developing Countries. *Energy Policy, 38*(1), 661–666. http://dx.doi.org/10.1016/j.enpol.2009.09.005

Narayan, P. K., & Smyth, R. (2008). Energy Consumption and Real GDP in G7 Countries: New Evidence from Panel Cointegration with Structural Breaks. *Energy Economics, 30*(5), 2331–2341. http://dx.doi.org/10.1016/j.eneco.2007.10.006

Nasse, E. (2016). V. Lombardstreet: A Description of the Money Market by Walter Bagehot. *Jahrbücher für Nationalökonomie und Statistik, 22*(1), 38–43. http://dx.doi.org/10.1515/jbnst-1874-0108

Neal, B. T. (2015a). *Estimating Heterogeneous Coefficients in Panel Data Models with Endogenous Regressors and Common Factors*. Working Paper.

Neal, T. (2015b). XTCCE: Stata Module to Implement the Common Correlated Effects Estimator. *Statistical Software Components*.

Nguyen, Q. K. (2023). Macroeconomic Determinants of Economic Growth in Low- and Mid-Income Countries: New Evidence Using a Non-Parametric Approach. *Applied Economics Letters, 32*(1), 680–685. http://dx.doi.org/10.1080/13504851.2023.2283774

Obstfeld, M. (2020). Globalization Cycles. *Italian Economic Journal, 6*(1), 1–12. http://dx.doi.org/10.1007/s40797-020-00121-4

Obstfeld, M. (2021). Trilemmas and Tradeoffs: Living with Financial Globalization. In C. Raddatz, D. Saravia, & J. Ventura (Eds.), *Global Liquidity, Spillovers to Emerging Markets and Policy Responses* (1 ed., Vol. 20, pp. 013–078): World Scientific.

Obstfeld, M., Ostry, J. D., & Qureshi, M. S. (2021). A Tie that Binds: Revisiting the Trilemma in Emerging Market Economies. *IMF Working Paper 17*(130). http://dx.doi.org/10.5089/9781484302620.001

Odhiambo, N. M. (2023). Financial Development and Economic Growth: A Review of International Evidence. *Research in Globalization, 12*, 100123.

Omri, A. (2013). CO2 Emissions, Energy Consumption and Economic Growth Nexus in MENA Countries: Evidence from Simultaneous Equations Models. *Energy Economics, 40*(C), 657–664. http://dx.doi.org/10.1016/j.eneco.2013.09.003

Ozturk, I. (2010). A Literature Survey on Energy-Growth Nexus. *Energy Policy, 38*(1), 340–349. http://dx.doi.org/10.1016/j.enpol.2009.09.024

Paceskovski, V. G. S. K. N. V. (2013, 30 Dec 2013). *Positive and Negative Effects of Financial Globalization on Developing and Emerging Economies.* Paper presented at the International Scientific Conference "Regional Economic Cooperation in the Process of Globalization".

Padilla, E., & Serrano, A. (2006). Inequality in CO2 Emissions Across Countries and its Relationship with Income Inequality: A Distributive Approach. *Energy Policy, 34*(14), 1762–1772. http://dx.doi.org/10.1016/j.enpol.2004.12.014

Pao, H. T., & Tsai, C. M. (2010). CO2 Emissions, Energy Consumption and Economic Growth in BRIC Countries. *Energy Policy, 38*(12), 7850–7860. http://dx.doi.org/10.1016/j.enpol.2010.08.045

Pesaran, M. H. (2004). General Diagnostic Tests for Cross-Sectional Dependence in Panels. *SSRN Electronic Journal, 69*(7), 13–50. http://dx.doi.org/10.2139/ssrn.572504

Pesaran, M. H. (2006). Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica, 74*(4), 967–1012. http://dx.doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M. H. (2007). A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence. *Journal of Applied Econometrics, 22*(2), 265–312. http://dx.doi.org/10.1002/jae.951

Pesaran, M. H. (2021). General Diagnostic Tests for Cross-Sectional Dependence in Panels. *Empirical Economics, 60*(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Pesaran, M. H., Shin, Y., & Smith, R. P. (1999). Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. *Journal of the American Statistical Association, 94*(446), 621–634. http://dx.doi.org/10.1080/01621459.1999.10474156

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A Bias-Adjusted LM Test of Error Cross-Section Independence. *The Econometrics Journal, 11*(1), 105–127. http://dx.doi.org/10.1111/j.1368-423X.2007.00227.x

Pesaran, M. H., & Yamagata, T. (2008). Testing Slope Homogeneity in Large Panels. *Journal of Econometrics, 142*(1), 50–93. http://dx.doi.org/10.1016/j.jeconom.2007.05.010

Prasad, E. S., Rogoff, K., Wei, S. J., & Kose, M. A. (2007). Financial Globalization, Growth, and Volatility in Developing Countries. In A. Harrison (Ed.), *Globalization and Poverty* (pp. 457–516): University of Chicago Press. http://dx.doi.org/10.7208/chicago/9780226318004.003.0012

Purewal, K., & Haini, H. (2022). Re-examining the Effect of Financial Markets and Institutions on Economic Growth: Evidence from the OECD Countries. *Economic Change and Restructuring, 55*(1), 311–333. http://dx.doi.org/10.1007/s10644-020-09316-2

Quinn, D., Schindler, M., & Toyoda, A. M. (2011). Assessing Measures of Financial Openness and Integration. *IMF Economic Review, 59*(3), 488–522. http://dx.doi.org/10.1057/imfer.2011.18

Saci, K., Giorgioni, G., & Holden, K. (2009). Does Financial Development Affect Growth? *Applied Economics, 41*(13), 1701–1707. http://dx.doi.org/10.1080/00036840701335538

Sadorsky, P. (2010). The Impact of Financial Development on Energy Consumption in Emerging Economies. *Energy Policy, 38*(5), 2528–2535. http://dx.doi.org/10.1016/j.enpol.2009.12.048

Sahay, R., Čihák, M., Barajas, A., Bi, R., Ayala, D., Gao, Y., . . . Sommer, M. (2015). Rethinking Financial Deepening: Stability and Growth in Emerging Markets. *IMF staff discussion note, 15*(8), 73–107. http://dx.doi.org/10.5089/9781498312615.006

Sarafidis, V., Yamagata, T., & Robertson, D. (2009). A Test of Cross Section Dependence for a Linear Dynamic Panel Model with Regressors. *Journal of Econometrics, 148*(2), 149–161. http://dx.doi.org/10.1016/j.jeconom.2008.10.006

Sarkodie, S. A., & Ozturk, I. (2020). Investigating the Environmental Kuznets Curve Hypothesis in Kenya: A Multivariate Analysis. *Renewable & Sustainable Energy Reviews, 117*(January), 109481. http://dx.doi.org/10.1016/j.rser.2019.109481

Sarkodie, S. A., & Strezov, V. (2018). Assessment of Contribution of Australia's Energy Production to CO2 Emissions and Environmental Degradation Using Statistical Dynamic Approach. *The Science of the Total Environment, 639*(C), 888–899. http://dx.doi.org/10.1016/j.scitotenv.2018.05.204

Schumpeter, J. (1911). *The Theory of Economic Development: An Inquiry into Profits, Capital, Interest, and the Business Cycle*: Harvard University Press.

Schumpeter, J. A. (1934). *The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*: Harvard University Press.

Sencer Atasoy, B. (2017). Testing the Environmental Kuznets Curve Hypothesis Across the U.S.: Evidence from Panel Mean Group Estimators. *Renewable and Sustainable Energy Reviews, 77*(4), 731–747. http://dx.doi.org/10.1016/j.rser.2017.04.050

Shuai, C., Shen, L., Jiao, L., Wu, Y., & Tan, Y. (2017). Identifying Key Impact Factors on Carbon Emission: Evidences from Panel and Time-Series Data of 125 Countries from 1990 to 2011. *Applied Energy, 187*(C), 310–325. http://dx.doi.org/10.1016/j.apenergy.2016.11.029

Singh, S., Arya, V., Yadav, M. P., & Power, G. J. (2023). Does Financial Development Improve Economic Growth? The Role of Asymmetrical Relationships. *Global Finance Journal, 56*(C), 100831. http://dx.doi.org/10.1016/j.gfj.2023.100831

Stern, D. I. (2011). The Role of Energy in Economic Growth. *Annals of the New York Academy of Sciences, 1219*(1), 26–51. http://dx.doi.org/10.1111/j.1749-6632.2010.05921.x

Stiglitz, J., & Weiss, A. (1983). Incentive Effects of Terminations: Applications to the Credit and Labor Markets. *The American Economic Review, 73*(5), 912–927.

Stulz, R. M. (2005). The Limits of Financial Globalization. *The Journal of Finance, 60*(4), 1595–1638. http://dx.doi.org/10.1111/j.1540-6261.2005.00775.x

Svirydzenka, K. (2016). Introducing a New Broad-based Index of Financial Development. *IMF Working Paper, 16*(5), 1. http://dx.doi.org/10.5089/9781513583709.001

Tang, C. F., & Tan, B. W. (2015). The Impact of Energy Consumption, Income and Foreign Direct Investment on Carbon Dioxide Emissions in Vietnam. *Energy, 79*(C), 447–454. http://dx.doi.org/10.1016/j.energy.2014.11.033

Toumi, S. (2025). Unveiling Impact of Financial Development, Renewable Energy, and Technological Innovation on Ecological Footprint in Major Remittance-Receiving Economies–A PQARDL Approach. *International Journal of Renewable Energy Development, 14*(1), 180–199. http://dx.doi.org/10.61435/ijred.2025.60762

University of York. (2022). National Ecological Footprint and Biocapacity Accounts | Ecological Footprint Initiative. from YORKU https://footprint.info.yorku.ca/data/

Van Wijnbergen, S. (1983). Interest Rate Management in LDC's. *Journal of Monetary Economics, 12*(3), 433–452. http://dx.doi.org/10.1016/0304-3932(83)90063-6

Wang, J., & Dong, K. (2019). What Drives Environmental Degradation? Evidence from 14 Sub-Saharan African Countries. *The Science of the Total Environment, 656*(C), 165–173. http://dx.doi.org/10.1016/j.scitotenv.2018.11.354

Wang, Y., Ibrahim, R. L., Oke, D. M., & Al-Faryan, M. A. S. (2024). Investigating Green Energy–Environment Nexus in Post-COP26 Era: Can Technological Innovation, Financial Development and Government Expenditure Deliver Africa's Targets? *International Journal of Finance & Economics, 29*(3), 3263–3285. http://dx.doi.org/10.1002/ijfe.2824

Westerlund, J. (2005). New Simple Tests for Panel Cointegration. *Econometric Reviews, 24*(3), 297–316. http://dx.doi.org/10.1080/07474930500243019

Westerlund, J. (2007). Testing for Error Correction in Panel Data. *Oxford Bulletin of Economics and Statistics, 69*(6), 709–748. http://dx.doi.org/10.1111/j.1468-0084.2007.00477.x

World Bank. (2021). World Development Indicators (Publication no. 10.4135/9781412952613.n571). (1029-4325). from Sage

Zhou, D., Saeed, U. F., Kongkuah, M., & Wiredu, I. (2024). Examining the Moderating Role of Environmental Regulations on Financial Development and Ecological Footprint in the MENA Region. *Environment, Development and Sustainability, 28*(5), 11497–11524. http://dx.doi.org/10.1007/s10668-024-05430-7

ANNEX

List of countries

Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, The Bahamas, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Chad, Chile, China, Colombia, Congo, Dem. Rep., Congo, Rep., Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, Egypt, Arab Rep., El Salvador, Estonia, Eswatini, Ethiopia, Fiji, Finland, France, Gabon, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guyana, Honduras, Hungary, India, Indonesia, Iran, Islamic Rep., Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Rep., Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, St. Lucia, Suriname, Sweden, Switzerland, Tanzania, Thailand, Togo, Tunisia, Türkiye, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vietnam, Yemen, Rep., Zambia.

Scientific Annals of Economics and Business
73 (3), 2026, 577-592
DOI: 10.47743/saeb-2026-0032

Profitability of US Small Banks pre-during-post 2008 Global Financial Crisis: Evidence from Ratio Analysis

Rasoul Rezvanian[*], Seyed Mehdian[**], Kevin Jaklin[***], Nafise Aalipour[§]

Abstract: This study contributes to the banking literature by examining the impact of the 2008 Global Financial Crisis (2008 GFC) on the profitability of U.S. small banks. Using U.S. small banks' financial data from 2001 to 2025, we partition data into three distinct periods: pre-(2001-2006), during- (2007-2011), and post-(2011-2025) 2008 GFC, and utilize several commonly used profitability ratios. The results indicate that the 2008 GFC had a significant negative impact on the profitability of U.S. small banks: The small U.S. banks had high profitability scores pre-2008 GFC, a declining trend that started three years before the 2008 GFC, a sharp decline during the 2008 GFC, and a profitability recovery that started in 2010 and continued until 2025. Two conclusions can be drawn from the results. First, small banks used the low-interest-rate environment during and after the 2008 GFC to sharply reduce their interest expense and remain profitable. This indicates that the Fed's expansionary monetary policy to counter the 2008 GFC, by reducing market interest rates, benefited small banks. Next, the decline in profitability of small banks began three years before the 2008 GFC, and the increase in profitability occurred before the 2008 GFC ended. This suggests that changes in the profitability of U.S. small banks may have predictive value for the start and end of major financial crises.

Keywords: Bank profitability; Ratio Analysis; 2008 Global Financial Crisis.

JEL classification: F65; G01; G21.

[*] Cofrin School of Business, University of Wisconsin Green Bay, USA; e-mail: *rezvanir@uwgb.edu* (corresponding author).
[**] School of Management, University of Michigan - Flint, USA; e-mail: *seyed@umich.edu*.
[***] Cofrin School of Business, University of Wisconsin Green Bay, USA; e-mail: *jaklink@uwgb.edu*.
[§] School of Management, University of Michigan - Flint, USA; e-mail: *aalipour@umich.edu.*

Article history: Received 3 June 2026 | Accepted 8 September 2026 | Published online 29 September 2026

To cite this article: Rezvanian, R., Mehdian, S., Jaklin, K., Aalipour, N. (2026). Profitability of US Small Banks pre-during-post 2008 Global Financial Crisis: Evidence from Ratio Analysis. *Scientific Annals of Economics and Business*, 73(3), 577-592. https://doi.org/10.47743/saeb-2026-0032.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

The U.S. banking industry has undergone significant changes over the last twenty years. From 2001 to 2025, the banking industry witnessed 563 bank failures with total assets of $1.05 trillion, many of which were small banks. The industry also suffered from several crises, the major one being the 2008 global financial crisis (2008 GFC) meltdown, followed by a wave of bank failures. Most recently, in 2023, the industry witnessed the collapses of Silicon Valley Bank and Signature Bank.

Due to the importance of the banking industry in the economy, the banking regulatory and supervisory agencies such as the Federal Reserve System, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency, as well as state banking regulatory agencies, pay special attention to the safety and soundness of the banking industry. In response to the regulatory and supervisory agencies' attention, an extensive body of literature has been developed in academia to examine banking firms' cost and profit efficiency, productivity growth, and financial performance.

One indicator of banking safety and soundness is profitability (Ahmad *et al.*, 2007) and its change in response to unexpected events such as financial crises. Athari and Bahreini (2023) and Dietrich and Wanzenried (2011) suggest that, given the critical role of banks in facilitating private investment and promoting economic growth, identifying and understanding the primary determinants of their profitability is essential. Nguyen and Le (2022) show there is a positive relationship between banks' profitability and stability. Xu *et al.* (2019) provide evidence suggesting that policymakers should strive to understand the sources of bank profitability better.

Begenau *et al.* (2026), argue that a bank's market value is closely linked to its financial position. In line with this study, we apply key financial ratios such as profit margin (PM), return on assets (ROA), and return on equity (ROE) to investigate the profitability of small banks over 25 years, focusing on three distinct phases: pre-, during, and post- 2008 GFC, with an understanding that the broader economic environment also significantly influences these ratios. This longitudinal analysis enhances our understanding of small banks' profitability in response to the crises.

The financial management strategies of the banking industry have also transformed over the last two decades, as banks have increased their appetite for leverage and loaded their asset portfolios with risky mortgage loans backed by subprime lending. These managerial strategies were justified by corporate finance theory related to the magnification of return on assets and equity and the tax effect of borrowing. However, regarding these strategies, some analysts argue that the causes of the 2008 GFC could be that households increased their appetite for borrowing, particularly risky borrowing to purchase houses. Regardless of the cause of the 2008 GFC, we believe that the 2008 GFC impacted both the asset and liability sides of banks' balance sheets, as well as their profitability. The impact may be more pronounced in the case of small banks because of their peculiar nature of assets and liabilities and their limited access to the financial market.

Small banks play an essential role in the growth of the regional economy and are also major providers of funds to small regional businesses. During the financial crisis, in the absence of government agencies' intervention, the role played by the small banks became even more critical to regional economic growth because many small businesses were denied access to funds provided by larger financial institutions. Therefore, for the policymakers

responsible for providing liquidity in the financial markets and the regional economic architects concerned about the sustainability of their regional economic well-being, it is important to examine the profitability of small banks and changes in profitability in response to an unexpected event because of their essential role in providing liquidity and financing regional economic growth.

While there are many studies on measuring banking performance using cost and profit efficiency measures, only a limited number use financial statement and ratio analysis to evaluate the financial position of banks[1]. Most financial statement and ratio analysis studies focus on the profitability determinants of banks using cross-sectional and time-series data[2].

Short (1979) and Smirlock (1985) examine the relationship between banking industry profitability and market concentration across Canada, Western Europe, Japan, and the United States. Bassell and Brady (2001) investigate U.S. small banks with assets under $331 million from 1985 to 2000, finding that these institutions consistently achieved faster growth in deposits and assets than larger banks, leading to higher profitability. This superior performance is attributed to a lending-focused portfolio strategy.

Nal and Cai (2020) investigate the effects of the 2008 GFC on the four largest U.S. banks using data from 2002 to 2020. Using ROA as a profitability ratio, they show that profit ratios were relatively higher before the crisis, dropped during the crisis, and have since returned to pre-crisis levels. Nippani and Ling (2021) examine the relationship between the size and financial performance of U.S. banks before and after the 2008 GFC using accounting ratios such as return on equity and return on assets. They report that the banks' financial positions deteriorated after the crisis, and the decline in financial position is more pronounced among small banks than among larger banks.

The profitability of the banking industry outside the U.S. and its response to the 2008 GFC have been the focus of many recent studies. For example, Alper and Anbar (2011) examine banks' profitability in Turkey from 2002 to 2010. Using panel data, they provide evidence to indicate that the non-interest income-to-asset ratio and banks' asset size positively and significantly affect banks' profitability in Turkey.

Widyastuti *et al.* (2017) studied the profitability of Indonesian banks for the period 2010-2015. They noted that net interest margin, loan-to-deposit ratio, and operating efficiency have a significant impact on bank profitability in Indonesia. However, neither of these two studies focuses on small banks or on the impact of the 2008 GFC on banks' profitability. Verma (2021) examines the financial positions of two Indian banks, HDFC Bank Limited and State Bank of India, using financial ratios. The author provides evidence suggesting that HDFC Bank's financial performance, with total assets of $280 billion in 2022, is superior to that of the State Bank of India, with total assets of $ 624 billion in 2022. Chaki *et al.* (2019) also studied the responsiveness of private and public banks in India during and after the 2008 GFC. They show that before the 2008 GFC, India's banking sector's financial performance was stable. During and after the 2008 GFC, the stability and financial performance of banks declined, reaching a low point by 2014-15. They claim that concerns about the stability and profitability of banks in India led the Reserve Bank of India to intervene by introducing massive corrective measures in 2016. These banks, post-2016, were able to contain the steep fall in financial and soundness parameters.

Banerjee (2018) studies the predictive power of financial ratios for forecasting the financial performance of banks in the United Arab Emirates. The author proposes several financial ratios that may be used to predict banks' future performance. Contrary to this

finding, study by Financial Crisis Insights on Bank Performance (2014) concludes that profitability, as measured by ROE and ROA, is positively associated with the Price/Book (P/B) ratio and the stock price. However, this relationship weakened during the crisis because, in a recession, the cost of equity exceeds ROE. This implies that ROE does not have predictive power for future ROE, and that lower ROE during a recession is associated with a low P/B ratio and a lower stock price. Molyneux and Thornton (1992) and Staikouras and Wood (2004) examine the profitability of European banks in a multi-country setting. The first study claims a significant positive impact of interest rates, bank concentration, and government ownership on banks' profitability measured by the return on equity. The second study reports that bank profitability is positively related to the equity-to-asset ratio and negatively related to the loan-to-asset ratio.

The current literature does not provide adequate information on the impact of the 2008 GFC on the profitability of small banks in the U.S. However, we believe the 2008 GFC negatively affected the profitability of U.S. small banks and increased the volatility of their profitability. Therefore, this paper aims to expand the literature by focusing on the impact of the 2008 GFC on U.S. small banks. Specifically, this study aims to examine the following:

- The trend of profitability ratios of U.S. small banks from 2001 to 2025.
- The impact of the 2008 GFC on the profitability of U.S. small banks.
- Change in the profitability of U.S. small banks pre-, during, and post- 2008 GFC.
- The sources of change in the profitability of U.S. small banks.
- The volatility of change in the profitability of U.S. small banks pre-, during, and post-2008 GFC.

The results indicate that small U.S. banks enjoyed high profitability prior to the 2008 GFC; they experienced a relative decline in profitability three years before the 2008 GFC, and a sharp decrease during the 2008 GFC. The profitability of U.S. small banks began to increase in 2010 and continued through 2025. The rest of the paper proceeds as follows. Section 2 explains the data and methodology. Section 3 presents empirical results, and Section 4 contains a summary and conclusions.

2. DATA AND METHODOLOGY

2.1. DATA

Data for this study were collected from the consolidated Report of Condition (balance sheet) and Report of Income (income statement) published by the Federal Deposit Insurance Corporation (FDIC) website at https://ww7.fdic.gove/sdi/download large list outside asp. The glossary of the variables can also be found at https://www7.fdic.gove/sdi/sitemap.asp. Our period of analysis in this study is 25 years, from 2001 to 2025. Using the FDIC website, we selected a group of small FDIC-insured banks with total assets of less than $200,000,000 from the 2001 Call Report. We limited our sample to small banks at least for two reasons: (1) the portfolio of assets and liabilities of small banks is different from that of medium- and large-sized banks, and (2) because of that, we believe that small banks should respond to a financial crisis differently than medium and large banks. We did not consider the banking corporation's structure or its geographic locations.

To ensure a homogeneous banking sample throughout the study, we further refined our 2001 small bank sample to include only the banks that continued operating through 2025. We

also eliminated a few banks with missing values. Our sample consists of 624 small banks with complete data that continuously operated from 2001 to 2025, with a total of 15,600 year-bank observations[3, 4].

2.2. Methodology

The role of a manager at any privately held or publicly traded small bank, like any other profit-generating institution, is to maximize profit, which in turn maximizes the bank's financial value. Two major methodologies are used to study banking profitability: the Frontier profit efficiency measure (Parametric and non-parametric profit efficiency techniques), and ratio analysis. Each of these profit efficiency techniques has its own advantages and disadvantages. However, combining these techniques may provide a more comprehensive understanding of banking efficiency and its major causes. Elyasiani *et al.* (1994) studied the association between a bank's financial performance, measured by accounting-based ratios, and production performance proxied by efficiency indexes. They report a significant association between financial and production performance. The authors suggest combined use of efficiency indexes and financial ratios in on-site bank examinations.

Financial ratio analysis alone is a valuable and straightforward diagnostic tool that can be used to assess bank performance on a cross-sectional and time-series basis (Lardic and Terraza, 2019). We employ financial ratio analysis on a time series basis to measure the performance of the small banks in our sample. Three widely used bank profitability ratios in the banking literature are Profit Margin (PM), Return on Assets (ROA), and Return on Equity (ROE). We use these commonly used financial ratios and their six components to gauge the profitability performance of the small banks during our sample periods, as discussed below.

Profit Margin (PM) is defined as the ratio of net income available to common stockholders divided by total operating income (sum of interest income and non-interest income)[5]. PM reflects the percentage of each dollar of income from the operation remaining, after all costs and expenses (interest and non-interest expenses and taxes). This ratio is also used to measure cost efficiency and to manage and control expenses.

Return on Assets (ROA) is defined as the ratio of net income available to common stockholders to total assets. This ratio shows the dollar amount of operating income generated per dollar of assets and indicates how well a bank's assets are utilized to generate net income. The link between the PM and ROA ratios is the Asset Utilization (AU) ratio, which is the ratio of total operating income to total assets. The AU ratio provides information on productivity and efficient utilization of assets. This ratio is a sign of managerial efficiency and indicates management's success in generating income per dollar of assets. Therefore, more efficient banks are expected to generate higher operating income per dollar of assets and higher net income per dollar of operating income through cost efficiency. The calculation of PM, ROA, and AU can be summarized as follows:

$$PM = \text{Net Income}/\text{ Total Operating Income}$$

$$AU = \text{Total Operating Income}/\text{Total Assets}$$

$$ROA = (PM)\,(AU) = (\text{Net income}/\text{Total Operating Income})\,(\text{Total Operating Income}/\text{Total Assets}) = \text{Net Income}/\text{Total Assets}.$$

The third profitability ratio used in the banking literature is the return on equity (ROE), defined as net income available to common stockholders divided by the book value of

common equity. ROE is the most comprehensive indicator of profitability because it reflects all the bank's activities and decisions during the year. ROE conveys information on how equity capital is used to generate net income. ROE reflects a bank's operating and investment decisions as well as the bank's financing and tax-related decisions. Cole (1972) decomposes the ROE into its components as follows:

ROE = (ROA)(EM) = (PM)(AU)(EM), or ROE = (Net Income Available to Common Stockholders / Total Operating Income) (Total Operating Income / Total Assets) (Total Assets / Common Equity)

ROE = Net Income Available to Common Stockholders / Common Equity.

Where EM stands for equity multiplier and is defined as the ratio of Total Assets to Common Equity. This ratio measures a bank's capital structure. The benefit of using the extended form of the ROE ratio is that it allows financial analysts to explain the source(s) of volatility in ROE. Although ROA and ROE are used extensively as measures of bank profitability, they represent different measures of profitability: ROE represents the net return on capital invested by shareholders, whereas ROA is the net return on all assets financed by debt and equity, and it is also a good measure of managerial efficiency. Athanasoglou *et al.* (2005) argue that ROA is a better measure of profitability because it accounts for the risks associated with leverage. However, Goddard *et al.* (2004) argue that ROE is a better measure of bank profitability because ROA does not include off-balance-sheet items. This argument may not be relevant to this study, since small banks have very few off-balance-sheet items.

3. EMPIRICAL RESULTS

We first examine the profitability of US small banks from 2001 to 2025 using time-series data. Next, to examine the impact of the 2008 GFC on small banks' profitability, we develop a {6, 4, 15} event window: 6 years before the 2008 GFC, 4 years during the 2008 GFC, and 15 years post-2008 GFC. The period of 2001-2006 refers to the profitability of banks in the six-year pre-2008 GFC with a sample size of 3,744 bank-year observations; 20007-2010 refers to the profitability of banks during the 2008 GFC with a sample size of 2,496 bank-year observations; and finally 2011-2025 refers to the post-2008 GFC period with a sample size of 9,360 bank-year observations.

According to Jahan (2020), bank profitability is influenced by both internal and external factors. Empirical studies mostly indicate that internal factors under bank management's control provide a better explanation of bank profitability (Yuan *et al.*, 2022). Therefore, in explaining changes in the profitability of US small banks from pre- to during and post-2008 GFC, this study considers internal factors that influence these changes. Using the ratios explained in the methodology section, we calculate the values for the three profitability ratios (PM, ROA, and ROE) and the internally controllable components (AU, EM, IER, NIER, IIR, and NIIR). Tables no. 1-3 present per-year summary statistics (Mean, Max, Min, and STD) for profitability ratios and their six components for the pre-, during-, and post-2008 GFC periods, respectively. The summary statistics of the profitability ratios (and their six components) for each of the entire three periods (pre-, during, and post-) are also given in bold at the end of each table. Figure no. 1 presents the graphical representation of the mean values of three profitability ratios (ROE, ROA, and PM) over the entire study period from

2001 to 2025. The data is divided by vertical lines to distinguish among the three periods: pre-2008 GFC, during the 2008 GFC, and post-2008 GFC.

Table no. 1 – Statistics of the Profitability Ratios and Their Components Pre 2008 GFC (2001-2006)

Year	Statistic	ROE (%)	ROA (%)	PM (%)	EM	AU (%)	IER (%)	NIER (%)	IIR (%)	NIIR (%)
	Mean	8.78	0.98	12.96	9.43	7.58	42.23	39.24	6.96	0.62
	STD	6.55	0.69	8.62	2.74	1.09	8.03	9.4	0.89	0.46
2001	Max	36.2	4.04	50.11	17.34	17.14	73.97	87.97	16.19	4.77
	Min	-47.26	-4.13	-56.23	2.85	1.54	14.57	15.35	1.17	0.04
	N	624	624	624	624	624	624	624	624	624
	Mean	9.18	1.04	15.59	9.21	6.67	32.61	45.47	6.03	0.64
	STD	7.07	0.69	9.93	2.61	1.06	8.11	10.73	0.88	0.47
2002	Max	36.94	4.12	63.82	17.65	14.19	72.78	88.34	13.56	4.39
	Min	-55.93	-3.55	-52.07	3.16	0.93	8.39	19.77	0.84	-0.11
	N	624	624	624	624	624	624	624	624	624
	Mean	8.9	1	16.67	9.29	6.02	26.53	50.83	5.35	0.67
	STD	7.07	0.7	10.92	2.59	1.1	7.95	12.11	0.9	0.51
2003	Max	34.51	3.62	50.29	17.72	12.35	62.43	105.82	11.33	5.87
	Min	-70.24	-4.85	-72.74	3.24	0.29	3.48	18.87	0.2	0.04
	N	624	624	624	624	624	624	624	624	624
	Mean	9.69	1.08	18.34	9.26	5.84	22.68	53.22	5.17	0.67
	STD	6.68	0.71	10.77	2.58	1.16	7.45	11.75	0.94	0.52
2004	Max	46.21	5.96	63.92	19.47	17.99	58.19	95.78	15.79	5.4
	Min	-29.75	-2.7	-46.59	3.24	1.04	2.94	7.76	0.93	-0.14
	N	624	624	624	624	624	624	624	624	624
	Mean	10.02	1.1	17.96	9.34	6.13	25.81	50.79	5.46	0.67
	STD	7.44	0.81	12.3	2.67	1.09	7.5	11.17	0.86	0.5
2005	Max	39.35	5.6	81	20.14	17.11	54.1	130.88	14.72	5.78
	Min	-71.82	-9.23	-152.47	3.44	1.25	2.71	8.8	1.02	-0.05
	N	624	624	624	624	624	624	624	624	624
	Mean	9.72	1.1	16.08	9.2	6.68	32.75	46.36	6.03	0.65
	STD	7.4	0.73	10.57	2.67	1.1	8.64	10.26	0.88	0.49
2006	Max	35.48	4.89	50.19	18.91	13.46	77.44	115.34	10.91	5.2
	Min	-92.01	-7.01	-93.06	3.45	0.39	4.55	8.25	0.38	-0.37
	N	624	624	624	624	624	624	624	624	624
	Mean	**9.38**	**1.05**	**16.27**	**9.29**	**6.49**	**30.44**	**47.65**	**5.83**	**0.65**
	STD	**7.05**	**0.72**	**10.72**	**2.64**	**1.25**	**10.21**	**11.87**	**1.07**	**0.49**
PRE GFC	**Max**	**46.21**	**5.96**	**81**	**20.14**	**17.99**	**77.44**	**130.88**	**16.19**	**5.87**
	Min	**-92.01**	**-9.23**	**-152.47**	**2.85**	**0.29**	**2.71**	**7.76**	**0.2**	**-0.37**
	N	**3744**	**3744**	**3744**	**3744**	**3744**	**3744**	**3744**	**3744**	**3744**

Note: This table reports descriptive statistics for the 624 sample banks over the 2001–2006 period: Pre GFC. Annual statistics are calculated separately for each year, while the period statistics are pooled across all bank-year observations from 2001 through 2006. Variable definitions are ROE is net income divided by total equity capital; ROA is net income divided by total assets; PM is net income divided by total operating income; EM is total assets divided by total equity capital; AU is total operating income divided by total assets; IER is interest expense divided by total operating income; NIER is noninterest expense divided by total operating income; IIR is interest income divided by total assets; and NIIR is noninterest income divided by total assets. All ratios are reported as percentages except the equity multiplier (EM).

Table no. 2 – Statistics of the Profitability Ratios and Components During 2008 GFC (2007-2010)

Year	Statistic	ROE (%)	ROA (%)	PM (%)	EM	AU (%)	IER (%)	NIER (%)	IIR (%)	NIIR (%)
	Mean	9.02	1.05	14.94	9.08	6.95	36.52	44.07	6.3	0.65
	STD	7.34	0.74	9.6	2.63	1.13	8.79	10.22	0.92	0.49
2007	Max	32.25	4.68	57.41	19.72	13.18	81.62	108.78	12.31	5.18
	Min	-70.42	-3.57	-46.98	3.1	0.36	4.12	10.11	0.34	-0.02
	N	624	624	624	624	624	624	624	624	624
	Mean	7.11	0.83	13.01	9.21	6.42	32.5	48.07	5.77	0.65
	STD	9.86	0.92	13.82	2.72	1	8.33	11.25	0.75	0.55
2008	Max	34.56	4.67	52.29	24.51	12.38	63.79	102.15	9.18	6.59
	Min	-90.59	-6.39	-91.81	3.28	2.98	4.29	10.53	2.6	-0.41
	N	624	624	624	624	624	624	624	624	624
	Mean	4.53	0.59	10.29	9.39	5.7	25.95	55.7	5.11	0.59
	STD	12.39	1.03	18.16	2.76	0.99	8.37	13.46	0.78	0.5
2009	Max	35.12	3.15	47.07	23.61	10.17	58.71	137.42	8.96	4.45
	Min	-125.47	-8.33	-165.84	3.27	2.75	3.74	10.82	2.55	-0.89
	N	624	624	624	624	624	624	624	624	624
	Mean	5.21	0.65	12.04	9.55	5.3	21.22	59.03	4.73	0.57
	STD	11.43	0.95	18.39	2.86	1.03	7.41	14.8	0.84	0.48
2010	Max	34.82	4.29	56.64	29.26	10.4	53.96	179.64	8.65	3.69
	Min	-118.4	-7.48	-167.93	3.2	0.16	3.57	17.73	0.15	-0.95
	N	624	624	624	624	624	624	624	624	624
	Mean	**6.47**	**0.78**	**12.57**	**9.31**	**6.09**	**29.05**	**51.72**	**5.48**	**0.61**
	STD	**10.57**	**0.93**	**15.5**	**2.75**	**1.22**	**10.12**	**13.89**	**1.02**	**0.51**
During GFC	**Max**	**35.12**	**4.68**	**57.41**	**29.26**	**13.18**	**81.62**	**179.64**	**12.31**	**6.59**
	Min	**-125.47**	**-8.33**	**-167.93**	**3.1**	**0.16**	**3.57**	**10.11**	**0.15**	**-0.95**
	N	**2496**	**2496**	**2496**	**2496**	**2496**	**2496**	**2496**	**2496**	**2496**

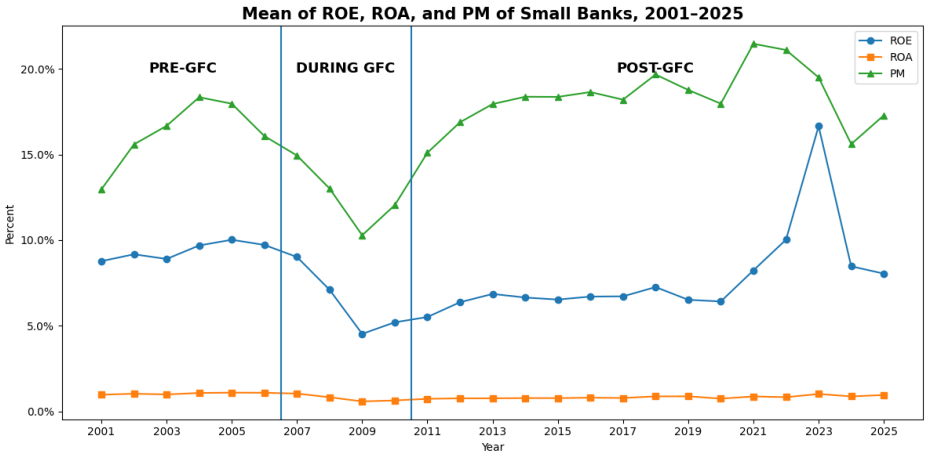
Note: This table reports descriptive statistics for the 624 sample banks over the 2007–2010 period: During GFC. Annual statistics are calculated separately for each year, while the period statistics are pooled across all bank-year observations from 2007 through 2010. Variable definitions are provided in Table no. 1.

Table no. 3 – Statistics of the Profitability Ratios and Components Post 2008 GFC (2011-2025)

Year	Statistic	ROE (%)	ROA (%)	PM (%)	EM	AU (%)	IER (%)	NIER (%)	IIR (%)	NIIR (%)
	Mean	5.52	0.74	15.1	9.46	4.91	17.06	61.72	4.36	0.55
	STD	20.47	0.91	19.4	4.2	1.03	6.77	14.55	0.84	0.48
2011	Max	31.08	4.02	67.76	72.14	9.55	71.55	150.78	9.15	3.47
	Min	-452.06	-7.3	-230.26	3.43	2.01	2.93	19.95	1.77	-1.11
	N	624	624	624	624	624	624	624	624	624
	Mean	6.38	0.77	16.88	9.4	4.53	13.62	64.86	4	0.53
	STD	10.8	0.84	17.65	2.78	1.04	6.19	15.39	0.85	0.48
2012	Max	30.43	4.5	59.36	30.58	10.01	71.08	166	8.22	4.85
	Min	-134.16	-5.35	-119.46	3.47	0.62	2.19	17.92	0.56	-0.92
	N	624	624	624	624	624	624	624	624	624
	Mean	6.86	0.77	17.94	9.83	4.36	11.01	66.76	3.82	0.54
	STD	8.3	0.73	16.47	2.96	1.04	5.34	15.17	0.85	0.47
2013	Max	31.6	4.46	72.07	25.84	9.58	54.72	146.62	7.88	4.33
	Min	-70.58	-5.45	-184.27	3.71	1.26	1.84	20.77	1.1	-0.54
	N	624	624	624	624	624	624	624	624	624
	Mean	6.65	0.79	18.37	9.32	4.28	9.51	67.73	3.77	0.51
	STD	8.15	0.73	15.8	2.64	0.97	4.79	15.75	0.8	0.42
2014	Max	30.1	3.8	59.87	26.35	8.48	47.6	154.54	7.59	3.32
	Min	-117.43	-7.63	-147.93	3.59	0.14	1.43	19.58	0.13	-0.22
	N	624	624	624	624	624	624	624	624	624
	Mean	6.54	0.78	18.36	9.2	4.27	8.79	68.41	3.76	0.51
	STD	6.99	0.67	14.57	2.76	0.97	4.57	15.54	0.81	0.44
2015	Max	29.96	3.94	60.33	31.72	9.49	49.95	173.23	9.13	4.23
	Min	-47.49	-3.87	-88.3	3.31	1.53	1.32	18.58	1.39	-0.26
	N	624	624	624	624	624	624	624	624	624
	Mean	6.71	0.81	18.64	9.22	4.33	8.58	67.85	3.8	0.53
2016	STD	8.03	0.66	14.12	3.27	1.03	4.33	15.06	0.84	0.5
	Max	33.11	3.36	61.7	51.35	10	39.02	148.69	9.19	5.93

Year	Statistic	ROE (%)	ROA (%)	PM (%)	EM	AU (%)	IER (%)	NIER (%)	IIR (%)	NIIR (%)
	Min	-98.64	-3.15	-67.65	3.34	0.48	1.16	18.29	0.47	-0.82
	N	624	624	624	624	624	624	624	624	624
	Mean	6.72	0.79	18.2	8.98	4.38	8.94	67.17	3.85	0.52
	STD	6.43	0.71	15.03	2.59	1.07	4.49	14.52	0.77	0.62
2017	Max	41.57	3.74	54.58	24.69	13.32	39.49	150.1	8.48	8.39
	Min	-47.87	-6.45	-140.88	2.59	1.85	1.13	18.27	1.76	-0.62
	N	624	624	624	624	624	624	624	624	624
	Mean	7.26	0.89	19.66	8.85	4.58	10.71	64.74	4.07	0.52
	STD	8.52	0.79	14.93	2.67	1.11	5.35	14.89	0.76	0.66
2018	Max	27.62	3.96	64.3	31.2	17.71	45.55	175.56	7.64	11.69
	Min	-108.67	-7.07	-82.18	2.35	1.44	0.78	19.96	1.38	-0.38
	N	624	624	624	624	624	624	624	624	624
	Mean	6.52	0.89	18.77	8.47	4.76	13.77	63.12	4.24	0.52
	STD	19.38	0.82	16.96	3.17	1.1	6.61	16.39	0.76	0.68
2019	Max	32.6	4.08	55.55	58.88	16.31	54.03	250.18	7.1	11.55
	Min	-447.25	-7.6	-171.03	2.35	0.44	1.08	18.98	0.41	-1.78
	N	624	624	624	624	624	624	624	624	624
	Mean	6.42	0.75	17.97	9	4.15	12.36	66.16	3.64	0.5
	STD	9.82	0.79	17.97	2.78	1.1	6.09	19.25	0.76	0.75
2020	Max	46.49	4.56	63.14	33.15	12.02	40.69	329.87	6.77	8.43
	Min	-176.75	-8.06	-180.78	2.39	1.15	0.42	20.35	1.1	-0.37
	N	624	624	624	624	624	624	624	624	624
	Mean	8.24	0.88	21.46	9.49	3.93	8.19	67.1	3.37	0.57
	STD	6.99	0.77	18.9	2.88	1.26	4.46	19.33	0.96	0.76
2021	Max	51.07	5.36	68.48	42.9	12.13	33.38	320.58	10	9.24
	Min	-67.13	-7.39	-255.74	2.34	0.46	0.36	22.33	0.43	-0.08
	N	624	624	624	624	624	624	624	624	624
	Mean	10.03	0.84	21.1	12.32	3.97	8.53	66.76	3.47	0.5
	STD	43.64	0.74	18.45	41.26	1.42	4.61	19.29	0.77	1.06
2022	Max	547.92	3.85	60.68	505.61	27.4	25.56	359.65	7.62	22.43
	Min	-864.96	-9.18	-290.03	-793.2	1.31	0.53	23.52	0.84	-0.08
	N	624	624	624	624	624	624	624	624	624
	Mean	16.65	1.02	19.5	89.82	5.16	20.82	55.69	4.52	0.64
	STD	160.06	0.96	15.15	1971	2.95	9.73	15.05	1.66	2.31
2023	Max	4000	7.08	57.93	49246	58.15	57.62	193.71	38.2	51.96
	Min	-103.09	-5.24	-143.62	-123.77	1.9	0.2	20.38	1.77	-0.15
	N	624	624	624	624	624	624	624	624	624
	Mean	8.48	0.88	15.61	10.38	5.71	28.6	51.83	5.19	0.52
	STD	10.21	0.89	15.31	10.51	4.13	10.92	15.57	3.69	1.84
2024	Max	41.15	4.92	58.99	100.2	94.1	63.56	185.75	93.86	42.48
	Min	-146.62	-6.04	-121.43	-193.46	0.91	1.53	21.92	0.87	-0.15
	N	624	624	624	624	624	624	624	624	624
	Mean	8.05	0.96	17.28	9.55	5.79	27.04	51.38	5.27	0.51
	STD	15.47	0.93	16.11	4.09	4.33	10.03	15.92	4.11	1.3
2025	Max	36.04	3.84	69.65	58.92	105.34	78.54	171.9	105	25.71
	Min	-284.13	-6.13	-114.16	2.38	1.11	1.29	21.32	0.93	0
	N	624	624	624	624	624	624	624	624	624
	Mean	**7.8**	**0.84**	**18.32**	**14.89**	**4.61**	**13.83**	**63.42**	**4.08**	**0.53**
	STD	**44.23**	**0.8**	**16.61**	**509.05**	**2.06**	**9.26**	**17.12**	**1.74**	**1.01**
Post GFC	**Max**	**4000**	**7.08**	**72.07**	**49246**	**105.34**	**78.54**	**359.65**	**105**	**51.96**
	Min	**-864.96**	**-9.18**	**-290.03**	**-793.2**	**0.14**	**0.2**	**17.92**	**0.13**	**-1.78**
	N	**9360**	**9360**	**9360**	**9360**	**9360**	**9360**	**9360**	**9360**	**9360**

Note: This table reports descriptive statistics for the 624 sample banks over the 2011–2025 period: Post GFC. Annual statistics are calculated separately for each year, while the period statistics are pooled across all bank-year observations from 2011 through 2025. Variable definitions are provided in Table no. 1.



Note: The figure presents annual standard deviation values of return on equity (ROE), return on assets (ROA), and profit margin (PM) for the 624 sample banks. The sample period is divided into the pre-GFC period (2001–2006), during-GFC period (2007–2010), and post-GFC period (2011–2025). Variable definitions are provided in Table no. 1.

Figure no. 1 – Mean of ROE, ROA, and Profit Margin of Small Banks, 2001–2025

As is evident from Tables no. 1-3 and the corresponding Figure no. 1, the three profitability ratios increased from 2001 to 2004 but began to decline in 2005, three years before the 2008 GFC. This declining trend continued through the 2008 GFC period and into 2009, then reversed upward beginning in 2010). Ozgur and Gorus (2016) also report that the 2008 GFC hurt the profitability of Turkish banks. The upward trend that began in 2010 continued through 2023.

To examine the sources of changes in profitability, we use the extended ROE formula (ROE = ROA * EM) discussed in section 2.2. As shown by Tables no. 1 and no. 2, the sharp decline in the mean value of ROE from the pre- (9.38%) to the during (6.47%) 2008 GFC period was the result of a decline in ROA (from 1.05% to 0.78%) rather than a change in EM. Because of capital adequacy requirements, the mean EM for the pre-, and during, 2008 GFC periods remained relatively stable, ranging from 9.29 to 9.30. The sharp decline in ROA (ROA = PM *AU) in turn was the result of a sharp decline in PM (from 16.27% to 12.57%) and a slight decline in AU (from 6.49% to 6.09%).

Contrasting the mean ROE values during and after the 2008 GFC reveals a sharp increase (from 6.47% to 7.8%). The increase in ROE was the result of increases in ROA (from 0.78% to 0.84%) and EM (from 9.31 to 14.89), and, in turn, the increase in ROA was the result of an increase in PM (from 12.57% to 18.32%). This implies that small banks were able to improve their profitability by implementing better cost-control policies and increasing leverage. Putting together the results from the above analysis indicates that a sharp decline in PM from the pre- to the during 2008 GFC periods and a gradual increase in PM from the during 2008 GFC to the post- 2008 GFC periods are the major contributors to the overall change in the ROE of small US banks in response to the 2008 GFC.

We tested the mean differences among the three profitability ratios across the three sub-periods: pre-2008, during the 2008 financial crisis, and post-2008. All three pairwise differences are statistically significant. The methodology used and the detailed results of the mean differences are presented in the Annex.

To further analyze the sources of changes in PM (PM = Net Income / Total Operating Income) from pre-, during and post-2008 GFC, we examine the sources of operating income and operating expenses (IIR, NIIR, IER, and NIER)[6] that shape the PM ratio. The IIR and NIIR are measures of the effective utilization of assets and show the extent to which banks' assets are used to generate interest and noninterest income[7]. The IER and NIER measure the proportion of total operating income used to pay interest and noninterest expenses. Comparing the IIR and NIIR for the pre-, during-, and post-2008 GFC clearly indicates that the major source of income for small U.S. banks has been interest income rather than noninterest income. Further, both the interest and non-interest income generated per dollar of assets have been steadily declining. The sum of IIR and NIIR ratios pre-2008 GFC is 6.48% (5.83% for IIR and 0.65% for NIIR), meaning that, on average, U.S. small banks could produce 6.48 cents in revenue per dollar of assets. The same ratios for the periods during and post-2008 GFC are lower, at 6.09% and 4.61%, respectively[8].

On the expense side, during the periods of pre-, during-, and post-2008 GFC, the IER has been steadily decreasing, while NIER has been steadily increasing. At the same time, the values of NIER are much higher than those of IER, indicating a larger portion of the revenue generated by U.S. small banks is used to pay for non-interest expenses[9]. The sum of IER and NIER ratios for pre- 2008 GFC is 78.09, meaning that 78.09 percent of the small banks' operating income is used to pay for interest (30.67) and noninterest expenses (47.65). The sum of the same ratios for the during, and post-2008 GFC are 80.77% (29.05% for IER and 51.73% for NIER) and 77.25% (13.83% for IER and 63.42%for NIER), respectively[10]. The analysis of the income and expense ratios shows a declining trend in the IIR, NIIR, and IER, while the NIER is rising. Overall, the summary of the six components of profitability ratios, illustrated in Figure no. 1, reveals a U-shaped trend in profitability from 2001 to 2024, with the lowest point in 2009. Notably, in 2025, profit margins (PM) increase while return on equity (ROE) decreases.

We calculate the standard deviation of profitability ratios to measure the volatility of profitability. The data indicates that the standard deviation remained stable until 2007; after the 2008 GFC, it rose sharply from 2007 to 2010. Following that period, it declined until 2019, leading to high volatility in profitability ratios. The standard deviation of the profitability ratios was stable until 2007, but sharply increased from 2007 to 2020 and then began to decline until 2019. We tested the STD differences of the three profitability ratios across the three sub-periods: pre-, during, and post-2008 financial crisis. The methodology used and the results of the mean differences are presented in the Annex.

4. SUMMARY AND CONCLUSIONS

This paper investigates the financial performance of small U.S. banks from 2001 to 2025, with special attention to the impact of the 2008 GFC on their profitability. We partition the period of study into three periods: pre-, during, and post-2008 GFC, and investigate the profitability performance of the U.S. small banks over time and in response to the 2008 GFC. While small commercial banks may hold minimal U.S. banking assets and even less market share, these banks perform a crucial function in the U.S. economy by offering financial services to small and medium-sized companies that are important to regional economic growth. Given the importance of small banks to the regional economy, the banking regulatory and supervisory agencies, as well as the local and regional authorities responsible for regional economic growth, should pay special attention to the safety and soundness of regional banks.

The study used 624 of the same small banks from 2001 to 2025 to examine their profitability pre-, during, and post-2008 GFC. Three measures of ROE, ROA, and PM, along with their six component ratios, are considered. On a time-series basis, the results indicated that the profitability trend follows a flat U (saucer) pattern: high profitability from 2001 to 2005, declining profitability from 2005 to 2009, and gradually increasing profitability after 2009. The major source of profitability change was PM, rather than AU or EM. In turn, the major cause of the change in PM has been a continuous decline in interest and noninterest income, a sharp decline in interest expense, and an increase in noninterest expense. Concerning the impact of the 2008 GFC on small banks' profitability, two conclusions emerge. First, small banks were able to take advantage of the low-interest-rate environment during and after the 2008 GFC to reduce their interest expense sharply and remain profitable. This indicates that the Fed's expansionary monetary policy to counter the 2008 GFC by reducing market interest rates benefited small banks. Next, the decline in profitability of small banks began three years before the 2008 GFC, and the increase in profitability occurred before the 2008 GFC ended. This leads us to suspect that changes in the profitability of U.S. small banks may have predictive value for the start and end of major financial crises.

Acknowledgements

We appreciate the assistance provided by graduate students Diep Nghiem from the Cofrin School of Business, University of Wisconsin Green Bay, and Laci Whiting from the School of Management, University of Michigan-Flint.

ORCID

Rasoul Rezvanian https://orcid.org/0009-0008-8801-4541
Seyed Mehdian https://orcid.org/0000-0003-3385-1656
Nafise Aalipour https://orcid.org/0009-0003-4297-7549

References

Ahmad, R., Ariff, M., & Skully, M. (2007). Factors determining mergers of banks in Malaysia's banking sector reform. *Multinational Finance Journal, 11*, 1–31. http://dx.doi.org/10.17578/11-1/2-1

Alper, D., & Anbar, A. (2011). Bank Specific and Macroeconomic Determinants of Commercial Bank Profitability: Empirical Evidence from Turkey. *Business and Economics Research J., 2*(2), 139–152.

Ashton, J. K., & Hardwick, P. (2000). Estimating inefficiencies in banking. *Journal of Interdisciplinary Economics, 11*(1), 1–33. http://dx.doi.org/10.1177/02601079X00001100102

Athanasoglou, P. P., Briss, S. N., & Delis, M. D. (2005). *Bank-Specific, Industry-Specific and Macroeconomic Determinants of Bank Profitability* (25). Retrieved from Athens, Greece:

Athari, S. A., & Bahreini, M. (2023). The impact of external governance and regulatory settings on the profitability of Islamic banks: Evidence from Arab markets. *International Journal of Finance & Economics, 28*(2), 2124–2147. http://dx.doi.org/10.1002/ijfe.2529

Banerjee, A. (2018). Can ratios predict the financial performance in banks: A case of national banks in United Arab Emirates (UAE). *8*(4), 227–247. http://dx.doi.org/10.5296/ijafr.v8i4.13802

Begenau, J., Bigio, S., Majerovitz, J., & Vieyra, M. (2026). A Q-Theory of Banks. *The Review of Economic Studies, 93*(1), 106–143. http://dx.doi.org/10.1093/restud/rdaf035

Berger, A. N. (2007). International Comparisons of Banking Efficiency. *Financial Markets, Institutions and Instruments, 16*(3), 119–144. http://dx.doi.org/10.1111/j.1468-0416.2007.00121.x

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of Financial Institutions: International Survey and Directions for Future Research. *European Journal of Operational Research, 98*(2), 175–212. http://dx.doi.org/10.1016/S0377-2217(96)00342-6

Bhatia, V., Basu, S., Mitra, S. K., & Dash, P. (2018). A Review of Bank Efficiency and Productivity. *OPSEARCH, 55*(3–4), 557–600. http://dx.doi.org/10.1007/s12597-018-0332-2

Casu, B., & Molyneux, P. (2001). Efficiency in European Banking. In J. A. Goddard, P. Molyneux, & J. O. S. Wilson (Eds.), *European Banking: Efficiency, Technology and Growth* (pp. 99–139). Chichester, England: John Wiley and Sons Ltd.

Chaki, S., Chauhan, K., & Daryal, A. (2019). Financial Performance of Banks in India: Are Banks Sound Enough to be Banked Upon? *International Journal of Innovative Technology and Exploring Engineering, 8*, 1004–1010. http://dx.doi.org/10.35940/ijitee.I1161.0789S19

Cole, D. W. (1972). Return of equity model for banks. *The Bankers Magazine, 155*(3), 40–47.

Dietrich, A., & Wanzenried, G. (2011). Determinants of bank profitability before and during the crisis: Evidence from Switzerland. *Journal of International Financial Markets, Institutions and Money, 21*(3), 307–327. http://dx.doi.org/10.1016/j.intfin.2010.11.002

Elyasiani, E., Mehdian, S., & Rezvanian, R. (1994). An empirical test of association between production and financial performance: The case of commercial banking industry. *Applied Financial Economics, 4*(1), 55–60. http://dx.doi.org/10.1080/758522125

Fethi, M. D., & Pasiouras, F. (2010). Assessing Bank Efficiency and Performance with Operational Research and Artificial Intelligence Techniques: A Survey. *European Journal of Operational Research, 204*(2), 189–198. http://dx.doi.org/10.1016/j.ejor.2009.08.003

Financial Crisis Insights on Bank Performance, R. (2014). *(Part 1), Assessing the Key Factors Influencing Price-to-Book Ratios*: CFA Institute.

Goddard, J., Molyneux, P., & Wilson, J. (2004). Dynamics of Growth and Profitability in Banking. *Journal of Money, Credit and Banking, 36*(6), 1069–1090. http://dx.doi.org/10.1353/mcb.2005.0015

Jahan, N. (2020). Determinants of Profitability of Banks: Evidence from Islamic Banks of Bangladesh. *39*(1–2), 136–149.

Lardic, S., & Terraza, V. (2019). Financial Ratios Analysis in Determination of Bank Performance in the German Banking Sector. *International Journal of Economics and Financial Issues, 9*(3), 22–47. http://dx.doi.org/10.32479/ijefi.7888

Molyneux, P., & Thornton, J. (1992). Determinants of European Banks Profitability: A note. *Journal of Banking & Finance, 16*(6), 1173–1178. http://dx.doi.org/10.1016/0378-4266(92)90065-8

Nal, O., & Cai, A. (2020). Analyzing Impact of a Crisis on Bank Financial Ratios. *9*(4), 17–31. http://dx.doi.org/10.5430/afr.v9n4p17

Nguyen, D. T., & Le, T. D. (2022). The interrelationships between bank risk and charter value in ASIAN-5. *Journal of Applied Econometrics, 25*(1), 1182–1199. http://dx.doi.org/10.1080/15140326.2022.2118514

Nippani, S., & Ling, R. (2021). Bank size and performance: An analysis of the industry in the United States in the post-financial-crisis era. *Journal of Financial Research, 44*(3), 587–606. http://dx.doi.org/10.1111/jfir.12255

Ozgur, O., & Gorus, M. S. (2016). Determinants of Deposit Bank Profitability: Evidence from Turkey. *Journal of Applied Economics and Business Research, 6*(3), 218–231.

Paradi, J. C., & Zhu, H. (2013). A Survey on Bank Branch Efficiency and Performance Research with Data Envelopment Analysis. *Omega, 41*(1), 61–79. http://dx.doi.org/10.1016/j.omega.2011.08.010

Short, B. (1979). The Relationship Between Commercial Bank Profit Rates and Banking Concentration in Canada, Western Europe and Japan. *Journal of Banking & Finance, 3*(3), 209–219. http://dx.doi.org/10.1016/0378-4266(79)90016-5

Smirlock, M. (1985). Evidence on the (Non) Relationship Between Concentration and Profitability in Banking. *Journal of Money, Credit and Banking, 17*(1), 69–83. http://dx.doi.org/10.2307/1992507

Staikouras, C., & Wood, G. (2004). The Determinants of European Bank Profitability. *International Journal of Economics and Business Research, 3*(6), 57–68.

Verma, R. (2021). Comparative analysis of financial performance of HDFC and SBI bank on the basis of ratio analysis. *12*(2), 111–114. http://dx.doi.org/10.52711/2321-5763.2021.00016

Widyastuti, U., Purwana, D., & Zulaihati, S. (2017). Internal Determinants of Commercial Bank Profitability in Indonesia. *Mediterranean Journal of Social Sciences, 8*(3), 219–223. http://dx.doi.org/10.5901/mjss.2017.v8n3p219

Xu, T., Hu, K., & Das, U. S. (2019). *Bank Profitability and Financial Stability* (19/5). Retrieved from

Yuan, D., Gazi, M. A. I., Harymawan, I., Dhar, B. K., & Hossain, A. I. (2022). Profitability determining factors of banking sector: Panel data analysis of commercial banks in South Asian countries. *Frontiers in Psychology, 13*. http://dx.doi.org/10.3389/fpsyg.2022.1000412

ANNEX

Tests of Differences Across GFC Periods

Methodology

To examine whether bank profitability differs across economic periods, the sample is divided into three subperiods: the pre-GFC period (2001-2006), the GFC period (2007-2010), and the post-GFC period (2011-2025). The analysis focuses on return on equity (ROE), return on assets (ROA), and profit margin (PM). The sample contains 624 banks observed annually over 2001-2025, yielding 15,600 bank-year observations.

Differences in Mean Profitability

Differences in mean profitability across the three periods are examined using the following regression:

$$Ratio_it = Intercept + b1 \times During_GFC_t + b2 \times Post_GFC_t + Error_it \quad (1)$$

where Ratio_it represents ROE, ROA, or PM for bank i in year t. During_GFC equals one for observations from 2007-2010 and zero otherwise, while Post_GFC equals one for observations from 2011-2025 and zero otherwise. The pre-GFC period (2001-2006) is the reference category. Therefore, the intercept represents the mean profitability ratio during the pre-GFC period, b1 measures the difference between the GFC and pre-GFC periods, and b2 measures the difference between the post-GFC and pre-GFC periods.

Because the same banks are observed repeatedly over time, standard errors are clustered at the bank level. A linear restriction test comparing b1 and b2 is additionally used to test whether mean profitability differs between the GFC and post-GFC periods.

Differences in Profitability Dispersion (standard deviation test)

The analysis also examines whether the dispersion of bank profitability differs across the three periods. Because the profitability ratios, particularly ROE, contain extreme observations, a Brown-Forsythe-type approach based on deviations from the median is used.

First, the absolute deviation of each bank-year observation from the median of its corresponding period is calculated as:

$$Absolute\ deviation_it = |\ Ratio_it - Median\ ratio\ for\ the\ corresponding\ period\ | \quad (2)$$

The resulting absolute deviations are then estimated using:

$$Absolute\ deviation_it = Intercept + b1 \times During_GFC_t + b2 \times Post_GFC_t + Error_it \quad (3)$$

The pre-GFC period again serves as the reference category. A positive coefficient indicates greater profitability dispersion relative to the pre-GFC period, whereas a negative coefficient indicates lower

dispersion. Standard errors are clustered at the bank level. A linear restriction test is used to compare dispersion during the GFC with dispersion in the post-GFC period. The values used in this test are mean absolute deviations from the period-specific median and should not be interpreted as the actual standard deviations of the profitability ratios.

RESULTS

Mean Profitability

Table no. A1 reports the results of the mean-comparison tests. Mean profitability differs significantly across the three periods for all three profitability measures. ROE averages 9.38% in the pre-GFC period and declines to 6.46% during the GFC, a statistically significant reduction of 2.92 percentage points. ROE subsequently increases to 7.80% in the post-GFC period but remains 1.58 percentage points below its pre-GFC level. The post-GFC mean is also significantly higher than the GFC-period mean.

ROA follows a similar pattern. Average ROA declines from 1.05% before the GFC to 0.78% during the GFC and then increases to 0.84% after the GFC. Although the post-GFC level represents a statistically significant improvement relative to the GFC period, it remains significantly below its pre-GFC level.

Profit margin exhibits a different post-crisis pattern. Average PM decreases from 16.27% before the GFC to 12.57% during the GFC. It then increases to 18.33% in the post-GFC period, exceeding both its pre-GFC and GFC-period levels. All three pairwise differences are statistically significant.

Table no. A1 – Differences in Mean Profitability Across GFC Periods

Ratio	Pre-GFC Mean	GFC Mean	Post-GFC Mean	GFC - Pre	Post - Pre	GFC - Post
ROE	9.38%	6.46%	7.80%	-2.92*** *(p < 0.001)*	-1.58*** *(p = 0.001)*	-1.34*** *(p = 0.008)*
ROA	1.05%	0.78%	0.84%	-0.27*** *(p < 0.001)*	-0.21*** *(p < 0.001)*	-0.06** *(p = 0.010)*
PM	16.27%	12.57%	18.33%	-3.70*** *(p < 0.001)*	+2.06*** *(p < 0.001)*	-5.75*** *(p < 0.001)*

Note: This table reports mean profitability ratios and pairwise differences across the pre-GFC (2001-2006), GFC (2007-2010), and post-GFC (2011-2025) periods. Differences are reported in percentage points. The pre-GFC period is the reference category in the regression. Standard errors are clustered at the bank level. The GFC versus post-GFC comparison is obtained from a linear restriction test. Overall period tests are: ROE, $F = 59.98$ ($p < 0.001$); ROA, $F = 68.13$ ($p < 0.001$); and PM, $F = 113.10$ ($p < 0.001$). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Profitability Dispersion

Table no. A2 reports the results of the mean dispersion tests. ROE dispersion is significantly greater both during and post- 2008 GFC periods relative to the pre- 2008 GFC period. The mean absolute deviation increases from 4.60% before the GFC to 5.81% during the GFC and 5.72% after the GFC. However, there is no statistically significant difference in ROE dispersion between the GFC and post-GFC periods.

ROA dispersion increases significantly during the 2008 GFC, from approximately 0.49% to 0.61%. In the post- 2008 GFC period, it declines to approximately 0.51%, which is not statistically different from its pre- 2008 GFC level. ROA dispersion is also significantly greater during the 2008 GFC than during the post-GFC period.

Profit-margin dispersion increases from 7.33% pre- 2008 GFC to 9.80% during- 2008 GFC and further to approximately 10.52% in the post- 2008 GFC period. Both later periods exhibit significantly

greater dispersion than the pre- 2008 GFC period. In addition, PM dispersion is significantly greater in the post-GFC period than during the GFC.

Overall, the dispersion results indicate that the GFC was associated not only with reductions in average profitability but also with increased heterogeneity in profitability outcomes across banks. The persistence of this increased dispersion varies across profitability measures. ROA dispersion largely returns to its pre-GFC level after the crisis, whereas greater dispersion persists for ROE and becomes even more pronounced for profit margins.

Table no. A2 – Tests of Differences in Profitability Dispersion Across GFC Periods

Ratio	Pre-GFC	GFC	Post-GFC	GFC - Pre	Post - Pre	GFC - Post
ROE	4.60%	5.81%	5.72%	+1.21*** *(p < 0.001)*	+1.12** *(p = 0.032)*	0.09 *(p = 0.860)*
ROA	0.49%	0.61%	0.51%	+0.12*** *(p < 0.001)*	0.02 *(p = 0.195)*	+0.10*** *(p < 0.001)*
PM	7.33%	9.80%	10.52%	+2.47*** *(p < 0.001)*	+3.19*** *(p < 0.001)*	-0.71** *(p = 0.022)*

Note: This table reports mean absolute deviations from the period-specific median and tests whether profitability dispersion differs across the pre-GFC (2001-2006), GFC (2007-2010), and post-GFC (2011-2025) periods. The reported values are measures used in the Brown-Forsythe-type dispersion test and are not standard deviations. Standard errors are clustered at the bank level. Positive pairwise differences indicate greater dispersion in the first listed period. The GFC versus post-GFC comparison is obtained from a linear restriction test. Overall period tests are: ROE, $F = 14.25$ ($p < 0.001$); ROA, $F = 23.69$ ($p < 0.001$); and PM, $F = 53.85$ ($p < 0.001$). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Notes

[1] For a review of the recent studies on the determinants of bank profitability, please refer to Yuan *et al.* (2022).

[2]The study by Berger and Humphrey (1997) comprehensively reviews 130 papers on the banking efficiency frontier techniques study up to 1995. The survey of the most recent studies can be found in Ashton and Hardwick (2000), Casu and Molyneux (2001), Berger (2007), Fethi and Pasiouras (2010), Paradi and Zhu (2013), and Bhatia *et al.* (2018).

[3]The yearly summary statistics of the variables used in the calculations of ratios are also available, but, for the sake of saving space, are not provided; they are available upon request.

[4]Although the yearly samples consisted of almost the same banks, the sizes of those banks varied, which makes the average bank size differ from year to year.

[5]In recent years, banks have increased the non-interest income portion of their total operating income by offering a more diversified set of fee-generating services. However, since this study focuses on small banks, the non-interest income portion of total operating income remains small, averaging about 9.5%.

[6]The Net income (NI) in banking is calculated as NI = (IIR + NIIR) – (IER + NIER) – Provision for Loan Losses -Tax. In this study, we do not consider the riskiness of the earning assets portfolio and its possible tax differential. Therefore, we do not consider the impact of Provision for Loan Losses and Tax in our analysis.

[7]Interest Income Ratio = IIR = Interest Income / Total Assets; NIIR = Non-interest Income Ratio = Non-interest Income / Total Assets; IER = Interest Expense Ratio = Interest Expense / Total Operating Income; NIER = Non-interest Expense Ratio = Non-interest Expense / Total Operating Income.

[8]As expected, a large portion of operating income for U.S. small banks comes from interest income, and only a small portion comes from non-interest income activities.

[9]Employee wages, salaries, and benefits are the most significant expenses.

[10]It is worth noting that interest expense is a smaller share of US small banks' total expenses and has declined from 2001 to 2025. Non-interest expenses account for a much larger share of total expenses. It is not given here, but employee salaries and fringe benefits are a large portion (87%) of non-interest expenses.

Scientific Annals of Economics and Business
73 (3), 2026, 593-616
DOI: 10.47743/saeb-2026-0030

Technical and Non-Technical Employees' Perceptions on How Low-Code and No-Code Development Platforms Impact the Democratization of Coding: A fsQCA Analysis

Emil Lucian Crișan[*], **Diana Maria Chiș**[**], **Elias Appiah-Kubi**[***], **Eniko Elisabeta Bodea**[§], **Alin Mihăilă**[0], **Napoleon-Alexandru Sireteanu**[00]

Abstract: Democratization of coding - the increased accessibility of software development to non-technical employees - is an emerging but under-conceptualized dimension of digital workplace transformation. This study examines how IT and non-IT employees in Romanian large companies perceive the influence of low-code and no-code development platforms (LC/NCDP) on this phenomenon. Data were collected via a structured questionnaire from 212 respondents (88 IT, 124 non-IT) and analyzed using fuzzy-set Qualitative Comparative Analysis (fsQCA), building on a conceptual model grounded in the Technology Acceptance Model. Results show that both IT and non-IT employees generally expect LC/NCDP to replace aspects of traditional coding, driven mainly by perceived usefulness (benefits, work impact) and ease of use, with organizational use and, for non-IT employees, age also playing a core role. A minority in both groups hold low expectations, primarily where perceived benefits are low. Because these findings capture perceptions and expectations rather than observed organizational outcomes, they should be read as evidence of anticipated, not demonstrated, impact. We recommend that organizations offer LC/NCDP training, particularly for non-IT staff, and propose that policymakers support LC/NCDP

[*] Department of Management, Faculty of Economics and Business Administration, Babes-Bolyai University, Romania; e-mail: *emil.crisan@econ.ubbcluj.ro*.
[**] Department of Management, Faculty of Economics and Business Administration, Babes-Bolyai University, Romania; e-mail: *diana.chis@econ.ubbcluj.ro*.
[***] Institute of Chartered Accountants, Ghana; e-mail: *EliasAppiah-Kubi@upet.ro*.
[§] Faculty of Economics and Business Administration, Babes-Bolyai University, Romania; e-mail: *eniko.bodea@econ.ubbcluj.ro*.
[0] Department of Management, Faculty of Economics and Business Administration, Babes-Bolyai University, Romania; e-mail: *alin.mihaila@econ.ubbcluj.ro*.
[00] Faculty of Economics and Business Administration, Alexandru Ioan Cuza University of Iasi, Iasi, Romania; e-mail: *alexandru.sireteanu@feaa.uaic.ro* (corresponding author).

Article history: Received 26 March 2026 | Accepted 2 September 2026 | Published online 29 September 2026

To cite this article: Crișan, E.L., Chiș, D.M., Appiah-Kubi, E., Bodea, E.E., Mihăilă, A., Sireteanu, N.A. (2026). Technical and Non-Technical Employees' Perceptions on How Low-Code and No-Code Development Platforms Impact the Democratization of Coding: A fsQCA Analysis. *Scientific Annals of Economics and Business*, 73(3), 593-616. https://doi.org/10.47743/saeb-2026-0030.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

adoption as part of digital transformation strategy. The study contributes a conceptual model and an fsQCA-based empirical account of democratization of coding, and outlines avenues for future research on the organizational and demographic factors shaping this process.

Keywords: : Low-code development platform; no-code development platform; Fuzzy-Set Qualitative Comparative Analysis; democratization of coding; digital work transformation.

JEL classification: O32; M50; M15; M12.

1. INTRODUCTION

The nature of work has undergone significant changes due to digitalization (Fossen and Sorgner, 2021; Mendonça and Kougiannou, 2023). Initially, IT solutions were regarded as tools to perform various business tasks. However, users were often dissatisfied with pre-developed software and expressed a desire to create their own tools. The increasing adoption of no-code and low-code platforms has allowed non-technical users to build customized applications more easily, addressing the demand for tailored solutions and greater flexibility in software development (Razak *et al.*, 2024). The philosophy of model-driven development (MDD) has emerged as a powerful approach in software engineering, facilitating faster development cycles, improved collaboration with non-technical stakeholders, and the creation of more scalable solutions. Recent literature emphasizes how model-driven development (MDD) aligns with modern trends like Artificial Intelligence (AI) integration, aiding software development processes and expanding its scope to AI-specific applications (Bucchiarone *et al.*, 2020). In this context, low-code and no-code platforms (LC/NCDP) are practical manifestations of model-driven development (MDD), allowing both IT and non-IT employees to create software solutions with minimal coding. These platforms, which have grown in popularity, leverage the power of model-driven development (MDD) while lowering entry barriers for non-programmers. Recent studies have examined how low-code tools align with model-driven development (MDD) principles, highlighting that both are essentially methodologies that simplify software development, yet low-code approaches have gained traction by being more accessible to a broader audience (Cabot, 2022)

Despite the increasing adoption of low-code and no-code platforms (LC/NCDP), it remains unclear whether employees fully perceive these tools as democratizing coding or significantly influencing their work and employment opportunities (Mannan and Pek, 2024). Recent studies suggest that these platforms empower non-technical employees to independently address workplace challenges by creating custom applications, fostering a sense of ownership and innovation within their roles (Quixy, 2023). However, existing research still emphasizes employee attitudes toward advanced technologies, such as Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA), which non-IT employees often find complex and less accessible (Oosthuizen, 2019; Bhargava *et al.*, 2021). This contrast highlights the need for further exploration of how low-code and no-code platforms (LC/NCDP) can bridge the gap between technical and non-technical users, ultimately transforming workplace dynamics. For this reason, the democratization of coding - defined as the increased accessibility of coding for non-technical employees - remains under-conceptualized and less integrated within existing literature (Baptista *et al.*, 2020; Ongalo and Wanjare, 2022). The rise of low-code and no-code development platforms (LC/NCDP) offers

a transformative avenue for digital workplace innovation, yet their influence on democratizing coding is not fully explored. Addressing this gap, our study investigates the perceptions of IT and non-IT employees regarding the impact of low-code and no-code development platforms (LC/NCDP) on coding democratization in the context of Romanian large companies. This approach contributes to the literature on emerging technologies, work, and employment by examining how these platforms drive accessibility, collaboration, and skill-building across diverse employee roles. We define democratization of coding as the process by which software-development capability is extended from a bounded population of trained IT professionals to a broader population of employees, regardless of formal programming training, through platforms that substitute visual, configuration-based interaction for hand-written code (see Section 2.1.2 for how this differs from adjacent constructs).

Considering the above, we conducted a fuzzy-set qualitative comparative analysis (fsQCA) to explore the various pathways influencing IT and non-IT employees' perceptions of the role of low-code and no-code development platforms (LC/NCDP) in the democratization of coding. This phenomenon contributes significantly to digital workplace transformation. Our analysis included factors such as perceived usefulness, perceived ease of use, real use, and the demographics of both IT and non-IT employees. Based on these variables, we developed a conceptual model that illustrates the democratization of coding and its implications for workplace transformation (see Figure no. 1). By addressing the study's objectives, this paper contributes to the literature by conceptualizing the democratization of coding. The findings highlight that the adoption of low-code and no-code development platforms (LC/NCDP) platforms is perceived as a transformative shift in the coding landscape, with the potential to democratize coding practices. This democratization can significantly impact workplace innovation by enabling the development of new solutions and enhancing the productivity of both technical and non-technical employees.

To provide a clear structure for the study, Section 2 presents the literature review, followed by the methodology in Section 3. Sections 4 and 5 detail the findings and discussion, respectively. Finally, the conclusion is outlined in Section 6.

2. LITERATURE REVIEW

2.1. Democratization of coding

Bhargava *et al.* (2021) emphasized that democratization extends beyond IT teams, allowing non-technical employees to participate in software development, while Ongalo and Wanjare (2022) highlighted the increasing accessibility of these tools to non-technical users. Earlier, Rao (2012) suggested democratization was primarily about expanding access to coding resources like GitHub, a view that aligns with modern shifts toward collaborative development platforms. Talagala (2022) later synthesized these perspectives, proposing that low-code and no-code development platforms (LC/NCDP) not only enable non-IT employees to tackle simpler coding tasks but also elevate the role of IT professionals by automating routine processes, allowing them to focus on complex tasks like algorithm optimization and advanced design.

Recent studies underscore the broader organizational impacts of low-code and no-code development platforms (LC/NCDP) adoption. According to Yan (2021), these platforms accelerate digital transformation by significantly improving the productivity of both technical and non-technical employees. Fernandes (2024) highlighted that low-code and no-code

development platforms (LC/NCDP) adoption fosters agility and reduces dependency on large IT teams, empowering line-of-business managers to directly contribute to software tailored for specific needs. This dual empowerment-enhancing capabilities of both IT and non-IT staff-positions low-code and no-code development platforms (LC/NCDP) as transformative tools in modern workplaces, driving innovation and productivity at unprecedented levels.

By integrating these perspectives, we argue that democratization of coding encompasses more than solving immediate organizational problems with IT tools. It represents a paradigm shift where the workforce collectively leverages technological advancements, enhancing overall efficiency and enabling innovation across all organizational levels.

2.1.1. Practitioners' perspective concerning democratization of coding

We noticed that there is a huge gap between the interest of practitioners and researchers concerning this field. This is because the searches performed in August 2022 of the key terms associations 'democratization of coding' and 'democratization of programming' generated 16,600 and 27,600 results on google.com, and only 5 and 30 results on Google Scholar, respectively. While research papers mention the terms sporadically, with very little quality journals publishing papers containing these key terms associations in title, they have been given the needed attention in the professional literature. Democratization of coding/programming is interpreted in two different ways, its definition and factors influencing. It encompasses making more people, beyond coders, capable to create software (Mixson, 2021), one definition which we consider in this paper. In August 2024, searches for the terms "democratization of coding" and "democratization of programming" showed notable growth in interest. Google searches returned approximately 42,000 and 58,000 results, respectively, indicating increasing attention in professional and industry-focused literature. However, academic exploration remains limited, with Google Scholar showing only 18 and 55 results.

These findings align with Navarro (2024), who emphasized that low-code platforms primarily gain traction in industry contexts, reflecting the evolving role of these technologies in workforce empowerment and digital transformation. This shift fosters inclusivity in software development and innovation.

Practitioners view the democratization of coding as the deployment of technologies enabling non-coders to create IT solutions, primarily through Low-Code and No-Code Development Platforms (LC/NCDP) (Mixson, 2021; Di Ruscio *et al.*, 2022; Ongalo and Wanjare, 2022). LCDP-NCDP reduce the coding required for technical users and simplify application creation for non-technical users, thus addressing developer shortages and cutting costs (Pantelimon *et al.*, 2019; Silva *et al.*, 2021). Additionally, they support workflows, track efficiency during development phases, and even enable the creation of data schemas (Sanchis *et al.*, 2019). At an organizational level, these platforms represent transformative solutions to workforce challenges while maintaining the rigor of traditional development processes.

Low-code development platforms (LCDPs) are powerful tools that streamline application development by reducing or eliminating traditional coding requirements. They support diverse functionalities, such as workflow automation, data management, and user interface design (Cai *et al.*, 2022). LCDP-NCDP solutions prioritize ease of use, enabling rapid deployment with minimal effort in configuration, user training, and implementation. This makes them especially versatile for organizations with limited technical resources, as highlighted by Waszkowski

(2019). While professional literature highlights their role in digital transformation, academic research remains sparse, underscoring the need for deeper exploration.

2.1.2. Researchers' perspective concerning democratization of coding

Democratization of coding, as explored in scientific literature, integrates paradigms that enhance the ability of non-technical individuals to develop IT-based solutions (Tsahat *et al.*, 2023). Low-code and no-code platforms (LC/NCDP) automate labor-intensive coding tasks using transformation rules (Panach *et al.*, 2015). These platforms elevate abstraction levels, simplify software complexity, and reduce errors, building upon the principles of model-driven development (MDD). Model-driven development (MDD) employs conceptual models to represent systems, generating executable code automatically (Panach *et al.*, 2015; Hoppe and Souza, 2023), thus bridging technical gaps and fostering accessibility in IT development.

In scientific terms, one of the closest concepts to the democratization of coding/programming is End-User Development (EUD), defined as "a set of methods, techniques, and tools that allow users of software systems, who are acting as non-professional software developers, at some point to create, modify, or extend a software artifact" (Lieberman *et al.*, 2006; Barricelli *et al.*, 2019). Recent research has expanded this definition to incorporate its applications in emerging technologies, such as artificial intelligence (AI) and robotics. For instance, Esposito *et al.* (2023) examine how End-User Development (EUD) supports personalization and adaptability in artificial intelligence (AI) systems, empowering non-technical users to create AI-driven solutions. Similarly, Stegner *et al.* (2024) explore the role of End-User Development (EUD) in human-robot interaction (HRI), where non-expert users can customize robotic behaviors through accessible interfaces. These developments demonstrate that End-User Development (EUD) continues to evolve, not only as a tool for modifying software artifacts but also as a critical enabler of inclusivity in advanced technology adoption. Related paradigms such as end-user programming (EUP) and end-user software engineering (EUSE) reinforce this perspective, focusing on enabling users to actively contribute to software customization and development (Barricelli *et al.*, 2019; Stegner *et al.*, 2024). Democratization of coding is related to, but conceptually distinct from, EUD/EUP/EUSE. EUD/EUP/EUSE describe individual-level practices of end users modifying or extending existing software artifacts (Lieberman *et al.*, 2006; Barricelli *et al.*, 2019); their unit of analysis is the individual user-artifact interaction. Democratization of coding, by contrast, is an organizational and occupational-level construct: it concerns the redistribution of who is structurally enabled to create software within an organization and how the division of labor between IT and non-IT roles is reconfigured as a result. LC/NCDP are the technological enabler of this shift; democratization of coding is the broader organizational outcome, not a relabeling of EUD-enabled tool use.

2.2. Employees perceptions concerning the impact of information technologies

Information technologies, particularly low-code and no-code development platforms (LC/NCDP), are increasingly recognized as critical enablers of workplace digital transformation (Ohlert *et al.*, 2022). These technologies systematically influence workplace dynamics, embedding themselves within organizational processes and creating novel human-technology configurations (Baptista *et al.*, 2020). The evolution of workplace technologies

reflects a progression from basic standalone software applications to integrated digital ecosystems that leverage artificial intelligence (AI), automation, and collaborative tools (Maran *et al.*, 2022). Unlike traditional applications designed for discrete tasks, these platforms enable complex human-machine collaboration, fostering innovation and efficiency in organizational workflows. This shift highlights the transformative potential of information technologies in reshaping workplace structures and enhancing employee productivity across both technical and non-technical roles.

Beyond the positive effects of digital work such as fostering an environment conducive to innovation, improving collaboration among employees, boosting productivity, and enhancing flexibility for workers (Dittes and Smolnik, 2019; Marsh *et al.*, 2022) - there are significant negative effects as well. These include technology-related stress, information overload, anxiety, interruptions, distractions, addiction, and excessive use (Beare *et al.*, 2020; Marsh *et al.*, 2022). Consequently, employees' intention to use technology has been shown to depend on their information and digital literacy, as well as their perceptions of the usefulness and ease of use of these technologies (Nikou *et al.*, 2022).

2.3. Conceptual Model

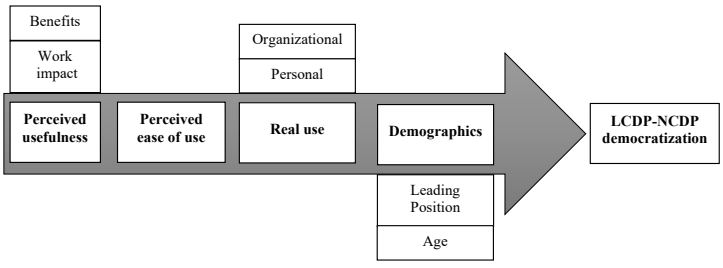
Considering the above discussion, we employed the Technology Acceptance Model (TAM) to propose a conceptual framework for democratization of coding, a concept that remains underexplored in academic literature. TAM, a widely recognized model for understanding individual adoption of technology (Mujahed *et al.*, 2024), posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the two primary beliefs influencing user acceptance and behavior (Bhattarai *et al.*, 2010; Rafique *et al.*, 2020). Despite its extensive application in various domains, there is limited research on how these constructs contribute to democratization of coding within organizational contexts. Our study addresses this gap by identifying specific perceived usefulness factors of LC/NCDP that shape employee perceptions of democratization of coding. This contribution broadens existing literature by linking TAM to the transformative potential of LC/NCDP in fostering inclusive technological engagement across diverse employee profiles. Because the adoption of LC/NCDP for the purpose of democratizing coding is shaped not only by individual beliefs but also by organizational context and workforce composition, we extend the core TAM constructs (perceived usefulness, perceived ease of use) with organizational-use and demographic conditions (personal use, organizational use, leading position, age). We treat the resulting framework as an extended TAM: perceived usefulness and ease of use remain the individual-belief core, while organizational use, leading position, and age are included as boundary conditions that prior technology-acceptance research has shown to shape how usefulness and ease-of-use beliefs translate into adoption outcomes (Kolnhofer-Derecskei *et al.*, 2017; Ivanov *et al.*, 2020).

LC/NCDP platforms provide numerous advantages, including robust security features, seamless data integration, straightforward updates, and access to pre-built applications that accelerate development processes (Frank *et al.*, 2021). These platforms are equipped with integrated components designed to present information in an intuitive and comprehensible manner, facilitating better user engagement and understanding (Pantelimon *et al.*, 2019; Gao and Fagerholm, 2024). Moreover, LC/NCDP significantly reduce the effort required for environment installation, configuration, training, and implementation, making them accessible to a wider range of users (Waszkowski, 2019; Talagala, 2022). In addition to these practical

benefits, LCDP-NCDP support diverse functionalities such as reporting, data analysis, event processing, user interface development, and business logic (Razak *et al.*, 2024), all of which encourage coding democratization and broaden their appeal across organizational roles (Frank *et al.*, 2021). By simplifying entry-level tasks for non-IT employees while simultaneously enabling IT professionals to focus on high-level activities such as advanced algorithm design, user experience enhancement, and code optimization, these platforms bridge the gap between technical and non-technical contributors to digital transformation (Talagala, 2022).

It has been well-documented that employees' information and digital literacy significantly influence their intention to adopt and utilize technology effectively (Nikou *et al.*, 2022). While no-code platforms are designed for users with no technical background, low-code platforms demand some degree of technical proficiency, necessitating a mix of digital literacy and minimal programming skills (Wolff, 2019; Silva *et al.*, 2021). Additionally, beyond perceived usefulness and ease of use, the compatibility of a system with existing processes and tools is a critical factor that affects its adoption, particularly in complex organizational settings (Benbya *et al.*, 2020). Organizations must address the challenges associated with IT system compatibility while fostering user awareness and training. Research has also highlighted that job position influences the extent of employee involvement in decision-making regarding the adoption of automation technologies, suggesting that seniority plays a role in technology acceptance (Ivanov *et al.*, 2020). Furthermore, demographic factors such as age are recognized as significant in mitigating fears surrounding automation, with younger employees often displaying greater adaptability toward technological innovation (Kolnhofer-Derecskei *et al.*, 2017). These insights underscore the importance of tailoring strategies to address both organizational and individual factors in promoting the democratization of low-code and no-code platforms (LC/NCDP).

Based on the above discussion, we identified seven critical factors encompassing literacy, compatibility, job position, and demographics, that influence perceived democratization through LC/NCDP. These variables form the foundation of our conceptual model (see Figure no. 1). Specifically, benefits and work impact operationalize perceived usefulness; ease of use operationalizes perceived ease of use; personal use and organizational use capture actual behavioral engagement with LC/NCDP, which TAM treats as the outcome of usefulness and ease-of-use beliefs and which we include here as boundary conditions on expectations; and leading position and age capture workforce-composition factors previously shown to shape technology-adoption attitudes (Kolnhofer-Derecskei *et al.*, 2017; Ivanov *et al.*, 2020), rather than being derived directly from TAM's belief constructs.



Source: authors' own creation

Figure no. 1 – The Conceptual Model for Democratization of Coding

3. METHODOLOGY

3.1. Data collection

Data were collected from a survey conducted in May 2023 – September 2023, whose respondents were IT and non-IT employees from Romanian large companies. Large companies are usually resourced to engage in IT development and adoption. We considered Romania to be appropriate for the study since the country has a low level of digital workplace transformation (Herman, 2020), despite its larger number of qualified IT specialists per capita (Yoruk *et al.*, 2021; Bunduchi *et al.*, 2022). We further delimited our geographical scope to Cluj-Napoca, Romania's second biggest city for software development (Yoruk *et al.*, 2021) because it is a large hub for IT development and adoption. Structured questionnaire was used for the data collection. It was sent by email to the organisations' employees, which comprises both the targeted groups of respondents. The emails of the respondents were sourced from the websites of the organizations, using convenient sampling method to select available and willing respondents. After a five-week data collection period, a total of 212 responses were received. Since the questionnaire was developed in such a way that all sections needed to be completed before submission, all the responses were valid (Appiah-Kubi, 2024; Bordean *et al.*, 2024). The questionnaire was administered in Romanian, the respondents' native language, and covered four blocks of items: outcome expectations regarding LC/NCDP, perceived-usefulness items (benefits, work impact), perceived ease of use and real-use items, and demographic items (age, leading position). Prior to distribution, item wording was reviewed internally by the research team for clarity and face validity. Because convenience sampling via organizational email lists was used, the sample is subject to self-selection: employees already interested in, or aware of, LC/NCDP may be over-represented relative to the wider workforce, and non-response bias cannot be ruled out. Likewise, restricting the sample to large companies in Cluj-Napoca chosen for its concentration of IT activity - means the findings describe perceptions in a specific organizational and regional context rather than the Romanian workforce at large; we return to both limitations in Section 6.

3.2. Variables

Five-point Likert scale of 1=Strongly disagree to 5=Strongly agree was used to measure both the outcome variable (democratization of coding) and condition variables, with the exception of personal use, leading position, and age. There were seven conditions including perceived benefits, work impact, perceived ease of use, personal use, organizational use, executive position, and age. The measurement items were self-developed to suit the purpose of the study. In order to assess the perceived benefits generated due to these platforms' development, we included the following items – low-code and no-code development platforms (LC/NCDP) lead to reduced costs with operational activities in the organization; reduce the cost of software development in the organization; lead over time to the faster development of IT solutions developed at the organizational level; increase the quality of services provided by the organization; and increase the profitability of the organization. These items reflect employees' self-reported perceptions of organizational benefits rather than independently verified financial or operational outcomes. The expectation that LC/NCDP reduce operational and software-development costs is consistent with prior accounts of

LC/NCDP lowering the technical and staffing effort required to build and maintain applications (Pantelimon *et al.*, 2019; Waszkowski, 2019; Silva *et al.*, 2021), though we treat these as perceived, not audited, cost effects.

In assessing the work impact perceived by respondents, the following items were considered - low-code and no-code development platforms (LC/NCDP) usage leads to an increase in employee productivity at the operational level; these platforms make it easier for other employees to use the IT solutions developed; their usage leads to a change in the way the work is performed and the related procedures for the activity performed by the employees at the operational level; they simplify the work of people with IT background in application development; they lead in the long run to the replacement in software development of people who have IT background with people who do not have that experience; they can increase the number of people who develop IT solutions, even if they do not have IT background; the need for classic/traditional programmers will decrease due to the existence of these platforms.

When referring to the perceived ease of use within the organization, we analyzed the responses regarding the increase of the number of IT solutions developed in organizations due to these platforms, and if these software development platforms easily integrate with existing infrastructure in organizations. With regards to personal use, we considered three ordinal levels, respectively: 1: have not heard, 2: heard of such platforms in which simple users develop software, and 3: have used such platforms in which they do not use code writing to develop IT solutions. Moreover, with respect to organizational use, in our questions we explored if the employees are advanced in the use of such platforms in their organizations, if they currently use these platforms to develop applications within their organization, whether they have a thorough knowledge of software development through the use of these platforms, and if the people from their team/department believe that the use of platforms is important in their organization. For the first demographic variable which is the leading position, we considered the following – employee without leadership role; operational team coordinator (Operational Management) or top management position (Organization Activity Coordination or Extended Area); and entrepreneur/associate. For the last demographic variable, which is age, we considered the following categories: age - under 25 years, between 26 and 35 years, between 36 and 45 years; between 46 and 55 years, and over 55 years.

As in other similar quantitative studies (Pappas *et al.*, 2019; Pappas and Woodside, 2021), we proceeded to evaluate the constructs for reliability and validity. Therefore, based on the Cronbach alpha indicator, reliability showed acceptable indices of internal consistency since all our constructs exceeded the cut-off threshold of 0.70. To further assess convergent and discriminant validity beyond internal-consistency reliability, we conducted confirmatory factor analysis (CFA) on the item-level responses for the five multi-item constructs (Benefits, Ease of use, Work impact, Organizational use, Outcome expectations), separately for the IT sample (n=88 complete cases) and the non-IT sample (n=124 complete cases). All constructs except Work impact (IT sample) and Organizational use (non-IT sample) exceeded the average variance extracted (AVE) threshold of 0.50, and all constructs exceeded the composite reliability threshold of 0.70 except Ease of use in the IT sample (CR=0.688). Discriminant validity, assessed via the Heterotrait-Monotrait ratio (HTMT), was not fully established between Benefits, Ease of use, and Work impact: HTMT ratios among these three constructs ranged from 0.87 to 1.01 across both samples, exceeding the conventional 0.85 threshold (Henseler *et al.*, 2015). This pattern suggests that these conceptually distinct components of perceived usefulness under TAM were not fully distinguishable empirically, a

common challenge when operationalizing closely related sub-dimensions of a single higher-order construct as separate first-order factors. Future studies could test a single composite perceived-usefulness condition or refine the item pool through pilot testing and expert review, which were not conducted for the present self-developed scale. We note that fsQCA, unlike covariance- or variance-based SEM, treats conditions as calibrated set-membership scores rather than orthogonal latent variables (Ragin, 2009), so this limitation concerns measurement precision rather than the validity of the configurational analysis itself.

3.3. Fuzzy-Set Qualitative Comparative Analysis

We carried out Fuzzy-Set Qualitative Comparative Analysis (fsQCA) due to its capacity to analyze complex causation, defined as a situation in which an outcome may follow from several different combinations (or configurations) of causal conditions (Ragin, 2009). Moreover, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) is able to overcome several limitations of both Crisp-Set Qualitative Comparative Analysis (csQCA) and Multi-value QCA (mvQCA), integrating fuzzy-sets and fuzzy-logic principles with Qualitative Comparative Analysis (QCA) principles (Rihoux and Ragin, 2008) that offers a more realistic approach since variables values range between 0–1 (Pappas and Woodside, 2021). As stated by Pappas and Woodside (2021), Fuzzy-Set Qualitative Comparative Analysis (fsQCA) is not employed to measure the unique contribution of each variable to the overall observed data, but to identify complex solutions and combinations of independent variables. As such, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) approach was suitable for our research since we focused on identifying and analyzing the possible pathways that are formed by interdependencies between our organizational and individual variables, and that jointly lead to high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) (Yoruk *et al.*, 2021).

The variables were calibrated to form fuzzy sets with values ranging from 0 to 1 (Ragin, 2009), where 1 stands for the full-set membership and 0 is the full non-set membership (Pappas and Woodside, 2021). Here, considering Pappas and Woodside (2021), the three thresholds were based on the questionnaire scale. While we used percentiles for the five-point Likert scale variables because they allow the calibration of any measure regardless of its original values, the thresholds 3, 2, 1 were used for the three-point Likert scale variables because they provide a more accurate representation of our sample. Ragin (2009), all these variables are calibrated on a logistic function to fit into the three thresholds.

Thereafter, both necessary condition and sufficient analyses were conducted. The necessary conditions procedure presents consistency and coverage scores for conditions. According to Schneider and Wagemann (2012), a consistency threshold of at least 0.9 should be reached in order to consider a necessary condition. On the other hand, the sufficiency condition presents configurations of causal conditions that guarantee a specific outcome if present in a case (Ragin, 2009). As stated by Soto Setzke *et al.* (2023), in comparison to the necessary conditions, a specific configuration does not always have to be present to produce the outcome, hence multiple configurations can be obtained for the same outcome. We used SPSS 13.0, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) 3.0 software package and Fuzzy-Set Qualitative Comparative Analysis (fsQCA) R package as the analyses software. Table no. 1 presents the true table for high/low expectations of IT respondents, concerning the replacement of traditional coding with LCDP. Also, Table no. 2 features the true table for high/low

expectations of Non-IT respondents, concerning the replacement of traditional coding with LCDP. Beyond consistency and coverage, Tables no. 1 and no. 2 also report PRI and SYM consistency for each configuration in the truth tables, and Tables no. 4 and no. 5 report raw coverage, unique coverage, raw consistency, and overall solution coverage/consistency for each sufficient configuration, following Fiss (2011) and Ragin (2009).

Table no. 1 – True Table for high/low expectations of IT respondents concerning the replacement of traditional coding with LC/NCDP

Benefits (usefulness)	Work impact (usefulness)	Ease of use	Personal (real use)	Organizational (real use)	Leading position	Age	High expectations of IT respondents	Number of cases	Raw consistency	PRI consistency	SYM consistency
1	1	1	1	0	1	0	1	1	0.92	0.69	0.69
1	1	1	1	0	0	0	1	1	0.89	0.68	0.68
1	0	1	1	1	1	0	1	1	0.89	0.28	0.28
0	1	0	1	1	0	1	1	1	0.88	0.56	0.56
0	1	1	1	0	0	1	1	1	0.86	0.47	0.47
1	0	1	1	1	0	1	1	1	0.85	0.29	0.30
1	1	1	1	1	0	1	0	4	0.83	0.61	0.62
1	1	1	1	1	0	0	0	2	0.81	0.50	0.51
0	0	0	1	0	1	0	0	1	0.80	0.34	0.34
0	0	0	0	0	0	1	0	2	0.77	0.16	0.17
0	0	0	1	0	0	0	0	1	0.76	0.29	0.29
0	0	0	1	0	0	1	0	2	0.74	0.29	0.30
0	0	0	1	0	1	1	0	1	0.74	0.25	0.27
0	0	0	0	0	1	1	0	1	0.73	0.17	0.17
Benefits (usefulness)	Work impact (usefulness)	Ease of use	Personal (real use)	Organizational (real use)	Leading position	Age	Low expectations of IT respondents	Number of cases	Raw consistency	PRI consistency	SYM consistency
1	0	1	1	1	1	0	1	1	0.96	0.72	0.72
0	0	0	0	0	1	1	1	1	0.94	0.83	0.83
0	0	0	0	0	0	1	1	2	0.94	0.79	0.83
1	0	1	1	1	0	1	1	1	0.94	0.68	0.70
0	0	0	1	0	0	0	1	1	0.90	0.71	0.71
0	0	0	1	0	1	0	1	1	0.90	0.66	0.66
0	0	0	1	0	1	1	1	1	0.89	0.68	0.73
0	0	0	1	0	0	1	1	2	0.88	0.68	0.70
0	1	1	1	0	0	1	1	1	0.87	0.53	0.53
0	1	0	1	1	0	1	1	1	0.85	0.44	0.44
1	1	1	1	0	1	0	0	1	0.82	0.31	0.31
1	1	1	1	1	0	0	0	2	0.80	0.49	0.49
1	1	1	1	0	0	0	0	1	0.78	0.32	0.32
1	1	1	1	1	0	1	0	4	0.73	0.38	0.38

Source: authors' own creation

Table no. 2 – True Table for high/low expectations of non-IT respondents concerning the replacement of traditional coding with LC/NCDP

Benefits (usefulness)	Work impact (usefulness)	Ease of use	Personal (real use)	Organizational (real use)	Leading position	Age	High expectations of Non-IT respondents	Number of cases	Raw consistency	PRI consistency	SYM consistency
0	1	1	0	0	0	1	1	1	0.98	0.85	0.85
0	0	0	0	1	1	0	1	1	0.93	0.45	0.51
1	1	1	0	1	0	1	1	1	0.93	0.82	0.82
1	1	1	1	0	0	1	1	1	0.90	0.55	0.55
1	1	1	1	1	0	1	1	2	0.85	0.52	0.53
1	0	1	1	1	0	1	1	1	0.85	0.31	0.31
0	0	0	0	0	0	1	1	4	0.83	0.26	0.28
0	0	0	0	0	0	0	0	2	0.83	0.29	0.29

Benefits (usefulness)	Work impact (usefulness)	Ease of use	Personal (real use)	Organizational (real use)	Leading position	Age	High expectations of Non-IT respondents	Number of cases	Raw consistency	PRI consistency	SYM consistency
0	0	0	1	0	1	1	0	1	0.77	0.25	0.25
0	0	0	1	0	0	0	0	1	0.73	0.15	0.15
0	0	0	1	0	0	1	0	4	0.66	0.13	0.13

Benefits (usefulness)	Work impact (usefulness)	Ease of use	Personal (real use)	Organizational (real use)	Leading position	Age	Low expectations of non-IT respondents	Number of cases	Raw consistency	PRI consistency	SYM consistency
0	0	0	1	0	0	0	1	1	0.95	0.85	0.85
0	0	0	1	0	0	1	1	4	0.95	0.86	0.87
1	0	1	1	1	0	1	1	1	0.93	0.69	0.69
0	0	0	0	0	0	0	1	2	0.93	0.70	0.71
0	0	0	0	1	1	0	1	1	0.93	0.43	0.49
0	0	0	0	0	0	1	1	4	0.92	0.66	0.72
0	0	0	1	0	1	1	1	1	0.92	0.75	0.75
1	1	1	1	0	0	1	1	1	0.87	0.45	0.45
0	1	1	0	0	0	1	1	1	0.87	0.15	0.15
1	1	1	1	1	0	1	1	2	0.83	0.45	0.47
1	1	1	0	1	0	1	0	1	0.67	0.18	0.18

Source: authors' own creation

4. RESULTS

The results of the necessary condition analysis are presented in Table no. 3, revealing that for high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP), the consistency values range between 0.37 and 0.87 (for IT respondents) and between 0.42 and 0.78 (for non-IT respondents), for the negation of the causal conditions. On the other hand, for low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP), the consistency values range between 0.39 and 0.80 (for IT respondents) and between 0.46 and 0.79 (for non-IT respondents), for both the presence and absence (i.e. negation) of the causal conditions. Therefore, none of the causal conditions exceeded the consistency threshold of 0.9 (Schneider and Wagemann, 2012), which represents the threshold for a condition to be considered as a superset of the outcome of interest (Pappas *et al.*, 2019). Hence, none of our conditions can be considered necessary/indispensable for high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). Also, the coverage levels reveal that these conditions explain a considerable part of the outcome (Ragin, 2009).

4.1. Configurations for IT people high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP)

Having achieved the required thresholds for the necessary condition analysis, we conducted the fuzzy-set analysis in order to identify sufficient combinations of the causal conditions that explain high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). The results of the fuzzy set analysis are presented in Table no. 4 and Table no. 5. Each column represents an alternative combination of conditions that are associated with the outcome, Considering the Fuzzy-Set Qualitative Comparative Analysis (fsQCA) convention, the presence of a condition is indicated with a black circle (●), the absence/negation with a crossed-out circle (⊗), and the "do not care" condition

with a blank space (Fiss, 2011), indicating that the condition is not relevant for explaining the outcome (Soto Setzke *et al.*, 2023). Moreover, large circles indicate core conditions with high empirical relevance, while small circles represent peripheral conditions that surround core conditions (Fiss, 2011; Soto Setzke *et al.*, 2023). As proposed by Fiss (2011), solutions are grouped by their core conditions. Our solution tables indicate the presence of both core and peripheral conditions as well as neutral permutations of some configurations.

Considering the IT respondents, as Table no. 4 shows, we identified four and three configurational groupings for high and low expectations, respectively concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). All the required thresholds including the consistency levels, and coverage levels were met in our proposed solutions (Ragin, 2009). Configuration A1 indicates that in the case of young IT-employees, high work impact, high ease of use, and low organizational use of low-code and no-code platforms (LC/NCDP) are core conditions that lead to employees' high expectations. Configuration A2 shows that in the case of older IT-employees with no leading position in the firm, low benefits, high work impact, high ease of use, and low organizational use of low-code and no-code platforms (LC/NCDP) are the core conditions that result in employees' high expectations. Configuration A3 suggests that in the case of older IT-employees with no leading position in the firm, low benefits, high work impact, and low organizational use of low-code and no-code platforms (LC/NCDP) are the core conditions that influence employees' high expectations. Configuration A4.1 shows that in the case of older IT-employees with no leading position in the company, high benefits, low work impact, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) are core in affecting employees' high expectations. Similarly, configuration A4.2 shows that in the case of young IT-employees with leading position in the company, high benefits, low work impact, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) are crucial in impacting employees' high expectations. Although, personal use of low-code and no-code platforms (LC/NCDP) appeared to be peripheral condition in all the four configurations, all our IT respondents present a high background regarding low-code and no-code platforms (LC/NCDP). In general, considering our solutions, low benefits and low work impact are core constructs, pointing out employees' low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP).

Table no. 3 – Necessary conditions for high/low expectations concerning the replacement of traditional coding with LC/NCDP

Conditions	IT group of respondents				Non-IT group of respondents			
	High expectations concerning the replacement of traditional coding with LCDP		Low expectations concerning the replacement of traditional coding with LCDP		High expectations concerning the replacement of traditional coding with LCDP		Low expectations concerning the replacement of traditional coding with LCDP	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
Benefits (usefulness)	0.74	0.64	0.61	0.65	0.74	0.75	0.58	0.51
Work impact (usefulness)	0.81	0.71	0.58	0.61	0.78	0.81	0.56	0.50
Ease of use	0.78	0.66	0.63	0.65	0.74	0.79	0.55	0.52
Personal (real use)	0.87	0.56	0.80	0.63	0.52	0.63	0.69	0.72
Organizational (real use)	0.68	0.62	0.60	0.66	0.74	0.75	0.62	0.54
Leading position	0.37	0.56	0.39	0.73	0.43	0.69	0.46	0.64
Age	0.70	0.57	0.68	0.68	0.72	0.65	0.79	0.63

Conditions	IT group of respondents				Non-IT group of respondents			
	High expectations concerning the replacement of traditional coding with LCDP		Low expectations concerning the replacement of traditional coding with LCDP		High expectations concerning the replacement of traditional coding with LCDP		Low expectations concerning the replacement of traditional coding with LCDP	
	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage	Consistency	Coverage
~ Benefits (usefulness)	0.59	0.55	0.66	0.76	0.51	0.58	0.72	0.71
~ Work impact (usefulness)	0.56	0.52	0.72	0.83	0.51	0.57	0.78	0.76
~ Ease of use	0.59	0.56	0.67	0.79	0.55	0.59	0.78	0.72
~ Personal (real use)	0.42	0.64	0.43	0.81	0.77	0.74	0.65	0.54
~ Organizational (real use)	0.63	0.56	0.66	0.72	0.55	0.62	0.72	0.71
~ Leading position	0.83	0.53	0.77	0.60	0.78	0.62	0.78	0.54
~Age	0.60	0.61	0.57	0.70	0.59	0.77	0.56	0.63

Source: Based on Fiss (2011). ~ logical NOT; Necessity consistency threshold: 0.9

Table no. 4 – Sufficient configurations for high/low expectations of IT respondents concerning the replacement of traditional coding with LC/NCDP

Causal Conditions	High expectations of IT respondents					Low expectations of IT respondents					
	A1	A2	A3	A4.1	A4.2	B1.1	B1.2	B2.1	B2.2	B3.1	B3.2
Benefits (usefulness)	●	⊗	⊗	●	●	⊗	⊗	⊗	⊗	●	●
Work impact (usefulness)	●	●	●	⊗	⊗	⊗	⊗	●	●	⊗	⊗
Ease of use	●	●	⊗	●	●	⊗	⊗	●	⊗	●	●
Personal (real use)	●	●	●	●	●		●	●	●	●	●
Organization (real use)	⊗	⊗	⊗	●	●	⊗	⊗	⊗	●	●	●
Leading position		⊗	⊗	⊗	●			⊗	⊗	⊗	●
Age	⊗	●	●	●	⊗	●		●	●	●	⊗
Raw coverage	0.36	0.26	0.27	0.28	0.17	0.38	0.41	0.22	0.22	0.25	0.15
Unique coverage	0.11	0.01	0.02	0.03	0.02	0.05	0.08	0.01	0.01	0.05	0.02
Raw consistency	0.88	0.86	0.88	0.85	0.89	0.88	0.87	0.87	0.85	0.94	0.96
Overall solution coverage	0.50					0.59					
Overall solution consistency	0.81					0.84					

Source: Based on Fiss (2011). Black circle indicate presence of a condition, Crossed-out circle absence of a condition, Empty row may be either present or absent, Large circle indicate core condition, Small circle peripheral condition

Table no. 5 – Sufficient configurations for high/low expectations of non-IT respondents concerning the replacement of traditional coding with LC/NCDP

Causal Conditions	High expectations of non-IT respondents						Low expectations of non-IT respondents					
	C1.1	C1.2	C2	C3	C4	C5	D1.1	D1.2	D1.3	D2	D3.1	D3.2
Benefits (usefulness)	●	●	●	⊗	⊗	⊗	⊗	⊗	⊗	⊗	●	●
Work impact (usefulness)	●		●	⊗	⊗	●	⊗	⊗	●	⊗	●	
Ease of use	●	●	●	⊗	⊗	●	⊗	⊗	●	⊗	●	●
Personal (real use)		●	●	⊗	⊗	⊗		⊗	⊗	●	●	●
Organization (real use)	●	●		⊗	●	⊗	⊗	●	⊗	⊗		●
Leading position	⊗	⊗	⊗	⊗	●	⊗	⊗	●	⊗		⊗	⊗
Age	●	●	●	●	⊗	●		⊗	●	●	●	●
Raw coverage	0.39	0.25	0.27	0.22	0.16	0.20	0.46	0.18	0.20	0.39	0.29	0.28
Unique coverage	0.12	0.01	0.02	0.06	0.04	0.01	0.12	0.02	0.01	0.05	0.01	0.01
Raw consistency	0.87	0.83	0.85	0.83	0.93	0.98	0.90	0.93	0.87	0.92	0.80	0.83
Overall solution coverage	0.55						0.71					
Overall solution consistency	0.82						0.81					

4.2. Configurations for non-IT people high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP)

Considering the non-IT respondents, as Table no. 5 shows, we identified five and three configurational groupings for high and low expectations, respectively concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). All the required thresholds including the consistency levels, and coverage levels were met in our proposed solutions (Ragin, 2009). Configuration C1.1 indicates that in the case of older non-IT employees with no leading position, high benefits, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) are pertinent in leading to employees' high expectations. Configuration C1.2 depicts that in the case of older non-IT employees with no leading position, high benefits, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) are important in influencing employees' high expectations. Configuration C2 shows that in the case of older non-IT employees with no leading position, high benefits, and high ease of use, are core in affecting employees' high expectations. Configuration C3 depicts that in the case of older non-IT employees with no leading position, low personal use of low-code and no-code platforms (LC/NCDP) is core in impacting employees' high expectations.

It is worth indicating that age as a demographic variable was a core condition in this configuration. Configuration C4 portrays that in the case of young non-IT employees with leading position, high organizational use of low-code and no-code platforms (LC/NCDP) is crucial in influencing employees' high expectations. Configuration C5 depicts that in the case of older non-IT employees with no leading position, high ease of use, and low personal use of low-code and no-code platforms (LC/NCDP) are crucial in affecting employees' high expectations. Just like configuration C3, age as a demographic variable was a core condition in this configuration. In general, considering our solutions, low benefits and high personal use of low-code and no-code platforms (LC/NCDP) are core constructs, pointing out to employees' low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP).

5. DISCUSSION

This paper presents an advanced and new technique for analyzing IT and non-IT employees' perceptions concerning the influence of low-code and no-code platforms (LC/NCDP) on democratization of coding. Since our research focused on identifying and analyzing the possible pathways that are formed by interdependencies between our organizational and individual variables, and that jointly lead to high/low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) implementation, a more complex model, Fuzzy-Set Qualitative Comparative Analysis (fsQCA) approach was suitable for the study (Crișan and Stanca, 2021).The majority of IT-employees expect democratization of coding to transform the way coding is performed to contribute to digital workplace transformation (Talagala, 2022). This finding supports previous studies on employees' perception concerning the impact of technologies on workplace digital transformation (Bryant *et al.*, 2021). Employees' intention to use technology has been found to be determined by employees' information and digital literacy, and their perceptions concerning the usefulness and ease of use of these technologies (Nikou *et al.*, 2022; Niță *et al.*, 2024).

With respect to the path of the anticipated changes, a lion's share of the IT employees in Romanian companies expect low-code and no-code platforms (LC/NCDP) to replace the traditional coding (Pathways A1 to A4), this perception relating to both young and older IT-employees with or without leading position. This decision was arrived in variety of ways. High benefits and high work impact which both contribute to perceived usefulness are crucial in influencing IT-employees expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) (Pantelimon *et al.*, 2019; Waszkowski, 2019; Bock and Frank, 2021). Perceived usefulness is revealed as a major determinant of attitude towards the intention to use technology (Brachten *et al.*, 2021). Low-code and no-code platforms (LC/NCDP) are perceived to improve employees' productivity, thereby encouraging them to have positive perception towards it (Baptista *et al.*, 2020). Nevertheless, high ease of use was revealed as a significant core factor that leads to high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) (Sanchis *et al.*, 2019). Low-code and no-code platforms (LC/NCDP) encourage IT-staff to work on higher-level projects such code designs, user experiences, and algorithm selections with ease (Talagala, 2022). Although, personal use of low-code and no-code platforms (LC/NCDP) appeared to be peripheral condition in all the four configurations

(Pathways A1 to A4), all our IT respondents demonstrate a high background regarding low-code and no-code platforms (LC/NCDP). Similar to benefits, work impact and ease of use, we found organizational use of low-code and no-code platforms (LC/NCDP) be core in influencing high expectations concerning the replacement of traditional coding with LC/NCDP. This category of employees expect democratization to influence workplace digital transformation (Dery *et al.*, 2017).

In light of the above discussion, we found minority of the IT employees in Romanian companies to have low expectations of LCDP-NCDP to replace the traditional coding. This finding is in tandem with past studies on employees' perception concerning expectations of LCDP-NCDP to replace the traditional coding (Pathways B1 to B3), this perception relating to both young and older IT-employees with or without leading position. We discovered that low benefits and low work impact which make up perceived usefulness are core factors that lead to low expectations concerning the replacement of traditional coding with LC/NCDP among Romanian IT employees. Ease of use, personal use of LCDP-NCDP, and organizational use of LCDP-NCDP were all found to be peripheral conditions for perceived usefulness. This perception might be due to the fear of losing their jobs to non-IT employees (Sahay *et al.*, 2020; Di Ruscio *et al.*, 2022). This finding is in congruence with Van Looy (2022) which revealed that workers appear to have a very good attitude about robots in the workplace and are at ease delegating minor jobs to them, although employees are skeptical about their usage.

Parallel to the IT-employees, we found majority of non-IT-employees to expect low-code and no-code platforms (LC/NCDP) to replace the impact of technologies on workplace digital transformation. Mainly, professionals suggest that routine, and repeatable business processes can be automated/transformed by regularly business users (Ongalo and Wanjare, 2022) by the use of low-code and no-code platforms (LC/NCDP). With respect to the path of the anticipated changes, a significant number of the non-IT employees in Romanian companies equally expect low-code and no-code platforms (LC/NCDP) to replace the traditional coding (Pathways C1 to C5), this perception relating to both young and older non-IT employees with or without leading position. Although benefits and work impact which constitute perceived usefulness in our study were revealed to account for the high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) among non-IT employees in Romanian companies, they were considered to be more of peripheral that core.

However, high ease of use was found to be core condition leading to high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) among Romanian non-IT employees. Low-code and no-code platforms (LC/NCDP) encourage non-IT employees to easily code simpler tasks (Talagala, 2022). Similar to perceived usefulness, personal use of low-code and no-code platforms (LC/NCDP) portrayed to be more of peripheral to influence the high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) among Romanian non-IT employees. This finding supports the idea that low-code and no-code platforms (LC/NCDP) provides access to non-technical users to democratization since no knowledge of specific languages is required (Sanchis *et al.*, 2019). Contrary to this, high organizational use of low-code and no-code platforms (LC/NCDP) was revealed to be a crucial factor that impacts the high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP) among Romanian non-IT employees. Organizational consideration of the complexity of IT system compatibility as well as user awareness influences democratization of coding (Benbya *et al.*, 2020). Low-code and

no-code platforms (LC/NCDP) include some built-in components that allow the presentation of information in an understandable format regardless of the technology knowledge of the user. These platforms can provide encryption, and authentication mechanisms to ensure that applications developed using the platform are secure and immune to cyber threats. One of the key contributions of our study is premise on the finding that age is a core factor that influences Romanian non-IT employees' high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). Older people are less adaptable and less ready to put in the time necessary to retrain themselves for the workforce, whereas younger people are more flexible and hopeful (Ivanov *et al.*, 2020). Due to the difficulty of being proactive and learning new skills to use automation technology in the workplace, older employees may favor corporate and social solutions over individual ones (Ivanov *et al.*, 2020).

On account of the above, we found minority of the non-IT employees in Romanian companies to have low expectation of LC/NCDP to replace the traditional coding (Pathways D1 to D3), this perception relating to both young and older IT-employees with or without leading position. In general, low benefits as a determinant of perceived usefulness and high personal use of LC/NCDP as a determinant of real use are core factors that accounted for the low expectations concerning the replacement of traditional coding with LC/NCDP. The other conditions including work impact, ease of use, and organizational use of LC/NCDP demonstrated to possess peripheral impacts on the low expectations of non-IT employees of Romanian companies concerning LC/NCDP democratization. Our findings support Ivanov *et al.* (2020) which revealed that some groups of people who are identified by their views and demographics are more afraid of their occupations becoming automated than others. Employees' fears about automation originate from their beliefs that they would lose their employment to automation and, in the event that they do, how simple it will be for them to find another work in the same or a different field, keeping them out of financial hardship (Ivanov *et al.*, 2020).

By considering the above results for IT and non-IT employees' perceptions concerning the influence of low-code and no-code platforms (LC/NCDP) on democratization of coding as a path for digital workplace transformation, our conceptual model confirms to be effective in explaining democratization of coding. In addition to literature, our Fuzzy-Set Qualitative Comparative Analysis (fsQCA) analysis reveals seven important factors that drive democratization of coding. Although extant studies on digital transformation have recognized perceived usefulness, ease of use, benefits, and work impact as factors influencing digital workplace transformation (Dittes and Smolnik, 2019; Brachten *et al.*, 2021; Marsh *et al.*, 2022; Nikou *et al.*, 2022), we found additional factors including personal use of low-code and no-code platforms (LC/NCDP), organizational use of low-code and no-code platforms (LC/NCDP), leading position, and age to be significant in contributing to digital workplace transformation through democratization of coding.

6. CONCLUSIONS

A pivotal contribution of this study to the digital transformation literature is the use of Fuzzy-Set Qualitative Comparative Analysis (fsQCA) to reveal IT and non-IT employees' perceptions concerning the influence of low-code and no-code platforms (LC/NCDP) on democratization of coding. Aside shedding light on the less conceptualized but important concept (democratization of coding) which impact digital transformation, we developed a conceptual model to present the factors that lead to the phenomenon. We found that a lion's share of the IT employees in Romanian

companies highly expected low-code and no-code platforms (LC/NCDP) to replace the traditional coding. These employees arrived at this decision with the perceptions that high benefits, high work impact, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) will lead to high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP).

We also found minority of the IT employees in Romanian companies to have low expectation of low-code and no-code platforms (LC/NCDP) to replace the traditional coding with the perceptions that low benefits and low work impact will lead to low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). We found a significant number of the non-IT employees in Romanian companies to equally expect low-code and no-code platforms (LC/NCDP) to replace the traditional coding. The high level of benefits, high work impact, high ease of use, and high organizational use of low-code and no-code platforms (LC/NCDP) were revealed to be crucial in leading to high expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP). Finally, we found minority of the non-IT employees in Romanian companies to have low expectation of low-code and no-code platforms (LC/NCDP) to replace the traditional coding. In general, low benefits and high personal use of low-code and no-code platforms (LC/NCDP) are pertinent reasons that accounted for the low expectations concerning the replacement of traditional coding with low-code and no-code platforms (LC/NCDP).

In light of our findings, majority of IT and non-IT employees of Romanian companies expect low-code and no-code platforms (LC/NCDP) to lead to democratization of coding, a right direction for digital workplace transformation. The few IT and non-IT employees of Romanian companies who had low expectation of low-code and no-code platforms (LC/NCDP) to replace the traditional coding largely attributed this to low benefits of low-code and no-code platforms (LC/NCDP). Hence, practitioners are advised to organize low-code and no-code platforms (LC/NCDP) training programs for them. This will expose them to the benefits and background regarding LC/NCDP. Furthermore, employees are encouraged to embrace low-code and no-code platforms (LC/NCDP) to customize their own platforms for the execution of their responsibilities. This is expected to improve the productivity of both employees and businesses. As a policy implication, the government of Romania in specific and other governments in general, should motivate businesses to integrate low-code and no-code platforms (LC/NCDP) in their value chain.

Our study, which is the first to explore IT and non-IT employees' perceptions concerning the influence of low-code and no-code platforms (LC/NCDP) on democratization of coding, comes with limitations, hence, provides future research suggestions. First, the sample was restricted to large companies in Cluj-Napoca; given the uneven level of digital transformation across Romania's regions, findings may not generalize to smaller firms or to other regions of the country, and future studies should extend data collection to a broader national and international sample. Second, convenience sampling via organizational email lists introduces a risk of self-selection and non-response bias, potentially over-representing employees already engaged with LC/NCDP; probability-based sampling would strengthen external validity in future work. Finally, structured questionnaire was deployed as the data collection instrument. Since structured questionnaire limits the ability of respondents' own perceptions to be considered, future studies are encouraged to include both questionnaire and interviews.

ORCID

Emil Lucian Crișan https://orcid.org/0000-0001-7076-3386
Diana Maria Chiș https://orcid.org/0000-0002-2804-7113
Elias Appiah-Kubi https://orcid.org/0000-0003-4305-2305
Alin Mihăilă https://orcid.org/0000-0002-6570-8304
Napoleon-Alexandru Sireteanu https://orcid.org/0000-0002-3555-4391

References

Appiah-Kubi, E. (2024). Management Knowledge and Sustainability Reporting in SMEs: The Role of Perceived Benefit and Stakeholder Pressure. *Journal of Cleaner Production, 434*(January), 1–8. http://dx.doi.org/10.1016/j.jclepro.2023.140067

Baptista, J., Stein, M. K., Klein, S., Watson-Manheim, M. B., & Lee, J. (2020). Digital Work and Organisational Transformation: Emergent Digital/Human Work Configurations in Modern Organisations. *The Journal of Strategic Information Systems, 29*(2), 1–10. http://dx.doi.org/10.1016/j.jsis.2020.101618

Barricelli, B. R., Cassano, F., Fogli, D., & Piccinno, A. (2019). End-User Development, End-User Programming and End-User Software Engineering: A Systematic Mapping Study. *Journal of Systems and Software, 149*(March), 101–137. http://dx.doi.org/10.1016/j.jss.2018.11.041

Beare, E. C., O'Raghallaigh, P., McAvoy, J., & Hayes, J. (2020). Employees' Emotional Reactions to Digitally Enabled Work Events. *Journal of Decision Systems, 29*(sup1), 226–242. http://dx.doi.org/10.1080/12460125.2020.1782085

Benbya, H., Davenport, T. H., & Pachidi, S. (2020). Artificial Intelligence in Organizations: Current State and Future Opportunities. *SSRN Electronic Journal, 19*(4), 1–15. http://dx.doi.org/10.2139/ssrn.3741983

Bhargava, A., Bester, M., & Bolton, L. (2021). Employees' Perceptions of the Implementation of Robotics, Artificial Intelligence, and Automation (RAIA) on Job Satisfaction, Job Security, and Employability. *Journal of Technology in Behavioral Science, 6*(1), 106–113. http://dx.doi.org/10.1007/s41347-020-00153-8

Bhattarai, S., Zhao, Z., & Crespi, N. (2010). *Consumer Mashups: End-User Perspectives and Acceptance Model.* Paper presented at the Proceedings of the 12th International Conference on Information Integration and Web-based Applications & Services, Paris, France.

Bock, A. C., & Frank, U. (2021). Low-Code Platform. *Business & Information Systems Engineering, 63*(6), 733–740. http://dx.doi.org/10.1007/s12599-021-00726-8

Bordean, O. N., Chiș, D. M., Beleiu, I. N., Salanță, I. I., Crișan, E. L., & Mihăilă, A. A. (2024). Pathways to Academics' Entrepreneurial Intention: A Configurational Analysis of Individual Determinants. *IEEE Transactions on Engineering Management, 71*(January), 10885–10895. http://dx.doi.org/10.1109/TEM.2024.3406150

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The Acceptance of Chatbots in An Enterprise Context – A Survey Study. *International Journal of Information Management, 60* (October), 1–15. http://dx.doi.org/10.1016/j.ijinfomgt.2021.102375

Bryant, D., Dash, A., Ford, P., Henney, K., Danielle, J., & Olshansky, A. (2021). Low-Code and the Democratization of Programming Rethinking Where Programming Is Headed. Retrieved from https://www.oreilly.com/radar/low-code-and-the-democratization-of-programming/

Bucchiarone, A., Cabot, J., Paige, R. F., & Pierantonio, A. (2020). Grand Challenges in Model-Driven Engineering: An Analysis of The State of The Research. *Software & Systems Modeling, 19*(1), 5–13. http://dx.doi.org/10.1007/s10270-019-00773-6

Bunduchi, R., Crișan-Mitra, C., Salanță, I. I., & Crișan, E. L. (2022). Digital Product Innovation Approaches in Entrepreneurial Firms – The Role of Entrepreneurs' Cognitive Frames. *Technological Forecasting and Social Change, 175*(February), 1–15. http://dx.doi.org/10.1016/j.techfore.2021.121343

Cabot, J. (2022). Low-Code vs Model-Driven: Are They The Same? Retrieved from https://modeling-languages.com/low-code-vs-model-driven/

Cai, F. Z., Huang, S. Y., Kessler, T. S., & Fottner, F. J. (2022). A Case Study: Digitalization of Business Processes of SMEs with Low-Code Method. *IFAC-PapersOnLine, 55*(10), 1840–1845. http://dx.doi.org/10.1016/j.ifacol.2022.09.666

Crișan, E. L., & Stanca, L. (2021). The Digital Transformation of Management Consulting Companies: A Qualitative Comparative Analysis of Romanian Industry. *Information Systems and e-Business Management, 19*(4), 1143–1173. http://dx.doi.org/10.1007/s10257-021-00536-1

Dery, K., Sebastian, I. M., & van der Meulen, N. (2017). The Digital Workplace is Key to Digital Innovation. *MIS Quarterly Executive, 16*(2), 135–152.

Di Ruscio, D., Kolovos, D., De Lara, J., Pierantonio, A., Tisi, M., & Wimmer, M. (2022). Low-Code Development and Model-Driven Engineering: Two Sides of The Same Coin? *Software & Systems Modeling, 21*(2), 437–446. http://dx.doi.org/10.1007/s10270-021-00970-2

Dittes, S., & Smolnik, S. (2019). Towards A Digital Work Environment: The Influence of Collaboration and Networking on Employee Performance within An Enterprise Social Media Platform. *Journal of Business Economics, 89*(8–9), 1215–1243. http://dx.doi.org/10.1007/s11573-019-00951-4

Esposito, A., Calvano, M., Curci, A., Desolda, G., Lanzilotti, R., Lorusso, C., & Piccinno, A. (2023). End-User Development for Artificial Intelligence: A Systematic Literature Review. In L. D. Spano, A. Schmidt, C. Santoro, & S. Stumpf (Eds.), *End-User Development* (pp. 19–34): Springer Nature Switzerland. http://dx.doi.org/10.1007/978-3-031-34433-6_2

Fernandes, J. (2024). Democratizing Software Development with No Code/Low Code. Retrieved from https://www.kmworld.com/Articles/Editorial/ViewPoints/Democratizing-software-development-with-no-code-low-code-162984.aspx?pageNum=2

Fiss, P. C. (2011). Building Better Causal Theories: A Fuzzy Set Approach to Typologies in Organization Research. *Academy of Management Journal, 54*(2), 393–420. http://dx.doi.org/10.5465/amj.2011.60263120

Fossen, F. M., & Sorgner, A. (2021). Digitalization of Work and Entry into Entrepreneurship. *Journal of Business Research, 125*(March), 548–563. http://dx.doi.org/10.1016/j.jbusres.2019.09.019

Frank, U., Maier, P., & Bock, A. (2021). *Low Code Platforms: Promises, Concepts and Prospects. A Comparative Study of Ten Systems*. Retrieved from

Gao, D., & Fagerholm, F. (2024). Measuring End-user Developers' Episodic Experience of a Low-code Development Platform. A Preliminary Study. *E-Informatica Software Engineering Journal, 18*(1), 1–24. http://dx.doi.org/10.37190/e-Inf240105

Herman, E. (2020). The Influence of ICT Sector on the Romanian Labour Market in the European Context. *Procedia Manufacturing, 46*(January), 344–351. http://dx.doi.org/10.1016/j.promfg.2020.03.050

Hoppe, P. H. B., & Souza, V. E. S. (2023). *Support for Single Page Application Frameworks on FrameWeb.* Paper presented at the Proceedings of the 29th Brazilian Symposium on Multimedia and the Web.

Ivanov, S., Kuyumdzhiev, M., & Webster, C. (2020). Automation fears: Drivers and solutions. *Technology in Society, 63*(November), 1–22. http://dx.doi.org/10.1016/j.techsoc.2020.101431

Kolnhofer-Derecskei, A., Reicher, R. Z., & Szeghegyi, A. (2017). The X and Y Generations' Characteristics Comparison. *Acta Polytechnica Hungarica, 14*(8), 107–125. http://dx.doi.org/10.12700/APH.14.8.2017.8.6

Lieberman, H., Paternò, F., Klann, M., & Wulf, V. (2006). End-User Development: An Emerging Paradigm. In H. Lieberman, F. Paternò, & V. Wulf (Eds.), *End User Development* (pp. 1–8): Springer Netherlands. http://dx.doi.org/10.1007/1-4020-5386-X_1

Mannan, M., & Pek, S. (2024). Platform Cooperatives and The Dilemmas of Platform Worker-Member Participation. *New Technology, Work and Employment, 39*(2), 219–237. http://dx.doi.org/10.1111/ntwe.12273

Maran, T. K., Liegl, S., Davila, A., Moder, S., Kraus, S., & Mahto, R. V. (2022). Who Fits into The Digital Workplace? Mapping Digital Self-Efficacy and Agility onto Psychological Traits. *Technological Forecasting and Social Change, 175*(February), 1–16. http://dx.doi.org/10.1016/j.techfore.2021.121352

Marsh, E., Vallejos, E. P., & Spence, A. (2022). The Digital Workplace and its Dark Side: An Integrative Review. *Computers in Human Behavior, 128*(March), 1–21. http://dx.doi.org/10.1016/j.chb.2021.107118

Mendonça, P., & Kougiannou, N. K. (2023). Disconnecting Labour: The Impact of Intraplatform Algorithmic Changes on The Labour Process and Workers' Capacity to Organise Collectively. *New Technology, Work and Employment, 38*(1), 1–20. http://dx.doi.org/10.1111/ntwe.12251

Mixson, E. (2021). Low-Code Automation and the Democratization of Innovation (Intelligent Automation Network). Retrieved from https://www.intelligentautomation.network/transformation/articles/low-code-automation-and-the-democratization-of-innovation

Mujahed, H. M. H., Ahmed, E. M., & Samikon, S. A. (2024). Palestinian Small and Medium Enterprises Digital Technology Adoption Intention. *Journal of Open Innovation, 10*(4), 1–16. http://dx.doi.org/10.1016/j.joitmc.2024.100426

Navarro, G. (2024). Digital Transformation in SMEs: Addressing Skill Gaps through Low-Code Technology. *Sustainability, 16*(14).

Nikou, S., De Reuver, M., & Mahboob Kanafi, M. (2022). Workplace Literacy Skills—How Information and Digital Literacy Affect Adoption of Digital Technology. *The Journal of Documentation, 78*(7), 371–391. http://dx.doi.org/10.1108/JD-12-2021-0241

Niță, D., Stoicuța, N., Nițescu, A., Dobre-Baron, O., & Isac, C. (2024). Constructing a Quantification Tool of the Progress Towards the Green Economy: Aggregation Perspective. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 19*(4), 1139–1184. http://dx.doi.org/10.24136/eq.3336

Ohlert, C., Giering, O., & Kirchner, S. (2022). Who is Leading the Digital Transformation? Understanding the Adoption of Digital Technologies in Germany. *New Technology, Work and Employment, 37*(3), 445–468. http://dx.doi.org/10.1111/ntwe.12244

Ongalo, S., & Wanjare, J. (2022). Analytics and Automation of Ifrs 9 Modeling and Reporting: A Case Study of Kenyan Banks. *European Journal of Business and Management Research, 7*(6), 221–226. http://dx.doi.org/10.24018/ejbmr.2022.7.6.1738

Oosthuizen, R. M. (2019). Smart Technology, Artificial Intelligence, Robotics and Algorithms (STARA): Employees' Perceptions and Wellbeing in Future Workplaces. In I. L. Potgieter, N. Ferreira, & M. Coetzee (Eds.), *Theory, Research and Dynamics of Career Wellbeing* (pp. 17–40): Springer International Publishing. http://dx.doi.org/10.1007/978-3-030-28180-9_2

Panach, J. I., España, S., Dieste, O., Pastor, Ó., & Juristo, N. (2015). In search of evidence for model-driven development claims: An experiment on quality, effort, productivity and satisfaction. *Information and Software Technology, 62*(June), 164–186. http://dx.doi.org/10.1016/j.infsof.2015.02.012

Pantelimon, S. G., Rogojanu, T., Braileanu, A., Stanciu, V. D., & Dobre, C. (2019). *Towards a Seamless Integration of IoT Devices with IoT Platforms Using a Low-Code Approach.* Paper presented at the 2019 IEEE 5th World Forum on Internet of Things (WF-IoT).

Pappas, I. O., Mikalef, P., Giannakos, M. N., & Kourouthanassis, P. E. (2019). Explaining User Experience in Mobile Gaming Applications: An fsQCA Approach. *Internet Research, 29*(2), 293–314. http://dx.doi.org/10.1108/IntR-12-2017-0479

Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management, 58*(June), 1–23. http://dx.doi.org/10.1016/j.ijinfomgt.2021.102310

Quixy. (2023). The Future of Work: How No-Code is Transforming Job Roles and Requirements. Retrieved from https://quixy.com/blog/how-no-code-is-transforming-job-roles-and-requirements/

Rafique, H., Almagrabi, A. O., Shamim, A., Anwar, F., & Bashir, A. K. (2020). Investigating the Acceptance of Mobile Library Applications with an Extended Technology Acceptance Model (TAM). *Computers & Education, 145*(February), 1–13. http://dx.doi.org/10.1016/j.compedu.2019.103732

Ragin, C. C. (2009). *Redesigning Social Inquiry: Fuzzy Sets and Beyond*: University of Chicago Press. http://dx.doi.org/10.7208/chicago/9780226702797.001.0001

Rao, V. (2012). GitHub and the Democratization of Programming. Retrieved from https://www.forbes.com/sites/venkateshrao/2012/03/27/github-and-the-democratization-of-programming/

Razak, S. F. A., Ernn, Y. P., Yussoff, F. I., Bukar, U. A., & Yogarayan, S. (2024). Enhancing Business Efficiency through Low-Code/No-Code Technology Adoption: Insights from an Extended UTAUT Model. *Journal of Human, Earth, and Future, 5*(1), 85–99. http://dx.doi.org/10.28991/HEF-2024-05-01-07

Rihoux, B., & Ragin, C. C. (2008). *Configurational Comparative Methods: Qualitative Comparative Analysis (QCA) and Related Techniques*: Sage Publications. http://dx.doi.org/10.4135/9781452226569

Sahay, A., Indamutsa, A., Di Ruscio, D., & Pierantonio, A. (2020). *Supporting the understanding and comparison of low-code development platforms.* Paper presented at the 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA).

Sanchis, R., García-Perales, Ó., Fraile, F., & Poler, R. (2019). Low-Code as Enabler of Digital Transformation in Manufacturing Industry. *Applied Sciences (Basel, Switzerland), 10*(1), 1–17. http://dx.doi.org/10.3390/app10010012

Schneider, C. Q., & Wagemann, C. (2012). *Set-Theoretic Methods for The Social Sciences: A Guide to Qualitative Comparative Analysis*: Cambridge University Press. http://dx.doi.org/10.1017/CBO9781139004244

Silva, C., Vieira, J., Campos, J. C., Couto, R., & Ribeiro, A. N. (2021). Development and Validation of A Descriptive Cognitive Model for Predicting Usability Issues in A Low-Code Development Platform. *Human Factors, 63*(6), 1012–1032. http://dx.doi.org/10.1177/0018720820920429

Soto Setzke, D., Riasanow, T., Böhm, M., & Krcmar, H. (2023). Pathways to Digital Service Innovation: The Role of Digital Transformation Strategies in Established Organizations. *Information Systems Frontiers, 25*(3), 1017–1037. http://dx.doi.org/10.1007/s10796-021-10112-0

Stegner, L., Porfirio, D., Hiatt, L. M., Lemaignan, S., Mead, R., & Mutlu, B. (2024). *End-User Development for Human-Robot Interaction.* Paper presented at the Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction.

Talagala, N. (2022). Where Is Coding Headed? 7 Trends For 2022 And Beyond Retrieved from https://www.forbes.com/sites/nishatalagala/2021/12/13/where-is-coding-headed-7-trends-for-2022-and-beyond/?sh=7f86b0e1849d

Tsahat, C. O. O., Ngoulou, A. N., & Kwai, P. A. A. (2023). Prospects of Using Low-Code in the Creation of Automated Systems. *Open Journal of Applied Sciences, 13*(10), 1864–1869. http://dx.doi.org/10.4236/ojapps.2023.1310147

Van Looy, A. (2022). Employees' Attitudes Towards Intelligent Robots: A Dilemma Analysis. *Information Systems and e-Business Management, 20*(3), 371–408. http://dx.doi.org/10.1007/s10257-022-00552-9

Waszkowski, R. (2019). Low-Code Platform for Automating Business Processes in Manufacturing. *IFAC-PapersOnLine, 52*(10), 376–381. http://dx.doi.org/10.1016/j.ifacol.2019.10.060

Wolff, I. (2019). Making in-House Apps with Ash Low-Code, No-Code Platforms. *Manufacturing Engineering, 163*(4), 58–67.

Yoruk, D. E., Bunduchi, R., Yoruk, E., Crișan-Mitra, C., Salanță, I. I., & Crișan, E. L. (2021). Pathways to Innovation in Romanian Software SMEs: Exploring the Impact of Interdependencies between Internationalisation and Knowledge Sources. *Journal of International Management, 27*(4), 1–22. http://dx.doi.org/10.1016/j.intman.2021.100874

Scientific Annals of Economics and Business
73 (3), 2026, 617-639
DOI: 10.47743/saeb-2026-0031

Unveiling the Dynamics of Irregular Migration and Border Mission Expenditures at the Serbian - Romanian Frontier: A Wavelet-Based Approach

Iliuta Cumpanasu[*], Mihai Mutascu[**]

Abstract: This study examines the dynamic relationship between irregular and smuggled migration flows and border mission expenditures at the Serbian - Romanian frontier using wavelet methods, over January 2018 to April 2025. Baseline wavelet analyses reveal that the interactions between migration flows and border mission expenditures are predominantly short-run, high-frequency and time-varying, with no evidence of persistent long-run relationships. The results identify clear lead-lag patterns, showing that sudden increases in irregular and smuggled migration are typically followed by higher border mission expenditures, reflecting reactive policy responses, whereas increased expenditures subsequently contribute to reducing migration flows, indicating a corrective feedback mechanism. Medium-run interactions are also observed, particularly for smuggled migration, suggesting that structural policy interventions gradually influence migration dynamics. Robustness checks using wavelet cohesion and partial wavelet coherency confirm the stability of these dynamic relationships while highlighting the moderating effects of geopolitical shocks, economic uncertainty, regulatory changes and weather conditions. These findings support the adoption of a multi-horizon policy strategy that combines rapid operational responses, medium-term adaptive resource allocation and strengthened transnational cooperation to combat migrant smuggling. Future research should extend the analysis to multiple border regions using disaggregated data and complementary causal approaches.

Keywords: Serbian - Romanian frontier; irregular migration; border mission expenditures; co-movements; wavelet.

JEL classification: F22; H56; C14.

[*] Faculty of Economics and Business Administration, West University of Timisoara, Romania; e-mail: *iliuta.cumpanasu78@e-uvt.ro*.
[**] Faculty of Economics and Business Administration, West University of Timisoara, Romania; e-mail: *mihai.mutascu@e-uvt.ro* (corresponding author).

Article history: Received 22 April 2026 | Accepted 22 July 2026 | Published online 29 September 2026

To cite this article: Cumpanasu, I., Mutascu, M. (2026). Unveiling the Dynamics of Irregular Migration and Border Mission Expenditures at the Serbian - Romanian Frontier: A Wavelet-Based Approach. *Scientific Annals of Economics and Business*, 73(3), 617-639. https://doi.org/10.47743/saeb-2026-0031.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

Since 2015, Europe has experienced unprecedented migration pressures, driven primarily by armed conflicts and persecution in countries such as Syria, Afghanistan and Iraq, political instability in Libya, and persistent poverty, insecurity and environmental degradation across the Sahel and Sub-Saharan Africa. These interconnected push factors have made migration one of the most significant humanitarian, political and socio-economic challenges facing Europe.

In this context, immigrants arriving in Europe have originated predominantly from conflict-affected countries in the Middle East, including Syria, Afghanistan, and Iraq; from North and Sub-Saharan Africa, notably Morocco, Tunisia, Nigeria, Eritrea, Sudan, Mali and Guinea; from South Asia, particularly Pakistan and Bangladesh; and from Latin America, especially Venezuela and Colombia (EUAS, 2025). Since 2022, Ukraine has also become a major country of origin following Russia's full-scale invasion.

In addition to these humanitarian drivers, economic incentives play a significant role in attracting migrants to Europe. Higher wages, better employment opportunities, and improved living standards encourage individuals to seek work in countries such as Germany, France and Netherlands, where labour markets offer greater economic prospects than many countries of origin. Moreover, demographic aging and labour shortages have increased demand for migrant workers in sectors including healthcare, construction, agriculture, manufacturing and information technology. For example, Germany has actively recruited healthcare professionals and engineers, while Italy and Spain continue to rely on seasonal migrant labour in agriculture. Together with access to high-quality education, healthcare and comprehensive social protection systems, these economic opportunities make Europe an attractive destination for both skilled and low-skilled migrants.

At the same time, migration has become politically controversial in Europe because it intersects with sensitive issues such as border security, national sovereignty, economic integration and humanitarian obligations. Frontline countries such as Greece, Italy and Spain received a disproportionate number of arrivals, leading to disputes over the distribution of asylum seekers among member states. Differences in national approaches, with some countries advocating greater solidarity and others prioritizing stricter border controls, have hindered the development of a common Europe migration policy. Moreover, rapid migration flows can place pressure on housing, healthcare, education and social welfare systems, while concerns about irregular migration, security and the integration of newcomers continue to shape political debates. These challenges have also fuelled the rise of populist and nationalist parties, which often portray migration as a threat to national identity and security, contributing to increasing political polarization across Europe.

Between 2018 and 2025, Europe's immigrant population reached a record high of 64.2 million, while irregular border crossings declined after 2023 due to strengthened external border management and enhanced migration control measures (Vallentine *et al.*, 2025). Germany remains the largest destination country in Europe, hosting nearly 18 million foreign-born residents, who account for approximately 21% of its total population (Jones, 2025). Spain has recorded one of the fastest increases in its immigrant population, adding around 700,000 immigrants in recent years to reach approximately 9.5 million foreign-born residents (Martinez, 2026). Together, Germany, France, Spain and Italy host nearly 70% of the foreign-born population in the European Union (Ruda, 2025). In relative terms, however, smaller

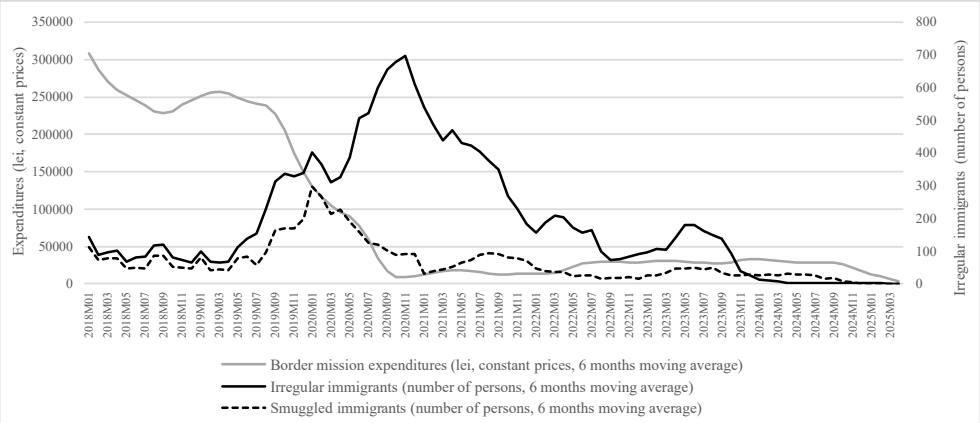
states, such as Luxembourg, Malta and Cyprus, have the highest shares of immigrants, with foreign-born residents constituting a substantial proportion of their populations.

The dynamics of irregular migration and border management have become increasingly central to contemporary policy debates, particularly in regions situated along major migration corridors. The Serbian - Romanian frontier represents a critical node in the broader European migration system (EC, 2025), where irregular and smuggled migration flows interact with institutional responses shaped by security priorities, fiscal constraints and external shocks.

Irregular migrants often rely on smuggling networks because legal pathways to enter Europe are limited or inaccessible, particularly for individuals fleeing conflict, persecution, or severe economic hardship. Strengthened border controls, combined with persistent migration pressures, have increased the demand for smuggling services despite the significant financial costs and risks to migrants' safety (UNODC, 2025).

In recent years, migration patterns in this region have been influenced by a combination of structural drivers, such as economic disparities and labour market conditions as well as transitory shocks, including geopolitical tensions, regulatory changes and extreme weather events. These factors contribute to a highly volatile environment in which migration flows fluctuate rapidly and policy responses must continuously adapt. In this context, border mission expenditures are not only a reflection of policy priorities but also a key instrument through which states attempt to manage and influence migration dynamics. However, the effectiveness of such expenditures remains an open question, particularly in terms of their timing, persistence and interaction with different types of migration flows.

Understanding how these flows evolve over time and how public expenditures respond to them, is essential for designing effective and adaptive border policies. Figure no. 1 illustrates the dynamics of irregular immigrants, smuggled immigrants and border mission expenditures at the Serbian - Romanian border, over January 2018 - April 2025, presented as six-month moving averages.



Source: author's calculations based on TIBPT (2025).

Figure no. 1 – Irregular immigrants, smuggled immigrants and border mission expenditures at the Serbian - Romanian border, over January 2018 - April 2025

Figure no. 1 shows that public mission expenditures decline steeply from 2018 to 2021, while irregular and smuggled migration surge, indicating a strong inverse relationship that peaks during 2020-2021. This spike aligns with disruptions from the COVID-19 pandemic, when border controls, economic stress and reduced enforcement capacity likely altered migration dynamics and increased reliance on smuggling networks. After 2021, both irregular and smuggled flows fall markedly, even though expenditures remain low, suggesting the easing of pandemic pressures, restoration of controls, and adaptive policy responses. A modest rebound in 2023 reflects lingering post-pandemic volatility but remains far below peak levels. By 2024-2025, flows converge to minimal levels, consistent with tighter coordination and regulatory reinforcement under the updated Schengen Borders Code, which likely contributed to stabilizing migration pressures.

The relationship between immigration and border mission expenditures operates through two theoretical channels: a proactive (control) channel, in which higher expenditures lead to subsequent declines in migration flows (negative co-movement), and a reactive (adaptive) channel, in which increases in migration flows prompt subsequent increases in expenditures (positive co-movement).

The literature on irregular migration and border enforcement expenditures remains relatively limited, with most major contributions focusing on the classical push-pull determinants of migration (Kuhnt, 2019). While these studies shed light on the economic, social and political factors influencing migration flows, there is a notable gap in research examining how these determinants intersect with government spending on border security, migration control strategies and the cost-effectiveness of various enforcement policies.

Even so, two strands of literature can be identified. First strand treats the interaction between the irregular immigration and border mission expenditures. For example, Akkerman (2023) highlights that in recent years, the United States (US) has allocated more funding to immigration enforcement than at any other time in its history. He notes that these enforcement budgets have been rising consistently over an extended period, regardless of which political party controls the federal government. Similarly, Bier *et al.* (2023) argue that immigration enforcement reflects the costs of excluding immigrants rather than inherent costs of immigration, with political opposition - not immigrants - driving these expenditures. Unlike them, Jones *et al.* (2023) claim that the adoption of new technologies in migration and asylum management is closely tied to expanding state control over non-European Union (EU) citizens. This trend has fuelled the growth of the EU's security and surveillance industry, supported by public funding, Frontex-led research and projects and the repeated use of crisis narratives to justify exceptional measures. In a different approach, some researchers have contended that the humanitarian roles assigned to EU maritime missions serve to obscure the real human toll of the EU's border enforcement (Tazzioli, 2016; Pallister-Wilkins, 2017; Cusumano, 2019). Even though, D'Alfonso (2021) notes that while these policy areas still account for a small portion of the EU budget - 2.1%, excluding Next Generation EU funds - their funding has grown markedly compared to 2014-2020. In the same vein, Zardo (2025) shows that since 2000, EU development funds have grown unevenly, with the largest increases in protection and development, despite rising support for border control and returns.

The second strand of literature, though limited, focuses on the relationship between smuggled migrants and spending on border missions. Smuggling of migrants is a

transnational industry that, for payment, enables irregular and typically unlawful entry into a country (MacKellar, 2022).

In this context, Gathmann (2008) examines how intensified border enforcement shapes the illicit migration market along the Mexico - US border. By merging panel data on unauthorized migrants with enforcement records, she finds that stricter controls have only modest impacts: the fees charged by smugglers, or "coyotes," rose by 17 percent. Moreover, overall demand for their services remained stable, while the border patrol's budget has increased sevenfold since 1986, underscoring the resilience of smuggling networks despite intensified enforcement. Although the Serbian - Romanian border experiences substantially lower migration flows than the US - Mexico border, both corridors share similar migration dynamics. While the US - Mexico route is driven primarily by economic disparities, violence, and political instability in Latin America, the Serbian - Romanian border forms part of the Western Balkans route, serving migrants mainly from Syria, Afghanistan, Iraq, Pakistan, Bangladesh and several African countries fleeing conflict, persecution and poverty. In both cases, migrants rely on smuggling networks to circumvent strengthened border controls. However, unlike the US - Mexico border, which is governed through bilateral cooperation, the Serbian - Romanian corridor is embedded within the EU's multilevel migration and asylum governance framework.

For De Haas (2015), the billions spent on militarizing borders have largely failed to stop migration. According to author, the research and recent crises show that stricter controls mainly redirect flows, deepen reliance on smugglers, and amplify the financial and human costs of crossing. Along the same lines, Suber (2025) emphasizes that migrant smuggling networks adapt to border enforcement by specializing in certain routes, coordinating between groups and creating roles, such as the "reberie," responsible for safely guiding migrants across borders.

Within this framework, the study examines the relationship between irregular, smuggled, and total migration flows and border mission expenditures from January 2018 to April 2025. Moving beyond traditional theoretical models and classical time-series approaches, it employs wavelet-based techniques to analyse co-movements across both time and frequency. This methodological approach is particularly suited to capturing the dynamic, non-linear nature of migration systems, where relationships shift across time horizons in response to evolving economic, geopolitical and climatic conditions.

The empirical analysis reveals that the interaction between migration flows and expenditures is neither stable nor unidirectional, but instead characterised by alternating periods of positive and negative co-movements, varying across short- and medium-term horizons. These patterns suggest the coexistence of reactive and proactive policy responses, as well as the presence of lagged feedback mechanisms between migration pressures and expenditure adjustments. Furthermore, the robustness of these findings is assessed through alternative wavelet-based measures, confirming the stability of the core relationships while also highlighting the influence of external factors, such as pandemic and regulatory shocks, geopolitical risk, economic uncertainty and climate conditions.

This study makes three main contributions. First, it provides new empirical evidence on the dynamic relationship between irregular migration and border mission expenditures at the Serbian - Romanian border, using smoothed high-frequency data to uncover co-movement behaviour. Existing studies focus on theoretical frameworks (De Haas, 2015; Akkerman, 2023; Jones *et al.*, 2023), time-series analyses (Gathmann, 2008) or qualitative

approaches (Suber, 2025), but completely overlook time-frequency patterns. Although conventional time-series methods remain the dominant analytical approaches in migration research, they generally assume that relationships between variables are stable over time and are often examined at a single temporal scale (Mutascu *et al.*, 2026). However, migration processes are inherently dynamic, being shaped by short-term shocks (e.g., conflicts, policy changes, border closures) as well as long-term structural factors, including economic disparities and demographic trends. Wavelet analysis provides a non-parametric alternative that simultaneously captures both the time and frequency dimensions of these relationships, enabling the identification of transient, non-stationary and scale-dependent patterns that conventional time-series techniques may overlook. Consequently, wavelet methods are particularly well suited for analysing complex migration dynamics characterised by structural breaks, evolving interdependencies and heterogeneous temporal responses.

Second, it conceptualizes and tests two competing mechanisms - proactive (control) versus reactive (adaptive) - thereby offering a clearer theoretical framework to interpret the direction of interaction between policy effort and migration flows. The prevailing literature does not directly examine how border mission expenditures influence irregular migration flows through a proactive mechanism, but instead focuses on the immediate effects of regulatory measures (Angelucci, 2012; Helbling and Leblang, 2019). Similarly, no literature directly addresses the reactive mechanism in which migration flows drive border mission expenditures. Most studies instead focus on how overall immigrant inflows influence border enforcement (Massey *et al.*, 2016) or offer not conclusive results in terms of budget enforcement (Facchini and Testa, 2021).

Third, it situates the dynamics between immigration and border mission expenditures within the context of recent external shocks, geopolitical shifts, economic trends and climatic conditions, highlighting how these factors reshape migration pressures and enforcement responses across sub-periods and time-horizons through budgetary resources. The existing literature addresses these factors individually, such as pandemics (Benton *et al.*, 2021; Klein *et al.*, 2024; Chi *et al.*, 2025; González-Leonardo *et al.*, 2025), border regulation (Angelucci, 2012; Helbling and Leblang, 2019), geopolitical risk (Hyndman, 2012), economic uncertainty (Moridian *et al.*, 2024) and climate conditions (Benveniste *et al.*, 2025; Yang *et al.*, 2025), but does not examine them within an integrated framework that captures their dynamics across both time and frequency.

The remainder of the paper is structured as follows: Section 2 describes the methodology and dataset; Section 3 presents and discusses the findings; and Section 4 provides robustness checks. Section 5 concludes with a summary of the policy implications, while Section 6 outlines the study's limitations and directions for future research.

2. METHODOLOGY AND DATASET

2.1. Methodology

The interaction between irregular immigration and border mission expenditures at the Serbian-Romanian border from January 2018 to April 2025 is analysed using a time-domain approach.

Wavelet analysis offers several advantages over classical time-series methods. It effectively handles non-stationary data by allowing relationships to evolve over time. Compared with

Fourier-based approaches, it provides simultaneous time-frequency localization, enabling the identification of both short-term fluctuations and long-term cycles, as well as the timing of their occurrence. Additionally, wavelets capture multi-scale dynamics by decomposing series into different frequencies, distinguishing between short-run shocks and long-run trends. They are also well suited for detecting localized events and structural breaks, such as crises or policy changes. Finally, wavelet methods accommodate nonlinear and time-varying relationships, revealing dynamic correlations that conventional techniques may overlook.

Unlike conventional regression-based approaches, wavelet analysis does not estimate structural causal effects but instead characterizes the strength, timing and frequency of associations between variables across different time horizons. By simultaneously examining the time and frequency domains, it identifies localized co-movements and lead-lag relationships, revealing when and at which temporal scales variables move together. Consequently, wavelet analysis provides valuable insights into the dynamic evolution of relationships but should be interpreted as identifying temporal dependence rather than causal effects.

The methodology involves decomposing a time series into two components: one in time, and another in frequency. This procedure is facilitated by a wavelet function, which has zero mean and finite energy. This decomposition is performed using a wavelet function, which has zero mean and finite energy. Among various wavelet functions (e.g., Coiflet, Daubechies, Haar, Meyer, Mexican hat), the Morlet wavelet is often preferred in socio-economic applications, as it provides an optimal balance between time and frequency localization (Grinsted *et al.*, 2004, p. 563).

Compared with other wavelet functions, the Morlet wavelet offers a superior balance between time and frequency localization, enabling the simultaneous identification of localized co-movements and phase differences across multiple time scales. This feature makes it especially appropriate for examining dynamic associations and lead-lag relationships across multiple time horizons, which constitute the primary objective of the present study. Consequently, the Morlet wavelet has become the standard choice in economics and finance, where the emphasis is on understanding how relationships between variables vary over both time and frequency.

Let η denote a dimensionless time parameter and $\omega_0 = 6$ the dimensionless central frequency, chosen to satisfy the admissibility condition outlined by Farge (1992), with $= \sqrt{-1}$. Moreover, setting the central frequency to 6 has become the standard specification in economic and financial wavelet applications, thereby enhancing the comparability of the results with the existing literature. Under these definitions, the Morlet wavelet $\psi_0(\eta)$ is given by:

$$\psi_0(\eta) = \pi^{-\frac{1}{4}} e^{i\omega_0\eta} e^{-\frac{1}{2}\eta^2} \tag{1}$$

Using the Morlet wavelet, the Continuous Wavelet Transform (CWT) of a time series x_n can be derived by incorporating key parameters, including the time step δt, the translation parameter τ and the scale factor s, as follows:

$$w_n^x(s,\tau) = \frac{\delta t}{\sqrt{s}} \sum_{n=0}^{N-1} x_n \psi^* \left((n-m) \frac{\delta t}{s} \right) \tag{2}$$

with $n = 0 \ldots N-1$,and $m = 0, 1, \ldots, N-1$ (Grinsted *et al.*, 2004).

In this framework, no assumption of stationarity is imposed on the time series (Aguiar-Conraria and Soares, 2011). More precisely, the wavelet analyses a time series locally, not globally. Instead of assuming that the entire series behaves the same way over time as classical methods do, wavelet breaks the series into small time segments and studies each segment at different frequencies.

The interaction between two decomposed time series x_n (irregular immigration) and y_n (border mission expenditures) is facilitated by the Wavelet Coherency (WTC) method. Unlike traditional correlation, it captures both the strength and timing of co-movements in the time-frequency domain, allowing identification of periods and frequencies where the series are strongly correlated. Additionally, it provides information on phase relationships, indicating which variable leads or lags the other, and is particularly suitable for non-stationary and nonlinear socio-economic data.

WTC is conducted through the following procedure (Aguiar-Conraria and Soares, 2011):

$$R_n(s) = \frac{\left|S\left(s^{-1}W_n^{xy}(s)\right)\right|}{S(s^{-1}|W_n^x|)^{\frac{1}{2}}\, S\left(s^{-1}\left|W_n^y\right|\right)^{\frac{1}{2}}} \tag{3}$$

with, S representing the smoothing operator.

CWT enables the identification of the phase difference $\phi_{x,y}$ between the series x_n and y_n, capturing not only the co-movement but also the lead-lag dynamics between the two series. It is computed as follows (Aguiar-Conraria and Soares, 2011):

$$\phi_{x,y} = tan^{-1}\left(\frac{\Im\{W_n^{xy}\}}{\Re\{W_n^{xy}\}}\right) \tag{4}$$

Here, $\phi_{x,y} \in [-\pi, \pi]$, with $\Re$ and $\Im$ denoting the real and imaginary parts of a complex number, respectively.

The phase difference $\phi_{x,y}$ indicates the synchronization and lead-lag relationship between the series at a given frequency. A phase difference of zero signifies in-phase movement and positive connection. When $\phi_{x,y}$ lies between 0 and $\pi/2$, series x leads y, whereas a value between $-\pi$ and $-\pi/2$ indicates that y leads x. Conversely, a phase difference of $\pm\pi$ corresponds to anti-phase synchronization, reflecting negative connection. Accordingly, x leads y when $\phi_{x,y}$ lies between $-\pi$ and $-\pi/2$, while y leads x when $\phi_{x,y}$ lies between $\pi/2$ and π.

In all WTC plots, the thick black contour denotes the 5% significance level, while the shaded region marks the cone of influence (COI), where edge effects may affect the results. The colour scale represents power, ranging from intense blue for low coherence to intense yellow for high coherence. Arrows indicate the phase difference. Arrows pointing to the right show a positive (in-phase) relationship, with x leading when they point upward and y leading when they point downward. Arrows pointing to the left indicate a negative (out-of-phase) relationship, with x leading when pointing downward and y leading when pointing upward.

Strategically, the baseline WTC estimations include the interaction between immigration, alternatively captured through total irregular immigrants, irregular immigrants and smuggled immigrants, and border mission expenditures.

2.2. Dataset

The study focuses on the Serbian - Romanian border, covering the period from January 2018 to April 2025, data availability. Stretching 541.8 kilometres in total, the border comprises 230.5 kilometres along the Danube River and 311.3 kilometres of overland frontier.

Border mission expenditures (expenditures) is the dependent variable and measures the mission-related public expenditures, encompassing travel, accommodation and per diem for deployed officers, along with costs for fuel, vehicles, equipment, communications, surveillance and other specialized operational resources necessary for the mission. The variable is expressed in constant prices to eliminate the bias caused by inflation.

Irregular immigration is the variable of interest and is alternatively measured using *irregular immigrants (irregular)*, *smuggled immigrants (smuggled)* and *total immigrants (total). Irregular immigrants* are foreign citizens officially recorded as entering Romania without legal authorization, whereas *smuggled immigrants* are those irregular migrants documented as having used smugglers for a fee.

Finally, *total immigrants* is an aggregate variable and represents the sum of *irregular immigrants* and *smuggled immigrants.*

The dataset originates from the Territorial Inspectorate of the Border Police Timisoara (2025), a regional branch of the Romanian Border Police. Responsible for border security in South-Western Romania, including the counties of Timis, Caras-Severin and Mehedinti, it operates under the Ministry of Internal Affairs to enforce legal compliance and combat illicit cross-border activities.

An extended set of **control variables**, drawn from the literature, is also included for robustness checks. This set comprises pandemic, regulatory, geopolitical, economic, and climatic factors.

Pandemic shock (pandemic) is a dummy variable and controls for COVID-19 disease. For example, Chi *et al.* (2025) state that the global migration flows declined by 64% in 2020, partly due to the implementation of border controls. In the same vein, Klein *et al.* (2024) show that stricter domestic restrictions unrelated to international travel were linked to declines in migrant stocks in affected countries, suggesting that reduced inflows were the primary driver. In contrast, Benton *et al.* (2021) note that travel restrictions and border closures left many regular migrants and travellers stranded, confronting significant financial and logistical obstacles to returning home. (González-Leonardo *et al.*, 2025) partially corroborate this finding, documenting a general decline in immigration in 2020, followed by a rebound to expected levels in 2021, with the exception of Spain.

Regulatory shock (regulatory) also is a dummy and captures the effects of Schengen Borders Code. This code, which came into effect in July 2024, aims to enhance external-border management by clarifying operational procedures and strengthening coordination among EU member states. These changes are likely to affect enforcement practices and the allocation of border resources, making it essential to account for this institutional shift when analysing the link between irregular migration pressures and border mission expenditures. A

substantial body of literature examines the implications of immigration regulations (Angelucci, 2012; Helbling and Leblang, 2019).

Geopolitical risk (GPR) is measured using the GPR Index developed by Caldara and Iacoviello (2022) and captures uncertainty arising from political instability, policy shifts, military conflicts, terrorism or diplomatic tensions that can influence countries, regions or global markets. There is a large body of literature linking the geopolitical risk to migration. For instance, Hyndman (2012, p. 243) observes that 'migration has long been a barometer of geopolitics,' underscoring the importance of understanding regional political processes that shape migration patterns.

Economic status (EPU) is captured via Economic Policy Uncertainty (EPU) proposed by Baker *et al.* (2016). This index quantifies economic policy uncertainty, reflecting how businesses, investors, and the public perceive ambiguity about future government policies and their potential economic effects. Immigration flows are strongly shaped by the economic conditions of both origin and destination countries, typically rising during periods of economic growth and declining during recessions (Moridian *et al.*, 2024).

Finally, climatic conditions on border is captured through *temperature (temp)* and *precipitations (precip)* as main climatic variables to account for seasonal or extreme weather effects that could affect migration flows, border enforcement or human mobility. Climate conditions, particularly the temperature and precipitations, act as a physical constraint along migration routes, shaping the timing, scale and location of irregular border crossings (Benveniste *et al.*, 2025). Temperature and precipitations are reliable, continuous and globally comparable metrics that capture both direct human impacts and indirect livelihood pressures, making it ideal indicators of climate conditions in socio-economic and migration research (Yang *et al.*, 2025).

All variables are seasonally adjusted using the additive moving-average method, which assumes that seasonal fluctuations are roughly constant in absolute terms. This approach allows for clear separation of seasonal effects from the underlying trend and it is particularly suitable for socio-economic series, such as irregular migration and public expenditures, where seasonal variations do not scale with the level of series. After adjustment, the variables appear in their natural logarithms for all estimations, facilitating variance stabilization and interpretation as elasticities. Negative deseasonalized variables (i.e., *irregular* and *smuggled*) have been rescaled by adding the absolute value of their minimum plus one, ensuring strictly positive values suitable for logarithmic transformation.

Table no. A1 (Annex) summarizes the variable descriptions, units of measurement and corresponding data sources. Their descriptive statistics are shown in Table no. A2.

3. RESULTS

The baseline WTC plots are illustrated in Figures no. 2-4 and reveal the interaction between irregular immigrants, smuggled immigrants and total irregular immigrants, and border mission expenditures, at the Serbian - Romanian frontier, over January 2018 - April 2025.

Figure no. 2 shows the WTC of *log(irregular)* and *log(expenditures)* pair. All significant co-movements are registered in the short-run, until 12 months band of scale (The classification of time horizons follows conventional practice in economics: the short-run spans up to 12 months, the medium-run covers 12 to 60 months, and the long-run extends beyond 60 months).

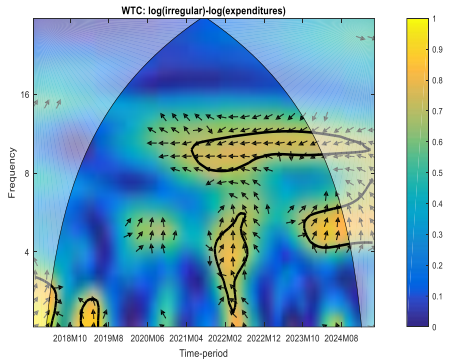


Figure no. 2 – WTC of pair log(irregular) vs log(expenditures)

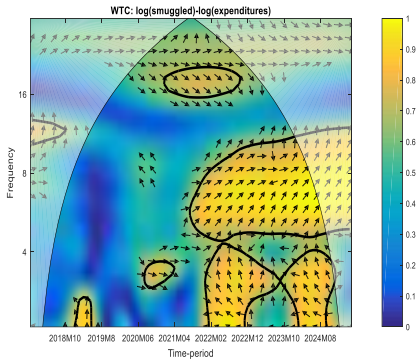


Figure no. 3 – WTC of pair log(smuggled) vs log(expenditures)

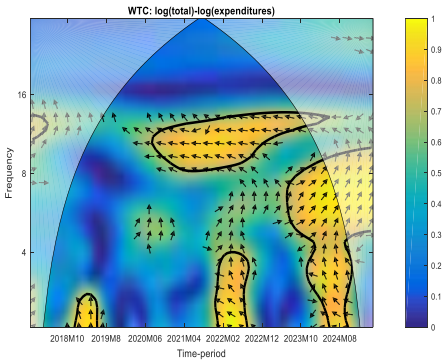


Figure no. 4 – WTC of pair log(total) vs log(expenditures)

There are four zones exhibiting significant and strong co-movements. The first zone corresponds to the period from 2019M1 to 2019M5, within a scale band of up to 2 months, indicating high frequency dynamics (i.e., short-run). As the arrows are nearly perpendicular to the OX axis, the results are conclusive. Similar patterns are observed over the period 2021M11-2022M8, within a scale band of up to 4 months, reflecting high-frequency dynamics (i.e., short-run), with the arrows predominantly oriented perpendicular to the OX axis.

The third zone spans 2023M11-2024M9, within 5-7 months scale band, at high frequency (i.e., short-run), with arrows oriented to the right and upward, indicating a positive co-movement between *irregular* and *expenditures*, with the *irregular* leading. Importantly, the phase direction suggests that short-term shocks or fluctuations captured by the irregular component tend to precede and potentially drive changes in expenditures during this period, coinciding with a peak in irregular inflows, as shown in Figure no. 1. Such behaviour may be associated with heightened uncertainty, adjustment processes or external shocks, where border authorities adjust their spending decisions after observing irregular movements. The leading role of the irregular component therefore indicates a

transmission mechanism in which temporary shocks are not immediately absorbed but instead propagate into expenditure dynamics with a short delay.

In the fourth zone, the *irregular* negatively leads e*xpenditures* over 2021M6-2024M2, also at high frequency, within 8-12 months scale band, in the short-run. This indicates an inverse short-run transmission mechanism, possibly reflecting adjustment effects, delayed responses or corrective behaviour in border mission expenditures following the downward trend in irregular immigration starting in 2021M11, as shown in Figure no. 1.

Figure no. 3 reveals the WTC plot of *log(smuggled)* and *log(expenditures)* pair, with six zones of significant co-movements, at high and medium frequencies (i.e., short- and medium-run). The first and second zones are inconclusive, as the arrows are either nearly perpendicular to the OX axis (i.e., 2019M1-2019M5, within a scale band of up to 2 months) or nearly horizontal (2020M8-2021M4, within 2-4 months scale band).

The third and fourth zones exhibit strong negative co-movements within a 2-4 months scale band, at high frequency (i.e., short-run), over 2022M1-2024M12, with arrows oriented to the left and upward, indicating that *expenditures* are leading. The increase in expenditures corresponds to later decreases in irregular flows, reflecting a possible quick corrective mechanism.

Consistent positive co-movements are observed in the fifth zone, over 2021M8-2024M6, with arrows pointing to the right and upward, indicating that *smuggled* leading, within 5-10 months scale band, at high frequency (i.e., short-run). This suggests that sudden surges in immigrant flows, peaking around late 2020 and likely facilitated by smugglers (Figure no. 1), may have driven subsequent adjustments in expenditures.

Positive co-movements are also reported in the sixth zone, over 2021M03-2022M02, within 16-18 months scale band, at medium frequency i.e., medium-run), with arrows pointed to the right and downward. Here, *expenditures* leads *smuggled*. This indicates delayed responses in irregular migration to policy or resource adjustments. Therefore, the medium-run adjustments indicate that expenditure policies may anticipate changes in irregular flows but also reflect delayed feedback effects, likely due to temporary constraints in financial resources.

Finally, Figure no. 3 illustrates the WTC plot of *log(total)* and *log(expenditures)* pair. Herein, four zones indicate intensive and significant co-movements, all at high frequency (i.e., short-run).

As in the previous cases, the first zone shows no conclusive co-movements from 2019M1 to 2019M5, at high frequency, within a scale band of up to 2 months (i.e., short-run), as the arrows are largely perpendicular to the OX axis.

Second zone covering 2022M1-2022M8, with 2-4 months scale band, at high frequency (i.e., short-run), partially coincides with that from Figure no. 3. Here, the arrows are pointed to the left and upward, indicating a negative co-movement, with *expenditures* leading. When expenditures increase slightly, migrant numbers tend to decline shortly after (within a few months). Hence, short-run spending may be reactive or deterrent, reducing flows with a lag. Similar negative co-movements are observed over 2023M12-2024M11, with *expenditures* leading, with 2-4 months scale band, at high frequency (i.e., short-run). Furthermore, as the frequency increases within the 4-8 month scale band, at high frequency (i.e., short-run), from 2023M6 to 2024M7, the arrows shift to the right and upward, indicating a positive lead-lag relationship with *total* leading. In this case, the changes in

migrant flows are followed by similar-direction adjustments in expenditures, the authorities responding to migration pressure, rather than preempt it.

In contrast, a consistent negative interaction between *total* and *expenditures* characterizes the fourth zone, within the 8-12 month scale band, at high frequency (i.e., short-run), from 2020M8 to 2023M11. Here, the arrows point to the left and upward, indicating that *expenditures* are leading. Higher (or increasing) expenditures are associated with subsequent reductions in migrant flows, consistent with Figure no. 1, where the sharp decline in spending precedes the surge in migration. Conversely, later adjustments in expenditures tend to precede subsequent declines in migrant flows.

Overall, the findings suggest that financial border management is neither purely preventive nor purely reactive but instead adjusts continuously in response to evolving migration pressures over the short and medium-run, with the direction and strength of this relationship varying across time and frequency. No long-run co-movements are reported.

4. ROBUSTNESS CHECKS

Robustness checks are conducted by: (1) applying an alternative method to wavelet coherence and (2) isolating the effects of the variables of interest using a partial wavelet approach with an extended set of controls.

(1) Wavelet Cohesion (WC) from Rua (2010) is computed to replicate all three-baseline WTC scenarios. WC provides a coherence measure $\rho_{x_n y_n}$ ranging from -1 to 1, calculated as follows:

$$\rho_{x_n y_n} = \frac{\Re(W_n^x W_n^y)}{\sqrt{|W_n^x|^2 |W_n^y|^2}} \tag{5}$$

Positive co-movement between the variables is signalled when $\rho_{x_n y_n}$nears +1, while values approaching −1 indicate negative co-movement. In all WC computed plots, blue and yellow colours denote negative and positive co-movement, respectively.

The WC results across all three scenarios are presented in Figures no. 5-7 (Annex). The WC results fully reinforce the WTC findings in both terms of significance and sign of co-movement, indicating that the relationship between migration flows and border mission expenditures is primarily short-run and time-varying, with most significant co-movements occurring at high frequencies (up to 12 months). A dominant negative relationship is observed mainly over 2022-2024 (2-4 months scale band) and 2020M8-2023M11 (8-12 months scale band), where expenditures lead and are followed by reductions in migration, suggesting a corrective effect. In contrast, positive co-movements emerge during 2021-2024 (5-10 months scale band) and 2023M6-2024M7 (4-8 months scale band), where migration flows lead expenditures, indicating reactive policy responses. The positive co-movements observed between 2021M03 and 2022M02, within 16-18 months scale band, at medium frequency (i.e., medium-run), remain also robust under the WC method in the case of 'smuggled - expenditures' nexus. Overall, the findings are not sensitive to WC tool and highlight a dual dynamic of proactive control and reactive adjustment in border management.

(2) Partial Wavelet Coherency (PWC) developed by Mihanović *et al.* (2009) is employed for each of three-baseline scenarios by alternatively considering as controls pandemic shock, regulatory shock, geopolitical risk, economic status, temperature and precipitations. By controlling for selected observable confounding factors, this approach helps reduce the potential influence of omitted-variable bias, complementing the baseline wavelet coherence analysis and strengthening the assessment of the relationships of interest. Specifically, PWC estimates the association between the primary variables after accounting for the effects of the selected control variables, thereby revealing their conditional co-movement across time and frequency.

Concretely, PWC allows isolating the relationship between two time series while controlling for the influence of one additional variable. In fact, the tool removes the effect of confounding variables, revealing the "pure" association between the two primary series. PWC has this form:

$$\left(RP_n^{yx_1x_2}\right)^2 = \frac{\left|RP_n^{yx_1} - RP_n^{yx_2}RP_n^{yx_{1*}}\right|^2}{\left[1-\left(RP_n^{yx_2}\right)^2\right]\left[1-\left(RP_n^{x_1x_2}\right)^2\right]} \quad (6)$$

where, x_2 represents the control variable being removed, which in this study is alternately one of the following: pandemic shock, regulatory shock, geopolitical risk, economic status or temperature. In all PWC plots, the colour scale for power ranges from deep blue (low coherence) to deep yellow (high coherence).

The PWC estimations across all three scenarios are presented in Figures no. 8-25 (Annex). In this case, the PWC plots in Figures no. 8-13, related to '*irregular* - *expenditures*' nexus, reveal that the negative co-movements running from *irregular* disappear over 2021M6-2024M2, within 8-12 months scale band, in the short-run, under *GPR*, *EPU*, *temp* and *precip* impact. This indicates that the results are sensitive to geopolitical, economic and weather-related factors. High geopolitical risk induces stricter border controls, while economic uncertainty drives policy shifts and particular changes in spending patterns. These findings are consistent with Hyndman (2012) and Moridian *et al.* (2024), highlighting the crucial role of these factors in shaping irregular migration. Extreme weather conditions also generate disruptions, affecting both irregular flows and border enforcement, thereby confirming the influential role of climate conditions in migration dynamics, as emphasized by Benveniste *et al.* (2025) and Yang *et al.* (2025).

Notably, the positive co-movements observed between 2023M11 and 2024M9, within the 5-7 month scale band at high frequency, with *irregular* leading, appear highly sensitive to *regulatory* control. The effect disappears once the *regulatory* variable is removed, coinciding with the implementation of the Schengen Borders Code in July 2024.

PWC plots in Figures no. 15-20 refer to the '*smuggled* - *expenditures*' nexus. The co-movements remain robust when the control variables are removed, with the exception of *precip*, in the medium-run, as shown in Figure no. 19. Heavy rainfall conditions can reduce mission expenditures as such weather disrupts smuggling routes and operations, thereby affecting irregular flows.

Finally, PWC plots in Figures no. 20-25 reflect the '*total* - *expenditures*' nexus. As in the previous case, the co-movements remain robust across various controls. Only the *regulatory* variable appears to have a distinct effect, exerting a notable influence on the relationship

between 2023M11 and 2024M9, coinciding with the implementation of the Schengen Borders Code. This highlights the particular role of this code in shaping smuggling activities.

Overall, the robustness checks confirm that the main findings are stable across alternative methods and model specifications. While the WC results validate the sign, timing and frequency of co-movements, the PWC analysis highlights that these relationships are partly shaped by geopolitical, economic, weather and regulatory factors. Together, these results underscore both the robustness of the core dynamics and the importance of controlling for external shocks in explaining migration - border mission expenditures linkages.

5. CONCLUSIONS AND POLICY IMPLICATIONS

Overall, the study reveals a predominantly short-run and time-varying interaction between irregular migration (irregular, smuggled and total) and border mission expenditures along the Serbian - Romanian frontier over January 2018 - April 2025. Most significant co-movements occur within the high-frequency domain, indicating that the relationship is largely driven by short-term dynamics rather than persistent long-run linkages.

At very short-run (≈ 2 months), the co-movements are often either inconclusive or dominated by rapid adjustments. This horizon reflects operational responses by border authorities (e.g., patrol deployment, surveillance adjustments), immediate detection of migration spikes, especially in smuggled flows, and limited time for strategic planning. Here, the system behaves almost like a real-time monitoring mechanism, where authorities react to observable inflows with minimal delay and smuggling networks also respond quickly to enforcement pressure.

The short-run dynamics (≈ 2-4 months) is one of the most prominent and consistent bands in the results. In this case, increased spending (e.g., enforcement, patrols) is followed by a decline in irregular or total flows, while sudden surges in irregular or smuggled migration trigger subsequent increases in spending. The mechanism is characterised by strategic interaction between authorities and migrants/smugglers. At 4-8 months scale, the relationship becomes more complex, with authorities adjust their spending after observing sustained migration pressure, but with smoothed or delayed responses, rather than immediate reactions. This is a transition from tactical response to resource reallocation**.** At superior band (≈ 5–10 months), smuggled migration leading expenditures (positive co-movement), indicating that migration pressures drive budgetary expansion with a lag. Here, authorities learn from repeated migration surges, recognizing the structural migration pressure, especially through smuggling networks. At 10-12 months scale, spending today is followed by reduced migration later, while migration spikes eventually induce budgetary increases. This horizon reflects administrative inertia, with enforcement begins to have measurable deterrent effects, but also reflects post-crisis adjustments (e.g., scaling up after migration surges).

Finally, at medium-run (16-18 month scale), there is a particular smuggled - expenditure relationship, indicating that policy interventions eventually influence migration patterns, but with a long delay. This horizon captures structural policy impacts**,** not just tactical responses.

The findings suggest that border management at the Serbian - Romanian frontier may benefit from a multi-horizon policy approach that reflects the temporal dynamics identified in the analysis. First, the predominance of short-run interactions, at high-frequency, indicates that migration flows and border mission expenditures respond rapidly to one

another. This pattern is consistent with the need for timely monitoring, early detection systems, rapid response capabilities, and flexible operational resource allocation. National border authorities and interior ministries, with operational and analytical support from EU agencies, including Frontex, could coordinate such measures.

Second, the observed lead-lag relationships, whereby migration surges are followed by subsequent adjustments in border expenditures, suggest that greater budgetary flexibility and adaptive planning may improve the responsiveness of border management. Rolling risk assessments, contingency funding mechanisms, and flexible staffing and procurement arrangements could help align operational resources with evolving migration pressures rather than relying solely on fixed annual planning cycles.

Third, the medium-run associations identified for smuggled migration indicate that structural policy measures may influence migration dynamics over longer time horizons. Although the present analysis does not establish causality, these patterns are consistent with the importance of sustained cross-border cooperation, intelligence sharing and coordinated action against migrant smuggling networks. Strengthening collaboration among national border authorities, judicial institutions, EU agencies such as Europol, Eurojust and Frontex, together with international organizations including the International Organization for Migration (IOM) and the United Nations High Commissioner for Refugees (UNHCR), may therefore contribute to addressing the structural dimensions of irregular migration.

6. LIMITS AND FUTURE DIRECTIONS OF RESEARCH

The study has several limitations. First, the analysis focuses solely on the Serbian - Romanian frontier, which may limit the generalizability of the findings to other migration corridors characterised by different institutional settings, enforcement capacities or geopolitical conditions. Second, although wavelet coherence and partial wavelet coherency identify dynamic associations, lead-lag relationships, and co-movements across time and frequency, they do not establish structural causal mechanisms. While partial wavelet coherency controls for selected observable confounders, other unobserved factors may still influence the estimated relationships. Third, the analysis relies on administrative data on irregular and smuggled migration flows and border mission expenditures, which may be subject to measurement error arising from underreporting, detection biases and changes in enforcement intensity. In particular, smuggled migration is inherently difficult to observe, as detected cases represent only a fraction of total smuggling activity. Finally, the use of aggregate indicators may mask heterogeneity across migrant groups, smuggling networks, border sectors, and categories of operational expenditure, potentially overlooking important micro-level dynamics.

Future studies could extend the framework to multiple border regions or migration routes to assess whether the identified time-horizon dynamics are consistent across different institutional and geopolitical contexts. Moreover, incorporating individual-level migration data, differentiated expenditure categories or detailed smuggling network information would allow for a more granular understanding of mechanisms driving the observed relationships. Not least, future research could combine wavelet-based approaches with causal identification strategies (e.g., instrumental variables, natural experiments or structural models) to better isolate the direction and magnitude of causal effects between migration flows and border expenditures.

ORCID

Mihai Mutascu https://orcid.org/0000-0003-3837-3243

References

Aguiar-Conraria, L., & Soares, M. J. (2011). Oil and the macroeconomy: Using wavelets to analyze old issues. *Empirical Economics, 40*, 645–655. http://dx.doi.org/10.1007/s00181-010-0371-x

Akkerman, M. (2023, May 31). Global spending on immigration enforcement is higher than ever and rising. *Migration Information Source*. Retrieved from https://www.migrationpolicy.org/journal/feature/global-spending-immigration-enforcement-higher-ever-and-rising

Angelucci, M. (2012). US border enforcement and the net flow of Mexican illegal migration. *Economic Development and Cultural Change, 60*(2), 311–357. http://dx.doi.org/10.1086/662575

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics, 131*(4), 1593–1636. http://dx.doi.org/10.1093/qje/qjw024

Benton, M., Batalova, J., Davidoff-Gore, S., & Schmidt, T. (2021). *COVID-19 and the state of global mobility in 2020*: International Organization for Migration.

Benveniste, H., Huybers, P., & Proctor, J. (2025). Global climate migration is a story of who and not just how many. *Nature Communications, 16*(1), 7752. http://dx.doi.org/10.1038/s41467-025-62969-3

Bier, D. J., Howard, M., & Salazar, J. (2023). *Immigrants' Recent Effects on Government Budgets: 1994–2023*. Retrieved from Washington, DC: https://www.cato.org/white-paper/immigrants-recent-effects-government-budgets-1994-2023#list-variables-fiscal-effects-model

Caldara, D., & Iacoviello, M. (2022). Measuring geopolitical risk. *American Economic Review, 112*(4), 1194–1225. http://dx.doi.org/10.1257/aer.20191823

Chi, G., Abel, G. J., Johnston, D., Giraudy, E., & Bailey, M. (2025). Measuring global migration flows using online data. *Proceedings of the National Academy of Sciences of the United States of America, 122*(18), e2409418122. http://dx.doi.org/10.1073/pnas.2409418122

Cusumano, E. (2019). Migrant rescue as organized hypocrisy: EU maritime missions offshore Libya between humanitarianism and border control. *Cooperation and Conflict, 54*(1), 3–24. http://dx.doi.org/10.1177/0010836718780175

D'Alfonso, A. (2021). *Migration and border management. Heading 4 of the 2021-2027 MFF*. Retrieved from www.europarl.europa.eu/RegData/etudes/BRIE/2021/690544/EPRS_BRI(2021)690544_EN.pdf

De Haas, H. (2015). Don't blame the smugglers: the real migration industry. *World Bank Blog*.

EC. (2025). *Western Balkans route*. Retrieved from https://www.consilium.europa.eu/en/policies/western-balkans-route

EUAS. (2025). *Asylum Report 2025*. Retrieved from https://www.euaa.europa.eu/sites/default/files/2025-06/AR2025-Annex-Statistical-tables.pdf

Facchini, I., & Testa, C. (2021). The rhetoric of closed borders: Quotas, lax enforcement and illegal immigration. *Journal of International Economics, 129*, 103415. http://dx.doi.org/10.1016/j.jinteco.2020.103415

Farge, M. (1992). Wavelet transforms and their applications to turbulence. *Annual Review of Fluid Mechanics, 24*, 395–458. http://dx.doi.org/10.1146/annurev.fl.24.010192.002143

Gathmann, C. (2008). Effects of enforcement on illegal markets: Evidence from migrant smuggling along the southwestern border. *Journal of Public Economics, 92*(10–11), 1926–1941. http://dx.doi.org/10.1016/j.jpubeco.2008.04.006

González-Leonardo, M., Rowe, F., Potančoková, M., & Goujon, A. (2025). Assessing the differentiated impacts of COVID-19 on immigration flows to Europe. *The International Migration Review, 59*(4), 2258–2273. http://dx.doi.org/10.1177/01979183241242445

Grinsted, A., Moore, J. C., & Jevrejeva, S. (2004). Application of the cross wavelet transform and wavelet coherence to geophysical time series. *Nonlinear Processes Geophys., 11*(5/6), 561–566. http://dx.doi.org/10.5194/npg-11-561-2004

Helbling, M., & Leblang, D. (2019). Controlling immigration? How regulations affect migration flows. *European Journal of Political Research, 58*(1), 248–269. http://dx.doi.org/10.1111/1475-6765.12279

Hyndman, J. (2012). The geopolitics of migration and mobility. *Geopolitics, 17*(2), 243–255. http://dx.doi.org/10.1080/14650045.2011.569321

INSSE. (2026a). TOX1332 - Tinta 3 - Mediu - Temperatura medie lunara/anuala la nivelul Romaniei. from National Institute of Statistics http://statistici.insse.ro/tempoins/index.jsp?page=tempo3&lang=ro&ind=TOX1332

INSSE. (2026b). TOZ1334 - Tinta 3 - Mediu - Cantitatea lunara/anuala de precipitatii la nivelul Romaniei. from National Institute of Statistics http://statistici.insse.ro/tempoins/index.jsp?page=tempo3&lang=ro&ind=TOZ1334

Jones, C., Lanneau, R., & Maccanico, Y. (2023). *Europe's techno borders*. Retrieved from https://euromedrights.org/wp-content/uploads/2023/07/EuroMed-Rights_Statewatch_Europe-techno-borders_EN-1.pdf

Jones, T. (2025). Record number of immigrants reside in EU in 2025. Retrieved from https://www.dw.com/en/record-number-of-immigrants-reside-in-eu-in-2025/a-76890285

Klein, J. D., Weber, I., & Zagheni, E. (2024). Stop, in the name of COVID! Using social media data to estimate the effects of COVID-19-related travel restrictions on migration. *Demography, 61*(2), 493–511. http://dx.doi.org/10.1215/00703370-11229946

Kuhnt, J. (2019). *Literature review: drivers of migration. Why do people leave their homes? Is there an easy answer? A structured overview of migratory determinants*. Retrieved from https://EconPapers.repec.org/RePEc:zbw:diedps:92019

MacKellar, L. (2022). The Smuggling of Migrants. In K. F. Zimmermann (Ed.), *Handbook of Labor, Human Resources and Population Economics*: Springer. http://dx.doi.org/10.1007/978-3-319-57365-6_88-1

Martinez, M. (2026). Number of immigrants in EU reaches record high of 64.2 million in 2025, study shows. *Reuters*.

Massey, D. S., Durand, J., & Pren, K. A. (2016). Why border enforcement backfired. *American Journal of Sociology, 121*(5), 1557–1600. http://dx.doi.org/10.1086/684200

Mihanović, H., Orlić, M., & Pasarić, Z. (2009). Diurnal thermocline oscillations driven by tidal flow around an island in the Middle Adriatic. *Journal of Marine Systems, 78*, S157–S168. http://dx.doi.org/10.1016/j.jmarsys.2009.01.021

Moridian, A., Radulescu, M., Kumar, P., Radu, M. T., & Mohammad, J. (2024). New insights on immigration, fiscal policy and unemployment rate in EU countries - A quantile regression approach. *Heliyon, 10*(13), e33519. http://dx.doi.org/10.1016/j.heliyon.2024.e33519

Mutascu, M., Strango, C., & Cumpanasu, I. (2026). *Irregular Migration at the Serbian-Romanian Frontier and Border Mission Expenditures*: International Migration & Integration. http://dx.doi.org/10.1007/s12134-026-01386-x

Pallister-Wilkins, P. (2017). Humanitarian rescue/sovereign capture and the policing of possible responses to violent borders. *Global Policy, 8*(S1), 19–24. http://dx.doi.org/10.1111/1758-5899.12401

Rua, A. (2010). Measuring comovement in the time–frequency space. *Journal of Macroeconomics, 32*(2), 685–691. http://dx.doi.org/10.1016/j.jmacro.2009.12.005

Ruda, E. (2025). *Migration in the EU: data, trends, and policy shifts in 2025*. Retrieved from https://immigrantinvest.com/reports/eu-migration-statistics

Suber, D. L. (2025). Smuggler's Adaptation Strategies to Border Enforcement. In A. Aliverti, A. C. Diener, & J. Hagen (Eds.), *Oxford Intersections: Borders* (pp. 0): Oxford University Press. http://dx.doi.org/10.1093/9780198945222.003.0042

Tazzioli, M. (2016). Border displacements: Challenging the politics of rescue between Mare Nostrum and Triton. *Migration Studies, 4*(1), 1–19. http://dx.doi.org/10.1093/migration/mnv042

TIBPT. (2025). Reports of Territorial Inspectorate of the Border Police Timisoara, officially compiled from the inspectorate's database. from Inspectoratul Teritorial Timișoara

UNODC (Producer). (2025). Irregular migration vs. migrant smuggling - what is the difference? Retrieved from https://www.unodc.org/unodc/en/frontpage/2025/January/irregular-migration-vs--migrant-smuggling--what-is-the-difference.html

Vallentine, J., Frouws, B., & Forin, R. (2025). *Mixed Migration Review 2025. Highlights. Interviews. Essays. Data*: Mixed Migration Centre.

Yang, X., Chen, D., Wahab, I., & Burman, A. (2025). Evidence of climate and economic drivers affecting migration in an unequal and warming world. *Communications Earth & Environment, 6*, 782. http://dx.doi.org/10.1038/s43247-025-02811-2

Zardo, F. (2025). Following AENEAS' Route: Unpacking Two Decades of Migration-Related Measures in EU Development Funds. *Journal of Immigrant & Refugee Studies, 23*(1), 16–33. http://dx.doi.org/10.1080/15562948.2024.2424163

ANNEX

Table no. A1 – Dataset description

Variable	Explanation	U.M.	Source
Border mission expenditures *(expenditures)*	Captures all mission-related public expenditures, encompassing travel, accommodation and per diem for officers deployed away from their regular posts. It also covers the costs for fuel, vehicles, equipment, communication, surveillance and other specialized operational tools necessary for the mission.	lei (constant prices)	TIBPT (2025)
Irregular immigrants *(irregular)*	Count of foreign nationals officially recorded as entering Romania without legal authorization.	persons	TIBPT (2025)
Smuggled immigrants *(smuggled)*	Measures the irregular immigrants officially recorded as having used paid smuggling services.	persons	TIBPT (2025)
Total irregular immigrants *(total)*	Calculated as the sum between number of officially identified irregular immigrants and smuggled immigrants.	persons	TIBPT (2025)
Pandemic *(pandemic)*	Dummy variable controlling for COVID-19 disease, coded 1 for March 2020 - May 2023 and 0 otherwise (the dates are officially declared pandemic period in Romania).	dummy	Constructed
New border code *(code)*	Dummy variable controlling for the new Schengen Borders Code, coded 1 for July 2024 - April 2025 and 0 otherwise.	dummy	Constructed
Geo-political risk *(GPR)*	Measures the intensity of global geopolitical tension at a given time, with values above 100 signalling elevated risk relative to the historical average.	index	Caldara and Iacoviello (2022)
Economic Policy Uncertainty *(EPU)*	Captures the level of economic policy uncertainty over time, calculated as the average for selected Western European countries (France, Germany, Greece, Ireland, Italy, Spain, the UK, and Sweden). Values above 100 signify elevated uncertainty, whereas values below 100 indicate reduced uncertainty.	index	Baker *et al.* (2016)
Temperature *(temp)*	Captures the monthly average temperature, in the Romania's Vest Region, comprising the counties Timis, Caras-Severin and Mehedinti.	C°	INSSE. (2026a)
Precipitations *(precip)*	Captures the monthly average of precipitations, in the Romania's Vest Region, comprising the counties Timis, Caras-Severin and Mehedinti.	millimetres	INSSE. (2026b)

Table no. A2 – Descriptive statistics

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Sum	Obs.
expenditures	97539.24	32485.12	406315.3	7675.766	108757.9	8583453	88
irregular	200.6932	107	986	0	218.1244	17661	88
smuggled	70.07955	28	637	0	107.148	6167	88
total	270.7727	152.5	1338	0	287.2543	23828	88
GPR	110.3448	105.365	318.95	58.42	39.19345	9710.34	88
EPU	230.8927	219.8548	581.7749	135.1105	73.97973	20318.56	88
temp	11.38125	11.415	23.9	-1.47	7.399371	1001.55	88
precip	56.51523	49.94	157.6	10.59	32.57673	4973.34	88

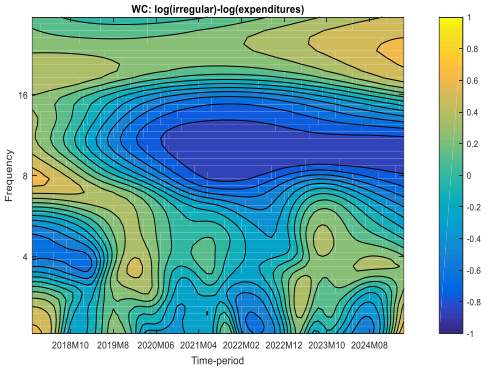


Figure no. 5 – WC of pair log(irregular) vs log(expenditures)

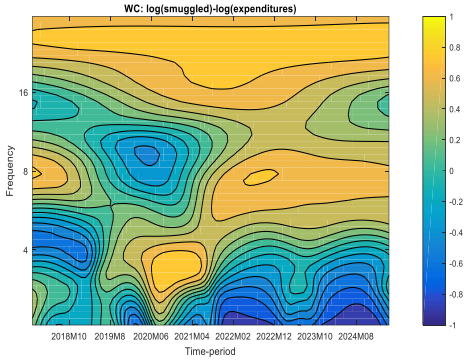


Figure no. 6 – WC of pair log(smuggled) vs log(expenditures)

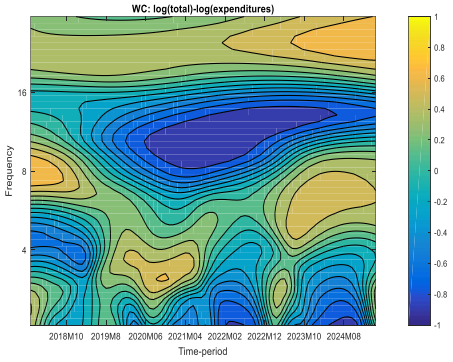


Figure no. 7 – WC of pair log(total) vs log(expenditures)

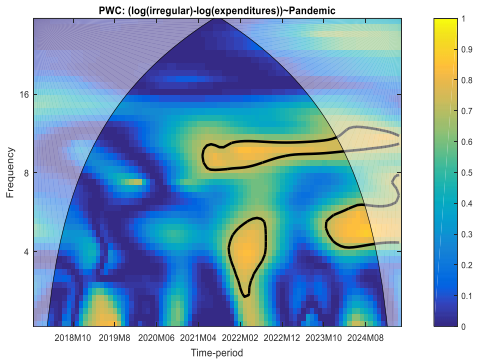


Figure no. 8 – PWC of pair log(irregular) vs log(expenditures), removing log(pandemic)

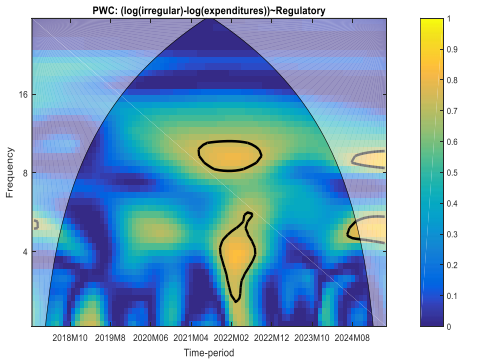


Figure no. 9 – PWC of pair log(irregular) vs log(expenditures), removing log(regulatory)

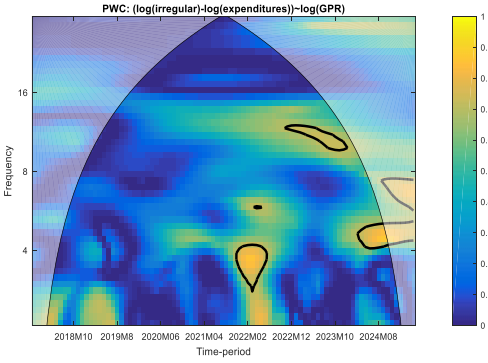


Figure no. 10 – PWC of pair log(irregular) vs log(expenditures), removing log(GPR)

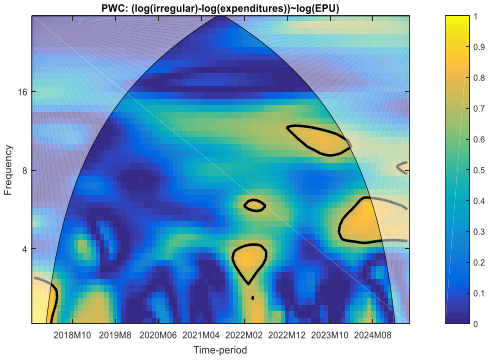


Figure no. 11 – PWC of pair log(irregular) vs log(expenditures), removing log(EPU)

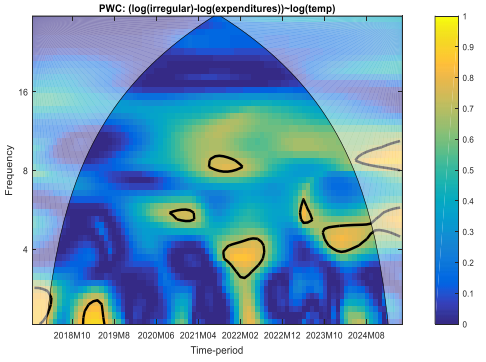


Figure no. 12 – PWC of pair log(irregular) vs log(expenditures), removing log(temp)

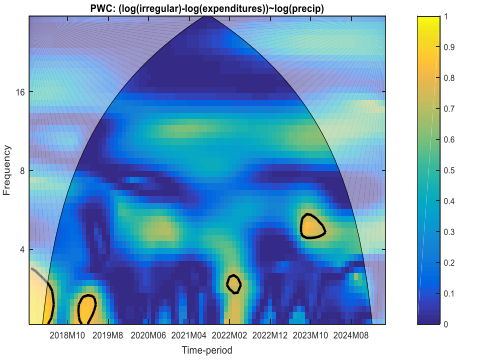


Figure no. 13 – PWC of pair log(irregular) vs log(expenditures), removing log(precip)

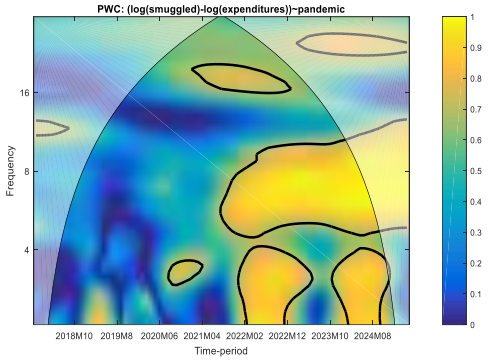


Figure no. 14 – PWC of pair log(smuggled) vs log(expenditures), removing log(pandemic)

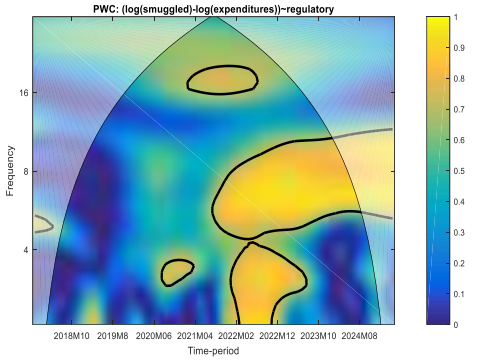


Figure no. 15 – PWC of pair log(smuggled) vs log(expenditures), removing log(regulatory)

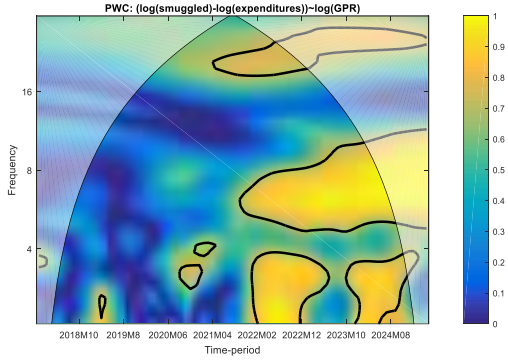


Figure no. 16 – PWC of pair log(smuggled) vs log(expenditures), removing log(GPR)

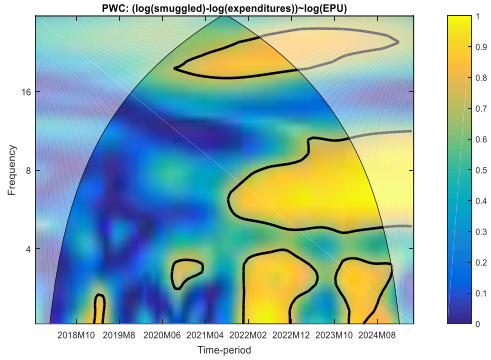


Figure no. 17 – PWC of pair log(smuggled) vs log(expenditures), removing log(EPU)

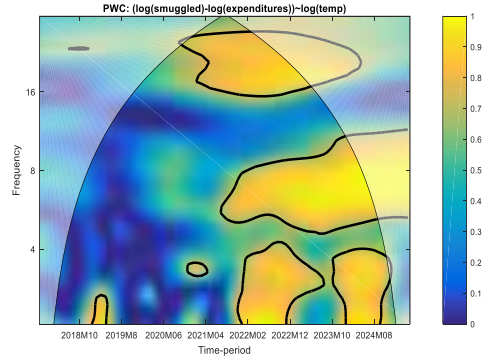


Figure no. 18 – PWC of pair log(smuggled) vs log(expenditures), removing log(temp)

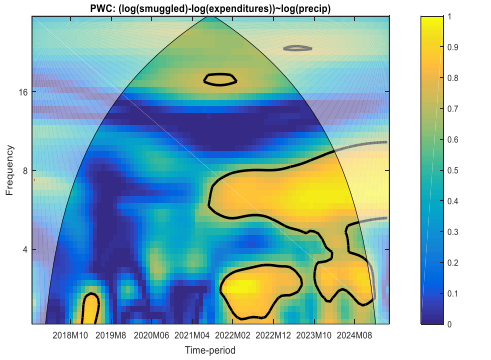


Figure no. 19 – PWC of pair log(smuggled) vs log(expenditures), removing log(precip)

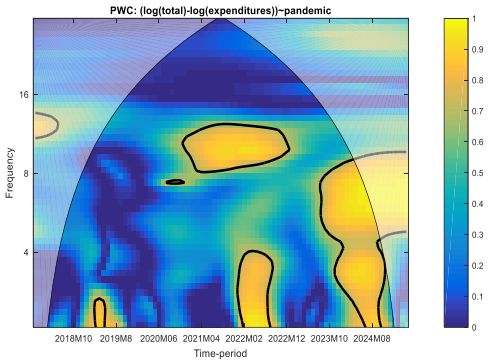


Figure no. 20 – PWC of pair log(total) vs log(expenditures), removing log(pandemic)

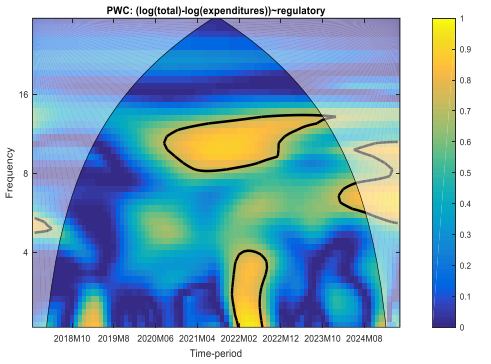


Figure no. 21 – PWC of pair log(total) vs log(expenditures), removing log(regulatory)

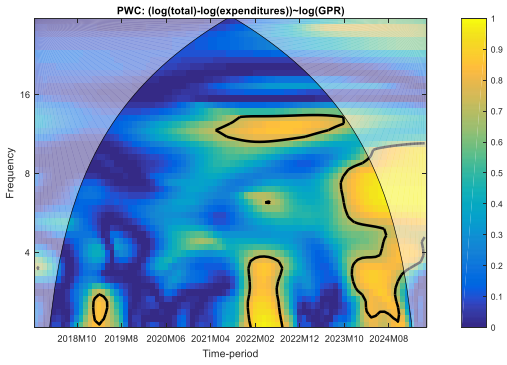


Figure no. 22 – PWC of pair log(total) vs log(expenditures), removing log(GPR)

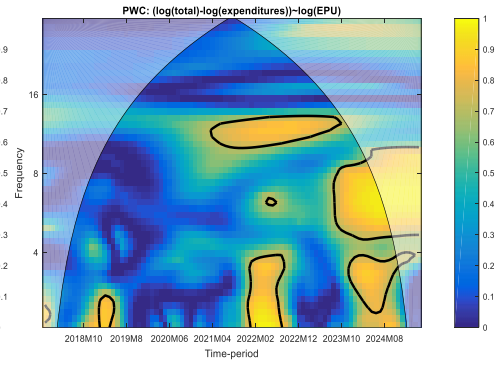


Figure no. 23 – PWC of pair log(total) vs log(expenditures), removing log(EPU)

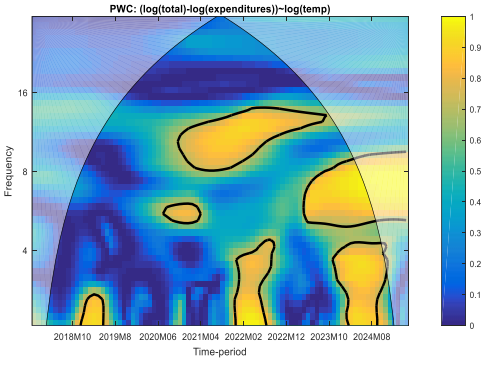


Figure no. 24 – PWC of pair log(total) vs log(expenditures), removing log(temp)

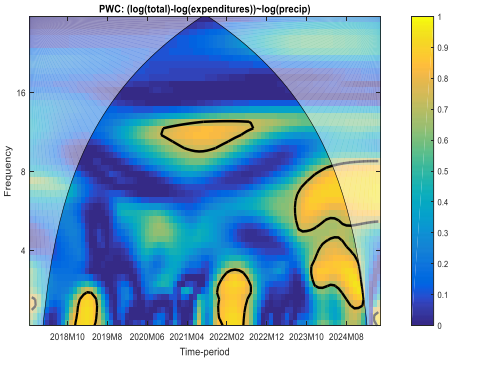


Figure no. 25 – PWC of pair log(total) vs log(expenditures), removing log(precip)

Scientific Annals of Economics and Business
73 (3), 2026, 641-655
DOI: 10.47743/saeb-2026-0037

Organisational Capacity and Membership: An Analysis of Professional Associations of Economists in Spain

Eduardo Infante Rejano[*], **Asunción Rodríguez-Ramos**[**], **Maria Claudia Scurtu Tura**[***]

Abstract: Professional associations play a central role in regulating, training and collectively representing modern economies. However, research has documented a long-term decline in membership and participation across many such organisations, which raises concerns about their sustainability and future relevance. This study examines the relationship between internal organisational capabilities and membership size among professional associations of economists in Spain. Using a quantitative cross-sectional design (N = 23) and an Ordinary Least Squares (OLS) model estimation, the analysis explores the association between membership size and five key organisational variables: administrative capacity, training activity, digital presence, sex composition, and number of professional associations within the school. The findings indicate a positive and statistically significant association between technical-administrative staffing and membership size; the remaining variables, meanwhile, do not show statistically significant effects. This exploratory and associative study contributes to the literature by shifting the analytical focus from individual motivations to the structural constraints of organisational supply.

Keywords: professional associations; organisational capacity; membership; econometric analysis; institutional management.

JEL classification: C21; L31; J44.

[*] Universidad de Sevilla, Spain; e-mail: *einfante@us.es*.
[**] Universidad de Sevilla, Spain; e-mail: *asunrod@us.es*.
[***] Universidad de Sevilla, Spain; e-mail: *mscurtu@us.es* (corresponding author).

Article history: Received 21 March 2026 | Accepted 15 September 2026 | Published online 29 September 2026

To cite this article: Infante Rejano, E., Rodríguez-Ramos, A., Scurtu Tura, M.C. (2026). Organisational Capacity and Membership: An Analysis of Professional Associations of Economists in Spain. *Scientific Annals of Economics and Business*, 73(3), 641-655. https://doi.org/10.47743/saeb-2026-0037.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

Professional associations are a fundamental institutional mechanism for organising professions. They regulate access to professional practice, provide ongoing professional development, represent collective interests, and promote a sense of professional identity. Therefore, membership numbers are an important indicator not only of organisational success, but also a determinant of institutional legitimacy and financial sustainability. In recent decades, numerous studies have documented a stagnation or decline in membership rates across various professional sectors (Wang and Ki, 2018; Naidoo and Rajcoomar, 2020; Friedman and Afitska, 2023; Jeza, 2025; Mickevičiūtė, 2026). This phenomenon is linked to structural changes, such as the individualisation of career paths and evolving professional expectations, as well as the proliferation of alternative digital socialisation and networking platforms (Stevens *et al.*, 2023). This has made analysing membership an empirical priority for both academic research and organisational management, particularly for organisations whose only source of income is non-recurring, such as professional associations (Wang and Ki, 2018).

The existing literature mainly addresses this phenomenon from a demand perspective, focusing on individual motivations for joining and remaining in professional associations (Deleskey, 2003; Ki and Wang, 2016). However, this approach implicitly assumes that organisations have homogeneous capacities to generate institutional value, ignoring the structural constraints that condition their internal functioning.

This paper adopts an alternative perspective, focusing on the organisational aspects of institutional supply. It is based on the assumption that a structural determinant of an association's ability to attract, retain and sustain members is its internal capacity, expressed in terms of human resources, administrative infrastructure and management professionalisation. The study's objective is to analyse the relationship between internal organisational capacity and membership size in professional associations of economists in Spain. In line with this objective, the study addresses the central research question: What organisational characteristics explain the differences in membership size between professional associations?

2. REVIEW OF THE LITERATURE

2.1. Demand-centred approaches: perceived benefits and membership decisions

A wide range of literature has analysed membership decisions from the perspective of the perceived benefits to individuals. Evidence shows that professional development opportunities, networking and career-related benefits can substantially influence individuals' intentions to join and remain in professional associations (Ki and Wang, 2016; Taylor *et al.*, 2018). Similarly, Deleskey (2003) found that decisions to join professional associations depend on the perceived relevance of the services offered, as well as the usefulness of professional representation and promotional activities. Members develop a more favourable attitude towards their association when they perceive that their needs are being met and that they are receiving support from the organisation (White and Olson, 2004). This positive attitude translates into greater commitment, as evidenced by participation in volunteering activities and a willingness to donate. Similarly, perceived organisational support has been found to be associated with higher levels of member involvement (Wang and Ki, 2018).

These studies consolidate an approach focused on membership demand, whereby affiliation is explained as the result of individual cost-benefit assessment processes. However, this approach does not directly address the organisational constraints that affect the effective provision of these benefits.

2.2. Organisational capacity, participation and commitment

From sociological and organisational perspectives, associative participation is closely linked to internal structural factors (Hagedorn and Labovitz, 1967). Organisational capacity influences the ability to coordinate activities, manage communication, maintain stable relationships with members, and sustain long-term commitment dynamics. Recent studies suggest that insufficient organisational adaptation and internal resource constraints are often associated with declining membership (Stevens *et al.*, 2023). From a relational marketing perspective, effective participation requires professional management structures and sustained organisational efforts (Vincent and Webster, 2013).

2.3. Organisational determinants of membership growth

Empirical research on institutional growth suggests that internal organisational characteristics are more important than external visibility. Goldman *et al.* (2016) argue that membership growth depends on a combination of service quality, organisational engagement and institutional capacity. Recent research reinforces this thesis by emphasising the importance of participation and organisational engagement for the sustainability of professional associations (Rodríguez-Rad and Sánchez del Rio-Vázquez, 2023; Fernandez and Castellanos, 2024).

Taken together, this body of work shifts the analytical focus progressively from individual factors to organisational determinants of membership, although a fully integrated structural theoretical framework has yet to be articulated.

3. THEORETICAL FRAMEWORK

From the perspective of contemporary organisational theory, professional associations can be conceptualised as organisations that are intensive in terms of relational resources, institutional capital, and management capabilities. In this framework, organisational capacity is a strategic asset that influences the coordination of activities, the provision of services, the management of member relations, and institutional sustainability, rather than merely an operating cost. The dynamic capabilities perspective reinforces this view by conceptualising the administrative structure as a mechanism for converting resources into institutional value. Agustí-Pérez *et al.* (2025) show that associations that develop adaptive internal capabilities simultaneously strengthen their institutional legitimacy and organisational competitiveness, thereby consolidating the administrative structure as strategic infrastructure.

From an organisational institutionalist perspective, administrative capacity acts as a mechanism for institutional stabilisation. Bolleyer (2024) conceptualises membership associations as organisations characterised by tensions between professionalisation, governance, and representation. In these organisations, the internal structure supports legitimacy and professional authority. In the field of non-profit organisations and sectoral

associations, Frasier (2025) identifies structural barriers to membership associated with resource scarcity, administrative inadequacy, and organisational limitations. This supports the idea that institutional supply constraints influence membership growth. Similarly, literature on perceived organisational support shows that internal structure directly influences member behaviour. Wang and Ki (2018) illustrate that organisational support and the quality of internal management predict commitment, active participation, and membership retention. This suggests an association between organisational capacity and membership behaviour.

Finally, studies on digital practices and organisational engagement suggest that digitalisation is a complementary factor to, rather than a substitute for, core organisational capacity. Although digital tools can improve communication, participation and the exchange of information, they are only effective when established organisational structures, governance mechanisms and managerial capabilities are in place. In this sense, digitalisation amplifies existing capacities rather than compensating for their absence. This argument aligns with broader research on digital transformation, which highlights the importance of organisational readiness and complementary resources (Singh *et al.*, 2025). Similarly, Potnis *et al.* (2024) found that information practices only generate sustained organisational effects when supported by robust institutional and managerial foundations. These findings suggest that, to understand the dynamics of membership in professional associations, it is essential to examine both their digital practices and the organisational capacities that underlie them.

4. THEORETICAL EXPECTATION AND RESEARCH HYPOTHESIS

Building on Resource Dependence Theory and Institutional Theory, this study argues that the ability of professional associations to attract and retain members depends not only on individual motivations but also on their internal organisational capacity. Organisations with stronger administrative structures, greater managerial resources, and more developed organisational capabilities are better positioned to provide higher-quality services, strengthen institutional legitimacy, and enhance their capacity to recruit and retain members.

In this study, internal organisational capacity is conceptualised as a multidimensional construct represented by several complementary organisational indicators rather than as a single observable characteristic. Accordingly, the empirical model estimates the joint contribution of these indicators to explain variation in membership size across professional associations.

Based on this theoretical framework, the following hypothesis is proposed:

***H1**: Higher levels of internal organisational capacity are positively associated with the membership size of professional associations.*

Thus, the empirical analysis evaluates whether multiple organisational indicators representing a single multidimensional construct - internal organisational capacity - collectively explain differences in membership across professional associations.

5. METHODOLOGY

5.1. Design and sample

Data cleaning and sample reduction

A quantitative cross-sectional design was employed, with the professional association of economists as the unit of analysis. Data were obtained from public administrative records and official institutional sources. Initially, information was collected from all 39 professional associations of economists in Spain. Seven associations were excluded because they corresponded to duplicated institutional records, leaving 32 unique professional associations.

Data completeness was evaluated prior to model estimation. Missing data accounted for less than 5% of the overall variable matrix. However, these missing values were concentrated within nine associations, primarily because key administrative, staffing, or training information was not publicly disclosed. Consequently, complete-case analysis (listwise deletion) resulted in the exclusion of these nine associations, yielding a final analytical sample of 23 associations.

Listwise deletion was preferred over data imputation because imputing institutional-level variables in a relatively small sample could introduce artificial covariance structures and underestimate standard errors. Nevertheless, because the excluded associations lacked sufficient publicly available information to construct all study variables, the possibility of selection bias cannot be completely ruled out. Accordingly, the findings should be interpreted as representative of professional associations with sufficient publicly available information rather than the entire population of associations.

Sample coverage. The final analytical sample consists of 23 professional associations, representing 71.8% of the 32 independent professional associations initially identified after removing duplicated institutional records. Although some associations were excluded because complete information was unavailable, the final sample provides broad coverage of the eligible population and includes professional associations from all major geographical areas of Spain.

5.2. Data processing and refinements

Information on various structural and institutional factors was collected as explanatory variables. In total, nine quantitative variables were considered. A preliminary analysis of these variables was carried out to select the most appropriate ones and to minimise the risk of overfitting, given the small sample size.

Variable definition

Logarithmic transformations were applied to the volume variables to reduce the influence of extreme values and improve model stability.

Dependent variable:

v1. Absolute number of registered members: total number of active professionals registered in the association, representing organisational size. The dependent variable is expressed in logarithms to reduce dispersion and mitigate heteroscedasticity problems.

Explanatory variables:

v2. Relative number of members (Territorial Affiliation Rate): the percentage of all eligible professionals within the Association's geographical area who are formally registered members. This is calculated as the ratio of active members in the association to the theoretical average of new graduates in economic fields (Economics, ADE, etc.) that each Economists Association in Spain could potentially recruit[1].

v3. Sex composition of members: The proportion of female members relative to total registered members, expressed as a percentage. Because official public directories provided member names without explicit demographic indicators, an automated AI-assisted name-classification algorithm was used to assign binary demographic sex based on first-name registries. Later, this algorithmic classification has been manually validated against official public administration sex records.

v4. Number of professional associations within the school: Counts the number of societies or firms composed of economists that, under Law 2/2007 on Professional Societies, are required to register with professional associations when carrying out a joint professional activity. It is recorded as a direct numerical value based on the lists available on each association's website.

v5. Diversity of presence on digital channels: refers to the organisation's digital channels for disseminating content beyond the main website. It is measured by directly counting the number of potentially usable high-reach platforms (Facebook, Instagram, Twitter/X, LinkedIn, YouTube, RSS or webmail).

v6. Number of employees and technical/administrative staff at the association: represents the total number of contracted staff (technical and administrative) involved in its daily operations. This figure is usually listed in the 'Structure' section of the association's website.

v7. Number of courses, seminars or conferences offered in the last year: refers to the number of training and continuing professional development (CPD) activities organised by the Association in the last year. It includes the total number of training activities, seminars, or specialised conferences offered during the year 2024**.**

v8. Number of specialised certifications or registrations managed: represents the number of specialised professional registers (such as REAF for tax advisers or REA for auditors) managed and reported by the Association.

v9. Number of agreements or conventions signed: refers to the total number of formal agreements or collaborations established between the Association and external entities (public administrations, universities, or private companies), such as agreements with the DGT for traffic-related administrative procedures.

These variables capture structural, strategic, and organisational dimensions emphasised in the literature. From a preliminary analysis of the explanatory variables, a logarithmic transformation was applied to those with a high degree of dispersion. Likewise, variable 8, which contains many null values, and variable 9**,** which shows a high correlation with variables 3 and 7**,** were excluded from the final analysis.

5.3. Descriptive statistics

Table no. 1 shows the descriptive statistics for the study variables. The average female representation is 29.18%**,** with values ranging from a residual minimum of 0.13% to almost half

of the registered members (46%). In the digital sphere, the institutions show a relatively diversified presence, with an average of 3.91 platforms out of the six considered. However, the most notable feature of the table is the high dispersion in collective and structural reach (v4).

The number of professional associations shows a standard deviation (15.42) that is more than double the mean (6.39), revealing a pronounced asymmetry between associations that appear to focus mainly on individual membership and those that manage up to 67 professional associations. This variability highlights significant differences in organisations' structural capacity to provide network support to their members (Lv1), the logarithmic mean of which is 6.99. Table no. 1 presents the descriptive statistics for the variables included in the analysis.

Table no. 1 – Descriptive statistics

Variable	Min	Max	Mean	SD
Lv1	5.86	9.05	6.99	0.93
v3	0.13	46	29.18	12.42
v4	0.00	67	6.39	15.42
v5	0.00	6	3.91	1.31
Lv2	3.98	7.17	5.12	0.93
Lv6	2.08	3.53	2.69	0.45
Lv7	0.69	5.56	3.74	1.34

Notes: SD = standard deviation; N (sample size) = 23.
Source: authors' elaboration

5.4. Correlation analysis

A correlation analysis was conducted prior to model estimation to examine bivariate relationships and identify potential multicollinearity issues among the variables. Table no. 2 presents the Pearson correlation matrix, including the dependent variable (Lv1) and all candidate explanatory variables.

Table no. 2 – Correlation matrix

Variable	Lv1	v3	v4	v5	Lv2	Lv6	Lv7
Lv1	–						
v3	.449*	–					
v4	-.189	-.477*	–				
v5	.633**	.610**	-.225	–			
Lv2	1**	.449*	-.189	.633**	–		
Lv6	.829**	.359	.089	.596**	.829**	–	
Lv7	.698**	.690**	-.333	.643**	.698**	.653**	–

Notes: N = 23. Values are Pearson's correlation coefficients. *p < .05 (two-tailed). **p < .01 (two-tailed).
Source: authors' elaboration

The dependent variable, total membership size (Lv1), shows a strong and statistically significant positive correlation with technical-administrative staff (Lv6; r = .829, p < .01), training activity (Lv7; r = .698, p < .01), and digital presence (v5; r = .633, p < .01). A moderate positive correlation is also observed with sex composition (v3; r = .449, p < .05), while the association with structural reach (v4; r = -.189, p > .05) is weak and not statistically significant.

Among the explanatory variables, training activity (Lv7) correlates moderately to strongly with sex composition (v3; $r = .690$, $p < .01$), digital presence (v5; $r = .643$, $p < .01$), and technical-administrative staff (Lv6; $r = .653$, $p < .01$), suggesting a degree of overlap between organisational capacity indicators. Structural reach (v4) is the only variable displaying negative associations throughout the matrix, most notably with sex composition (v3; $r = -.477$, $p < .05$), indicating that associations with a larger number of affiliated professional bodies tend to report a lower proportion of female members.

Overall, correlation coefficients among the explanatory variables remain below the conventional threshold of concern for multicollinearity ($r < .80$), with the exception of the relationship between Lv1 and Lv2.

5.5. Research model

Due to the small sample size, a parsimonious model specification has been adopted, selecting only the variables that are most theoretically relevant and least statistically redundant. Indicators of organisational capacity, training activity, demographic composition and digital strategy are included, while highly correlated variables that could introduce multicollinearity issues are excluded.

The estimated model was as follows:

$$Lv1 = \beta 0 + \beta 1Lv6 + \beta 2Lv7 + \beta 3v3 + \beta 4v4 + \beta 5v5 + \varepsilon$$

The model was estimated using ordinary least squares (OLS).

5.6. Diagnostic Tests

To assess the validity of the regression estimates, several diagnostic tests were performed.

Multicollinearity: Variance inflation factors (VIFs) for all explanatory variables were below the conventional threshold of 5, indicating no evidence of problematic multicollinearity.

Normality of residuals: The Shapiro–Wilk test did not provide evidence to reject the null hypothesis of normality ($W = .932$, $p = .120$), indicating that the residuals did not significantly depart from a normal distribution.

Homoscedasticity: Visual inspection of the residual-versus-fitted plot revealed no obvious evidence of heteroscedasticity. This assessment was further supported by the Breusch–Pagan test, which did not reject the null hypothesis of homoscedasticity ($F = 2.502$, $p = .071$) although the result was close to the conventional threshold and should therefore be interpreted with some caution.

Overall model significance: The statistical significance of the regression model was assessed using the F-test. All analyses were conducted using IBM SPSS Statistics 29.

6. RESULTS

Table no. 3 – Estimation results

Model summary

R	R^2	Adjusted R^2	Std. Error
.877	.770	.702	.50803

Notes: Predictors: v4, Lv6, v3, v5, Lv7. Dependent variable: Lv1

Source: authors' elaboration

The model shows a strong multiple correlation coefficient (R = .877) and explains a substantial proportion of the variance in total membership size, with an R^2 of .770. After adjusting for the number of predictors relative to sample size, the adjusted R^2 remains high at .702, indicating that the five explanatory variables jointly account for approximately 70% of the variance in the dependent variable (Lv1). The standard error of the estimate (.508) reflects the average deviation between observed and predicted values on the log scale.

Table no. 4 – ANOVA results

Model	SS	df	MS	F	Sig.
Regression	14.676	5	2.935	11.372	<.001
Residual	4.388	17	.258		
Total	19.063	22			

Notes: SS = Sum of Squares; df = Degrees of Freedom; MS = Mean Square; F = F-statistic; Sig. = Significance
Source: authors' elaboration

The ANOVA results confirm that the overall regression model is statistically significant ($F(5, 17) = 11.372$, $p < .001$), indicating that the set of predictors, taken together, explains a significantly greater share of variance in membership size than would be expected by chance. However, given the small sample size (N = 23) relative to the number of predictors (five), this high explanatory power should be interpreted with caution, as it may partly reflect sample-specific overfitting rather than a stable population-level relationship.

Table no. 5 presents the individual contribution of each predictor to the model. Among the five explanatory variables, technical-administrative staff (Lv6) is the only statistically significant predictor of membership size (B = 1.489, SE = .378, 95% CI [.691, 2.287], β = .721, t = 3.943, p = .001). Given the log–log specification of the model, this coefficient can be interpreted as an elasticity: on average, a 1% increase in technical-administrative staff is associated with an estimated 1.49% increase in total membership. The standardised coefficient (β = .721) indicates that Lv6 is, by a wide margin, the strongest predictor in the model.

None of the remaining predictors reach statistical significance at conventional thresholds:

Structural reach (v4) shows a negative but non-significant association with membership size (B = -.013, β = -.219, t = -1.517, p = .148). The 95% confidence interval [-.032, .006] includes zero, so this relationship cannot be confirmed with the available data.

Training activity (Lv7) shows a small positive but non-significant effect (B = .092, β = .132, t = .630, p = .537).

Sex composition (v3) shows an effect close to zero and non-significant (B = -.006, β = -.075, t = -.408, p = .688).

Digital presence (v5) likewise shows a small positive but non-significant effect (B = .082, β = .115, t = .669, p = .513).

In all four non-significant cases, the 95% confidence intervals for B cross zero, confirming the lack of a reliable linear association with membership size once the effect of the other predictors is held constant.

Overall, the results suggest that, within this model, internal organisational capacity - as captured specifically by technical-administrative staffing levels - is the dominant driver of membership size, while training activity, sex composition, digital presence, and structural reach do not contribute significant explanatory power once Lv6 is accounted for.

Table no. 5 – OLS Regression Results

Predictor	B	SE	95% CI for B [Lower, Upper]	β	t	p
Constant	2.579	.700	[1.102, 4.056]	-	3.684	.002
v3	-.006	.014	[-0.036, 0.024]	-.075	-.408	.688
v5	.082	.122	[-0.175, 0.339]	.115	.669	.513
Lv6	1.489	.378	[0.691, 2.287]	.721	3.943	.001
Lv7	.092	.145	[-0.214, 0.398]	.132	.630	.537
v4	-.013	.009	[-0.032, 0.006]	-.219	-1.517	.148

Notes: Dependent variable: Lv1; B = unstandardised coefficient; SE = Std. Error; β = standardised coefficient.
Source: authors' elaboration

6.1 Robustness analysis

To assess whether the results were influenced by regional differences in the size of the economist population, an auxiliary robustness analysis was performed using the **Affiliation Rate (v2)** as an alternative dependent variable. This variable measures the proportion of economists affiliated with the regional professional association, thereby normalizing membership by the total number of economists in each region. The same set of explanatory variables used in the baseline model was retained to evaluate the consistency of the estimated relationships.

As shown in Table no. 5, the auxiliary model remains statistically significant ($F = 5.520$, $p = 0.003$; $R^2 = 0.619$). Most importantly, the main explanatory variable (Lv6) continues to exhibit a positive and statistically significant association with the affiliation rate ($\beta = 0.701$, $p = 0.008$), while the remaining predictors do not materially alter the substantive conclusions. These findings indicate that the main results are not driven by regional differences in the size of the underlying population of economists and therefore support the robustness of the baseline model.

Table no 6 – Auxiliary OLS Regression Results

Predictor	B	SE	95% CI for B [Lower, Upper]	β	t	p
Constant	-1242.691	330.158	[-1939.264, -546.118]	–	-3.764	.002
v3	2.573	6.489	[-11.116, 16.263]	.094	.397	.697
v4	-2.259	4.117	[-10.945, 6.427]	-.102	-.549	.590
v5	-23.711	57.617	[-145.273, 97.851]	-.091	-.412	.686
Lv6	531.089	178.086	[155.360, 906.817]	.701	2.982	.008
Lv7	33.157	68.515	[-111.397, 177.711]	.130	.484	.635

Notes: Dependent variable: v2; B = unstandardised coefficient; SE = Std. Error; CI = Confidence Interval. β = standardised coefficient.
Source: authors' elaboration

Table no. 6 presents the results of the auxiliary regression model, in which the affiliation rate (v2) replaces total membership size as the dependent variable, in order to assess whether the main findings are driven by regional differences in the underlying population of economists. Consistent with the baseline model, technical-administrative staff (Lv6) remains the only statistically significant predictor (B = 531.089, SE = 178.086, 95% CI [155.360, 906.817], β = .701, t = 2.982, p = .008). The standardised coefficient (β = .701) is very close to that obtained in the main model (β = .721 for Lv6 in Table no. 4), indicating a consistent

pattern across specifications. Taken together, the auxiliary model reproduces the substantive pattern of the baseline analysis, with organisational capacity (Lv6) emerging as the sole significant driver, and no material change in the sign, magnitude, or significance ranking of the remaining predictors.

7. DISCUSSION

This study examined the relationship between the organisational capacity of professional associations of economists in Spain and their membership size. The results suggest a positive correlation, showing that associations with greater internal resources tend to have larger membership bases. This finding is consistent with theoretical approaches suggesting that organisational management constitutes a strategic organisational capacity rather than merely an administrative function. One possible explanation is that larger staff structures allow for more effective administration, service delivery, and member support. Alternatively, larger associations may generate greater financial resources, enabling them to employ more staff. However, the cross-sectional design of this study does not allow these alternative explanations to be fully explored, and it is not possible to establish causal relationships conclusively. Nevertheless, these results are consistent with previous research emphasising the importance of organisational resources in sustaining member participation and institutional functioning (Vincent and Webster, 2013; Ki and Wang, 2016; Stevens *et al.*, 2023). Overall, the findings support existing theoretical expectations regarding organisational capacity, even though the underlying mechanisms remain unclear.

The lack of statistical significance in terms of training activity and digital presence may be explained by the concept of supply saturation. Once professional associations offer broadly similar training programmes and have an online presence, these services no longer differentiate organisations in terms of membership size. In other words, such offerings no longer provide a competitive or strategic advantage once they become standard practice. This is consistent with the argument that organisational growth may be associated with both the range of services offered and the extent to which these services are integrated with internal capabilities, such as administrative efficiency, member engagement mechanisms, and strategic planning (Singh *et al.*, 2025).

Similarly, the absence of a statistically significant effect of sex composition suggests that the overall growth dynamics of professional associations are driven primarily by structural and managerial factors rather than workforce demographics. While sex diversity may influence organisational culture, collaboration patterns or decision-making styles, these factors do not appear to be associated with differences in aggregate membership size. This finding suggests that variation in membership size is more closely associated with institutional and managerial capacities than with workforce demographic composition. It is important to note that non-significant results do not imply that these factors are unimportant. For example, training activities may be more closely associated with member satisfaction, retention or engagement - outcomes that are not directly captured by overall membership size. Similarly, a digital presence may be associated with improved communication and engagement without necessarily causing an immediate increase in membership. These interpretations are consistent with previous research emphasising the importance of participation behaviour and organisational commitment rather than activity volume alone (Beaton, 2010; Rodríguez-Rad and Sánchez del Rio-Vázquez, 2023). While sex composition does not appear to influence

total membership size, it may affect other organisational performance dimensions, such as governance quality, representativeness and inclusivity. However, these were beyond the scope of this study.

7.1. Theoretical implications

From a theoretical perspective, these findings provide support for organisational-level explanations of professional association membership. They imply that strategies centred solely on individual motivations or perceived advantages could overlook the structural limitations and institutional capabilities that influence membership outcomes. Thus, internal organisational capacity emerges as a crucial determinant of membership size, emphasising the importance of considering strategic and managerial factors, as well as individual-level motivations, in the study of professional associations.

7.2. Practical implications

From a practical standpoint, the results suggest that associations may be able to maintain or grow their membership by strengthening their internal organisational capacity. However, this should not be interpreted as a recommendation for the indiscriminate expansion of staff or resources. Rather, the results emphasise the importance of aligning organisational resources with strategic objectives related to service provision, member engagement and institutional functioning. Associations should focus on effectively integrating staff, financial and managerial resources to support sustainable growth.

Finally, due to the cross-sectional design and the potential for reverse causality, these findings should be considered indicative of associations rather than indicating causal relationships. Future research using longitudinal or experimental designs could provide further insight into the causal mechanisms linking organisational capacity and membership size.

7.3. Methodological limitations

This study has several structural limitations that should be acknowledged. Endogeneity and reverse causality. It is plausible that there is a bidirectional relationship between organisational capacity and membership size. Organisations with larger memberships may have greater financial resources, enabling them to expand their administrative structures. This creates potential simultaneity bias in the OLS estimates. The absence of valid instruments and longitudinal data prevents causal identification.

Cross-sectional design: The lack of longitudinal data precludes analysis of temporal dynamics and organisational adjustment processes, limiting findings to static associations.

Sample size and selection bias. Although the sample represents a substantial proportion of active professional associations, the final analytical sample was limited to N = 23 due to complete-case (listwise deletion), as some organizations did not publicly disclose the administrative, staffing, or training information required to construct all study variables. This reduction from 32 to 23 associations may have introduced selection bias if excluded organizations differ systematically from those included, limiting the representativeness of the findings to associations with sufficient publicly available information. In addition, the small sample size provides limited statistical power and a low cases-to-predictor ratio

(approximately 4.6:1), increasing the risk of overfitting. Therefore, despite the high adjusted R^2 (0.702), the regression results should be considered exploratory, and future studies with larger and more diverse cross-sectoral samples are needed to confirm the stability and generalizability of these findings.

Construct validity: Some proxy variables (e.g. training activity and digital presence) capture volume or diversity, but do not adequately reflect quality, intensity of use or perceived value for members.

Omitted variables: Additional factors that may influence membership size were not included in the analysis.

Regional target population heterogeneity: Although the robustness analysis using the affiliation rate (v2) suggests that the main findings are not driven by differences in the regional size of the economist population, unobserved regional socioeconomic and institutional characteristics may still influence organizational performance. Future studies with larger samples should incorporate additional regional-level variables and, where appropriate, multilevel analytical approaches to better capture contextual effects.

Future research could consider factors such as membership fees, payment structures (e.g. differentiated fees for practising, non-practising or unemployed members) and multiple affiliations (e.g. membership of both a professional association and REAF).

Although these limitations do not invalidate the study's contribution as an exploratory analysis, they do constrain its inferential scope. Future research using longitudinal designs, larger samples, or mixed-methods approaches could provide stronger evidence of the mechanisms linking organisational capacity to membership outcomes.

8. CONCLUSIONS

This study examined organisational factors associated with membership numbers in Spanish professional associations of economists. The results revealed a positive and statistically significant relationship between organisational size, as measured by the number of administrative and technical staff, and membership size. In contrast, factors frequently emphasised in the literature, such as training activities, digital presence and sex composition, did not exhibit statistically significant associations within the estimated model. These findings provide further evidence that organisational characteristics are associated with membership outcomes and supplement prior research, which has primarily focused on individual motivations for joining professional associations.

However, the results should be interpreted with caution. The cross-sectional design and limited sample size constrain causal inference and generalisability, and the observed relationships may reflect reciprocal effects or unobserved mechanisms. From a practical perspective, the analysis suggests that professional associations seeking to maintain or expand their membership base should consider the importance of internal organisational resources. However, the findings do not imply that increasing staff numbers alone will necessarily lead to membership growth. Rather, they emphasise the importance of aligning organisational capacity with strategic objectives concerning member services and engagement. As White and Olson (2004) observed in their analysis of associations in the complex healthcare sector, membership among 81 highly qualified professionals depended on being well-informed, having access to professional networks and receiving tangible benefits. These factors

encourage associations to establish specialised committees to provide comprehensive, personalised services to potential members.

In the case of economists, the variety of potential areas of specialisation - such as REA (Auditor Economists), REAF (Tax Advisor Economists), REFOR (Forensic Economists), EC (Accounting Economists), EAL (Labour Advisors), EAF (Financial Advisors), EMK (Marketing/Commercialisation Expert Economists) and REDI (Teachers and Researchers) - highlights the need for organisational structures that offer both quantitative and qualitative responsiveness. Likewise, Fernandez and Castellanos (2024) note that professionals form associations to collectively shape their fields through advice, promotion, training, and mutual adjustment.

Future research could build on these findings by employing longitudinal data, expanding the analysis to other professional sectors and incorporating qualitative indicators of organisational effectiveness. Such extensions could help identify the mechanisms underlying the observed associations and strengthen the empirical basis for policy and management recommendations.

In summary, the results indicate a systematic association between organisational capacity and membership numbers in professional associations of economists. While the results do not support strong claims about cause and effect, they contribute to a growing body of evidence suggesting that internal organisational resources are an important factor in membership outcomes. This perspective is a useful starting point for future empirical research and reflective organisational practice.

ORCID

Eduardo Infante Rejano https://orcid.org/0000-0002-5252-1858
Asunción Rodríguez-Ramos https://orcid.org/0000-0003-2761-9236
Maria Claudia Scurtu Tura https://orcid.org/0000-0003-1914-1084

References

Agustí-Pérez, M., Orta Perez, M., & Oliva, L. (2025). Dynamic capabilities and legitimacy in professional associations: Impact on member competitiveness in the auditing field. *Meditari Accountancy Research, 33*(7), 492–512. http://dx.doi.org/10.1108/medar-03-2025-2950

Beaton, G. (2010). Why Professionalism is Still Relevant. *U of Melbourne Legal Studies Research Paper*(445). http://dx.doi.org/10.2139/ssrn.1545509

Bolleyer, N. (2024). The Distinct Internal Logics of Associations and Professionalised Voluntary Organisations *Civil Society's Democratic Potential: Organisational Tradeoffs between Participation and Representation* (pp. 36–58): Oxford University Press. http://dx.doi.org/10.1093/oso/9780198884392.003.0002

Deleskey, K. (2003). Factors affecting nurses' decisions to join and maintain membership in professional associations. *Journal of Perianesthesia Nursing : Official Journal of the American Society of PeriAnesthesia Nurses, 18*(1), 8–17. http://dx.doi.org/10.1053/jpan.2003.18030008

Fernandez, K., & Castellanos, T. (2024). Member-serving associations: The co-creation of professionalism and expertise within a field. *Voluntary Sector Review, 15*(2), 298–316. http://dx.doi.org/10.1332/204080521X16675565628948

Frasier, C. W. (2025). Barriers to Membership in Nonprofit Trade Associations. *Public Organization Review, 25*, 465–482. http://dx.doi.org/10.1007/s11115-024-00806-9

Friedman, A. L., & Afitska, N. (2023). Professional bodies. *Journal of Professions and Organization, 10*(1), 21–35. http://dx.doi.org/10.1093/jpo/joad001

Goldman, L. M., Arnolds, C. A., & Eksteen, B. (2016). Increasing the organisational effectiveness of professional associations in South Africa. *Journal of Contemporary Managemen, 13*(1), 246–270.

Hagedorn, R. H., & Labovitz, S. (1967). An analysis of community and professional participation among occupations. *Social Forces, 45*(4), 483–491. http://dx.doi.org/10.1093/sf/45.4.483

Jeza, P. (2025). *Examining the value gap: Aligning professional bodies' value proposition with member expectations*. ProQuest Dissertations & Theses Global.

Ki, E. J., & Wang, Y. (2016). Membership benefits matter: Exploring the factors influencing members' behavioural intentions in professional associations. *Nonprofit Management & Leadership, 27*(2), 199–217. http://dx.doi.org/10.1002/nml.21230

Mickevičiūtė, G. (2026). *Balancing mission and financial sustainability: Business model innovation in non-profit organizations* Doctoral dissertation.

Naidoo, S., & Rajcoomar, A. (2020). Towards management excellence: The case of south African professional bodies. *South African Journal of Industrial Engineering, 31*(2), 62–75. http://dx.doi.org/10.7166/31-2-2355

Potnis, D., Gala, B., Seifi, L., Warraich, N., Lamba, M., & Reyes, V. (2024). Factors Influencing Professional Associations' Member Engagement Online: An "Information Practices Approach. *Proceedings of the Association for Information Science and Technology, 61*(1), 314–325. http://dx.doi.org/10.1002/pra2.1030

Rodríguez-Rad, C., & Sánchez del Rio-Vázquez, M. E. (2023). The relevance of participation behaviour, organisational commitment, and attitudinal loyalty to the management of professional associations. *Journal of Business Research, 154*, 113324. http://dx.doi.org/10.1016/j.jbusres.2022.113324

Singh, R., Joshi, A., Singh, A., Raghuveer, K., & Kumar, V. (2025). Synergising HR practices and social performance for adoption of digital circular economy: A case of developing country perspective. *Strategy and Leadership, 53*(4), 434–456. http://dx.doi.org/10.1108/SL-12-2024-0146

Stevens, R., Silver, L., Richards, R., & Whitlock, D. (2023). The decline of a professional academic organisation: Examining a regional association. *Journal of Higher Education Theory and Practice, 23*(17). http://dx.doi.org/10.33423/jhetp.v23i17.6529

Taylor, S., Ekinci, E., Hatton Kolpek, J., Byrnes, H., Policastri, A., Oakley, R. S., & Herald, M. (2018). Factors influencing professional state association membership decisions among recent pharmacy graduates. *Currents in Pharmacy Teaching & Learning, 10*(1), 28–33. http://dx.doi.org/10.1016/j.cptl.2017.09.001

Vincent, N. A., & Webster, C. M. (2013). Exploring relationship marketing in membership associations. *European Journal of Marketing, 47*(10), 1622–1640. http://dx.doi.org/10.1108/EJM-06-2011-0296

Wang, Y., & Ki, E. J. (2018). Membership Matters: Why Members Engage with Professional Associations. *Voluntas, 29*(1), 71–82. http://dx.doi.org/10.1007/s11266-017-9873-x

White, M. J., & Olson, R. S. (2004). Factors affecting membership in specialty nursing organizations. *Rehabilitation Nursing : The Official Journal of the Association of Rehabilitation Nurses, 29*(4), 131–137. http://dx.doi.org/10.1002/j.2048-7940.2004.tb00331.x

Notes

[1] It was estimated that 28,000 people graduate annually in Spain with degrees related to economics and are potentially members of the Associations of Economists (Economics, Business Administration and Management, Finance, etc.). Dividing this number by the 32 existing associations, the theoretical average number of new potential pre-members or members that each association could have recruited is approximately 875 graduates

Scientific Annals of Economics and Business
73 (3), 2026, 657-680
DOI: 10.47743/saeb-2026-0029

A Hybrid MCDM Approach Using Fuzzy AHP–TOPSIS to Evaluate Digital Logistics Market Performance in Selected Asian Economies

Thanh Tung Bui*

Abstract: National logistics benchmarks such as the Logistics Performance Index (LPI) still focus mainly on operational performance and say little about the digital capacity of logistics systems. To address this gap, this paper combines two complementary sources: the Agility Emerging Markets Logistics Index (AEMLI) and the IMD World Digital Competitiveness Ranking (DCI). Using these sources, the study evaluates digital logistics market performance in 11 selected Asian economies. The analysis applies a fuzzy multi-criteria decision-making framework. Fuzzy AHP is first used to derive criterion weights from expert pairwise comparisons, allowing subjective judgments to be expressed as triangular fuzzy numbers. Fuzzy TOPSIS is then used to rank the countries according to their closeness to the fuzzy positive ideal solution and distance from the fuzzy negative ideal solution. The assessment uses seven criteria: domestic logistics opportunities, international logistics opportunities, business fundamentals, digital readiness, knowledge, technology, and future readiness. The results place the UAE and China in the two leading positions, followed by Qatar. Malaysia and Saudi Arabia form the next group, while Jordan and the Philippines appear at the lower end of the ranking. Cross-checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS produce broadly consistent rankings. The originality of this paper lies in linking these two indicator sets with fuzzy weighting and ranking procedures, offering a novel and practical way to compare digital logistics readiness across the selected economies.

Keywords: MCDM; AEMLI; DCI; Fuzzy AHP; Fuzzy TOPSIS.

JEL classification: L91; O57; D81.

* International Institute of Political Economy, University of Finance - Marketing (UFM), Ho Chi Minh City, Vietnam; e-mail: *bttung@ufm.edu.vn*.

Article history: Received 7 May 2025 | Accepted 1 August 2026 | Published online 29 September 2026

To cite this article: Bui, T.T. (2026). A Hybrid MCDM Approach Using Fuzzy AHP–TOPSIS to Evaluate Digital Logistics Market Performance in Selected Asian Economies. *Scientific Annals of Economics and Business*, 73(3), 657-680. https://doi.org/10.47743/saeb-2026-0029.

Copyright

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.

1. INTRODUCTION

In emerging economies, logistics competition is no longer decided only by ports, roads, customs clearance, warehouse capacity, or freight cost. Those variables still matter, and in many countries they remain binding constraints. The change is that logistics systems are now judged increasingly by their ability to coordinate data, connect firms across platforms, support real-time visibility, and adapt to disruptions in global supply chains. For macroeconomic policy, this shift is not cosmetic. A country with growing trade volumes can still lose competitiveness if its logistics sector cannot absorb digital technologies, integrate information flows, and support faster decision-making across firms, regulators, and service providers.

The established literature has treated logistics as a major channel through which economies improve trade performance, productivity, and participation in global value chains. For cross-country evidence, the usual reference point is the Logistics Performance Index (LPI). It reports six dimensions of national logistics systems: customs, infrastructure, international shipments, logistics competence, tracking and tracing, and timeliness (Arvis *et al.*, 2023). Studies using LPI data generally find that better logistics conditions go together with stronger trade performance, although the estimated relationship changes by sample, period, and empirical design (Martí *et al.*, 2014; Bugarčić *et al.*, 2023; Ejaz and Naz, 2023). Infrastructure alone does not explain these outcomes. Skills, institutional openness, and firms' capacity to operate across different regulatory and market settings also matter These findings are useful, but they do not fully capture the new source of differentiation among national logistics systems: digital capacity (Özmutlu and Arun, 2025).

This limitation becomes clearer when logistics is viewed through the lens of digital transformation. Digital logistics is not merely the installation of software in transport firms. Platform-based logistics can reduce coordination costs among carriers, shippers, intermediaries, and public agencies, but realizing those gains requires digital infrastructure deep enough to support real-time data exchange, and institutions capable of acting on that data operationally — neither of which is uniformly present across the emerging markets examined here (Barykin *et al.*, 2021; Kocaoglu, 2024). Kuhlmann and Klumpp (2017) document a related constraint at the workforce level: where managers and logistics workers lack the skills to operate digital systems, those systems tend to remain either underused or internally fragmented rather than delivering the coordination benefits intended. Research on maritime logistics reaches a consistent conclusion — digital adoption raises performance only where organizational readiness and institutional support are already in place (Yang and Lin, 2024). Firm-level evidence from China indicates that digital transformation raises supply-chain efficiency primarily through improvements in information processing and inter-firm coordination (He *et al.*, 2024), but whether national economies can capture these gains depends on conditions that differ sharply across markets — knowledge infrastructure, technological absorptive capacity, and institutional readiness for digital change (Młynarzewska-Borowiec, 2022). Physical throughput and market size tell only part of the story; the digital layer that determines whether logistics systems can learn, adapt, and coordinate under uncertainty must also enter the assessment.

Standard benchmarks address this incompletely. The Agility Emerging Markets Logistics Index (AEMLI) scores countries across four dimensions — domestic logistics opportunities, international logistics opportunities, business fundamentals, and digital readiness — and sits close to the logistics market itself (Agility, 2023). The IMD World

Digital Competitiveness Ranking (DCI) was developed from a different starting point — national technological capacity — and covers knowledge, technology, and future readiness rather than logistics-market conditions specifically (IMD World Competitiveness Center, 2022). The two rankings therefore speak to different sides of the same issue. AEMLI remains closer to logistics-market conditions, while DCI captures the broader digital environment in which those markets operate. Neither source alone is sufficient for assessing digital logistics performance. Combining the two is therefore analytically useful, provided that the criteria are not treated as mechanically equivalent.

Asia offers a suitable empirical setting for this problem. The region contains several of the world's largest manufacturing, trade, energy, and logistics hubs, while also displaying wide differences in digital readiness, institutional quality, and market maturity. China, India, ASEAN economies, Gulf economies, and selected Central and West Asian markets are exposed to different supply-chain pressures, yet they are all increasingly judged by their ability to support digitally enabled logistics. This diversity is useful for the analysis because the sample includes large logistics markets, energy-based trade hubs, manufacturing exporters, and middle-income economies still building digital capacity. The Asian sample used in this study is also constrained by data availability: only countries with complete and comparable information across the seven selected AEMLI and DCI criteria are retained. This keeps the assessment consistent, although it narrows the country coverage.

Multi-criteria decision-making methods have often been used to compare logistics performance across countries because such evaluation requires several criteria to be considered at the same time. A range of techniques — entropy weighting, WASPAS, MABAC, CoCoSo, SWARA, CRITIC, and Best Worst Method among others — have been brought to bear on logistics performance, logistics productivity, and market evaluation across different country samples and regional contexts (Rezaei *et al.*, 2018; Arikan Kargi, 2022; Kara *et al.*, 2022; Mešić *et al.*, 2022; Özekenci, 2023; Pehlivan *et al.*, 2024; Stević *et al.*, 2024). Taken together, this body of work has established two things: that logistics rankings shift meaningfully depending on how criteria weights are constructed, and that structured decision models offer more analytical leverage than simple index comparison (Bulut and Abacıoğlu, 2025). Many of these approaches, however, still rely on crisp weights and exact performance values. This makes the models easier to implement, but it also narrows the way uncertainty is represented.

The restriction is more serious in digital logistics evaluation than in conventional logistics benchmarking. Country-level digital logistics performance involves measurable indicators, but it also contains judgmental components: how experts interpret readiness, how they compare the importance of logistics-market conditions and digital capabilities, and how they assess economies whose strengths are uneven across criteria. Kara and Yalçın (2022) evaluated digital logistics market performance in developing countries by drawing on AEMLI and DCI data within an MCDM framework, and Özbek and Özekenci (2023) extended this line of work through a hybrid multi-method design covering seven criteria from the same two sources — demonstrating that logistics-market conditions and digital competitiveness indicators can be evaluated within a single analytical structure. What remains less developed is the handling of uncertainty in the weighting and evaluation process itself. Collapsing expert judgments into point estimates discards information about the range and imprecision of those judgments rather than incorporating it into the analysis.

Fuzzy set theory offers a way to address this directly. Rather than requiring experts to assign exact numerical values, it represents judgment as a membership function that spans a bounded

range (Zimmermann, 2010). This is relevant in the present context because expert assessments in digital logistics are rarely precise: a practitioner may be confident that future readiness matters more than domestic logistics opportunities without being able to specify by exactly how much. Triangular fuzzy numbers formalize this kind of bounded, ordered judgment through lower, modal, and upper values (Zhang *et al.*, 2014; Anand and Bharatraj, 2017), and decision-making frameworks built around such numbers allow imprecision to be retained through the analysis rather than resolved prematurely (Lee-Kwang and Lee, 1999; Natraj *et al.*, 2020).

Fuzzy AHP and Fuzzy TOPSIS serve different roles in this structure. In standard AHP, each pairwise comparison between criteria is entered as a precise numerical ratio, following the structure of the original method proposed by Saaty (1980). Later work has focused on the consistency and reliability of such comparison matrices (Alonso and Lamata, 2006). In practice, however, experts assessing national digital logistics systems rarely hold views precise enough to justify a single number; they can rank criteria and indicate rough magnitudes, but the boundaries are genuinely uncertain. The fuzzy extension handles this by replacing each crisp ratio with a triangular fuzzy value drawn from a linguistic scale, so that the imprecision in expert judgment is carried forward into the weights rather than discarded at the point of data collection (Singh, 2016; Liu *et al.*, 2020). Fuzzy TOPSIS is then used to rank alternatives according to their distance from the fuzzy positive ideal solution and the fuzzy negative ideal solution. In the present setting, Fuzzy AHP captures uncertainty in criterion importance, and Fuzzy TOPSIS converts the weighted fuzzy evaluations into a country ranking.

The gap addressed here is narrower but important. Existing logistics performance studies have produced useful cross-country rankings, but many rely on deterministic MCDM structures that leave limited room for judgmental uncertainty. Studies on digital logistics performance have started to combine logistics and digital indicators, yet the joint use of logistics-market conditions and broader digital competitiveness indicators remains underdeveloped. This study asks the following research question: how can digital logistics market performance in selected Asian economies be compared when logistics-market indicators and digital competitiveness indicators must be assessed together under uncertain expert judgment?

To answer this question, the study evaluates 11 selected Asian economies using seven criteria derived from AEMLI and DCI: domestic logistics opportunities, international logistics opportunities, business fundamentals, digital readiness, knowledge, technology, and future readiness. The selected economies are China, India, Indonesia, Jordan, Kazakhstan, Malaysia, the Philippines, Qatar, Saudi Arabia, the United Arab Emirates, and Thailand. Fuzzy AHP is used to obtain criterion weights from expert pairwise comparisons, and Fuzzy TOPSIS is used to rank the countries. Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS are then used as supporting stability checks, not as separate claims of methodological novelty.

The study makes three main contributions. First, it links AEMLI logistics-market indicators with DCI digital-competitiveness indicators in a single country-level assessment structure, thereby treating digital logistics performance as both a logistics-market and digital-capability problem. Second, it models expert uncertainty explicitly through fuzzy pairwise weighting and fuzzy distance-based ranking, rather than converting expert judgments into crisp values at the outset. Third, it provides comparative evidence for 11 selected Asian economies and examines whether the main ranking pattern remains stable when alternative fuzzy aggregation procedures are applied.

The remainder of the paper is organized as follows. Section 2 presents the methodological framework, including fuzzy sets, Fuzzy AHP, and Fuzzy TOPSIS. Section 3 describes the

criteria, data sources, expert assessments, fuzzy weights, and country rankings. Section 4 reports the supporting stability checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS. Section 5 discusses the main findings and their policy and methodological implications. Section 6 concludes with the main findings, limitations, and directions for future research.

2. MATERIALS AND METHODS

This study adopts a two-stage hybrid MCDM framework grounded in fuzzy set theory, which provides the analytical basis for converting uncertain expert judgments into triangular fuzzy numbers. In the weighting stage, Fuzzy AHP is employed to build fuzzy pairwise comparison matrices and to obtain the relative weights of the criteria. The resulting weights indicate how strongly experts regard each criterion in comparison with the others. In the ranking stage, Fuzzy TOPSIS evaluates the 11 countries by comparing their distances from two reference points: the fuzzy positive ideal solution and the fuzzy negative ideal solution. The role of each method is therefore distinct: Fuzzy AHP handles the elicitation of subjective criterion weights, while Fuzzy TOPSIS translates those weights into a distance-based country ranking.

2.1. Fuzzy sets

Expert judgments in this study are not treated as exact scores. They are expressed with fuzzy sets, in which membership is measured by degree rather than by a binary yes/no rule; the value ranges from 0 to 1 (Zadeh, 1965; Zimmermann, 2010). This notation fits MCDM problems where information is incomplete, imprecise, or stated in linguistic terms (Natraj *et al.*, 2020). A fuzzy number gives that idea a computable form (Lee-Kwang and Lee, 1999). This study adopts triangular fuzzy numbers because three points — lower, modal, and upper — are sufficient to represent the range of an expert assessment without adding unnecessary complexity (Zhang *et al.*, 2014; Anand and Bharatraj, 2017).

A typical TFN is expressed as $\tilde{d} = \left(\underline{d}, d, \overline{d}\right)$, where $\underline{d}$, d, and $\overline{d}$ denote the lower bound, modal value, and upper bound, respectively. The membership function takes a piecewise linear form, as shown in Equation (1):

$$\mu_{\tilde{d}}(\xi) = \begin{cases} 0, & \xi < \underline{d}, \\ \dfrac{\xi - \underline{d}}{d - \underline{d}}, & \underline{d} \le \xi \le d, \\ \dfrac{\overline{d} - \xi}{\overline{d} - d}, & d \le \xi \le \overline{d}, \\ 0, & \xi > \overline{d}. \end{cases} \tag{1}$$

Figure no. 1 illustrates the membership function of a TFN defined by these three parameters.

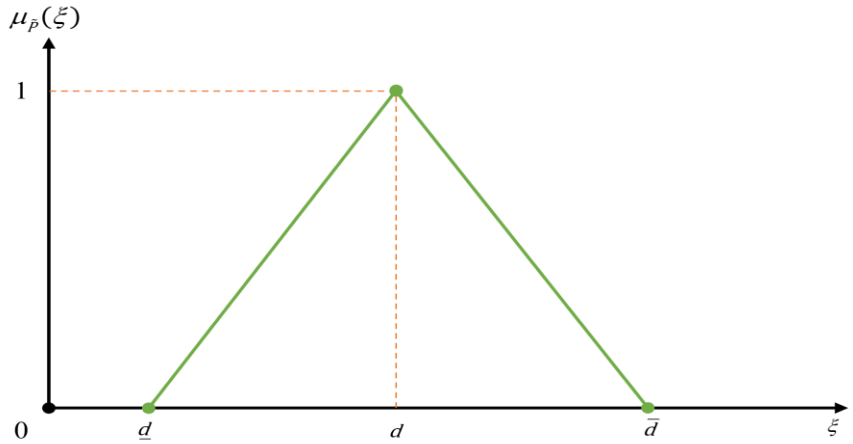


Figure no. 1 – Triangular-shaped fuzzy representation

2.2. Fuzzy AHP

Saaty (1980)'s AHP is a pairwise-comparison method for deriving criterion weights. It has been applied in engineering, management, and environmental assessment, among other fields (Alonso and Lamata, 2006). In its standard form, however, each comparison is entered as a precise ratio; this is difficult when experts work with uncertain or qualitative judgments. This study therefore uses Fuzzy AHP. The method keeps the comparison logic of AHP, but expresses expert preferences through fuzzy linguistic scales grounded in fuzzy set theory (Buckley, 1985; Singh, 2016; Liu *et al.*, 2020). The implementation follows these steps.

Step 1: Establish pairwise comparisons between evaluation criteria.
Decision-makers compare criteria using the fuzzy linguistic scale shown in Table no. 1.

Table no. 1 – Scores for the weight vector's fuzzy evaluation

Linguistic term	Label	Fuzzy value
Equal importance rating	EIR	(1, 1, 1)
Very weak importance rating	VIR	(1, 2, 3)
Weak importance rating	WIR	(2, 3, 4)
Weakly to moderately important rating	WMR	(3, 4, 5)
Moderate importance rating	MIR	(4, 5, 6)
Moderate to strong importance rating	MSR	(5, 6, 7)
Strong importance rating	SIR	(6, 7, 8)
Very strong importance rating	VSR	(7, 8, 9)
Extreme importance rating	EXR	(8, 9, 10)

Step 2: Construct the pairwise comparison matrix.

$$\tilde{P}^k = \begin{bmatrix} \tilde{d}_{11}^k & \tilde{d}_{12}^k & \cdots & \tilde{d}_{1n}^k \\ \tilde{d}_{21}^k & \tilde{d}_{22}^k & \cdots & \tilde{d}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{n1}^k & \tilde{d}_{n2}^k & \cdots & \tilde{d}_{nn}^k \end{bmatrix} \tag{2}$$

where $\tilde{d}_{ij}^k$ represents the preference of decision-maker k when criterion i is compared with criterion j.

Step 3: Aggregate the pairwise comparison matrices.

$$\tilde{d}_{ij} = \frac{1}{K}\sum_{k=1}^{K} \tilde{d}_{ij}^k \tag{3}$$

The aggregated comparison matrix is:

$$\tilde{P} = \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \cdots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \cdots & \tilde{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{n1} & \tilde{d}_{n2} & \cdots & \tilde{d}_{nn} \end{bmatrix} \tag{4}$$

Step 4: Calculate the fuzzy geometric mean of each criterion.

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{d}_{ij} \right)^{1/n}, \quad i = 1, 2, \ldots, n \tag{5}$$

Step 5: Calculate fuzzy weights.

$$\tilde{w}_i = \tilde{r}_i \otimes \left(\tilde{r}_1 \oplus \tilde{r}_2 \oplus \cdots \oplus \tilde{r}_n \right)^{-1} \tag{6}$$

Step 6: Defuzzify fuzzy weights using the centroid method.

$$M_i = \frac{dw_i^L + dw_i^M + dw_i^U}{3} \tag{7}$$

Step 7: Normalize the defuzzified weights.

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i} \tag{8}$$

2.3. Fuzzy TOPSIS

Fuzzy TOPSIS ranks alternatives according to their distance from the fuzzy positive ideal solution and the fuzzy negative ideal solution (Hwang and Yoon, 1981; Chen, 2000). The procedure is as follows.

Step 1: Determine the evaluation criteria and alternatives.

$$\tilde{x}_{ij}^{k} = \left(t_{ij1}^{k}, t_{ij2}^{k}, t_{ij3}^{k}\right) \tag{9}$$

The fuzzy weight of criterion C_j is:

$$\tilde{w}_{j}^{k} = \left(w_{j1}^{k}, w_{j2}^{k}, w_{j3}^{k}\right) \tag{20}$$

Table no. 2 – Fuzzy rating scale for evaluating alternatives

Linguistic term	Label	Fuzzy value
Very poor rating	VPR	(0, 0, 1)
Poor rating	PR	(0, 1, 3)
Medium poor rating	MPR	(1, 3, 5)
Fair rating	FR	(3, 5, 7)
Medium good rating	MGR	(5, 7, 9)
Good rating	GR	(7, 9, 10)
Very good rating	VGR	(9, 10, 10)

Step 2: Aggregate the fuzzy ratings and criterion weights.

$$t_{ij1} = \min_k \{t_{ij1}^{k}\}, \quad t_{ij2} = \frac{1}{K}\sum_{k=1}^{K} t_{ij2}^{k}, \quad t_{ij3} = \max_k \{t_{ij3}^{k}\} \tag{11}$$

$$w_{j1} = \min_k \{w_{j1}^{k}\}, \quad w_{j2} = \frac{1}{K}\sum_{k=1}^{K} w_{j2}^{k}, \quad w_{j3} = \max_k \{w_{j3}^{k}\} \tag{12}$$

Step 3: Normalize the fuzzy decision matrix.

For benefit-type criteria:

$$\tilde{\xi}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right), \quad c_j^* = \max_i \{c_{ij}\} \tag{13}$$

For cost-type criteria:

$$\tilde{\xi}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}} \right), \quad a_j^- = \min_i \{a_{ij}\} \tag{14}$$

Step 4: Compute the weighted normalized fuzzy decision matrix.

$$\tilde{v}_{ij} = \tilde{\xi}_{ij} \otimes \tilde{w}_j \tag{15}$$

Step 5: Identify FPIS and FNIS.

$$A^+ = \{\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\}, \quad \tilde{v}_j^+ = \max_i \{\tilde{v}_{ij}\} \tag{16}$$

$$A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\}, \quad \tilde{v}_j^- = \min_i \{\tilde{v}_{ij}\} \tag{17}$$

Step 6: Calculate distances from FPIS and FNIS.

$$\hat{D}_i^+ = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^+), \quad \hat{D}_i^- = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_j^-) \tag{18}$$

Step 7: Calculate the closeness coefficient.

$$KT_i = \frac{\hat{D}_i^-}{\hat{D}_i^+ + \hat{D}_i^-} \tag{19}$$

The best alternative is the one with the highest closeness coefficient.

3. RESULTS

To evaluate digital logistics performance, this study applies a three-stage empirical procedure. First, the evaluation criteria and country sample are defined. Second, expert judgments are used to derive fuzzy criterion weights through Fuzzy AHP. Third, Fuzzy TOPSIS is applied to rank the countries according to their distance from the ideal solutions.

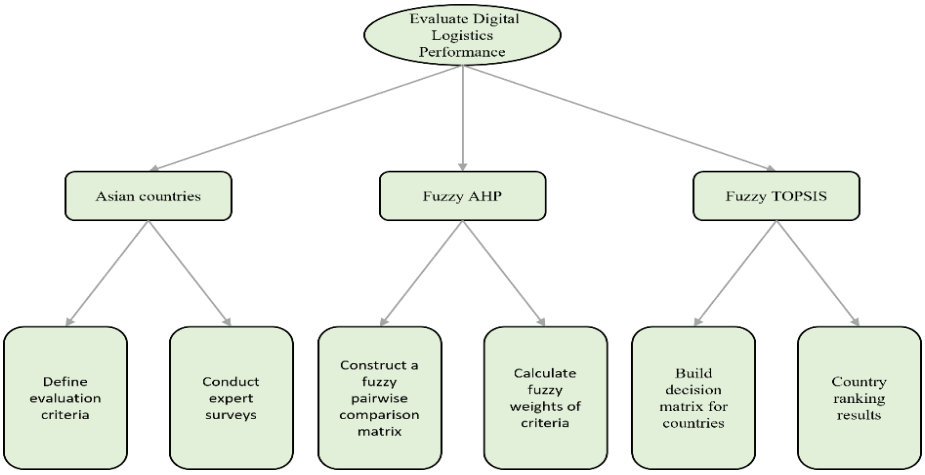


Figure no. 2 - Digital logistics market performance evaluation process

Step 1: Define evaluation criteria

From AEMLI, this study uses four logistics-side criteria: domestic logistics opportunities, international logistics opportunities, business fundamentals, and digital readiness. They cover local logistics demand, cross-border logistics capacity, the business environment, and the digital readiness of the logistics sector. To avoid treating digital logistics as a purely market-based issue, three DCI dimensions are added: knowledge, technology, and future readiness. Together, these criteria reflect an economy's capacity to develop, adopt, and adapt to digital technologies. Table no. 3 lists the seven criteria used in the analysis.

Table no. 3 – List of key criteria used in digital logistics evaluation

Symbol	Criteria	Report	Description	Type
C1	Domestic logistics opportunities	AEMLI	Assesses the ability to sustain and grow local demand through competitive logistics.	Benefit
C2	International logistics opportunities	AEMLI	Measures trade logistics demand and capacity for international operations.	Benefit
C3	Business fundamentals	AEMLI	Evaluates market openness, legal strength, and economic fairness.	Benefit
C4	Digital readiness	AEMLI	Tracks progress toward a digital, skilled, innovative, and sustainable economy.	Benefit
C5	Knowledge	DCI	Measures the ability to discover and understand new technologies.	Benefit
C6	Technology	DCI	Captures the environment supporting digital technology development.	Benefit
C7	Future readiness	DCI	Measures preparedness to leverage digital transformation.	Benefit

Source: IMD World Competitiveness Center (2022); Agility (2023)

All seven criteria are treated as benefit-type measures, so higher values indicate stronger national performance; Equation (13) is therefore used for normalization across the full dataset. The original AEMLI and DCI rankings cover more economies, but this study retains only

countries with complete observations for all seven criteria. The final sample includes 11 Asian economies: China, India, Indonesia, Jordan, Kazakhstan, Malaysia, the Philippines, Qatar, Saudi Arabia, the UAE, and Thailand. The sample is dictated by data availability, especially for indicators linked to logistics-market conditions and digital readiness. The input data come from the 2023 AEMLI report and the 2022 IMD World Digital Competitiveness Ranking, which together provide the most complete compatible source for the criteria used here. Since the analysis uses cross-sectional index data, Section 5 treats the results as time-bound rather than longitudinal evidence.

Table no. 4 – Raw data of country performance based on AEMLI and DCI

Country	C1	C2	C3	C4	C5	C6	C7
China	8.47	9.75	7.11	6.63	79.27	76.69	80.93
India	8.04	7.45	5.94	7.61	53.95	60.25	55.20
Indonesia	6.34	5.89	5.77	6.21	42.20	55.33	50.31
Jordan	4.88	4.75	6.72	5.14	48.63	51.19	45.91
Kazakhstan	4.66	4.66	6.19	5.10	67.64	61.56	67.51
Malaysia	5.29	5.88	7.85	6.72	70.08	71.45	65.33
Philippines	5.02	5.28	4.31	5.99	40.51	51.58	43.95
Qatar	5.91	4.96	7.92	6.38	59.11	78.65	74.98
Saudi Arabia	5.38	5.74	7.86	6.30	61.96	72.92	64.34
UAE	5.60	5.89	9.10	7.37	80.67	93.78	77.40
Thailand	5.11	5.98	5.77	6.04	55.52	74.97	51.70

Source: IMD World Competitiveness Center (2022); Agility (2023)

Step 2: Conduct expert survey

To support the weighting and evaluation process, the study uses the judgments of three experts in logistics and supply chain management. The experts were selected based on academic qualifications and professional experience.

Table no. 5 – List of experts

Expert	Age	Educational background	Experience in the field
Expert 1 (DM1)	55	PhD in Logistics and SCM	>15 years
Expert 2 (DM2)	60	PhD in Logistics and SCM	>20 years
Expert 3 (DM3)	57	PhD in Logistics and SCM	>15 years

Using the linguistic scale in Table no. 1, the experts conducted pairwise comparisons of the seven criteria. The results are reported in Tables no. 6–8.

Table no. 6 – Pairwise comparison matrix provided by Expert 1

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	WIR	EIR	-	-	-	-	-
C3	MIR	WIR	EIR	-	-	-	-
C4	SIR	MIR	WIR	EIR	-	-	-
C5	VSR	SIR	MSR	MIR	EIR	WMR	-
C6	MSR	MIR	WIR	VIR	-	EIR	-
C7	EXR	VSR	SIR	MSR	VIR	WMR	EIR

Table no. 7 – Pairwise comparison matrix provided by Expert 2

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	VIR	EIR	-	-	-	-	-
C3	WMR	VIR	EIR	-	-	-	-
C4	MIR	WMR	WIR	EIR	-	-	-
C5	SIR	MSR	MSR	WMR	EIR	WIR	-
C6	MSR	MIR	WMR	VIR	-	EIR	-
C7	VSR	SIR	SIR	MIR	WIR	WMR	EIR

Table no. 8 – Pairwise comparison matrix provided by Expert 3

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	EIR	-	-	-	-	-	-
C2	VIR	EIR	-	-	-	-	-
C3	WMR	WIR	EIR	-	-	-	-
C4	SIR	MIR	WIR	EIR	-	-	-
C5	VSR	SIR	MSR	MIR	EIR	WIR	-
C6	MSR	MIR	WMR	WIR	-	EIR	-
C7	EXR	VSR	SIR	MSR	WIR	WMR	EIR

Step 3: Construct the aggregated fuzzy pairwise comparison matrix

After collecting the expert assessments, linguistic terms were converted into triangular fuzzy numbers. The fuzzy values were aggregated using Equation (3). The resulting average comparison matrix is shown in Table no. 9.

Table no. 9 – Average pairwise comparison matrix of the criteria

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	(1,1,1)	-	-	-	-	-	-
C2	(4/3,7/3,10/3)	(1,1,1)	-	-	-	-	-
C3	(10/3,13/3,16/3)	(5/3,8/3,11/3)	(1,1,1)	-	-	-	-
C4	(16/3,19/3,22/3)	(11/3,14/3,17/3)	(2,3,4)	(1,1,1)	-	-	-
C5	(20/3,23/3,26/3)	(17/3,20/3,23/3)	(5,6,7)	(11/3,14/3,17/3)	(1,1,1)	(7/3,10/3,13/3)	-
C6	(5,6,7)	(4,5,6)	(8/3,11/3,14/3)	(4/3,7/3,10/3)	-	(1,1,1)	-
C7	(23/3,26/3,29/3)	(20/3,23/3,26/3)	(6,7,8)	(14/3,17/3,20/3)	(5/3,8/3,11/3)	(3,4,5)	(1,1,1)

Step 4: Calculate fuzzy weights

Before calculating the fuzzy weights, the pairwise comparison matrix of each expert was checked for consistency. The modal values of the triangular fuzzy numbers were first defuzzified, and the consistency ratio (CR) was then computed following Saaty (1980)'s procedure. The results are acceptable for all three experts: DM1 has $\lambda_{max} = 7.644$, $CI = 0.107$, and $CR = 0.081$; DM2 has $\lambda_{max} = 7.495$, $CI = 0.083$, and $CR = 0.063$; and DM3 has $\lambda_{max} = 7.662$, $CI = 0.110$, and $CR = 0.084$. Since all CR values are below the 0.10 threshold for a seven-criterion matrix, the judgments are consistent enough to be used in the fuzzy weighting stage.

Using the aggregated pairwise comparison matrix in Table no. 9, fuzzy weights were calculated with Equation (6). The results are shown in Table no. 10.

Table no. 10 – Fuzzy weight value of each criterion

Fuzzy weight	Value
$\tilde{w}_1$	(0.015, 0.021, 0.032)
$\tilde{w}_2$	(0.022, 0.032, 0.050)
$\tilde{w}_3$	(0.036, 0.054, 0.083)
$\tilde{w}_4$	(0.064, 0.096, 0.149)
$\tilde{w}_5$	(0.180, 0.265, 0.395)
$\tilde{w}_6$	(0.089, 0.139, 0.214)
$\tilde{w}_7$	(0.268, 0.393, 0.564)

The fuzzy weights are concentrated on the digital-capability criteria. Future readiness (C7) receives the largest weight, followed by knowledge (C5) and technology (C6). Domestic and international logistics opportunities are weighted lower. This result indicates that market scale is not the decisive factor in digital logistics performance; stronger results depend more on knowledge capacity, technological depth, and readiness for future digital change.

Step 5: Construct the fuzzy decision matrix

The experts evaluated each country under the seven criteria using the linguistic scale defined in Table no. 2. The resulting linguistic assessments are reported in Tables no. 11–17. These assessments were then converted into triangular fuzzy numbers and aggregated to construct the fuzzy decision matrix presented in Table no. 18.

Table no. 11 – Experts' assessments of countries according to criterion C1

Criterion	Country	DM1	DM2	DM3
C1	China	VGR	VGR	GR
C1	India	VGR	GR	GR
C1	Indonesia	MGR	MGR	MGR
C1	Jordan	MPR	MPR	PR
C1	Kazakhstan	MPR	MPR	FR
C1	Malaysia	MGR	MGR	FR
C1	Philippines	FR	FR	FR
C1	Qatar	MGR	FR	MGR
C1	Saudi Arabia	FR	FR	FR
C1	UAE	MGR	FR	FR
C1	Thailand	FR	FR	MGR

Table no. 12 – Experts' assessments of countries according to criterion C2

Criterion	Country	DM1	DM2	DM3
C2	China	VGR	VGR	VGR
C2	India	GR	GR	MGR
C2	Indonesia	MGR	GR	GR
C2	Jordan	MPR	MPR	MPR
C2	Kazakhstan	PR	PR	MPR

Criterion	Country	DM1	DM2	DM3
C2	Malaysia	MGR	MGR	MGR
C2	Philippines	FR	FR	FR
C2	Qatar	FR	FR	MPR
C2	Saudi Arabia	MGR	FR	FR
C2	UAE	MGR	MGR	MGR
C2	Thailand	MGR	MGR	FR

Table no. 13 – Experts' assessments of countries according to criterion C3

Criterion	Country	DM1	DM2	DM3
C3	China	MGR	MGR	MGR
C3	India	FR	FR	FR
C3	Indonesia	FR	FR	MPR
C3	Jordan	MGR	FR	FR
C3	Kazakhstan	FR	FR	FR
C3	Malaysia	MGR	MGR	MGR
C3	Philippines	PR	PR	PR
C3	Qatar	GR	GR	GR
C3	Saudi Arabia	GR	GR	MGR
C3	UAE	VGR	VGR	VGR
C3	Thailand	FR	FR	MPR

Table no. 14 – Experts' assessments of countries according to criterion C4

Criterion	Country	DM1	DM2	DM3
C4	China	MPR	FR	FR
C4	India	GR	GR	MGR
C4	Indonesia	PR	PR	PR
C4	Jordan	VPR	VPR	VPR
C4	Kazakhstan	VPR	VPR	VPR
C4	Malaysia	FR	FR	FR
C4	Philippines	PR	PR	VPR
C4	Qatar	MPR	MPR	MPR
C4	Saudi Arabia	MPR	PR	MPR
C4	UAE	MGR	MGR	MGR
C4	Thailand	PR	PR	VPR

Table no. 15 – Experts' assessments of countries according to criterion C5

CRITERION	COUNTRY	DM1	DM2	DM3
C5	China	GR	GR	GR
C5	India	FR	FR	FR
C5	Indonesia	MPR	MPR	MPR
C5	Jordan	FR	MPR	MPR
C5	Kazakhstan	MGR	MGR	MGR
C5	Malaysia	MGR	MGR	MGR
C5	Philippines	MPR	MPR	PR
C5	Qatar	MGR	FR	MGR
C5	Saudi Arabia	MGR	FR	MGR
C5	UAE	VGR	GR	GR
C5	Thailand	FR	FR	FR

Table no. 16 – Experts' assessments of countries according to criterion C6

Criterion	Country	DM1	DM2	DM3
C6	China	GR	GR	GR
C6	India	FR	FR	FR
C6	Indonesia	MPR	FR	FR
C6	Jordan	PR	PR	PR
C6	Kazakhstan	FR	FR	FR
C6	Malaysia	MGR	MGR	MGR
C6	Philippines	PR	PR	PR
C6	Qatar	GR	GR	GR
C6	Saudi Arabia	GR	MGR	GR
C6	UAE	VGR	VGR	VGR
C6	Thailand	GR	MGR	GR

Table no. 17 – Experts' assessments of countries according to criterion C7

Criterion	Country	DM1	DM2	DM3
C7	China	VGR	VGR	VGR
C7	India	FR	FR	FR
C7	Indonesia	FR	MPR	MPR
C7	Jordan	PR	PR	PR
C7	Kazakhstan	MGR	MGR	MGR
C7	Malaysia	MGR	MGR	FR
C7	Philippines	PR	PR	PR
C7	Qatar	MGR	GR	MGR
C7	Saudi Arabia	MGR	FR	FR
C7	UAE	GR	GR	GR
C7	Thailand	FR	MPR	MPR

Based on these linguistic assessments, the aggregated fuzzy decision matrix was constructed using the transformation scale in Table no. 2 and the aggregation procedure described in Equation (11). The resulting matrix is presented in Table no. 18.

Table no. 18 – Fuzzy decision matrix

Country	C1	C2	C3	C4	C5	C6	C7
China	(8.33, 9.67, 10)	(9, 10, 10)	(5, 7, 9)	(2.33, 4.33, 6.33)	(7, 9, 10)	(7, 9, 10)	(9, 10, 10)
India	(7.67, 9.33, 10)	(6.33, 8.33, 9.67)	(3, 5, 7)	(6.33, 8.33, 9.67)	(3, 5, 7)	(3, 5, 7)	(3, 5, 7)
Indonesia	(5, 7, 9)	(6.33, 8.33, 9.67)	(2.33, 4.33, 6.33)	(0, 1, 3)	(1, 3, 5)	(2.33, 4.33, 6.33)	(1.67, 3.67, 5.67)
Jordan	(0.67, 2.33, 4.33)	(1, 3, 5)	(3.67, 5.67, 7.67)	(0, 0, 1)	(1.67, 3.67, 5.67)	(0, 1, 3)	(0, 1, 3)
Kazakhstan	(1.67, 3.67, 5.67)	(0.33, 1.67, 3.67)	(3, 5, 7)	(0, 0, 1)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
Malaysia	(4.33, 6.33, 8.33)	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(4.33, 6.33, 8.33)
Philippines	(3, 5, 7)	(3, 5, 7)	(0, 1, 3)	(0, 0.67, 2.33)	(0.67, 2.33, 4.33)	(0, 1, 3)	(0, 1, 3)
Qatar	(4.33, 6.33, 8.33)	(2.33, 4.33, 6.33)	(7, 9, 10)	(1, 3, 5)	(4.33, 6.33, 8.33)	(7, 9, 10)	(5.67, 7.67, 9.33)

Country	C1	C2	C3	C4	C5	C6	C7
Saudi Arabia	(3, 5, 7)	(3.67, 5.67, 7.67)	(6.33, 8.33, 9.67)	(0.67, 2.33, 4.33)	(4.33, 6.33, 8.33)	(6.33, 8.33, 9.67)	(3.67, 5.67, 7.67)
UAE	(3.67, 5.67, 7.67)	(5, 7, 9)	(9, 10, 10)	(5, 7, 9)	(7.67, 9.33, 10)	(9, 10, 10)	(7, 9, 10)
Thailand	(3.67, 5.67, 7.67)	(4.33, 6.33, 8.33)	(2.33, 4.33, 6.33)	(0, 0.67, 2.33)	(3, 5, 7)	(6.33, 8.33, 9.67)	(1.67, 3.67, 5.67)

Step 6: Normalize the fuzzy decision matrix

Since all seven criteria are of the benefit type, normalization is performed exclusively using Equation (13). Equation (14), which applies to cost-type criteria, is not relevant to this study. The resulting normalized fuzzy decision matrix $\tilde{R}$ is presented in Table no. 19.

Table no. 19 – Normalized fuzzy decision matrix $(\tilde{R})$

Country	C1	C2	C3	C4	C5	C6	C7
China	(0.833, 0.967, 1.000)	(0.900, 1.000, 1.000)	(0.500, 0.700, 0.900)	(0.241, 0.448, 0.655)	(0.700, 0.900, 1.000)	(0.700, 0.900, 1.000)	(0.900, 1.000, 1.000)
India	(0.767, 0.933, 1.000)	(0.633, 0.833, 0.967)	(0.300, 0.500, 0.700)	(0.655, 0.862, 1.000)	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)
Indonesia	(0.500, 0.700, 0.900)	(0.633, 0.833, 0.967)	(0.233, 0.433, 0.633)	(0.000, 0.103, 0.310)	(0.100, 0.300, 0.500)	(0.233, 0.433, 0.633)	(0.167, 0.367, 0.567)
Jordan	(0.067, 0.233, 0.433)	(0.100, 0.300, 0.500)	(0.367, 0.567, 0.767)	(0.000, 0.000, 0.103)	(0.167, 0.367, 0.567)	(0.000, 0.100, 0.300)	(0.000, 0.100, 0.300)
Kazakhstan	(0.167, 0.367, 0.567)	(0.033, 0.167, 0.367)	(0.300, 0.500, 0.700)	(0.000, 0.000, 0.103)	(0.500, 0.700, 0.900)	(0.300, 0.500, 0.700)	(0.500, 0.700, 0.900)
Malaysia	(0.433, 0.633, 0.833)	(0.500, 0.700, 0.900)	(0.500, 0.700, 0.900)	(0.310, 0.517, 0.724)	(0.500, 0.700, 0.900)	(0.500, 0.700, 0.900)	(0.433, 0.633, 0.833)
Philippines	(0.300, 0.500, 0.700)	(0.300, 0.500, 0.700)	(0.000, 0.100, 0.300)	(0.000, 0.069, 0.241)	(0.067, 0.233, 0.433)	(0.000, 0.100, 0.300)	(0.000, 0.100, 0.300)
Qatar	(0.433, 0.633, 0.833)	(0.233, 0.433, 0.633)	(0.700, 0.900, 1.000)	(0.103, 0.310, 0.517)	(0.433, 0.633, 0.833)	(0.700, 0.900, 1.000)	(0.567, 0.767, 0.933)
Saudi Arabia	(0.300, 0.500, 0.700)	(0.367, 0.567, 0.767)	(0.633, 0.833, 0.967)	(0.069, 0.241, 0.448)	(0.433, 0.633, 0.833)	(0.633, 0.833, 0.967)	(0.367, 0.567, 0.767)
UAE	(0.367, 0.567, 0.767)	(0.500, 0.700, 0.900)	(0.900, 1.000, 1.000)	(0.517, 0.724, 0.931)	(0.767, 0.933, 1.000)	(0.900, 1.000, 1.000)	(0.700, 0.900, 1.000)
Thailand	(0.367, 0.567, 0.767)	(0.433, 0.633, 0.833)	(0.233, 0.433, 0.633)	(0.000, 0.069, 0.241)	(0.300, 0.500, 0.700)	(0.633, 0.833, 0.967)	(0.167, 0.367, 0.567)

Note: Normalization is performed using $c_j^* = \max_i \left(c_{ij}\right)$. The divisor for C1–C3 and C5–C7 is 10.000. The divisor for C4 is 9.670.

The normalized fuzzy decision matrix is then multiplied by the fuzzy criterion weights according to Equation (15), yielding the weighted normalized fuzzy decision matrix. Since all criteria are benefit-type and are therefore maximized, the FPIS for each criterion is determined by the maximum weighted normalized fuzzy value across all countries, whereas the FNIS is determined by the corresponding minimum value, as specified in Equations (16) and (17). The distances of each country from the FPIS and FNIS are computed using Equation (18), and the results are presented in Table no. 20.

Table no. 20 – Distance of countries to FPIS and FNIS

Country	$\hat{D}_i^+$	$\hat{D}_i^-$
China	0.049	0.497
India	0.246	0.300
Indonesia	0.382	0.164
Jordan	0.494	0.046
Kazakhstan	0.241	0.310
Malaysia	0.175	0.377
Philippines	0.520	0.020
Qatar	0.159	0.395
Saudi Arabia	0.216	0.335
UAE	0.043	0.507
Thailand	0.318	0.229

Step 7: Rank countries using Fuzzy TOPSIS

The closeness coefficient KT_i is calculated using Equation (19). A higher value indicates a stronger digital logistics performance.

Table no. 21 – Closeness coefficients of countries in digital logistics performance

Country	KT_i	Rank
UAE	0.923	1
China	0.909	2
Qatar	0.713	3
Malaysia	0.682	4
Saudi Arabia	0.608	5
Kazakhstan	0.563	6
India	0.550	7
Thailand	0.418	8
Indonesia	0.300	9
Jordan	0.085	10
Philippines	0.037	11

The ranking results are illustrated in Figure no. 3.

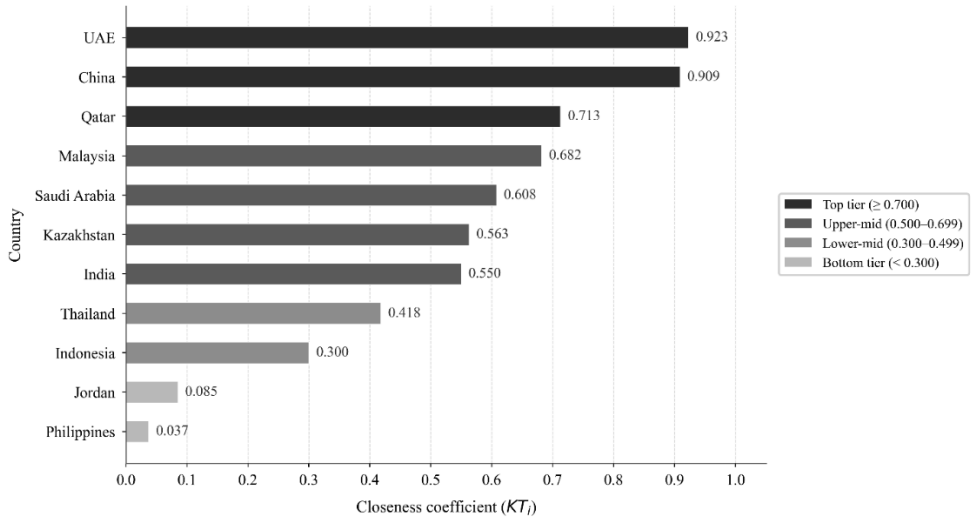


Figure no. 3 – Digital logistics performance ranking by country, sorted in descending order of closeness coefficient (KT_i)

The ranking separates the selected economies into three broad groups. At the top, the UAE ranks first, just ahead of China. Its advantage comes from a high AEMLI score for digital transformation and strong DCI performance in knowledge, technology, and future readiness. China's position is supported by large domestic and international logistics opportunities, together with an advanced digital profile. Qatar ranks third, mainly because of its technology and future-readiness scores. Malaysia and Saudi Arabia form the upper-middle group, while Kazakhstan and India sit near the centre of the distribution. Thailand, Indonesia, Jordan, and the Philippines occupy the lower positions, largely because their scores are weaker on digitally oriented criteria.

4. ROBUSTNESS ANALYSIS USING ALTERNATIVE FUZZY MCDM METHODS

The Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS methods presented in this section were independently implemented by the authors using the same expert assessments, fuzzy criterion weights reported in Table no. 10, and fuzzy decision matrix reported in Table no. 18. They were not adopted or reproduced from prior empirical studies. Their purpose is to serve as cross-validation benchmarks for assessing whether the Fuzzy AHP–TOPSIS rankings remain stable when alternative aggregation logics are applied.

The fuzzy criterion weights applied across all three methods are identical, as are the fuzzy decision matrix and the country sample. This design ensures that any observed ranking differences are attributable to the aggregation procedures rather than to changes in input data. The results of the Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS implementations are presented in Tables no. 22 and no. 23.

Table no. 22 – Ranking of digital logistics performance using Fuzzy AHP–ARAS

Country	S_i^L	S_i^M	S_i^U	S_i	Q_i	Rank
China	0.120	0.148	0.181	0.150	0.969	2
India	0.068	0.099	0.145	0.104	0.675	5
Indonesia	0.026	0.058	0.104	0.063	0.406	9
Jordan	0.011	0.031	0.071	0.037	0.242	10
Kazakhstan	0.062	0.091	0.139	0.097	0.631	7
Malaysia	0.077	0.111	0.163	0.117	0.756	4
Philippines	0.005	0.025	0.066	0.032	0.208	11
Qatar	0.079	0.115	0.163	0.119	0.772	3
Saudi Arabia	0.064	0.098	0.148	0.103	0.670	6
UAE	0.122	0.152	0.188	0.154	1.000	1
Thailand	0.040	0.072	0.119	0.077	0.499	8

The Fuzzy AHP–ARAS results support the main ranking structure identified by the primary method. The UAE and China retain the two leading positions, with utility degrees of 1.000 and 0.969, respectively. Qatar remains in third place. At the lower end, the Philippines and Jordan again record the weakest performance. Some differences appear in the mid-tier group. India rises to fifth place under ARAS, while Kazakhstan falls to seventh. These shifts reflect differences in the way each method aggregates weighted performance across criteria rather than changes in the underlying input data.

Table no. 23 – Ranking of digital logistics performance using Fuzzy AHP–COPRAS

Country	S_P^L	S_P^M	S_P^U	Q^L	Q^M	Q^U	Q_i	Rank
China	0.495	0.890	1.427	0.495	0.890	1.427	0.987	2
India	0.239	0.555	1.109	0.239	0.555	1.109	0.668	7
Indonesia	0.113	0.359	0.829	0.113	0.359	0.829	0.456	9
Jordan	0.046	0.195	0.575	0.046	0.195	0.575	0.287	10
Kazakhstan	0.265	0.570	1.123	0.265	0.570	1.123	0.687	6
Malaysia	0.306	0.665	1.272	0.306	0.655	1.272	0.784	4
Philippines	0.023	0.154	0.523	0.023	0.154	0.523	0.245	11
Qatar	0.336	0.700	1.288	0.336	0.770	1.288	0.815	3
Saudi Arabia	0.272	0.603	1.176	0.272	0.603	1.176	0.720	5
UAE	0.448	0.898	1.464	0.488	0.898	1.464	1.000	1
Thailand	0.178	0.455	0.958	0.178	0.455	0.958	0.558	8

The Fuzzy AHP–COPRAS results further reinforce this pattern. Under COPRAS, the UAE again ranks first, with the normalized utility score set at 1.000; China and Qatar follow. The Philippines and Jordan remain the two lowest-ranked economies. The middle group also changes little from the TOPSIS ordering. India, for example, stays in seventh place in both calculations. The main ranking, then, is not an artefact of a single fuzzy aggregation procedure.

Table no. 24 – Comparative ranking of digital logistics performance across MCDM methods

Country	Fuzzy AHP–TOPSIS	Fuzzy AHP–ARAS	Fuzzy AHP–COPRAS
China	2	2	2
India	7	5	7
Indonesia	9	9	9
Jordan	10	10	10
Kazakhstan	6	7	6
Malaysia	4	4	4
Philippines	11	11	11
Qatar	3	3	3
Saudi Arabia	5	6	5
UAE	1	1	1
Thailand	8	8	8

As shown in Table no. 24, the ranking results from the three approaches exhibit a high degree of consistency, especially for countries at both ends of the performance spectrum. The UAE, China, and Qatar consistently occupy the top three positions, while Jordan and the Philippines consistently rank near the bottom. This stability supports the reliability of the fuzzy weight structure and decision matrix used in the assessment.

5. DISCUSSION

The ranking results suggest that digital logistics performance is not determined by logistics-market size alone. The UAE, China, and Qatar lead the sample because their logistics conditions are supported by stronger digital-capability indicators, particularly knowledge, technology, and future readiness. Scale matters. But it is not enough. China benefits from large domestic and international logistics opportunities, while the UAE and Qatar perform strongly in digitally oriented criteria that reflect institutional readiness, technological capacity, and the ability to absorb new systems. This pattern is important because conventional logistics indicators may capture throughput and market access, but they do not fully reflect whether a logistics system can coordinate data, platforms, and actors under digital conditions.

For the middle and lower-ranked economies, the results point to a different policy issue. Malaysia and Saudi Arabia show relatively strong positions, yet their rankings remain below the leading group because performance is less even across criteria. Kazakhstan and India occupy intermediate positions, indicating that selected advantages in market size or digital capacity do not automatically translate into balanced digital logistics readiness. The lower-ranked economies face a sharper constraint. Thailand, Indonesia, Jordan, and the Philippines are not simply disadvantaged by logistics-market conditions; their weaker positions are closely associated with digitally oriented criteria. Policy attention should therefore move beyond physical infrastructure expansion. Investment in data systems, digital skills, interoperable platforms, regulatory coordination, and technology adoption capacity is likely to matter more for improving digital logistics performance than isolated improvements in transport assets.

The methodological results also carry a useful implication. Although AEMLI provides a logistics-market view and DCI captures broader digital competitiveness, neither index alone is sufficient for evaluating digital logistics performance. Their joint use is more informative, but it also raises a weighting problem: the relative importance of market opportunities, institutional conditions, digital readiness, knowledge, technology, and future readiness cannot be assumed to

be fixed across contexts. Fuzzy AHP was used to retain uncertainty in expert judgments rather than forcing them into exact values at the start of the analysis. Fuzzy TOPSIS then converted those weighted fuzzy assessments into a ranking. The stability checks using Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS support the main ordering, especially at the top and bottom of the distribution. Still, the small shifts in the middle group are informative. They show that ranking outcomes can vary when aggregation rules change, even when the input data remain the same. Digital logistics rankings should therefore be read as structured comparative evidence, not as absolute measures of national performance.

6. CONCLUSION

Digital logistics market performance across selected Asian economies is evaluated here through a combined Fuzzy AHP–TOPSIS approach. Fuzzy AHP is used to obtain the criterion weights, while Fuzzy TOPSIS ranks the countries by measuring how close each alternative is to the fuzzy positive ideal solution. The use of fuzzy logic allows expert uncertainty and judgmental imprecision to be reflected in the evaluation process. Seven criteria are considered, taken from the AEMLI and DCI datasets, representing two main aspects of performance: logistics-market conditions and digital transformation capacity. To our knowledge, this is among the first studies to integrate these two index families within a unified fuzzy MCDM framework for evaluating digital logistics performance in Asian economies.

The findings indicate that the UAE, China, and Qatar achieve the strongest overall performance among the 11 economies. Their high rankings are mainly linked to better scores in knowledge, technology, and future readiness, together with stronger logistics-market conditions — a pattern broadly consistent with Özbek and Özekenci (2023), though the country ordering differs somewhat given the distinct weighting structure applied here. Malaysia and Saudi Arabia also show relatively favorable results. Kazakhstan and India occupy intermediate positions. Thailand, Indonesia, Jordan, and the Philippines fall into the lower group, largely because of weaker performance in several dimensions of digital readiness. For these economies, the results suggest that targeted investment in digital infrastructure and knowledge-intensive capacity — rather than conventional logistics expansion alone — is the more pressing policy priority.

The robustness checks based on Fuzzy AHP–ARAS and Fuzzy AHP–COPRAS confirm the general stability of the ranking results. The leading and lowest-performing countries remain mostly consistent across the three methods, suggesting that the main findings are not dependent on one specific aggregation procedure. The proposed framework can therefore provide practical decision support for policymakers, logistics enterprises, and investors when comparing digital logistics readiness across national markets.

Several limitations deserve acknowledgment. Expert input came from three specialists — well-credentialed, but inevitably a narrow base for capturing the full range of institutional and country-specific nuances across 11 diverse economies. Data constraints are equally worth noting: the analysis draws on the 2023 AEMLI and 2022 DCI editions, so what emerges is a fixed cross-sectional snapshot rather than any account of directional change. Country inclusion was itself dictated by where complete seven-criterion data existed, not by theoretical sampling logic. Future work might widen this scope by drawing on updated index releases, extending coverage to additional economies, running the framework across multiple time points, or folding in LPI dimensions to allow a side-by-side comparison of conventional and digitally oriented logistics performance.

AI use statement

This study did not use any AI tool or Large Language Model for autonomous content creation. Standard tools for grammar and spelling correction were used in the preparation of this manuscript.

Acknowledgements

This research is funded by the University of Finance - Marketing.

ORCID

Thanh Tung Bui https://orcid.org/0009-0004-3390-7618

References

Agility. (2023). *Agility Emerging Markets Logistics Index 2023*. Retrieved from https://emergingmarketsindex.agility.com/wp-content/uploads/2023/12/Agility-Emerging-Markets-Logistics-Index-2023-EN.pdf?utm_source=chatgpt.com

Alonso, J. A., & Lamata, M. T. (2006). Consistency in the analytic hierarchy process: A new approach. *International Journal of Uncertainty, Fuzziness and Knowledge-based Systems, 14*(4), 445–459. http://dx.doi.org/10.1142/S0218488506004114

Anand, M. C. J., & Bharatraj, J. (2017). *Theory of triangular fuzzy number. In Proceedings of NCATM*. Paper presented at the Conference on Advanced Trends in Mathematics (NCATM-2017), Vellore, India.

Arikan Kargi, V. S. (2022). Evaluation of logistics performance of the OECD member countries with integrated entropy and WASPAS method. *Yönetim ve Ekonomi Dergisi, 29*(4), 801–811. http://dx.doi.org/10.18657/yonveek.1067480

Arvis, J.-F., Ojala, L., Shepherd, B., Ulybina, D., & Wiederer, C. (2023). Connecting to compete 2023: Trade logistics in an uncertain global economy—The Logistics Performance Index and its indicators. *World Bank*.

Barykin, S. E., Kapustina, I. V., Korchagina, E. V., Sergeev, S. M., Yadykin, V. K., Abdimomynova, A., & Stepanova, D. (2021). Digital logistics platforms in the BRICS countries: Comparative analysis and development prospects. *Sustainability (Basel), 13*(20), 11228. http://dx.doi.org/10.3390/su132011228

Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy Sets and Systems, 17*(3), 233–247. http://dx.doi.org/10.1016/0165-0114(85)90090-9

Bugarčić, F. Ž., Mićić, V., & Stanišić, N. (2023). The role of logistics in economic growth and global competitiveness. *Zbornik Radova Ekonomskog Fakulteta u Rijeci, 41*(2), 499–520. http://dx.doi.org/10.18045/zbefri.2023.2.499

Bulut, E., & Abacıoğlu, S. (2025). How criteria weights influence performance in evaluating logistic productivity: An application in the Emerging Markets Logistics Index. Verimlilik Dergisi. *Verimlilik Dergisi. Productivity for Logistics*(Special Issue), 1–28. http://dx.doi.org/10.51551/verimlilik.1518693

Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy Sets and Systems, 114*(1), 1–9. http://dx.doi.org/10.1016/S0165-0114(97)00377-1

Ejaz, M., & Naz, A. (2023). Role of logistics and transport sector in globalization: Evidence from developed and developing economies. *Sir Syed University Research Journal of Engineering & Technology, 13*(1), 48–52. http://dx.doi.org/10.33317/ssurj.534

He, J., Fan, M., & Fan, Y. (2024). Digital transformation and supply chain efficiency improvement: An empirical study from a-share listed companies in China. *PLoS One, 19*(4), e0302133. http://dx.doi.org/10.1371/journal.pone.0302133

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications: A state-of-the-art survey* http://dx.doi.org/10.1007/978-3-642-48318-9

IMD World Competitiveness Center. (2022). IMD World Digital Competitiveness Ranking 2022. Retrieved from https://www.imd.org/centers/wcc/world-competitiveness-center/rankings/world-digital-competitiveness-ranking/

Kara, K., Bentyn, Z., & Yalçın, G. C. (2022). Determining the logistics market performance of developing countries by entropy and MABAC methods. *Logforum, 18*(4), 421–434. http://dx.doi.org/10.17270/J.LOG.2022.752

Kara, K., & Yalçın, G. C. (2022). Digital logistics market performance of developing countries. *Uluslararası Akademik Birikim Dergisi, 5*(4), 260–272. http://dx.doi.org/10.53001/uluabd.2022.38

Kocaoglu, B. (2024). Digital transformation in logistics *Logistics information systems: Digital transformation and supply chain applications in the 4.0 era* (pp. 1–35): Springer. http://dx.doi.org/10.1007/978-3-031-60290-0_1

Kuhlmann, A. S., & Klumpp, M. (2017). *Digitalization of logistics processes and the human perspective.* Paper presented at the Digitalization in Maritime and Sustainable Logistics: City Logistics, Port Logistics and Sustainable Supply Chain Management in the Digital Age.

Lee-Kwang, H., & Lee, J. H. (1999). A method for ranking fuzzy numbers and its application to decision-making. *IEEE Transactions on Fuzzy Systems, 7*(6), 677–685. http://dx.doi.org/10.1109/91.811235

Liu, Y., Eckert, C. M., & Earl, C. (2020). A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Systems with Applications, 161*, 113738. http://dx.doi.org/10.1016/j.eswa.2020.113738

Martí, L., Puertas, R., & García, L. (2014). The importance of the Logistics Performance Index in international trade. *Applied Economics, 46*(24), 2982–2992. http://dx.doi.org/10.1080/00036846.2014.916394

Mešić, A., Miškić, S., Stević, Ž., & Mastilo, Z. (2022). Hybrid MCDM solutions for evaluation of the Logistics Performance Index of the Western Balkan countries. *ECONOMICS: Innovative and Economics Research Journal, 10*(1). http://dx.doi.org/10.2478/eoik-2022-0004

Młynarzewska-Borowiec, I. (2022). Digital competitiveness gap between the US and EU member states in the 21st century. *European Research Studies, 25*(4), 364–380. http://dx.doi.org/10.35808/ersj/3087

Natraj, P., Sandhiya, S., & Selvakumari, K. (2020). Fuzzy sets and its application in decision making problems by comparing three methods. *PalArch's Journal of Archaeology of Egypt/Egyptology, 17*(7), 4841–4848.

Özbek, H. E., & Özekenci, E. K. (2023). Investigation of digital logistics market performance in developing countries with hybrid MCDM methods. *JOEEP: Journal of Emerging Economies and Policy, 8*(2), 559–576.

Özekenci, E. K. (2023). Assessing the logistics market performance of developing countries by SWARA-CRITIC based CoCoSo method. *Logforum, 19*(3), 375–394. http://dx.doi.org/10.17270/J.LOG.2023.857

Özmutlu, S. Y., & Arun, K. (2025). Proactive or reactive resilience: Does it matter on logistics performance index with the digitalization effect? *IIMBG Journal of Sustainable Business and Innovation, 3*(1), 109–128. http://dx.doi.org/10.1108/IJSBI-05-2024-0024

Pehlivan, P., Aslan, A. I., David, S., & Bacalum, S. (2024). Determination of logistics performance of G20 countries using quantitative decision-making techniques. *Sustainability (Basel), 16*(5), 1852. http://dx.doi.org/10.3390/su16051852

Rezaei, J., van Roekel, W. S., & Tavasszy, L. (2018). Measuring the relative importance of the Logistics Performance Index indicators using Best Worst Method. *Transport Policy, 68*, 158–169. http://dx.doi.org/10.1016/j.tranpol.2018.05.007

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*: McGraw-Hill.

Singh, B. (2016). Analytical hierarchical process (AHP) and fuzzy AHP applications: A review paper. *International Journal of Pharmacy and Technology, 8*(4), 4925–4946.

Stević, Ž., Ersoy, N., Başar, E. E., & Baydaş, M. (2024). Addressing the global Logistics Performance Index rankings with methodological insights and an innovative decision support framework. *Applied Sciences (Basel, Switzerland), 14*(22), 10334. http://dx.doi.org/10.3390/app142210334

Yang, C. S., & Lin, M. S. M. (2024). The impact of digitalization and digital logistics platform adoption on organizational performance in maritime logistics of Taiwan. *Maritime Policy & Management, 51*(8), 1884–1901. http://dx.doi.org/10.1080/03088839.2023.2234911

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353. http://dx.doi.org/10.1016/S0019-9958(65)90241-X

Zhang, X., Ma, W., & Chen, L. (2014). New similarity of triangular fuzzy number and its application. *TheScientificWorldJournal, 2014*, 215047. http://dx.doi.org/10.1155/2014/215047

Zimmermann, H. J. (2010). Fuzzy set theory. *Wiley Interdisciplinary Reviews: Computational Statistics, 2*(3), 317–332. http://dx.doi.org/10.1002/wics.82