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AI-Driven Transformation in Employment and Labor Income: A Global Analysis of Workforce Dynamics

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Abstract: Artificial intelligence (AI) technology has profoundly transformed the landscape of work, exerting substantial influence on employment and labor income dynamics. This study leverages global AI index data to investigate the implications of AI adoption on employment rates and labor income shares. The findings reveal a detrimental effect of AI on both employment opportunities and the proportion of income allocated to labor, with these impacts varying significantly among different worker demographics and across various countries. By unpacking the current effects of AI technology on the labor market, this paper provides valuable insights and potential strategies to address and mitigate the adverse outcomes associated with the integration of AI in the workforce.

Keywords: artificial intelligence; employment; labor income share.

JEL classification: F01; J21; J31.

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1. INTRODUCTION

Artificial Intelligence (AI), a term first used by John McCarthy in 1955 at the Dartmouth Conference, refers to the field of creating intelligent machines. It can be broadly categorized into Narrow AI, which excels in specific tasks, and General AI, which possesses a broader cognitive ability (Poole and Mackworth, 2010)[1,2]. Advances in machine learning and deep learning have led to AI systems that improve autonomously, recognize patterns, and make decisions using large datasets and complex algorithms (Goodfellow *et al.*, 2016). Today, AI is widely understood as intelligent systems or machines capable of understanding, learning, reasoning, perceiving, and making decisions (Russell and Norvig, 2020), drawing inspiration from and simulating aspects of human cognitive processes.

This transformative technology has seamlessly integrated into our daily lives, revolutionizing sectors such as transportation, customer service, finance, and healthcare. Innovations like self-driving cars, automated customer service bots, and sophisticated financial analytics are now part of our reality. The launch of ChatGPT-3.5 by OpenAI in November 2022 marked a significant milestone in natural language processing, significantly enhancing human-computer interactions and further expanding the potential of AI applications.

Economically, the impact of AI is expanding rapidly, reflecting its growing importance and influence. Investment in generative AI surged in 2023, reaching $25.2 billion, nearly eight times the previous year's investment (Perrault and Clark, 2024), underscoring the significant financial stakes associated with AI development. This economic shift is not limited to traditional tech sectors; AI is transforming work and production across various industries, leading to significant changes in employment and income distribution.

Unlike previous automation waves, AI's impact extends beyond routine tasks, leveraging continuous learning to improve predictions and recommendations. This shift has profound implications for the job market, posing threats to high-skilled jobs such as stock analysts and lawyers, previously considered immune to automation. The World Economic Forum predicts that digitization and automation could displace 26 million jobs by 2027 but also create 4 million new digital roles, raising concerns about job market stability. The rise of AI is also reshaping income distribution, fueling demand for experts in AI engineering, data science, and machine learning, while traditional low-skilled jobs face falling wages and fewer opportunities, potentially widening the income gap.

Understanding the effects of AI on employment and income is crucial for navigating the challenges and opportunities presented by this technological transformation. By examining these impacts, insights can be gained into the potential societal and economic implications of AI and recommendations can be provided for policymakers to foster sustainable economic development and ensure that individuals can benefit from the AI era.

This paper contributes to the ongoing discourse on AI's economic impact by leveraging the Global AI Index, a standardized indicator that has not been utilized in previous research to conduct a comprehensive global analysis of AI's influence on employment rates and labor income shares. Additionally, the paper demonstrates that the specific impact of AI on employment varies depending on individual and national characteristics, providing a nuanced understanding of AI's multifaceted effects on the global economy and society.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature and outlines research hypotheses. Section 3 describes data selection and empirical strategies employed. Section 4 presents empirical results, followed by a conclusion and recommendations in Section 5.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 The dual impact of AI on employment

The impact of AI on employment remains a subject of debate, primarily due to the interplay between the substitution effect and the creation effect. According to the substitution effect, AI causes job displacement through "machine substitution," potentially reducing employment opportunities. The creation impact, on the other hand, claims that the adoption of AI engenders the emergence of new job opportunities, increases labor productivity, fosters the creation of new occupations, and contributes to the overall enhancement of employment levels.

AI diminishes labor demand via the substitution effect. Technological progress leads to the replacement of labor with capital, particularly in industries where AI excels at repetitive tasks through robotics. This shift results in technological unemployment, as companies opt for robots to enhance efficiency and lower costs, displacing workers (Acemoglu and Restrepo, 2020c). Internationally, Frey and Osborne (2017) estimate that nearly half of U.S. occupations are at risk from AI, with a higher replacement rate of 77% in China. In China's manufacturing sector, Yan *et al.* (2020) found that a 1% increase in industrial robot usage corresponds to a 4.6% monthly decline in jobs. Wang and Dong (2020) further substantiate these findings, highlighting a predominant substitution effect over job creation.

Moreover, the impact of AI on the labor market extends beyond straightforward job displacement. The rise of AI has increased the demand for technical skills and continuous learning from workers, leading to a discrepancy between existing skills and job requirements. This mismatch has the potential to result in structural unemployment (Acemoglu and Restrepo, 2018). Unlike previous technological advancements, AI can simulate human behavior in more sophisticated ways using big data and machine learning, thereby amplifying its potential to replace human labor. In particular, the advent of generative AI, exemplified by ChatGPT, puts jobs that involve mental tasks such as data analysis, information retrieval, and content generation at risk of displacement. Research by Cai and Chen (2019) shows that the integration of AI in China has intensified the challenge of aligning job structures with the age composition of the workforce. This issue is more pronounced when overall educational attainment is low, which could lead to significant concerns about structural unemployment in the short to medium term.

Conversely, AI boosts labor demand through its creation effects. Firstly, AI adoption fosters the development of new products and services, generating new jobs and expanding employment (Barro and Davenport, 2019; Raisch and Krakowski, 2021). In manufacturing, robot deployment has led to roles in maintenance and AI development. AI's integration in sectors like finance, healthcare, and education has also spawned new professions, such as data scientists and AI specialists, enriching labor market diversity. U.S. data confirms that AI adoption has led to new tasks and occupations (Acemoglu *et al.*, 2022; Autor *et al.*, 2024). Similarly, Chinese manufacturing data indicates a positive long-term job impact from robot use (Wang *et al.*, 2022b). Secondly, AI enhances production efficiency, boosting supply and stimulating demand, which in turn increases employment (Trajtenberg, 2018). Graetz and Michaels (2018) show that robot use raises labor productivity and total factor productivity, lowering output prices. Studies by Autor and Salomons (2017) and Gregory *et al.* (2016) suggest that productivity gains drive up consumption, income, and employment. Thus, the creation effect partially offsets the substitution effect of AI, contributing to employment stability.

In essence, the overall effect of AI on employment hinges on the balance between substitution and creation effects, with current opinions divided. Some research suggests AI's employment impact could be neutral, forecasting stable total employment in the future (Cai and Chen, 2019). As Dauth *et al.* (2017) showed with German data, robot adoption does not necessarily lead to job losses, as manufacturing declines are counterbalanced by service sector gains. Current empirical studies on the impact of AI on employment mostly focus on single-country cases, which makes it difficult to reflect cross-border differences and global structural impacts. However, the latest research based on global data shows that AI has a negative impact on the job market (Georgieff and Hyee, 2022; Hui *et al.*, 2024). Thus, the hypothesis is proposed:

H1*: The adoption of AI technology has a net negative effect on employment rates.*

2.2 AI's role in shaping job structures and employment dynamics

The debate over AI's impact on employment volume persists, yet its potential to reshape job structures is universally recognized. The nuanced influence of AI on labor markets is evident through the interplay of worker skills, education, job types, and the varying levels of economic development and AI adoption across countries.

AI's influence on the workforce is closely tied to skills, education, and job types. It has led to employment polarization, with a rise in demand for both high- and low-skilled jobs at the expense of middle-skilled positions (Felten *et al.*, 2019; Sholler and MacInnes, 2024). Non-routine tasks, often complex or adaptable, are less susceptible to AI, while standardized, automatable middle-skilled jobs are more at risk (Lassébie and Quintini, 2022). This trend is supported by data from the U.S., EU, and China (Autor and Dorn, 2013; Autor, 2015; Sun and Hou, 2019). However, the effect on low-skilled labor is unclear, with some studies showing a decline in employment due to robotics in manufacturing (Graetz and Michaels, 2018; Xie *et al.*, 2021).

Education level correlates with job vulnerability to AI. Higher education generally means higher skills and non-routine work, making less educated workers more at risk of replacement, especially in routine roles (Autor *et al.*, 2003; Zhou *et al.*, 2020). Those with lower qualifications, particularly bachelor's degrees or less, face the toughest challenges in adapting to AI (Wang and Dong, 2020). Bughin *et al.* (2018) predict a decrease in jobs involving repetitive, low-digital-skill tasks from 40% to 30% by 2030.

AI's effect on employment varies with a country's economic development, industrial composition, and AI adoption level. AI has widened the employment gap between developed and developing regions, known as spatial employment polarization. AI challenges the traditional growth model in developing areas, diminishing their labor-cost advantage in attracting investment (Cheng and Peng, 2018). Developed countries may experience a manufacturing revival, risking deindustrialization in developing economies (Hui, 2020). Within the manufacturing sector, AI has a profound impact on employment (Cao and Xu, 2020). The industry's reliance on repetitive labor makes it ripe for AI-driven automation, leading to job displacement and the creation of new, technically demanding roles. Additionally, the impact of AI on employment is phased, with leading regions in AI adoption experiencing industry clustering that draws talent and services (Wang *et al.*, 2017). In contrast, regions that lag in AI industry-related innovation may suffer labor outflow due to a lack of investment and development opportunities. Given the diverse factors at play, the hypothesis is formulated as follows:

H2: *Variations in individual (education attainment) and national characteristics (economic development, industrial composition, AI adoption intensity) affect the employment impact of AI.*

2.3 AI's role in shaping job structures and employment dynamics

The evolution of the employment structure is paralleled by shifts in income distribution, heightening concerns about income inequality (Acemoglu and Autor, 2012). The impact of AI on income distribution is pronounced in its effect on the labor income share. The adoption of AI in production has increased capital's share, widening the wage gap between labor and capital (Ernst *et al.*, 2019). Since the 1980s, a notable decline in the labor income share across various countries and sectors has been attributed to the spread of information and computer technologies, prompting a shift towards capital-intensive production methods (Karabarbounis and Neiman, 2014).

AI alters income distribution by reshaping the workforce structure. One perspective is that AI-driven employment polarization reduces low-skilled job opportunities, leading to increased competition and lower wages for these workers. In contrast, the scarcity of high-skilled labor drives up their wages, widening the wage gap between high- and low-skilled workers (Autor and Salomons, 2017). Studies across countries support this pattern. Acemoglu and Autor (2011) found that the income gap between educated and less-educated Americans has widened since 1980. Dauth *et al.* (2017) noted that industrial robots in Germany reduced middle-skilled wages while increasing those of high-skilled managers. Wang *et al.* (2020) observed a similar trend in China, with AI contributing to an annual 0.75% increase in the income gap between high- and low-skilled labor. Another viewpoint is that AI exacerbates skill disparities, enhancing productivity for high-skilled workers and contributing to the widening income gap (Korinek and Stiglitz, 2018). Over time, this trend could indirectly benefit capital owners and deepen social class divisions (Acemoglu and Restrepo, 2020c). The hypothesis is:

H3: *The use of AI reduces the labor income share, exacerbating income inequality between labor and other economic agents.*

In summary, existing literature has extensively examined AI's impact on employment, centering on job numbers, employment structures, and income distribution. These studies offer valuable insights and analytical tools. However, empirical research predominantly focuses on the micro level and lacks sufficient macro-level analysis, such as AI's influence on economic development across countries. Additionally, macro-level studies are biased towards developed nations and China, neglecting a broader, comparative approach across various regions. This oversight calls for research on the commonalities and differences in AI's employment effects across countries, which is essential for informing national strategies and policies.

3. DATA SELECTION AND RESEARCH DESIGN

3.1 Data selection

This study undertakes a comprehensive analysis of the impact of AI on employment and labor income share by using data from a diverse range of sources. The data spans 45 countries over the period from 2000 to 2022, offering a broad perspective on the influence of AI in

different economic and social contexts, examining factors such as educational level, AI development, industrial disparities, and stages of economic growth (*H2*). This 22-year timeframe is pivotal in the narrative of AI, commencing amidst the AI winter of 2000, traversing the renaissance circa 2010, and peaking with the introduction of the AI landmark, ChatGPT, in 2022. This era shows AI's transformative trajectory, marked by progressive evolution and exponential breakthroughs. All the data used in this study are annual data.

Dependent Variables: The employment level is measured by the employment rate of the population over 15 years old (*employ*). This variable is sourced from the International Labor Organization database. It serves as a crucial indicator to assess how adoption of AI affects the proportion of the working-age population that is gainfully employed. The labor income share (*labor_share*) is calculated as the labor income as a percentage of GDP. This metric, which captures the distribution of economic output between labor and capital, is obtained from the World Bank database.

Independent Variable: The primary explanatory variable is the AI level (*AI*), which reflects the degree of AI adoption in each country. Conventionally, studies measure AI levels using data on industrial robots from the International Federation of Robotics (IFR) and AI patent counts. However, these methods are not without their shortcomings. IFR data, being industry-specific, overlooks sectors such as healthcare. Moreover, it defines industrial robots narrowly as multi-jointed machines for production automation, failing to encapsulate the full breadth of AI. Additionally, data delays limit a comprehensive view of the global robot market. AI patent data is also subject to delays, incomplete coverage, inconsistent international standards, and the risk of double counting. In this analysis, the Global AI Index by AI Rankings is utilized instead[3]. This index evaluates AI across six critical domains: computer vision, natural language processing, machine learning, cognitive reasoning, robotics, and multi-agent systems. The AI Index provides a more holistic and interdisciplinary evaluation by computing the geometric means of pertinent publications, which mirrors global AI research capabilities. It is an objective, extensive measure that enables meaningful international comparisons.

Control Variables: Drawing on studies by Jiang *et al.* (2023), Wang *et al.* (2022a) and Wang *et al.* (2023), several control variables are incorporated to account for factors influencing employment and labor income share. Economic development is represented by the logarithm of GDP per capita (*ln gdp*), sourced from the World Bank database. Population size, measured as the logarithm of the total population (*ln population)*, also comes from the World Bank. Educational attainment, indicated by the logarithm of average years of education (*ln school*), is obtained from the Global Data Lab database. The proportion of the population aged 65 and older (*aging*), reflecting the level of aging, the proportion of value added by the secondary industry in GDP (*indu*) for industrial structure, and the proportion of the urban population in the total population (*urban*) for urbanization level are all sourced from the World Bank. The cost of living, represented by the Consumer Price Index with 2010 as the base year (*cpi*), is from the Global Data Lab database. The degree of international trade, measured by the share of the value of imports and exports of goods and services in GDP (*open*), is sourced from the World Bank.

For detailed information of the data see Annex. Table no. 1 provides a comprehensive overview of the descriptive statistics for each variable.

Table no. 1 – Descriptive statistics

Variable	Observations	Mean	Standard deviation	Min	Max
employ	1035	56.805	8.933	34.995	88.206
labor_share	765	51.759	10.374	14.93	68.43
AI	889	9.37	30.785	0	342.54
ln gdp	1034	10.32	0.805	7.726	11.701
ln population	1035	16.879	1.791	12.874	21.072
ln school	963	2.318	.282	1.19	2.648
aging	1035	12.667	6.169	0.172	29.925
indu	1014	27.106	10.15	2.759	73.469
urban	1035	75.319	17.252	23.59	100
cpi	995	107.036	52.604	20.595	1031.658
open	1027	94.026	72.515	19.56	437.327

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). *employ* (employment rate of the population over 15 years old). *labor_share* (labor income as a percentage of GDP). *AI* (Global AI Index). For the control variables: *ln_gdp* (logarithm of GDP per capita), *ln_population* (logarithm of total population), *ln_school* (logarithm of average years of education), *aging* (proportion of population aged 65 and older), *indu* (proportion of value added by the secondary industry in GDP), *urban* (proportion of urban population in total population), *cpi* (Consumer Price Index with 2010 as the base year), and *open* (share of value of imports and exports of goods and services in GDP).

3.2 Research design

Model (1) and Model (2) were established as baseline models to evaluate the influence of AI on employment (*H1*) and labor income share (*H3*).

$$employ_{it}=\alpha_0+\alpha_1\times AI_{it}+A\times X_{it}+\mu_i+\xi_t+\varepsilon_{it} \quad (1)$$

$$labor\_share_{it}=\beta_0+\beta_1\times AI_{it}+B\times X_{it}+\mu_i+\xi_t+\varepsilon_{it} \quad (2)$$

where subscripts i and t represent the country and year respectively, μ_i and ξ_t respectively represent the country fixed effect and year fixed effect, and ε_{it} is the error term, using robust standard errors. *employ* indicates the employment level, *labor_share* represents the labor income share. *AI* serves as the primary explanatory variable. The variable set X includes control variables (*ln gdp*, *ln population, ln school, aging, indu, urban, cpi, open*).

4. EMPIRICAL RESULTS

4.1 Baseline results

Columns (1) and (2) of Table no. 2 present the findings from the stepwise regression analysis applied to the baseline regression Model (1). Column (1) restricts the analysis to year and country fixed effects. Expanding the scope, Column (2) incorporates a range of national characteristics, including the level of economic development, population size, educational attainment, aging demographics, industrial composition, urbanization rates, cost of living, and the extent of international trade.

The results are statistically significant at the 1% level, revealing a pronounced association between the advancement of AI and employment rates. Specifically, for each unit improvement in AI capabilities, the employment rate experiences a decrease of 0.018% in Column (1) and 0.014% in Column (2). This indicates that even after accounting for country-specific traits and year and country fixed effects, the proliferation of AI exerts a noticeable dampening effect on employment levels, in support of H1.

Columns (3) and (4) of Table no. 2 elaborate on the outcomes for the baseline regression Model (2), which also employs the stepwise regression method. These results underscore AI's adverse influence on the labor income share. With every unit increase in AI's strength, the labor income share diminishes by 0.016% and 0.012% respectively, suggesting a widening income gap between labor and other economic agents. This pattern highlights the potential for AI to exacerbate income disparities between labor and other economic agents, in support of H3.

Table no. 2 – Baseline results

Variable	employ		labor_share	
	(1)	(2)	(3)	(4)
AI	-0.018***	-0.014***	-0.016***	-0.012***
	(-4.178)	(-3.810)	(-4.000)	(-3.123)
Control variable	No	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	889	795	673	636

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex).The first two columns present the results of Model (1) and the last two columns show the results of Model (2). The coefficients are obtained from the stepwise regression analysis of the baseline regression models. In column (1) control for country and time fixed effects and in column (2) add control variables mentioned in Section 3.1. The same as column (3) and (4). The values in parentheses are robust standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels respectively. The following tables are the same.

4.2 Endogeneity problems

The COVID-19 pandemic has undoubtedly impacted both the progression of AI technology and employment rates from 2020 to 2022. This presents a risk of endogeneity bias due to common determinants. To address this issue, we exclude the data from 2020 to 2022 from our regression analysis. The results in columns (1) and (2) of Table no. 3 demonstrate that even after removing this period, a significant negative correlation persists between AI advancement and employment rates, with coefficients of -0.017 and -0.013, respectively. This reinforces the stability of our baseline findings.

Conversely, reverse causality is a consideration: shifts in labor's income share could potentially influence a country's AI development. Typically, a higher labor income share suggests more funding available for AI research and development, thereby enhancing AI capabilities. To tackle this, we adopt the methodology proposed by Acemoglu and Restrepo (2020a), utilizing the AI levels of countries with comparable income levels as an instrumental variable (*IV*). Firstly, the AI level of peer countries in terms of income can serve as a reasonable proxy for a given country's AI standing, fulfilling the relevance condition. Secondly, this AI level is independent of the country's labor income distribution, satisfying

the exclusivity condition. Considering the significant AI disparities across geographic regions (ANOVA test P-value< 0.000), we use the average AI level of countries with similar income levels within the same region as our IV. Specifically:

Geographic Regions: Countries are first grouped into 4 World Bank geographic regions (AM, AS, AU, EU).

Income Grouping: Within each region, countries are further classified into four income quartiles based on logarithm of GDP per capita (constant 2017 international USD) from the World Bank WDI.

Columns (3) and (4) of Table no. 3 show that the coefficient for this IV is significantly positive at the 1% significance level. Moreover, the F statistic exceeds its critical value, alleviating concerns about weak instruments. In the second stage of the analysis, the regression result for the IV is notably negative (-0.00946) at the 10% significance level, further solidifying the robustness of the baseline results.

Table no. 3 – Endogeneity test

Variable	employ		AI	labor_share
	(1)	(2)	(3)	(4)
AI	-0.017***	-0.013***		-0.00946*
	(-3.931)	(-3.556)		(-2.55)
IV			0.980***	
			(173.94)	
Control variable	No	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	764	717	626	626
F-statistic			30256.7	

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). In the first two columns related to employment (employ), the coefficients for the AI variable are obtained from regression analysis after excluding the data from 2020-2022. The calculation of these coefficients follows the same regression procedures as in Table no. 2. For the instrumental variable (IV) analysis in columns (3) and (4), the coefficient of the IV is estimated through a two-stage least square (2SLS) regression. In the first stage, the AI level of the country regressed on the IV and control variables mentioned in Section 3.1. In the second stage, the labor income share is regressed on the predicted AI level from the first stage and the control variables mentioned in Section 3.1.

4.3 Robustness test

(1) Change core explanatory variables

Considering the potential time lag in the employment effects of AI technology as measured by the AI index, the AI index from the previous year is used for robustness checks. The results in columns (1) and (2) of Table no. 4 continue to align with the baseline results.

AI Index represents scientific research in the AI field and not the integration of AI into daily operations performed by the workforce, I utilize the industrial robots stock data of IFR, which directly measures automation in manufacturing operations. This choice aligns with prior literature (Acemoglu and Restrepo, 2020a) that identifies robot density as a key proxy for workplace automation implementation. As shown in Table no. 4, columns (3)-(4), the coefficients for robot stock (-0.000008***, -0.000009***) maintain statistical significance

and directionality consistent with the baseline results. This confirms that the negative employment effect persists across different operationalizations of AI adoption, whether measured through research capabilities or industrial deployment metrics.

(2) Poisson regression

Considering that *employ* and *labor_share* does not perfectly follow the normal distribution, a panel Poisson regression model was utilized, controlling for year-fixed effects and country-fixed effects. The results in columns (5) and (6) of Table no. 4 remain consistent with the baseline findings.

Table no. 4 – Robustness check

Variable	employ	labor_share	employ	labor_share	employ	labor_share
	(1)	(2)	(3)	(4)	(5)	(6)
AI	-0.013***	-0.019***			-0.000239***	-0.000204***
	(-3.532)	(-4.135)			(-4.0)	(-3.1)
Robots stock			-0.000008***	-0.000009***		
			(-4.1)	(-3.9)		
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	876	716	713	573	795	636

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, World Bank database and International Federation of Robotics (for detailed information refer to Annex).In terms of replacing the core explanatory variable, the columns (1) and (2) conduct regression analyses using the AI Index of the previous year, while the columns (3) and (4) perform regression analyses using the Robots stock of the IRF. In columns (5) and (6), the coefficients are estimated using the Poisson regression technique. Control variables are the control variables mentioned in Section 3.1.

4.4 Heterogeneity analysis

(1) Heterogeneity analysis based on individual characteristics

AI, characterized by its self-learning abilities, presents a unique model of labor displacement distinct from previous technological breakthroughs. The impact of AI on high-skilled versus low-skilled labor varies markedly. For high-skilled labor, AI holds the potential to displace jobs involving cognitive tasks, yet simultaneously generates new employment opportunities and boosts the demand for skilled workers. In contrast, low- and medium-skilled labor is more susceptible to the substitution effects of AI, especially in roles involving routine tasks, while the automation of non-routine tasks remains a more formidable challenge. Consequently, an in-depth examination is undertaken to understand how AI influences employment rates across different skill levels within the labor force.

Educational attainment is frequently regarded as a credible proxy for employee skill levels (see Acemoglu and Restrepo, 2020b). In light of this, the heterogeneity analysis employs the employment rate among individuals with different educational qualifications as the dependent variable, thereby capturing the labor force's employment status across various skill strata. Table no. 5 presents the differential effects of AI on employment rates within the labor force stratified by educational background. The results indicate a statistically significant negative impact of AI on the employment rates of individuals with higher and secondary education levels at the 1% significance level, with respective coefficients of -0.019 and -0.016.

Conversely, a significant positive effect is observed on the employment rate of those possessing only a basic education (0.019), while no significant effect is detected on the employment rate of individuals with an education below the basic level. This suggests that AI exerts a differentiated influence on the employment of high- versus low-skilled labor. The technology's capability to perform certain cognitive and routine tasks through self-learning is evident. However, the negligible impact on the employment rate of low-skilled labor may correspond to the intrinsic challenges associated with automating jobs that require manual dexterity and physical labor.

Table no. 5 – Individual heterogeneity

Variable	employ			
	Advanced	**Secondary**	**Basic**	**Less than basic**
	(1)	(2)	(3)	(4)
AI	-0.019***	-0.016***	0.019***	-0.003
	(-4.907)	(-3.190)	(4.186)	(-0.345)
Control variable	Yes	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	613	615	607	443

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). The coefficients are derived from regression models, controlling for year and country fixed effects as well as control variables mentioned in Section 3.1, where the dependent variable is the employment rate among individuals with different educational qualifications (advanced, secondary, basic, and less than basic).

(2) Heterogeneity analysis based on country attributes

Prior research has logically posited that the effects of AI on employment vary across stages of economic development (Cheng and Peng, 2018) and among industries (Cao and Xu, 2020), exhibiting stage-specific characteristics (Wang *et al.*, 2017). However, these studies lack data validation. Recognizing the disparities in AI's impact on employment due to country heterogeneity, this study investigates the manner in which AI influences employment across different stages of economic development, levels of AI proficiency, and industrial sectors. Table no. 6 presents the results of estimations that account for country-specific characteristics in the AI employment relationship.

Panel A of Table no. 6 discloses pronounced differences in the experience of AI's impact between developed and developing countries. High-income economies defined by World Bank are recognized as developed countries, otherwise as developing countries. The developed countries in the dataset are Australia, Austria, Belgium, Canada, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Israel, Italy, Japan, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Qatar, Saudi Arabia, Singapore, Spain, Sweden, Switzerland, United Arab Emirates, United Kingdom and United States. The developing countries in the dataset are Argentina, Bangladesh, Brazil, Chile, China, India, Iran, Lebanon, Malaysia, Pakistan, Philippines, Poland, South Korea, Thailand and Turkey. In developed economies, advancements in AI are associated with a detrimental effect on employment rates. Specifically, a one-unit increase in AI proficiency corresponds to a 0.012% decrease in the employment rate, a finding that is statistically significant at the 1% level. The influence on labor income, however, is not pronounced. This suggests that in developed

countries, while AI may displace certain jobs, the overall income levels of the workforce are maintained with relative stability. In stark contrast, developing nations confront more acute challenges. The enhancement of AI proficiency has exerted a significant and negative influence on both the employment rate and the labor income share in these countries, with respective coefficients of -0.074 and -0.087, both statistically significant at the 1% level.

A plausible economic interpretation is that developed countries, with their stronger technological and R&D capacities (Autor, 2019), are better equipped to integrate AI into their industrial sectors, thus cushioning the adverse impacts on employment and labor income. In contrast, developing countries, which often depend heavily on traditional industries, are inherently more vulnerable to the automation and disruption brought about by AI technologies (Arntz *et al.*, 2016). Moreover, these nations may grapple with labor market inflexibilities that hinder workers' ability to adapt quickly to emerging technologies, leading to diminished employment rates and exacerbated income inequalities between labor and other economic agents (Horne *et al.*, 2016).

Table no. 6 Panel B delves into the varied effects of AI on employment, considering the differing degrees of AI adoption across nations. Sort the countries according to their average AI Index from 2000 to 2022. The top 15 countries are classified as having a high AI level (threshold: average AI Index > 3.1), the middle 15 countries as having a medium AI level (threshold: average AI Index > 0.47), and the last 15 countries as having a low AI level. The advancement in AI level exerts a significant negative effect on employment rates in both high and low AI-level countries, with a particularly pronounced impact in the latter (coefficient: -0.074). This indicates that more sophisticated AI technology may lead to a contraction in job opportunities, and countries with less technological readiness are more susceptible to the disruptions caused by AI, potentially facing more severe unemployment issues. In contrast, countries with moderate levels of AI integration do not show a substantial effect of AI progress on employment rates. This could be because these nations are still in the nascent phase of AI technology assimilation, maintaining a more stable labor market status quo.

As for the labor income share, in high AI-level countries, the uptick in AI level correlates with a decline in the proportion of labor income. This might stem from the diminished bargaining power of workers in highly automated and intelligent settings, contributing to a widening income gap between labor and other economic agents. Conversely, in countries with an intermediate level of AI, the enhancement of AI has resulted in an increase in the labor income share, suggesting that moderate AI technology can bolster work efficiency and, in turn, elevate workers' earnings. Notably, in countries with low AI levels, AI development exerts no significant effect on the labor income share. This is likely due to these nations' weaker economic structures and technological progress, which limit the influence of AI on the distribution of labor income.

Table no. 6 Panel C analyzes the differential impacts of AI on employment across various sectors. Within primary industry, the integration of AI technology has bolstered the employment rate. This upward trend in employment can be credited to the heightened production efficiency that AI brings to agriculture and natural resource management, thereby spawning new job opportunities. Additionally, given that the primary industry is largely agrarian and labor-intensive by nature, it is inherently less prone to the detrimental effects of AI adoption. In contrast, the tertiary industry has witnessed a downturn in employment figures. Consisting mainly of service-based enterprises, this sector is highly susceptible to job displacement through advancements in AI, leading to a contraction in employment options.

As for secondary industry, there has been no notable change in employment levels. This stability may stem from the sector's diverse composition, where certain segments swiftly embrace automation while others continue to depend heavily on manual labor, maintaining a relatively steady employment trajectory.

Table no. 6 – National heterogeneity

Panel A: Economic level				
Variable	***employ***		***labor_share***	
	Developed (1)	**Developing (2)**	**Developed (3)**	**Developing (4)**
AI	-0.012*** (-3.174)	-0.074** (-2.103)	-0.006 (-1.636)	-0.087*** (-2.793)
Control variable	Yes	Yes	No	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes
N	601	194	476	160
Panel B: AI level						
Variable	***employ***			***labor_share***		
	High (1)	**Medium (2)**	**Low (3)**	**High (4)**	**Medium (5)**	**Low (6)**
AI	-0.020*** (-4.964)	-0.414 (-1.433)	-3.211* (-1.864)	-0.012*** (-3.202)	0.494** (1.972)	1.002 (0.840)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	328	316	151	254	251	131
Panel C: Different sector			
Variable	***employ***		
	Primary (1)	**Secondary (2)**	**Tertiary (3)**
AI	0.008*** (5.527)	0.003 (1.537)	-0.011*** (-5.664)
Control variable	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes
N	795	795	795

Notes: Data from the International Labor Organization database, AI Index database, Global Data Lab database, and World Bank database (for detailed information refer to Annex). The coefficients for the AI variable in Panel A related to developed and developing countries are obtained from regression models that account for country-specific characteristics. The coefficients in Panel B are calculated from regression models considering the different degrees of AI adoption. The coefficients for the AI variable in the employment rate in Panel C for primary, secondary, and tertiary industries are obtained from regression models specific to each industry. The control variables are control variables mentioned in Section 3.1.

5. DISCUSSION

The findings of this study align with an expanding body of research documenting the negative influence of AI on employment rates and labor income shares. The results support the theoretical framework of Acemoglu and Restrepo (2020c), in which AI-driven automation reduces labor demand through substitution effects. Similarly, the global evidence presented by Georgieff and Hyee (2022) and Hui *et al.* (2024) on employment-displacing effects of AI is consistent with the baseline results of this study. Building on these existing findings, this study offers unique contributions. By analyzing 22 years of global data from 2000-2022, it uncovers the differential impacts of AI across educational attainment, economic development levels, and industries. This long-term and comprehensive analysis not only provides a more in-depth understanding of AI's effects but also controls pandemic-related disruptions and validates results using alternative AI proxies.

The heterogeneity analysis in this study further enriches the understanding of AI's impact. For instance, while Frey and Osborne (2017) predicted higher automation risks for low-skilled workers, the results here show significant negative effects on groups with secondary and advanced education. This deviation from previous expectations indicates that AI's influence transcends traditional skill categorizations. This finding is in line with the discovery of Felten *et al.* (2023) that AI increasingly substitutes cognitive tasks previously done by high-skilled workers. The positive effect on the employment rates of those with basic education, as noted in Acemoglu and Restrepo (2020c), might be due to the challenges in automating manual tasks. These findings related to skill levels are closely tied to the overall impact of AI on employment, which in turn is a key factor influencing labor income shares.

Regarding labor income shares, the results of this study support the hypothesis of capital-biased technological change in Karabarbounis and Neiman (2014). However, this study goes a step further by directly linking this trend to AI adoption. The observed decline in labor shares contradicts the projection of stable income distribution until 2030 in Dolls *et al.* (2019). This contradiction, in the context of the employment-related findings, reflects how AI-induced changes in the labor market, such as job displacement and skill-based employment shifts, contributes to the acceleration of AI's economic transformation.

The differential impacts of AI on employment and income distribution also vary across countries. The discovery that developing countries experience more severe employment declines and income contractions provides empirical support for the theoretical arguments in Cheng and Peng (2018). These countries, lacking the adaptive capabilities of developed economies, are more vulnerable to AI-induced structural changes. This aligns with the warnings about automation risks in lower-income countries with rigid labor markets in Schlogl and Sumner (2020). The differential country-level impacts are intertwined with the sectoral impacts of AI.

The differential sectoral impacts identified in this study, with negative effects in the tertiary sector and positive effects in the primary sector, offer a new perspective. While previous studies often focused on the manufacturing sector (Graetz and Michaels, 2018; Wang and Dong, 2020), this study shows that service sectors are more vulnerable to disruption. This is consistent with the predictions about non-routine cognitive tasks in Brynjolfsson and McAfee (2011). The resilience of the primary sector emphasizes the role of labor-intensive industries in buffering automation effects. These sector-specific impacts are part of the broader picture of AI's influence on employment and income distribution, which is shaped by factors like skill levels and country-level economic characteristics.

6. CONCLUSIONS AND SUGGESTIONS

This longitudinal analysis of 22 years of global data (2000–2022) contributes to understanding AI's economic impacts by documenting significant negative effects on employment rates and labor income shares. In conclusion, our analysis yields two principal insights. Firstly, there is a discernible negative correlation between the adoption of AI and employment rates, as well as labor's proportion of income, in support of H1 and H3. Secondly, the influence of AI on employment and income distribution is marked by substantial heterogeneity among various groups and across nations, in support of H2. The impact is not uniform, with workers in different sectors and professions experiencing a spectrum of effects. Furthermore, the distinct economic frameworks and policy environments of individual countries give rise to a mosaic of outcomes related to AI integration.

Based on this, we propose the three recommendations below for how countries could address the challenge of AI employment.

First, making training and education investments. Improve education systems to foster lifelong learning and give opportunities for workers to learn new skills and information. Governments can help people adjust to the demands of evolving technology and occupations by funding online education and job retraining programs.

Secondly, encouraging new industries and innovation. Create new jobs by promoting innovation and growing sectors through policies. Encouragement of innovation and entrepreneurship, particularly in the sectors of AI, green technology, digitalization, and high technology, can assist in creating job possibilities and support economic growth.

Finally, promoting industrial reform and upgrading. Encourage traditional industries to adopt innovative technology to increase production efficiency, while also encouraging industrial upgrading and transformation. To ensure economic diversification and employment market stability, the government can provide financial and policy support.

However, several limitations merit consideration. First, while the Global AI Index captures interdisciplinary research capabilities, it may overstate real-world AI adoption in specific industries. Second, the macro-level analysis presented here does not disaggregate effects by occupation, leaving generative AI's impact on cognitive tasks underexplored. Third, although instrumental variables address endogeneity concerns, unobserved factors like national innovation policies could influence results.

Future research should address these gaps by incorporating micro-level data on AI adoption, exploring occupation-specific effects, and examining policy moderators. Longitudinal updates post-2022 are also critical to capture generative AI's accelerating impacts. By addressing these limitations, scholars can provide policymakers with more nuanced insights to navigate AI's transformative potential.

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ANNEX

Data detail

Data	Detail	Source	Frequency
Country	Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Canada, Chile, China, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, India, Iran, Israel, Italy, Japan, Lebanon, Luxembourg, Malaysia, Malta, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Qatar, Saudi Arabia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, United Arab Emirates, United Kingdom, United States	/	Annual
employ	Employment rate of the population over 15 years old	International Labor Organization database	Annual
labor_share	Labor income as a percentage of GDP	World Bank database	Annual
AI	Global AI Index	AI Rankings	Annual
ln gdp	Logarithm of GDP per capita	World Bank database	Annual
ln population	Logarithm of the total population	World Bank database	Annual
ln school	Logarithm of average years of education	Global Data Lab database	Annual
aging	Proportion of the population aged 65 and older	World Bank database	Annual
indu	Proportion of value added by the secondary industry in GDP	World Bank database	Annual
urban	Proportion of the urban population in the total population	World Bank database	Annual
cpi	Consumer Price Index with 2010 as the base year	Global Data Lab database	Annual
open	Share of the value of imports and exports of goods and services in GDP	World Bank database	Annual
Robots stock	Stock of robots in use	International Federation of Robotics	Annual

Notes

[1]Narrow AI refers to systems designed for specific tasks, such as language translation and image recognition, commonly found in voice assistants and recommendation systems. In contrast, General AI refers to hypothetical systems that can understand, learn, and apply intelligence across a broad range of tasks, similar to human abilities (Poole and Mackworth, 2010).

[2] Considering that General AI remains a theoretical concept and has not yet been realized, the AI discussed in this article refers to Narrow AI.

[3]The original data is available at https://airankings.org/

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Economic Complexity – High Technological Product Nexus for Selected EU Countries: Panel Data Analysis

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Abstract: Making high-tech goods is the main requirement for scoring highly on the economic complexity index (ECI). Importing high-tech goods can help nations that lack access to these entire resources boost their production capacity. The purpose of this study is to determine whether five European Union (EU) countries can rise to the top of the ECI by importing high-tech products as determined by the EU statistical office (Eurostat). This will be done by using the autoregressive distributed lag (ARDL)/Pooled Average Group (PMG) method and accounting for the 2007–2021 period. The chosen nations have the lowest ECI value, and all are full members of the EU. Recurring data indicates that no high-tech product alters the position of nations in the ECI. To rise to the top of the ECI, countries should import high-tech goods based on their own production systems.

Keywords: international economics; economic complexity; import; European Union; high technological product.

JEL classification: F14; 014; B17.

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1. INTRODUCTION

The production of high-tech products is now thought to have begun with the industrial revolution of the Eightieth century. The concept of high-tech items was made possible by advancements that have occurred since the industrial revolution. Regarding whether products qualify as high-tech and which products ought to be in this category, many viewpoints have been expressed. Products like aerospace, Electronic-Communications, and pharmaceuticals have been classified as high-tech products by internationally renowned economic and scientific organizations like OECD (The Organization for Economic Co-operation and Development), TUBITAK (The Scientific and Technological Research Council of Türkiye), and Eurostat (The Statistical Office of The European Union). It has also been acknowledged that the nations that make these goods can produce high-tech goods. A high-tech product is a product that is used extensively in all stages of the production process of the goods and services that are subject to production, from start to finish. It is also referred to as a sophisticated product concept. Research and development (RD) activities are heavily integrated into all stages of process management and organization, marketing, sales, and post-sales. Hidalgo and Hausmann (2009) proposed the concept of economic complexity, while the notion of sophisticated product has actively found its place in study in recent years (Grupp, 1995; Bustos, 2007; Córcoles *et al.*, 2014; Baliamoune-Lutz, 2019). The economic complexity index (ECI), which measures the technological development of countries and ranks them in the context of a technological country, is directly affected by the production of sophisticated products. The primary goal of the study is to determine how beneficial it would be for the five fully-member EU nations (Bulgaria, Greece, Lithuania, Portugal, and Romania) to import the necessary goods in order to move up ECI in the event that they were unable to manufacture the high-tech goods that were chosen for the analysis.

Although quite a few empirical research (Katırcıoğlu *et al.*, 2010; Lapatinas, 2016; Lee and Lee, 2020; Ikram *et al.*, 2021; Mealy and Teytelboym, 2022; Özekenci, 2023) have been conducted on the potential causal relationship between economic complexity, unemployment rate, green economy, international trade, low income, research and development (RD), and foreign direct investment (FDI); comparatively less focus has been placed on effect of various variables on ECI for countries those are low and mid economic developed. In several research conducted in high technology that is related with economic complexity and innovations. Santos-Paulino (2010) examines the export composition of China, India, Brazil, and South Africa using the productivity level associated to a country's exports (EXPY) variable. The study's conclusion is that productivity rises when high-tech products are exported. Moagar-Poladian *et al.* (2017) examine the research and innovation competitiveness of member states of the EU from the standpoint of obtaining research money from the EU, as well as from the perspective of important science and innovation performance indicators for the years 2007-2015. By writers, RD spending lays the groundwork for the introduction of new goods and manufacturing techniques as well as the use of improved and more sophisticated technology, as several writers have demonstrated. Popovici (2018) made an explanation in the export capacity in the EU countries. The author used the FDI and domestic investment to find export performance in manufacturing and services and used GMM approach with the period from 1999-2012. By the result, based on the type of economic activity and the group of nations involved, the empirical data indicates that FDI has varying effects on exports. Akın and Güneş (2018) investigated that economic complexity, and foreign trade has positive and

significant relationship. The authors have been used the Johansen cointegration test and Zivot-Andres one structural unit root test to prove the correlation. Mewes and Broekel (2022) found that complicated technologies provide significant economic advantages. They applied the dynamic panel regression for 2000-2014 periods to reach the result by assessing the complexity of technological activities in 159 European NUTS 2 regions. Goryushkin and Khalimova (2023) make a paper that is about high technological businesses and their roles on economic growth. This paper is research paper and not used the econometric models. By the paper, having the technological advantages for the countries bring the growth of regional advantages, market expansion, and interregional collaboration. Thus, countries could get higher stand on technology league. Aalami *et al.* (2022) state that national IQ, innovation, educational attainment, nutrition explains the nations in terms of the production of high-tech. They focus on twenty-three countries with panel analyses.

Upon examination of the literature review, this study closes the gap to the body of knowledge in a number of ways, including the following: (1) The researcher uses an Autoregressive distributed lag (ARDL) estimating technique based on a PMG panel. This approach is being investigated in published works on economic complexity, aeronautics, electronic communications, pharmaceuticals, research and development, and foreign direct investment. With these characteristics, the research deviates significantly from the other publications. (2) Importantly, selection of lower developed EU countries if compared with the other countries those are full membered of EU also separates this paper from similar ones. (3) Although there is quiet research that examines the effect of various variables on ECI, this study examines with several regression models to find the reactions on ECI. (4) Lastly, the effect of higher technological products on ECI distinguishes this study from others sharply. Thus, this study has been filled the gap in literature.

The study is organized as follows: Section 2 outlines the theoretical model specifications and research technique employed in the empirical experiments. The econometric method is covered in the same section. Empirical results with further pertinent investigations are included in Section 3. The analysis is concluded with policy suggestions in Section 4.

2. RESEARCH METHODOLOGY

2.1 Theoretical model specification

With the aim of examining the causal relationship amid variables, this study adopts ARDL/ PMG method. Levin *et al.* (2002) Panel Unit Root Test (LLC thereafter) prefer to reach the significant results that provides a unit root of model before ARDL. By literature review of economic complexity (Bhaumik and Co, 2011; Kannen, 2020; Khan *et al.*, 2020; Nguyen and Su, 2021; Yeung and Huber, 2024), the estimation model and the variables used for this study is ECI: f (AERO, EE, PHAR, RD, FDI). As on the mentioned on the previous section and avoid repetition, variables are not explained once again. There are three different but similar models used for this study.

ECI_{it} is a dependent variable for all regressions and stands for economics complexity index for five different countries.

$$ECI_{it} = \beta_{it} + AERO_{1t} + RD_{2t} + FD_{3t} + u_{it}\ i = 1, \dots, N, t = 1, \dots, T \quad (1)$$

Regression A (1) is finding the effect of importing of Aerospace goods to five different countries. $AERO_{it}$ is representing with the percentage of total import, RD_{it} is representing the research and development and FD_{it} is the foreign direct investment. i stands for countries in t time. u_{it} is error term in regression.

$$ECI_{it} = \beta_{it} + EE_{1t} + RD_{2t} + FD_{3t} + u_{it}\ \ i = 1, \dots, N\ , t = 1, \dots, T \quad (2)$$

Regression B (2) is finding the effect of importing of Electronic-Communications goods to five different countries. EE_{it} is representing with the percentage of total import as well. RD_{it} is representing the research and development and FD_{it} is the foreign direct investment as regression A. i stands for countries in t time. u_{it} is error term in regression.

$$ECI_{it} = \beta_{it} + PHAR_{1t} + RD_{2t} + FD_{3t} + u_{it}\ i = 1, \dots, N,\ \ t = 1, \dots, T \quad (3)$$

Regression C (3) is finding the effect of importing of Pharmaceuticals goods to five different countries. $PHAR_{it}$ is representing with the percentage of total import as on regression A and B, RD_{it} is representing the research and development and FD_{it} is the foreign direct investment. i stands for countries in t time. u_{it} is error term in regression as well.

The variables (RD_{it} and FD_{it}) are representing the percent of RD_{it} respectively FD_{it} in gross domestic product (GDP) of each country. On the other hand, the control variables such as $AERO_{it}$, EE_{it} and $PHAR_{it}$ are representing the percent of total import of each country.

The next section would be the econometric approach that is about what methods used for the research.

2.2 Econometric Approach

Homogeneity and cross-sectional dependency among the variables are significant for choosing additional econometric tests (such unit roots) that are employed in the analysis. Thus, the Pesaran and Yamagata (2008) modified delta tilde test was used to assess homogeneity, and the Pesaran CD test of Pesaran (2004) was utilized to test cross-sectional independency among the series. Subsequently, Levin *et al.* (2002) unit roots used to analyze the variable integration levels regarding cross-sectional dependence. The long-term and short-term coefficients as well as the causalities between the variables were also estimated using the Pesaran *et al.* (1999) intermediate econometric estimator (PMG estimator), which uses the ARDL model to allow the short-term coefficients to vary between country groups while enforcing the similarity of long-term parameters. As previously mentioned, this estimator maintains consistent long-term parameters across several nation groups but allows for variations in the short-term estimates, error variance, and intercepts. Because the ARDL model may be used to create both short-term and long-term estimates concurrently, regardless of whether the series is I(0) or I(1), it has been increasingly popular in recent years.

2.2.1 Levin, Lin, and Chu (2002) Panel Unit Root Test

Unit root tests of the first-generation panel divide into two groups: first group tests and second group testing, based on whether ρ remains constant or varies from unit to unit. The LLC test in the first group takes into account individual constants and time trends. Higher ordinary serial correlation and inter-unit error variance are permitted to fluctuate freely in this test.

This test was developed by Levin *et al.* (2002) using three distinct models:

$$\Delta y_{it} = \delta y_{it-1} + u_{it} \tag{4}$$

$$\Delta y_{it} = \alpha_{0i} + \delta y_{it-1} + u_{it} \tag{5}$$

$$\Delta y_{it} = \alpha_{0i} + \alpha_{1i} t + \delta y_{it-1} + u_{it} \tag{6}$$

The models without constant, with constant, and with constant trend are referred to by these three terms, respectively. The error process, represented by u_{it} in this instance, is correlated across units and adheres to the stationary reversible ARMA process.

$$u_{it} = \sum_{j=1}^{\infty} \theta_{ij} u_{it-j} + \varepsilon_{it}, \quad i = 1, \dots, N \quad , \quad t = 1, \dots, T \tag{7}$$

If the main hypothesis in LLC panel unit root test generalized by considering model 2 (5):

$$\Delta y_{it} = \delta y_{it-1} + \sum_{L=1}^{P_i} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \quad m = 1,2,3 \tag{8}$$

In Equation (8), d_m indicates the vector of deterministic variables, while their parameters are shown (Levin *et al.*, 2002). The best lag length (L) in the equation can be found by applying any information criterion.

The standard deviation in the LLC panel unit root test is computed by dividing the cross-sectional data's long-term standard deviation by the short-term standard deviation. Corrected t statistics are computed using computed standard deviations. Equation (6) expresses the revised t statistic formulation.

$$t_{\delta}^{*} = \frac{t_{\delta} - N\tilde{T}\widehat{S_N}\sigma_{\tilde{\varepsilon}}^{-2}\widehat{STD(\delta)}\mu_{m\tilde{T}}^{*}}{\sigma_{m\tilde{T}}^{*}} \tag{9}$$

The study's mean $\mu_{m\tilde{T}}^{*}$ and standard deviation $\sigma_{m\tilde{T}}^{*}$ corrections table includes the mean correction and standard deviation values (Levin *et al.*, 2002, pp. 7-8).

2.2.2 Panel ARDL/PMG

Examining the data set's characteristics reveals that the variables' relationships are comparable to those found in Pesaran *et al.* (1999) and Pesaran and Smith (1995). It appears that the Panel ARDL approach established by Pesaran and Smith (1995) is the best appropriate

method to examine it. Due to the better qualities of the Panel ARDL approach over other dynamic panel data regression techniques, as demonstrated by the research of Arellano (1989), Anderson and Hsiao (1981) and Arellano and Bover (1995), fixed effects, and instrumental factors are among the techniques. Alternative approaches are likely to yield inaccurate results unless the predicted coefficients are consistent across national boundaries. Panel ARDL found to be the most successful approach in situations where the data set exhibited comparable features in the study by Karadam (2015). Based on the research and applications found in the literature, Panel ARDL was determined to be the most appropriate approach.

The ARDL (p,q,q,..,q) model can be defined as follows:

$$Y_{it} = \sum_{j=1}^{p} a_{ij} Y_{i,t-j} + \sum_{j=1}^{q} \delta'_{ij} X_{i,t} + \mu_i + \varepsilon_{it} \tag{10}$$

The dependent variable in the equation above is Y, and the explanatory variables are X. The model assumes the following structure when it is parameterized once again.

$$\Delta Y_{it} = \emptyset_i \left(Y_{i,t-1)} - \beta'_i X_{it}\right) + \sum_{j=1}^{p-1} \alpha^*_{ij} \Delta Y_{i,t-j} + \sum_{j=1}^{q-1} \delta^{*\prime}_{ij} X_{i,t-j} + \mu_i + \varepsilon_{it} \tag{11}$$

The coefficients in the model above, denoted as β_i, are intended to be obtained and provide insight into the long-term impact on economic complexity of the explanatory variables included in the model. Furthermore, the coefficient known as Error Correction Mechanism Impact is represented by $\emptyset_i$. The model's other variables display the nations' short-term coefficients. The error term, ε_{it}, has a mean of zero and a variance of constant, and it is independent of time and units. Upon closer inspection, the model allows us to investigate the short- and long-term effects of the variables independently. Being able to see the short- and long-term correlations between variables independently is an advantage. By reviewing the literature, Pesaran *et al.* (1999) and Pesaran and Smith (1995) demonstrated that the MG (Mean Group) approach can reliably estimate the model found in Equation (10). This method involves calculating and averaging coefficients for each cross-sectional data set. On the other hand, a more successful approach known as PMG is advised if the long-term coefficients included in the equation demonstrate homogeneity for each nation, as in this study, Pesaran *et al.* (1999), Pesaran and Smith (1995). According to PMG, short-term coefficients differ between nations even while the long-term structure of the relationship between the variables is the same. Considering this circumstance, the PMG method was used and established as the foundational approach for the investigation. The fourth next section will be about empirical findings which gives the estimations for the research.

3. EMPIRICAL FINDING

The following data set summary and descriptive statistics for the variables used in the study are shown in Table no. 1 for a selected number of years:

Table no. 1 – Summary of data set

Variables	Explanations	Sources
ECI	Economic Complexity Index	M.I.T. - The Observatory of Economic Complexity Index
AEOR	Aerospace (% of Total Import)	World Bank Development Indicators
EE	Electronic-Communications (% of Total Import)	World Bank Development Indicators
PHAR	Pharmaceuticals (% of Total Import)	World Bank Development Indicators
FDI	Foreign Direct Investment (% of GDP)	World Bank Development Indicators
RD	Research & Development (% of GDP)	World Bank Development Indicators

In summary, Table no. 2 shows the descriptive statistics for the factors described above for a sample of five EU nations between 2007 and 2021. Statistics in Table no. 2. descriptively reveals for the sample of EU countries, economic complexity on average (M) is 0.5177 which is nearly with standard deviation (SD) of 0.2286 compared to Aerospace (M. 0.7609, SD. 0.5944), research and development (M. 0.8834, SD. 0.3596). Conversely, the three variables with the greatest mean values – pharmaceuticals (M. 4.2554, SD. 1.1456), foreign direct investment (M. 3.5997, SD. 4.1838), and electronic communications (M. 9.1169, SD. 2.9796) - were the others. Generally speaking, if the normal values for skewness and kurtosis are "zero" and "three," respectively, then the observed series is said to be normally distributed or symmetric. The skewness and kurtosis results in Table no. 2 suggest that none of the observed series have a normal distribution. Specifically, skewness-based figures show that all variables skewed favorably and positively to the right. This suggests that for the first four distributions, the bulk of the study's observations distributed on the positive side. The values in Table no. 3 the Spearman coefficient analysis is computed and showed in Table no. 3.

Table no. 2 – Summary statistic of variables

Statistics	ECI	AEOR	EE	PHAR	FDI	RD
Mean	0.517733	0.760933	9.169867	4.255467	3.599791	0.883465
Median	0.450000	0.620000	8.430000	3.970000	2.856728	0.830840
Max.	1.070000	3.970000	16.00000	7.310000	31.22753	1.680720
Min.	0.210000	0.150000	5.310000	2.230000	-0.963401	0.382080
Std. Dev.	0.228672	0.594404	2.979642	1.145617	4.183871	0.359680
Num. of Count.	5	5	5	5	5	5
Obs.	75	75	75	75	75	75

Note: Data from 2007 to 2021 taken into consideration for normal distribution or not, apply the Jarque-Bera test. It examines the proposition that a particular series has a normal distribution.

Table no. 3 – Correlation analysis

Variables	ECI	EE	PHAR	AEOR	FDI	RD
ECI	1					
EE	6.468489	1				
PHAR	-2.447877	-1.251326	1			
AEOR	-3.300299	-0.285757	0.130572	1		
FDI	1.706935	2.735676	-5.566842	-0.417200	1	
RD	-2.450421	-4.742849	-0.145382	4.305667	0.651865	1

Unlike Levin and Lin (1992), Levin *et al.* (2002) known to allow for homogeneity and autocorrelation. Therefore, it is not necessary to display the tables for the two outcomes in

this work. According to Table no. 4, the level value of the dependent variable ECI seen to be statistically insignificant in the model with constant and constant and trend, therefore the null hypothesis "H_0: There is no unit root" rejected. The first difference value of the variable found to be statistically significant in the model with constant and constant and trend, so the null hypothesis "H_0: There is no unit root" accepted and it determined as I (1). Additionally, It seen that the level values of the independent variables PHAR and RD statistically insignificant in the constant and constant and trend model, therefore the null hypothesis "H_0: There is no unit root" rejected. For this reason, the first difference value of the variable found to be statistically significant in the model with constant and constant and trend, and therefore the null hypothesis "H_0: There is no unit root" accepted. In this case, the variables determined as I (1). It seen that the level value of the FDI and AERO independent variables statistically significant in the model with constant and constant and trend, therefore the null hypothesis"H_0: There is no unit root" accepted. The variables are designated as I (0).

Table no. 4 – Levin-Lin-Chu (2002) panel unit root test

Variables	Constant		Constant &Trend	
	t-Statistic	P-Value	t- Statistic	P-Value
ECI	-1.5318	0.0628	-1.3402	0.0901
ΔECI	-3.1247	0.0009***	-2.1279	0.0167**
AERO	-2.4419	0.0073***	-4.3588	0.0000***
EE	-4.3774	0.0000***	-4.4310	0.0000***
PHAR	0.6706	0.7488	-1.3144	0.0944
ΔPHAR	-4.4055	0.0000***	-6.5255	0.0000***
RD	0.7244	0.7656	-1.3253	0.0925
ΔRD	-3.6859	0.0001***	-1.7939	0.0364**
FDI	-5.7764	0.0000***	-6.6325	0.0000***

Note: ** and *** denote statistical significance at the 1% and 5% levels, respectively, while Δ denotes the initial differences.

The findings of regressions A, B, and C are displayed in Tables no. 5, no. 6, and no. 7. When the ARDL limit test results are analyzed for every model, several assessments can be made. First, a closer look at Table no. 5 reveals that the relevant nations have the potential to move up the ECI rankings by gradually increasing their imports of aeronautical goods. In another way, it is anticipated that the relevant nations would advance technologically and be able to rank better in the ECI as a result of rising import statistics in the aerospace industry.

Table no. 5 – ARDL result of variable aero

Variables		Coeff.	Prob.
Long Run (LR)	**AERO**	0.0986	0.0000***
	RD	-0.0166	0.0000***
	FDI	0.5448	0.0000***
Short Run (SR)	**Ec__**	0.4011	0.3571
	D(AERO)	0.0527	0.0628
	D(RD)	0.1034	0.5019
	D(FDI)	0.0156	0.3440

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance.

A similar situation can be said in the results obtained in Table no. 6 and Table no. 7 Importing electronic-communications and pharmaceutical products from abroad helps the relevant countries advance technologically and climb to the top of the ECI. The fact that the effects of technological developments generally seen in the long term also supports the results obtained. An important detail is that importing Pharmaceuticals products from abroad will enable the relevant countries to rank higher in the ECI in the long run, faster than other products. When Tables no. 5, no. 6, and no. 7 examine, Pharmaceuticals products have the biggest impact on ECI with 0.1362 (0.0031***). In addition, the fact that the developments achieved in the long-term don not observed in the short term is compatible with the idea that the returns on investments made in technology receives in the long term.

Table no. 6 – ARDL result of variable ee

Variables		Coeff.	Prob.
Long Run (LR)	**EE**	0.0346	0.0473**
	RD	-3.6475	0.1015
	FDI	1.2644	0.0998
Short Run (SR)	**Ec__**	-0.0197	0.0862
	D(EE)	-0.0016	0.9472
	D(RD)	0.0761	0.4895
	D(FDI)	-0.0135	0.3115

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance

Table no. 7 – ARDL result of variable phar

Variables		Coeff.	Prob.
Long Run (LR)	**PHAR**	0.1362	0.0031***
	RD	-0.0782	0.6066
	FDI	0.0129	0.4030
Short Run (SR)	**Ec_____**	0.0129	0.5715
	D(PHAR)	0.0064	0.6833
	D(RD)	0.0711	0.3598
	D(FDI)	0.0013	0.8148

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance.

Following the evaluation of the findings with all countries, each country's results looked at separately. The numbers in Tables no. 8, no. 9, and no. 10 obtained when the impacts of the pertinent variables studied independently for the study's focal countries, Bulgaria, Greece, Lithuania, Portugal, and Romania.

Upon closer inspection of the data shown in Tables no. 8, all nations except Lithuania have considerable error correction parameters. Although it is not negative, Bulgaria and Romania's error-correction parameter is considerable. Thus, aside from these three nations, Greece and Portugal may be considered to have a long-standing partnership between ECI and AERO. From this point on, almost 19% of the imbalances in the ECI that would arise in the next period as a result of AERO imports into Greece will be fixed. In a similar vein in Portugal, the next period will make up for about 1% of any imbalances in the ECI that may arise from AERO imports during a given period. As a result, Greece values AERO imports more than Portugal does, is able to address import imbalances more quickly, and can react to a spike in ECI more quickly. It is clear from these findings that Greece needs to prioritize AERO imports.

Table no. 8 – PMG result of variable aero

	AERO		RD		FDI		EC_	
Countries	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Bulgaria	0.1325	0.0000***	0.4688	0.0026***	-0.0010	0.0000***	2.1127	0.0001***
Greece	0.0165	0.0000***	-0.2770	0.0001***	0.0803	0.0000***	-0.1528	0.0000***
Lithuania	0.0114	0.0071***	-0.0716	0.2716	-0.0008	0.0001***	-0.0038	0.6711
Portugal	-0.0012	0.0000***	0.4605	0.0000***	0.0071	0.0000***	-0.0162	0.0000***
Romania	0.1044	0.0004***	-0.0631	0.2790	-0.0072	0.0000***	0.0659	0.0000***

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance

Following examination, the statistics shown in Table no. 9 show that each country's error correction parameter is considerable. Although it is not negative, Lithuania's error correction parameter is considerable. Thus, for all nations with the exception of Lithuania, a long-term link between ECI and EE may be noted. Examining the data reveals that imbalances in the ECI that can arise from EE imports into Greece in one period can be addressed in the subsequent month with a value less than 1%. Likewise, in Portugal, the correction of ECI imbalances resulting from EE imports in a given period will only account for around 2% of the imbalances in the subsequent period. Merely 5% of the potential imbalances in the ECI resulting from EE imports into Romania during a given period will be rectified in the subsequent quarter. Ultimately, the next period will only rectify around 2% of the imbalances in the ECI that could arise from Bulgaria's EE imports during that particular time. This indicates that Romania values EE imports more than Portugal does, that Portugal can address import imbalances more rapidly than Bulgaria, allowing it to react to the rise in ECI more swiftly, and that the other three nations are able to address their imbalances in comparison to Greece. It is acknowledged that a quicker correction is possible. This condition leads one to believe that Romania need to prioritize EE imports.

Table no. 9 – PMG result of variable ee

	EE		RD		FDI		EC_	
Countries	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Bulgaria	-0.0414	0.0000***	0.2464	0.0483**	-0.0149	0.0000***	-0.0226	0.0000***
Greece	-0.0348	0.0000***	0.1930	0.1043	-0.0127	0.0080***	-0.0096	0.0001***
Lithuania	-0.0235	0.0000***	-0.0901	0.0008***	0.0152	0.0000***	0.0145	0.0000***
Portugal	0.0922	0.0000***	-0.2667	0.0000***	-0.0179	0.0000***	-0.0273	0.0000***
Romania	-0.0005	0.0004***	0.2980	0.0001***	0.0087	0.0000***	-0.0533	0.0000***

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance.

Lastly, a closer look at Table no. 10 reveals that every country's error correction parameter is considerable. Although it is not negative, the error correction parameter for Romania and Lithuania is noteworthy. As a result, not all nations can have a long-term association between ECI and PHAR. Upon analysis of the data, it is possible to rectify imbalances in the ECI that may arise in a certain period as a result of PHAR imports into Greece by less than 1% in the subsequent month. Comparably, in Portugal, the next period will make up for around 20% of any imbalances in the ECI that may arise from PHAR imports during a given period. Ultimately, in Bulgaria, the subsequent period will rectify around 24% of the imbalances that can arise in the ECI as a result of PHAR imports during one period. This suggests that Portugal can adjust import imbalances more quickly than Romania, which

allows Portugal to react to a rise in ECI more quickly than Bulgaria, which places a higher value on PHAR imports. This condition leads one to believe that PHAR imports should be Bulgaria's top priority.

Table no. 10 – PMG result of variable phar

	PHAR		RD		FDI		EC__	
Countries	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
Bulgaria	-0.2402	0.0159**	-0.1124	0.0022***	-0.0002	0.0002***	-0.2402	0.0159**
Greece	0.0136	0.0000***	-0.0437	0.0520	0.0222	0.0000***	-0.0070	0.0007***
Lithuania	-0.0208	0.0000***	0.0510	0.0303**	-0.0091	0.0000***	0.1324	0.0000***
Portugal	-0.0151	0.0003***	0.1290	0.0012***	8.3805	0.0169**	-0.2028	0.0263**
Romania	0.0649	0.0000***	0.3318	0.1238	-0.0064	0.0000***	0.0999	0.0002***

Note: At the 1% and 5% levels, respectively, *** and ** denote statistical significance.

4. CONCLUSION AND RECOMMENDATION

This study looked at the casual link between high technology products (aero, ee, phar) and eci for five EU full member countries (Bulgaria, Greece, Lithuania, Portugal and Romania) for the period 2007-2021. The following is a summary of the study's findings-based policy suggestion and conclusion: First, looked at the summary statistic of variables. Second, applied the LLC panel unit root test by the result of cross-sectional correlation. Third, used the ARDL to show for long and short-run relationship with ECI for each control variables. Last, result from the PMG for each country through the panel ARDL model.

According to the results obtained from the analysis, imports of relevant high-tech products generally take the countries selected in the study higher in the ECI. As expected, the effects of high-tech product imports are consistent with the idea that the results of high-tech products obtained as a result of RD can be seen in the long term, not in the short term. When the relevant high-tech products examined for each selected countries, previously unobtainable and interesting results can be obtained. When examined for the aerospace, Greece is better than Portugal at valuing AERO imports, addressing import imbalances faster, and responding swiftly to an increase in ECI. These results demonstrate that Greece must give AERO imports first priority. If examined for electronic-communications, Romania places a higher value on EE imports than does Portugal, that Portugal is able to react to the growth in ECI more quickly than Bulgaria due to its ability to fix import imbalances more quickly, and that the other three countries are able to address their imbalances more quickly than Greece. It is accepted that a speedier fix is achievable. This criterion suggests that Romania should give EE imports priority. On the other hand, when looking at pharmaceuticals, Portugal can respond to an increase in ECI faster than Bulgaria, which places a greater value on PHAR imports, since Portugal can correct import imbalances more rapidly than Romania. One would seem that Bulgaria's main priority should be PHAR imports based on this circumstance.

All these findings have especially important policy implications. The results give an idea that being a member of the EU paves the way for technological development for member countries. The funds available from the EU enable development. However, it is an important detail in how these funds should be used to climb to the top of the ECI, which is an indicator of technological development. In this sense, this study provides information to the countries selected in the study about which areas they should invest in to develop their technologies, and if they do not have the opportunity and conditions to invest, which areas they should

import and develop their technologies. When looked at, it seems essential for Greece to import in the field of aerospace. On the other hand, Romania should give importance to the import of electronic-communications products. Finally, one-step of Bulgaria's rise to the upper leagues technologically is through the import of pharmaceutical products.

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The Contribution of Digitalization to FDI Inflows – Private Investment Nexus in Advanced Countries

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Abstract: Foreign direct investment (FDI) is crucial for economic advancement as it brings in physical capital, facilitates technology transfer, and promotes innovation. Concurrently, private investment stands as a fundamental driver of economic growth. The emergence of digital technology offers nations fresh prospects to cut costs, decrease emissions, and move towards a more sustainable, environmentally friendly economy. Does digitalization contribute to FDI inflows – private investment nexus in advanced countries? We provide the answer by applying the two-step system and difference GMM estimators to explore the effects of FDI, digitalization, and their interaction terms on private investment in 37 advanced countries from 2010 to 2023. The findings note that FDI crowds out private investment, but digitalization and interaction terms promote it. Furthermore, labor force increases private investment, while inflation decreases it. These results propose that advanced countries can adopt suitable policy strategies to maximize the benefits of FDI and digitalization for enhancing private investment.

Keywords: FDI; digitalization; private investment; advanced countries.

JEL classification: E22; F21; F23.

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1. INTRODUCTION

The impact of FDI on private investment is a contentious issue among economists, mainly due to conflicting crowd-in and crowd-out theories. Drawing from the insights of Agosin and Machado (2005), numerous studies have investigated this relationship to determine whether FDI and private investment complement each other or serve as substitutes. FDI inflows are crucial external factors for both developing and advanced economies. They are significant in facilitating technology transfer, acquiring expertise, promoting innovation, and building capital (Agosin and Machado, 2005). Consequently, several countries are revising their policies and regulations to attract more FDI. Meanwhile, private investment, an internal economic driver, fuels economic growth and development. Khan and Reinhart (1990) emphasize its role in stimulating economic expansion, creating jobs, and ensuring social stability.

Digital technology is quickly becoming an integral and irreversible global force. It enables individuals access to knowledge and skills, enhancing their ability to secure high-paying jobs while improving businesses' efficiency and competitiveness in management and production by effectively reducing transaction costs. Many governments rely on digitalization to stimulate economic activity, drive growth, and reduce the gap with advanced economies (Nguyen, 2022). Strengthening digital technology is a powerful approach to helping low-income individuals gain access to knowledge and develop skills that can increase their earnings. In several countries, digital technology is also central to advancing e-government initiatives. However, its rapid expansion has underscored the existence of a digital divide, with wealthier individuals enjoying greater access than those from poorer communities. This gap is often due to the high costs and technical expertise required to use digital tools, presenting difficulties for lower-income populations (Nguyen, 2023).

Advanced countries are characterized by high levels of education and technological progress, which support widespread digital literacy and skills (Nguyen, 2022). Many of the world's leading scientific and technological innovations come from companies based in these countries. Governments in these economies dedicate significant portions of their national budgets to research and development (R&D), promoting the growth of domestic businesses. Moreover, private companies place a strong emphasis on R&D investments to foster innovation and maintain a competitive edge.

The relationship between FDI inflows and private (or domestic) investment has been a prominent focus in the literature, attracting increasing attention from researchers. The literature shows that the effect of FDI inflows on private investment varies based on factors such as the research sample (e.g., individual country versus a group of countries), time frame, and estimation methods used. This study stands out from previous research in three significant ways. First, it utilizes private investment data from the IMF database, setting it apart from most studies that primarily rely on domestic investment figures. Second, to the best of our knowledge, no studies have yet examined the role of digital technology in the FDI inflows–private investment relationship. Third, the paper applies the two-step system and difference GMM estimators for its analysis. These features are central to the study's unique contribution to the literature. As a result, this paper investigates the role of digitalization in the relationship between FDI inflows and private investment, using the two-step system and difference GMM estimators for a panel dataset of 37 advanced countries from 2010 to 2023.

The paper is organized as follows: Section 1 outlines the motivation for the study. Section 2 presents figures for FDI inflows and digital technology in advanced economies.

Section 3 covers the theoretical framework and literature review, focusing on the influence of FDI inflows on private investment. Section 4 details the model and research data. Section 5 presents the results. Lastly, Section 6 concludes by summarizing the findings and providing policy recommendations.

2. FDI INFLOWS AND DIGITAL TECHNOLOGY IN ADVANCED COUNTRIES

2.1 FDI inflows

According to a recent United Nations (2024) report, global FDI inflows amounted to $1.33 trillion in 2023, a slight 2% decline from the previous year. This total was significantly influenced by large fluctuations in several small European transit economies.

FDI inflows into developed economies, excluding intermediary channels, dropped by 15%. Within these economies, the financial activities of multinational corporations led to fluctuations in FDI levels. When accounting for intermediary flows, FDI increased by 9%, but without these flows, the decline remained at 15%. Developed countries accounted for 35% of global FDI, a share that has been gradually decreasing. However, they continue attracting most new investment projects and international financing deals. FDI inflows into Europe experienced a high shift, rising from -$106 billion in 2022 to $16 billion in 2023. Certain countries, including Ireland, Luxembourg, the Netherlands, Switzerland, and the United Kingdom, reported significant negative figures when comparing combined inflows over the two years. North America also saw a drop in FDI inflows, as did most other developed nations. All developed regions experienced a sharp decline in M&A, with the value of cross-border M&A shrinking by $300 billion in 2023. Additionally, greenfield project announcements in developed economies fell by 6%, while project finance deals decreased by 21%.

FDI inflows fell in many reporting economies, with about two-thirds of developed countries experiencing drops. The United States continued being the largest recipient, accounting for nearly a quarter of global FDI, while China and Hong Kong made up 21%. Among the top 20 host economies, the steepest declines were recorded in France, Australia, China, the United States, and India.

2.2 Global digital technology

The World Bank (2024) published a report outlining global digital progress and trends. The report highlights that between 2018 and 2022, 1.5 billion new internet users were added worldwide, with the surge mainly driven by middle- and low-income countries as the COVID-19 pandemic accelerated growth. By 2022, the global internet user base had reached 5.3 billion, representing two-thirds of the world's population.

The COVID-19 pandemic has helped reduce the internet usage gap between high- and middle-income countries, though low-income countries still lag significantly. By 2022, 92% of people in high-income countries were online, up from 87% in 2018. Middle-income countries experienced faster growth, narrowing the gap with wealthier nations. In upper-middle-income countries, 79% of the population had internet access by 2022, an increase of 16% since 2018, while lower-middle-income countries saw a 25% rise, reaching 56% of the population. Although low-income countries also experienced a sharp increase in internet adoption, especially between 2021 and 2022, the gap with high-income nations remains large. By 2022, only 25% of people

in low-income countries had internet access. Worldwide, 2.7 billion people, mostly from low- and middle-income countries, are still without internet access.

The gap in fixed broadband access between wealthy and poorer nations widened during the pandemic, with middle-and high-income countries achieving higher coverage while low-income nations fell behind. By 2022, fixed broadband reached 38% of the population in high-income and 31% in upper-middle-income countries. In comparison, lower-middle-income countries had just 4% coverage, and in low-income countries, access remained almost nonexistent due to infrastructure challenges and high costs.

Mobile broadband penetration exceeds fixed broadband and continues to expand steadily across all income levels, though progress in low-income countries has been slow. As mobile devices like smartphones, tablets, and smartwatches have grown more advanced and versatile, mobile broadband has emerged as the primary method for accessing the Internet. While fixed broadband remains too costly for most people in low-income nations, mobile broadband is increasingly affordable. Nevertheless, the lack of widespread fixed broadband remains a high barrier to achieving universal connectivity, as many individuals in low-income countries still cannot afford it.

The gap in computer ownership is stark, showing significant disparities between high- and low-income countries and between urban and rural areas. From 2017 to 2021, more than 80% of households in nations such as Belgium, Poland, Japan, Israel, and Australia had a computer, with low variation between urban and rural regions.

3. THEORETICAL BACKGROUND AND LITERATURE REVIEW

3.1 Theoretical background

FDI is crucial in promoting economic development, though its effects on private investment can be complex. For instance, when foreign investors tap into domestic credit markets to fund their activities, local interest rates can be driven higher. This increase in borrowing costs can lead domestic businesses to miss out on potential opportunities, a situation referred to as the crowding-out effect of FDI on domestic investment (Delgado and McCloud, 2017). By contrast, FDI can also promote domestic investment by fostering collaboration opportunities. For example, joint ventures between foreign and local companies can boost capital flows and facilitate technology transfers. In addition, local firms might become suppliers of raw materials or provide contract manufacturing services to foreign enterprises, gaining access to knowledge and modern technologies that help reduce production costs. This beneficial interaction is known as the crowding-in effect of FDI on domestic investment (Agosin and Machado, 2005). However, Nguyen (2021) notes that in advanced economies with rule-based systems, foreign companies compete directly with domestic firms for market share and resources like raw materials and labor. As a result, the relationship between FDI and private investment often becomes substitutionary.

In contrast to FDI inflows, we argue that digitalization positively impacts private investment in advanced countries. These economies, characterized by advanced technological infrastructure and economic development, have established strong digital platforms. Most businesses in these regions have successfully integrated digital technologies into their trading and commercial operations, resulting in low transaction costs. As these economies move from traditional to digital systems, propelled by high education levels, increased incomes, and

significant digital advancement, online transactions become quicker and more convenient, ultimately encouraging private investment.

3.2 Literature review

The effect of FDI inflows on domestic and private investment is a key focus in economic research. The literature presents diverse findings: while some studies suggest a negative impact, others indicate a positive correlation, and many offer mixed evidence on the effects of FDI inflows on domestic and private investment levels.

Eregha (2012), Deok-Ki Kim and Seo (2003), Mutenyo and Asmah (2010), Szkorupová (2015), all indicate that FDI inflows tend to displace private investment. Wang (2010) suggests that while FDI inflows may initially suppress domestic investment, cumulative FDI can have a beneficial impact based on analyses using fixed and random effects models as well as GMM estimators. Pilbeam and Oboleviciute (2012) document a crowding-out effect of FDI on domestic investment across 14 EU countries from 1990 to 2008, utilizing the one-step GMM estimator. Elheddad (2019) shows that FDI inflows decreased private investment in six GCC economies from 2003 to 2013, employing fixed effects and FE-IV estimators. More recently, Chitambara (2021) applied the fixed effects model and two-step system GMM estimator to data from 48 African countries between 1980 and 2016, finding similar crowding-out effects of FDI on domestic investment in this context.

Several studies indicate a crowding-in effect of FDI inflows on domestic investment. For example, Ang (2009), Ang (2010), Desai *et al.* (2005), Ndikumana and Verick (2008), Prasanna (2010), and Tang *et al.* (2008) support this hypothesis. Al-Sadig (2013) shows that FDI inflows can enhance private investment in 91 developing economies from 1970 to 2000, especially when the host country has a high human capital base. Munemo (2014) finds that the complementarity between FDI and domestic investment is significantly affected by business start-up regulations, based on a balanced panel of 139 economies from 2000 to 2010 using a two-step difference GMM estimator. He suggests that improving these regulations could strengthen this positive relationship. Similarly, Tan *et al.* (2016) demonstrate that FDI inflows promote domestic investment in the long term for eight ASEAN economies from 1986 to 2011, utilizing the PMG technique. Boateng *et al.* (2017) confirm the crowding-in effect for 16 sub-Saharan African economies between 1980 and 2014, employing fixed effects models, pooled OLS regression, and FMOLS estimation. Jude (2019) reports a similar effect in 10 Eastern and Central European economies from 1995 to 2015, based on the one-step system GMM estimator. More recently, Ha *et al.* (2022) applied the system GMM estimator to sector-level data from Vietnam (2010–2015) and observed that foreign investment crowds in private investment within the same sector.

Notably, many studies provide mixed evidence regarding the relationship between FDI inflows and domestic investment (Jan Mišun, 2002; Agosin and Machado, 2005; Apergis *et al.*, 2006; Onaran *et al.*, 2013; Ahmed *et al.*, 2015). For instance, Lin and Chuang (2007) find that FDI inflows increase domestic investment in large enterprises while reducing it in smaller ones, based on the Heckman 2SLS technique for 1993–1995 and 1997–1999. Chen *et al.* (2017) observe a neutral overall effect of FDI inflows on private investment in China from the first quarter of 1994 to the fourth quarter of 2014 using the ARDL technique. They note that joint-venture FDI inflows tend to boost private investment, whereas wholly foreign-funded FDI inflows generally decrease it.

From the literature perspective, we note that no existing papers investigate the FDI inflows – private investment with the presence of digitalization. Therefore, we propose the hypotheses as follows:

H1*: FDI inflows negatively affect private investment in advanced countries from 2010 to 2023*

H2*: Digitalization positively affects private investment in advanced countries from 2010 to 2023*

H3*: The interaction term between FDI inflows and digitalization positively affects private investment in advanced countries from 2010 to 2023*

4. EMPIRICAL EQUATION AND DATA

4.1 Empirical equation

From the literature review, the empirical model is proposed as follows:

$$INV_{it} = \gamma_0 + \gamma_1 INV_{it-1} + \gamma_2 FDI_{it} + \gamma_3 TEC_{it} + \gamma_4 (FDI \times TEC)_{it} + Y_{it}\gamma' + \mu_i + \xi_{it} \quad (1)$$

where i and t represent the country and time indices, respectively. INV_{it} is the private investment (% GDP), INV_{it-1} is the initial level of private investment, FDI_{it} is the foreign direct investment, net inflows (% GDP), TEC_{it} is Individuals using the Internet (IND) or Fixed broadband subscriptions (SUB). Y_{it} is a vector comprising economic growth, labor force, and inflation, which serve as control variables.. μ_i is fixed effects, ξ_{js} is the error term, γ_i is parameters. In line with existing literature, we have chosen to include economic growth (Muthu, 2017) and inflation (Delgado and McCloud, 2017) as control variables. Additionally, we posit that the labor force can impact private investment, as it is a crucial resource for the growth and success of businesses.

Estimating Equation (1) presents several significant challenges in econometrics. First, there may be a bidirectional interaction between inflation and economic growth with private investment, which can lead to endogeneity issues. Furthermore, unobserved fixed effects in μ_i could be correlated with the independent variables. The lagged variable INV_{it-1} may also result in substantial serial autocorrelation. Additionally, the panel dataset consists of many countries ($N = 39$) observed over a relatively short time frame ($L = 14$), which could bias OLS regression results. Both the random effects model (REM) and fixed effects model (FEM) have difficulty addressing serial autocorrelation and endogeneity. The Instrumental Variables (IV-2SLS) estimator necessitates appropriate instruments beyond those used in the empirical model. Following the approach of Judson and Owen (1999), we utilize the system and difference GMM estimator.

Holtz-Eakin *et al.* (1988) were the pioneers in introducing the general method of moments (GMM), which was subsequently refined by Arellano and Bond (1991). It led to the development of two types of GMM estimators: difference GMM and system GMM. In estimation, the two-step system and difference GMM estimators (2SGMM and 2DGMM) can provide greater efficiency than the one-step version. However, applying 2SGMM to smaller

samples, like the one in this study, presents challenges (Roodman, 2009). This issue arises from the rapid increase in instrumental variables, which grows quadratically as the time dimension expands, leading to a situation where the number of instruments surpasses the number of panel units. A guideline suggests that the number of panel units should be equal to or greater than the number of instruments (Roodman, 2009) to address this issue. In this study, we employ the Arellano-Bond, Sargan, and Hansen statistics to assess the validity of the instruments in 2SGMM and 2DGMM. The Arellano-Bond AR(2) test checks for serial autocorrelation of the errors in first differences, while the Sargan and Hansen tests evaluate the presence of endogenous variables.

4.2 Research data

The dataset comprises private investment (% of GDP), net FDI inflows (% of GDP), real GDP per capita, labor force (%), and inflation (%). Except for private investment data sourced from the IMF, the other variables are obtained from the World Bank. The research sample focuses on 37[1] advanced countries from 2010 through 2023.

Table no. 1 defines the dataset, Table no. 2 provides summary statistics, and Table no. 3 presents the correlation matrix. Table no. 3 indicates a positive correlation between Internet usage, economic growth, and labor force with private investment. Internet usage and fixed broadband subscriptions show a strong correlation; therefore, they are treated separately in the empirical model.

Table no. 1 – Data description

Variable	Definition	Type	Source
Private investment (INV, %)	"Gross fixed capital formation (% GDP)"	%	IMF
FDI inflows (FDI, %)	"Foreign direct investment, net inflows (% of GDP)"	%	World Bank
Individuals using the Internet (IND, %)	"Internet users are individuals who have used the Internet (from any location) in the last 3 months. The Internet can be used via a computer, mobile phone, personal digital assistant, games machine, digital TV, …"	%	World Bank
Fixed broadband subscriptions (per 100 people) (SUB, value)	"Fixed broadband subscriptions refers to fixed subscriptions to high-speed access to the public Internet (a TCP/IP connection), at downstream speeds equal to, or greater than, 256 kbit/s."	log	World Bank
Economic growth (GDP, USD)	"GDP per capita (constant 2010 US$)"	log	World Bank
Labor force (LAB, %)	"Labor force participation rate is the proportion of the population ages 15-64 that is economically active: all people who supply labor for the production of goods and services during a specified period."	%	World Bank
Inflation (INF, %)	"Inflation, consumer prices (annual %)"	%	World Bank

Table no. 2 – Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
INV	518	26.643	33.354	2.041	234.969
FDI	518	6.584	36.308	-395.67	279.361
IND	518	84.086	10.546	44.4	99.83
SUB	518	33.389	6.749	16.250	49.64
GDP	518	41525.61	21624.73	10962.2	109714.9
LAB	518	74.876	5.940	0.658	89.205
INF	518	2.307	2.644	-2.096	19.705

Table no. 3 – The matrix of correlation

	INV	FDI	IND	SUB	GDP	LAB	INF
INV	1						
FDI	-0.021	1					
IND	0.131***	-0.177***	1				
SUB	-0.023	-0.102***	0.704***	1			
GDP	0.081*	-0.092**	0.538***	0.450***	1		
LAB	0.079*	-0.068	0.496***	0.344***	0.344***	1	
INF	0.001	-0.088**	0.177***	0.110***	0.004	0.122***	1

Note: *, **, and *** refer to significance level at 10%, 5%, and 1%, respectively.

5. EMPIRICAL FINDINGS

5.1 2SGMM estimates

Table no. 4 presents the results of the basic regression model (without interaction terms), while Table no. 5 shows the outcomes of the full regression model (with interaction terms). Each table contains two columns corresponding with two measures of digitalization: individuals using the Internet and fixed broadband subscriptions. The estimation process acknowledges FDI as an endogenous regressor, so this paper treats it as an instrumented in the GMM style, and the other variables are used instruments in the IV style instruments.

Table no. 4 – FDI inflows, digitalization, and private investment: 2SGMM (without interaction term)

Variables	Individuals using the Internet	Fixed broadband subscriptions
Private investment (-1)	0.993***	0.993***
	(0.0004)	(0.0005)
FDI	-0.0036***	-0.0039***
	(0.0000)	(0.0000)
Digitalization	0.007***	0.004***
	(0.0015)	(0.001)
Economic growth	-0.002	-0.0032
	(0.0001)	(0.0002)
Labor force	0.034***	0.034***
	(0.001)	(0.004)

Variables	Individuals using the Internet	Fixed broadband subscriptions
Inflation	-0.169***	-0.151***
	(0.007)	(0.0108)
Instrument	31	31
Country/Observation	37/481	37/481
AR(2) test	0.542	0.543
Sargan test	0.463	0.422
Hansen test	0.314	0.256

Note: *, **, and *** refer to significance level at 10%, 5%, and 1%, respectively.
Dependent variable: Private investment (%)

Table no. 5 – FDI inflows, digitalization, and private investment: 2SGMM (with interaction term)

Variables	Individuals using the Internet	Fixed broadband subscriptions
Private investment (-1)	0.993***	0.993***
	(0.0003)	(0.0005)
FDI	-0.022***	-0.072***
	(0.0007)	(0.0015)
Digitalization	0.010***	0.004***
	(0.002)	(0.001)
FDI*Digitalization	0.0002***	0.0001***
	(0.0000)	(0.0000)
Economic growth	-0.002	-0.003
	(0.0002)	(0.0002)
Labor force	0.039***	0.033***
	(0.002)	(0.004)
Inflation	-0.208***	-0.165***
	(0.012)	(0.007)
Instrument	31	32
Country/Observation	37/481	37/481
AR(2) test	0.538	0.543
Sargan test	0.628	0.559
Hansen test	0.208	0.340

Note: *, **, and *** refer to significance level at 10%, 5%, and 1%, respectively.
Dependent variable: Private investment (%)

Without the interaction term between FDI inflows and digitalization, Table no. 4 indicates that FDI inflows reduce private investment while digitalization enhances it. Additionally, the labor force stimulates private investment, whereas inflation constrains it. When the interaction term is included, Table no. 5 confirms that the sign and significance of the estimated coefficients remain unchanged, suggesting the robustness of the estimated results. In short, the results across models indicate that FDI crowds out private investment. Conversely, digitalization and interaction term reduces private investment. These results support the proposed hypotheses in the paper. It means that FDI negatively affects private investment, and this negative nexus is moderated by digitalization. Moreover, the labor force promotes private investment, while inflation hinders it.

The negative effect of FDI inflows on private investment in advanced economies further supports the "crowding-out" hypothesis, which suggests that FDI can displace domestic private investment rather than complement it. This result is highly consistent with the findings of Eregha (2012), Deok-Ki Kim and Seo (2003), Mutenyo and Asmah (2010), Szkorupová

(2015). Specifically, Nguyen (2021) highlights that FDI inflows crowd out private investment in these advanced countries. He explains that in economies where rule-based governance prevails, foreign companies often compete head-to-head with domestic firms for market share and resources such as labor, capital, and raw materials. This competition between foreign and domestic firms creates an environment where foreign investors, with their substantial financial resources and technological advantages, may gain the upper hand, thus limiting the growth opportunities for domestic companies. As a result, the relationship between FDI inflows and private investment is frequently characterized by substitution.

Unlike FDI, digitalization fosters private investment in advanced countries. This finding aligns with Xu and Jin (2024), who report that government digitalization enhances investment efficiency in China's private sector. We posit that in these economies where technological infrastructure and economic progress are highly developed, digital platforms are firmly established. Most businesses in advanced nations have successfully adopted digital technologies, reducing transaction costs. With the advantages of higher education levels, higher incomes, and substantial digital advancements, these countries are transitioning from traditional methods to fully digital systems. This transformation enhances the efficiency and ease of online transactions, further encouraging private investment.

Similarly, the interaction between FDI and digitalization enhances private investment in advanced economies. We believe that FDI inflows introduce modern digital technologies into these developed markets, accelerating their digital adoption. When foreign companies bring advanced technology and innovation, domestic firms are encouraged to upgrade their digital capabilities, driving further investment. Although FDI alone may lead to a decline in private investment due to competition, this effect is less significant compared to the boost by digitalization. Thus, the interaction between FDI and digitalization promotes private investment by fostering technological progress and business efficiency in advanced countries.

A highly skilled and disciplined labor force in developed countries plays a crucial role in fostering private investment. In these economies, workers often possess advanced education, specialized training, and significant expertise, contributing to increased productivity and innovation. This skilled labor force enables businesses to operate more efficiently and effectively, making these countries attractive destinations for domestic and foreign investors. As a result, the availability of a well-trained workforce directly stimulates private investment by reducing operational risks and enhancing the potential for business success. Therefore, the labor force in developed countries plays a crucial role in driving private investment.

Meanwhile, the negative impact of inflation on private investment in advanced economies is consistent with the conclusions of Wang (2010) and Delgado and McCloud (2017). Inflation increases transaction costs and reduces business profitability, which, in turn, leads to a decline in private investment. Moreover, inflation elevates the price of goods, eroding purchasing power and ultimately lowering production due to decreased consumption.

5.2 Robustness check by 2DGMM

The paper applies 2DGMM to test the robustness of the 2SGMM estimates. Table no. 6 follows a similar structure to Table no. 5, presenting the estimated model with two digitalization measures and incorporating the interaction term between FDI inflows and private investment. Consistent with the 2SGMM results, the 2DGMM estimates reveal that FDI hinders private investment, while digitalization and the interaction term enhance it. These

findings further validate the moderating effect of digitalization on the relationship between FDI inflows and private investment, particularly in advanced economies.

Table no. 6 – FDI inflows, digitalization, and private investment: 2DGMM (with interaction term)

Variables	Individuals using the Internet	Fixed broadband subscriptions
Private investment (-1)	0.717***	0.831***
	(0.089)	(0.059)
FDI	-0.058***	-0.238***
	(0.004)	(0.014)
Digitalization	0.0236***	0.098***
	(0.023)	(0.007)
FDI*Digitalization	0.0007***	0.0006***
	(0.0000)	(0.0000)
Economic growth	-0.131	-0.100
	(0.014)	(0.008)
Labor force	-0.153	0.032
	(0.115)	(0.020)
Inflation	0.173	-0.046
	(0.116)	(0.070)
Instrument	18	17
Country/Observation	37/407	37/407
AR(2) test	0.434	0.445
Sargan test	0.284	0.232
Hansen test	0.736	0.672

Note: *, **, and *** refer to significance level at 10%, 5%, and 1%, respectively.
Dependent variable: Private investment (%)

6. CONCLUSION AND POLICY LESSONS

This paper highlights the crucial role of digitalization in the relationship between FDI inflows and private investment. It employs 2SGMM and 2DGMM techniques to assess the effects of FDI, digitalization, and their interaction on private investment in 37 advanced countries from 2010 to 2023. The analysis reveals that FDI has a crowding-out effect on private investment, while digitalization and the interaction terms encourage private investment. In addition, labor force and inflation are significant factors influencing private investment in these countries.

From a policy standpoint, the findings of this study offer significant insights for policymakers in advanced economies. While it is evident that FDI can crowd out private investment, the research underscores the essential role of digitalization in fostering private investment. To fully harness this potential, policymakers should prioritize initiatives to advance digital progress. It can be achieved by promoting creativity and innovation within digital-based businesses, which can drive economic growth and competitiveness. Additionally, it is crucial to ensure widespread access to and adoption of digital tools among the general population. By doing so, governments can create an environment conducive to investment and entrepreneurship, ultimately leading to more robust economic development and resilience in the face of global challenges. For the business environment, the government should foster investment collaboration between domestic enterprises and FDI investors by facilitating public investment projects and promoting partnerships in digital technology development. Policies should actively promote the digitalization of economic activities in

domestic businesses to reduce transaction costs and enhance investment appeal for local and foreign enterprises.

This study utilizes World Bank data on Internet usage and fixed broadband subscriptions as proxies for digitalization due to their accessibility. However, future research could expand on this by incorporating additional indicators like secure Internet servers and mobile cellular subscriptions from the World Bank database. Furthermore, more comprehensive digital metrics – such as Digital Economy Metrics, Digital Society Metrics, Digital Industry Metrics, Digital Enterprise Metrics, Digital Client Metrics, and Digital Investment Metrics, as proposed by Kotarba (2017) when available – should be employed.

Future studies should explore the influence of digitalization in other economic contexts, such as the relationships between FDI and income inequality or FDI and environmental quality. Moreover, this research relied on internet users and fixed broadband subscriptions as indicators of digitalization based on the data provided by the World Bank. Future research should explore a wider range of measures, provided the necessary data is available.

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Notes

[1] Austria, Belgium, Canada, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong SAR, China, Iceland, Ireland, Israel, Italy, Japan, Korea, Rep., Latvia, Lithuania, Luxembourg, Macao SAR, China, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.

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Exploring the Channels of Financial Inclusion's Impact on Poverty Reduction in Sub-Saharan Africa

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Abstract: There is no doubt that Sub-Saharan Africa (SSA) is home to many financially excluded persons, and the sub-region accounts for a high proportion of the world's poor. Despite the co-existence of low level of financial inclusion (FI) and high poverty level in SSA, little attention has been given to empirical linkage between these two phenomena. This research attempts to unravel the channels through which FI (measured by the composite financial inclusion index developed using the Principal Component Analysis) impact poverty reduction in a sample of 25 SSA countries. The system-Generalized Method of Moments (i.e., system-GMM) estimator was employed to analyze data for the 2004-2022 period. The empirical outcomes portray that the FI-poverty reduction relation is non-linear, and it identify income growth, consumption expenditure, agricultural output, and unemployment as the channels through which FI influences poverty reduction in the SSA region. The findings further reveal that an FI value beyond thresholds of 1.44 and 5.25 increases income growth and reduces unemployment, thereby reducing poverty. Additionally, an FI value below thresholds of 2.87 and 1.40 positively impacts consumption expenditure and agricultural output, leading to poverty reduction. The study recommends that the monetary authorities in SSA adopt policies which increase the access to financial services and promote financial literacy to enhance financial inclusion and reduce poverty.

Keywords: financial inclusion; poverty reduction; Principal Component Analysis; system-GMM.

JEL classification: E52; C12; O10.

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1. INTRODUCTION

Over the years, financial inclusion (FI) and poverty reduction have remained topical issues commonly discussed in economics literature (Abu *et al.*, 2022; Aracil *et al.*, 2022; Felix *et al.*, 2022; Jiang and Liu, 2022; Sakanko *et al.*, 2024). Interestingly, the nexus between these economic phenomena has generated heated debate on whether improvements in FI reduce poverty. The finance-growth hypothesis earlier advanced by Shaw (1973), suggests that poor access to finance is a significant driver of income disparity (inequality) and sluggish growth, which in turn results to poverty. A strand of empirical researches appears to support this claim that greater FI lessens poverty (Bakari *et al.*, 2019; Sakanko *et al.*, 2020; Andrian *et al.*, 2021; Dogan *et al.*, 2022; Nasution *et al.*, 2023).

In a bid to attain high economic growth rates and sustainable development, various countries adopt different policies (or strategies) during different stages of their development. Although meaningful progress has been made in lowering poverty and raising affluence in other regions particularly developed economies, a significant population in SSA economies are still very poor (Omar and Inaba, 2020), partly due to incoherent economic and financial policies including weak institutional frameworks. The Development Initiatives (2023) disclosed that the SSA region hosts 42.6% of world's population living in extreme poverty, with South Asia accounting for 13.7% in 2022. A major factor blamed for the slow reduction in poverty in developing nations (SSA inclusive) is excessive income disparity, which poses a serious threat to improvements in economic conditions (Schmied and Marr, 2016; Omar and Inaba, 2020; World Bank, 2022b).

To end extreme poverty and boost the shared prosperity of each nation's bottom (40%) population by 2030, the World Bank has set targets for reducing income inequality (Omar and Inaba, 2020). As a result, FI has risen to the top of global reform agenda, owing to its potential in breaking generational cycle of poverty (Sakanko *et al.*, 2018). In addition, given that global financial systems are not completely inclusive, there is a growing clamour for FI, due to its perceived potential in promoting inclusive and sustainable development (Nsiah *et al.*, 2021; Shihadeh, 2021; Ozili, 2022; Adams and Atmanti, 2023). Interestingly, the SSA region's FI level increased sharply from 23% in 2011 to 55% in 2021, thus, further stressing the importance of the discussion on the role it (FI) plays in enhancing livelihoods of citizens of these nations (World Bank, 2022b).

Nevertheless, an emerging issue of interest amongst scholars and policymakers, centers on the channel via which the impacts of FI are transmitted to poverty reduction. Besides, empirical research on this subject remains scanty, with inconclusive and mixed findings. A number of researches have explored antithetic proxies to quantify poverty reduction in nexus with FI while including per capita income, households' consumption expenditure, (un)employment, and agricultural output, among others. For instance, Abimbola *et al.* (2018) found that improvements in FI (captured by the number of deposits and customers with bank accounts) lower poverty via a rise in per capita income. Similar outcomes have been documented by Susiyanti (2019) for ASEAN member-countries, and Omar and Inaba (2020) for 116 developing nations. A more recent research by Nasution *et al.* (2023) portrayed that FI reduces poverty via increased households' investment, consumption, education, and income. Overall, the exploration of the channels via which FI transmits its effect to poverty reduction remains inconclusive and needs further examination. Besides, no study (to our knowledge) has explored the subject, focusing primarily on the SSA region.

Therefore, this research is timely and concentrates on SSA for the following reasons. First, despite the various strategies and/or interventions to reduce poverty, 35.1% of SSA's population still lives on less than $2.15 per day (World Bank, 2022a), while FI in the region (measured by account ownership) stands at 55% in 2021 up from 43% in 2017 (World Bank, 2022b). Second, the dimensions of FI vary significantly in terms of depth in SSA countries compared to other regions of the world. Coupled with these are the differences in economic structure from one region (or country) to another. Thus, it is insufficient to draw inference(s) on the channels via which FI transmits poverty reduction in the region based on the outcomes of research covering other regions or country-specific studies.

This research extends the literature by identifying the channels through which FI transmits to poverty reduction in SSA. Also, unlike prior researches which assumed linearity in their empirical analysis, the present research explores whether (or not) the identified channels transmit non-linear effects from FI to poverty reduction. This is motivated by the conflicting findings on FI-poverty reduction link via the identified channels. For instance, Park and Mercado (2021) and Omar and Inaba (2020) established a positive relation between FI and income, while Boukhatem (2016), Kim (2011), and Schmied and Marr (2016) found evidences suggesting a negative relation. Also, Chakrabarty and Mukherjee (2022) and Cavoli and Gopalan (2023) attributed improvements in consumption to greater FI, but Li *et al.* (2022) suggested a diminishing influence of FI. Yet Liu and Yao (2024) confirmed an asymmetric link between FI and consumption.

Moreover, mixed results have been observed for FI and agricultural output nexus. For example, Atakli and Agbenyo (2020) and Farooq *et al.* (2023) disclosed a negative relation, while Hu *et al.* (2021) and Xu and Wang (2023) documented a positive effect of FI on agricultural output. Furthermore, varying impacts of FI on unemployment have been reported. Whereas Okoro *et al.* (2020) and Amakor and Eneh (2021) reported an increasing influence of FI on unemployment, Wu *et al.* (2023) and Wibowo *et al.* (2023) recorded contrasting results.

Besides, FI may have the least influence on poverty reduction until a certain threshold (or turning point) is reached, beyond which its influence becomes more pronounced. Thus, identifying the turning point and determining the channel(s) from FI to poverty reduction provides useful information to policymakers on the strategies to deploy to improve FI so as to reduce poverty in SSA region. Following the introduction, section 2 presents literature review and conceptual framework. The 3rd section addresses the methodology, and section 4 discusses the results. Section 5 concludes the study.

2. LITERATURE REVIEW

2.1 Conceptual review

FI implies the availability, accessibility, and affordability of financial services to the underprivileged segment of the society, and it emphasizes access to financial services and products including loans, savings, insurance, credit, financial advice, transfers and payment, etc., which can lift the poor out of poverty (Demirgüç-Kunt *et al.*, 2018; Tran and Le, 2021). According to Van Doeveren (2018), FI refers to free access to, and use of, appropriate financial services for all people and businesses at affordable cost and participation in society of disadvantaged groups based on equal rights and duties. Furthermore, FI implies access to

financial services like savings, credit, loans, equity, and insurance, which can help them build wealth (Mckinsey & Company, 2023).

On the other hand, Poverty is defined as the lack of essential resources needed for survival (Felix *et al.*, 2022). It refers to a condition where individuals/households cannot afford the basic necessities of life including food, clean water, shelter, and clothing (Sakanko, 2023). It is a situation where individuals/households have significantly less income or resources than the average in their community or country (Abosedra *et al.*, 2016; Aracil *et al.*, 2022). According to Dogan *et al.* (2022), poverty is the lack of access to education, healthcare, social services, and political participation. Poverty also involves being excluded from full participation in the society, facing discrimination, and having limited opportunities to improve one's circumstances (Abimbola *et al.*, 2018; Adams and Atmanti, 2023).

2.2 Theoretical review

To comprehensively explain the FI and poverty relationship, this study builds on McKinnon (1973); King and Levine (1993) finance-growth theory. This theory posits that financial development, including access to financial services, leads to economic growth, which in turn reduces poverty. It emphasises that FI ensures individuals and businesses have access to affordable financial services, enhancing income-generating opportunities, smoothing consumption, and promoting investment in education, health, and businesses, ultimately helping to lift people out of poverty (Schmied and Marr, 2016; Sakanko, 2023). Additionally, the transmission from FI to poverty reduction is portrayed through two channels: the direct channel (King and Levine, 1993; Rajan and Zingales, 1998) and the indirect channel (Schumpeter, 1934; McKinnon, 1973; Shaw, 1973). The former asserts that functioning financial systems create an enabling environment for increased access to financial services, mobilizing savings, boosting investments, and promoting efficient resource allocation. These, in turn, foster economic growth, leading to poverty reduction. In fact, when households or individuals have access to formal financial services such as bank accounts, credit, and insurance, they gain more opportunities to increase their income (Demirgüç-Kunt *et al.*, 2015), whether by starting or expanding businesses, accessing credit for investment or education, or saving for future needs. As income grows, individuals and households acquire more resources to meet their basic needs, resulting in improvements in overall well-being and poverty reduction (Omar and Inaba, 2020).

Proponents of the indirect nexus between FI and poverty reduction argue that improved FI first induces economic growth, which subsequently leads to job creation and increased government spending on public services like health, education, and social protection. These improvements enhance the welfare of the poor and contribute to a decline in poverty levels (Perotti, 1993; King, 2014; Abosedra *et al.*, 2016; Li, 2018; Anga *et al.*, 2021).

2.3 Empirical review

Scholars have attempted to explore the empirical nexus between FI and income, unemployment, agriculture and consumption. A review of the studies are presented in the sub-sections.

2.3.1 Financial inclusion and income

Some efforts have gone into exploring FI and income nexus. For example, in a study of five lower middle-income economies, Nasution *et al.* (2023) adopted the ARDL panel estimation procedure and disclosed that FI significantly reduces poverty. Kanga *et al.* (2022) analyzed the diffusion of financial technology, FI and income per capita in 137 countries using the dynamic heterogeneity panel techniques. They disclosed that Fintech and FI exhibit greater positive and significant influence on per capita income.

Also, in a study of 106 developing nations, Omar and Inaba (2020) used the Fixed Effects (FE) estimator on data over the 2004-2016 period, and portrayed that FI impacts poverty mainly through per capita income. Moreover, Park and Mercado (2021) investigated FI's impact on poverty and income inequality in 151 countries, and observed that greater FI considerably lower poverty rates. Others including Demirgüç-Kunt *et al.* (2018) found that greater FI is associated with higher levels of income growth, suggesting a link between FI and poverty reduction through economic growth.

In Africa, Mohammed Jabir *et al.* (2017) explored FI and poverty reduction relation among low-income households in a panel of 35 SSA economies. They obtained that FI significantly reduced poverty in the sub-region. But Evans and Alenoghena (2017) used a Bayesian VAR method and reported that FI is insignificant in raising income in 15 African economies. Elsewhere, Evans and Lawanson (2017)) established a bidirectional nexus between FI and economic output, including reporting that FI enhances economic growth which tends to lessen poverty.

In Nigeria, Sakanko *et al.* (2020) employed the ARDL estimation technique to investigate FI's role on inclusive growth (poverty, inequality, households' expenditure, and unemployment) from 2007 to 2018, and revealed that higher FI boosts households' income. Employing the OLS estimator, Ogbeide and Igbinigie (2019) found a strong and increasing influence of FI on per capita income in Nigeria during the 2002-2015 period, suggesting poverty reduction impact of FI. Also, Abimbola *et al.* (2018) found that FI (captured by the number of deposits and customers with bank accounts) lowers poverty via a rise in per capita income.

2.3.2 Financial inclusion and consumption

Researchers have also looked at the empirical relation between FI and consumption. For example, Cavoli and Gopalan (2023) investigated FI and consumption smoothing relation in emerging economies during the 1995-2017 period. Using the heterogeneous ARDL panel, they found FI to smoothen households' consumption. Also, Yang and Zhang (2022) documented that higher financial technology considerably increased households' consumption and reduced consumption inequality in China.

Similarly, Chakrabarty and Mukherjee (2022) adopted the standard FE estimator to analyze FI and consumption nexus in India, and observed that households' consumption expenditure increased significantly with improvements in FI. Furthermore, Luo and Li (2022) employed a FE estimator to analyze digital FI's impact on households' consumption over the 2015-2017 period in China. They portrayed that improvements in digital FI considerably lessened consumption inequality. In the same vein, Lai *et al.* (2020) discovered that digital FI enhanced individuals' consumption smoothening over the 2010-2016 period in China.

In Africa, Mwangi and Atieno (2018) explored the FI and households' welfare nexus in Kenya using a dynamic panel regression to analyze data for the 2009-2016 period. They reported that households' welfare increased with greater FI. In Nigeria, Sakanko *et al.* (2020) employed the ARDL method and submitted that FI (measured by consumers' deposit and credit to the private sector) promoted households' consumption during the long-term.

2.3.3 Financial inclusion and agricultural output

Empirical research on FI and agriculture abounds. For example, Xu and Wang (2023) adopted heterogeneity panel technique to analyze digital FI and agriculture output in Chinese 33 cities and provinces, and observed a strong positive influence of digital FI on agricultural productivity.

Also, using ARDL and DOLS estimators, Farooq *et al.* (2023) portrayed that FI (proxied by broad money) significantly boosts agricultural growth, whereas FI (measured by domestic credit) has a significant adverse influence on agricultural growth. In addition, employing a dynamic panel FE estimator, Zhai *et al.* (2023) explored the effect of digital FI on agricultural productivity in China, and showed that electronic-FI boosts agricultural output. Similarly, Hu *et al.* (2021) adopted the dynamic panel estimation method, and found that FI promotes agricultural growth in China's provinces.

In Africa's context, Atakli and Agbenyo (2020) explored FI, gender, and agricultural output relations in Ghana using the OLS technique. They discovered a strong positive influence of FI on agricultural output. Also, Mhlanga *et al.* (2020) investigated the FI and poverty relation amongst Zimbabwean smallholder farmers using simple regression method. The results suggest that improving smallholder farmers' access to FI is an important channel for lowering poverty. Agbenyo *et al.* (2019) used the FMOLS estimator to explore the long-term FI and agricultural output nexus in Ghana. The results portrayed that FI (proxied by domestic credit to the private sector) adversely impact agricultural growth, while FI (proxied by lending interest rate) has a significant and increasing influence on agricultural growth.

Besides, Abu and Haruna (2017) found agricultural commercialization to increase with FI in Ghana using the endogenous switching regression (ESR) and Heckman treatment effect (HTE) technique. In Nigeria, Umaru and Eshiozemh (2022) confirmed a strong positive influence of FI on agricultural output using both NARDL and Stepwise Least Squares (STEPLS) estimators. A Similar finding was established by Fowowe (2020) in Nigeria's case.

2.3.4 Financial inclusion and unemployment

Some studies focused on the FI and unemployment relation. For instance, using two stage least squares (2SLS) and GMM estimators, Wu *et al.* (2023) showed that unemployment declines with increases in FI for seven (7) Asian countries. Also, Wibowo *et al.* (2023) used both FE and RE estimators to assess FI's influence on economic growth and unemployment in Indonesia, Malaysia, Thailand, Philippines, and Cambodia. The results point to a strong negative influence of FI on unemployment. Similarly, using the GMM estimator, Mehry *et al.* (2021) disclosed that FI lowers unemployment in 43 emerging economies. Also, Erra and Venkatachalapathy (2018) employed the system-GMM estimator, and confirmed that FI significantly reduces unemployment and poverty in India.

Moreover, concentrating on non-oil-producing Middle East and North Africa (MENA) group (including Egypt, Jordan, Lebanon, Morocco, and Tunisia), Alshyab *et al.* (2021) used the RE estimator and observed that unemployment decreases with greater FI. In India, Tp (2014) employed the OLS technique, and documented that FI has a strong dampening influence on unemployment via empowerment and poverty reduction. In the context of Africa, Okoro *et al.* (2020) adopted FE and RE estimators, and established that FI exerts a strong and negative influence on unemployment in SSA countries.

2.4 Literature gap

Despite the volume of research exploring FI-poverty reduction relation, some gaps remain, particularly in the SSA context. While numerous studies have investigated FI's impact on income, consumption, agricultural output, and unemployment across various regions, critical gaps persist in understanding the specific channels through which FI influences poverty reduction in SSA.

First, much of the research focused on broader cross-country analyses that encompass diverse economies with varying financial structures and development stages (Park and Mercado, 2021; Kanga *et al.*, 2022; Nasution *et al.*, 2023). Although insightful, the studies may not have adequately captured the unique socioeconomic and institutional dynamics of SSA, where financial infrastructure, literacy, and access to formal financial services remain relatively underdeveloped.

Second, whereas scholars have explored the direct impact of FI on poverty and income growth (Mohammed Jabir *et al.*, 2017; Demirgüç-Kunt *et al.*, 2018), limited attention has been given to understanding the distinct channels via which FI operates to alleviate poverty in SSA. For instance, while Omar and Inaba (2020) highlighted FI's role in enhancing per capita income in developing nations, the pathways through which FI contributes to poverty reduction (including consumption smoothing, job creation, and agricultural productivity) remain under-explored in the SSA context.

Third, studies on SSA region have produced mixed findings regarding FI's effectiveness. For example, Mohammed Jabir *et al.* (2017) found a significant poverty-reducing impact of FI in 35 SSA economies, whereas Evans and Alenoghena (2017) reported that FI had an insignificant influence on raising income across 15 African countries. This inconsistency underscores the need for further investigation into the mechanisms via which FI influences poverty reduction in SSA.

Furthermore, while studies like Sakanko *et al.* (2020) and Ogbeide and Igbinigie (2019) explored FI's impact on inclusive growth, they focused on single-country or deemed it unnecessary to unravel the direct and indirect channels of FI's impact on poverty reduction. Additionally, existing research predominantly emphasizes income-related aspects, overlooking other critical dimensions such as consumption patterns, agricultural productivity, and employment generation.

Moreover, research concentrating on FI-poverty reduction in the SSA region is almost non-existent, and related studies used indicators (including money supply, bank branches, number of borrowers, savings, number of depositors, credit to private sector, number of Automatic Teller Machines, domestic credit-GDP ratio, etc.,) considered bias as a measure of FI.

2.5 Conceptual framework

Given the theoretical foundation and empirical literature, we develop a framework on how poverty reduction is linked to FI via channels like income, consumption, agricultural output, and unemployment (Figure no. 1). This research proposes that FI acts as a catalyst for poverty reduction by boosting income growth, promoting consumption stability, reducing unemployment, and enhancing agricultural output. The discussion on these is done in the subsequent sub-sections.

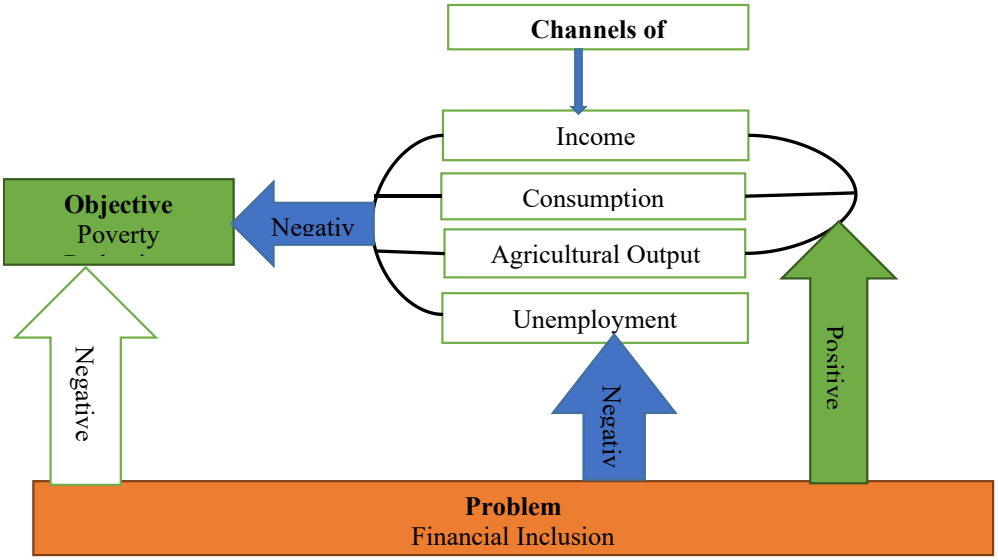

Figure no. 1 – Financial inclusion and poverty reduction conceptual framework
Source: authors' own representation

2.5.1 Financial inclusion and income

The literature argues that if individuals (or households) have increased access to formal financial services (like bank accounts, credit, and insurance, etc.,) they have greater opportunities to increase their incomes. Rising income can be brought about via starting a new business or expanding an existing one, accessing credit for investment or education, or saving for future needs. As income grows, it can contribute to poverty reduction through providing households with more resources to meet their basic needs, resulting to improvements in their overall wellbeing.

The hypothesis testable is:

H*$_{01}$: Financial inclusion does not transmit a significant effect from income to poverty reduction.*

2.5.2 Financial inclusion and consumption

FI can also impact households' consumption. As individuals witnessed increased access to formal financial services, they can save and invest their resources (or money) efficiently, thus, allowing them to smooth consumption over time. This results to improved financial stability and resilience to economic shocks, hence, a reduction in the likelihood of falling into poverty. Additionally, greater access to credit enables people to make valuable investments including purchasing durable goods or investing in education, which further enhances their consumption capabilities and contributing to poverty reduction.

The hypothesis testable is:

***H_{02}**: Financial inclusion does not transmit a significant effect from consumption to poverty reduction.*

2.5.3 Financial inclusion and agricultural output

Greater FI can raise agricultural output. Fowowe (2020) suggested that access to formal financial services can provide farmers with credit, insurance, and other financial tools to invest in their agricultural activities. These result in improved farming techniques, more efficient use of resources and increased productivity. As agricultural output expands, so do farmers' incomes, leading to poverty reduction within rural communities where agriculture is primarily the source of livelihood (Baba *et al.*, 2023).

The hypothesis testable is:

***H_{03}**: Financial inclusion does not transmit a significant impact from agricultural output to poverty reduction.*

2.5.4 Financial inclusion and unemployment

The literature portrays that improved access to financial services increases the easy with which individuals can start their own businesses or engage in entrepreneurship activities, leading to creation of employment opportunities (Tp, 2014). When people are employed and have a regular income, poverty rates tends to decline because individuals can meet basic needs and improve their living conditions (Erra and Venkatachalapathy, 2018).

The hypothesis testable is:

***H_{04}**: Financial inclusion does not transmit a significant impact from unemployment to poverty reduction.*

3. METHODOLOGY

To explore the channel that transmit FI's influence on poverty reduction in SSA, this study concentrates on (and tests) four channels (i.e., income per capita, households' consumption expenditure, agricultural output, and unemployment rate). In essence, this research explores FI's impact on each channel to ascertain how individually they contribute

to poverty reduction. The significance of each channel will disclose whether (or not) it serves as an avenue in the FI-poverty reduction nexus in SSA region. For each of the channels, the dynamic model employed is:

$$W_{it} = \beta_i W_{it-1} + \gamma_i' FI_{it} + \delta_i FI_{it}^2 + \theta_i X_{it} + \mu_i + \varepsilon_{it} \quad (1)$$

where the cross-sectional unit and time i and t, respectively. W is the dependent variable and channel (proxied by each of income growth, consumption expenditure, agricultural output, and unemployment rate) to be investigated, while FI and FI^2 are the financial inclusion and its squared term variables, respectively. X is the vector of control variables (i.e., trade, interest rate, inflation, money supply, exchange rate, and population), while W_{it-1} is the lagged dependent variable. μ_i represents country-specific individual effect, and it denotes unobserved heterogeneity among the countries. ε is the error term. The same control variables are used to account for each dependent variable's behaviour due to their potential influence on the identified channels.

For example, studies of Freund and Bolaky (2008) and Kim (2011) established that increasing trade positively impacted per capita income. Similarly, income per capita growth is influenced by interest rate (Husain *et al.*, 2020), money supply and inflation (Razia and Omarya, 2022), and exchange rate (Guillaumont Jeanneney and Hua, 2001). However, Hajamini (2015) disclosed that population growth has an asymmetric influence on per capita income.

Furthermore, Muthayya *et al.* (2014) documented that more trade raises consumption expenditure, while Gong (2018) obtained the opposite. Moreover, households' consumption decreases with interest rate (Kapoor and Ravi, 2009; Jappelli and Scognamiglio, 2018) and inflation (Ihugba *et al.*, 2021), but it increases with money supply (Ihugba *et al.*, 2021). Other core drivers of consumption are real and nominal exchange rates (Mumtaz and Ali, 2020; Derindag *et al.*, 2022) and population growth (Schneider *et al.*, 2011).

Additionally, agricultural output is impacted negatively by trade openness (Hart *et al.*, 2015), while population growth boosts agricultural output (Schneider *et al.*, 2011). Other significant determinants of agricultural output include money supply, interest rate, inflation rate, and exchange rate (Kadir and Tunggal, 2015).

Moreover, unemployment reduces with greater trade (Felbermayr *et al.*, 2011; Marzan *et al.*, 2020) and inflation (Shighweda, 2020), but it increases with interest rate (Doğrul and Soytas, 2010) and money supply (Shighweda, 2020). Lastly, unemployment declines with exchange rate (Bakhshi and Ebrahimi, 2016), while Maijama'a *et al.* (2019) reported that exchange rate and population growth contribute to unemployment.

Besides, the inclusion of the squared term of FI in the model is to ascertain whether (or not) the channels under consideration (i.e., income per capita, households' consumption expenditure, agricultural output, and unemployment rate) exhibit non-linear (asymmetric) influence from FI to poverty reduction. This is due to the conflicting findings on the link between FI and these transmission channels. For instance, certain studies including Park and Mercado (2021) and Omar and Inaba (2020) found an increasing influence of FI on income, but others like Kim (2011), Boukhatem (2016) and Schmied and Marr (2016) disclosed a negative relation between them. In addition, researchers like Chakrabarty and Mukherjee (2022) and Cavoli and Gopalan (2023) linked improved consumption to FI, but Li *et al.* (2022) obtained a dampening influence of FI on consumption. Yet Liu and Yao (2024) reported a non-linear nexus between FI and consumption. Also, Atakli and Agbenyo (2020) and Farooq *et al.* (2023) discovered a negative connection between FI and agricultural output, while Hu

et al. (2021) and Xu and Wang (2023) disclosed a positive influence. In addition, Okoro *et al.* (2020) and Amakor and Eneh (2021) reported that FI promoted unemployment, whereas Wu *et al.* (2023) and Wibowo *et al.* (2023) recorded contrasting results.

Given the mixed and/or conflicting empirical outcomes, it is possible that FI will have the least/highest impact until a certain threshold/turning point is reached, beyond which its effects become more/less pronounced. The squared term of FI is included in the model to determine whether the channels under consideration transmit non-linear effects from FI to poverty reduction. Thus, for any channel to be adjudged as transmitting a non-linear influence, the coefficients γ_i and δ_i must bear opposite signs and significance. Suppose the former (γ_i) is positive and the latter (δ_i) is negative, the relation is said to be concave (or inverted U-shaped). But if γ_i is negative and δ_i is positive and are both significant, then, the relation is convex (or U-shaped). The threshold (turning point) is computed from Equation (1) via partial derivative regarding FI, expressed in Equation (2) as:

$$\frac{\partial W_{it}}{\partial FI_{it}} = \frac{\gamma_i}{-2\delta_i} = \text{concave} \quad \text{or} \quad \frac{\partial W_{it}}{\partial FI_{it}} = \frac{-\gamma_i}{2\delta_i} = \text{convex} \tag{2}$$

A concave relation denotes a function that curves downward (i.e., decreasing). For a convex relationship, the function curves upward (i.e., increasing). The coefficient of the squared term/variable (FI^2) is calculated by differentiating the estimation with respect to FI in Equation (1), expressed as:

$$\frac{\partial W_{it}}{\partial FI_{it}} = \gamma_i + 2\delta_i FI_{it} \tag{3}$$

3.1 Data

This research uses yearly data that span 2004-2022 for 25 SSA economies (including Angola, Benin, Botswana, Burkina Faso, Cameroon, Cote D'Ivoire, D.R. Congo, Ethiopia, Gabon, Ghana, Guinea, Guinea-Bissau, Liberia, Madagascar, Malawi, Mali, Niger, Nigeria, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zambia, and Zimbabwe). The data were gathered from the World Bank (2023) Development Indicators. Income growth is measured by GDP per capita growth (in %), consumption by households' consumption expenditure (% of GDP), agricultural output by agricultural value added (% of GDP), unemployment rate by total unemployment as a % of total labour force, trade as a % of GDP, interest rate by lending interest rate (in %), money supply by broad money supply (% of GDP), inflation by consumer prices annual changes (in %), exchange rate by official exchange rate of the local currency per US$, and population by annual population growth (in %). The measurement procedure of FI is provided in the next sub-section.

3.2 Financial inclusion index

The literature portrays several approaches involved in the measurement of FI. The indicators include credit to private sector, number of Automatic Teller Machines (ATM), bank branches, money supply, depositors, borrowers, savings, domestic credit-GDP ratio, etc. However, the indicators were criticized of bias (Nguyen, 2021; Cavoli and Gopalan, 2023),

leading to the development (or construction) of a composite Financial inclusion index (FII) with global acceptance. The index adopts a multi-dimensional measurement of the level and dimensions of FI that is comprehensive and robust (Nguyen, 2021; Sakanko *et al.*, 2024). Two techniques used to develop the composite FII are parametric and non-parametric. Interestingly, the non-parametric method is criticized due to the subjective weight of importance it assigns to indicators exogenously based on the researcher's intuition, resulting in the preference for its parametric counterpart, i.e., principal component analysis (PCA).

We follow Nguyen (2021) and Sakanko *et al.* (2024) two-stage PCA method to develop the index. The first stage involves estimating sub-indices of three dimensions of financial inclusion (i.e., access, availability, usage dimensions) based on series of macroeconomic indicators of the dimensions. The second stage includes using the PCA approach to construct the overall index (i.e., composite FII) via the sub-indices generated during the first stage.

3.3 Estimation technique

To achieve the goal of this research, the system-Generalized Method of Moment (i.e., system-GMM) estimator is employed to analyze data for the 2004-2022 period. The justification for adopting the system-GMM lies in the dimension of the dataset, where the number of cross-section is greater than the time-series (Roodman, 2009; Hassan and Meyer, 2021). The system-GMM model combines level equation, first-difference, and the lagged level of the regressor(s). The validity of the estimator is based on the assumption of constant country-specific effect and the level of the regressors over time including the possibility of an absence of correlation between both (Uddin *et al.*, 2017; Abdul Karim *et al.*, 2022).

The appearance of lagged dependent variable (W_{it-1}) in Equation (1) suggests the possibility of endogeneity in the (FI) model as established in the literature (Erra and Venkatachalapathy, 2018; Mehry *et al.*, 2021; Wu *et al.*, 2023). Thus, using static panel data techniques like Pooled OLS, FE and RE methods to estimate FI-poverty reduction relation will be inappropriate. To address this problem, this research adopts the GMM estimator (Arellano and Bond, 1991; Blundell and Bond, 1998) that supports differencing of Equation (1) given as:

$$\Delta W_{it} = \beta_i \Delta W_{it-1} + \gamma_i' \Delta FI_{it} + \delta_i \Delta FI_{it}^2 + \theta_i \Delta X_{it} + \Delta \varepsilon_{it} \quad (4)$$

Taking the first-differencing in Equation (1), the expected linear correlation between W_{it-1} (lagged dependent variable) and the country-level specific effect (μ_i), is removed. However, the endogeneity problem that arises due to the linear association between W_{it-1} and the new error term (ε_{it}) still persists ($W_{it-1} * \varepsilon_{it} \neq 0$). To this end, Arellano and Bond (1991) opined the problem can be resolved via using lagged value of exogenous variable(s) as an instrument. Thus, the GMM estimator is advantageous due to its ability to address problems relating to country-specific effect and simultaneity bias. Notwithstanding, Blundell and Bond (1998) added that the inclusion of lagged dependent and independent variables may result to faulty inferences because of weak instrument(s). Moving forward, Arellano and Bover (1995) and Blundell and Bond (1998) collectively advanced the system-GMM method to address this limitation.

To validate and/or ascertain the robustness of the results generated based on the system-GMM, two tests are conducted. They include the Sargan's test for over-identifying restriction which is performed to validate the instrument(s) used, and the Arellano and Bond (1991)

autoregressive test of first-order autocorrelation (i.e., AR(1)) and second-order autocorrelation (i.e., AR(2)) to see if (or not) the error terms in the differenced regression exhibit auto (serial) correlation. Whereas it's not uncommon that the error terms in the first-differenced estimation have AR(1), the presence of AR(2) renders the results invalid and/or inconsistent. If the probability of the Sargan's statistic is greater than 0.05, then, we do not accept the null hypothesis, thus, implying that over-identifying restrictions are not valid. In addition, if the probability of the AR(2) test statistic exceeds 0.05, the null hypothesis of the presence of second-order autocorrelation is not accepted.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1 Descriptive statistics

The summary of descriptive statistics of the variables (Table no. 1) portrays the mean/average financial inclusion(FI) for the studied period (i.e., 2004-2022) as 4.680. The average income (INC), consumption (CON), agricultural output (AGR), and unemployment (UNE) are 6.003, 66.176, 24.098, and 1.819, respectively, for the same period. Furthermore, the mean population (POP) is 3.115, trade (TRD) is 57.885, interest rate (INT)is 14.760, log of exchange rate (LnEXR) is 5.870, money supply (MOS) is 25.175, and inflation rate (INF) is 9.761.

The highest (maximum) and lowest (minimum) values for FI are 4.830 and -2.993, respectively. The highest and lowest values for the remaining variables are: 21.852% and 0.320% for INC, 119.413% and 12.449% for CON, 66.033% and 1.739% for AGR, 19.939% and -22.383% for UNE, 11.244 and 0.524 for POP, 143.982 and 2.886 for TRD, 131.813 and 3.105 for INT, 22.629 and -0.106 for LnEXR, 53.548 and 4.530 for MOS, and 557.202 and -3.233 for INF. The standard deviations for the variables including INC (5.537), CON (21.407), AGR (13.372), UNE (3.887), TRD (24.271), INT (13.353), LnEXR (3.302), MOS (10.049), and INF (29.237), except those of FI (1.160) and POP (1.662) portray that the data points are dispersed around their average values.

Table no. 1 – Summary statistics

	Mean	Std. Dev.	Min.	Max.	Obs.	N	T
FI	4.680	1.160	−2.993	4.830	475	25	19
INC	6.003	5.537	0.320	21.852	475	25	19
CON	66.176	21.407	12.449	119.413	475	25	19
AGR	24.098	13.372	1.739	66.033	475	25	19
UNE	1.819	3.887	−22.383	19.939	475	25	19
POP	3.115	1.662	0.524	11.244	475	25	19
TRD	57.885	24.271	2.886	143.981	475	25	19
INT	14.760	13.353	3.105	131.813	475	25	19
InEXR	5.870	3.302	−0.106	22.629	475	25	19
MOS	25.175	10.049	4.530	53.548	475	25	19
INF	9.761	29.237	−3.233	557.202	475	25	19

Note: FI = Financial inclusion, INC = Per capita income, CON = Household consumption expenditure, AGR = Agricultural output, UNE = Unemployment rate, POP = Population growth rate, TRD = Trade, INT = Interest rate, EXR = Exchange rate, MOS = Money supply, INF = Inflation, Ln = Logarithm.

4.2 Results of system-GMM estimation

The use of time series data for estimation purpose can lead to problems such as serial-correlation and heteroscedasticity. The presence of these problems can invalidate or make unreliable any estimates generated. To ascertain the reliability of the estimated results, diagnostic tests were conducted. The results of diagnostic tests are reported in Table no. 2.

The results were generated using the system-GMM estimator for four models of income (INC), consumption (CON), agricultural output (AGR), and unemployment (UNE) as dependent variables (and measure of poverty) given in columns II, III, IV and V, respectively. The coefficient of the lagged dependent variable (W_{t-1}) is statistically significant at 5% in all models, suggesting the persistence of the dependent (endogenous) variable in the sample. The diagnostic tests' results portray that the probability of AR(2) test statistic in all models exceeds 5%, indicating absence of the second-order serial correlation. The Sargan's test result is significant at 5% in all the models, and it portrays that the system-GMM model is not over-identified. The Wald test result implies that the explanatory variables are jointly significant at 5% level.

The income model estimates (Column II) show that the coefficient of FI is negative and the squared variable (FI^2) is positive, and both are statistically significant at 5% level. These results imply a convex relation between FI and income growth, indicating that the non-linear influence of FI on poverty reduction is transmitted via income growth. The coefficient of FI is -0.467[or $-1.537 + 2(0.535)$] (computed from Equation (3)), while the turning point for FI and income growth relation is -1.44[$= \frac{-1.537}{2(0.535)} = \frac{-1.537}{1.07}$] (computed from Equation (2)).

Table no. 2 – Results of system-GMM estimation

Dependent Variable	INC	CON	AGR	UNE
(I)	(II)	(III)	(IV)	(V)
W_{t-1}	0.098^{**}	0.790^{***}	0.832^{***}	0.816^{***}
FI	-1.537^{**}	1.778^{**}	0.765^{**}	0.546^{***}
FI^2	0.535^{**}	-0.310^{**}	-0.274^{**}	-0.052^{*}
TRD	0.105^{***}	0.040^{*}	0.006	0.001
INT	-0.006	-0.058^{*}	-0.011	0.015^{***}
MOS	-0.235^{***}	0.014	0.045^{*}	0.016^{*}
INF	-0.028^{***}	0.005	-0.003	0.003^{*}
InEXR	0.022	-0.081	-0.192^{*}	0.075^{***}
POP	0.710	1.390	1.334^{***}	0.038
Threshold of FI	1.436%	2.868%	1.396%	5.25%
AR(1)	0.003	0.004	0.003	0.028
AR(2)	0.278	0.392	0.868	0.280
Sargan Test	301.702^{***}	265.826^{***}	284.171^{***}	259.677^{***}
Wald Test	92.50^{***}	759.75^{***}	8107.10^{***}	7465.28^{***}

Note. *, ** and *** represents statistical significance at 1%, 5% and 10%, respectively. FI = Financial inclusion, INC = Per capita income, CON = Households' consumption expenditure, AGR = Agricultural output, UNE = Unemployment rate, POP = Population growth rate, TRD = Trade, INT = Interest rate, EXR = Exchange rate, MOS = Money supply, INF = Inflation, Ln = Logarithm.

A unit increase in FI results in 0.467% decline in income growth (and poverty elevation) in SSA. The positive coefficient on FI^2 portrays convexity (i.e., an upward relation). That is, whereas the financial inclusion and income growth relation is negative, the (adverse) impact

begins to reduce once financial inclusion reaches 1.44. This is the threshold beyond which financial inclusion starts to impact income growth positively. It signifies that income growth begins to transmit a negative influence from financial inclusion to poverty reduction on the far side of the threshold of financial inclusion. The supportive role of FI can be attributed to increased households' knowledge of financial services and products, regulatory environment, and consumer protection beyond this threshold. Thus, they can increase their savings, invest in income-generating activities, and make informed investment decisions, leading to increased income and welfare, and as a result poverty reduction. This finding substantiates the outcomes of related studies (Evans and Alenoghena, 2017; Evans and Lawanson, 2017; Ogbeide and Igbinigie, 2019; Sakanko *et al.*, 2020; Kanga *et al.*, 2022).

The coefficient of trade (TRD) is positive and statistically significant at 1% level. A percentage increase in TRD raises income by 0.105%. This portrays the significant role of trade in income growth. Rising trade increases the access of households who engage in production activities to markets for goods and services, leading to higher sales and profits including their income. In addition, trade can promote competition and push down goods/services prices. Falling prices in turn raise households' buying power, resulting in the consumption of more goods/services and declines in poverty. This outcome affirms the findings of Freund and Bolaky (2008) and Kim (2011).

Moreover, a percentage increase in money supply (MOS) and inflation (INF) is found to impact income negatively by 0.235% and 0.028%, respectively, at 1% level. The diminishing influence of MOS and INF implies that more money supply and inflationary pressure erode households' buying power, create macroeconomic uncertainty, and foster complex interest rates via tight monetary policy. These leave undesirable impacts on households' income and earnings of businesses, with their tendency to elevate poverty. The result conforms to the work Razia and Omarya (2022) that rising inflation and money supply hurt income.

The results of the consumption model (Column III) portray that households' consumption constitutes a channel for transmitting financial inclusion non-linear impact to poverty reduction, given the opposite signs and statistical significance of FI and FI^2. The coefficient of FI is 1.158[or $1.778 - 2(0.310)$], while the turning point for financial inclusion and consumption relation is -2.87[or $\frac{1.778}{-2(0.310)} = \frac{1.778}{-0.62}$]. These findings entail a concave (or downward) relation between them.

The coefficient of FI signifies a positive relation between consumption and financial inclusion at 5% level. A unit increase in FI results in 1.158% improvement in households' consumption (and poverty reduction) in SSA region. The negative coefficient on FI^2 shows a downward relation, and the threshold between financial inclusion and consumption is 2.87. Thus, the relationship turns negative once financial inclusion reaches 2.87, and it is the threshold/turning point beyond which consumption starts to launch a positive influence from FI to poverty reduction. The finding suggests that households' consumption contributes to poverty reduction before financial inclusion reaches 2.87. The negative influence of FI beyond this point may be due to excessive borrowing (for consumption purposes) and associated debts which reduces households' ability to finance future consumption. Besides, rising interest rates occasioned by inflationary pressures in the SSA region reduces not only accessibility but also affordability of financial services. Moreover, rising risks of financial fraud which accompany growing FI may discourage households from accessing financial services in an attempt to avoid losing their assets to fraudsters. These can reduce savings, investment and consumption,

and as a result increase the poverty level. The outcome lays credence to the research of Li *et al.* (2022) suggesting a dampening influence of FI on consumption, but it contradicts the findings of others on its supportive role on consumption (Mwangi and Atieno, 2018; Sakanko *et al.*, 2020; Chakrabarty and Mukherjee, 2022; Cavoli and Gopalan, 2023).

The coefficient of TRD is significant at 10% level, demonstrating that a percentage gain in trade raises households' consumption by 0.040%. This suggests that trade can boost consumption in SSA via expansion in job opportunities and income generation for individuals involved in export-oriented activities including increased households' access to a wide range of goods/services. The increased consumption will lead to improved welfare and poverty reduction. The result is consistent with outcomes of Muthayya *et al.* (2014).

More so, interest rate (INT) is shown to hurt households' consumption and the relation is significant at 10% level. A percentage increase in INT dampens households' consumption by a 0.058%. This portrays that higher interest rates can reduce consumption in SSA due to increased borrowing costs which in turn hinder investment growth. The implications of these are reduced production capacity and employment opportunities including declining consumer spending, which all result in elevating poverty. This discovery conforms to empirical findings of Kapoor and Ravi (2009) and Jappelli and Scognamiglio (2018).

Furthermore, the results of agriculture output (AGR) model (Column IV) disclose that both FI and FI^2 are significant at 5% level, respectively. The FI coefficient bears a positive sign and FI^2 a negative sign, thus, portraying a non-linear relation between agricultural output and financial inclusion. The coefficient of FI is 0.217[or$0.765 - 2(0.274)$], while the turning point for financial inclusion and agricultural output relation is -1.40[or$\frac{0.765}{-2(0.274)} = \frac{0.765}{0.548}$].

A unit increase in FI leads to 0.217% improvement in agricultural output (and poverty reduction) in SSA region. The negative coefficient on FI^2 shows a downward link, and the threshold between financial inclusion and agricultural output is 1.40. Thus, financial inclusion and agricultural output relation rises into negative after financial inclusion reaches 1.40. Beyond this point, agricultural output transmits a positive impact from financial inclusion to poverty reduction. The negative influence of financial inclusion after this threshold could pass off from possible diversion of funds meant for agricultural development to non-agricultural purposes or higher interest rates.

For example, loans or credit provided through financial inclusion programmes designed to boost agricultural productivity may be diverted to consumption or non-agricultural businesses. Also, despite financial inclusion programme goals to provide affordable credit, mounting interest rates present obstacles to smallholder farmers in via increased borrowing costs. These may produce a declining influence on agricultural output, leading to falling incomes and elevating poverty level. In addition, if agricultural production is export-biased rather than boosting domestic consumption, it will create scarcity and raise domestic prices as was the case recently in Nigeria. This is accompanied by lower households' buying power and consumption, resulting to increased poverty. This result is in line with the findings of previous studies like Agbenyo *et al.* (2019), but it contrasts the positive effect obtained by others (Atakli and Agbenyo, 2020; Hu *et al.*, 2021; Umaru and Eshiozemh, 2022; Farooq *et al.*, 2023; Xu and Wang, 2023; Zhai *et al.*, 2023).

The coefficients of MOS and population (POP) are positive and significant at the 10% level and 1% level, respectively. Specifically, 0.045% and 1.334% increase in agricultural output are associated with a percentage increase in money supply and population growth,

respectively. Raising money supply may contribute to reduced interest rates and improvements in investment in agricultural infrastructure (like irrigation systems, storage facilities, better seeds, and mechanization, etc.,) for farmers. These in turn enhance agricultural productivity and output. In addition, a growing population induces governments to prioritise agricultural expansion via policies aimed at improving access to credit, inputs, market infrastructure, and extension services for farmers to stimulate agricultural production. These contribute to boosting consumption and reducing poverty. This finding validates the studies of Kadir and Tunggal (2015) and Schneider *et al.* (2011) that money supply and population are increasing determinants of agricultural output.

Also, the coefficient of exchange rate (LnEXR) is negative and significant at 10% level. A percentage depreciation in the exchange rate dampens agricultural output by 0.192%. Given that most SSA countries have limited domestic production capacity and rely heavily on agricultural imported inputs (such as machinery and fertilizers), depreciation makes these inputs very costly, thus, slowing down agricultural productivity. These contribute to higher agricultural produce prices, falling consumption, and poverty elevation. The result conforms to the finding of Kadir and Tunggal (2015).

The results of unemployment (UNE) model (Column V) reveal that the FI and FI^2 are statistically significant at 1% level and 10% level, respectively. In addition, both bear opposite signs, implying a non-linear between FI and unemployment. The coefficient of FIis 0.442[or $0.546 - 2(0.052)$]. The turning point for FI and unemployment relation is -5.25[or $= \frac{0.546}{-2(0.052)}$ $= \frac{0.546}{-0.104}$]. The positive coefficient of FI suggests an upward relation between financial inclusion and unemployment. A unit increase in FI results in 0.442% rise in unemployment (and poverty elevation) in SSA countries. However, FI and unemployment relation becomes negative once the financial inclusion reaches 5.25. This is the threshold beyond which unemployment (begins to decline and) transmits a negative impact from financial inclusion to poverty reduction. This finding portrays that if greater financial inclusion increases households' access to financial services, they can invest and engage in income generating activities with ease leading to declines in unemployment and poverty reduction. The outcome is consistent with previous research (Erra and Venkatachalapathy, 2018; Okoro *et al.*, 2020; Alshyab *et al.*, 2021; Mehry *et al.*, 2021; Wibowo *et al.*, 2023).

In addition, interest rate (INT), money supply (MOS), inflation (INF), and exchange rate (LnEXR) coefficients are positive and significant at 5% level, respectively. A percentage increase in these variables increases unemployment by 0.015%, 0.016%, 0.003%, and 0.075%, respectively. The results affirm outcomes of prior researches (Doğrul and Soytas, 2010; Maijama'a *et al.*, 2019; Shighweda, 2020). The studies disclosed that interest rate, money supply, and exchange rate significantly increased unemployment, while Shighweda (2020) reported that higher inflation reduced unemployment.

5. CONCLUSION

This research explores the channels through which financial inclusion (proxied by the financial inclusion index constructed based on the principal component analysis) transmits its influence to poverty reduction in SSA countries during the 2004-2022 period using the system-GMM estimation technique. The empirical outcomes portray that financial inclusion transmits non-linear influence to poverty reduction in SSA nations via income growth, households'

consumption, agricultural output, and unemployment. Moreover, the findings disclose that an FI value beyond thresholds of 1.44 and 5.25 would boost income growth and reduce unemployment, thereby reducing poverty. In addition, an FI value below thresholds of 2.87 and 1.40 positively impacts consumption expenditure and agricultural output, leading to poverty reduction.

Policy implications emanating from this research outcome include the need for SSA's governments and policy makers to prioritise raising individuals' access to financial services and promoting financial literacy through increased awareness on the importance of mobile banking services, insurance products, remittance services, savings, managing credit or debt, and investing wisely to reduce the otherwise impacts on the identified channels. These will enhance individuals' capacity to earn income and/or increase their chances of employment opportunities. Besides, greater access to financial products like credit (or loan) raises people's capacity to consume goods and services, leading to improved welfare. In addition, increased access to financial services makes it easier for individuals engaged in agricultural production or business to raise their output. Sustained expansion in output can bring down prices of agricultural produce, resulting in higher purchasing power and consumption for households. Coupled with these are the increased sales and profits that accrue to operators in the agricultural sector. All of these can contribute to poverty reduction.

As a limitation, the current study focuses on the transmission channels of financial inclusion to poverty reduction in SSA countries. Therefore, future research should explore the role of digital financial inclusion on poverty reduction in addition to exploring regional variation across SSA, especially in light of the growing adoption of FinTech solutions and digital banking services.

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Digital Divide on Financial Development in Asia-Pacific Region: The Role of Contextual Factors

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Abstract: This study delves into the influence of the digital divide on financial development, considering contextual factors, particularly institutional frameworks. The Asia-Pacific region, chosen for its diverse variables across countries, was pivotal in elucidating this relationship. This research reveals that the impact of the digital divide on financial development becomes evident about two years post-implementation by addressing time lag and endogeneity concerns with instrumental variables. Notably, the study highlights how the digital divide affects financial inclusion advancements, with institutional quality moderating the strength of this relationship but not altering its trajectory. Monopoly is recognized as a constraint on financial development, supporting previous research. Policymakers in transitioning economies should heed the delayed effects of digital transformation, emphasizing long-term strategies considering multifaceted impacts on financial development.

Keywords: digital divide; financial development; Asia-Pacific Region; institutional quality.

JEL classification: O16; O33; G2; E44.

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1. INTRODUCTION

The Asia-Pacific region, home to a highly significant proportion of the world's population, more than half of the global workforce, and diverse economies provides a compelling case for studying the digital divide and financial development (Vo *et al.*, 2021; ESCAP, 2025). This region exhibits tremendous heterogeneity in terms of economic development, technological infrastructure, and levels of financial inclusion. Additionally, the Asia-Pacific region has witnessed a rapid proliferation and diversity of digital technologies and the emergence of innovative digital financial solutions, which was massively widening during the recent global pandemic. The region's diverse economic landscape, ranging from advanced economies (e.g., Australia) to emerging markets (e.g., Vietnam), brings a fertile ground for studying the impacts of digital technologies on financial development and understanding the potential for streamlining institutional quality to foster inclusive growth (Nguyen *et al.*, 2019). Examining the digital divide within the context of financial development in the Asia-Pacific is the most digitally divided region in the world (Kim *et al.*, 2022), therefore, offers valuable insights into the unique challenges and opportunities that arise from the interplay of diverse socioeconomic factors and technological advancements (Hutton, 2003).

Financial development in the rapidly evolving landscape of global economics has emerged as a critical field of open inquiry (Sethi *et al.*, 2020). With the intricate interplay between financial systems and economic growth becoming increasingly evident, governments and policymakers alike recognize the pressing need to comprehend the intricate dynamics and underlying mechanisms that shape financial development (World Bank, 2012; Prochniak and Wasiak, 2017). More importantly, in an era defined by rapid technological advancements and the digital transformation of various sectors, the study of financial development has taken on new dimensions (Svirydzenka, 2016; Mignamissi and Djijo T, 2021). For example, Shiller (2013) has observed that the use of big data collected from customers by large companies has enabled them to achieve near-perfect price discrimination at the first-degree level, while the increasing difficulty in controlling the new algorithms has led to an asymmetry of information between big techs and their customers, widening the gap with suppliers as the winners (Cherbib *et al.*, 2021; Dinh *et al.*, 2023; Van Le and Tran, 2024). Thus, as societies embrace digital technologies, the importance of understanding the relationship between financial development and the digital divide referring to the disparities in access to and utilization of digital technologies has become progressively obvious (Lythreatis *et al.*, 2022; Nam and Lee, 2023).

Although extensive research explores the digital divide and financial development, the role of institutional quality in this relationship, particularly in the Asia-Pacific region, remains underexplored. Existing studies often overlook regional diversity, the moderating role of governance and regulatory quality, and cross-country variations in institutional strength. Additionally, empirical evidence using robust econometric methods is scarce, limiting insights into how digital divide influence financial development. Addressing these gaps will provide a nuanced understanding of the topic and inform targeted policy interventions to enhance financial development in diverse institutional contexts. This study delves into providing insights into strategies that can promote inclusive financial ecosystems and bridge the digital divide to pursue sustainable development goals in the Asia-Pacific region (Azmeh, 2025). By examining the role of institutional quality, it highlights how governance, regulatory frameworks, and policy effectiveness shape digital financial development. First, it would assess the relationship between the digital revolution and the financial development of 31

countries in the Asia-Pacific region under the influence of contextual factors. There would be prominent characteristics of the Asia-Pacific region in terms of research and measuring suitable indices for financial development (FD) and the digital divide (DD) in the Asia-Pacific region and second, utilizing the generalized method of moments (GMM) estimator with instrumental variables to assess the causal relationship, which allows for effective resolution of endogeneity issues. Third, this study offers an explanation for how the digital divide influences financial development, both in linear and non-linear forms. Therefore, for the academic community, this research introduces a more comprehensive perspective and fresh insights to researchers and scholars in economics, finance, and technology-related disciplines who have been actively investigating the effects of digital d on financial systems, all while taking into account the influence of contextual factors in shaping this connection. Additionally, researchers could have a reference for further examining the importance of institutional quality in creating an enabling environment for digitalization to thrive and contribute to financial development (Beck *et al.*, 2016; Khan *et al.*, 2019).

The paper is structured as follows: Section 2 reviews recent literature on digital divide, financial development, and institutional quality, and applies the DOI theory, focusing on the complex economic landscape of Asia Pacific economies. Section 3 explains the methodology and data used, while Section 4 presents the findings. Section 5 discusses these findings and concludes with final remarks.

2. LITERATURE REVIEW

2.1 Digital divide is a driven force for financial development

Financial development encompasses the evolution of financial systems, institutions, and policies that facilitate economic growth, resource allocation, and risk management (World Bank, 2019b; Wade, 2023), while the digital divide represents the disparities in access to information and communication technologies (ICTs), including internet connectivity, mobile devices, and digital literacy (Mignamissi and Djijo T, 2021; Raihan *et al.*, 2024). These concepts may initially appear distinct, but they are intrinsically linked as digital technologies increasingly streamline the landscape of paperless financial services, inclusive growth, and socioeconomic well-being.

The diffusion of innovation (DOI) theory provides a valuable framework for understanding the role of digital divide as a driving force for financial innovation (Rogers, 2010; Chien *et al.*, 2020; Drori *et al.*, 2024). According to DOI theory, the adoption and diffusion of new technologies follow a predictable pattern, influenced by various factors such as the characteristics of the innovation itself, the communication channels used to promote it, and the social system in which it is introduced (García-Avilés, 2020; Drori *et al.*, 2024). In the context of financial development, digital divide improvement represents the innovation that has the potential to reshape financial systems and promote inclusive growth. In particular, DOI theory describes the dissemination of technology-enabled business procedures, undeliberately at times, within a group or nation (Bara, 2016). In terms of paperless business procedures, DOI supports technology-backed innovation in the technology-based business transactions (Ong and Chong, 2023), digitized operation processes and paperless financial services (Kaur *et al.*, 2020), expedites digitizing and digital transforming (Wójcik *et al.*, 2021). Launching digitized business innovation has improved enterprise value and boosted user attraction (Kaur *et al.*, 2020).

Notably, digital divide will reinforce access to the government's online services, strengthen investment buildout, and enrich public-private sector ties (Legowo *et al.*, 2021b). Furthermore, previous studies have investigated into the spread of financial innovations and their effects on financial development. For instance, Allen *et al.* (2014) did a study analyzing mobile money in Kenya, Tanzania, and Uganda and found it enhanced financial inclusion for the previously unbanked, leading to increased savings, better risk management, and improved economic opportunities. Another study by Aghion *et al.* (2017) on credit information-sharing systems across countries revealed that their adoption positively influences financial development by enabling the sharing of credit data among financial institutions.

The development of financial technology (Fintech), the most observable space presenting digital transformation's impact on financial development with faster and more efficient financial transactions, with real-time processing and instant access to funds (Agarwal and Chua, 2020; Badra *et al.*, 2025), greater convenience through mobile and digital platforms, allowing users to access financial services anytime, anywhere (Hwang *et al.*, 2021; Duc *et al.*, 2024), and lowers costs for both consumers and businesses by reducing transaction fees and overhead expenses associated with traditional banking services (Demirguc-Kunt *et al.*, 2018). Additionally, Fintech promotes financial inclusion by reaching previously underserved populations, such as the unbanked and underbanked, through innovative solutions like mobile banking and digital wallets (Demirguc-Kunt *et al.*, 2018). However, digitalization-based effects on financial development to each country in the Asia-Pacific area are diversely distinct as a result of differences in culture, ICT level, national resources, and quality of governance (Bukht and Heeks, 2017; Ozili, 2018; Rhee *et al.*, 2022).

By contrast, digitalization can lead to financial exclusion when certain populations, such as the elderly, low-income groups, or those in rural areas, lack access to digital infrastructure, digital literacy, or the necessary technology. Barriers like limited internet connectivity, high costs of digital services, cybersecurity concerns, and complex digital banking systems can prevent these groups from fully participating in financial markets. Without inclusive policies and support systems, the shift to digital finance may widen the financial gap rather than close it (Weber, 2024; Shaban, 2025).

2.2 Digital divide and financial development under contextual conditions

Some studies indicate that in the context of developing countries versus developed ones whose impact lies in the internal conditions, adopter's heterogeneity, and external influences (Owusu-Agyei *et al.*, 2020; Runtev, 2020; Ekinci, 2021; Horobet *et al.*, 2022; Ong *et al.*, 2023). Another point is that external disturbances such as Remittance inflows to GDP and External loans and deposits can also affect the application of technology in the financial development (Fromentin, 2017; Alam *et al.*, 2019; Sobiech, 2019; Azizi, 2020; Bindu *et al.*, 2022; Van *et al.*, 2023). These factors should be controlled in the empirical model.

Digital divide has emerged as a pivotal force reshaping financial landscapes, with its evolving impact proving both substantial and complex over time. Studies by several researchers highlight digitalization's potential to revolutionize financial development, citing its ability to enhance financial inclusion and efficiency (Machkour and Abriane, 2020). However, this transformative journey is dynamic. As emphasized by some studies, certain aspects exhibit a non-linear relationship, such as the proliferation of ATMs or bank branches initially fueling rapid growth but potentially reversing impact upon transitioning into a

trajectory of digital divide's influence on financial development, thus unveiling a nuanced narrative, characterized by both progressive advancements and intermittent plateaus, illustrating a dynamic relationship necessitating comprehensive evaluation across temporal domains (Kumari and Khanna, 2017; Ramya *et al.*, 2017; Fujiki, 2021; Urhie *et al.*, 2021).

In the context of inefficient institutions, such as a monopoly or a former authoritarian regime, the government can utilize technological development to exert control over its citizens. This is evident in countries like North Korea, where the government restricts access to external financial resources and tightly regulates financial services to maintain a monopoly and exercise control (Carlin and Lee, 2021; Da-gyum, 2022). Similarly, in former authoritarian regimes, technology is used for surveillance, censorship, and repression to suppress dissent and maintain power (Dragu and Lupu, 2021). These control mechanisms have wide-ranging implications, stifling innovation, and limiting individual freedoms (Michaelsen, 2018). Monopolistic or authoritarian regimes create barriers to competition in financial services, business processes, and financial market development, preventing the full realization of the benefits of technological progress and digital dividends. Likewise, countries with poor institutional quality, such as some developing economies in South Asia, face challenges in fully harnessing the potential of digitalization for financial development due to inadequate regulations, weak enforcement mechanisms, and insufficient consumer safeguards (Sudan, 2020). Addressing these challenges requires promoting transparency, accountability, supportive investment, and good governance to prevent the concentration of power while fostering an enabling environment for digital transformation, innovation, and competition, which is crucial for financial resilience and sustainability. Conversely, countries with better institutional quality, such as Singapore and Hong Kong, have witnessed accelerated digitalization and experienced remarkable progress in their financial sectors (Son, 2022).

The impact of digitalization on financial development can vary significantly depending on the contextual conditions in a given country or region. For example, institutional factors, such as regulatory frameworks, legal systems, and governance structures, shape the environment in which digitalization unfolds and influences financial development outcomes. Barth *et al.* (2013) examine the impact of digital financial services on financial inclusion in a sample of countries and find that the effectiveness of digitalization in promoting financial inclusion depends on the quality of a country's legal and regulatory environment. They argue that well-functioning institutions are necessary to establish trust, protect consumer rights, and ensure the stability and security of digital financial services. Similarly, a study by Claessens *et al.* (2018) explores the role of institutional factors in driving fintech adoption and financial development. The researchers found that countries with more supportive regulatory frameworks and stronger institutional environments experience higher fintech adoption rates and greater financial development. In the same vein, Demirgüç-Kunt and Singer (2017) find that the adoption of digital financial services (e.g., mobile money and electronic payments) positively correlates with financial inclusion and economic development.

From the discussions above regarding (i) institutional influence, (ii) diverse specificities leading to distinct impact channels, and (iii) spatial and temporal effects, it becomes evident that simplifying research contexts solely into categories of developing versus developed nations risks overlooking crucial factors. This oversight could result in significant biases within studies, prompting us to examine these impacts within a highly dynamic region to accentuate the role of contextual factors, taking Asia-Pacific as an example. This region presents significant differences in stakeholders' involvement in adaptation and rapid changes

across variables among nations and within individual countries (e.g., ongoing transitions, digital financial services, and institutional quality). Furthermore, existing experimental studies have predominantly focused on the digital divide using conventional indices (e.g., internet user numbers and ICT indices), neglecting various facets of the digital divide's impact on distinct aspects of financial development. Therefore, this experimental study aims to provide a more comprehensive explanation of the digital divide's influence on different dimensions of the financial development index.

2.3 Asia-Pacific's context

Digitalization in Asia Pacific countries has emerged as a transformative force, shaping various aspects of society, economy, and governance. The region has witnessed rapid advancements in technology adoption, digital infrastructure development, and innovative digital solutions, seeing mobile internet subscribers increase by 20% to 1.29 billion users from 2019 to 2022 (GSMA, 2022). Governments and regulatory authorities in the region have been proactive in fostering a conducive environment for digital financial innovation, including implementing supportive regulations, promoting collaboration between traditional financial institutions and fintech companies, and investing in digital infrastructure (ESCAP, 2022).

Asia-Pacific has emerged as a global leader in digitalization, with countries like China, Japan, South Korea, and Singapore at the forefront of this transformation. These countries have witnessed significant growth in digital financial services, such as mobile payments and e-commerce. For example, China's digital payment ecosystem, led by mobile payment platforms like Alipay and WeChat Pay, has revolutionized how people conduct financial transactions. The rapid adoption of these digital payment solutions has transformed China into a predominantly cashless society, with mobile payments accounting for a substantial share of total transactions.

Good institutions are vital for maximizing the positive impact of digitalization on financial development in the Asia-Pacific region. By providing a conducive regulatory environment, protecting consumer rights, and ensuring stability and trust in the financial system, these institutions contribute to the growth and sustainability of digital financial services (Keane *et al.*, 2020; Corning, 2022).

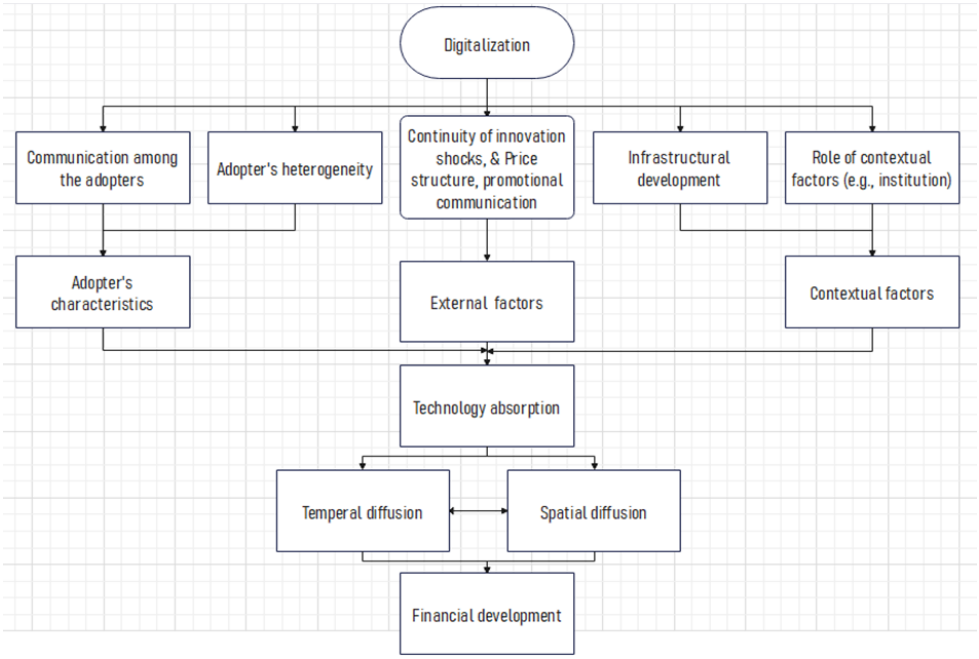
3. METHODOLOGY AND DATA

3.1 Theoretical framework and basic setup

The Diffusion of Innovations (DOI) theory provides a valuable framework for understanding how digital financial technologies spread across different institutional contexts in the Asia-Pacific region. According to Rogers (2010), the successful adoption and diffusion of new technologies depend on institutional factors such as perceived relative advantage, compatibility, complexity, trialability, and observability. These factors shape how digital financial services are integrated into existing financial systems and influence their accessibility across different economies. Institutional governance, regulatory effectiveness, and legal frameworks directly impacts these DOI attributes by either facilitating or hindering the adoption process. Thus, institutional factors play a crucial role in determining both the uptake and long-term impact of digital financial services. By applying DOI theory, this study examines how variations in institutional quality affect the diffusion of digital financial

innovations, ultimately identifying key barriers and enablers. The methodological motivation of this paper is driven from the diffusion of innovations (DOI) theory; which elucidates the stages and factors influencing the adoption and diffusion of innovation in a social system and explains how the adoption of innovative digitized services foster a more inclusive financial ecosystem (Rogers, 2010; Kingiri and Fu, 2020; Legowo *et al.*, 2021a, 2021b; Mignamissi and Djijo T, 2021). Indeed, the DOI theory extends our understanding of technological-based business transactions, digitalized financial services, and the overall process of digitalization (Blakstad and Allen, 2018).

Digitalization affects financial development through various mechanisms and different components within the economy. To illustrate, Das (2022) categorizes the factors into three main groups: (i) adopters' characteristics (i.e., communication among adopters and adopter heterogeneity), (ii) external factors (i.e., innovation continuity, shocks, price structure, and promotional communication), and (iii) contextual factors (i.e., infrastructure development and the role of institutions). These factors determine the adaptation of new technologies in both spatial and temporal dimensions (Rao and Kishore, 2010). Figure no. 1 illustrates the basic analytical framework in this study, with the institutional aspect governing the relationship between digitalization and financial development as the primary focus. Therefore, to assess the impact of digitalization on financial development while focusing on contextual conditions, studies need to shut down the remaining channels by managing control variables.



Note: The framework show the process of how Digitalization impacts on Financial development through the Adopter's characteristics, External Factors, and acontextual factors in both temporal and spatial diffusion.

Figure no. 1 – Theoretical framework

Source: author synthesized and adapted from Rao and Kishore (2010); Das (2022)

Based on this theory, there is substantial empirical evidence that elucidates the impact of digital divide on the development of financial systems through various mechanisms (Mignamissi and Djijo T, 2021). *First*, it stimulates the financial efficiency of financial enterprises, thereby expanding the number of businesses operating within this domain (Bunje *et al.*, 2022). *Second*, it reduces costs associated with remittance, thus enhancing personal financial flexibility through this source of funds (Jemiluyi and Jeke, 2023). *Third*, it promotes the participation of nations in the global value chain, consequently fostering the development of accompanying financial services for facilitating payments related to significant and systemic contracts (Ha, 2022). *Fourth*, it enhances market performance (Oladunjoye and Tshidzumba, 2023; Yu *et al.*, 2023). The DOI theory also explains how the adoption of innovative digitized services in the financial sector increases accessibility to government services, fostering a more financial ecosystem (Nchofoung and Asongu, 2022). Thus, the empirical model in this framework will be estimated using the following equation:

$$Y_{ijt} = \beta_0 + \beta_1 . DD_{ijt} + \sum_{k=2}^{K} \beta_k Z_{ijkt} + \delta_i + \varphi_j + \lambda t + u_{ijt} \quad (1)$$

where Y_{ijt} represents the financial development (FD) level in the ith country, the jth geographical specific region, in year t. DD_{ijt} represents the digital divide, which reflects the level of digital transformation in the ith country, jth geographical specific region in a given year, denoted as t. Z refers to selected control variables that are derived from previous studies. These control variables are structured based on the analytical framework, categorizing them into adopter's characteristics (e.g., bank-specific attributes) and external factors (e.g., external financial shocks or flows). In other words, these control variables are primarily designed to mitigate the influences stemming from external factors and the characteristics of the adopters, specifically banks. δ_i refers to the unchanging and unobservable variables in each country, encompassing elements such as its historical background, cultural heritage, geographical attributes, and various ethnic components. φ_j and λ represent the invariant-unobservable variables specific to each economic region and factors that are not directly measurable and subject to changes over time (e.g., the structure of the economy across different years), while u_{ijt} denotes the error term.

It should be noted that equation (1) only allows for examining correlation rather than causal relationships. Thus, in the next part of the study, the research will further set the methodology to establish causal relationships using instrumental variables. The impact of digital divide on financial development under the role of institutional settings across Asia-Pacific countries will be empirically assessed by utilizing interaction variables; accordingly, the empirical model will be transformed as follows.

$$Y_{ijt} = \beta_0 + \beta_1 . DD_{ijt} + \sum_{k=2}^{K} \beta_k Z_{ijkt} + \gamma DD_{ijt} \times IQ_{ijt} + \delta_i + \varphi_j + \lambda t + u_{ijt} \quad (2)$$

where, IQ_{ijt} represents the variable indicating the institutional quality of country i within geographical region j in year t, the estimated coefficient γ reflects the impact of digital divide on financial development under the influence of institutional quality. Accordingly, if γ is statistically significant positive, it implies that improving institutional quality contributes to enhancing the impact of digital divide on financial development. It is also important to note that the institutional quality index in the model (2) can be used as either a continuous variable or a set of dummy variables representing different levels of institutional quality.

3.2 Endogeneity

One major concern in this study is the issue of endogeneity arising from reverse causal effects (Ong and Chong, 2023) and confounding factors. According to Ong and Chong (2023), increased adoption of cashless payments promotes internet and mobile banking, which, in turn, encourages businesses to invest more in developing new digital services. Financial development stimulates customer demand for faster, lower-cost, and lower-risk payment methods. It should be noted that the fintech industry faces lower risks of losing customers and lower profit risks than traditional banking, approximately two times and 1.5 times, respectively (Feyen *et al.*, 2021). These factors contribute to the occurrence of reverse causal effects in this paper.

Furthermore, the confounding factor highlights other factors influencing simultaneous improvements or declines in digital divide and financial levels. For instance, the ideological shift facilitating access to the global financial market economy and new technologies led to rapid expansion and digital divide changes. In such cases, using ordinary least squares (OLS) with fixed effects would result in biased and inconsistent estimates. To solve the endogeneity problem, the study concentrates on examining the shifts in exogenous factors (identified as instrumental variables) that affect financial development exclusively through the digital divide channel. In other words, in the first stage, we identify factors that are more likely to be exogenous and lead to fluctuations in the digital divide. The prediction derived from this stage are then used to assess their impact on outcomes in the second stage (Van Le *et al.*, 2022; Van Le and Tran, 2024, 2025). Accordingly, DD_{ijt} can be decomposed into several terms: (i) digital level at the graphical regional-specific (DD_{jt}), (ii) speed of internet download in each regional area (Dengler *et al.*, 2022; Wu and Shao, 2022; Chen and Kim, 2023), and (iii) idiosyncratic component (η_{ijt}). Mathematically,

$$DD_{ijt} = DD_{jt} + IV_{jt} + \eta_{ijt} \quad (3)$$

where, DD_{jt} represents the (average) amount of digital level to regional-location j, determined by the local endowments, while η_{ijt} denotes an idiosyncratic component. In this study, the regional geographical location is assumed to be determined by geopolitical and historical factors (*), making it exogenous to the nations and uncorrelated with any omitted variables in the model (1). This ensures that the exclusion condition of the instrumental variable is satisfied, mathematically $cov(DD_{jt}, u_{ijt} | X, Z) = 0$. IV_{jt} reflects the speed of internet download in each regional area. According to Dengler *et al.* (2022); Chen and Kim (2023), this variable significantly influences the level of digital transformation at the current time, while assuming that IV_{jt} is independent of the model's error term (u_{ijt}), which can be ensured (**).

Given two assumptions (*) and (**), using the 2-stage least square (2SLS) with fixed effect (i.e., the IVXTREG option in Stata) ensures that the coefficients obtained from the estimation are consistent. Notably, to optimize the estimation and address the potential issue of dynamic endogeneity – occurs when past levels of financial development influence the current level of digital divide, the study suggests using the generalized method of moments (GMM) estimator alongside external instrumental variables. By incorporating lagged variables as internal instruments, the GMM estimator aims to generate optimal results in the estimation process (Blundell and Bond, 1998; Van Le and Tran, 2022, 2025).

3.3 Data

Data collection depends on the definition and measurement of financial development and digital divide during the period 2014-2021. There are various definitions of financial development for different countries, particularly in regions with disparities in financial development levels, especially the Asia-Pacific region. Commonly used definitions in empirical studies include financial system deposits to GDP, deposit monay banks assets to GDP, and liquidity liability to GDP. These simplistic definitions partly stem from data limitations in less developed regions where data availability needs to be completed.

In this work, we adopt a financial development index based on the works of Svirydzenka (2016), considering (i) data availability and (ii) scientific appropriateness in index design. Specifically, the new FD index is structured hierarchically, consisting of two sub-indexes: the financial intermediaries' development index (FIDI) and the financial markets development index (FMDI). Each index comprises two dimensions measuring the accessibility and efficiency. The dataset builds upon previous efforts, including the World Bank's *"Financial Development and Structure"* database (World Bank, 2024).

Measuring digital divide also encounters challenges regarding definition, measurement methodology, and data availability (Thordsen *et al.*, 2020). One widely cited work in classifying digitalization levels is the World Bank (2016) publication; accordingly, it categorizes digital technologies into (i) the digital divide and (ii) digital dividends. Although measuring digital dividends holds significance in this study, we approach digitalization as the digital divide due to data availability (see more in Figure no. A1).

In this study, the study aimed to collect data for all 48 countries (as classified by the United Nations) in the Asia-Pacific region. However, due to data availability issues, only 31 out of the 48 countries could be included in the analysis. The details of the countries included in the dataset are listed in Table no. A1. The final dataset is a balanced panel consisting of 31 countries in the Asia-Pacific region, covering the period from 2014 to 2021 (8 years). Additionally, we collected additional data on each country's economic and geographic characteristics to examine the relationship between digital divide and financial development across different geographical/ economic groups. Table no. 1 summarizes the components, proxies/descriptions, and sources for measuring the two indices: financial development and digital divide.

Table no. 1 – Methodology of measuring digital divide and financial development

Index	Sub-index	Components (Weight)	Description/proxy	Sources
Digital divide	Accessible Infrastructure	Network coverage (30%)	The proportion of the population covered by 2G, 3G, and 4G networks.	GSMA Intelligence
			Percentage of people covered by 5G networks (only from 2019 to 2021)	
		Network performance (30%)	Average download and upload speeds for mobile broadband	Ookla's Speedtest Intelligence
			Latencies in mobile broadband on average	
		Other enabling infrastructure (20%)	Percentage of people who have access to electricity	World Bank
			Per internet user, international internet bandwidth	ITU

Index	Sub-index	Components (Weight)	Description/proxy	Sources
			Secure Internet Servers per 1 million people	World Bank
			Internet Exchange Points (IXPs) per 10 million people	Packet Clearing House
		Spectrum (20%)	Per operator, digital dividend spectrum Other sub-1GHz, 1GHz-3GHz, above 3GHz, and mmWave spectrum per operator	GSMA Intelligence
	Affordability	Mobile tariffs (30%)	Cost of 100MB, 500MB, 1GB, and 5GB data (% of monthly GDP per capita)	Tarifica
		Handset prices (30%)	Cost of the cheapest internet-enabled device (as a percentage of monthly GDP per capita)	Tarifica
		Taxation (20%)	Tax as a percentage of overall cost of mobile ownership Sector-specific tax as a percentage of overall mobile ownership cost	GSMA Intelligence
		Inequality (20%)	Income inequality (%)	UNDP
	Open & safe	Local Relevance (40%)	Per individual, one generic top-level domain (gTLD) and one country code top-level domain (ccTLD).	ZookNIC
			E-Government Online Service Index score	UN
			Mobile social media penetration	Datareportal
			Mobile apps developed per person	Apps
		Availability (40%)	The number of mobile apps accessible in the country's native language(s).	Apps and Ethnologue
			The availability of the most popular smartphone apps	
		Security (20 %)	ITU Global Cybersecurity Index	ITU
Financial develop-ment	Financial intermediaries' development	Accessibility (PCA Weight)	Bank branches per 100,000 adults ATMs per 100,000 adults	Global financial development index
		Efficiency (PCA Weight)	Liquid Liabilities To GDP Domestic credit to private sector (% of GDP)	
	Financial markets development	Accessibility (PCA Weight)	Financial System Deposits To GDP	
		Efficiency (PCA Weight)	Bank Deposits To GDP	

Note: Weighting the components of the digital divide index is based on GSMA Intelligence (GSMA, 2022), while the weighting for the financial development index is calculated using the principal component analysis (PCA) technique (World Bank, 2024).

Sources: author's synthetic.

Utilizing a PCA methodology, we compute the financial development index from two sub-indices: financial intermediaries and financial markets development. As a result, this index exhibits considerable variation between and within Asia-Pacific countries, with a standard deviation approximating the mean, while the digital divide demonstrates comparatively lower variability. Detailed statistical descriptions are presented in Table no. 2.

Table no. 2 – Descriptive statistics

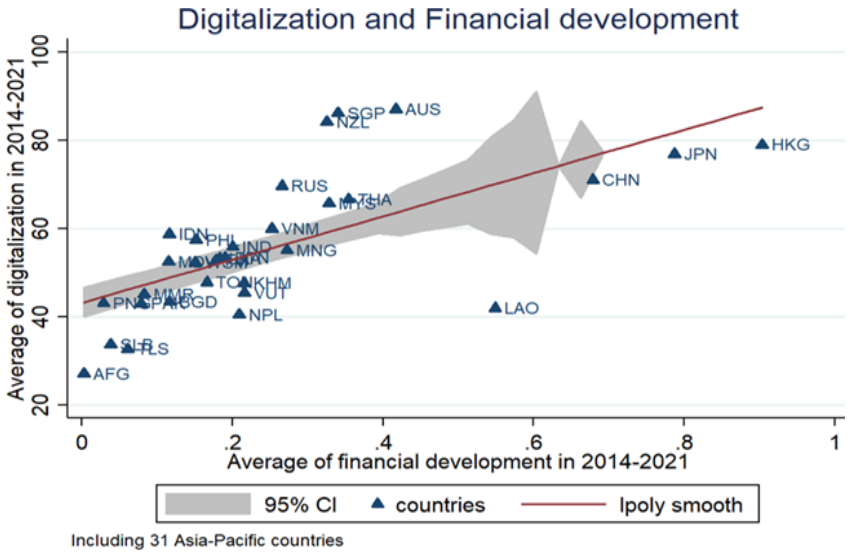
	UNITS	SOURCES	MEAN	SD	MIN	MAX
Dependent variables						
Financial Development Index	[0,1]	using PCA	0.257	0.216	0.000	1.000
Bank Branches Per 1000 Adults	1 bank branch	Global Financial Development Index	0.167	0.140	0.015	0.712
ATMs Per 1000 Adults	1 ATM		0.482	0.435	-0.171	1.854
Deposit Money Banks Assets To GDP	/100 (%)		0.934	0.684	0.027	3.747
Liquid Liabilities To GDP	/100 (%)		0.976	0.791	0.228	4.547
Financial System Deposits To GDP	/100 (%)		0.829	0.722	0.146	4.157
Bank Deposits To GDP	/100 (%)		0.828	0.722	0.146	4.157
Independent variables						
Digital divide $= \frac{1}{3}\sum_{i=1}^{3} sub - index_i$	[0,1]	Authors	0.558	0.168	0.234	0.917
$Sub - index_1$: Accessible Infrastructure	[0,1]	GSMA Intelligence	0.561	0.175	0.210	0.941
$Sub - index_2$: Affordability	[0,1]		0.570	0.141	0.281	0.894
$Sub - index_3$: Open and safe	[0,1]		0.542	0.219	0.080	0.965
Institutional quality & control variables						
Institutional Quality	z-score	WDI	-0.028	0.832	-1.681	1.859
Covariates 1: Internal controls						
Central Bank Assets To GDP	%	"Financial Development and Structure" WB database	5.742	14.140	0.013	92.239
Bank Net Interest Margin	%		3.191	1.547	0.521	7.703
Bank Overhead Costs To Total Assets	%		1.869	1.180	0.442	14.419
Bank Return On Equity, After Tax	%		10.921	4.917	-3.244	39.314
Bank Concentration	%		56.811	21.205	16.144	100.000
Covariates 2: External controls						
Liquid liabilities, 2000 constant	billion USD	"Financial Development and Structure" WB database	1325.99	4425.66	0.19	28700.00
Remittance inflows to GDP	%		5.206	7.697	0.000	38.981
External loans and deposits of reporting banks	%		20.294	26.489	0.277	119.813
Instruments and mechanism tests						
Regional Digital Development (2 year-lagged)	[0,100]	(Dengler *et al.*, 2022; Wu and Shao, 2022; Chen and Kim, 2023)	55.775	8.391	35.162	76.773
Regional Average Mobile Broadband Download Speeds (2 year-lagged)	[0,100]		32.080	14.576	7.055	56.987
Digital Financial Consumer Protection	[0,1]	Dinh *et al.* (2023)	0.535	0.243	0.000	0.937

Sources: conducted by authors.

4. RESULTS

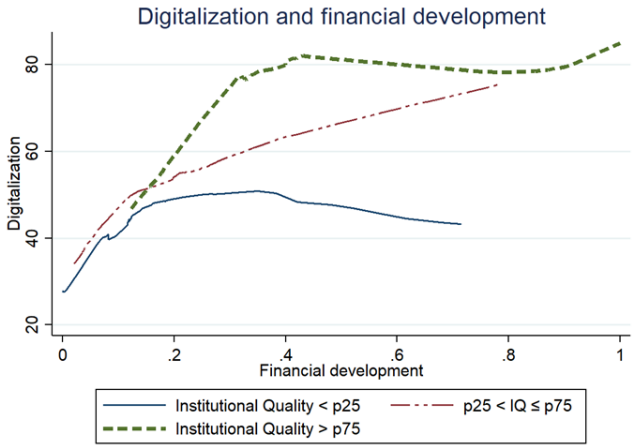
4.1 Descriptive statistics

In examining the suitability of our case study (i.e., Asia-Pacific region), this section presents several demonstrations. To begin with, Figure no. 2 exemplifies the linear association between the digital divide and financial development in the Asia-Pacific region from 2014 to 2021; accordingly, initial findings validate a positive correlation between these variables. Notably, some countries with a high level of digital divide (i.e., Singapore, Australia, and New Zealand) remain at an intermediate level of financial development, relatively lower than that of China and Japan. This phenomenon can be attributed to these nations' proclivity for prioritizing the quality of financial services (digital dividends) over the sheer quantity of services (digital divide). In contrast, Laos demonstrates a rapid increase in financial services while experiencing limited digitalization, primarily due to international financial growth, mainly emanating from China (Stuart-Fox, 2009). This underscores the imperative need for controlling external factors once again.



Note: A line graph shows the relation between Digitalization and Average financial development with triangle dots presenting each observed nation from 2014 to 2021

Figure no. 2 – Linear relationship between digitalization and financial development, Asia-Pacific region
Sources: conducted by authors

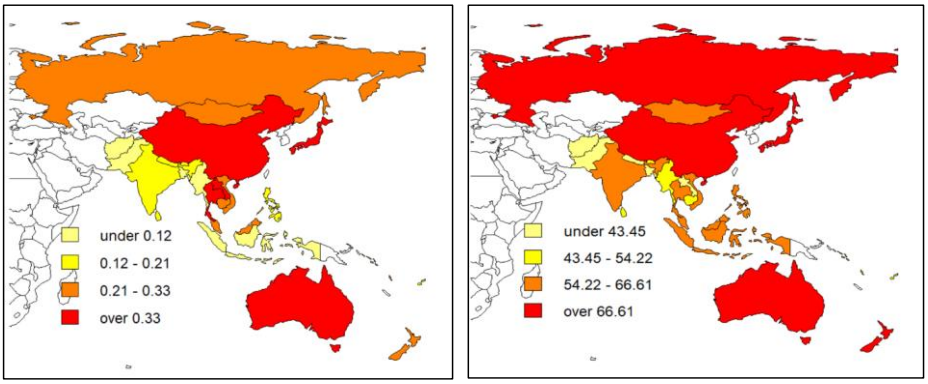


Note: A three-line graph compares the non-linear correlation between the digital divide and financial development in different institutional quality level including 3 groups: below 25th percentile, above 75th percentile and the middle of those. Observation includes 31 Asia Pacific countries from 2014 to 2021.

Figure no. 3 – Digital divide and financial development nexus, classified by institutional quality
Source: author's own work.

Figure no. 3 illustrates the non-linear correlation between the digital divide and financial development among a cohort of 31 Asia-Pacific nations from 2014 to 2021. These countries are classified based on their varying institutional contexts and categorized explicitly into three groups: those falling below the 25th percentile, those between the 25th and 75th percentile, and those exceeding the 75th percentile regarding institutional quality. Preliminary results also indicate that countries with lower institutional quality (below the 25th percentile) exhibit a shallower intercept. Countries within the 25th-75th percentile of institutional quality display the steepest slope, while the highest and lowest institutional levels have a similar slope. These results imply that regions positioned at a middling level of institutional development, typically encompassing transitioning nations such as Vietnam and China, hold the potential to achieve the most rapid enhancements in their financial performance when they embark on improvements in their digitalization processes.

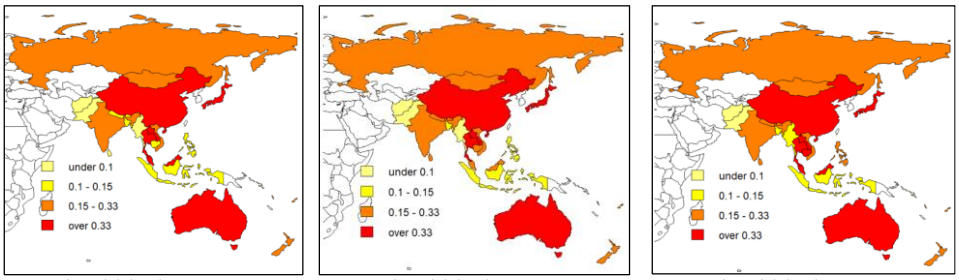
Third, one of the criteria for selecting an appropriate research region is the presence of heterogeneity among the countries concerning both variables of interest. Figure no. 4 portrays the current state of digitalization and financial development across the 31 countries within the Asia-Pacific region. This visual representation suggests substantial disparities in the levels of financial development and digital divide among these nations in comparison to the global map (see more in Figures no. A2 and A3), underscoring the region's suitability for analysis aimed at discerning the relationship between the two variables. Of equal importance, the figure presented below provides a visual depiction of the progress and regressions in the status of financial development and digitalization across the 31 Asia-Pacific countries during the period spanning from 2014 to 2021. Accordingly, Figure no. 5 elucidates that the significant shifts in financial performance predominantly transpired within the southeast Asian region, marked by the continuous growth in Cambodia, Nepal, and Bhutan over time, while Malaysia experienced a slight decline in 2018 before rebounding in 2021. In Figure no. 6, the discernible color shift (from yellow to red) distinctly reflects the rapid upsurge in digital processes across most regions.



Financial Development Digital Divide

Note: 2 maps of Asia-Pacific region portray the current state of digital divide and financial development across the 31 countries with 4 colors of development showing each country level

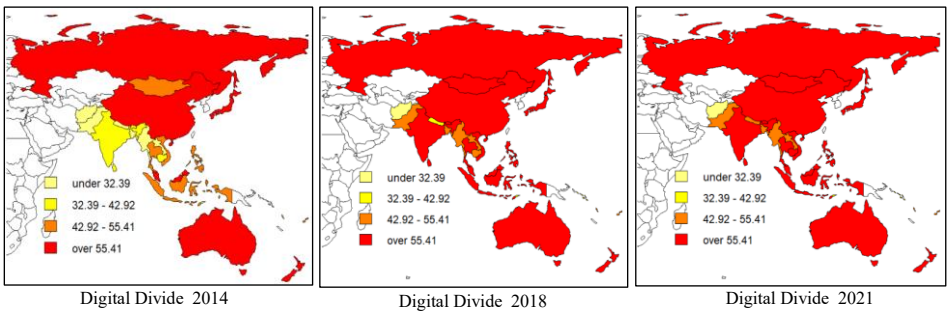
Figure no. 4 – Financial and digital level, Asia Pacific region 2014-2021
Source: author's own work.



Financial development 2014 Financial development 2018 Financial development 2021

Note: three maps of Asian Pacific conuntries demonstrate the changes of Financial development in 2014, 2018 and 2021 with four colors presenting different level for each nation.

Figure no. 5 – Financial evolution in Asia Pacific countries, 2014-2021
Source: author's own work.



Digital Divide 2014 Digital Divide 2018 Digital Divide 2021

Note: three maps of Asian Pacific conuntries demonstrate the changes of Digital Divide in 2014, 2018 and 2021 with four colors presenting different level for each nation. It does not include islands and archipelagos.

Figure no. 6 – Digital evolution in Asia Pacific countries, 2014-2021
Source: author's own work.

4.2 Basic results

Using a fixed-effect model, Table no. 3 presents the regression results concerning the linear nexus between the digital divide and its lag effect on the financial development (FD) index. In columns [1]-[3], we observe the current effects of the digital divide on the dependent variable. To shut down the channel of adopter characteristics and external shocks, the study controls for additional internal banking variables (e.g., banking structure and bank costs and profits) in column [2] and for external factors (i.e., the size of liquid liabilities, remittance inflows, and external loans and deposits) in column [3]. The reduction in the magnitude of the coefficients aligns with the theoretical framework, indicating that the heterogeneity among adopters and external factors significantly moderates the nexus (Rao and Kishore, 2010; Demirguc-Kunt *et al.*, 2018; Das, 2022). It should be noted that controlling these variables helps clarify the impact of institutional quality on the relationship in question, directly related to research examining influences on financial development, such as remittance inflows (Donou-Adonsou *et al.*, 2020), financial structure (Ruiz-Porras, 2009), and degree of banking concentration (Michaelsen, 2018; Sudan, 2020; Dragu and Lupu, 2021). This strand also accounts for the divergence in research outcomes when scholars conducted within different contexts, particularly between developing and developed nations.

Regarding the lagged effects, columns [4]-[6] in Table no. 3 reveal consistent results, indicating a lag of approximately two years. In other words, the effects of the digitalization process become most discernible after approximately two years. To further validate this finding, our study employs the local projection technique offered by Jordà (2005); accordingly, as illustrated in Figure no. 7, the results confirm the two-year delayed impact of the digital divide (DD) on financial development. In subsequent analyses, we examine the current effects of the digital divide on financial development for several reasons. One reason is data availability; employing the 2-year lag of DD reduces the number of observations in the sample, particularly when controlling for relevant factors, resulting in just 112 observations across 23 countries (column [6]). Another reason is the emphasis on the present-day impact of the digital divide, which holds more significant policy implications for the countries in the Asia-Pacific region, given that policies are typically based on current data. To minimize potential underestimation of the current effects, if any, we employ the two-system generalized method of moments (GMM) estimator with two external instruments (i.e., regional digitalization and regional average mobile broadband download speeds) with a 2-year lag, as outlined in the study design in sub-section 3.3. The study design, therefore, ensures optimal observations while maintaining the consistency of the estimated results.

Table no. 3 – Basic regression results

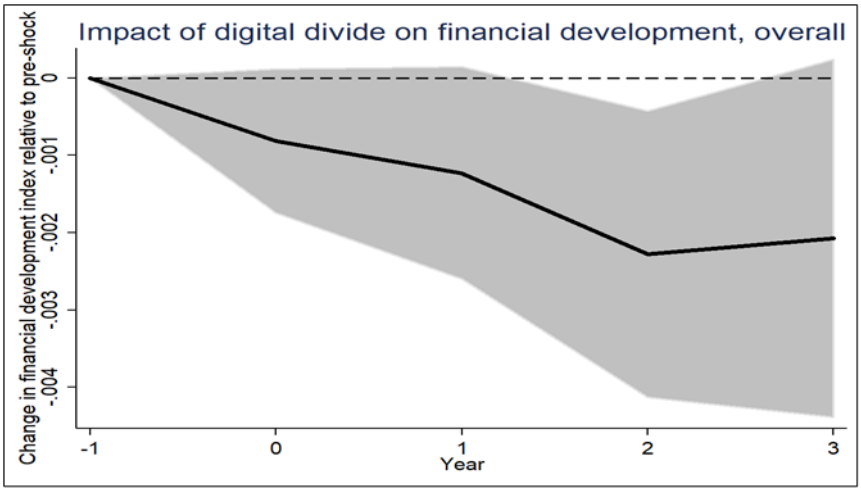
Dependent variable:	**Financial development index**					
	Fixed effect model					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Digital divide$_t$	0.348***	0.200***	0.119***			
	(0.035)	(0.045)	(0.038)			
Digital divide$_{t-1}$				-0.041	-0.057	-0.058
				(0.124)	(0.134)	(0.106)
Digital divide$_{t-2}$				0.349***	0.266**	0.198**
				(0.109)	(0.114)	(0.092)
Institutional quality	-0.013	0.064*	0.036	-0.003	0.054	0.022

Dependent variable:	**Financial development index**					
	Fixed effect model					
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	(0.025)	(0.036)	(0.028)	(0.029)	(0.044)	(0.035)
Central bank assets to GDP		0.001**	0.001		0.001	0.001**
		(0.001)	(0.001)		(0.001)	(0.001)
Bank net interest margin		-0.008*	-0.010**		-0.004	-0.004
		(0.005)	(0.004)		(0.009)	(0.007)
Bank overhead costs to total assets		0.002	-0.001		0.002	-0.007
		(0.003)	(0.002)		(0.015)	(0.015)
Bank return on equity (after tax)		-0.001*	-0.001*		-0.002**	-0.001**
		(0.001)	(0.000)		(0.001)	(0.001)
Bank concentration		-0.000	-0.002***		0.000	-0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Liquid liabilities			0.000***			0.000***
			(0.000)			(0.000)
Remittance inflows to GDP			-0.004			-0.007*
			(0.003)			(0.004)
External loans and deposits of reporting banks			-0.000			0.000
			(0.000)			(0.000)
ID controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.063***	0.197***	0.298***	0.103***	0.144**	0.264***
	(0.020)	(0.056)	(0.053)	(0.026)	(0.065)	(0.072)
Observations	248	171	154	186	129	112
R-squared	0.325	0.397	0.597	0.307	0.388	0.586
Number of countries	31	23	23	31	23	23

Note: The numbers in parentheses represent the standard errors, with *** indicating significance at p<0.01, ** at p<0.05, and * at p<0.1.

Source: author's own work.

Following the argument above, in Table no. 4, columns [1]-[3], this study employs a two-stage regression with instrumental variables (XTIVREG option in Stata), while columns [4]-[6] present the results utilizing GMM estimator. The coefficients in Table no. 4 are consistent with previous studies and align with our expectations; accordingly, these results consistently indicate that the impact of the digital divide on financial development is statistically significant and positive. The coefficients obtained with XTIVREG are similar to the previous Table, while those from the two-system GMM estimator are approximately three times larger. This can be attributed to (i) the consideration of local average treatment effects (LATE) and (ii) the GMM design allowing for an examination of the impact of the regional digital divide with a lag of 2 years on financial development, which, as discussed, tends to be larger than the current effects.



Note: a line graph covered with a grey area shows the year-delayed impact of Digital divide on Financial development through the change in the financial development index.

Figure no. 7 – Change in financial development index relative to pre-shock
Source: author's own work.

Both XTIVREG and GMM estimators yield consistent coefficients when the instruments are valid. In our case, the instrumental variables are assessed for theoretical validity based on previous research applications (Dengler *et al.*, 2022; Wu and Shao, 2022; Chen and Kim, 2023) and for technical validity through four tests (i.e., AR(1), AR(2), Hansen test of overidentification restrictions, and Difference-in-Hansen tests of the exogeneity of instruments (Wintoki *et al.*, 2012; Van Le and Tran, 2022). However, in cases where the changes in instruments are uncorrelated with the fixed effects (δ), or in mathematical terms, $E(\Delta Instruments_{it}, \delta i) = 0$ for all i and t, the GMM estimators effectively account for unobservable heterogeneity, simultaneity, and potential endogeneity. Conversely, if the additional assumptions are not met, this estimator can produce spurious results, which can be challenging to discern due to the complexity of this technique.

Table no. 4 – XTIVREG and 2-system GMM estimators results

Dependent variable:	**Financial development index**					
	IVREG	**IVREG**	**IVREG**	**GMM 2-sys**	**GMM 2-sys**	**GMM 2-sys**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Digital divide	0.368***	0.194***	0.110***	0.874**	0.696**	0.693***
	(0.037)	(0.047)	(0.040)	(0.351)	(0.333)	(0.197)
Institutional quality	-0.017	0.066*	0.038	0.048	0.055	0.044
	(0.025)	(0.036)	(0.027)	(0.073)	(0.076)	(0.035)
Central bank assets to GDP		0.001**	0.001		0.002	0.002
		(0.001)	(0.001)		(0.003)	(0.004)
Bank net interest margin		-0.008*	-0.010**		0.013	0.005
		(0.005)	(0.004)		(0.037)	(0.016)
Bank overhead costs to total assets		0.002	-0.002		-0.009	-0.004

Dependent variable:	**Financial development index**					
	IVREG	**IVREG**	**IVREG**	**GMM 2-sys**	**GMM 2-sys**	**GMM 2-sys**
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
		(0.003)	(0.002)		(0.046)	(0.012)
Bank return on equity (after tax)		-0.001*	-0.001*		-0.001	-0.002
		(0.001)	(0.000)		(0.005)	(0.002)
Bank concentration		-0.000	-0.002***		-0.002	-0.003
		(0.001)	(0.001)		(0.002)	(0.004)
Liquid liabilities			0.000***			0.000
			(0.000)			(0.000)
Remittance inflows to GDP			-0.004			0.002
			(0.003)			(0.013)
External loans and deposits of reporting banks			-0.000			0.000
			(0.000)			(0.001)
ID controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant				-0.176	0.002	0.058
				(0.160)	(0.191)	(0.407)
Observations	248	171	154	248	171	154
R-squared	0.324	0.396	0.597			
Number of countries	31	23	23	31	23	23
Year lagged instruments				2-year lagged	2-year lagged	2-year lagged
Exogeneous instruments	2	2	2	2	2	2
Cragg-Donald Wald F statistic:	789.491	373.000	290.793			
Sargan statistic (overidentify–cation test of all instruments):	0.0358	0.0410	0.5354			
AR(1)				0.955	0.918	0.461
AR(2)				0.030	0.083	0.076
Hansen test of overid. Restrictions (p-value)				1.000	1.000	1.000
Difference-in-Hansen tests of exogeneity of instrument (p-value)				1.000	1.000	1.000

Note: The numbers in parentheses represent the standard errors, with *** indicating significance at p<0.01, ** at p<0.05, and * at p<0.1.

Source: author's own work.

4.3 Contextual factors & mechanism tests

One of the crucial contextual factors influencing the relationship under examination is the quality of institutional frameworks. The Asia-Pacific region is characterized by a diverse range of institutional regimes, spanning from the institutional framework in Australia to the centrally-planned socialist economy in Vietnam. Accordingly, Table no. 5 presents results derived from Equation (3), wherein institutional quality is divided into three categories based on percentiles: 25th and 75th. Columns [2]-[4] examine the impacts of various sub-indices of the digital divide, while column [1] investigates the impact of the composite index. While variations in the intercept are observed under the influence of institutional quality on the

nexus, there are no discernible differences in the slopes between them, as indicated by the lack of statistical significance in the interaction term coefficients. Furthermore, concerning the effects of control variables, it should be noted that the degree of banking concentration, representing banking market monopoly, has a negative influence on financial development, consistent with findings from previous studies (Michaelsen, 2018; Sudan, 2020; Dragu and Lupu, 2021).

Table no. 5 – The nexus under the institutional condition

Dependent variable:	**Financial development index**			
	Fixed effect model			
Independent variable (DD)	**Digital divide**	**Sub-index: Infrastructure**	**Sub-index: Affordability**	**Sub-index: Open and safe**
	(1)	**(2)**	**(3)**	**(4)**
Independent variable (DD)	0.167***	0.067*	0.157***	0.188***
	(0.052)	(0.039)	(0.054)	(0.050)
Middle level of institutional quality	0.045	0.014	**0.063***	**0.064****
	(0.032)	(0.025)	(0.036)	(0.032)
High level of institutional quality	0.081	**0.070***	0.119	0.055
	(0.052)	(0.037)	(0.079)	(0.043)
Middle level of institutional quality × X	-0.043	0.020	-0.063	-0.080
	(0.057)	(0.044)	(0.065)	(0.053)
High level of institutional quality × X	-0.107	-0.074	-0.160	-0.070
	(0.086)	(0.056)	(0.135)	(0.070)
Central bank assets to GDP	0.001	0.001*	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Bank net interest margin	-0.009**	-0.011**	-0.012***	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
Bank overhead costs to total assets	-0.000	-0.001	-0.002	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)
Bank return on equity (after tax)	-0.001*	-0.001*	-0.001*	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Bank concentration	-0.001**	-0.002***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Liquid liabilities	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Remittance inflows to GDP	-0.002	-0.003	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
External loans and deposits of reporting banks	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ID controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	0.240***	0.320***	0.271***	0.240***
	(0.063)	(0.059)	(0.061)	(0.057)
Observations	154	154	154	154
R-squared	0.608	0.595	0.592	0.619
Number of countries	23	23	23	23

Note: The numbers in parentheses represent the standard errors, with *** indicating significance at p<0.01, ** at p<0.05, and * at p<0.1. In Table no. A2, we present results with a lag of 2, where the impact is more clearly demonstrated, with statistical significance at the 1% alpha level.
Source: author's own work.

In terms of the operative mechanisms, Table no. 6 examines the impact of the digital divide on the following channels: financial market boost (e.g., number of bank branches and ATMs, deposit money banks' assets) and intermediate market expand (e.g., liquid liabilities and financial system deposits). The research results are in line with prior findings; accordingly, column [3] confirms the findings of Demirguc-Kunt *et al.* (2018) that the integration of digital technologies, such as online banking and digital payment systems, enhances the efficiency and reach of deposit money banks (DMBs) assets, enabling them to expand their services and customer base. Similarly, Ping (2014) emphasizes that digitalization streamlines operations reduces administrative costs, and enhances the overall profitability of DMBs.

Column [4] aligns with Aziz and Naima (2021), who suggest that digitalization is pivotal in reshaping a nation's economic landscape, particularly concerning its liquid liabilities. Indeed, digitalization has various mechanisms that facilitate a positive impact; for instance, integrating digital payment systems and online banking channels reduces reliance on physical cash as digital financial transactions become more prevalent in this era. As the demand for physical currency in circulation diminishes, there is potential for a change in liquid liabilities as a proportion of GDP. Moreover, digitalization fosters greater financial inclusion, making credit and financial services more accessible to underserved populations (Demirguc-Kunt *et al.*, 2018). The expanded access to credit can facilitate a more efficient allocation of financial resources, thus, in turn, reducing the necessity for excessive liquidity. Notably, automating and streamlining financial processes through digital technologies can result in expedited settlements and fewer payment delays (Claessens *et al.*, 2018), reducing the cash reserves businesses need to maintain for transaction purposes.

Columns [5] and [6] verify that digitalization also exerts a transformative influence on the financial landscape and, consequently, enhances accessibility to the financial system, increasing deposit mobilization across various financial institutions, including banks (Demirguc-Kunt *et al.*, 2018). Digital banking platforms, online payment systems, and mobile banking applications facilitate convenient deposit-taking, transcending geographical constraints. Notably, a recent study by Dinh *et al.* (2023) asserts that information and communication technology (ICT) can enhance the protection of digital customers in a global sample, thereby improving consumer trust. In other words, the digital divide can enhance financial demand by improving trust in the financial system, particularly in countries undergoing transitions (such as Vietnam), given that their payment behavior relies sizably on cash (World Bank, 2019a). We corroborate these findings in the Asia-Pacific region in Table no. 7, and the results are consistent with our expectations.

Table no. 6 – Mechanism results

Dependent variables:	**Bank branches per 1000 adults**	**ATMs per 1000 adults**	**Deposit money banks assets to GDP**	**Liquid liabilities to GDP**	**Financial system deposits to GDP**	**Bank deposits to GDP**
			Fixed effect model			
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Digital divide$_t$	0.072	-0.045	0.550***	0.458***	0.352***	0.354***
	(0.056)	(0.129)	(0.157)	(0.145)	(0.125)	(0.125)
Institutional quality	0.010	0.248**	0.095	0.061	0.069	0.069
	(0.042)	(0.096)	(0.118)	(0.108)	(0.094)	(0.094)
Central bank assets to GDP	-0.001	-0.003	-0.005**	0.010***	0.006***	0.006***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)

Dependent variables:	Bank branches per 1000 adults	ATMs per 1000 adults	Deposit money banks assets to GDP	Liquid liabilities to GDP	Financial system deposits to GDP	Bank deposits to GDP
			Fixed effect model			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Bank net interest margin	-0.005	-0.034**	-0.019	-0.038**	-0.024*	-0.023*
	(0.006)	(0.014)	(0.017)	(0.016)	(0.014)	(0.014)
Bank overhead costs to total assets	0.007*	0.003	-0.008	-0.011	-0.016*	-0.016*
	(0.004)	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)
Bank return on equity (after tax)	-0.001	0.001	-0.005**	-0.001	-0.004**	-0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank concentration	-0.001	-0.006***	-0.004*	-0.006***	-0.004**	-0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Remittance inflows to GDP	-0.011***	-0.006	-0.019*	0.002	0.003	0.003
	(0.004)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)
External loans and deposits of reporting banks	-0.000	0.000	-0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ID controls	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.240***	1.023***	0.997***	1.037***	0.852***	0.850***
	(0.080)	(0.183)	(0.224)	(0.206)	(0.178)	(0.178)
Observations	154	154	154	154	154	154
R-squared	0.177	0.257	0.425	0.493	0.407	0.408
Number of countries	23	23	23	23	23	23

Note: The numbers in parentheses represent the standard errors, with *** indicating significance at p<0.01, ** at p<0.05, and * at p<0.1.

Source: author's own work.

Table no. 7 – Mechanism test: Digital financial consumer protection channel

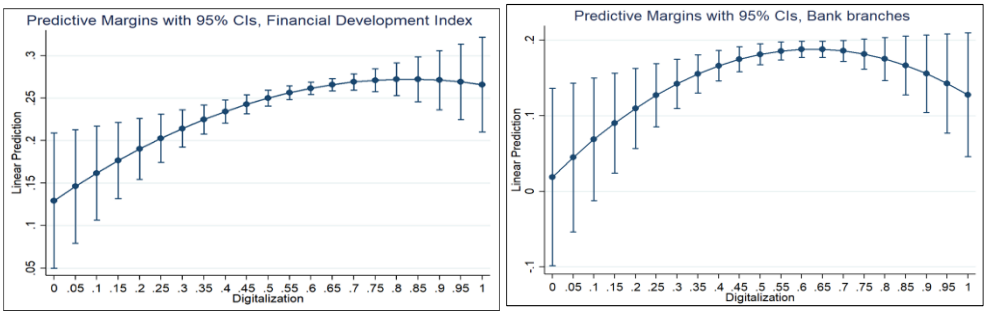
Dependent variable:	Digital financial consumer protection			
	Fixed effect model			
VARIABLES	(1)	(2)	(3)	(4)
Digital divide	0.491***			
	(0.070)			
Sub-index 1: Infrastructure		0.260***		
		(0.044)		
Sub-index 2: Affordability			0.211*	
			(0.107)	
Sub-index 3: Open and safe				0.458***
				(0.065)
Institutional quality	-0.055	-0.050	0.028	0.005
	(0.049)	(0.053)	(0.065)	(0.047)
Central bank assets to GDP	0.001	0.001	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.001)
Bank net interest margin	0.007	0.012	0.002	0.008
	(0.008)	(0.009)	(0.011)	(0.008)
Bank overhead costs to total assets	-0.004	-0.005	-0.011***	-0.006**
	(0.003)	(0.003)	(0.004)	(0.003)
Bank return on equity (after tax)	0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)

Dependent variable:	**Digital financial consumer protection**			
	Fixed effect model			
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**
Bank concentration	-0.001	-0.001	-0.002**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Liquid liabilities	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Remittance inflows to GDP	0.007	0.003	-0.002	0.007
	(0.007)	(0.007)	(0.009)	(0.007)
External loans and deposits of reporting banks	-0.002	-0.002*	-0.001	-0.002*
	(0.001)	(0.001)	(0.002)	(0.001)
ID controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	0.208**	0.361***	0.521***	0.282***
	(0.091)	(0.084)	(0.117)	(0.082)
Observations	75	75	75	75
R-squared	0.669	0.616	0.390	0.671
Number of countries	15	15	15	15

Note: The numbers in parentheses represent the standard errors, with *** indicating significance at p<0.01, ** at p<0.05, and * at p<0.1.

Source: author's own work.

Last but not least, the impact of the digital divide on financial development may exhibit non-linear characteristics. Indeed, in some sub-indexes of financial development, such as financial infrastructure, the increasing level of digitalization can alter the modes of utilizing financial services, for example, shifting from online payments through ATMs to integrated payment methods. Consequently, this can give rise to a parabolic curve in lieu of linear trends (Aterido *et al.*, 2011). Regression results with this non-linear form are presented in the Table no. A3 and illustrated in Figure no. 8. Accordingly, the impact of the digital divide on the bank branches component adheres to parabolic trends and is consistent with the expectations of previous studies.



Note: 2 graphs show the near parabolic curves of predictive margins with 95% confidence intervals for Financial Development and its component as Bank branches.

Figure no. 8 – Digital divide on financial development and its components

Source: author's own work.

5. DISCUSSION AND POLICY IMPLICATION

This study provides insight into the impact of the digital divide on financial development while considering contextual factors, such as institutional frameworks. Several key highlights emerge from this investigation. First, we chose the Asia-Pacific region due to its favorable characteristics for determining the relationship under study, including significant variability among variables between and within countries. Second, we took into account the time lag in the impact of the digital divide on financial development and addressed endogeneity issues by employing appropriate instrumental variables. Third, we elucidated the impact of the relationship through various mechanisms. The research results affirm the role of the digital divide in a nation's financial development, which becomes observable after approximately two years of implementation. This is particularly evident through the channels of (i) expanding the scale of the financial market, (ii) the scale of intermediate financial markets, and (iii) increasing consumer financial demand due to improved consumer protection (Dinh *et al.*, 2023).

Notably, given the shutdown of the adopter's characteristic and external channel, we confirm the significant role of contextual factors in the digital divide's impact on financial development. Institutional quality, as expected to be a key moderator of the relationship, can influence the intercept of the relationship but does not alter its slope. In other words, a better institutional framework does not determine the effectiveness of absorbing digital advancements, as we control for adopter's characteristics and external factors. Additionally, this study validates the notion that monopoly is a constraint on the financial development process, as predicted by numerous prior studies. Therefore, this study implies that future research on the digital divide's impact on financial development should emphasize the control of contextual factors.

Indeed, in the initial phases, a lack of digital services leads to an increase in physical bank branches to maintain financial accessibility. However, as digital infrastructure improves, especially in urban areas, the need for numerous physical branches diminishes, reflecting the declining phase of the parabol. This trend is evident as urban centers stabilize or reduce branch numbers in response to widespread digital banking adoption, while rural areas may experience a similar, albeit delayed, pattern – see a case in Vietnam (Van Le and Tran, 2023). This dynamic aligns with theories predicting that technological advances lead financial institutions to adapt their physical presence towards a more efficient, digital-first approach (Sardana and Singhania, 2018). In Table no. A4, we summarize the main findings of this study.

For policymakers, especially in transitioning countries, the digital transformation process may exhibit delayed effects through various intermediary financial market channels and the enhancement of consumer trust in the digital era. Consequently, digital transformation policies require a long-term strategy, considering their multifaceted impact rather than focusing solely on specific aspects. To bridge the digital divide and enhance financial development in the diverse institutional and economic landscape of the Asia-Pacific region, targeted policy measures are essential. Governments should prioritize strengthening digital infrastructure and connectivity by expanding broadband access, fostering public-private partnerships, and promoting regional cooperation to share best practices. Enhancing institutional and regulatory frameworks is equally critical, requiring adaptive regulations that balance innovation with consumer protection, stronger cybersecurity measures, and the implementation of regulatory sandboxes to facilitate fintech experimentation. Additionally, promoting financial and digital literacy through nationwide education programs, school curriculums, and interactive mobile content can empower individuals to confidently engage with digital financial services.

Supporting inclusive fintech innovation by providing incentives for startups, developing localized financial solutions, and fostering collaborations between traditional banks and fintech firms can further drive financial accessibility. Given the region's institutional diversity, policies should be tailored to different economic contexts developed economies should refine fintech regulations, emerging markets should focus on digital infrastructure and financial education, while low-income economies should prioritize mobile banking and microfinance initiatives. Lastly, leveraging emerging technologies such as AI, big data, blockchain, and central bank digital currencies (CBDCs) can optimize financial inclusion strategies and drive sustainable economic growth. By implementing these targeted and context-specific policies, governments and financial institutions can effectively promote the diffusion of digital financial innovations and foster inclusive financial ecosystems across the Asia-Pacific region.

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ANNEXES

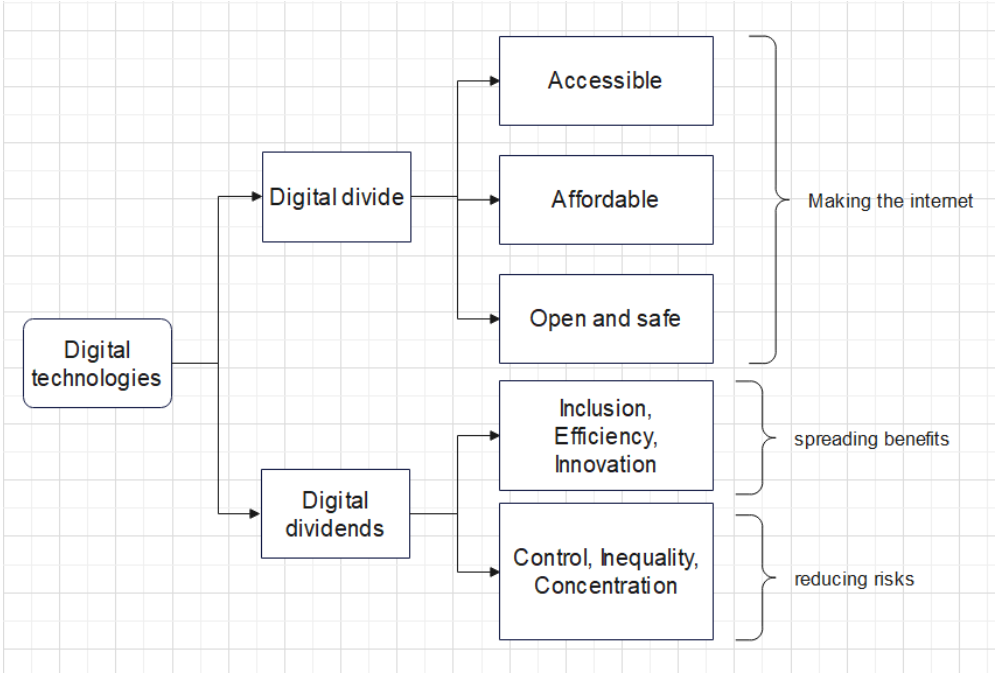

Figure no. A1 – Digital divide and digital dividends

Source: authors' synthetic from World Bank (2016).

Table no. A1 – List of 31 Asia-Pacific countries in the sample from 2014 to 2021

Country name	Frequency	Country name	Frequency	Country name	Frequency
Afghanistan	8	Japan	8	Philippines	8
Australia	8	Laos	8	Russian Federation	8
Bangladesh	8	Malaysia	8	Samoa	8
Bhutan	8	Maldives	8	Singapore	8
Cambodia	8	Mongolia	8	Solomon Islands	8
China	8	Myanmar	8	Sri Lanka	8
Fiji	8	Nepal	8	Thailand	8
Hong Kong	8	New Zealand	8	Timor-Leste	8
India	8	Pakistan	8	Tonga	8
Indonesia	8	Papua New Guinea	8	Vanuatu	8
Vietnam	8	Total	248		

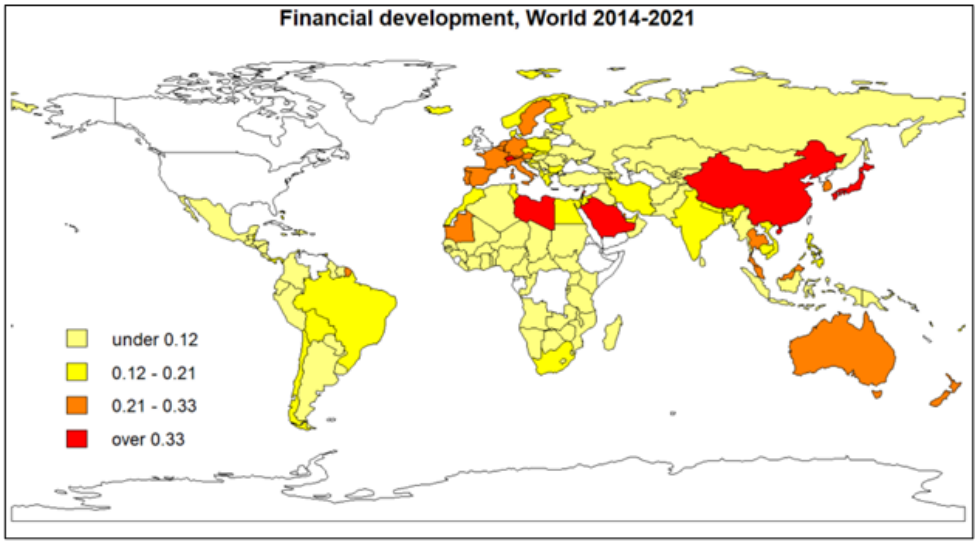

Figure no. A2 – Financial development, World 2014-2021

Source: authors' own work

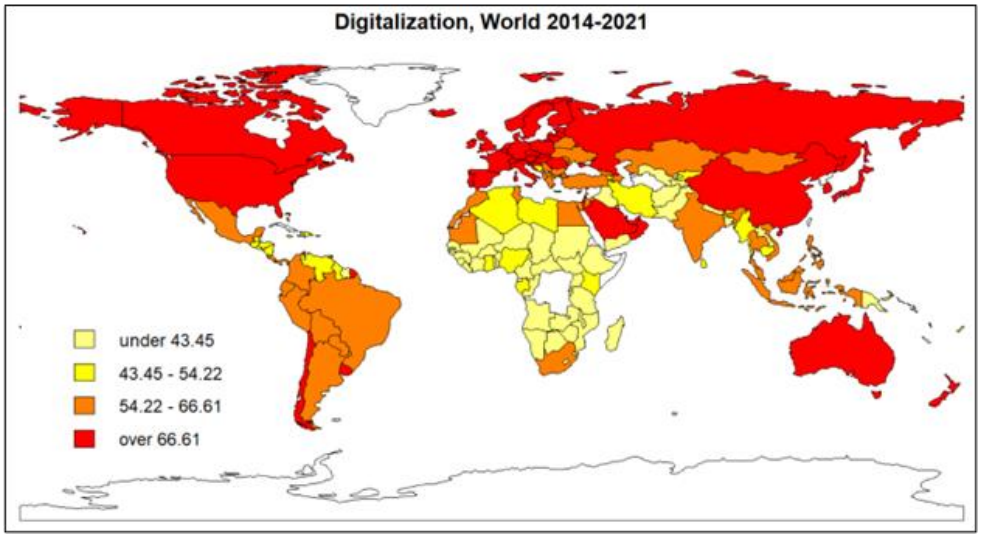

Figure no. A3 – Digitalization, World 2014-2021

Source: authors' own work

Table no. A2 – The nexus under the institutional condition (2-years lag)

Dependent variable:	**Financial development index**			
	Fixed effect model			
Independent variable (DD)	**Digital divide**	**Sub-index: Infrastructure**	**Sub-index: Affordability**	**Sub-index: Open and safe**
	(1)	**(2)**	**(3)**	**(4)**
Independent variable [Equation]	0.002***	0.105**	0.223***	0.261***
	(0.001)	(0.042)	(0.059)	(0.093)
Middle level of institutional qualityt-2	0.082**	0.067**	0.104***	0.113**
	(0.035)	(0.027)	(0.039)	(0.049)
High level of institutional qualityt-2	0.110**	0.090**	0.165*	0.141**
	(0.055)	(0.038)	(0.085)	(0.060)
Middle level of institutional quality t-2 [Equation]	-0.001	-0.047	-0.117	-0.152
	(0.001)	(0.050)	(0.094)	(0.104)
High level of institutional qualityt-2 [Equation]	-0.001	-0.035	-0.177	-0.153
	(0.001)	(0.063)	(0.149)	(0.120)
Central bank assets to GDP	0.001**	0.001**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Bank net interest margin	-0.001	0.002	-0.005	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Bank overhead costs to total assets	-0.004	-0.012	-0.004	-0.008
	(0.016)	(0.016)	(0.015)	(0.016)
Bank return on equity (after tax)	-0.001**	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Bank concentration	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Liquid liabilities	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Remittance inflows to GDP	-0.008**	-0.009**	-0.005	-0.008**
	(0.004)	(0.004)	(0.004)	(0.004)
External loans and deposits of reporting banks	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ID controls	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	0.164**	0.215***	0.141*	0.180**
	(0.072)	(0.069)	(0.076)	(0.074)
Observations	112	112	112	112
R-squared	0.646	0.622	0.650	0.631
Number of countries	23	23	23	23

Note: standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table no. A3 – Regression on FDI and its components

Dependent variables:	Financial development index	Bank branches per 100,000 adults	ATMs per 100,000 adults	Deposit money banks assets to GDP	Liquid liabilities to GDP	Financial system deposits to GDP	Bank deposits to GDP
				Fixed effect model			
VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Digital divide [Equation]	0.346**	0.541**	0.693	0.736	0.654	0.834*	0.819*
	(0.145)	(0.214)	(0.496)	(0.613)	(0.563)	(0.486)	(0.486)
[Equation]	-0.209	-0.432**	-0.681	-0.171	-0.180	-0.444	-0.430
	(0.129)	(0.191)	(0.442)	(0.546)	(0.502)	(0.433)	(0.433)
Institutional quality	0.030	-0.002	0.229**	0.090	0.056	0.057	0.057
	(0.028)	(0.042)	(0.097)	(0.119)	(0.110)	(0.095)	(0.095)
Central bank assets to GDP	0.001*	-0.001	-0.002	-0.004*	0.011***	0.006***	0.006***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank net interest margin	-0.008**	-0.003	-0.030**	-0.018	-0.037**	-0.021	-0.021
	(0.004)	(0.006)	(0.014)	(0.018)	(0.016)	(0.014)	(0.014)
Bank overhead costs to total assets	-0.002	0.006*	0.003	-0.008	-0.011	-0.016**	-0.016**
	(0.002)	(0.003)	(0.008)	(0.010)	(0.009)	(0.008)	(0.008)
Bank return on equity (after tax)	-0.001*	-0.001	0.001	-0.005**	-0.001	-0.003**	-0.003**
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bank concentration	-0.001**	-0.000	-0.006***	-0.004	-0.006**	-0.004*	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Liquid liabilities	0.000***	0.000	0.000***	0.000***	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Remittance inflows to GDP	-0.003	-0.010**	-0.004	-0.019*	0.003	0.004	0.004
	(0.003)	(0.004)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)
External loans and deposits of reporting banks	0.000	-0.000	0.001	-0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.222***	0.083	0.776***	0.935***	0.972***	0.691***	0.695***
	(0.071)	(0.104)	(0.242)	(0.300)	(0.275)	(0.238)	(0.237)
Observations	154	154	154	154	154	154	154
R-squared	0.606	0.211	0.271	0.425	0.494	0.412	0.413
Number of ID	23	23	23	23	23	23	23

Note: standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table no. A4 – Summary of Research Findings

Type of Effects	Description	Empirical Results
Direct (linear) impact of DD on FD	DD causally influences the aggregated financial development index, with a lag of about 2 years	Supported
Direct impact of Institutional quality on FD	Institutional quality is positively correlated with the financial development index	Supported
Moderator effects of Institutional quality: interaction effects	Institutional quality affects the DD-FD nexus	No
Impact mechanisms of DD on FD: mediation effects	The impact is manifested through mechanisms improving Digital financial consumer protection	Supported
Impact mechanisms of DD on FD: mediation effects	The impact is manifested through mechanisms boosting the financial market and expanding the intermediate market	Supported
Non-linear impact of DD on sub-index of FD	The impact of the digital divide on the bank branches component follows parabolic trends and aligns with the expectations of previous studies	Supported

Source: authors.

Limitations: The selection of the Asia-Pacific region, while advantageous for research design, is constrained by the limited number of observations. Moreover, the additional control of adopters' characteristics and external factors led to excluding 31 countries from this region, leaving only 23 countries in the analysis. Therefore, future research with more extensive data may further solidify the research findings with richer datasets. Given the post-COVID-19 context, there is increased interest in how digitalization has shaped financial markets differently. However, given the limitations of the observations and the countries included in this study, we encourage future research to explore this relationship with sub-group analyses based on the periods before, during, and after COVID-19. Additionally, we acknowledge that using national-level data may introduce inevitable noise into the analysis, especially when considering the impact of external factors. Therefore, more insights may be gained from examining this relationship using individual or sub-national level data that combines multiple countries within the region (e.g., Vietnam, China, Australia, New Zealand, and India).

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Foreign Direct Investment, Institutions and Economic Growth: Evidence from South Africa

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Abstract: The association between Foreign Direct Investment (FDI), institutions, and economic growth in South Africa is examined in this study from 1996Q1 through 2019Q4 using Autoregressive Distributed Lag (ARDL). FDI was found to have a negative effect on economic growth in the long run. Institutions and economic growth, on the other hand, have no long-term relationship. However, an interaction between FDI and political stability is discovered to have a direct effect on economic growth in both long and short run. As a result, there is no reliable proof that an interaction between FDI and institutions may induce economic growth. However, there is a short-run link between FDI and economic growth. In the short run, regulatory quality and political stability have a positive effect on economic growth. The study recommends that to invite more FDI inflows into South Africa, the government must prioritize on protecting foreign businesses in the country through minimizing xenophobic attacks in order to boost their confidence hence leading to economic growth. In addition, to achieve economic growth, favorable tax policies that are fair to protect foreign and local investors must be implemented.

Keywords: foreign direct investment; institutions; economic growth; ARDL.

JEL classification: C22; F21; O43.

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1. INTRODUCTION

During the Great Depression of 2008-2009, global Foreign Direct Investment (FDI) flows were not spared, with up to $1.2 trillion in FDI inflows received worldwide, compared to $1.833 trillion the previous year (UNCTAD, 2020). Tracking FDI inflows in the global economy, a peak of $2 trillion was observed in 2015, and FDI flows have been moderately dropping since 2016, with the 2019 worldwide pandemic aggravating the situation (UNCTAD, 2020). Following the reduction in FDI inflows induced by the coronavirus pandemic, there has been and will continue to be a global economic slowdown in terms of growth (UNCTAD, 2020). Global economic growth fell by 3.5% in 2020 and is expected to stay low until 2022, with most emerging and developing countries' per capita incomes unlikely to recover rapidly (World Bank Group, 2021).

South Africa is recognized as Africa's largest market, and it received significant foreign direct investment between 1997 and 2000. In contrast, as a result of the global pandemic, FDI inflows have declined from $4.6 billion in 2019 to $2.5 billion in 2020 (UNCTAD, 2021). On the other hand, economic growth contracted by -7.8% in 2020 compared to 2018, and it fell by 3.2% in the first quarter of 2021. With that in mind, South Africa requires more FDI flows to enhance its economy, as FDIs are seen as drivers of economic growth, and they have historically played an important role in increasing output production (Awolusi and Adeyeye, 2016). Apart from encouraging economic growth, FDI creates jobs in host countries. South Africa now has a 32.6% unemployment rate, with young adults being the most impacted category (Statistics South Africa, 2021), indicating the need for more FDI inflows.

According to the research, the most essential factors that provide stability to foreign investors are trade openness, market size, infrastructure, natural resource abundance, labor cost, human capital availability, and return on investment (Asiedu, 2002; Nunnenkamp, 2002). By extension, the idea that FDI boosts economic growth has no bearing unless the nature of the host country into which FDI is expected to flow is understood. Meanwhile, in a changing world, foreign investors are increasingly concerned about the host country's institutional structure, which has a significant impact on their return on investment, profitability, and the FDI-growth nexus. With that said, it is critical to examine the institutional policies that govern FDI as they relate to economic growth.

In this instance, South Africa is anticipated to have a strong government structure to attract more FDI. Kaufmann *et al.* (2011) define a good governance system as one that includes rule of law, political stability and the lack of violence, voice and accountability, corruption control, regulatory quality, and government performance. For example, because equality, transparency, and freedom make South Africa's constituency more democratic, the Protection of Investment Act was passed to ensure equal treatment of foreign and domestic investors (Republic of South Africa, 2015). This will encourage more foreign direct investment, ultimately boosting growth. On the contrary, a number of xenophobic attacks and looting against foreigners have been documented in South Africa, which has deterred FDI over time.

Numerous studies have only focused on the impact of FDI on South African growth (Asafo-Adjei, 2007; Masipa, 2014; Mazenda, 2014; Sunde, 2017), but others have investigated the causes of FDI flows to South Africa (Jadhav, 2012). Few studies have explored the function of institutions in South Africa's FDI-growth nexus. Meyer and Habanabakize (2018), for example, reviewed the significance of political instability in South Africa's FDI-growth nexus.

The above-mentioned studies' main flaw is that they did not sufficiently study the role of institutions in the FDI-growth nexus in SA. This makes this work particularly relevant since it contributes to understanding the interrelationships between FDI, institutions, and economic growth. This will help the country regardless of whether the institutions are well maintained in order to attract more FDI. The ARDL model, which has been widely used in similar studies, was used to fully examine the function of the governance system in the FDI-growth nexus. The study tackles the following questions: Does FDI stimulate economic growth? How do institutions influence the relationship between FDI and economic growth? To assist me in determining the answers, the study examines the effects of domestic investments, currency rates, population growth, and inflation on GDP growth rate.

Following Section 1, Section 2 reviews previous findings on the interconnectivity of FDI, institutions, and economic growth. Section 3 is based on the theoretical framework, methodology, and explanation of the data used. In Section 4 the empirical results of the study is presented while Section 5 concludes the paper.

2. LITERATURE REVIEW

Foreign Direct Investment (FDI) has been thoroughly studied and is generally regarded as a driver of economic growth in host countries. Numerous recent studies have focused on the factors influencing foreign direct investment (FDI) in host countries, as well as the relationship between FDI and economic growth, with insufficient attention paid to the role of interacting variables in the FDI-growth equation.

The relationship between FDI and growth is influenced by the host country's governance structure. According to Agbloyor *et al.* (2019), countries with more economic freedom and strong governance have better long-term growth outcomes. The research found that the favourable impact of FDI on economic growth is dependent on the strength of a country's institutions. Upreti (2015) finds a direct link between higher investment rates, longer life expectancy, and higher export volumes and GDP per capita growth in emerging countries. Jadhav (2012) discovers that, unlike institutional and political factors, economic characteristics such as trade openness and market size are positively connected with foreign direct investment (FDI). According to their findings, the BRICS countries (Brazil, Russia, India, and South Africa) are deemed exceptional in terms of rule of law, voice, and accountability.

Despite the augmented capital influx into African nations, including Nigeria, numerous African countries continue to exhibit poor per capita income and elevated unemployment rates; foreign direct investments are theoretically and empirically expected to address these issues. The Nigerian government has concentrated on policies aimed at attracting international investors; yet the economy continues to decline. Fasanya (2012) examines the influence of foreign direct investment on Nigeria's economic growth from 1970 to 2010, utilizing annual time series data within a neo-classical framework. The results indicate that foreign direct investments positively influence economic growth in Nigeria, as does domestic investment. The study recommends that to effectively Furthermore, Gani (2007) discovers that for Asian and Latin American countries, rule of law, corruption control, government effectiveness, regulatory quality, and political stability are all strongly associated with foreign direct investment inflows. Tax breaks, property protection rights, investment-friendly legislation, improvements to service support systems, and economic and political stability at the national

and regional levels, among other fiscal elements and regulations, all have a significant impact on FDI inflows Cleeve (2008).

An empirical study in Indonesia found a favourable relationship between foreign direct investment and total economic growth (Khaliq and Noy, 2007). In contrast, Yalta (2013) indicates that, at the aggregate level, foreign direct investment has no correlation with growth. The cross-country association between foreign direct investment (FDI) and economic growth is uncertain; nonetheless, research reveals a positive correlation between financial system development and FDI with economic growth. Nations with advanced markets, in particular, attract large FDI, which promotes economic growth (Alfaro *et al.*, 2004).

While foreign direct investment (FDI) has a significant impact on growth, other data show that economic expansion is not always driven by FDI. Two different studies were conducted in South Africa and Chile. These two studies found an equivocal association between FDI and economic growth, implying that economic growth drives FDI rather than the other way around (Chowdhury and Mavrotas, 2006; Asafo-Adjei, 2007). According to Ang (2009), economic improvement in Malaysia only increases foreign direct investment over time. Iamsiraroj (2016) found a bidirectional association between foreign direct investment (FDI) and economic growth. According to Iamsiraroj (2016) paper, foreign direct investment does not have a direct impact on growth and must be studied with other factors such as labour force levels, protectionist measures, and economic stability. In contrast, Mody (2004) investigated the influence of foreign direct investment (FDI) on the global economy and discovered that, while various forms of FDI have historically promoted economic integration, there is little evidence that FDI has accelerated income convergence across different regions of the world.

According to studies, the effects of foreign direct investment vary by sector. Foreign Direct Investment (FDI) in the secondary sector greatly boosts economic growth in host countries, but FDI inflows into non-manufacturing industries have little impact on growth (Ayanwale, 2007; Chakraborty and Nunnenkamp, 2008). Nair-Reichert and Nair-Reichert and Weinhold (2001) discovered that the link between FDI, domestic investment, and economic growth in emerging countries is highly variable. According to the research, the efficiency of foreign direct investment (FDI) in boosting future growth rates varies by country, with FDI having a stronger impact in open economies and growth being unconnected in closed countries. The evidence repeatedly shows that foreign direct investment (FDI) contributes greatly to economic growth, not just through FDI itself, but also through the use of interaction variables.

Following a detailed assessment of institutions, Driffield and Jones (2013) conclude that all sources of FDI have a positive and considerable impact on the economy. In contrast, Li and Liu (2005) and Baliamoune-Lutz (2004) show that foreign direct investment (FDI) has a direct or indirect impact on economic growth through its interaction characteristics. Nonetheless, research looking at the impact of FDI on economic growth found that FDI can improve political stability by effectively utilizing corporate resources (Baliamoune-Lutz, 2004). Obwona (2001) stressed macroeconomic stability, political consistency, and policy continuity over tax incentives in attracting foreign direct investment (FDI), which was found to be positively related to economic growth in Uganda. The association between foreign direct investment (FDI), institutions, and economic growth shows favourable and accelerated growth in many African nations at both the aggregate and individual levels (Adeleke, 2014).

Foreign Direct Investment (FDI) has been proved to have a favourable impact on both short- and long-term growth in emerging and developed economies (Freckleton *et al.*, 2012). Agbloyor *et al.* (2016) discovered that foreign direct investment (FDI), institutions, and

economic growth are not generally correlated in Sub-Saharan Africa (SSA) but are linked in a selection of countries with weak financial markets. In contrast, the study stressed that in countries with limited natural resources, foreign direct investment, institutions, and economic growth are all linked. Numerous studies have found that corruption and foreign direct investment are inextricably linked, whether directly or indirectly. Lower levels of corruption have a significant beneficial impact on FDI inflows, and vice versa (Asiedu, 2006; Bénassy-Quéré *et al.*, 2007). According to Cuervo-Cazurra (2006), high corruption attracts additional FDI inflows because investors from high-corruption nations are more likely to invest in countries with similar levels of corruption. Bénassy-Quéré *et al.* (2007) found that numerous institutions, including bureaucracy, information systems, banking, and legal frameworks, had an impact on incoming foreign direct investment, regardless of GDP per capita. According to Asiedu (2006), macroeconomic insecurity and political unrest all have a negative impact on FDI inflows into Africa.

Nations with strong democratic structures attract FDI, resulting in economic progress, as seen in Southern Africa (Malikane and Chitambara, 2017). Feng (1997) research found an indirect link between democracy and economic growth, mediated by constitutional changes among diverse political parties. Concurrently, the analysis discovered that growth has a limited relationship with regime transition but has a positive effect on the likelihood of the ruling party remaining in power, and that long-term economic growth enhances democracy. Schneider (2005) investigated the relationship between global commerce, patents, and FDI in order to determine the rate of technological innovation and growth among 47 mature and emerging economies from 1970 to 1990. According to the study, imported technology has a bigger impact on economic growth than native technology, while intellectual property rights (IPRs) have a greater impact on innovation rate, particularly in industrialized nations, whereas the implications of FDI remain unclear. Azman-Saini *et al.* (2010) demonstrated in a case study of 85 nations that FDI is not proportionate to output growth for its own sake, but rather its influence is dictated by the level of stability in the economy receiving FDI. Raza *et al.* (2019) discover that excellent governance leads to a positive association between FDI and economic growth, with regulatory quality and FDI having a two-way interaction with economic growth and the other interacting components having a one-way relationship, in OECD (Organization for Economic Cooperation and Development) countries from 1996 to 2013. Omri and Kahouli (2014) discovered a two-way interaction between FDI and economic growth, as well as domestic investment and growth, with FDI having a causal association with domestic investments.

A study by Nguyen *et al.* (2024) looks at how FDI affects small and medium-sized businesses' (SMEs) R&D spending in Vietnam. According to the report, SMEs' R&D efforts are impeded by FDI because of their limited market strength, technological gap, absorptive ability, and economies of scale. Institutions, however, attenuate this relationship. When local institutions reach a certain level of quality, they might encourage SMEs' R&D activities. The moderating effect of FDI from nations with poorer institutional quality is less pronounced. For scholars and policymakers examining FDI and R&D investment by domestic SMEs, institutions are essential. Bothner (2024) explores the relationship between institutional quality and FDI flows in developing countries. The study found that weak institutions attract FDI due to rent-seeking behaviour, but also increase uncertainty, discouraging investments with large initial costs. The study found that institutional quality positively affects FDI inflows only for countries with high natural resource endowment, contradicting previous research.

This suggests that higher endowment increases institutional quality's importance as a determinant of FDI.

Islam and Beloucif (2024) use a systematic literature review to assess 112 empirical investigations from 2000-2018 on factors influencing foreign direct investment in host nations. Results show market size is the most reliable factor, followed by trade openness, infrastructure quality, labour cost, macroeconomic stability, human capital, and growth potential. Using Principal Component Analysis (PCA), Lee *et al.* (2024) examine the factors that influence FDI inflows into 178 different nations. They discover that social factors have a greater impact on FDI inflows in mature economies, whereas emerging countries mostly rely on economic indicators. Nonetheless, there is very little correlation between FDI inflows and institutional features.

The relationship between democracy, corruption, economic growth, ICT, and carbon emissions in sub-Saharan Africa (SSA) is examined in Ganda (2024). The study, which uses data from 37 countries, concludes that democracy and carbon emissions are negatively correlated. Nonetheless, there is a positive relationship between FDI, ICT, economic growth, and environmental quality. The study recommends a targeted approach to boost FDI in order to fight corruption, promote democracy, ICT, and economic expansion for a green economy. Ali *et al.* (2025) examines the impact of FDI, GDP, income inequality, and CO2 emissions on renewable energy consumption in Asia from 1995 to 2020. It reveals that rising GDP and FDI support renewable energy consumption, while income inequality and CO2 emissions have context-sensitive effects. The findings provide valuable insights for Asian sustainable energy transition.

In the member nations of the Association of Southeast Asian Nations, Nam *et al.* (2023) look into how FDI affects technical advancement. The crucial responsibilities that governmental and financial institutions play as intermediaries in the relationship between foreign direct investment and technological advancement are highlighted by our investigation. The rule of law, one of the sub-indicators of the Worldwide Governance Indicators, has a strong mediating effect in this relationship, according to our empirical findings based on the 25-year panel dataset from 1996 to 2020. Even if they act as a mediator, FDI has a suppression effect, which means that it has a detrimental impact on financial institutions while having a beneficial impact on technological advancement. Governments should support the efficient operation of the rule of law and devise plans to remove financial barriers that could impede FDI in order to optimize its spillover effects. Sinha *et al.* (2024) investigates the effects of political regimes and institutional quality on US FDI outflows. It investigates property rights protection as a measure of institutional quality in 41 countries from 1984 to 2021. The findings demonstrate that protecting property rights can attract US foreign direct investment if countries become more democratic. The report concludes that incomplete reform or unconsolidated democratization are insufficient to attract US FDI. Stronger property rights protection and higher-quality infrastructure can make democratic countries more appealing to US investors.

Based on the reviewed literature, the report concludes that macroeconomic climate, trade openness, financial system development, economic freedom, natural resource richness, political stability, infrastructure, human capital, regulatory quality, and corruption have the greatest impact on the FDI-growth nexus. Despite substantial research on the relationship between FDI, institutions, and economic growth around the world, empirical studies in South Africa are scarce. Prior study has shown that institutions play a key role in FDI since they correspond with growth. This paper investigates whether or not this has occurred in South Africa.

3. THEORETICAL MODEL AND METHODOLOGY

3.1 Theoretical Framework

The Solow model best describes the FDI-growth nexus. The model implies that the introduction of technology enables labour and capital to rise through time, resulting in sustained growth (Solow, 1956), and it follows a production function which is expressed as:

$$Y(t) = F(K(t), A(t)L(t) \quad (1)$$

where total output (Y), capital (K), effectiveness of labour (A) and labour (L). Due to the equivalence of input payments and total output, this production function is reliant on the premise that returns remain constant across time as follows:

$$y = f(k) \quad (2)$$

This production function meets the following condition:

$$f(0) = 0, f'(0) = \infty, f'(\infty) = 0, f(k) > 0, f'' < 0 \quad (3)$$

The function then takes the Cobb-Douglas form:

$$F(K, AL) = K^{\beta}(AL)^{1-\beta}\ , \qquad 0 < \beta < 1 \quad (4)$$

Such that, $k = \frac{K}{AL}$ is the capital labour ratio which changes through time, and given as; $= k^{\beta}$.

According to Romer (2012), the difference between the amount of savings per unit of effective labour and break even investment influences the speed of change in the capital labor ratio. This is expressed as:

$$\dot{k}(t) = sf\big(k(t)\big) - (n + g + \delta)k(t) \quad (5)$$

A rise in s causes an upward shift in actual investment,$sf(k)$ resulting in an increase in $k*$. This will result in a continuous increase in k until it reaches a point where it equals to $k*$. A constant increase in s causes a brief increase in k. This means that over time, k increases until it reaches a point where the extra s is only used to contain the constant k. Conversely, an increase in s causes a rise in output per worker growth rate, until g no longer rises (Romer, 2012).

Ultimately, changes in s have level impacts on production per worker rather than growth effects. Capital per unit of effective labor is calculated as follows:

$$k = sf(k) - (n + g + \delta)k \quad (6)$$

Applying an intensive form of the Cobb-Douglas function –f (k)=k^{β}, results in:

$$k = sk^{\beta} - (n + g + \delta)k \quad (7)$$

As a result, the balanced growth path (k) is zero, indicating a balance between actual and break-even investments per unit of effective labour. As shown in the following expression, the balanced-growth path is indicated by$k*$.

$$sk^{\beta} = (n + g + \delta)k* \tag{8}$$

Equation (8) is rearranged to solve for $k*$, and yields:

$$k* = \left(\frac{s}{n + g + \delta}\right)^{\frac{1}{1-\beta}} \tag{9}$$

The intensive form of the production function is then applied, that is $y=k^{\beta}$, so as to obtain the balanced-growth path value of output per worker as follows:

$$y* = \left(\frac{s}{n + g + d}\right)^{\frac{\beta}{1-\beta}} \tag{10}$$

Considering the preceding equation is linear in logarithms, which are taken and differentiated with respect to time, with little letters denoting individual variable growth rates.

3.2 Methodology and Data

3.2.1 Model Specification

In developing the empirical model for this work, the purpose of this study is kept in mind, which is to thoroughly examine the connection between FDI and growth in the presence of interacting variables. Borensztein *et al.* (1998) discovered that FDI has a beneficial impact on economic growth because of the technology gains brought into host nations. According to Solow (1956), an increase in investment means an increase in total output (Y), ending in a country's growth speeding up towards a stable equilibrium. In absence of technological change, economic growth is attained through population growth and per capita incomes will remain constant in the long run (Solow, 1956). Firstly, considering that FDI brings technology to host countries, and the model to be estimated is modified to account for the effect of technological advancement through FDI while including population growth, domestic investments, CPI, and exchange rates because they have an effect on output in some way. Following the Solow Baseline model, the equation to be estimated is as follows:

$$LogGDP_t = \beta_0 + \beta_1 Log\frac{FDI_t}{GDP_t} + \beta_2 Log\frac{DI_t}{GDP_t} + \beta_3\, LogCPI_t + \beta_4 LogEXR_t + \beta_5 LogPOP_t + \varepsilon_t \tag{11}$$

Institutions, according to several studies, have a critical influence in the FDI-growth nexus. Equation (11) is then adjusted to account for the role of institutions in the FDI-growth nexus:

$$\begin{aligned} LogGDP_t = \beta_0 + \beta_1 Log\frac{FDI_t}{GDP_t} + \beta_2 Log\frac{DI_t}{GDP_t} + \beta_3 LogCPI_t + \beta_4 LogEXR_t + \beta_5 LogPOP_t \\ + \beta_6 Log\left(\frac{FDI_t}{GDP_t} * INST\right) + \varepsilon_t \end{aligned} \tag{12}$$

where GDP = GDP Growth rate, DI = Domestic Investments, CPI = Consumer Price Index, EXR = Real Exchange Rate, POP = Population Growth Rate and INST = Institutional Variables which are Control of Corruption (CC), Rule of Law (RL), Regulatory Quality (RQ), Government Effectiveness (GE), Voice & Accountability (VA) and Political Stability (PS).

3.2.2 Methodology

The study is undertaken using the ARDL model to estimate the prolonged dynamic relationships. The chosen model is more suitable when dealing with small samples (Pesaran *et al.*, 2001). The model was chosen as it facilitates the inclusion of variables with different orders of integration that is *I*(0) and *I*(1) variables can be included in the same model, and simultaneously allows variables with varying lag lengths to be introduced to the same model (Pesaran *et al.*, 2001). It also captures both short and long term variations (Pesaran *et al.*, 1999), making it a better fit for this research project. According to Pesaran *et al.* (2001), the ARDL model to be estimated is as follows:

$$\begin{aligned}\Delta LGDP_t = \varphi_0 + \sum_{i=1}^{d} \alpha_i \Delta\, LGDP_{t-i} + \sum_{i=1}^{e} \beta_i \Delta LFDI_{t-i} + \sum_{i=1}^{g} \gamma_i\, \Delta LDI_{t-i} + \sum_{i=1}^{k} \delta_i \Delta LCPI_{t-i} + \\ \sum_{i=1}^{m} \theta_i \Delta LEXR_{t-i} + \sum_{i=1}^{p} \sigma_i\, \Delta LPOP_{t-i} + \sum_{i=1}^{v} \vartheta_i \Delta LFDI * INST_{t-i} + \varphi_1 LGDP_{t-1} + \varphi_2 LFDI_{t-1} + \\ \varphi_3 LDI_{t-1} + \varphi_4 LCPI_{t-1} + \varphi_5 LEXR_{t-1} + \varphi_6 LPOP_{t-1} + \varphi_7 LFDI * INST_{t-1} + \varepsilon_t\end{aligned} \quad (13)$$

where φ_0 denotes the constant; $\alpha_i, \beta_i, \gamma_i, \delta_i, \theta_i, \sigma_i$ and ϑ_i signifies short run dynamics; whilst $\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6$ and φ_7 symbolizes the long run coefficients*; d, e, g, k, m, p* and *v* represent the model's lag length and ε_t reflects the disturbance error term.

In light of equation (13), the hypothesis to be tested is as follows:

H0: $\boldsymbol{\varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_6 = \varphi_7 = 0}$ **:** *Cointegration does not exist in the long run.*

H1: $\boldsymbol{\varphi^1 \neq \varphi^2 \neq \varphi^3 \neq \varphi^4 \neq \varphi^5 \neq \varphi^6 \neq \varphi^7 \neq 0}$: *Cointegration does not exist in the long run.*

Along with Pesaran *et al.* (2001), the ARDL model relies on the F-statistic when determining the long run association amongst the variables. Prior to performing the bound test, the lag structure is established using Akaike Information Criterion (AIC) or Schwarz Information Criterion (SIC) until serial correlation is no longer present. Suppose the determined F-stat is smaller than the lower constraint *I*(0), cointergration does not exist and the null (H_0) is acknowledged. Suppose the F-stat is higher above the upper bound *I*(1), cointergration prevails in the long run, and the null hypothesis (H_0) is rejected in such a case. If the obtained F-stat sits between *I*(0) and *I*(1), the results are deemed vague.

After proving the scope of cointergration, the error correction model (ECM) is derived to predict the long run connection. The ECM is necessary because it is utilized to detect any short-run changes from equilibrium Gujarati and Porter (2009). The ECM is as follows:

$$\begin{aligned}\Delta LGDP_t = \varphi_0 + \sum_{i=1}^{d} \alpha_i \Delta\, LGDP_{t-i} + \sum_{i=1}^{e} \beta_i \Delta LFDI_{t-i} + \sum_{i=1}^{g} \gamma_i\, \Delta LDI_{t-i} + \sum_{i=1}^{k} \delta_i \Delta LCPI_{t-i} + \\ \sum_{i=1}^{m} \theta_i \Delta LEXR_{t-i} + \sum_{i=1}^{p} \sigma_i\, \Delta LPOP_{t-i} + \sum_{i=1}^{v} \vartheta_i \Delta LFDI * INST_{t-i} + \lambda ECT_{t-1} + \omega_t\end{aligned} \quad (14)$$

while ECT_{t-1} signifies error correction term and λ gauges the speed of adjustment.

The coefficient of the ECT quantifies the rate of adjustment towards the equilibrium relationship. The rate of adjustment is projected to be negative and be between 0 and 1 (Gujarati and Porter, 2009).

3.3 Data Description and Sources

This paper examines the relationship between FDI and economic growth, and simultaneously assessing the role of institutions using quarterly time series data. The study concentrates at the period from 1996Q1 to 2019Q4, which incorporates the post-apartheid era, the Great Depression of 2008-2009, and the new Fourth Industrial Revolution era. The statistics for the institutional variables were derived from the World Governance Indicators. The World Bank Database is used to acquire statistics on FDI, Exchange Rates and Population Growth. The data for GDP growth rate, Direct Investments and Consumer Price Index is sourced from the OECD Database. Main variables are GDP growth rate (dependent variable), FDI (expressed as a proportion of GDP) and Institutional variables which are Control of Corruption, Rule of Law, Regulatory Quality, Government Effectiveness, Voice & Accountability and Political Stability. Control variables included in this model are Domestic Investments which is expressed as a proportion of GDP, CPI is logged to derive the inflation rate, Exchange rate is expressed as the nominal value of the South African Rand versus other foreign currencies and Population Growth is expressed as the growth rate of the total population.

4. RESULTS AND DISCUSSION

4.1 Preliminary Analysis

To begin with descriptive data, Table no. 1 shows that the average values are rather small, fluctuating between -0.1% and 4.5%, with the exception of domestic investments. The standard deviations for each of the variables in this paper are shown, with domestic investments and FDI being the most volatile among them. Apart from GDP growth rate and rule of law, the majority of the variables are skewed to the right. In most cases, the series appears to be skewed around zero, raising the possibility of normality. The Jarque-Bera statistics provide accurate findings for normality, and based on the reported findings, some series are distributed normally while others are not.

Prior cointegration analysis and unit root tests must be conducted. To verify for the quality of time series data, the unit root test is first performed using the graphical methods. According to Figure no. 1 graphical representation, CPI, domestic investments and exchange rates are trending upwards, while population growth is heading downwards, and this implies that the variables are non-stationary. FDI and GDP growth rate appear to have steady mean averages across time, while GDP growth rate appears to have no obvious trend as they change with time. The mean and variance of the majority of the variables appear to be time-varying, implying that these series in level form are non-stationary. Certain variables, such as GDP growth rate and FDI appear to be associated with shocks, suggesting the likelihood of structural breaks occurring around the Emerging Market Crisis of 1997-1998 and the Great Depression of 2008-2009. Firstly, the Augmented Dickey-Fuller is used, but since structural breaks are projected, the Phillips-Perron test is used thereafter.

Table no. 1 – Summary Statistics

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	Jarque-Bera	Obs
GDPGR	0.6357	0.6292	-1.5555	1.8730	-0.5880	3.5757	6.8576	96
FDI_GDP	1.5035	1.3038	-0.0281	6.3305	1.7408	6.6318	101.2441	96
DI_GDP	18.4370	2.0799	-15.0836	23.7173	0.3658	2.7426	2.4057	96
CPI	4.2107	0.3653	3.5444	4.8159	0.0081	1.8394	5.3886	96
EXR	2.1063	0.3442	1.3432	2.7487	0.1278	2.2483	2.5215	96
POPGR	1.4412	0.1748	1.2160	1.9950	0.9163	3.7037	15.4155	96
RQ	0.4342	0.1755	0.1209	0.8088	0.2547	2.3853	2.5491	96
VA	0.6738	0.0860	0.5675	0.8567	0.8413	2.6413	11.8393	96
PS	-0.1744	0.1743	-0.5520	0.2306	0.0492	2.9252	0.0611	96
RL	0.1200	0.0914	-0.1050	0.2773	-0.8124	3.6723	12.3681	96
GE	0.5298	0.1922	0.2859	1.0875	0.6843	2.8444	7.5883	96
CC	0.2842	0.2749	-0.1372	0.7413	0.1975	1.6468	7.9495	96

Note: GDPGR signifies GDP growth rate, POPGR signifies Population Growth Rate, FDI_GDP signifies FDI as a percentage of GDP while DI_GDP signifies Domestic Investment as a percentage of GDP.

Sources: authors own compilation

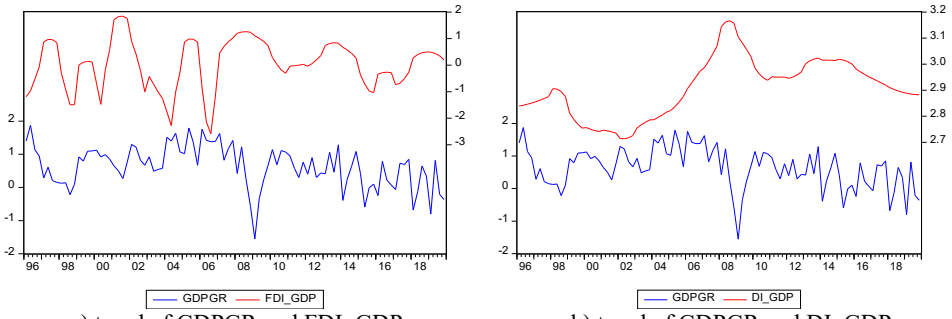
Table no. 2 – Unit Root Tests Results

	AUGMENTED DICKEY-FULLER			PHILLIPS-PERRON		
Variable	**Level form**	**1st diff**	***I*(d)**	**Level form**	**1st diff**	***I*(d)**
GDPGR	-5.2060 [a]*	-	*I*(0)	-5.0682[a]*	-	*I*(0)
FDI_GDP	-5.6383[a]*	-	*I*(0)	-3.2197[a]**	-	*I*(0)
DI_GDP	-1.9898[a]	-2.8054[a]***	*I*(1)	-1.5461[a]	-4.1607[a]*	*I*(1)
CPI	-3.1757[b]***	-	*I*(0)	9.3228[c]*	-	*I*(0)
EXR	-1.5453[a]	-8.1171[a]*	*I*(1)	-1.6329[a]	-8.1133[a]*	*I*(1)
POPGR	-0.2498[c]	-2.1886[c]**	*I*(1)	-3.3162[a]**	-	*I*(0)
RQ	-3.5832[b]**	-	*I*(0)	-0.9635[a]	-5.0949[a]*	*I*(1)
VA	-2.4204[a]	-2.9636[a]**	*I*(1)	-1.9275[a]	-4.9443[a]*	*I*(1)
PS	-2.0697[c]**	-	*I*(0)	-1.7392[a]	-5.0115[a]*	*I*(1)
RL	-1.6295[c]***	-	*I*(0)	-1.5669[a]	-5.3889[a]*	*I*(1)
GE	-3.2856[b]***	-	*I*(0)	-3.1576[a]**	-	*I*(0)
CC	-1.7687[c]***	-	*I*(0)	-1.9778**	-	*I*(0)

Note: The Null Hypothesis shows that the series is non-stationary. [a] indicates a model with constant but no time trend, [b] indicates a model with a constant and a time trend while [c] indicates a model without a constant and a time trend, while the exogenous lags are determined using the Schwarz Information Criterion (SIC). * signifies that a variable is stationary at 1%, whilst ** signifies that a variable is stationary at 5% and *** signifies that a variable is stationary at 10%.

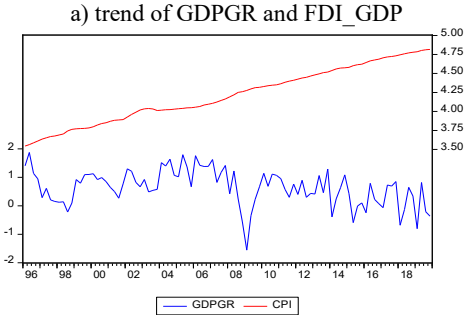
Sources: authors own compilation

Table no. 2 displays the unit root results for the Augmented Dickey Fuller and the Phillips Perron models respectively. There is evidently a combination series that are stationary at different orders of integration. Some test statistics were insignificant under the premises of constant without a time trend, constant with a time trend, and a model lacking a constant and a time trend; therefore, the presented ones generated better results. In some scenarios, stationarity is depicted in level form, implying that the series are integrated of order zero. Although in some series, unit roots existed on level form and onto differencing the series once, stationarity occurred, therefore these variables are integrated of order one.

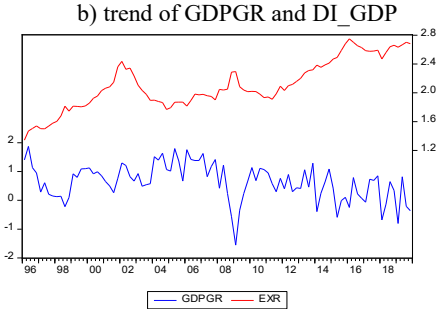


a) trend of GDPGR and FDI_GDP

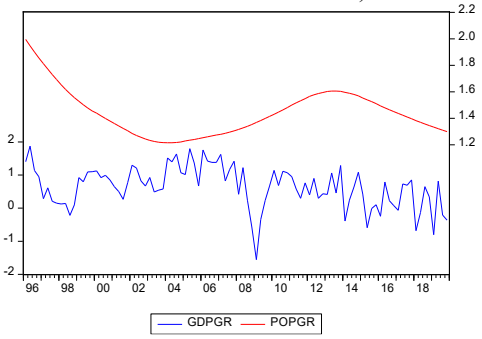
b) trend of GDPGR and DI_GDP



c) trend of GDPGR and CPI



d) trend of GDPGR and EXR



e) trend of GDPGR and POPGR

Figure no. 1 – Time-varying optimal hedge ratio (Single Graph)

4.2 Discussion of findings

The cointegration results confirmed the existence of a long run relationship between the series in all models, as evidenced from the computed F-stat, which was found to be greater than all the bound critical values at 1% level of significance. The economic logic underlying the linkage between investments and economic growth implies that FDI and domestic investments promote economic growth. Foreign investors' technological spillovers enhance productivity in host countries. Remarkably, from the reported results in Table no. 3, this opposes the case for South Africa. It is clear that FDI was found to be both negative and positive in some models, but it was insignificant in others both in the temporary and prolonged periods. Models 1 and 6 show a significant negative relationship between FDI and GDP

growth rate in the long run, which is supported by (Gui-Diby, 2014; Mazenda, 2014). One possible explanation for this negative association is the Great Depression of 2008, which caused FDI to suffer due to uncertainties brought about by the crisis, leading many foreign investors to refrain from investing abroad. The repercussions of this crisis are still being felt today, thereby resulting in economic decline. On the other hand, Model 7 discovered a short-run linkage between FDI and growth.

Institutions were found to be unimportant in the long run meaning there is no prolonged relationship and likewise Agbloyor *et al.* (2016) drew similar results for a case in Sub-Saharan Africa (SSA). Nevertheless, regulatory quality (RQ) and political stability (PS) have a positive association with economic growth temporarily (see, Model 2). Government effectiveness (GE), rule of law (RL), and voice and accountability (VA) all had a negative but minor relationship with growth.

Table no. 3 – Estimation results

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Long Run Results								
Constant	25.284	-1.598	66.565	25.734	49.443	28.796	25.766	24.348
	(2.964)*	(0.159)*	(7.319)*	(3.015)*	(5.414)*	(9.194)*	(3.017)*	(2.842)*
Trend	0.072	-	0.214	0.073	0.1556	0.088	0.074	0.071
	(0.009)*		(0.024)*	(0.009)*	(0.017)*	(0.032)	(0.009)*	(0.009)*
FDI_GDP	-0.101	-0.036	0.074	-0.024	0.072	-0.173	0.084	-0.218
	(0.048)**	(0.051)	(0.121)	(0.326)	(0.082)	(0.103)*	(0.605)	(0.212)
DI_GDP	-0.136	-0.055	-0.186	-0.143	-0.193	-0.141	-0.147	-0.130
	(0.043)*	(0.052)	(0.050)*	(0.052)*	(0.052)*	(0.047)*	(0.056)**	(0.045)*
CPI	-7.301	0.834	-21.161	-7.418	-15.198	-8.899	-7.373	-6.930
	(2.902)**	(0.844)	(4.951)*	(2.959)**	(4.137)*	(2.961)*	(2.922)**	(2.968)**
EXR	0.337	-0.133	2.302	0.333	1.853	0.439	0.268	0.213
	(0.567)	(0.403)	(0.945)**	(0.571)	(0.897)**	(0.610)	(0.613)	(0.607)
POPGR	0.103	0.468	1.5776	0.123	1.739	0.385	0.130	0.086
	(0.657)	(0.923)	(0.9299)***	(0.666)	(0.917)***	(0.730)	(0.665)	(0.656)
RQ	-	0.664	-	-	-	-	-	-
		(0.908)						
VA	-	-3.146	-	-	-	-	-	-
		(3.049)						
RL	-	0.957	-	-	-	-	-	-
		(1.440)						
PS	-	0.490	-	-	-	-	-	-
		(0.974)						
GE	-	2.007	-	-	-	-	-	-
		(1.628)						
CC	-	0.307	-	-	-	-	-	-
		(0.806)						
FDI_GDP*RQ	-	-	-	-	-	-	-	0.228
								(0.404)
FDI_GDP*VA	-	-	-	-	-	-	-0.268	-
							(0.872)	
FDI_GDP*RL	-	-	-	-	-	0.523		-
						(0.664)		
FDI_GDP*PS	-	-	-	-	0.736	-	-	-
					(0.322)**			
FDI_GDP*GE	-	-	-	-0.116	-	-	-	-
				(0.454)				
FDI_GDP*CC	-	-	-0.367		-	-	--	-
			(0.256)					

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Short Run Results								
Constant	25.284	-1.598	66.565	25.734	49.443	28.796	25.766	24.348
	(9.141)*	(4.369)	(15.369)*	(9.384)*	(12.701)*	(9.194)*	(9.325)*	(9.329)**
Trend	0.072	-	0.214	0.073	0.156	0.088	0.074	0.071
	(0.032)**		(0.053)*	(0.032)**	(0.044)*	(0.032)*	(0.033)*	(0.032)**
ΔFDI_GDP	-0.087	-0.035	0.066	-0.021	0.065	-0.145	0.073	-0.189
	(0.042)**	(0.050)	(0.108)	(0.281)	(0.076)	(0.086)***	(0.522)***	(0.186)
ΔDI_GDP	0.149	0.385	-0.165	0.143	-0.177	0.166	0.136	0.132
	(0.158)	(0.208)***	(0.047)*	(0.161)	(0.051)*	(0.162)	(0.164)	(0.162)
ΔCPI	-6.291	0.810	-16.790	-6.392	-13.906	-7.430	-6.365	-6.015
	(2.637)**	(0.815)	(8.096)**	(2.685)	(3.954)*	(2.636)*	(2.662)**	(2.693)**
ΔEXR	0.291	-0.130	0.214	0.287	0.040	0.366	0.231	0.185
	(0.491)	(0.392)	(0.832)	(0.494)	(0.822)	(0.513)	(0.531)	(0.528)
ΔPOPGR	-24.069	0.455	-25.320	-23.771	-31.744	15.051	-25.096	-25.280
	(29.912)	(0.901)	(29.910)	(30.109)	(29.635)	(7.293)**	(30.262)	(30.113)
ΔRQ	-	6.338	-	-	-	-	-	-
		(2.872)**						
ΔVA	-	-3.056	-	-	-	-	-	-
		(2.929)						
ΔRL	-	-7.261	-	-	-	-	-	-
		(2.635)*						
ΔPS	-	9.404	-	-	-	-	-	-
		(2.138)*						
ΔGE	-	-4.213	-	-	-	-	-	-
		(2.486)***						
ΔCC	-	0.298	-	-	-	-	-	-
		(0.786)						
ΔFDI_GDP*RQ	-	-	-	-	-	-	-	0.198
								(0.352)
ΔFDI_GDP*VA	-	-	-	-	-	-	-0.231	
							(0.753)	
ΔFDI_GDP*RL	-	-	-	-	-	0.436	-	-
						(0.550)		
ΔFDI_GDP*PS	-	-	-	-	0.674	-	-	-
					(0.310)**			
ΔFDI_GDP*GE	-	-	-	-0.100	-	-	-	-
				(0.417)				
ΔFDI_GDP*CC	-	-	-0.326	-	-	-	-	-
			(0.227)					
ECT_{t-1}	-0.862	-0.971	-0.890	-0.862	-0.915	-0.835	-0.863	-0.868
	(0.101)*	(0.095)*	(0.098)*	(0.101)*	(0.100)*	(0.102)*	(0.101)*	(0.102)*
F-Stat	15.142*	13.932*	8.682*	15.165*	10.781*	17.520*	15.180*	15.268*
Bound F-Stat	11.407*	7.479*	10.911*	9.674*	11.031*	8.998*	9.684*	9.742*
Adj. R^2	0.432	0.561	0.458	0.432	0.462	0.413	0.433	0.434
JB Stat	0.805	0.973	1.568	1..028	0.874	0.089	1.045	0.507
	[0.669]	[0.615]	[0.457]	[0.598]	[0.646]	[0.956]	[0.593]	[0.776]
LM Test	0.722	3.466	3.996	0.758	5.476	1.916	0.748	0.733
	[0.697]	[0.177]	[0.136]	[0.685]	[0.065]	[0.384]	[0.688]	[0.693]
ARCH	0.153	1.817	0.250	0.164	0.072	0.022	0.150	0.087
	[0.696]	[0.178]	[0.617]	[0.685]	[0.788]	[0.883]	[0.698]	[0.769]
Ramsey Reset	0.266	1.981	1.811	0.235	0.898	0.501	18.050	0.593
	[0.608]	[0.164]	[0.183]	[0.630]	[0.346]	[0.481]	[0.220]	[0.444]
Lag Selection (AIC)	(1,0,1,0,0,2)	(1,0,1,0,0,0, 4,0,1,1,1,0)	(1,0,0,0,2,4,2)	(1,0,0,1,0,0,2)	(1,0,0,0,0,4,2)	(1,0,0,1,0,0,1)	(1,0,0,1,0,0,2)	(1,0,0,1,0,0,2)
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable
CUS. SQR	Stable	Stable	Stable	Stable	Stable	Stable	Stable	Stable

Note: Standard errors are reported in parenthesis, while the probability values are presented in square brackets. *, ** and ***signifies significance at 1%, 5% and 10% respectively.

Sources: authors own compilation

Based on the interaction regression results, except for the interaction between FDI and political stability, the rest of the interactive terms were insignificant in the long run towards economic growth. This implies that FDI in the presence of political stability leads to prolonged and temporary economic growth (see, Model 5) which is similar to the results drawn by Agbloyor *et al.* (2016) on a full sample in SSA. One potential motive for this relationship is that South Africa is moderately stable in terms of democracy, as demonstrated in its ranking for this specific category of the World Bank's governance indicators, which is in the 40th percentile (World Bank Group, 2020). As a result, the study do not find compelling proof that FDI alongside institutions result in economic growth.

The study considered some of the elements that influence economic growth. Domestic investments have been found to be negatively related with GDP growth in both the long run (see all Models, except Model 2) and short run (see, Model 3 and 5) as confirmed by (Bakari, 2018) for an Algerian case study. This could be due to lack of proper management of local investments and weak growth strategy in South Africa. However, in the short run a positive association was observed (see, Model 2), which causes economic growth. Solow's theoretical reasoning that increased population growth leads to sustained growth, has been confirmed for South Africa in the long run (see, Model 3 and 5) and short run (see, Model 6) scenarios where POPGR was found to be significantly positive towards growth. Because FDI is related to economic growth in a negative manner, this proves that in the absence of technology, population expansion results in long-term growth, as proposed by Solow (1956).

According to the findings, when interactive terms are considered, the exchange rate and economic growth have a long-term significant association (see, Model 3 and 5). A unit increase in the exchange rate entails depreciation which may drag economic growth because depreciation reduces exports hence foreign currency profits will also decrease. However, in the short run, exchange rates were found to be insignificant. Economic growth results from a lower inflationary environment. In the case of South Africa, CPI has a negative link with economic growth in the prolonged period or temporarily, which contradicts the predicted results due to the Inflation Target Policy, which tries to keep rates between 3% and 6%. When the ECT is statistically significant, negative, and less than one, the model is well specified. According to the above-mentioned results, there is a high rate of adjustment. This means that every quarter, between 83% and 97 % of short-run and long-run discrepancies will be altered.

4.3 Diagnostic Tests

A series of diagnostic tests was undertaken to justify the fitness of the models adopted in all situations, with and without the interaction term. The results shown in Table no. 3 exhibits that the series are distributed normally and that the model is accurately stated. The results demonstrate the absence of autocorrelation as well as heteroscedasticity.

5. CONCLUSION

Using quarterly data, this paper investigates the impact of FDI on economic growth, taking into account the role of institutions in the FDI-growth nexus in South Africa. The ARDL Bound test is designed to identify both long-term and transient relationships between the variables under study. For the period under consideration, the analysis indicated that FDI and economic growth in South Africa have a negative long-run connection. As a result, there

is no meaningful long-term relationship between institutions and economic growth. When interaction variables were considered, a favorable short-term relationship between FDI and growth was established. The analysis incorporated interaction terms, and except for the interaction between FDI and political stability, the other institutional factors were shown to be insignificant in terms of growth. This means that there is no strong relationship between FDI, institutions, and economic growth.

The analysis shows that the government's investment policies have had little or no impact on attracting FDI into the country, and so the results do not follow Solow's economic theory of long-run linkage. Nonetheless, FDI has a beneficial short-term impact on economic growth, according to the same theory. Among other institutional variables, there was a temporary positive relationship between regulatory quality and political stability in terms of economic growth. The findings of this study should also serve as a starting point for policymakers in determining which areas should be targeted when encouraging FDI to South Africa in order to enhance growth. Desirable tax breaks promote international investment, which helps to boost GDP. Reduced xenophobic rallies against foreign nationals may encourage more foreign direct investment into the republic.

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The Causal Relationship between Banking, Capital Markets and Economic Growth in the European Union

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Abstract: The current paper investigates the causal relationship between financial development and economic growth in 27 European Union (EU) countries. Granger causality tests are applied, using the cointegration and Vector Error-Correction (VEC) methodology. Through the empirical analysis, we found evidence of the presence of Granger causality between finance and growth, sometimes even bi-directional causality, but the nature of the relationship is far from uniform across EU countries. Therefore, an one-size-fits-all approach of policymakers may not be effective for the financial sector to drive economic growth. The results suggest that there are different interactions between the financial sector and economic expansion, based on country specifics, as the causality is sustained by the banking sub-sector in some cases, especially in the case of countries that were part of the former communist bloc, and it is driven by the capital market in other cases. There are also cases in which both financial sectors Granger cause economic growth mostly in the countries that succeeded to better diversify their sources of funding. These findings highlight the presence of financial structural differences among EU countries, and, at the same time, the importance of tailored policies to support further economic expansion.

Keywords: economic growth; financial development; time-series; Granger causality.

JEL classification: F43; E44; G15; G21.

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1. INTRODUCTION

The worldwide economic challenges require customized responses from the national economies to promote sustainable growth, aligned to their specific needs. While the European Union is focusing on a deeper integration at various dimensions among its 27 member countries, some structural differences remain a threat to the process of promoting sustainable growth. Even more, when thinking about economic and financial integration, the structural differences between Eastern and Western economies might make uniform regulations difficult to implement. The present paper investigates in which way different financial structures are in a causality relationship with economic growth and provides updated empirical evidence useful for policy decisions, by employing a comparative analysis of all 27 European Union countries.

According to Statista (2023), from a total of 5,640 monetary financial institutions available in European Union countries in 2023, the credit institutions (banks), represented the majority (87.8%). Therefore, the European financial system is still dominated by banks in terms of financial institutions. Even so, the current paper searches for Granger causality not only between banking proxies and economic growth but also between capital market proxies and economic growth. These two could play a complementary role in financing the economy. While it is commonly thought that bank loans are essential for an economy, is there actually a Granger causal relationship between the banking sector and economic growth in the European Union countries? What about the capital market? If yes, which would be the significant financial measures that might sustain the presence of causality?

The academic and non-academic understanding of the relationship between finance and economic growth suffered some changes over time. The conclusions and empirical results are inconsistent across nations and regions, time spans, periods of crisis, and vary significantly across methodologies and interpretations (Pagano, 1993). The literature reveals a variety of opinions on key aspects of the nexus, including direction, significance, and the mechanisms and channels of causality. While there is plenty of evidence of a uni-directional causality from finance to growth in the specialized literature, for some economies there is also evidence of bi-directional causality or even cases of missing causality. In this study, we focus on testing the causality between finance and growth in European Union countries, and the interpretation is based on the empirical results of Vector-Error Correction (VEC) and cointegration methodology, with Granger causality tests. The analysis at the individual country level allows us to differentiate 3 categories of national economies: 11 countries, the ones with significant banking proxies that Granger cause growth, other 10 countries with capital market proxies that are in causal relationship with growth, and, the third category, 6 national economies with both banking and stock market being statistically significant in Granger causing economic growth.

Thus, we provide evidence that a higher level of productivity and economic growth can be achieved through promoted access and availability of financial markets and institutions in European Union countries. When these are in proper functioning, they could reduce economic volatility, absorb shocks, and promote economic resilience. We support the early well-known state, that efficient resource allocation and innovation are crucial in the process of creating opportunities, not only for individuals in fostering savings, and investments but also for the governments – Schumpeter (1911), apud Eliott (2017).

The current paper consists of the following sections: Section 2 presents the literature review, Section 3 describes the methodology, and Section 4 shows the results by

comprehending three subsections. These illustrate the findings while distinguishing three different categories of countries. The conclusions can be found in Section 5.

2. LITERATURE REVIEW

The relationship between finance and growth started to present interest since decades ago. By introducing the concept of „creative destruction" – Schumpeter (1911), apud Eliott (2017). is acknowledged as an important early contributor to this research area, drawing attention to the power of entrepreneurship and innovation, and the role of banking institutions in the efficient allocation of funds. In this way, the private sector could contribute significantly to the process of growth. Thus, a first theoretical view regarding the financial-growth nexus was born, the so-called „Supply-Leading Hypothesis", under which the development of the financial sector drives economic growth. Many other early contributors to the field agreed with this (Goldsmith, 1969; King and Levine, 1993a, 1993b; King and Levine, 1993c). Goldsmith (1969), supported the statement that financial development is essential for fostering economic growth and that an underdeveloped financial system could restrict it. In his empirical analysis, he tested cross-country regressions and time-series analysis on 35 countries, from which 19 developed and 16 less developed, with both market-based financial systems and banking-based financial systems. However, the findings indicated that the country's financial structure is not a statistically significant coefficient in fostering economic growth. It is relevant to say that the '90 years were dominated by intense theoretical frameworks in the specialized literature. The contributions of King and Levine (1993a, 1993b) aligned with this trend. The significance of innovative financial technologies that could decrease the problem of information asymmetry was emphasized by the authors. The informational asymmetry is thought to make it difficult to initiate investment projects and allocate financial resources effectively. Even more, in a third essential work, the authors came up with empirical evidence on the formerly socialist economies of Europe, during the years of the post World War II (King and Levine, 1993c). Through their cross-country multiple regressions, they validate their initial hypothesis of a positive relationship between finance and economic growth, underlining the importance of financial sector reform in the economic reconstruction process of these countries. We take further this empirical work by testing the causal relationship between finance and growth in all European Union countries after '90, including countries that were part of the former communist bloc. More recently, by employing regional panel estimations for 26 European Union countries over the period 1990-2016, Asteriou and Spanos (2019) obtained a positive statistically significant impact of finance on growth. Besides the financial proxies, there are included in the model additional variables such as trade openness, net inflows of foreign direct investments, and inflation. In another study that followed, the authors provided evidence of the capital market's importance in sustaining economic growth (Asteriou and Spanos, 2021). They show that its impact on growth is higher than the banking sector's impact in the pre-crisis years. The present paper extends the literature as it examines the finance-growth nexus bi-directionally.

A second key theoretical standpoint is the „Demand-Following Hypothesis", economic growth being the one driving financial development. Firms demand more financial services, both in quantity and efficiency, once the economies expand, promoting the growth of the financial sector. According to Robinson (1952), economic expansion supports the

development of the financial sector rather than the other way around because „where enterprise leads finance follows".

A third theoretical perspective, namely the „Feedback Hypothesis", supports a bi-directional causality between finance and growth, based on a feedback loop. Here the discussion is even more complex. The stage of growth of one economy and the structure of its financial sector are considered central factors that influence the presence of a bi-directional causality. The moment of introducing in the literature the „Granger causality" concept is believed to be extremely important in the evolution of studying the relationship between finance and growth (Granger, 1988). This type of causality assesses if past values of one variable could help in predicting future values of another variable. Therefore, we consider it very useful while assessing the finance-growth causality relationship, especially as it is a common approach in the specific literature. The Granger tests within an Error-Correction model show the presence of mutual causality between financial development and economic growth in many developing countries, over the years 1970-1999 (Al-Yousif, 2002). Only a small number of the 30 tested countries support the „Neutrality Hypothesis" or the „No Relationship Hypothesis", representing a fourth theoretical view, according to which there is no causal relationship between finance and growth. The methodology is completed by one additional approach, through panel analysis, and the results remain unchanged. Based on the final conclusions, the different levels of financial development and the dissimilarity between applied policies among the countries would be the reason for the different impact of the financial proxies on economic growth.

However, there are prior studies that support a bi-directional causality between finance and growth (Calderón and Liu (2003), for 29 high-income countries; Apergis *et al.* (2007), for 15 OECD and 50 non-OECD countries; Hassan *et al.* (2011), for low- and middle-income countries, but not for African countries). For a study over 25 years of another dimension of the financial sector, a probably narrower area, the authors focus on the insurance market, which is seen as a nevertheless important component of the financial sector (Dash *et al.*, 2018). The paper explores the causal link between insurance market penetration and economic development in 19 Eurozone countries between 1980 and 2014, through Granger causality tests. We consider the authors' decision to test the causality within two different methodologies useful. At first, they employed the Vector Error-Correction (VEC) methodology to study the causality at the individual country level, an empirical approach employed in the current study as well. Additionally, a panel data methodology is employed by the authors to gain an overview of the Granger causality between financial development proxied by the insurance market and economic growth. Both methodologies present mixed results regarding the insurance market penetration-economic growth relationship. In certain situations, the insurance market influences economic growth, in other cases the relationship is reversed. However, there are also cases when the insurance market and economic growth influence each other, so there is a bi-directional causal relationship, and cases when there is no statistically significant relationship that can be established between the two. While focusing on the main dimensions of the financial sector, banking and capital market, we also test for the presence of Granger causality.

Fuinhas *et al.* (2019) already addressed the finance-growth nexus in 12 European countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain. The analysis is performed for the years 1990-2015 and, through panel Vector Autoregressive model and Granger causality tests, it investigates the

presence of a bi-directional relationship between the banking sector development, stock market development, and economic growth. The authors constructed a composite Banking Sector Development index, and a Stock Market Development index, using 5 different variables. The proxies for both the banking sector and capital market are simultaneously included in the model while searching for dynamic interactions. Interestingly, there is evidence of a bi-directional relationship between the banking sector and the stock market, but only a uni-directional causal relationship from economic growth to banking, and from the stock market to economic growth. We take further the authors' work, not only by extending the sample of European countries and the analyzed period but also by employing a country-level analysis for all 27 European Union members instead of a panel analysis. This allows us to identify different interactions between finance and growth for each country in particular, revealing countries' specificities. Even more, the paper contributes by analyzing the causal relationship between economic growth and certain variables that are representative of the banking and stock market development, including them in our models individually. The applied methodology is described in the next chapter.

3. METHODOLOGY

We test for the presence of Granger causality between financial development and economic growth in 27 European Union countries, over 30 years. The empirical analysis is conducted through cointegration and Vector Error-Correction (VEC) methodology with Granger causality tests (Engle and Granger, 1987; Granger, 1988). The motivation for adding the VEC Granger Causality/Block Exogeneity Wald Tests to the individual-country data is to empirically check for predictive significance, or in other words, to assess the significance of one variable in forecasting another variable. The applied methodology is suitable when the time-series are non-stationary and cointegrated, meaning they share a long-run equilibrium relationship.

3.1 Data collection

We collected data published and maintained by the World Bank and included in the Global Financial Development Database (WB, 2023a) and World Development Indicators Database (WB, 2023c). Gross domestic product per capita is used to measure economic growth for the period 1990-2019, while four different measures of financial development are included in the analysis. The financial development proxies are chosen to respond to the depth and efficiency of the financial sector, both in the case of the banking sub-sector, as well as the capital market sub-sector, according to data availability. To ensure normality in the distribution of data, some variables were transformed by taking their natural logarithms.

When data for capital markets is available, our model includes two proxies for the depth and efficiency of the banking sector (credit to government and credit to private sector) and two proxies for depth and efficiency of the capital market (stock market capitalization and stock market turnover ratio). When data for capital markets is unavailable, we test only for banking proxies: credit to government and credit to private sector, including additionally deposit money banks' assets, considered as a second measure of financial depth, and bank non-performing loans, considered as a second measure of financial efficiency.

The extended model is constructed by incorporating trade openness (as a percentage of GDP), allowing us to check for the robustness of the results. International trade is considered to successfully contribute to stimulating growth, firstly by determining the expansion of production (WB, 2023b); that also leads to the necessity of increasing the labor force. Secondly, international competition eventually stimulates productivity. The used variables are presented in Table no. 1.

Table no. 1 – Variables used and the source of data

Variable	Abbreviation	Source
GDP per capita (current LCU)	GDP	WDI*
Trade (% of GDP)	T	WDI*
Credit to government and state owned enterprises to GDP (%)	CR	GFD**
Domestic credit to private sector (% of GDP)	DC	GFD**
Deposit money banks' assets to GDP (%)	DEP	GFD**
Bank non-performing loans to gross loans (%)	NP	GFD**
Stock market capitalization to GDP (%)	S	GFD**
Stock market turnover ratio (%)	STR	GFD**

Note: *World Development Indicators, World Bank Database; **Global Financial Development, World Bank Database

3.2 Data analysis

Firstly, the Unit-Root Test Augmented Dickey-Fuller is employed to check for the series' stationarity, and then the Johansen Cointegration Test follows. When two or more variables indicate a common trend, there is a sign of cointegration. Moreover, if there is a sign of cointegration, Granger causality must occur in at least one direction (Granger, 1988). Vector Error-Correction (VEC) methodology allows us to test for the long-run causality (Brooks, 2019). To determine the optimal number of lags, we employed selection criteria. The EViews software allows the comparison view, which includes the Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC/BIC), and Hannan-Quinn Criterion (HQC). As the Hannan-Quinn Criterion (HQC) is seen to be a more likely balanced criterion, we mainly used the number of lags indicated by this one. We also took into consideration that, for annual macroeconomic data, the generally used lag length is 1 or 2 (Wooldridge, 2012). Also, the Inverse Roots Test is employed for all 27 models, to check the stability of the models. Any root outside the circle would imply instability. Finally, diagnostic tests such as the VEC Heteroskedasticity and Residual Serial Correlation Tests are applied. The results can be found in the Annex, while data and EViews files are available upon request.

To include four different financial proxies, as well as trade openness as a control variable, the regression equation is expanded as follows (1):

$$\Delta GDPpercapita_t = \alpha\,(\beta_0 + \beta_1 GDPpercapita_{t-1} + \beta_2 F1_{t-1} + \beta_3 F2_{t-1} + \beta_4 F3_{t-1} + \beta_5 F4_{t-1} + \beta_6 Trade_{t-1} + \epsilon_{t-1}) + \gamma_1 \Delta GDPpercapita_{t-1} + \gamma_2 \Delta F1_{t-1} + \cdots + \gamma_6 \Delta Trade_{t-1} \quad (1)$$

where:

$\Delta GDPpercapita_t$ is the change (difference) in economic growth at time t;

α is the speed of adjustment coefficient, which determines how quickly deviations from the long-run equilibrium are corrected;

β_0, β_1, ..., β_6 are the cointegration coefficients, representing the long-run relationship between economic growth and the financial development proxies, as well as trade openness;

ϵ_{t-1} is the error-correction term, which shows the deviation from long-run equilibrium;

$\gamma 1i$, $\gamma 2i$, ..., $\gamma 6i$ are the short-run coefficients;

$\Delta F1_t$, $\Delta F2_t$, ..., $\Delta F4_t$, and $\Delta Trade_t$ are the short-run changes (differences) in the financial proxies and trade openness (calculated as the sum of exports and imports over GDP).

VEC Granger Causality/Block Exogeneity Wald Tests help to evaluate the presence of Granger causality, an understanding of the predictive significance between the independent and dependent variables. The null hypothesis (H_0) states that the financial development proxy does not Granger cause economic growth. To reject the null hypothesis, the probability needs to be less than the significance level of 10 percent.

4. RESULTS

We provide evidence of the presence of Granger causality between finance and growth. Some differences may be observed, based on country specifics, as in some cases the most statistically significant is the banking sub-sector, Granger causing economic growth, while for other countries the capital market shows a stronger relationship of causality with growth. A third category of countries is the one for which both banking and capital market proxies have a Granger causality relationship with growth. There are some cases of bi-directional Granger causality between finance and growth, compared to several prior studies that confirm only uni-directional causality – Christopoulos and Tsionas (2004), in case of 10 developing countries; Fuinhas *et al.* (2019) in the case of 12 European countries. However, we agree with the view that the presence of bi-directionality differs across economies, due to country specifics; the authors showed mixed results for the presence of bi-directional causality between finance and growth when analyzing MENA countries (Kar *et al.*, 2011). We also support the statement under which the presence of mutual causality might be connected to the economic structure of a certain country or group of countries, but also to the analyzed period (Čižo *et al.*, 2020). Similar to the authors' findings, we found evidence of bi-directional causality between finance and growth in countries like Bulgaria, Romania, and Greece, while in the case of Austria and Finland, our model only provides evidence of a uni-directional relationship, from finance to growth. Other countries for which our results support uni-directionality from finance to economic growth are: Cyprus, Denmark, France, Hungary, and Slovenia.

Additionally, the current analysis distinguishes between one financial sub-sector or another, supporting the presence of causality in each country. Most of the European Union countries rely on the banking system when choosing the sources of funding, a fact that is also shown by our results. However, the number of credit institutions (banks) is decreasing in the Euro area (Statista, 2024), showing that some of the members managed to diversify their sources of funding. As a matter of fact, the financial structure varies significantly across the 27 EU countries, the Southern and Eastern Europe being predominantly dependent on bank financing, while other countries such as France, Germany, or the Netherlands have a developed capital market.

Overall, there is no evidence of missing causality between financial development and economic growth in our models. The results for the Granger Causality/Block Exogeneity Wald Tests showing the direction of causality between finance and growth are summarized in Table no. 2. In the next subsections, we discuss further our findings, obtained through the individual country-level analysis (Subsections 4.1, 4.2, 4.3).

Table no. 2 – Summary for the direction of causality between financial development and economic growth

Country	CR	DC	DEP	NP	S	STR
Austria					⇨	⇨
Belgium					⇨	⇦
Bulgaria	⇨					⇦
Croatia		⇔			⇨	⇨
Cyprus		⇨				
Czech Republic					⇔	
Denmark						⇨
Estonia		⇔		⇔		
Finland	⇨					
France					⇨	⇨
Germany		⇦			⇔	⇔
Greece	⇨				⇔	⇦
Hungary	⇨	⇨				
Ireland	⇔	⇦				
Italy	⇨	⇔			⇨	⇨
Latvia				⇔		
Lithuania			⇦	⇔		
Luxembourg						⇔
Malta	⇦					⇨
Poland	⇨					⇦
Portugal	⇨	⇔			⇨	
Romania	⇦	⇨				
Slovak Republic		⇦			⇨	
Slovenia					⇨	
Spain	⇨	⇔			⇔	⇦
Sweden	⇦	⇦		⇨		
The Netherlands		⇨			⇨	⇦

Note: ***CR*** is Credit to government and state owned enterprises to GDP; ***DC*** is domestic credit to private sector; ***DEP*** is Deposit money banks' assets to GDP; ***NP*** is Bank non-performing loans to gross loans; ***S*** is Stock market capitalization to GDP; ***STR*** is Stock market turnover ratio; ⇨ from financial development to economic growth; ⇦ from economic growth to financial development; ⇔ from financial development to economic growth & from economic growth to financial development

Source: Authors' estimation results performed in EViews (version 12 University Edition, IHS Markit, London, UK, distributed via OnTheHub) by employing Vector Error-Correction (VEC) models

4.1 Countries with banking-oriented financial sectors

We consider the countries for which the empirical results support a stronger Granger causality relationship from banking proxies to economic growth, countries with banking-oriented financial sectors. These are: Bulgaria, Cyprus, Estonia, Finland, Hungary, Ireland, Latvia, Lithuania, Poland, Romania, and Sweden. In the case of Estonia, Latvia, Lithuania, and Sweden, only banking proxies were included in the estimations due to missing data for the capital market.

For Bulgaria, Cyprus, Finland, Hungary, Ireland, Poland, and Romania, our analysis shows that the banking loans Granger cause economic growth, be they to the private or the public sector. As the significant variables are relevant proxies for the efficiency and depth of

the financial sector, the policymakers in these countries should keep an eye on promoting the development of a healthy, dynamic, and accessible banking environment. Improving credit accessibility and, in the meantime, fostering competition in the area of banking institutions would support further economic growth. Additionally, we consider that creating a favorable environment for the private economic agents could boost even more sustainable growth. In Poland, state-owned enterprises seem to have a strategic role in the process of development. A very important aspect for policy markers would be to find solutions for maintaining favorable borrowing conditions. However, what should be kept in mind is that too much reliance on banks may increase credit risk exposure and create potential vulnerabilities in the banking industry. Another related aspect is the public debt. Until 2019, the Polish government managed to effectively maintain moderate levels of public debt, even below the European Union's average: 45.7% public debt of GDP in 2019 (FocusEconomics, 2023). The challenge is to maintain these levels even after the COVID-19 pandemic.

Besides regular loans to the private sector, the measure of non-performing loans presents causality with growth in Estonia. The country has a growing banking sector, but the policymakers should keep an eye on its efficiency but also stability. Similarly, the cases of Latvia, Lithuania, and Sweden, show presence of causality between non-performing loans and growth, highlighting that the quality and health of the banking sector play a critical role in the growth process.

In the cases of Bulgaria, Estonia, Ireland, Latvia, Lithuania, Poland, Romania, and Sweden, the finance-growth nexus appears to be mutually causal, partially following the findings of Gaffeo and Garalova (2014) who were testing the finance-growth nexus among Central and Eastern European countries. This could be explained by the structural differences between countries' financial systems and levels of growth. Interestingly, for some countries like Bulgaria and Poland, the bi-directional relationship is sustained by a capital market proxy, showing that historical values of economic growth could predict future values of the stock market activity.

4.2 Countries with capital market-oriented financial sectors

We consider the countries for which the empirical results support a stronger Granger causality relationship from the capital market to economic growth, countries with a capital market-oriented financial sector: Austria, Belgium, Czech Republic, Denmark, France, Germany, Luxembourg, Malta, Slovak Republic, and Slovenia. In these countries, the causality is supported by financial proxies representing the depth and/or efficiency of the capital market. Other studies showed as well that in the case of more developed countries, the stock market tends to be the one in a causal relationship with growth (Peia and Roszbach, 2015).

The results for these countries show the presence of Granger causality between financial development and growth, through stock market turnover ratio, and sometimes stock market capitalization as well. For supporting further economic growth, it would be important for policymakers to prioritize regulations in financial areas such as the depth and efficiency of the financial markets, but also their stability. One way would be by promoting market transparency and enhancing investor protection. Excepting the cases of Austria, Denmark, France, and Slovenia, we found a two-way relationship of causality between financial development and economic growth.

Even if Germany has a developed banking industry, the restructuring needs and the low profitability might impact the overall lending capabilities. Some other factors may explain why capital markets have shown a more significant causal effect on growth than banking proxies in recent years: the reforms focused on diversifying financial resources and strengthening capital markets since the early 2000s, the presence of institutional investors, and numerous corporates that have increasingly accessed capital markets for long-term funding. The results reinforce the importance of a well-functioning and dynamic, vibrant stock market in supporting economic development. The efficiency of the capital market can be encouraged, for example, through sustaining investor education.

The Czech Republic is reviewed as an emerging financial market in the yearly evaluation of equity markets, the „Global Market Accessibility Review", while the rest of the countries are considered developed markets (MSCI, 2023). As exceptions, Malta, Slovak Republic, and Slovenia could be classified as frontier markets. Policymakers need to continue to promote the development of the financial markets in these countries. However, stability should be also one main priority during the expansion period. While increasing their overall importance, the financial markets will eventually be more and more integrated into the global markets, which could lead to spillover effects on domestic conditions.

4.3 Countries with mixed financial sectors

The countries for which both banking and capital market Granger cause economic growth, are considered countries with mixed financial sectors: Croatia, Greece, Italy, the Netherlands, Portugal, and Spain. This means that the financial proxies can be used to determine future values of the dependent variable, economic growth. The results also support the „Feedback Hypothesis" for some countries, as there is evidence of a bi-directional relationship between financial development and economic growth.

In the cases of Croatia and the Netherlands, the loans taken by the private sector and stock market capitalization Granger cause economic growth, while there is also evidence that growth Granger causes stock market turnover ratio in the Netherlands. This supports the view that growth creates investment opportunities. The situation is similar for Greece, Spain and Portugal, as the empirical analysis shows that financial development Granger causes economic growth through banking loans and stock market capitalization. Evidence of mutual causality between finance and growth was found for all these countries. Besides encouraging the listing of companies on the stock exchange, policymakers should focus on boosting innovation and integrating new digital solutions, for example, by fostering collaboration between traditional financial institutions and fintech start-ups. This way, not only costs can be reduced, but also the speed of transactions can be enhanced. This could contribute to future high values of stock market capitalization, and economic growth.

Italy stands out with the presence of Granger causality in the case of all four tested proxies of financial development. Even though the banking proxies are more statistically significant, the capital market is also relevant and Granger causes economic growth. The mixed significance of both sectors reflects the country's diversified financial system, where the traditional dominance of banks is gradually being complemented by the capital market, especially after the post-crisis reforms. In Italy, we found evidence of two-way causality, for the loans to the private sector.

Figure no. 1 provides a geographical overview of the study's main findings. Countries where the banking proxies Granger cause economic growth are the ones shaded in yellow (Bulgaria, Cyprus, Estonia, Finland, Hungary, Ireland, Latvia, Lithuania, Poland, Romania, and Sweden). Countries where the capital markets present significance in Granger causing economic growth are shaded in blue (Austria, Belgium, Czech Republic, Denmark, France, Germany, Luxembourg, Malta, Slovak Republic, and Slovenia). Finally, the countries where both banking and capital market proxies Granger cause economic growth are shaded in green (Croatia, Greece, Italy, the Netherlands, Portugal, and Spain). Additionally, the map illustrates distinct regional trends in the finance-growth nexus within the European Union.

Thus, we consider that our results can help policymakers in understanding the key mechanisms of financial influence on economic growth, while taking into account the affinities of their national financial system.

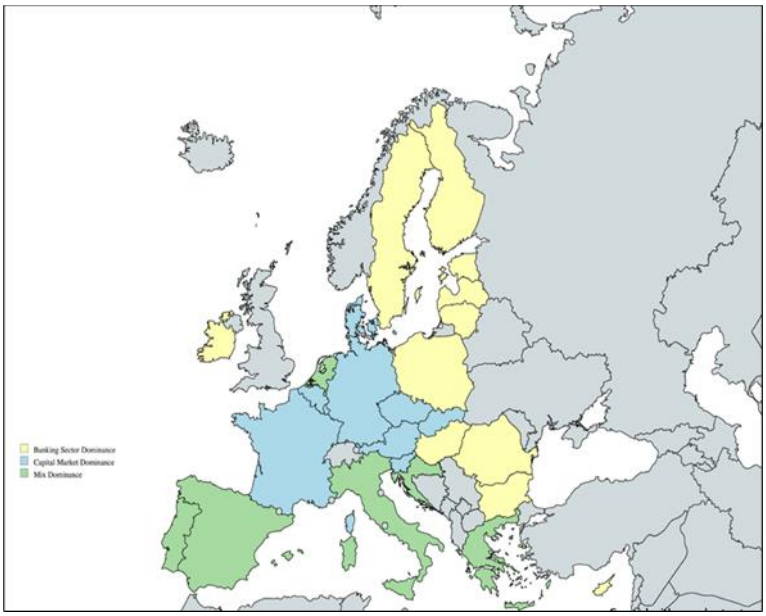

Figure no. 1 – Mapping the results
Source: authors, based on results

5. CONCLUSION AND FUTURE STUDIES

Based on our results, there is evidence of the presence of Granger causality between financial development and economic growth. As we test our hypothesis on 27 European Union countries over the years 1990-2019, we confirm the presence of Granger causality between growth and finance in all European Union countries, but with some alterations, as follows. For Bulgaria, Cyprus, Estonia, Finland, Hungary, Ireland, Latvia, Lithuania, Poland, Romania, and Sweden there is empirical evidence that their banking sectors Granger cause economic growth. Thus, promoting a stable and inclusive banking environment might support further economic growth. As many of these countries were part of the former communist bloc, targeted policy

decisions could perhaps foster financial diversification, so that the risk of too much reliance on the banking sector would be reduced. In Austria, Belgium, Czech Republic, Denmark, France, Germany, Luxembourg, Malta, Slovak Republic, and Slovenia, the capital market proxies have a stronger causal relationship with growth. In accordance with prior studies, generally, this is the case for countries that managed to better mitigate the risk of too much reliance on a main funding source, so they promoted financial variety. While continuing to foster the capital markets development in these countries, policymakers should take into consideration the side effects of the financial system deepening, both at the European and global levels, which might cause external shock and spillover effects. Only in 6 of 27 European Union countries, both the banking and capital market financial sub-sectors present significant Granger causality with growth: the cases of Croatia, Greece, Italy, the Netherlands, Portugal, and Spain. Additionally, to ensure a virtuous circle between financial development quantitative measures and economic growth, we believe that bi-directional causality is important. In most of the cases this condition was satisfied for our analyzed period. Policy makers should find ways to foster investments while efficiency in banking funding (such as an increased way of digitalization and reduction of bureaucracy) is ensured. Also, offering ways to increase financial literacy for own investors might increase the diversification of funding through capital markets. An important note is that investors should understand the risks involved, especially in turbulent times. Because the level of market integration is extremely high when referring to the European Union countries, we consider it absolutely economically rational that financial development successfully contributes to economic growth. Free capital flows, diversification in financial services, and several investment opportunities are the main pillars of promoting growth. Moreover, as many of the countries share the same currency (Euro), with 20 out of 27 countries being part of the Eurozone, financial stability is positively affected. Possible limitations of the study could be the unavailable data for stock markets in the case of certain countries, the methodological approach, which, while appropriate for the current analysis, may be enhanced by future econometric developments, but also the growing number of significant control variables presented in the specific literature, that could be included in further studies. Even more, future research such as employing threshold dynamic panel estimation could provide additional interesting insights.

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ANNEX

Table no. A 1 – Descriptive statistics: Austria

Austria									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	30.781,59	1.463,46	30.268,01	8.015,71	-1,23	0,06	17.915,00	44.724,19	30,00
T	88,89	2,70	89,16	14,81	-1,40	-0,32	63,27	107,92	30,00
CR	17,06	0,54	17,57	2,94	-0,86	-0,66	11,26	19,82	30,00
DC	90,27	0,71	89,71	3,89	-0,22	0,34	83,17	98,53	30,00
S	23,35	2,36	20,65	12,92	2,37	1,34	1,19	60,75	30,00
STR	63,49	22,88	32,34	125,31	24,04	4,77	19,38	694,43	30,00

Table no. A 2 – Descriptive statistics: Belgium

Belgium									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	28.758,85	1.343,63	29.035,06	7.359,35	-1,23	0,02	17.065,35	41.663,94	30,00
T	140,53	3,33	140,90	18,25	-1,39	-0,16	109,01	166,49	30,00
CR	30,61	1,95	29,79	10,67	-1,76	-0,07	13,42	42,05	30,00
DC	63,72	0,75	66,07	4,11	-0,21	-0,93	54,74	69,85	30,00
S	60,04	3,75	59,10	20,54	-1,09	0,06	27,30	97,04	30,00
STR	30,16	3,54	28,33	19,42	11,92	2,98	9,51	114,05	30,00

Table no. A 3 – Descriptive statistics: Bulgaria

Bulgaria									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	6.689,40	978,04	5.738,99	5.356,95	-1,16	0,26	5,21	17.251,45	30,00
T	100,52	4,04	96,39	22,11	-1,25	-0,05	55,26	130,27	30,00
CR	14,79	2,95	7,11	16,15	2,05	1,79	3,91	60,89	30,00
DC	47,49	4,14	50,52	22,66	-0,95	-0,40	8,55	82,80	30,00
S	12,41	2,26	12,51	12,36	0,68	0,84	0,05	48,80	30,00
STR	23,44	7,22	6,92	39,56	6,91	2,62	1,07	173,04	30,00

Table no. A 4 – Descriptive statistics: Croatia

Croatia									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	7.765,05	614,04	8.106,81	3.363,23	-1,52	-0,04	3.402,62	13.507,14	30,00
T	77,56	2,11	79,36	11,55	-0,63	0,34	62,79	101,38	30,00
CR	18,56	1,12	18,22	6,13	-0,90	0,56	10,85	31,82	30,00
DC	46,95	3,07	49,42	16,79	-1,64	-0,07	24,16	69,99	30,00
S	27,57	4,12	29,09	22,55	7,20	2,03	3,93	115,99	30,00
STR	10,20	2,29	4,18	12,55	0,34	1,47	1,20	34,52	30,00

Table no. A 5 – Descriptive statistics: Cyprus

Cyprus									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	17.720,56	1.057,15	19.551,92	5.790,24	-1,19	-0,42	7.530,07	26.280,18	30,00
T	122,56	2,98	117,62	16,33	-1,16	0,17	95,42	151,94	30,00
CR	17,16	1,51	16,03	8,29	-1,29	0,28	6,13	33,64	30,00
DC	175,04	8,10	147,27	44,36	-1,01	0,75	108,50	255,31	30,00
S	54,91	5,82	80,50	31,87	-1,75	-0,52	7,99	80,50	30,00
STR	15,15	1,38	19,47	7,57	-0,53	-1,02	1,31	25,88	30,00

Table no. A 6 – Descriptive statistics: Czech Republic

Czech Republic									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	299.333,21	24.411,01	311.866,40	133.704,62	-1,02	-0,10	70.761,81	542.688,21	30,00
T	112,03	5,44	113,14	29,82	-1,50	0,05	63,50	157,57	30,00
CR	11,29	0,95	11,30	5,18	-1,21	0,10	3,15	19,95	30,00
DC	48,54	2,26	49,91	12,37	-0,42	-0,55	23,67	65,75	30,00
S	13,85	1,32	11,22	7,24	2,19	1,27	4,26	36,24	30,00
STR	58,20	4,54	65,92	24,86	-0,81	-0,62	13,64	98,43	30,00

Table no. A 7 – Descriptive statistics: Denmark

Denmark									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	280.756,81	13.093,64	285.651,66	71.716,82	-1,27	-0,10	166.420,41	397.452,20	30,00
T	87,11	2,77	86,98	15,19	-1,61	-0,09	65,60	110,22	30,00
CR	9,64	0,35	9,71	1,94	0,06	-0,33	5,27	13,15	30,00
DC	123,07	11,86	151,60	64,96	-1,53	-0,55	30,26	201,26	30,00
S	51,82	2,42	60,21	13,25	-0,19	-1,15	21,25	68,12	30,00
STR	47,59	2,07	45,05	11,34	3,47	1,24	22,41	80,41	30,00

Table no. A 8 – Descriptive statistics: Estonia

Estonia									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	8.846,30	1.098,99	7.774,33	6.019,40	-1,10	0,42	1.991,90	20.924,54	30,00
T	141,86	2,44	139,09	13,37	-0,06	0,43	116,76	170,76	30,00
CR	11,82	1,94	3,30	10,60	-1,45	0,42	1,26	32,59	30,00
DEP	53,07	4,93	55,36	27,02	-1,20	0,08	17,09	104,13	30,00
DC	57,26	3,55	48,45	19,42	-0,75	0,69	40,31	101,39	30,00
NP	1,48	0,24	1,40	1,29	4,02	2,02	0,20	5,38	30,00

Table no. A 9 – Descriptive statistics: Finland

Finland									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	29.924,74	1.566,10	30.879,08	8.577,90	-1,32	-0,20	16.815,18	43.439,90	30,00
T	70,07	1,87	70,93	10,24	1,18	-1,09	43,49	86,18	30,00
CR	10,33	1,82	6,81	9,97	2,66	1,97	2,19	37,99	30,00
DC	70,77	3,31	66,49	18,14	-1,83	0,22	52,65	95,40	30,00
S	17,50	2,49	10,30	13,65	8,19	2,63	10,30	72,16	30,00
STR	621,35	75,12	927,82	411,47	-1,50	-0,71	10,66	941,15	30,00

Table no. A 10 – Descriptive statistics: France

France									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	27.036,13	1.023,78	27.558,47	5.607,47	-1,35	-0,13	18.150,60	36.173,13	30,00
T	53,12	1,35	54,42	7,38	-1,08	-0,26	39,91	64,44	30,00
CR	23,48	2,94	17,52	16,09	3,69	2,30	14,59	69,91	30,00
DC	85,91	1,91	78,56	10,44	-1,33	0,53	75,57	107,12	30,00
S	65,92	5,13	72,65	28,11	-1,01	-0,33	10,06	105,94	30,00
STR	78,12	12,09	63,61	66,21	20,39	4,25	34,47	399,59	30,00

Table no. A 11 – Descriptive statistics: Germany

Germany									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	29.051,60	1.181,86	27.583,23	6.473,29	-0,81	0,39	18.425,30	41.809,92	30,00
T	67,15	3,13	68,57	17,17	-1,59	-0,19	40,58	88,52	30,00
CR	30,81	2,84	25,93	15,57	-0,44	0,95	11,98	62,40	30,00
DC	99,56	2,61	105,95	14,29	-1,51	-0,53	77,45	112,42	30,00
S	41,22	2,64	42,34	14,47	-0,96	-0,11	15,42	65,25	30,00
STR	114,34	10,62	112,61	58,16	14,76	3,19	22,54	377,25	30,00

Table no. A 12 – Descriptive statistics: Greece

Greece									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	14.458,39	906,45	16.285,22	4.964,82	-0,71	-0,53	4.466,01	21.844,54	30,00
T	52,93	2,32	51,05	12,71	-0,27	0,55	36,16	81,89	30,00
CR	22,33	1,46	24,62	8,01	-1,73	-0,28	10,14	30,14	30,00
DC	75,50	4,95	67,15	27,14	-1,42	0,49	50,08	119,30	30,00
S	46,34	3,73	55,62	20,42	-1,42	-0,24	11,94	83,09	30,00
STR	43,40	2,39	43,81	13,10	4,97	1,84	28,75	90,69	30,00

Table no. A 13 – Descriptive statistics: Hungary

Hungary									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	2.081.473,65	243.660,17	2.164.310,59	1.334.581,72	-0,87	0,25	250.381,56	4.879.080,86	30,00
T	125,53	7,40	134,23	40,54	-0,99	-0,66	53,56	168,39	30,00
CR	13,97	0,83	13,62	4,57	0,71	-0,37	1,59	22,69	30,00
DC	37,90	2,15	34,73	11,79	-0,60	0,59	21,36	60,17	30,00
S	19,87	1,01	19,21	5,52	2,49	1,24	10,29	36,23	30,00
STR	58,59	4,49	51,14	24,62	5,56	2,09	26,36	149,27	30,00

Table no. A 14 – Descriptive statistics: Ireland

Ireland									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	34.723,37	3.109,72	37.042,31	17.032,65	-0,39	0,38	10.771,83	72.219,87	30,00
T	166,11	6,88	159,96	37,69	-0,37	0,34	105,03	252,50	30,00
CR	7,67	1,22	5,95	6,66	4,18	2,18	0,86	27,09	30,00
DC	88,61	6,70	71,78	36,72	-0,06	0,87	36,00	169,25	30,00
S	52,68	2,87	57,05	15,73	-0,18	-0,44	17,97	81,71	30,00
STR	23,39	2,79	19,19	15,27	1,38	1,06	5,24	65,55	30,00

Table no. A 15 – Descriptive statistics: Italy

Italy									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	23.343,71	944,38	25.471,23	5.172,60	-0,90	-0,68	12.887,00	30.079,96	30,00
T	48,98	1,36	49,67	7,43	-0,64	-0,45	33,88	60,30	30,00
CR	23,66	1,86	15,88	10,21	-1,27	0,68	14,02	42,22	30,00
DC	72,77	2,35	69,29	12,87	-1,51	0,40	60,35	94,06	30,00
S	29,18	2,76	27,17	15,13	0,30	0,63	0,02	67,01	30,00
STR	5.656,84	5.499,77	124,78	30.123,49	30,00	5,48	14,20	165.149,10	30,00

Table no. A 16 – Descriptive statistics: Latvia

Latvia									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	6.823,22	879,98	5.502,89	4.819,87	-1,36	0,39	1.633,50	15.974,77	30,00
T	97,22	3,58	90,87	19,63	-1,41	0,39	73,87	128,23	30,00
CR	5,30	1,09	3,29	5,96	3,13	2,17	1,26	20,09	30,00
DEP	44,41	5,39	41,19	29,54	-1,05	0,46	11,44	99,11	30,00
DC	81,69	3,94	94,68	21,56	-0,16	-1,25	34,37	94,68	30,00
NP	5,56	0,69	6,00	3,78	1,98	1,24	0,50	15,93	30,00

Table no. A 17 – Descriptive statistics: Lithuania

Lithuania									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	7.335,12	874,91	5.854,77	4.792,10	-0,91	0,58	2.138,53	17.522,10	30,00
T	112,89	4,82	104,97	26,39	-1,45	0,29	74,82	155,89	30,00
CR	10,21	1,04	6,78	5,72	-1,12	0,60	2,80	21,43	30,00
DEP	35,80	3,34	37,77	18,30	-1,54	0,21	13,64	65,41	30,00
DC	53,85	1,39	58,63	7,61	-0,76	-1,07	39,05	58,63	30,00
NP	9,42	1,18	11,44	6,47	-0,32	0,41	0,60	24,00	30,00

Table no. A 18 – Descriptive statistics: Luxembourg

Luxembourg									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	65.189,82	4.483,33	63.317,20	24.556,21	-1,52	-0,03	27.722,80	100.695,85	30,00
T	270,78	11,20	271,59	61,33	-1,12	-0,01	181,40	382,35	30,00
CR	6,37	0,69	5,28	3,79	19,80	4,11	4,11	24,66	30,00
DC	83,61	2,04	78,45	11,18	-0,10	0,75	66,00	108,68	30,00
S	132,37	9,56	120,95	52,36	4,62	1,61	63,01	321,94	30,00
STR	1,06	0,21	0,72	1,13	0,80	1,29	0,11	4,06	30,00

Table no. A 19 – Descriptive statistics: Malta

Malta									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	13.924,96	1.193,92	12.487,94	6.539,39	-0,36	0,70	5.324,18	28.340,97	30,00
T	251,24	9,15	251,23	50,13	-1,18	-0,26	164,48	322,68	30,00
CR	15,43	1,55	13,18	8,47	-1,36	0,22	3,49	29,01	30,00
DC	97,98	2,22	97,40	12,18	0,63	-0,35	71,64	122,11	30,00
S	45,12	1,85	46,74	10,11	0,51	0,72	30,73	71,08	30,00
STR	4,85	0,64	3,48	3,50	-1,80	0,37	0,89	9,18	30,00

Table no. A 20 – Descriptive statistics: Poland

Poland									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	27.367,46	3.142,77	25.195,71	17.213,66	-1,05	0,18	1.644,65	60.278,24	30,00
T	70,53	3,77	70,99	20,67	-1,39	0,06	43,72	103,45	30,00
CR	13,56	0,93	12,66	5,11	1,62	0,84	2,34	27,45	30,00
DC	33,64	2,79	26,77	15,27	-1,77	0,19	12,87	54,42	30,00
S	21,58	2,56	21,77	14,00	-1,13	0,12	3,21	49,33	30,00
STR	43,30	2,70	37,86	14,79	-0,93	0,03	11,43	66,20	30,00

Table no. A 21 – Descriptive statistics: Portugal

Portugal									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	13.766,37	772,62	14.808,82	4.231,81	-0,90	-0,40	5.606,75	20.840,87	30,00
T	68,31	1,69	65,07	9,26	-0,71	0,62	54,18	86,56	30,00
CR	11,24	1,28	6,69	6,99	-1,35	0,78	5,04	23,04	30,00
DC	123,71	3,26	115,00	17,86	-0,21	0,64	90,26	159,86	30,00
S	35,40	1,55	33,29	8,50	0,48	1,11	25,13	54,99	30,00
STR	63,88	3,38	54,67	18,53	0,02	0,95	40,35	110,21	30,00

Table no. A 22 – Descriptive statistics: Romania

Romania									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	17.292,46	3.088,27	12.430,86	16.915,17	-0,82	0,61	3,70	54.915,03	30,00
T	64,50	2,52	61,23	13,83	-0,94	0,29	39,14	87,16	30,00
CR	14,19	2,74	11,26	15,02	5,90	2,38	1,03	62,40	30,00
DC	18,80	2,55	17,92	13,95	-1,49	0,01	0,00	39,33	30,00
S	7,02	1,08	7,29	5,92	-0,68	0,52	0,86	20,68	30,00
STR	20,14	2,86	10,82	15,68	-1,50	0,68	5,75	42,42	30,00

Table no. A 23 – Descriptive statistics: Slovak Republic

Slovak Republic									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	9.106,20	905,61	8.995,80	4.960,24	-1,48	0,02	1.894,60	17.313,38	30,00
T	140,38	6,47	137,95	35,41	-0,78	-0,28	57,17	189,80	30,00
CR	14,70	0,40	15,01	2,19	2,16	-0,89	8,92	19,08	30,00
DC	40,88	1,79	33,75	9,82	-0,08	1,11	33,75	62,77	30,00
S	6,44	0,82	5,32	4,48	0,76	1,37	1,49	15,90	30,00
STR	41,16	11,99	2,20	65,67	0,88	1,47	0,10	215,51	30,00

Table no. A 24 – Descriptive statistics: Slovenia

Slovenia									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	13.268,71	1.090,20	14.194,05	5.971,28	-1,48	-0,10	5.307,28	23.263,10	30,00
T	118,91	4,39	112,34	24,06	-1,46	0,34	92,54	161,14	30,00
CR	12,38	0,59	11,54	3,24	2,16	1,27	6,26	21,06	30,00
DC	31,30	6,12	21,32	33,51	-1,63	0,33	0,19	85,06	30,00
S	17,13	1,94	13,95	10,64	8,77	2,65	9,03	60,04	30,00
STR	15,40	1,87	9,98	10,22	-1,82	0,32	1,89	29,73	30,00

Table no. A 25 – Descriptive statistics: Spain

Spain									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	18.511,75	1.040,94	20.633,52	5.701,45	-1,32	-0,43	8.456,87	26.424,47	30,00
T	53,85	1,75	54,93	9,60	-0,47	-0,62	35,48	67,57	30,00
CR	20,99	1,17	19,09	6,42	0,96	1,06	11,09	37,21	30,00
DC	119,11	5,48	102,73	30,04	-0,97	0,85	94,68	173,98	30,00
S	63,48	4,72	66,78	25,86	-0,27	-0,06	18,42	122,11	30,00
STR	104,24	13,21	90,31	72,33	3,70	1,92	32,60	318,33	30,00

Table no. A 26 – Descriptive statistics: Sweden

Sweden									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	320.963,23	17.414,08	319.650,86	95.380,87	-1,21	0,10	181.077,83	491.261,26	30,00
T	77,17	2,12	81,15	11,62	0,19	-1,00	50,77	92,56	30,00
CR	7,99	0,25	7,91	1,36	-0,41	0,08	5,13	10,88	30,00
DEP	96,39	7,38	106,33	40,44	-1,71	-0,35	39,68	139,93	30,00
DC	87,60	7,30	95,32	39,96	-1,69	-0,31	31,29	131,87	30,00
NP	1,47	0,15	1,20	0,84	-1,43	0,31	0,10	2,60	30,00

Table no. A 27 – Descriptive statistics: The Netherlands

The Netherlands									
Variable	Mean	Standard Error	Median	Standard Deviation	Kurtosis	Skewness	Minimum	Maximum	Count
GDP	32.149,38	1.625,00	33.131,62	8.900,52	-1,27	-0,24	17.592,64	46.875,81	30,00
T	126,27	3,52	121,42	19,29	-1,24	0,41	98,94	158,82	30,00
CR	19,69	2,47	12,24	13,54	-0,74	1,09	8,98	46,48	30,00
DC	111,52	0,63	110,47	3,47	3,76	-1,11	99,68	117,23	30,00
S	90,88	6,00	85,59	32,89	-0,72	0,30	37,64	155,25	30,00
STR	78,26	8,48	60,54	46,42	5,42	1,92	25,16	249,73	30,00

Table no. A 28 – VEC Residual Heteroskedasticity & Residual Serial Correlation Tests (1990-2019)

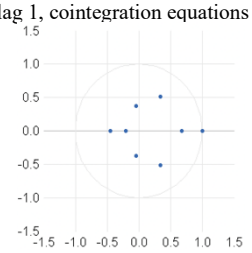
Test	VEC Residual Heteroskedasticity Test			VEC Residual Serial Correlation LM Test		
Null Hypothesis	No heteroskedasticity in the residuals			No serial correlation in the residuals		
Country	Chi-Sq	df	Probability	Lag	LRE Stat	Probability
Austria	308.0544	294	0.2749	1	22.54720	0.9608
Belgium	331.2217	336	0.5633	1	38.69089	0.3491
Bulgaria	397.5870	378	0.2344	2	48.87820	0.0744***
Croatia	410.6777	378	0.1190	1	30.39552	0.7319
Cyprus	313.0705	294	0.2126	1	49.33703	0.0684***
Czech Republic	402.4205	378	0.1857	1	29.53675	0.7682
Denmark	439.1452	420	0.2502	2	31.63651	0.6762
Estonia	411.6897	378	0.1122	1	45.36487	0.1362
Finland	363.6310	336	0.1438	1	23.85887	0.9397
France	329.8562	336	0.5842	1	43.81440	0.1739
Germany	384.6684	378	0.3954	1	49.96435	0.0609***
Greece	452.5874	420	0.1315	2	49.00915	0.0727
Hungary	471.1181	462	0.3745	1	41.34336	0.2486
Ireland	360.3055	336	0.1732	2	47.63059	0.0930***
Italy	392.6062	378	0.2916	1	42.49256	0.2116
Latvia	391.6434	378	0.3034	1	37.44959	0.4025
Lithuania	451.7508	420	0.1374	1	42.46099	0.2125
Luxembourg	425.3986	420	0.4174	2	37.97477	0.3795
Malta	433.7765	420	0.3109	1	23.46717	0.9467
Poland	336.6148	336	0.4803	1	40.06344	0.2946
Portugal	294.2111	294	0.4856	1	41.26737	0.2512
Romania	436.6654	420	0.2774	2	35.98183	0.4695
Slovak Republic	335.4493	336	0.4982	1	31.81541	0.6679
Slovenia	379.3164	336	0.0516	1	38.52840	0.3559
Spain	311.9437	294	0.2258	2	36.51208	0.4449
Sweden	431.6682	420	0.3366	1	30.47043	0.7286
The Netherlands	321.8353	294	0.1270	1	25.50233	0.9036

*, **, *** Indicate rejection of null hypothesis at the 1, 5, and 10 percent levels of significance

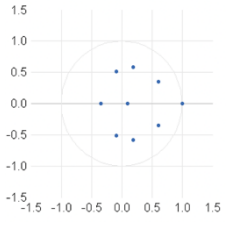
LRE Stat: Edgeworth expansion corrected likelihood ratio statistic

Source: Authors' estimation results performed in EViews (version 12 University Edition, IHS Markit, London, UK, distributed via OnTheHub), by employing Vector Error-Correction (VEC) models

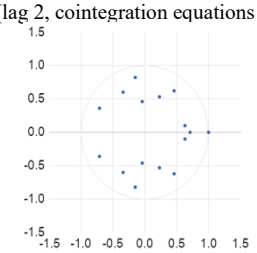
1. Austria
(lag 1, cointegration equations 1)



2. Belgium
(lag 1, cointegration equations 2)



3. Bulgaria
(lag 2, cointegration equations 3)



4. Croatia
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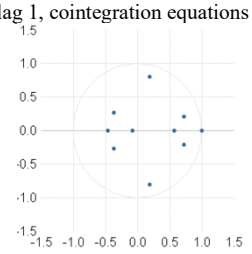
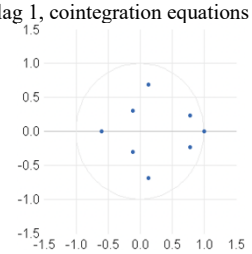
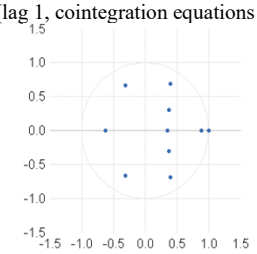


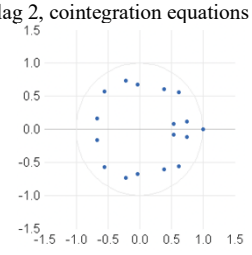
5. Cyprus
(lag 1, cointegration equations 1)



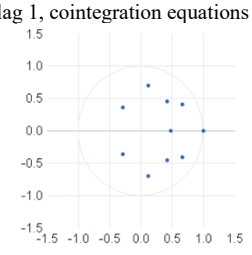
6. Czech Republic
(lag 1, cointegration equations 3)



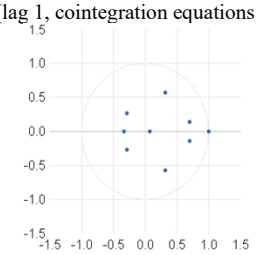
7. Denmark
(lag 2, cointegration equations 4)



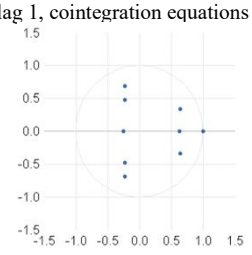
8. Estonia
(lag 1, cointegration equations 3)



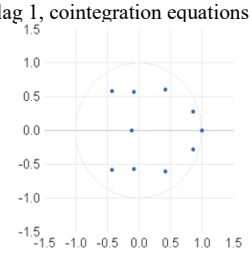
9. Finland
(lag 1, cointegration equations 2)



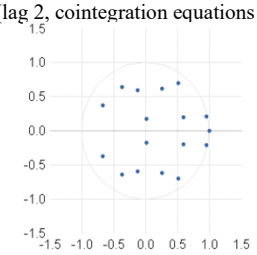
10. France
(lag 1, cointegration equations 2)



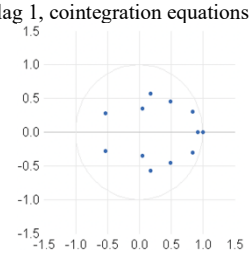
11. Germany
(lag 1, cointegration equations 3)



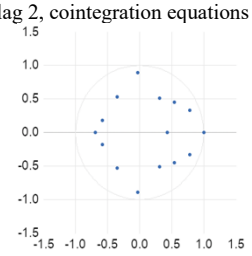
12. Greece
(lag 2, cointegration equations 4)



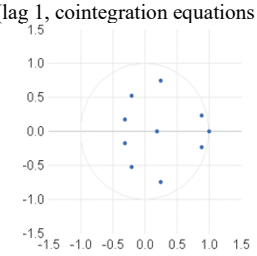
13. Hungary
(lag 1, cointegration equations 5)



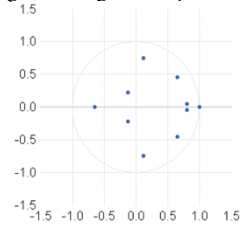
14. Ireland
(lag 2, cointegration equations 2)



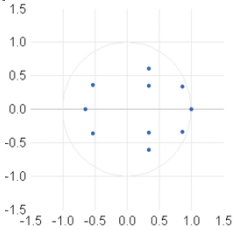
15. Italy
(lag 1, cointegration equations 3)



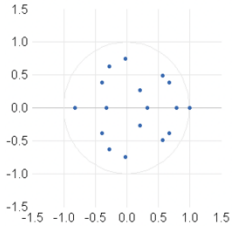
16. Latvia
(lag 1, cointegration equations 3)



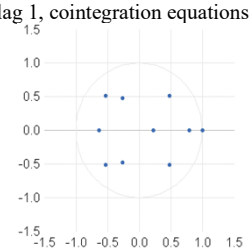
17. Lithuania
(lag 1, cointegration equations 3)



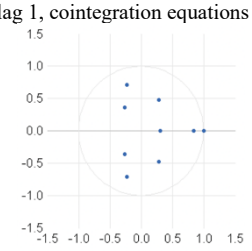
18. Luxembourg
(lag 2, cointegration equations 4)



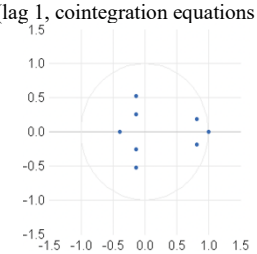
19. Malta
(lag 1, cointegration equations 3)



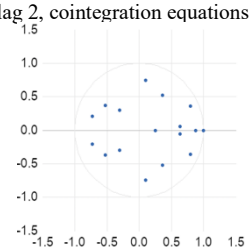
20. Poland
(lag 1, cointegration equations 2)



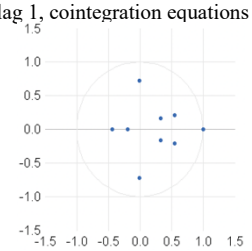
21. Portugal
(lag 1, cointegration equations 1)



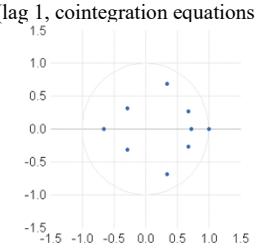
22. Romania
(lag 2, cointegration equations 4)



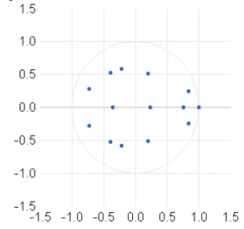
23. Slovak Republic
(lag 1, cointegration equations 2)



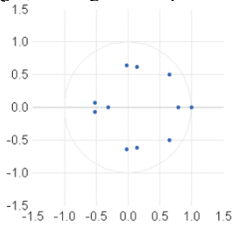
24. Slovenia
(lag 1, cointegration equations 2)



25. Spain
(lag 2, cointegration equations 4)



26. Sweden
(lag 1, cointegration equations 4)



27. The Netherlands
(lag 1, cointegration equations 1)

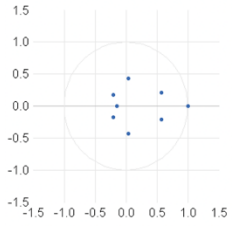


Figure no. A 1 – Inverse Roots of the AR Characteristic Polynomial

Source: Authors' estimation results performed in EViews (version 12 University Edition, IHS Markit, London, UK, distributed via OnTheHub), by employing Vector Error-Correction (VEC) models

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Financing and the Challenges of Developing the Innovation Capacity of Enterprises in Developing Countries: The Case of the MENA Region and Africa

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Abstract: Innovation currently represents a significant source of added value and competitiveness for companies on the international scale. However, financing innovation activities is a real challenge to overcome in order to successfully achieve the goals in emerging countries. The main objective of this paper is to conduct an empirical analysis on the identification of different sources of financing for firm innovation in the MENA region and Africa. To do this, we have constructed a battery of measures of the innovation capacity of firms: product, process, invention and innovation intensity of firms. In addition, the sources of financing were assessed by financing investments and working capital through bank debt, non-bank financial institutions, capital increase, equity, commercial debt and other sources of financing. The empirical study is based on the World Bank survey of more than 34,000 firms in the MENA region and Africa over the period 2011 and 2020. Through the use of several econometric modeling, the estimation results indicate the importance of bank financing, non-bank financial institutions, and trade credit in financing innovation of MENA and African firms.

Keywords: innovation; invention; R&D; access to finance; MENA; Africa.

JEL classification: O16; O31; G21; G23; C5.

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1. INTRODUCTION

Theories of industrial evolution (Lambson, 1991; Hopenhayn, 1992; Audretsch, 1995; Ericson and Pakes, 1995; Klepper, 1996) view innovation as the key to market entry, firm growth and survival, and how entire industries evolve over time. Sometimes, innovation is the source of the creation of entirely new industries. In today's environment, for companies of all sizes, innovation has become a kind of grail to be sought and encouraged, and the same is true for countries striving to see their economies grow. However, innovation is not limited to economic and/or monetary benefits for the organization that undertakes it. Innovation can also contribute to social and environmental well-being and to building a prosperous world.

Moreover, innovation is not an activity that is undertaken solely by private sector firms. In fact, large-scale, long-term public investment is behind the emergence of general-purpose technologies over the past two decades (e.g., nuclear power, space, the internet, vaccines, ...). Mazzucato (2018) argued that it is the state that funds, or even undertakes, much of the early-stage innovation (57% of R&D funding by the US government is for basic research in 2008). According to Janeway (2018), since the first industrial revolution, the state has served as a catalyst by subsidizing and taking responsibility for funding scientific and engineering advances, from which meaningful economic innovation flows. The private sector is seen as best able to commercialize opportunities.

The literature on innovation is vast. This article focuses specifically on innovation in its later stages, when it is exploitable and marketable, but also on the firm's decision to innovate through investment in research and development (R&D). Probably the simplest definition of innovation is "new ways of doing something." (Paul, 2020). Kanter (1983) defined innovation as "the generation, acceptance, and implementation of new ideas, processes, products, and services ... [that] involves creative use as well as original invention. Schumpeter (1996) described five types of innovation, with an emphasis on "*novelty*:" The introduction of a new or improved good or service; The introduction of a new process; The opening of a new market; The identification of new sources of raw material supply; and the creation of new types of industrial organization. More recently, Sugarhood *et al.* (2014), defined innovation more narrowly as "the practical application of new inventions into marketable products and services." A definition that excludes the last three categories of innovation above from Schumpeter (1996). In reality, there are dozens of definitions of innovation.

However, if innovation is risky, in a highly competitive environment, not innovating is riskier. Indeed, when innovations begin to push an organization into new and unfamiliar markets, the risks increase. Understanding an organization's core competencies is the basis for managing innovation risk. The further the organization moves away from its core competencies, the greater the risk. An organization faces both business risk - arising from the nature of the innovation project and its business environment - and funding risk - arising from the way the innovation activity is funded. Indeed, the use of external funds, whatever their nature, entails new risks and new constraints. Because of the inability to borrow or cede control, companies tend to limit the use of external funds, whether loans or equity. They may modify their business model to minimize the need for external financing and keep capital investment and fixed costs as low as possible. However, if the opportunity proves commercially viable, then companies may need to find external funding to finance the innovation project.

Financing any project with external loans involves paying fixed costs, which are due whether or not the project generates profits. The orthodoxy of prudent financing is to match

the nature and duration of the loan to the duration of its use. However, lenders are generally unwilling to finance the development of innovative projects over the long term. This is because the return is uncertain and will only materialize in the distant future. For these reasons, they consider such projects too risky and prefer to finance a well-established company that has a proven track record and assets that can be used as collateral for the loan. Indeed, the financing needs of different types of innovation, in volume and in kind (internal or external financing, equity or loans), can be very different.

It is generally accepted that longer-term and riskier projects require equity financing. For a well-established company, this type of financing can come from venture capitalists, and if the company is publicly traded, it is possible to raise money to finance an innovative project by issuing additional shares. Stock market investors are more sympathetic to the long periods of low or no cash flow for innovative companies. They believe that these companies could develop new industries or dominate huge new markets and generate profits in the future. On the other hand, investors may have a short-term orientation and demand dividends or share buybacks, which affects priorities in the optimal allocation of resources and hinders innovation. Similarly, a company with a diversified and balanced product/market portfolio can also generate the cash needed to finance innovation. All forms of external financing come with a new set of risks that cannot be ignored. These can be directly linked to the company's projects or to its portfolio of activities. Indeed, the financing needs of different types of innovation, in volume and in kind (internal or external financing, equity or loans), can be very different.

The contribution of this article to the literature review, is to answer the problem of what are the sources of financing for innovation, internal sources, external sources or both? To do this, we will exploit the World Bank's survey of firms in Africa and MENA between 2011 and 2020 on a sample of 35,763 firms. To our knowledge, this is the first empirical study on this topic that analyzes the effect of financing sources on innovation in the two regions.

The choice of the MENA region and Africa is justified by several reasons. These two regional blocs encompass diverse economies, ranging from resource-rich countries (such as the Gulf states) to emerging and developing economies. This diversity provides an opportunity to examine how different economic structures influence the financing mechanisms for innovation. Businesses in the MENA region and Africa often face difficulties in accessing external financing due to the underdevelopment of their financial markets, limited access to bank credit, and an understructured venture capital ecosystem. Although several countries have invested in research and development, the overall level of innovation remains relatively low compared to other regions of the world. Finally, juxtaposing the MENA region with Africa allows for insightful comparisons, particularly regarding similarities and differences in access to financing and their respective effects on innovation.

The contribution of this article is multifaceted. First, the study seeks to examine how the diversity of economic structures influences the financing modalities of innovation. In this context, analyzing both internal and external financing sources provides a significant contribution to the literature on innovation financing in developing and emerging economies. This, in turn, helps to better understand the obstacles and potential levers for strengthening the competitiveness of businesses in developing countries.

After presenting the introduction in this first point, we will present the literature review in Section 2. Section 3 will be devoted to the presentation of the data and the methodology. Section 4 is devoted to the presentation of the results. Finally, in the last Section, we will present the main conclusions of the work and their implications.

2. LITERATURE REVIEW

Investment in soft or hard innovation activities has unique characteristics compared to ordinary physical investment. These unique characteristics are the intangibility of assets (human capital, scientists, ...), uncertain and long-term returns, moral hazard, and asymmetric information (Ayalew *et al.*, 2019). Thus, it is difficult to assess with certainty which innovative projects at any given time require funding (Kerr and Nanda, 2015). This points to the conclusion that innovative firms face difficulties in raising the funds needed to finance their innovation activities.

The Pecking Order Theory (POT) suggests that firms prefer to finance new investment projects first from retained earnings (reserves), then, if necessary, resort to external financing through debt, and finally resort to external equity (capital increase) (Myers, 1984; Myers and Majluf, 1984). This hierarchy depends on the degree of asymmetry of the firm's information. Indeed, the informational opacity of innovative firms means that lenders are unable to assess the quality of financing requests and consequently assign an unrealistic risk rating to these firms. As a result, financial institutions fail to produce equilibrium prices and efficient transactions in the debt market (Stiglitz, 2000). Indeed, opacity emerges when innovative firms intentionally avoid revealing information about innovation projects to their lenders or competitors. These asymmetries are sources of agency costs and produce constraints in the credit market, which are manifested in the partial or total rationing of a financing request. In the case of the MENA region and Africa, where financial markets are underdeveloped or developing, these difficulties are necessarily more severe.

Sources of funding for innovation investment can be classified into internal and external sources. According to Modigliani and Miller (1958) In perfect capital markets, external financing is a substitute for internal financing. In reality, markets are characterized by informational asymmetries that are accentuated in innovative companies. It is in this sense that the financing strategy of firms has a direct influence on the intensity and direction of innovation. Internal financing, more precisely retained earnings and new equity from existing shareholders, is the main source of financing for most innovation projects (Czarnitzki and Hottenrott, 2011; Mare *et al.*, 2021). According to Brown *et al.* (2009) publicly traded start-ups, investing in cutting-edge technology, finance their R&D activities entirely from internal cash flow. Cash flow is a volatile source (Brown *et al.*, 2009). Raising new capital can be costly and, at times, unwarranted. As a result, innovative projects with high upfront costs may be delayed, deferred, or even abandoned due to a lack of external funding. This problem is likely to be more significant for smaller and younger firms that have more difficulty accessing external financing (Oudgou, 2021).

Recent literature shows the importance of the impact of different sources of finance (mainly debt and equity) on innovation intensity (Ullah, 2019; Wellalage and Fernandez, 2019; Wellalage and Locke, 2020). Early empirical studies focused on the bank financing-innovation relationship, and found that banks are not a prime source of financing for innovative firms. Indeed, banks require higher costs (interest and guarantees) than in the case of investments in physical assets (Hall and Lerner, 2010; Agénor and Canuto, 2017) knowing that the majority of innovative companies' assets are intangible and their profit is uncertain, which makes their projects too risky for bank financing (Mare *et al.*, 2021). Mann (2018) and Nanda and Nicholas (2014) provide empirical evidence on the importance of bank financing for innovative firms. Ayyagari *et al.* (2011) find that access to external finance (primarily

bank finance) is associated with higher innovation intensity among firms in 47 developing economies. Cornaggia *et al.* (2015) find that small innovative firms rely primarily on bank financing more than large and publicly traded firms.

External financing can also be provided in the form of equity. Public equity (stock market) is an important source for financing innovation projects and R&D investments (Brown *et al.*, 2009; Acharya and Xu, 2017; Ayalew *et al.*, 2019). They can have positive effects on the rate and quality of innovation, especially in sectors that are more dependent on external financing (Acharya and Xu, 2017; Mare *et al.*, 2021). Hsu *et al.* (2014) suggest that the development of the equity market promotes technological innovation while the credit market discourages it. Schäfer *et al.* (2004) found that firms use more equity financing to show better innovation performance. However, new equity financing may entail agency costs. Due to the lack of adequate oversight, managers may engage in long-term underinvestment against shareholders' pursuit of short-term goals. According to Bernstein (2015), going public is associated with less innovation because it is perceived as riskier by managers.

A compromise between equity financing and debt financing is always sought with respect to the issues of ownership control and the extension of strategic projects to competitors. Indeed, equity financing is generally more appropriate for investment projects characterized by a high level of risk and long term (Giudici and Paleari, 2000). Young and small companies bear high financial distress costs (Zizi *et al.*, 2020; Zizi *et al.*, 2021). This indicates that equity financing is more appropriate than bank debt. In this framework, venture capitalists engage in active monitoring of the innovative firm's activities (Hall and Lerner, 2010) as well as in providing experience and network resources (Denis, 2004; Wellalage and Locke, 2020).

The use of trade credit is more motivated than bank financing when firms suffer from negative cash flows or a temporary liquidity shock and a transactional banking relationship (Lin and Chou, 2015; Oudgou, 2021). Moreover, empirical studies show that trade credit is used more in contexts of underdeveloped financial markets and when the bank-firm relationship is purely transactional (Petersen and Rajan, 1997; Garmaise and Moskowitz, 2004; Lin and Chou, 2015; Oudgou, 2021). Innovation can also be financed by using credit from relatives, family, friends and intra-group financing. Other sets of empirical studies show that firms with government financial support grow faster and invest more in the most radical innovation activities (Garcia and Mohnen, 2010; Paul, 2020).

Recent studies continue to debate the costs and benefits and importance of informal versus formal financing (Ayyagari *et al.*, 2011; Ullah, 2019; Wellalage and Fernandez, 2019). Both financing modalities have advantages and disadvantages, and innovative firms can benefit from having both coexist in their financial structure (Degryse *et al.*, 2016). One perspective supports informal financing given that it reduces moral hazard and adverse selection problems through the personal relationship between lender and borrower (Allen *et al.*, 2019). However, this advantage may expose innovators to conflicts of interest over short-term maturity and high compensation. On the contrary, formal financing allows firms to benefit from longer repayment terms and long-term innovation outcomes (Armendáriz and Morduch, 2007; Wu *et al.*, 2016). Thus, firms benefit from a fair assessment of the degree of risk of their innovation project. The development of the formal financial sector has a positive effect on firm-level innovation (Cornaggia *et al.*, 2015).

In light of the challenges associated with innovation financing, theory and empirical evidence (Ayyagari *et al.*, 2011; Gorodnichenko and Schnitzer, 2013; Mare *et al.*, 2021)

support the idea that the type of financing affects firms' decision to innovate as well as the extent of their innovation.

There are two broad categories of empirical studies on innovation financing. The first, examines publicly traded firms in developed economies and is limited to examining debt and/or equity financing separately. The second, considers two categories of innovation financing sources, formal and informal (Ayyagari *et al.*, 2008; Ullah, 2019; Wellalage and Locke, 2020). In this study, we consider a broad spectrum of financing sources to be analyzed separately: banks, internal funds, supplier credits and customer advances, non-banking financial institutions, own funds, others such as family and friends. We will examine the association of these different sources of finance with innovation in MENA and African firms. In other words, the contribution of this paper is to show how heterogeneity of financing sources is associated with greater innovation stimulation of firms in MENA and Africa.

***Hypothesis**: Firms that have the ability to access external financing (such as bank financing, financing from non-bank financial institutions, trade credit, and other sources) are more likely to innovate.*

3. DATA, VARIABLES AND DESCRIPTIVE STATISTICS

3.1 Data

Our main source of data for this study is the World Bank's Enterprise Survey (available at: www.entreprisesurveys.org), using a standard, global methodology. This ensures that comparisons can be made across firms in more than 152 countries surveyed since 2006. Surveys conducted on African countries and some MENA countries before 2011 do not include questions on innovation. Because of this inconsistency, we drop the data for MENA countries conducted before 2011 and retain only the surveys conducted after 2011. This study will finally cover a sample of 45 countries and 35,763 firms between 2011 and 2020. Thus, the sample is composed of 15,662 firms from the MENA region and 20,101 from Africa. In the different models to be estimated, firms with missing information on some variables will be excluded.

The Table no. 1 indicates that the majority of the companies in the sample are industrial companies (49%), while companies in the trade and service sector represent 15.28% and 35.75% respectively. In terms of size, small companies (less than 20 permanent employees) represent 35.87%, medium and large companies represent 31% and 15.15% respectively.

Table no. 1 – Characteristics of the sample

Region	Sectors of activity			Size			Number	
	Industry	Trade	Service	Small (<20)	Average (20-99)	Great (100+)	Companies	Country
AFRICA	8,633	3,815	7,653	11,711	5,900	2,490	20,101	34
MENA	8,883	1,648	5,131	7,556	5,177	2,929	15,662	11
Total	**17,516**	**5,463**	**12,784**	**19,267**	**11,077**	**5,419**	**35,763**	**45**
%	***48.98***	***15.28***	***35.75***	***35.87***	***30.97***	***15.15***	**-**	**-**

Source: www.entreprisesurveys.org, created by the author using STATA 18

3.2 The variables

3.2.1 Measuring business innovation

Following the example of Ayalew *et al.* (2019), Okumu *et al.* (2019), and Oudgou (2021) we will adopt direct measures of the outcome of the innovation. Specifically, these are product/service innovation and process innovation. For product/service innovation (Product), firms were asked if: "*during the last three years, has this establishment introduced new or significantly improved products or services*? If the answer is "yes", the company is considered innovative in terms of products or services. For process innovation (*Process*), firms were asked if: "*during the last three years, has this establishment introduced any new or significantly improved process? (Including: methods of manufacturing products or offering services, logistics, delivery, or distribution methods for inputs, products, or services, or supporting activities for processes*". If the answer is "yes," this indicates that the firm has introduced a process innovation in the last three years as of the WBES survey date. We also construct a variable to measure the firm's decision to invest in innovation via the engagement of research and development (invention) activities. In other words, the firm's ability to invent (Mare *et al.*, 2021). This variable takes the value 1 if the firm has invested in research and development (R&D), otherwise, the variable takes the value 0.

In addition, a company can introduce one type of innovation, two at a time, or invest in research and development. Therefore, the fourth measure of innovation is developed and measures the innovation score (*inovsc*). The innovation score will take four values (from 0 to 3), 0 if the firm is not innovative and the value 3 if the firm is innovative and has introduced both product and process innovation and has invested in research and development. For the robustness tests, the innovation index is constructed by principal component analysis from the three innovation categories (*inovdx*).

3.2.2 Financing sources

The independent variable studied in this paper is the financial structure of firms, measured by the proportion of fixed assets and working capital financed by different sources of finance. Following the example of previous empirical studies, notably those of Ayalew *et al.* (2019), Mare *et al.* (2021) and Wellalage and Locke (2020). In this paper, we choose six sources of financing: internal funds or retained earnings; owner's equity contribution or equity financing; bank financing; financing by non-bank financial institutions (microfinance, finance companies, etc.); trade credit (credit due on purchases from suppliers) and customer advances; other sources of financing (lenders, friends, relatives, etc.). The detailed description of these variables is presented in the Table no. 2.

3.2.3 Control variables

Consistent with the existing literature (Wellalage and Fernandez, 2019; Wellalage and Locke, 2020; Mare *et al.*, 2021; Oudgou, 2021) we consider different independent control variables, including firm-specific characteristics and ownership structure. Firm-specific characteristics include age (age) measured by the number of years between the start of operations and the survey date; firm size (sizewk) measured by the natural logarithm of the

number of permanent employees; manager's years of experience in the industry (experience) and export activity (Export). We consider the financial transparency of the firms by the certification of their financial statements by an external auditor (audit) and the technological capacity of the firm (ICT) as follows Asiedu *et al.* (2013). The ownership structure is taken into account by three variables: the percentage of the firm's capital held by foreign owners (Forgien), by the government (Government) and the participation of women in the firm's capital (gend1) as follows Asiedu *et al.* (2013), Aterido *et al.* (2011), Aterido *et al.* (2013), Cole *et al.* (2019). Table no. 2 shows the measures of the dependent and independent variables used in this study.

Table no. 2 – Variables: definitions and measures

Variables	Definitions and measurements
	Innovation
Product	Takes value 1 if the firm introduced new or significantly improved products or services during the last three years of the survey, 0 otherwise
Process	Takes value 1 if the firm introduced new or significantly improved methods of manufacturing products or offering service during the last three years of the survey, 0 otherwise
R&D	Innovation inputs take 1 if the firm has invested in R&D activities during the last fiscal year, 0 otherwise
INOVDX	Principal Component Analysis (PCA) of Product, Process and spend on R&D
INOVSC	The sum of Product, Process and spend on R&D
Inovscd	Variable dummy takes 1 if the firm introduced at least one type of innovation, 0 otherwise
	Characteristics of the companies
sizewk	Natural logarithm of the number of permanent full-time workers.
Age	The number of years in which the firm began operations to date of the survey
Audit	Percentage of firms with their annual financial statement reviewed by an external auditor
Export	Percent of firms exporting directly or indirectly (at least 10% of sales)
Exper	Years of the top manager's experience working in the firm's sector
ICT	take 1 if the firm license from foreign companies, website and e-mail, 0 otherwise (sum t4a, t5, t6)
	Ownership structure
Forgien	Percentage (%) of the firm's capital held by foreign private owners
Govern-ment	Percentage (%) of the firm owned by the government or state.
Gend-owner	Takes 1 if at least one female among the owners in the firm, 0 otherwise
	Sources of funding
Internal	Proportion of investments and working capital financed by internal funds (%)
Banks	Proportion of investments and working capital financed by banks (%)
Supplier	Proportion of investments and working capital financed by supplier credit (%)
Equity	Proportion of investments financed by equity or stock sales (%)
Nbfi	Proportion of investments and working capital financed by non-bank financial institutions (%)
Others	Proportion of investments and working capital financed by other financing sources (%)

Sources: conducted by authors

3.3 Descriptive statistics

The descriptive statistics for the overall sample studied are shown in Table no. 3. The results indicate that 32% of the enterprises introduced a product or process innovation during the last three years preceding the date of the survey, while 15% of the enterprises surveyed had committed to Research and Development (R&D). Overall, 43% of enterprises are innovative enterprises, having introduced at least one type of innovation (inovcsd). Table no. 3 also shows that MENA and African firms are financed mainly by retained earnings (76.80%)

and 10% of the financing comes from private or public banks. As indicated in the literature review, firms that do not have easy access to external financing resort to internal financing.

MENA and African companies are relatively young with an average age of 18 years and 75% are less than 25 years old. 58% of companies have summary statements certified by an external auditor and 19% are exporting companies. Regarding the ownership structure, on average 8.5% of the companies' capital is foreign owned and 0.65% on average is government owned, knowing that there are companies that are totally foreign or totally government owned (100%); and among the owners for 25% of the companies there is at least one woman. Finally, 93% of the companies use a technological tool (website or e-mail) in their daily business activities and have a foreign license (ICT).

Table no. 3 – Descriptive statistics for the total sample

Variable	N	Mean	SD	Min	P25	Median	P75	Max
Product	34241	32.38	46.79	0.00	0.00	0.00	1.00	1.00
Process	33965	32.19	46.72	0.00	0.00	0.00	1.00	1.00
R&D	34112	15.07	35.78	0.00	0.00	0.00	0.00	1.00
inovsc	35763	75.95	99.48	0.00	0.00	0.00	1.00	3.00
Inovscd	35763	43.00	50.00	0.00	0.00	0.00	1.00	1.00
inovdx	33686	0.00	1.34	-1.05	-1.05	-1.05	1.60	2.95
sizewk	34967	2.99	1.28	0.00	1.95	2.71	3.69	8.29
Age	34728	18.99	15.75	0.00	8.00	15.00	25.00	162.00
Audit	35037	58.70	49.24	0.00	0.00	1.00	1.00	1.00
Export	34582	19.37	39.52	0.00	0.00	0.00	0.00	1.00
Exper	34748	17.79	11.27	0.00	9.00	15.00	25.00	60.00
Foreign	34885	8.55	25.43	0.00	0.00	0.00	0.00	100.00
Government	34908	0.65	5.78	0.00	0.00	0.00	0.00	100.00
Gend-owner	35194	25.49	43.58	0.00	0.00	0.00	1.00	1.00
ICT	35763	93.18	89.02	0.00	0.00	1.00	2.00	3.00
Internal	33857	76.80	31.40	0.00	56.25	100.00	100.00	100.00
Banks	34459	10.63	20.49	0.00	0.00	0.00	12.50	100.00
Supplier	33976	6.86	16.10	0.00	0.00	0.00	0.00	100.00
Equity	11076	4.91	16.69	0.00	0.00	0.00	0.00	100.00
NBFI	33748	1.38	7.29	0.00	0.00	0.00	0.00	100.00
Others	33418	5.08	17.22	0.00	0.00	0.00	0.00	100.00

Source: www.entreprisesurveys.org, created by the author using STATA 18

Table no. 4 shows the different indicators for measuring innovation (see Table no. 2) by country and by region (Africa and MENA). The individual indicators indicate that the most introduced innovations are at the process level, easy to introduce at low cost and low risk to be easily financed. In this sense, the most innovative countries in Africa, where more than 50 percent of firms introduced a product and process innovation, are Ghana, Malawi, Mauritania, Namibia, Tanzania, and Uganda. In the MENA region, innovative firms are located in Djibouti, Malta, and Yemen. On the other hand, fewer firms in both regions are engaged in research and development. The Republic of Central Africa (43.9%), Namibia (46%), and Zimbabwe (30%) have the most R&D-intensive firm samples. Therefore, at the level of the aggregate variables (inovsc and inovdx), a high value of these scores indicates that firms in these countries are more innovative (Central African Republic, Burundi, Ghana, Namibia). The countries least engaged in innovation are Benin, Eswatini, Lesotho, South Africa and Egypt.

Table no. 4 – Innovation Indicators for African and MENA Countries

Country	N	Product	Process	R&D	inovsc	inovscd	inovdx
				Africa			
Benin	150	0.262	0.141	0.128	0.527	0.340	-0.344
Burundi	157	0.465	0.675	0.223	1.363	0.745	0.761
Cameron	361	0.407	0.149	0.105	0.651	0.485	-0.204
Central African republic	150	0.480	0.633	0.439	1.547	0.807	1.001
Chad	153	0.366	0.158	0.118	0.641	0.458	-0.198
Ivory Coast	361	0.365	0.177	0.102	0.634	0.457	-0.206
Congo, Dem. Rep.	529	0.418	0.439	0.235	1.085	0.550	0.400
Eswatini	150	0.277	0.071	0.219	0.553	0.413	-0.368
Ethiopia	1,492	0.395	0.456	0.136	0.983	0.558	0.261
Gambia	151	0.477	0.207	0.099	0.781	0.510	-0.028
Ghana	720	0.515	0.670	0.222	1.396	0.728	0.813
Guinea	150	0.306	0.140	0.099	0.527	0.360	-0.341
Kenya	1,782	0.560	0.488	0.244	1.283	0.699	0.661
Lesotho	150	0.054	0.061	0.041	0.153	0.120	-0.841
Liberia	151	0.450	0.245	0.107	0.801	0.497	0.017
Malawi	523	0.539	0.661	0.221	1.392	0.740	0.849
Mali	185	0.359	0.326	0.144	0.822	0.503	0.031
Mauritania	150	0.553	0.691	0.223	1.460	0.760	0.893
Mozambique	601	0.334	0.173	0.093	0.601	0.408	-0.254
Namibia	580	0.639	0.796	0.465	1.848	0.864	1.482
Niger	151	0.336	0.180	0.106	0.616	0.411	-0.225
Nigeria	2,676	0.498	0.629	0.174	1.263	0.670	0.680
Rwanda	601	0.332	0.376	0.155	0.862	0.491	0.095
Senegal	601	0.476	0.572	0.072	1.110	0.661	0.426
Sierra Leone	152	0.342	0.191	0.112	0.645	0.408	-0.198
South Africa	1,097	0.049	0.025	0.239	0.312	0.271	-0.634
South Sudan	738	0.492	0.416	0.168	1.061	0.686	0.374
Sudan	662	0.554	0.446	0.253	1.230	0.606	0.590
Tanzania	813	0.520	0.598	0.167	1.260	0.683	0.656
Togo	150	0.367	0.153	0.173	0.693	0.453	-0.132
Uganda	762	0.645	0.729	0.279	1.633	0.768	1.153
Zambia	1,321	0.442	0.418	0.200	1.051	0.613	0.351
Zimbabwe	1,199	0.429	0.414	0.296	1.137	0.560	0.465
				MENA			
Djibouti	266	0.351	0.473	0.180	0.970	0.534	0.257
Egypt	7,786	0.115	0.098	0.049	0.261	0.179	-0.707
Israel	483	0.243	0.172	0.170	0.584	0.335	-0.277
Jordan	1,174	0.182	0.155	0.127	0.450	0.300	-0.475
Lebanon	1,093	0.282	0.249	0.122	0.652	0.399	-0.186
Malta	242	0.469	0.203	0.203	0.872	0.612	0.108
Morocco	1,503	0.121	0.149	0.115	0.373	0.243	-0.551
Tunisia	1,207	0.193	0.210	0.132	0.533	0.322	-0.347
West Bank and Gaza	799	0.199	0.202	0.097	0.494	0.309	-0.401
Yemen	353	0.408	0.438	0.137	0.980	0.530	0.242

Source: www.entreprisesurveys.org, created by the author using STATA 18

The Figure no. 1 repeats the results of the Table no. 4 to clearly show the innovation capacity of African firms compared to MENA firms. It is clear that for countries in both regions, investment in research and development is very low and product and process innovation indicators are the most important. On the other hand, firms in Africa have a higher innovation score than firms in the MENA region (inovsc).

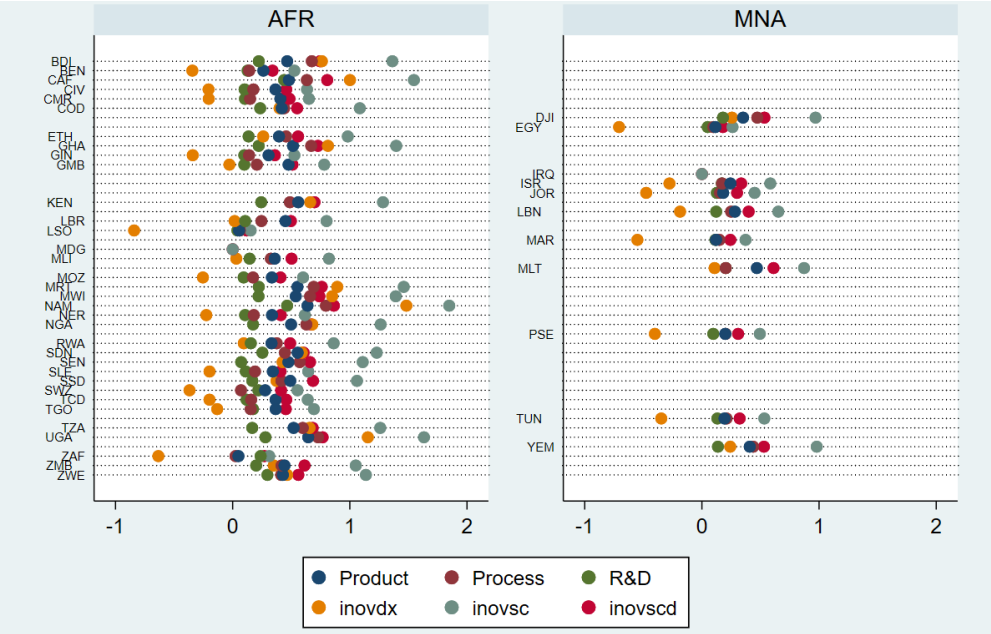

Figure no. 1 – Innovation Indicators for African and MENA Countries
Source: www.entreprisesurveys.org, created by the author using STATA 18

The Table no. 5 shows that the main sources of financing for MENA and African firms are internal funds and retained earnings. For some countries, firms finance more than 90 percent of their needs from retained earnings, most notably the Republic of Congo, Guinea, South Africa, and South Sudan, which are characterized by an underdeveloped financial system. External financing is largely dominated by banks, and a high rate of external financing is synonymous with low recourse to internal funds in several countries: Burundi, Lesotho, Namibia, Togo, Malta, Lebanon, Morocco and Tunisia. Overall, bank financing accounts for less than 26 percent of the financing needs of MENA and African firms. Trade credit is also an attractive source of financing for firms in several countries: Côte d'Ivoire (11.3%), Ghana (10.14%), Kenya (11.09%), Sudan (17.58%), and Tunisia (12%). Lesotho and Jordan make massive recourse to the issuance of shares, while other means of financing (friends and family, ...) are widely used among companies in Lesotho (14.6%), Liberia (10.76%) and Nigeria (16.9%).

Table no. 5 – Financing Modalities in African and MENA Countries

Country	N	Internal	Banks	Supplier	Equity	NBFI	Others
Africa							
Benin	150	71.527	17.457	7.605	4.559	3.588	3.095
Burundi	157	67.753	22.070	7.828	4.597	1.510	1.898
Cameroon	361	72.265	11.341	6.572	5.342	4.162	6.909
Central African	150	75.631	8.833	8.674	7.215	1.661	6.919
Chad	153	81.772	6.675	7.347	4.899	1.083	5.773
Ivory Coast	361	76.785	10.578	11.290	3.074	0.528	1.351
Congo, Dem. Rep.	529	90.145	4.526	4.013	2.353	1.226	2.451
Eswatini	150	69.807	9.928	5.198	7.170	3.686	9.000
Ethiopia	1,492	85.719	8.594	1.599	3.838	0.846	1.145
Gambia	151	85.420	9.354	6.523	5.045	1.262	1.469
Ghana	720	75.028	11.217	10.140	4.538	1.677	1.927
Guinea	150	90.011	7.735	2.381	2.690	0.187	2.188
Kenya	1,782	65.389	17.071	11.095	6.575	1.579	2.758
Lesotho	150	53.443	20.825	5.355	16.190	1.547	14.594
Liberia	151	72.943	10.457	4.555	7.233	2.144	10.765
Madagascar	532	79.311	9.843	7.761	5.055	1.551	4.073
Malawi	523	69.617	14.204	9.459	8.620	2.312	4.775
Mali	185	81.879	12.237	4.243	2.665	0.312	1.285
Mauritania	150	77.250	15.639	3.764	4.495	1.324	2.730
Mozambique	601	83.943	5.605	5.868	3.770	0.741	5.172
Namibia	580	62.814	26.364	2.818	1.667	0.390	3.275
Niger	151	74.243	15.430	7.950	1.181	0.175	4.684
Nigeria	2,676	54.337	8.795	7.330	7.779	3.563	16.900
Rwanda	601	74.440	17.667	4.047	6.956	1.918	2.010
Senegal	601	82.516	8.528	8.184	3.252	1.445	2.592
Sierra Leone	152	87.295	8.461	4.596	3.383	0.846	1.535
South Africa	1,097	93.113	8.278	1.497	5.625	0.353	0.276
South Sudan	738	90.147	5.777	2.968	2.746	0.741	3.694
Sudan	662	78.482	4.908	17.580	2.061	0.719	2.278
Tanzania	813	72.877	11.939	6.285	5.354	2.340	6.650
Togo	150	67.289	20.101	5.463	8.194	3.605	2.946
Uganda	762	76.526	12.322	5.346	7.831	3.698	3.089
Zambia	1,321	81.768	8.863	5.324	3.567	1.409	4.481
Zimbabwe	1,199	79.106	9.221	7.890	4.036	0.770	5.966
MENA							
Djibouti	266	82.664	14.339	2.895	2.143	0.344	1.660
Egypt	7,786	83.892	6.426	6.869	2.217	0.315	6.326
Iraq	756	84.882	4.821	6.766	1.496	0.875	5.605
Israel	483	75.795	19.508	3.063	3.278	0.490	0.875
Jordan	1,174	76.307	12.585	9.548	10.666	0.699	2.392
Lebanon	1,093	75.063	19.252	2.172	2.656	0.264	1.065
Malta	242	61.574	26.848	8.579	2.384	0.757	0.921
Morocco	1,503	65.242	16.861	7.429	7.777	2.435	7.110
Tunisia	1,207	59.707	17.120	11.970	6.663	5.822	4.094
West Bank And Gaza	799	77.712	8.333	9.936	4.577	0.688	5.356
Yemen	353	85.691	6.075	7.846	1.810	0.100	2.863

Source: www.entreprisesurveys.org, created by the author using STATA 18

Figure no. 2 shows the average proportion of financing, excluding equity financing, used in each country of the two regions. Financing through the banking system remains the most widely adopted means of financing and differs significantly from other sources of financing. On the other hand, the use of non-bank financial institutions is lowest in both regions.

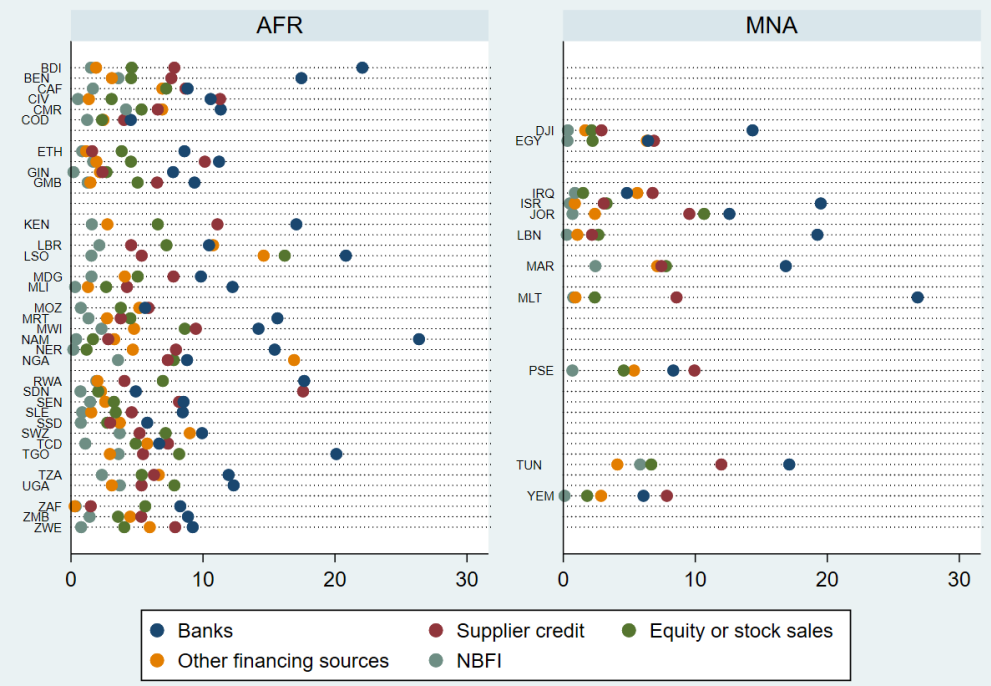

Figure no. 2 – Financing Modalities in African and MENA Countries
Source: www.entreprisesurveys.org, created by the author using STATA 18

3.4 Modeling and analysis strategy

Our empirical strategy is unpacked in three main points. We begin our analysis of the relationship between sources of finance and the innovation behavior of firms in MENA and Africa using a Probit model. The basic model is presented as follows:

$$\Pr(inov_{i,j,t} = 1/0) = \Phi(\alpha_{i,j,t} + \beta.\,Fin_{i,j,t} + \beta X_{i,j,t} + \varepsilon_{i,j,t}) \quad (1)$$

where $inov_{i,j,t}$ is a binary variable that takes 1 if the firm introduced an innovation (product or process), an invention (R&D) or if the firm introduced at least one type of innovation (inovscd), otherwise it takes 0. The subscripts i,j and t denote the firm, country and time respectively. Φ the cumulative standard normal distribution. $Fin_{i,j,t}$ denotes the variables of the funding sources. $X_{i,j,t}$ the vector of control variables shown above (Table no. 2).

In order to estimate the relationship between the sources of financing and the innovation score (inovsc), an ordinal Probit model (oprobit) is used where the dependent variable Y_i will

take 4 modalities from 0 (non-innovative firm) to 3 (firm has introduced three categories of innovation). Y_i This model can naturally be written with a latent variable as a generalization of the simple Probit model:

$$Y_i = \begin{cases} 0 & \text{si } Y_i^* \leq c_1 \\ 1 & \text{si } c_1 < Y_i^* \leq c_2 \\ \dots & \dots \\ m & \text{si } c_m < Y_i^*. \end{cases}$$

where the c_j are in ascending order and where the latent variable Y_i^* follows a linear model:

$$Y_i^* = x_i\beta + \varepsilon_i \quad (2)$$

Thus, we can calculate for all $= 0$ à 3 :

$$Pr(Y_i = j) = Pr(c_j < Y_i^* \leq c_{j+1} = F(c_{j+1} - x_i\beta) - F(c_j - x_i\beta) \quad (3)$$

Finally, the OLS regression is used to estimate the association between a firm's sources of finance and its innovation intensity as measured by its innovation index (inovdx) (see equation 4 below).

$$inovdx_{i,j,t} = \alpha_{i,j,t} + \beta.\,\mathrm{Fin}_{i,j,t} + \beta X_{i,j,t} + \varepsilon_{i,j,t} \quad (4)$$

For all the modeling, we will first deal with the overall sample of the study and secondly, for the robustness of the results, we will divide the sample into two subgroups: firms from Africa and firms from the MENA region. Finally, in all specifications we will include the date of the survey and the sector of activity according to the international industry coding (isic) as dummy variables in order to take into account their fixed effect. Countries are also retained in each estimation to control for possible heterogeneity between MENA and African countries (Coad *et al.*, 2016; Ullah, 2019; Mare *et al.*, 2021). To account for possible correlation of error terms across firms interviewed in each survey, we pool standard errors at the country level.

Before proceeding with the various estimations, we conducted an analysis to detect potential collinearity issues. Table no. 9 in the appendix shows that the correlation coefficients between the different independent variables are very low. Consequently, multicollinearity is not a concern in the context of our estimations.

4. RESULTS AND DISCUSSION

Table no. 6 traces the results of the estimations of the relationship between the different measures of innovation and the sources of financing of the firms in the overall sample. Models M1-M3 show individual innovation indicators (product, process and R&D) while models M4-M6 show aggregate indicators.

Across all models (M1 to M6), the results of Table no. 6 indicate the existence of a positive and significant relationship between bank financing, non-bank financial institution (NBFI) financing and the different innovation indicators. Moreover, commercial credit has a positive effect on product innovation (M1) and if the firm is innovative (M4). These initial results confirm our stated hypothesis: firms that have access to finance are the most likely to

innovate. These results are also consistent with the results of other studies conducted in similar contexts (Ayalew *et al.*, 2019; Bakhouche, 2021; Mare *et al.*, 2021).

Table no. 6 – Relationship between innovation and sources of funding (global sample)

Variables	Product (M1)	Process (M2)	R&D (M3)	Inovscd (M4)	Inovsc (M5)	Inovdx (M6)
sizewk	0.058	0.049	0.111	0.064	0.076	0.064
	(0.010)***	(0.012)***	(0.019)***	(0.011)***	(0.009)***	(0.014)***
Age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Audit	0.001	0.002	0.003	0.002	0.002	0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Export	0.002	0.001	0.003	0.002	0.002	0.002
	(0.000)***	(0.000)***	(0.001)***	(0.000)***	(0.000)***	(0.000)***
Exper	0.001	0.001	-0.002	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Forien	0.000	0.000	-0.001	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)***	(0.001)	(0.000)	(0.001)
Gover	0.001	0.003	0.003	0.003	0.002	0.003
	(0.001)	(0.002)	(0.002)	(0.002)*	(0.001)*	(0.001)**
Gend	0.170	0.129	0.160	0.174	0.170	0.168
	(0.025)***	(0.026)***	(0.026)***	(0.031)***	(0.022)***	(0.023)***
ICT	0.241	0.239	0.293	0.278	0.280	0.283
	(0.024)***	(0.028)***	(0.028)***	(0.029)***	(0.026)***	(0.037)***
Banks	0.003	0.003	0.003	0.003	0.003	0.003
	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Supplier	0.003	0.001	0.001	0.003	0.002	0.002
	(0.001)**	(0.001)	(0.001)	(0.001)*	(0.001)	(0.001)
Equity	0.000	0.000	0.001	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NBFI	0.003	0.007	0.005	0.005	0.005	0.006
	(0.001)**	(0.002)***	(0.001)***	(0.002)***	(0.001)***	(0.002)***
Others	-0.001	-0.000	0.000	-0.000	-0.000	0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
cut1					-0.346	
					(0.059)***	
cut2					0.369	
					(0.055)***	
cut3					1.343	
					(0.052)***	
_cons	-0.361	-0.048	-1.021	0.206		0.541
	(0.063)***	(0.072)	(0.073)***	(0.117)*		(0.080)***
N	23,148	23,009	23,091	23,216	24,104	22,898
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
ISIC FE	YES	YES	YES	YES	YES	YES

Note: * p<0.1; ** p<0.05; *** p<0.01

Table no. 6 also indicates firm characteristics that are associated with firm innovation behavior in MENA and Africa. Indeed, large firms are more innovative than small firms (at the 1% threshold). Exporting firms and firms with certified statements of accounts are more engaged in innovation activities (at the 1% threshold). As regards ownership structure, firms with female owners are more innovative (Oudgou, 2021). In terms of ownership structure, government involvement has a positive effect on aggregate innovation indicators. The use of technology (foreign license, e-mail, web-site, ...) has a positive effect on innovation. In this sense, the results associated with technology use (ict), certification (audit) and export orientation (export) can collectively reflect a quality of the firm's human capital (Bakhouche, 2021; Cirera *et al.*, 2021). The adoption of these managerial characteristics requires a skilled, competent and more experienced workforce. The increase in foreign ownership (Forgien) reduces the probability of investing in R&D (Oudgou, 2021). This result is comparable to those of Wellalage and Locke (2020) which supports the hypothesis that foreign participation supports hard innovation more than soft innovation.

In order to take into account, the specificities of each region and for the purpose of validating the above results (Table no. 6), the overall sample is divided into two subsamples representing firms from African countries on the one hand and firms from MENA countries on the other. Within this framework, the same estimates were rerun on each region and the results by region are reported at the Table no. 7.

The estimation results indicate that bank financing and non-bank financial institution (NBFI) financing positively impact the innovation activities of firms in Africa and the MENA region. However, in the MENA region, trade credit appears to be a primary source of financing for innovation activities. On the other hand, equity financing and other means of financing are important for product innovation only in the MENA region. It can be concluded that MENA firms benefit from a diversified financing offer compared to African countries. These results suggest that the diversity of financing sources could be a key factor in the intensity of a firm's pursuit of innovation (Allen *et al.*, 2019; Mare *et al.*, 2021). These findings are similar to those of Ayalew *et al.* (2019) in a study of firm innovation in Africa where he found that sources of finance have a positive and significant effect on the probability of innovating. The results of these estimates also support our hypothesis. The coefficients of the other variables (not reported in the table) remain unchanged.

One of the major theoretical controversies concerning the study of the sources of financing for innovation is related to the size of the firms. Table no. 8 presents the different econometric estimates of the sources of innovation finance in MENA and Africa by firm size. Overall, the three categories of firms (small, medium, and large) finance their various innovation activities mainly through banks in the MENA region and Africa. Unlike large firms, non-bank financial institutions (NBFIs) are an extremely important source of financing for small and medium-sized firms. This is because small firms face difficulties in accessing finance due to high informational opacity. Large companies use NBFIs to finance R&D activities whose outcome is uncertain and spread over several years. It is possible that this financing constitutes a kind of hedge against the risks of failure of R&D investments for large firms. This type of investment with uncertain results is a source of information asymmetry for banks and they generally refuse to grant financing.

Table no. 6 – Relationship between innovation and sources of finance: Africa Vs MENA

Variables	Product (M1)	Process (M2)	R&D (M3)	Inovscd (M4)	Inovsc (M5)	Inovdx (M6)
			AFRICA			
Banks	0.003	0.002	0.003	0.003	0.003	0.003
	(0.001)**	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Supplier	0.003	0.001	0.000	0.002	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Equity	-0.000	0.001	-0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NBFI	0.004	0.006	0.005	0.005	0.005	0.006
	(0.002)**	(0.002)***	(0.001)***	(0.002)**	(0.002)***	(0.002)***
Others	-0.002	-0.000	0.001	-0.001	-0.001	-0.001
	(0.001)**	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
_cons	-0.376	-0.101	-0.998	0.095		0.434
	(0.058)***	(0.057)*	(0.080)***	(0.059)		(0.060)***
N	14,209	14,114	14,164	14,251	14,520	14,039
			MENA			
Banks	0.003	0.004	0.003	0.004	0.004	0.004
	(0.001)***	(0.001)***	(0.001)**	(0.001)***	(0.001)***	(0.001)***
Supplier	0.005	0.003	0.002	0.004	0.004	0.003
	(0.001)***	(0.002)	(0.001)**	(0.002)**	(0.001)***	(0.001)*
Equity	0.002	-0.001	0.004	0.003	0.002	0.001
	(0.001)*	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
NBFI	0.004	0.008	0.006	0.007	0.007	0.006
	(0.001)***	(0.002)***	(0.003)**	(0.002)***	(0.002)***	(0.002)**
Others	0.003	-0.001	-0.002	0.001	0.001	0.001
	(0.001)***	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)
_cons	-0.912	-0.484	-1.906	-1.408		-0.225
	(0.112)***	(0.118)***	(0.110)***	(0.160)***		(0.105)*
N	8,939	8,895	8,927	8,965	9,584	8,859
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
ISIC FE	YES	YES	YES	YES	YES	YES

Note: * p<0.1; ** p<0.05; *** p<0.01

Table no. 7 – Financing of innovation by company size

Variable	Product (M1)	Process (M2)	R&D (M3)	Inovscd (M4)	Inovsc (M5)	Inovdx (M6)
			Small businesses			
Banks	0.003	0.003	0.003	0.003	0.003	0.003
	(0.001)**	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Supplier	0.003	0.001	0.002	0.003	0.002	0.002
	(0.001)***	(0.002)	(0.001)	(0.001)**	(0.001)*	(0.001)
Equity	-0.001	0.000	0.000	0.000	-0.000	-0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
NBFI	0.004	0.006	0.005	0.005	0.005	0.006
	(0.002)**	(0.003)**	(0.002)**	(0.002)**	(0.002)***	(0.002)**
Others	-0.001	-0.001	0.001	-0.001	-0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
_cons	-0.183	-0.131	-0.942	0.239		0.526
	(0.115)	(0.106)	(0.110)***	(0.186)		(0.120)***
N	12,742	12,663	12,719	12,782	13,431	12609

Variable	Product (M1)	Process (M2)	R&D (M3)	Inovscd (M4)	Inovsc (M5)	Inovdx (M6)
Medium-sized companies						
Banks	0.002	0.003	0.002	0.003	0.003	0.003
	(0.001)**	(0.001)***	(0.001)***	(0.001)***	(0.001)***	(0.001)***
Supplier	0.004	0.000	0.000	0.002	0.002	0.001
	(0.002)**	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Equity	0.000	0.001	0.002	0.003	0.001	0.001
	(0.001)	(0.001)	(0.001)*	(0.001)**	(0.001)*	(0.001)
NBFI	0.003	0.009	0.004	0.007	0.005	0.006
	(0.002)	(0.002)***	(0.002)	(0.002)***	(0.002)***	(0.002)***
Others	-0.001	0.000	0.000	0.001	-0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
_cons	-0.271	0.074	-0.459	0.488		0.794
	(0.116)**	(0.163)	(0.218)**	(0.154)***		(0.127)***
N	7,162	7,150	7,140	7,214	7,395	
Large companies						
Banks	0.004	0.005	0.003	0.005	0.004	0.005
	(0.001)***	(0.001)***	(0.001)**	(0.002)***	(0.001)***	(0.001)***
Supplier	0.002	0.004	-0.001	0.001	0.002	0.003
	(0.002)	(0.002)*	(0.001)	(0.002)	(0.002)	(0.002)
Equity	0.002	-0.000	0.000	0.001	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
NBFI	-0.002	0.004	0.010	0.001	0.004	0.004
	(0.003)	(0.004)	(0.003)***	(0.003)	(0.003)	(0.003)
Others	0.001	-0.002	-0.004	-0.003	-0.002	-0.001
	(0.001)	(0.002)	(0.003)	(0.001)**	(0.001)	(0.001)
_cons	-0.816	-0.492	-1.430	-0.273		0.014
	(0.134)***	(0.229)**	(0.291)***	(0.250)		(0.163)
N	3,207	3,145	3,185	3,201	3,278	3172
Year FE	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES
ISIC FE	YES	YES	YES	YES	YES	YES

Note: * p<0.1; ** p<0.05; *** p<0.01

Innovation firms and projects have unique characteristics: intangibility, random returns, moral hazard, and high information asymmetry, which directly affect the choice of a source of financing and access to external sources of finance (Lengnick-Hall, 1992; Hall and Lerner, 2010; Kerr and Nanda, 2015; Ayalew *et al.*, 2019).This is one reason why innovative firms in MENA and Africa show a low proportion of equity financing usage. In this context, banks would normally be the primary source of external financing since they dominate the financial systems. In this respect, the results of the different estimates confirm the fact that bank financing is the most important external source for financing innovation. About 10.63% of the total financing of innovative firms comes mainly from banks (Table no. 3), a contribution that remains quite low compared to the contribution of the sector to the financing of the economies of Africa and the MENA region. Furthermore, the results show the importance of non-bank financial institutions (NBFIs) in financing innovation, despite a very low recourse,

on average 4.9%, of firms to these organizations (Table no. 3). This is due to the fact that these institutions (microfinance, credit unions, finance companies, etc.) represent a small part of the financial systems and generally only finance projects for individuals or the creation of very small inclusive enterprises. However, over the past decade, non-bank financial institutions (NBFIs) have oriented their activities towards financing innovative entrepreneurship projects. The development of this sector could bring greater benefits to innovation than other sources of financing.

5. CONCLUSION

Innovation is a key factor for the growth and competitiveness of companies and for the development of economies. The financial literature on innovation has shown the importance of financing in the promotion, intensity and quality of innovation in various contexts. In this work, we tried to test the hypothesis of the importance of heterogeneity of financing sources on innovation, invention, and innovation intensity of firms in the MENA region and Africa. In this framework, a sample of over 35,000 firms from the World Bank Enterprise Survey covering the period 2011-2020 was used.

The main results of the various econometric estimations indicate that bank financing and funding from non-bank financial institutions (NBFIs) have a positive impact on the innovation behavior of firms in the MENA region and Africa. This suggests that access to these financing modalities increases the likelihood of firms in these regions engaging in innovation.

Furthermore, trade credit or inter-company credit also represents a significant source of innovation financing for firms in the MENA region. It is common in the region for businesses to engage in credit-based transactions. However, extending supplier payment periods may have negative effects on innovation and disrupt firms' procurement strategies.

In terms of magnitude, financing through NBFIs has the most significant impact on innovation compared to other financing modalities. Regular access to this form of financing could provide a competitive advantage for firms. Based on this finding, we strongly recommend that governments promote the development of non-bank financial intermediaries, as this could further enhance innovation efforts among businesses in the MENA region and Africa.

The study has certain limitations. In fact, we included all countries in the MENA region and Africa in the econometric estimations, either together or separately, without considering the economic development level of each country within the panel. It would therefore be valuable to incorporate additional macroeconomic indicators, as they may influence the innovation efforts of the firms analyzed.

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ANNEX

Table no. 9 – Correlation matrix of independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	1												
(2)	0.256	1											
(3)	0.273	0.138	1										
(4)	0.287	0.0885	0.0924	1									
(5)	0.187	0.447	0.169	0.0722	1								
(6)	0.164	-0.0257	0.0757	0.152	-0.0289	1							
(7)	0.0961	0.0759	0.0211	0.0737	0.00131	0.0115	1						
(8)	0.0698	0.0588	0.0853	0.0672	0.0306	0.0245	0.0129	1					
(9)	0.399	0.137	0.318	0.219	0.102	0.149	0.0387	0.143	1				
(10)	0.0933	0.0481	0.0868	0.0837	0.0376	0.00826	0.0172	0.0705	0.103	1			
(11)	0.0046	0.0132	0.00578	0.0287	0.0321	-0.00283	0.00639	0.0204	0.00523	-0.0134	1		
(12)	-0.0129	-0.0180	-0.00820	0.0597	-0.0471	0.0208	0.0362	0.0277	0.0151	0.0419	0.00772	1	
(13)	-0.0221	-0.0234	-0.0475	0.0607	-0.0213	-0.00503	0.0316	0.0517	-0.0140	0.0300	0.0268	0.0302	1
(14)	-0.0546	-0.0177	-0.0617	0.0514	-0.0395	-0.00918	0.0414	-0.0172	-0.102	-0.0543	-0.0237	0.0261	0.00951

Note: Sizewk (1); Age (2); Audit (3); Export (4); Exper (5); Forgien (6); Government (7); Gend-owner (8); ICT (9); Banks (10); Supplier (11); Equity (12); NBFI (13); Others (14).

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Regional Media Sentiment Analysis of AI in Entrepreneurship: A Comparative Study of the UK, USA and Europe

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Abstract: The rapid growth of the global economy is increasingly driven by innovation, with artificial intelligence being at the core of business processes transformation. As AI continues to reshape industries, the entrepreneurial economy must adapt to these changes to stay competitive. Often, media narratives influence perceptions and guide decision-making. Our study provides comparative sentiment analysis of how AI integration into entrepreneurship is portrayed by regional media in the UK, USA, and Europe. Analyzing 905 news articles collected via GNews API between August 5, 2024 and April 1, 2025, we applied the VADER tool to assess sentiment in headlines and article descriptions on a daily and weekly basis. The results reveal regional differences and distinct sentiment patterns between headlines and content, highlighting a complex media narrative around AI adoption. By associating media coverage to entrepreneurial perception, our research contributes to the literature on technology-driven economic changes and offers a foundation for future studies exploring the intersection of media news, innovation, and business strategy.

Keywords: sentiment analysis of news; entrepreneurship; artificial intelligence.

JEL classification: L26; O33.

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1. INTRODUCTION

As technology evolves, the innovation process becomes more accessible for companies. Artificial intelligence (AI) is playing a key role in driving competitive advantage and improving operational efficiency. Yet, AI adoption depends on factors such as company size, organizational culture, and technological readiness. Companies face challenges such as the need for IT infrastructure, digital skills, and strong leadership support (Ghani *et al.*, 2022; Kinkel *et al.*, 2022). Additionally, external pressures, such as government regulations and competitive dynamics, along with employee acceptance and the need for upskilling, further affect AI integration (Horani *et al.*, 2023; Vogel *et al.*, 2023).

Beyond these internal factors, media coverage is another powerful influence on corporate decisions and public perceptions of AI. Media outlets shape how AI is viewed, either as a beneficial innovation or a potential risk. Different channels, from social media to traditional newspapers and television, contribute to varying levels of public trust and caution (Cui and Wu, 2021; Neyazi *et al.*, 2023). These narratives shape how entrepreneurs view the risks and benefits of AI.

Our study is centered around an important research question: "How do media portrayals of AI differ across the UK, USA, and Europe, and what implications do these differences have for entrepreneurial decision-making and technological adoption?" To explore this question, we conduct empirical analysis. Our approach involves a comparative sentiment analysis that quantitatively evaluates the tone of media coverage regarding AI's transformative role in the economy. Through this, we aim to identify regional trends showing how varying media narratives may influence entrepreneurial perceptions and actions.

The decision to focus on the UK, USA, and Europe is intentional, reflecting their unique cultural attitudes and regulatory environments. The USA, has a rapid pace technological advancement environment. The UK, on the other hand, tends to take a more measured approach, weighing the potential benefits of innovation against potential risks. Meanwhile, European media often includes more regulatory and ethical considerations. Additionally, a common thread among all these regions is the shared language of English, which improves data availability.

By concentrating on these regions, our study addresses a gap in the existing literature, which has often prioritized the technical and organizational aspects of AI adoption over the influence of media in shaping public and entrepreneurial perceptions. The insights generated through our analysis contribute to the academic and business debate on AI-driven innovation. Moreover, we hope that our study will serve as a foundation for future research exploring the long-term effects of media sentiment on technological adoption and innovation.

2. NEWS MEDIA INFLUENCE

News media has a strong influence on how people see the world, especially in today's competitive and diverse markets. As news organizations compete for attention and revenue, they have adopted a mix of traditional and social media. This change has led to more personalized content, especially on regional platforms, making the news more engaging for consumers. People also participate more in creating and discussing news, which increases the media's impact. News outlets not only share information but also strengthen regional interests and shape public attitudes (Kerrigan and Graham, 2010).

Economic news, particularly about downturns or recessions, can significantly affect consumer confidence, regardless of the actual economic situation. For example, a study in the Netherlands showed that negative economic news could lower confidence even during stable times. This highlights the media's power in shaping how people feel and behave, especially in areas sensitive to economic changes (Hollanders and Vliegenthart, 2011; Damstra and Boukes, 2021). Also, studies have found that bias in economic reporting can influence how people feel about the economy and lead to changes in financial and political decisions. For example, Dutch newspapers sometimes add a "spin" to economic news to make it more memorable, which can affect how consumers view the economy. Even when this spin doesn't match the actual situation, it can cause a short-term drop in consumer confidence. Negative or dramatic news can make people more pessimistic about the economy, even if conditions are stable (Alsem *et al.*, 2008).

News media also shapes how people view innovation and technology. Urban areas, where economic growth is often tied to technological progress, tend to get more positive media coverage of new technologies. This helps speed up the adoption of these technologies in cities. In contrast, areas that focus less on innovation might see slower adoption because of how the media presents technological developments (Toole *et al.*, 2012; Sama, 2019; Ozgun and Broekel, 2021).

Media hype, as illustrated by the Gartner Hype Cycle, demonstrates how new technologies – such as AI, blockchain, and electric vehicles – experience phases of high expectations followed by disappointment and eventual productivity. While such hype can generate significant attention and investment, it may also lead to disillusionment when expectations are unmet (Bakker, 2010; Morini, 2016). Media hype can also influence government policies around technological innovations. Hype cycles can speed up or delay the creation of regulations, especially for areas like AI or green technologies. Some experts have noticed that AI hype is used to attract funding or shape policy, but it can also divert attention from important societal issues, making regulation more complex (Züger *et al.*, 2023).

The role of media becomes even more complex in the context of AI. AI hype in journalism can distort the understanding and regulation of technologies by emphasizing short-term productivity gains over journalism's civic role, thereby obscuring critical debates on ethics, accuracy, and societal implications (Spyridou and Ioannou, 2025). At the same time, a comprehensive review has highlighted that AI is rapidly transforming digital media through automation, personalization, and content curation. Despite these enhancements in creativity and efficiency, AI also presents challenges such as privacy concerns, job displacement, and algorithmic bias – underscoring the importance of responsible adoption. Public trust in AI is significantly influenced by how media frames its ethics and controllability. Long-term analysis of media coverage, such as that of New York Times articles, reveals that both the tone and perceived morality of AI critically impact public acceptance and subsequent technology adoption (Khan, 2022). Moreover, visual media representations – especially in German outlets – often depict AI with futuristic or dystopian imagery, amplifying either enthusiasm or skepticism depending on whether these portrayals evoke hope or fear (Krause, 2024).

Media coverage thus serves a double-edged role in innovation. While increased visibility can attract investment and stimulate technological progress, excessive scrutiny or an overemphasis on short-term outcomes may divert resources away from long-term research and development efforts, particularly in fast-evolving sectors like AI and blockchain (Dai *et al.*, 2021). Furthermore, the gap in media coverage between developed and developing countries increases the "digital divide" and affects the adoption of new technologies. Media

access and content availability about technologies like AI and blockchain often favor developed countries. In developing regions, limited access to media and technology slows down the spread of new technologies. Media in developed countries sometimes exaggerates the impact of emerging technologies, while media in developing areas may not have the resources to cover them in detail. This difference can further widen the digital divide (Freeman and Freeland, 2015). Local media markets also affect how people access and understand news. In the U.S., for example, people in large cities have more access to national and international news, while rural areas rely mostly on local media. This creates different "information cultures" in various regions, where local media strongly influences what people know and how they act (Althaus *et al.*, 2009).

3. SENTIMENT ANALYSIS

Sentiment analysis, or opinion mining, involves extracting emotions and opinions from text. A major aspect of this techniques is web content mining, which gathers information from online sources (Atanasova *et al.*, 2010). This is particularly valuable in areas like financial news, where analyzing online content helps organizations understand public sentiment and market trends.

Provost and Fawcett provided further methodological clarity by detailing how open-source libraries in Python and R can be utilized to vectorize text data, train classification models, and score sentiments without resorting to expensive software solutions (Provost and Fawcett, 2013). By utilizing these tools, companies can make better-informed decisions based on data insights. This approach is also, widely applied in market research, where companies track customer preferences and emotions, adjusting strategies based on feedback (Pang and Lee, 2008; Cambria *et al.*, 2013).

Research shows how sentiment analysis aids entrepreneurship. Palahan (2022) examines how sentiment analysis tools help entrepreneurs by extracting important business sentiments from a large number of news articles. This research highlights the value of AI in helping entrepreneurs make decisions in global trade and investment, showing its practical application in business intelligence (Palahan, 2022). Similarly, Shirsat *et al.* (2017) used sentiment analysis to categorize news articles based on their positive or negative tone, focusing on business and entrepreneurship news from BBC. Their study shows that computational techniques like tokenization and stop-word removal can provide useful insights into business trends (Shirsat *et al.*, 2017).

Complementing these approaches, Waters *et al.* (2021) also contribute to this area by analyzing the emotions of entrepreneurs on Twitter, applying sentiment scoring to measure the emotional expressions of social entrepreneurs. They found that social entrepreneurs tend to express more positive emotions, and those transitioning to entrepreneurship show more positive sentiments in online conversations. This is helpful for understanding how AI tools can analyze entrepreneur behavior on social media (Waters *et al.*, 2021).

4. METHODOLOGY

To start our sentiment analysis for the USA, UK, and European regions, we divided the process into three steps.

The first step involved selecting relevant keywords for our news search. We conducted a brief literature review to identify the potential benefits and challenges of AI adoption (Table no. 1). Our findings guided the keyword selection.

Table no. 1 – Potential benefits and challenges of AI adoption

Potential benefits and challenges	References
AI business growth automation	Soni *et al.* (2019); Malik *et al.* (2022); Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023); Paul *et al.* (2023); Rubab and Forman Christian (2023)
AI optimizing business processes	Nigmatov and Pradeep (2023); Paul *et al.* (2023); Rubab and Forman Christian (2023)
AI-enhanced decision making in business	Cubric (2020); Nigmatov and Pradeep (2023); Rubab and Forman Christian (2023)
AI reshaping business models	Soni *et al.* (2019)
AI driving innovation in business	Soni *et al.* (2019); Cubric (2020); Malik *et al.* (2022); Modhoriye *et al.* (2023); Rubab and Forman Christian (2023)
AI market deployment strategies	Soni *et al.* (2019)
AI in improving competitiveness for SMEs	Paul *et al.* (2023)
AI improving business competitiveness	Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023); Paul *et al.* (2023); Rubab and Forman Christian (2023)
AI-powered resource allocation optimization	Cubric (2020); Nigmatov and Pradeep (2023); Paul *et al.* (2023)
AI-driven revenue streams in business	Nigmatov and Pradeep (2023); Paul *et al.* (2023)
AI-enhanced customer experience personalization	Soni *et al.* (2019); Cubric (2020); Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023); Paul *et al.* (2023); Rubab and Forman Christian (2023)
AI boosting operational efficiency	Soni *et al.* (2019); Cubric (2020); Rubab and Forman Christian (2023)
AI predictive analytics in business	Cubric (2020); Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023); Paul *et al.* (2023); Rubab and Forman Christian (2023)
AI job security concerns	Soni *et al.* (2019); Cubric (2020); Malik *et al.* (2022)
AI job displacement in business	Soni *et al.* (2019); Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023)
Algorithmic bias in AI adoption	Cubric (2020); Nigmatov and Pradeep (2023)
AI cybersecurity vulnerabilities	Cubric (2020); Modhoriye *et al.* (2023); Nigmatov and Pradeep (2023)
AI privacy breaches in business	Cubric (2020); Malik *et al.* (2022); Modhoriye *et al.* (2023)
AI stress among employees	Malik *et al.* (2022); Nigmatov and Pradeep (2023)
AI increasing complexity in business operations	Cubric (2020); Malik *et al.* (2022); Paul *et al.* (2023)
AI employee trust issues	Soni *et al.* (2019); Cubric (2020)
Ethical challenges of AI in business	Soni *et al.* (2019); Nigmatov and Pradeep (2023); Rubab and Forman Christian (2023)

Source: own creation based on literature review

The keywords we used were simplified versions of the potential benefits and challenges identified in the literature.

Figure no. 1 – Keywords
Source: own creation

The second step involved using a free news API to gather relevant news articles. GNews API is a RESTful service that enables users to search and retrieve current and historical news articles worldwide. It offers two primary endpoints: a search function for querying articles based on keywords, and a top headline feature that provides trending news categorized by topics such as general, world, business, technology, entertainment, sports, science, and health. The API supports filtering by language and country, delivering results in JSON format. It has a free plan up to 100 request per day and additional paid ones (GNews, 2015).

We filter the result for each region and performed the search using Python and its libraries. The code imported libraries to manage HTTP requests (requests), data manipulation (pandas), time management (time), and interaction with the operating system (os). An API key was used for authentication, and the GNews API base URL was set up to fetch the necessary news data.

```
import requests
import pandas as pd
import time
import os

# GNews API token and base URL
api_token = "API_KEY"
base_url = "https://gnews.io/api/v4/search"
```

Figure no. 2 – Python libraries
Source: own creation

We collected titles and descriptions of 905 news articles between August 5, 2024, and April 1, 2025. These articles came from three regions: the US with 340 articles, Europe with 275 articles and UK with 290 articles. All this data was saved in Excel for further analysis.

Before analyzing how positive or negative the articles were using the VADER (Valence Aware Dictionary for Sentiment Reasoning) tool, we remove any duplicates. This tool helps us measure the sentiment of text, whether it's positive, negative, or neutral. VADER gives a score ranging from -1 (very negative) to +1 (very positive). We applied it to both the titles and descriptions of the articles.

After getting the sentiment scores, we compared the sentiment across the USA, UK, and Europe using bar charts, which helped us see the differences in how AI was discussed in each region. We also created charts to show how these scores changed each day and week. This allowed us to track how AI was being portrayed over time.

5. RESULTS

The sentiment analysis scores displayed in Figure no. 3, indicate that both titles and descriptions across all regions generally lean toward a positive sentiment, even if only marginally, with scores that remain close to zero. Nevertheless, descriptions generally exhibit a more positive sentiment than titles across all regions.

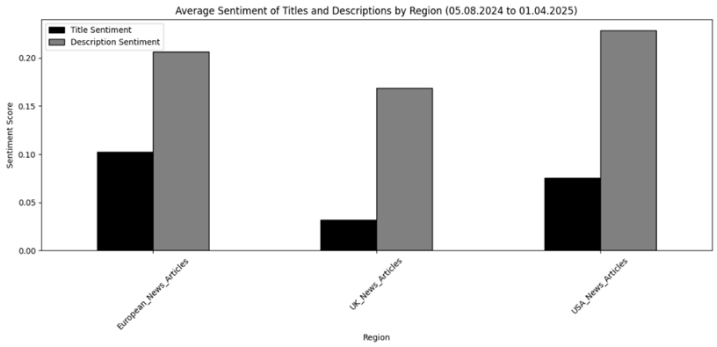

Figure no. 3 – Average sentiment of titles and description by region
Source: own creation

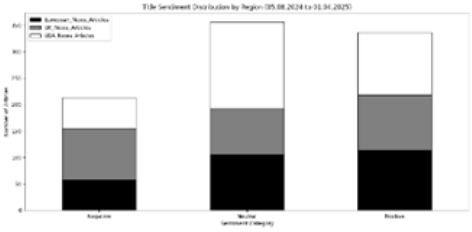

Figure no. 4 – Title sentiment distribution by region
Source: own creation

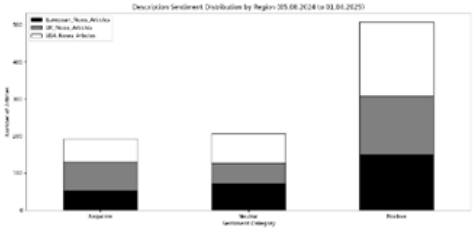

Figure no. 5 – Description sentiment distribution by region
Source: own creation

Figures no. 4 and no. 5 illustrate the distribution of title and description sentiment across European, UK, and USA news articles.

From these distributions, a few patterns emerge. Europe and the USA feature titles leaning more toward positive and neutral sentiment, while UK titles show a relatively higher share of negative sentiment. Additionally, descriptions across all three regions skew towards positive than their corresponding titles. This can be noticed in the UK and the USA, where half or more descriptions are categorized as positive. Overall, these results reinforce that news article descriptions tend to contain more positive language than the often more concise titles.

Overall, media portrayals of artificial intelligence tend to be neutral-to-positive. While headlines often use negative or attention-grabbing language, especially in the UK, the articles' content generally presents a more optimistic view of AI. This suggests that media outlets aim to balance the initial impact of headlines with content that emphasizes the benefits and potential of AI, despite critical tones in the titles.

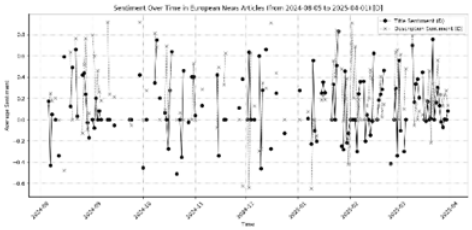

Figure no. 6 – Sentiment over time in European articles (days)
Source: own creation

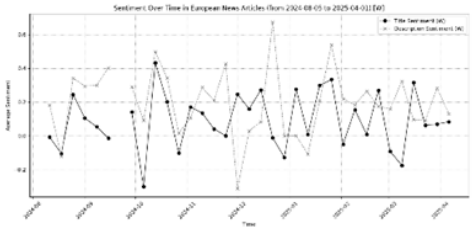

Figure no. 7 – Sentiment over time in European articles (weeks)
Source: own creation

Both the daily and weekly sentiment trends in European news articles show similar patterns of fluctuation, but differ in the timing and intensity of their peaks and troughs. In both cases, the description sentiment tends to show more extreme values compared to the title sentiment.

In the daily analysis of European News Articles, titles showed more volatile sentiment – bottoming at -0.51 (October 21, 2024) and peaking at 0.83 (January 25, 2025) – while descriptions ranged from a high of 0.92 (September 29, 2024) to a low of -0.65 (January 9, 2025). The weekly analysis displays a more moderated sentiment, with title scores between -0.30 (October 6, 2024) and 0.43 (October 13, 2024), and descriptions between -0.31 (December 1, 2024) and 0.67 (December 22, 2024).

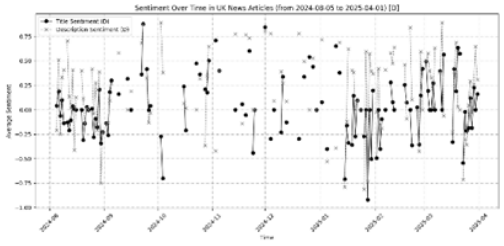

Figure no. 8 – Sentiment over time in UK articles (days)
Source: own creation

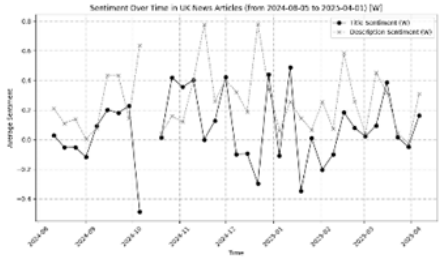

Figure no. 9 – Sentiment over time in UK articles (weeks)
Source: own creation

Combined with previous findings that titles and descriptions predominantly display neutral-to-positive sentiment results suggest that while headlines occasionally adopt sharper, negative tones to capture attention, the broader media narrative on artificial intelligence remains measured and slightly optimistic.

Overall, the daily trends capture sharper, more frequent shifts in sentiment, whereas the weekly trends show a smoother, averaged perspective of the sentiment changes over time.

The coverage of AI in the UK generally leans toward a neutral-to-positive portrayal, although there are notable negative spikes that highlight ongoing concerns about potential risks. This combination of skepticism and optimism reflects a media environment that recognizes AI's transformative potential while remaining mindful of its challenges.

Daily, sentiment scores for titles ranged from a strongly positive 0.88 on September 23, 2024, to a particularly negative -0.92 on January 28, 2025. Descriptive sentiment scores vary similarly, reaching a high of 0.89 on October 3, 2024, and a low of -0.81 on January 26, 2025. When viewed weekly, sentiment appears more moderate: title scores dipped to -0.49 on October 6, 2024, and peaked at 0.49 on January 12, 2025. Meanwhile, descriptive scores ranged between a high of 0.78 on December 22, 2024, and a low of -0.03 on March 30, 2025.

The daily coverage of AI shows significant fluctuations influenced probably by specific events or topics. However, the weekly patterns indicate a more consistent narrative.

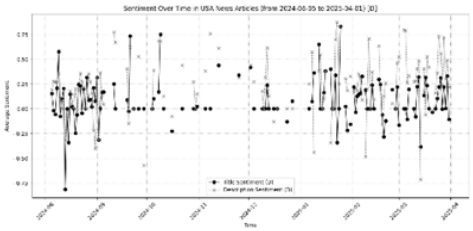

Figure no. 10 – Sentiment over time in USA articles (days)
Source: own creation

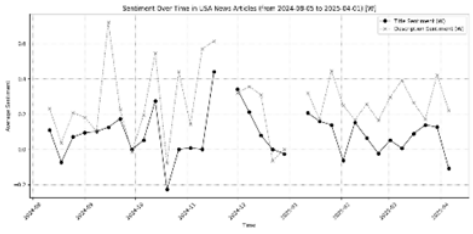

Figure no. 11 – Sentiment over time in USA articles (weeks)
Source: own creation

Both the daily and weekly sentiment trends in USA news articles exhibit fluctuations, but the daily analysis shows more shifts compared to the weekly analysis. In both cases, the findings align with trends in European and UK articles, where descriptions tend to be more positive.

In the day-to-day analysis, USA News Articles show notable swings, with title sentiment dipping to -0.81 (August 13, 2024) and rising as high as 0.83 (January 25, 2025). Descriptions follow a similarly broad range, peaking at 0.88 (January 23, 2025) and bottoming at -0.71 (March 14, 2025). These daily trends reflect sharper, more frequent sentiment changes in the news articles. In contrast, the weekly analysis shows a smoother trend. Title sentiment moves from 0.44 (November 17, 2024) to -0.23 (October 20, 2024), while description sentiment ranges from 0.72 (September 15, 2024) to -0.08 (October 20, 2024). This smoother pattern indicates that while individual daily reports can be highly positive or negative, the overall week-by-week portrayal skews neutral-to-positive.

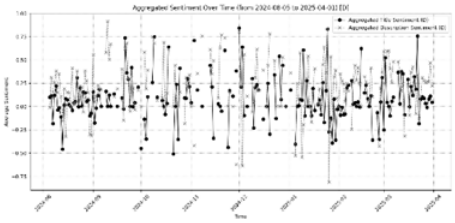

Figure no. 12 – Aggregated sentiment over time (days)
Source: own creation

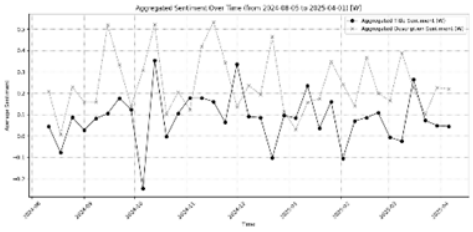

Figure no. 13 – Aggregated sentiment over time (weeks)
Source: own creation

These aggregated patterns align with observations in Europe, the UK, and the USA individually: while titles may occasionally spike sharply – positive or negative – descriptions tend to offer a more consistently positive or balanced view.

Headlines are often crafted to grab attention quickly, using sensational or extreme language. While headlines aim for immediate impact and engagement, often exaggerating sentiment, the body of the article tends to provide more detailed context. This gap in sentiment reflects a common editorial strategy: using headlines to spark interest while employing body text for detailed analysis and context.

European headlines may touch on ethical or regulatory challenges but ultimately focus on AI's innovative potential and its role in economic growth. In contrast, UK coverage displays a more divided sentiment in headlines, often leaning towards negative framing. This inclination may stem from cultural tendencies toward caution. Factors like post-Brexit uncertainty deepen this critical tone. However, similar to Europe, the descriptive content in UK articles tends to be more optimistic. Meanwhile, in the USA, while headlines occasionally emphasize the risks associated with AI, descriptions generally present a strong neutral-to-positive outlook. This reflects the country's strong tech industry and innovation-driven economy, which highlights AI's transformative potential despite some negative sentiments in headlines.

6. DISCUSSIONS

One of our findings was the notable difference in sentiment between titles and descriptions of articles. Descriptions across the USA, UK, and Europe generally displayed more positive sentiment compared to the titles. This divergence suggests that while the media may use more sensational or cautious headlines to capture readers' attention, the body of the articles provides a more balanced or optimistic perspective on AI. This aligns with previous research which has shown that media outlets often adopt a more critical or provocative tone in headlines to attract readership (Alsem *et al.*, 2008; Freeman and Freeland, 2015). For example, a news article from the USA discusses the impact of an IPO, featuring a title sentiment score of -0.49. It focuses on a significant entrepreneurial event: the challenges faced during CoreWeave's IPO. Despite the negative headline, the article's description has a score of 0.3626, indicating that there is still underlying confidence in emerging AI ventures (Yildirim, 2025). Additionally, there is a CNBC article covering LVMH CEO Bernard Arnault's family office investing in AI startups. This article has a neutral title, but its description carries a positive score of 0.47 (Frank, 2024).

In the UK, for example, the titles were more negative, reflecting a cautious stance towards AI. In contrast, the descriptions in UK media were generally positive, suggesting that while the initial media narrative may focus on risks or challenges, the detailed content reflects optimism about AI's potential benefits for business. This may reflect the public's mixed emotions about AI, where concerns about job displacement and ethical risks are balanced by recognition of AI's role in innovation and operational efficiency. For example, The Guardian's article on retail automation titled "Robot Packers and AI Cameras: UK Retail Embraces Automation to Cut Staff Costs" illustrates a similar dynamic. The headline has a sentiment score of -0.27, indicating a negative tone, while the article's overall description is neutral. Although the headline highlights the potential for job losses, the detailed discussion emphasizes that AI-driven automation can help reduce costs and improve operational efficiency. It encourages businesses to adopt technology while carefully managing the associated disruptions (Butler, 2025).

Our findings also resonate with studies that highlight how different regions exhibit varying levels of optimism about technological advancements (Morini, 2016). For instance, the USA showed more positive sentiment in both titles and descriptions compared to the UK and Europe. This finding could be explained by the USA's broader emphasis on entrepreneurial culture and its history of early adoption of emerging technologies, which media narratives reflect. By contrast, European media coverage tends to emphasize regulatory concerns and ethical implications more frequently, as reflected in the lower sentiment scores, particularly in titles (Kerrigan and Graham, 2010). For example, a report from SiliconRepublic highlights that Neura Robotics, based in Germany, recently raised €120 million. This significant investment comes with various regulatory challenges. Although the headline appears neutral, the article emphasizes the growing entrepreneurial rate and strategic shifts toward AI adoption. The description's sentiment score for this report is 0.34 (Mather, 2025).

Another finding was the notable fluctuation in sentiment over time, particularly daily. This volatility is influenced by factors such as new investments in technology, concerns about job displacement, and discussions surrounding the potential and tangible benefits of AI in fields like medicine, finance, artificial content creation, and robotics. Such fluctuations indicate that media portrayals of AI are highly responsive to short-term events and news cycles (Bakker, 2010). These dynamics prompt enterprises to re-assess their strategies, suggesting that while initial media narratives may produce caution, broader discussions ultimately create an environment that encourages AI adoption and innovation.

This study has several limitations that need to be considered in future research. Future studies should extend the analysis period to more than six months and include more regions, such as Asia and Africa, as well as diverse languages. This approach would help capture a broader perspective on the portrayal of AI in the media. Additionally, while sentiment analysis tools like VADER are useful, they may miss the complexity of emotions, and the study did not account for social media platforms, which play a growing role in shaping public opinion.

Future studies could investigate how these media sentiments translate into actual business decisions and AI adoption rates. Given the rapid evolution of AI, longitudinal studies that track sentiment over a longer period could offer deeper insights into how media narratives evolve alongside technological advancements (Palahan, 2022).

7. CONCLUSIONS

This study provided a comparative analysis of how media in the USA, UK, and Europe portrays AI, offering insights into regional differences in sentiment. Our findings reveal that while AI is generally portrayed positively in media descriptions, there are notable variations, particularly in the tone of article titles, which tend to be more cautious or negative in certain regions like the UK. The results suggest that media plays an important role in shaping public and entrepreneurial perceptions of AI, with potential implications for AI adoption rates and innovation.

This duality emphasizes the media's influential role in shaping public and entrepreneurial perceptions, which impacts AI adoption rates and strategic decision-making. In practical terms, for example, a more positive perception of AI in the USA could foster a culture that encourages rapid adoption and bold innovation. As a result, companies may be more inclined to invest quickly in new AI technologies. On the other hand, the more cautious approach observed in the UK and Europe, likely due to a stronger emphasis on regulations and ethics, suggests that businesses in these regions may adopt AI at a slower pace.

These findings suggest that business leaders should look past attention-grabbing headlines and focus on the full details when thinking about the risks and opportunities of AI. Policymakers and investors can use this deeper understanding to create fair rules and make smarter investment decisions. Given this context, companies should closely monitor media trends. Also, since views on AI differ from place to place, AI companies should adjust their messages to match local attitudes about technology and innovation. This approach may help reduce fears and shift the focus toward the long-term benefits of AI.

The study contributes to the existing literature by highlighting the influence of media sentiment on technological adoption and pointing out how regional media coverage reflects broader cultural attitudes toward AI and business innovation.

Future research should incorporate social media sources, extend the timeframe, and explore how media sentiment influences business decisions and policies. Expanding to more regions and languages will provide a deeper understanding of the global interplay between media, public perception, and AI adoption in business.

Acknowledgements

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