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Preface

Seyed Mehdian[*]

We are pleased to introduce this Special Issue of the ***Scientific Annals of Economics and Business***, published by Alexandru Ioan Cuza University of Iași, following the **Globalization and Higher Education in Economics and Business Administration** (GEBA) 2025 conference. This issue presents a collection of empirical studies that address contemporary challenges in business, economics, and finance. The included contributions explore diverse topics such as financial intermediation and economic growth within the European Union, asymmetric shocks and long-memory volatility in global oil and import dynamics, determinants of human capital, the influence of board gender diversity on sustainable development, attitudes toward euro adoption analyzed using machine learning techniques, and large-scale sentiment analysis of Google Business Reviews.

The study titled "Impact of Board Gender Diversity on Sustainable Development: Evidence from European Countries" (Dornean *et al.*, 2026) examines the relationship between board gender diversity and corporate sustainability performance in European firms, with particular attention to the moderating influence of national culture. Analysis of data from 818 firms across 31 countries between 2014 and 2024, employing a Difference-in-Differences GMM methodology, demonstrates that gender-diverse boards are associated with enhanced ESG outcomes. Nevertheless, the strength of this association varies across cultural contexts.

The study titled "Determinants of Human Capital: An Empirical Analysis Using System GMM" (Ungureanu and Pop-Silaghi, 2026) examines the factors influencing human capital in OECD countries from 2000 to 2024, employing the System GMM methodology and utilizing the Human Capital Index and life expectancy as primary indicators. The findings indicate that educational achievement, particularly at the upper-secondary level, significantly enhances human capital, whereas the effect of health expenditure remains inconclusive. Additionally, increased female labor force participation positively influences both human capital and life expectancy. The impacts of remittances, corruption, and research and development are found to be variable. The results further suggest that sustainable human capital development requires integrated policies that encompass education, health, gender inclusion, and innovation.

In "Asymmetric Shocks and Long-Memory Volatility: An EGARCH Approach to Global Oil and Local Import Dynamics" (Diavor and Pârțachi, 2026), the author analyzes the volatility of Moldova's commodity import prices and global Brent oil prices using advanced econometric models. Analysis of monthly data from 1992 to 2025 for Moldova and from 1990 to 2025 for Brent oil demonstrates that both series are integrated of order one, with no

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significant mean breaks, supporting the use of constant-parameter models. An AR (1)-GARCH (1,1) model captures persistent and symmetric volatility in Moldova's index, while Brent oil volatility displays asymmetry, as shown by an AR(1)-EGARCH (1,1) model. Diagnostic tests confirm the adequacy of these models. The findings suggest the need for symmetric risk management strategies for Moldova and asymmetric hedging approaches for oil markets, with key policy implications.

The paper, "Subjective determinants of attitudes towards Euro adoption in non-euro countries. A machine learning approach" (Giurgi *et al.*, 2026) applies machine learning techniques to analyze the determinants of attitudes toward euro adoption in European Union member states before they enter into the Euro Area, utilizing 2011–2024 Flash Eurobarometer data. The results indicate that price perceptions are the most significant predictors of support, while concerns about national identity and economic control correspond with lower levels of support. Additionally, higher self-perceived knowledge about the euro correlates with more favorable attitudes. These findings highlight the significance of subjective factors, alongside economic considerations, in shaping public support for euro adoption.

The article "Listening at Scale: A Replicable, Low-Cost Pipeline for Collecting and Analyzing Google Business Reviews with SerpApi and VADER" (Cristescu *et al.*, 2026) introduces a reproducible methodology for collecting, translating, and analyzing Google Business reviews using open-source tools. Analysis of 200 reviews for Klass Wagen Sibiu revealed that 85% were positive, 4% neutral, and 11% negative, with sentiment scores closely corresponding to star ratings. This workflow enables efficient review monitoring for small and medium-sized enterprises, though challenges such as self-selection bias, translation effects, and limitations inherent to sentiment analysis remain.

In "Financial Intermediation and Economic Growth: Empirical Evidence from the EU" (Cernavca and Căpraru, 2026) the authors examine the relationship between financial development and economic growth in the EU28 from 2000 to 2021, citing the Draghi Report (2024). The study employs panel data and the System GMM method to address endogeneity and dynamic effects, with a focus on potential nonlinearity. The findings indicate a negative linear effect of financial development on growth, while the squared term exerts a positive and significant influence, suggesting a U-shaped relationship. These results highlight the necessity of structural reforms in the EU's relatively underdeveloped financial sector to promote sustainable growth.

Collectively, these articles demonstrate the application of advanced empirical methods to significant economic and managerial questions, providing valuable insights for researchers, policymakers, and practitioners. We anticipate that this Special Issue will advance knowledge and encourage further research in these dynamic and evolving fields.

We express our gratitude to all authors, reviewers, and members of the editorial board for their time, expertise, and dedication. Their contributions have been essential to the successful completion of this Special Issue.

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Impact of Board Gender Diversity on Sustainable Development: Evidence from European Countries

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Abstract: This study investigates the link between board gender diversity and corporate sustainability performance, and how national cultural values influence this relationship in European countries. Based on Upper Echelons Theory, Stakeholder Theory, and Institutional perspectives, we posit that gender diversity on boards promotes a greater focus on environmental, social, and governance (ESG) goals for firms due to enhanced ethical monitoring, stakeholder engagement, and legitimacy, while we expect the impact of gender-diverse boards to be contingent on the surrounding cultural context. We employ a dynamic panel dataset of 8,197 firm–year observations corresponding to 818 listed companies from 31 European countries during the period 2014–2024, and we utilize the Difference Generalized Method of Moments (GMM) estimator to control for unobserved heterogeneity, persistence in ESG performance, and endogeneity. We find a strong positive relationship between board gender diversity and corporate sustainability performance, which is moderated by national cultural values in Europe.

Keywords: board gender diversity; gender equality; ESG; sustainable development.

JEL classification: G34; J16; K38; M14.

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1. INTRODUCTION

Stronger regulations with binding quotas for minimum gender representations are in place in many of the markets with the highest percentage of female directors, while markets with soft regulations or no mandates tend to have fewer female directors. In the European Union (EU), the exceptions were Sweden and Finland as the countries with the highest number of females on boards, whereas they had no targets regarding gender diversity (d'Hoop-Azar *et al.*, 2017).

In the EU, gender perspective regarding board composition appeared as an important issue of the corporate governance in 2011 when the European Commission issued "Green paper – EU corporate governance framework" (European Commission, 2011), in which it emphasized economic rationales for fostering gender diversity.

According to the Gender Statistics Database (EIGE, 2023) the average share of women in boards of the largest listed companies registered in the EU was 8.5% in 2003, 11.9% in 2010, 23.9% in 2016, and it reached 32,2% in 2022. In this context, although progress is evident, gender balance has still not been reached. The best results were registered in France where women made up 45.2% of board members in the largest listed companies. Also, there are significant differences among member states (from 45.2% in France to 10.2% in Cyprus). Despite some progress in recent years, according to the Gender Equality Strategy 2020-2025 (European Commission, 2020), women's under-representation in corporate boards persists.

In this context, with the aim to reduce gender gap on corporate boards, on 22 November 2022, the European Parliament adopted a new Directive on gender balance on corporate boards of listed companies (the so called "Women on Boards" Directive) and on 7 December 2022, Directive (EU) 2022/2381 was published in the Official Journal. According to the Directive, at least 40% of non-executive board seats or 33% of all board seats for listed companies must be occupied by the women by the end of June 2026. Meanwhile, by December 2024, member states must adopt national rules implementing the Directive's measures.

Previously to the Directive, according to Deloitte (2022), in 2020 seven EU countries (Belgium, France, Italy, Germany, Austria, Portugal, and Greece) had mandatory national quotas for the underrepresented sex for listed companies (women), nine countries (Denmark, Ireland, Spain, Luxembourg, the Netherlands, Poland, Slovenia, Finland, and Sweden) favoured a softer approach, and the other 11 member states did not take any significant action (no mandates). After the Directive, the last report of Deloitte (2024) emphasizes the progress towards increasing the number of women on corporate boards. Thus, in Europe, 33.8% of the board seats are occupied by women and 11% of the board chairs are women. This aspect is also strengthened by the fifth goal of the 2030 Agenda for Sustainable Development adopted by United Nations in 2015, respectively SDG5 - Achieve gender equality and empower all women and girls.

The studies about the influence of women directors on the company's performance presented mixed results, but there is a consensus that more diversity in boardrooms contributes to better decision-making and results. Also, according to the SDG5, increasing women's leadership roles and investments in gender equality are crucial at national, regional, and global levels(United Nations, 2024). At global level, from legislatures to corporate boards, women have made insufficient gains in leadership. According to United Nations (2024) women hold 40% of global employment, but they occupied only 27.5% of managerial positions in 2022, which represents the same share as in 2016. At this pace, 176 years are needed to accomplish parity in managerial roles.

In this context, our paper aims to analyse the extent to which the presence of women on boards of directors contributes to the achievement of SDG5, and in this way to the sustainable development. The contribution to the literature will consist in bringing useful results that will also accelerate the implementation of the "Women on Boards" Directive by EU countries which contribute to the accomplishment of the gender equality goal and at the same time to the sustainable development.

The paper is structured as follows: Section 2 reviews the literature, Section 3 presents the sample, data and the methodology used, Section 4 presents and discusses the results and finally, Section 5 concludes the paper, highlighting the practical and policy-relevant contributions.

2. LITERATURE REVIEW

2.1. Board gender diversity and corporate sustainability

Corporate governance, particularly in listed companies, is being studied and regulated through corporate governance codes, recommendations, and legislation. Of particular interest is the composition, and specifically gender diversity of boards of directors. This interest stems from the global underrepresentation of women in corporate governance bodies (Lee *et al.*, 2015; Dawson *et al.*, 2016).

The past two decades have seen a rise in the number of women serving on corporate boards, and the growing scholarly interest in the relationship between women on boards and environmental, social, and governance (ESG) performance reflects the more general understanding that board composition is not merely symbolic but a central factor in shaping strategic behaviour and governance effectiveness. A few theoretical perspectives provide a complementary explanation as to how gender diversity at the board level may affect sustainability outcomes.

From the perspective of Upper Echelons Theory (Hambrick and Mason, 1984), demographic characteristics, values, cognitive frames, and ethical orientations of top decision-makers explain organizational outcomes. Boards of directors are central to monitoring management and are also an important part of long-term strategy formulation. Thus, the presence of women brings a variety of perspectives, ethical sensitivities, and decision-making styles that may impact priorities on issues concerning stakeholder relations and corporate responsibility. Past research has found that female directors tend to be stronger monitors, more attentive to ethical issues, and more socially and environmentally conscious (Bear *et al.*, 2010; Li and Tang, 2010) and these behavioural characteristics are closely aligned with the multidimensional goals of ESG metrics that measure corporate social responsibility and responsible business conduct beyond short-term financial performance.

This theoretical logic is supported by Stakeholder Theory (Freeman, 1984), which posits that firms are successful in the long term by identifying and responding to the interests of multiple stakeholder groups, instead of solely maximising shareholder value. More diverse governing bodies are better able to appreciate the divergent expectations of different stakeholders and to bring wider social concerns into corporate strategy. Thus, gender-diverse boards would be better at having conversations with their employees, the community, regulators, and environmental organizations resulting in broader, more enduring forms of corporate governance (Lee *et al.*, 2015; Nadeem, 2020).

Second, Resource Dependence Theory (Hillman *et al.*, 2007) highlights the role of the board as a source of critical organizational resources, such as legitimacy, networks, expertise, and access to key external stakeholders. Female directors tend to enlarge the relational capital of the firm by establishing connections with other stakeholder constituencies and social organizations and by improving public legitimacy in areas such as equality, social inclusion, and ethical governance. These types of reputational and relational capital are especially relevant in the current ESG context in which firms are subject to greater scrutiny on their social and environmental disclosures and commitments, which will enable board gender diversity to enhance firms' abilities to design, implement, and credibly communicate sustainability strategies.

These theoretical perspectives are complementary and suggest that greater gender diversity on corporate boards should be associated with better ESG performance, because diverse boards are better equipped to exercise ethical oversight, meaningfully engage with stakeholders, and secure legitimacy-enhancing resources that facilitate sustainability-oriented governance.

In their empirical study, using a panel data methodology with fixed effects, Martínez *et al.* (2022) analysed the companies listed in the MSCI Europe and MSCI EM Europe indices for a period of ten years (2010-2019) and they found that CSR is impacted positively by the gender diversity on the board of directors, which confirmed that legislation should promote gender policies.

Going deeply and closer to the moment of our analysis, Fernández-Méndez *et al.* (2025) found that gender diversity on the corporate board from 22 European countries had a positive and significant impact on ESG scores. Taking into consideration the fact that the study was implemented for the period 2009–2018, previously to the Directive (EU) 2022/2381 of the European Parliament and of the Council, its results support this recent legislation and encourage to incorporate women into decision-making process, as a means of fulfilling the 2030 Agenda for Sustainable Development.

2.2. From token representation to effective influence

The term "tokenism" is used to refer to the low representation of women in decision-making and management positions in companies. This term indicates that the presence of minority groups, in this case women, in companies is due to external pressure to meet societal demands. It reflects the fact that the opinions of these minority groups are disregarded or undervalued, with no effect on business performance. Furthermore, any study of boards of directors from a gender perspective is complex, as women remain a minority group and their opinions are undermined by an environment of inequality (Mejía and Ribera, 2003).

This reality has led many countries to introduce initiatives aimed at increasing female representation on boards of directors. Depending on the country or geographic area, these initiatives range, as already mentioned, from recommendations on gender diversity in corporate governance codes to legislative initiatives establishing quotas, or percentages, for the underrepresented sex on boards. The UE proposed a Directive in 2022 that includes a European quota initiative. In Spain, these legislative initiatives have resulted in an increased presence of women on the boards of directors of listed companies and in senior management (Martínez García *et al.*, 2020; Martínez García and Gómez Díaz, 2021). On the other hand, the authors Martínez García *et al.* (2020) highlighted that the national regulations, codes, and quotas had a greater effect compared to the proposed European regulations. Besides, the scenarios estimated by Martínez García and Gómez Díaz (2021) suggested that the Ibex 35 (the benchmark stock market index of Spain that include the 35 most liquid Spanish stocks traded on the Madrid Stock Exchange) will meet the target (achieving 40% diversity) between 2023 and 2024, while the threshold for the rest of the listed companies would not be reached before 2026.

Although women are now represented on boards in increasing numbers in many jurisdictions, theoretical and empirical work warns against assuming that all types of diversity generate similar or immediate results (tokenism theory: Kanter (1977); the token director often faces stereotyping pressures, few opportunities to influence, and difficulty in forming alliances within male networks, so that she may be unable to have any impact on strategic decisions such as sustainability policies).

Based on this insight, Critical Mass Theory suggests that the impact of minority directors becomes significant only when the number of female directors on the board reaches a minimum threshold, which is generally believed to be three female directors or approximately 30 percent of the board (Kramer *et al.*, 2007; Joecks *et al.*, 2013). Here, women are no longer seen as tokens of a minority group but as valid, powerful members of the governance process, and group dynamics change, participation is more equal, and minority voices have a greater chance of making actual changes in organizational priorities. In empirical studies, once critical mass is reached, the positive effects of gender diversity on ethical oversight, monitoring quality, and CSR practices become significantly stronger (Bear *et al.*, 2010).

Since the early 2000s, Europe has been the continent with the greatest gender diversity on boards of directors and with the highest number of countries that have implemented gender quotas. This reflects how quotas boost women's careers in business (Martínez García, 2023). Martínez García (2023) pointed out the fact that European countries with quota legislation also have a higher proportion of female directors reflects how quotas boost women's careers in business, although exceptions exist. However, the intensity of this increase does not depend on the type of regulation, recommendations, or quotas, as Martínez García and Gómez Ansón (2023) found in their study implemented in the largest listed European companies over the period 2003 - 2022.

The characteristics of the European context have led most studies on quotas and gender diversity on boards of directors to focus on this institutional environment. However, analysing the international context, we arrive to the same conclusion that female presence benefits the economic dimension (profitability and liquidity), while the environmental and social dimensions are diminished. In this context, Reyes-Bastidas and Briano-Turrent (2018) who analysed the listed firms from Colombia and Chile suggested that in the Latin American context it is necessary to promote greater participation of women in strategic positions to increase their representation.

Another study investigating the impact of regulation on board gender diversity contradicted the implicit and widespread belief that regulatory interventions to increase women on boards leads to a strengthening of the trickle-down effect (Page *et al.*, 2024). In 2011, a new soft law regulation was introduced for firms listed on the United Kingdom's FTSE 350 index, which required to the FTSE 350 listed firms to increase the representation of women on the boards of at least twenty-five percent. The impact of this regulation consisted in a positive relationship between women on boards and women's representation in senior management during the pre-regulation era, known as the trickle-down effect. But the introduction of regulation had the unintended consequence of weakening the relationship between women on boards and women in senior management. Thus, the effect of regulation on board gender diversity had to be judged considering the different context and different frameworks. As suggested by Martínez-García *et al.* (2023), it is important to take into consideration firm ownership (single large shareholder versus multiple blockholders) and control structure when developing regulations to promote board gender diversity.

This institutional context makes the European corporate governance landscape particularly interesting to examine, because the introduction of gender quotas and regulatory initiatives have meant that many firms have moved beyond the symbolic presence of women to levels of gender diversity that are compatible with critical mass thresholds, which in turn increases the likelihood that board gender diversity will result in both appearance and substantive governance effects, such as improved ESG performance.

2.3. Institutional context and the role of national culture

While governance reforms and diversity mandates have increased the representation of women on boards across Europe, Institutional Theory (DiMaggio and Powell 1983) cautions that organizational behaviour is not entirely determined by formal rules, but also by a mixture of regulatory pressures, normative expectations, and deeply ingrained cultural values. Whereas quotas guarantee the numerical representation of women on boards, the degree to which diversity translates into real influence is largely contingent on informal institutional arrangements, specifically prevailing societal attitudes on gender and leadership.

Studies of national value systems have shown that they influence managerial behaviour as well as organizational priorities (Hofstede, 2001). The Masculinity dimension captures the degree to which a society is driven by competition, assertiveness, material success orientation, and traditional gender roles versus cooperation, empathy, social solidarity, and work-life balance. Whereas low-masculinity cultures value relational harmony and social responsibility, high masculinity cultures value performance achievement.

Previous research has found that corporate sustainability practices are more widely practiced and more effective in societies with low masculinity values, in which stakeholder cooperation and social welfare norms are deeply embedded (Ringov and Zollo, 2007), making the presence of women on boards more culturally acceptable and socially compatible with the dominant governance values of the society, which in turn empowers female directors to exert influence over sustainability strategies, stakeholder policies, and ethical standards in firms.

Conversely in more masculine societies where traditional gender stereotypes and hierarchical power structures remain strong and competitive norms and performance-centered leadership styles prevail, the board might still refuse to listen or consider stakeholder perspectives that are often aligned with sustainability agendas (even if women sit on boards), thus limiting their potential for ESG-oriented decision-making.

Gender prejudices and stereotypes persist, and women have not reached the highest management and control positions in companies, nor senior management positions, not due to a lack of qualifications and/or skills, but for reasons related to the mindsets, circumstances, and conditions of patriarchal societies (Pons Carmena, 2024). These include traditional gender roles, division of labour, educational options for women, and the glass ceiling (and steel barrier).

The term “steel barrier” refers to a new limitation hindering women's advancement in business due to their lack of international experience. Women are not assigned to positions abroad and, therefore, have fewer opportunities than their male counterparts to aspire to senior management positions in multinational companies. It is called a "steel barrier" because this barrier is more difficult to break than the "glass ceiling" (Domínguez, 2018).

These arguments imply that the impact of board gender diversity on sustainability outcomes should be moderated by national culture, and thus the influence of diverse boards on sustainability outcomes should systematically vary across countries depending on underlying cultural orientations.

In this context, our paper aims to contribute to the literature, investigating the relationship between women on board and ESG in order to establish the impact of board gender diversity on sustainable development, taking into consideration the surrounding cultural context. Compared to the prior studies which have analysed the impact of gender diversity boards on sustainability performance (ESG), our contribution will consist in taking into consideration along with Hofstede's Masculinity (MAS) dimension, the surrounding cultural context, by introducing the interaction term (Board Diversity × MAS) which examine whether national culture moderates the relationship between board gender diversity and ESG performance. This interaction has been largely neglected in prior literature and constitutes a key originality of this research. By integrating firm-level behavioural dynamics with cross-national cultural dimensions, the study bridges gaps between corporate governance theory, institutional theory, and cross-cultural management, offering a more context-sensitive explanation of ESG performance.

2.4. Hypotheses development

Combining these theoretical perspectives yields two main expectations. First, consistent with Upper Echelons, Stakeholder, and Resource Dependence theories, female representation on corporate boards should increase firm sustainability performance by improving quality of monitoring, ethical sensitivity, stakeholder orientation, and legitimacy. This is formulated as hypothesis H1:

H1*: Board gender diversity is positively related to ESG performance.*

Second, we expect this relationship to be contingent on national cultural values consistent with Institutional Theory (e.g., Greenwood and Hinings 1996) and cross-cultural management research (e.g., Hofstede 1980) because in cultures with lower masculinity (more social responsibility and inclusiveness), female directors are more likely to exert effective strategic influence (e.g., enhancing their impact) which in turn will enhance the impact of board diversity on ESG outcomes. In this context, we formulate hypothesis H2:

H2*: National cultural masculinity negatively moderates the relationship between board gender diversity and ESG performance, such that the positive effect of board diversity on ESG performance is less pronounced.*

3. SAMPLE, DATA AND METHODOLOGY

The sample consists of 8,197 firm-year observations for 818 listed companies from 31 European countries for the period of 2014 to 2024, including both financial data (total assets, *ROA*, total debt, cash flow and sales) and *ESG* scores (corporate environmental, social, and governance performance, standardized on a 0–100 scale) from Refinitiv Eikon (formerly Thomson Reuters ASSET4, (LSEG, 2023)). We also obtained financial data on total assets, return on assets (*ROA*), total debt, and cash flow from Refinitiv Eikon to ensure that we had consistent data across firms and years. The national cultural variables were sourced from the Hofstede Insights Database (Hofstede, 2001), which includes the Masculinity (*MAS*) dimension that measures the degree to which competitiveness, assertiveness, and achievement orientation prevail in social values.

The dependent variable, *ESG* Score, represents the overall sustainability performance of the firm and was normalized to eliminate outliers and make it comparable across countries and industries. To reduce the impact of extreme values, following previous studies (Li and Zeng, 2019; Nadeem, 2020), the *ESG* variable was winsorized at the 1st and 99th percentiles.

The primary independent variable, Board Diversity, was calculated as the percentage of women on the board of directors, which is a measure that aligns with the literature connecting gender representation to sustainability outcomes (Bear *et al.*, 2010; Harjoto *et al.*, 2015). The variable was standardized after cleaning for extreme observations.

The contextual moderator is the national cultural trait, Masculinity (*MAS*), which varies from 0 (feminine, consensus-oriented societies) to 100 (masculine, competitive societies), with higher scores reflecting performance and assertiveness and lower scores reflecting cooperation and quality of life (Hofstede, 2001).

The control variables were firm characteristics that influence ESG outcomes, including firm size, profitability, debt ratio, and cash ratio (Ullmann, 1985; Nadeem, 2020). *FIRM SIZE* was represented by the natural logarithm of total assets (ln Total Assets), profitability was proxied by return on assets (*ROA*), which is net income divided by total assets, *DEBT RATIO* was defined as total debt over total assets, and *CASH RATIO* as firm cash flow divided by total sales. This variable accounts for the firm liquidity and internal financing capability.

All continuous variables were normalized and cleaned to be comparable across countries or firm sizes, and the resulting panel is an unbalanced but robust sample of European listed companies with consistent ESG disclosure that represents 31 countries with 818 firms and 8,197 firm-year observations, with Great Britain (11.7%), Turkey (10.21%), Grece (6.73%), and Norway (5.7%) representing the most represented countries (Table no. 1).

Table no. 1 – List of countries

Country	Firms	Observations	% of total
Austria	20	194	2.37
Belgium	20	189	2.31
Bulgaria	23	221	2.70
Croatia	17	181	2.21
Czech Republic	11	100	1.22
Denmark	20	200	2.44
Estonia	20	183	2.23
Finland	23	236	2.88
France	40	398	4.86
Germany	31	317	3.87
Great Britain	96	959	11.70
Greece	57	552	6.73
Hungary	12	131	1.60
Ireland	21	207	2.53
Italy	27	279	3.40
Latvia	6	63	0.77
Lithuania	20	191	2.33

Country	Firms	Observations	% of total
Malta	24	246	3.00
Netherlands	22	218	2.66
Norway	47	467	5.70
Poland	18	170	2.07
Portugal	15	149	1.82
Romania	38	398	4.86
Russia	10	110	1.34
Serbia	4	39	0.48
Slovakia	3	42	0.51
Slovenia	9	83	1.01
Spain	35	342	4.17
Sweden	30	297	3.62
Switzerland	19	198	2.42
Turkey	80	837	10.21
Total	**818**	**8197**	**100.00**

Note: The table shows both the number of firms and firm-year observations by country. Percentages are calculated based on the total number of observations (8,197).
Source: authors' elaboration.

This distribution offers considerable cross-country variation to capture cultural effects (especially Hofstede's Masculinity (*MAS*) dimension) and to examine whether national culture moderates the relationship between board gender diversity and *ESG* performance.

The descriptive statistics in Table no. 2 reveal that the sample includes a variety of corporate characteristics and cultural environments, and the *ESG* variable exhibits sufficient variability (mean = 77.05, standard deviation = 19.17) to identify the determinants of sustainability outcomes within a dynamic panel framework, consistent with prior research that shows significant cross-country variation in sustainability practices (Eccles *et al.*, 2014; Fatemi *et al.*, 2018). Board gender diversity averages around 40 percent female directors, which mirrors the achievement of gender parity on boards in Europe after the implementation of the EU Directive on gender equality (European Commission, 2022). However, the 60 percent cap shows that full gender parity is still a rarity among listed firms. The masculinity (*MAS*) dimension from Hofstede describes the sample with an average of 45.5, spanning cultural contexts that range from relatively feminine societies (Sweden, Denmark) to more masculine societies (Germany, Turkey), which is important for testing whether the cultural dimension of masculinity affects the relationship between gender diversity and *ESG* performance, as found by Li and Tang (2010); Krüger *et al.* (2021).

With respect to control variables, *FIRM SIZ*e has a mean value of 15.75 and moderate dispersion. *ROA* exhibits a highly skewed distribution, which is characteristic of firm-level panel data (Baltagi, 2021), and Debt and Cash ratios also have long tails, validating the use of robust estimation techniques like System GMM to attenuate the effects of heteroskedasticity and outliers. The resulting normalization and mild winsorization procedures eliminated extreme outliers without losing the underlying variability in the firms' financial and governance indicators, thereby allowing for realistic distributions of *ESG* performance, gender diversity, and cultural context that are appropriate for testing the moderating effect of Hofstede's masculinity dimension on the gender-ESG relationship in a dynamic panel framework.

Table no. 2 – Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
ESG	77.05	19.17	18.22	93.26
BOARD DIVERSITY	42.60	17.74	0.00	60.00
MAS	45.52	21.03	5.00	88.00
SIZE	15.75	2.84	5.86	24.83
ROA	6.30	8.35	-22.39	41.71
DEBT RATIO	25.37	17.71	0.00	82.28
CASH RATIO	17.85	23.27	-108.62	97.99

Note: Variables: ESG (score of overall environmental, social, and governance performance, normalized 0–100); BOARD DIVERSITY (percentage of female board members); MAS (Hofstede's Masculinity index by country, 0 = feminine, 100 = masculine); SIZE (Firm size measured by the natural log of total assets); ROA (Return on Assets), DET RATIO (Total Debt divided by Total Assets); CASH RATIO (Cash Flow divided by Total Sales as measure of internal financing capacity).
Source: authors' elaboration

This study employs a dynamic panel data approach using the Difference Generalized Method of Moments (Difference GMM) estimator proposed by Arellano and Bond (1991) and extended by Blundell and Bond (1998). The estimator is particularly suited to corporate panel datasets where the dependent variable, here, the ESG score, is dynamic and potentially endogenous. Endogeneity issues may arise from reverse causality between sustainability performance and firm characteristics or from omitted variables that correlate with both.

Given the unbalanced panel structure of the dataset, covering firms from 31 European countries between 2014 and 2024, traditional estimation methods such as fixed effects or pooled OLS would produce biased estimates due to correlation between the lagged dependent variable and unobserved firm-specific effects (Baltagi, 2021). The Difference GMM estimator resolves this by first-differencing the data, which eliminates firm-specific heterogeneity, and then using lagged levels of endogenous variables as instruments. This method has become standard in corporate governance and sustainability studies where the number of firms (N) exceeds the time dimension (T) (Blundell and Bond, 1998; Roodman, 2009b).

Although the System GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) can increase efficiency by combining equations in levels and differences, the Difference GMM specification is preferred in this study for several reasons. First, the Difference GMM limits instrument proliferation, which can overfit endogenous variables and weaken the Hansen and Sargan overidentification tests (Roodman, 2009a). Second, pre-estimation diagnostics suggested possible violations of the stationarity assumptions required by the System GMM. Third, the Difference GMM provides more parsimonious models with stable coefficients and a stronger economic interpretation, consistent with empirical precedents in ESG research (Aouadi and Marsat, 2018; Fatemi *et al.*, 2018).

The empirical model (equation 1) can be expressed as follows:

$$ESG_{it} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 BoardDiv_{it} + \beta_3 (BoardDiv_{it} \times MAS_i) + \gamma X_{it} + \eta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where ESG_{it} denotes the firm's environmental, social, and governance score; $BoardDiv_{it}$ is the percentage of female board members; MAS_i is Hofstede (2001) masculinity index at the country level. This variable does not show temporal variation, since cultural values evolve slowly over time, it is assumed that the *MAS* remains constant within each country throughout the sample period. Finally, X_it is a set of firm-level control variables including logarithm of total assets, return on assets (*ROA*), total debt-to-assets ratio, and cash flow-to-sales ratio. Year dummies (λ_t) control for time effects, and η_i represents unobserved firm heterogeneity.

4. RESULTS

The Difference GMM estimations (Arellano and Bond, 1991) show a statistically significant positive relationship between board gender diversity and ESG performance of European SMEs.

As Model 1 shows, having more women on the board improves sustainability outcomes, which supports the existing evidence that gender-diverse boards are more likely to provide stronger ethical oversight and a longer-term stakeholder orientation (Bear *et al.*, 2010; Harjoto *et al.*, 2015). This finding supports Hypothesis 1, which predicted a positive relationship between board gender diversity and sustainability outcomes.

In Model 2, Hofstede's MAS index is added as a contextual control variable that controls for cross-national cultural heterogeneity and to test whether the diversity–ESG relationship holds before testing the moderating hypothesis. Although the direct effect of *MAS* on *ESG* performance is not statistically significant, this specification is not designed to test an independent cultural effect, but to establish the baseline context for the interaction analysis in Model 3.

The interaction term (*BOARD DIVERSITY* × *MAS*) is positive and highly significant, indicating that the effect of gender diversity on ESG performance is moderated by cultural values: The positive coefficient of the interaction term implies that in less masculine societies, where cooperation and equality are stressed, the effect of gender-diverse boards on ESG practices is stronger (Hofstede, 2001; Ringov and Zollo, 2007), which provides strong empirical support about a negative moderating effect of national masculinity on the diversity-ESG relationship.

For control variables, *FIRM SIZE* has a negative and significant coefficient, which is consistent with the hypothesis that smaller firms may perform relatively better in *ESG* because of their more flexible structures and the proximity of stakeholders. *DEBT RATIO* and *ROA* are both statistically insignificant, consistent with the mixed evidence in the literature (Ullmann, 1985). Cash flow generation (*CASH RATIO*) is also statistically insignificant, implying that *ESG* commitment is not influenced by short-term liquidity and relies more on managerial and governance characteristics.

Taken together, these findings confirm the importance of cultural context in framing the corporate governance–sustainability nexus, noting that gender diversity is a more effective contributor to responsible practices in socio-cultural contexts with lower masculinity and higher relational values (Li and Zeng, 2019; Nadeem, 2020). These diagnostics confirm that the Difference GMM specification is valid, and the Arellano–Bond AR(1) test is significant ($p < 0.001$) in all models, as would be expected because of the first-differencing transformation (Arellano and Bond, 1991).

Table no. 3 – Difference GMM Estimation Results (Arellan–Bond, 1991)

Variable	Model 1 Board Diversity	Model 2 Board Diversity + MAS	Model 3 Board Diversity × MAS
BOARD DIVERSITY	0.843*** (0.027)	0.841*** (0.028)	0.268*** (0.061)
BOARD DIVERSITY × MAS			0.009*** (0.001)
MAS		1.412 (1.653)	0.771 (1.116)
SIZE	-0.614* (0.347)	-0.807** (0.408)	-0.974** (0.421)
ROA	-0.003 (0.004)	-0.003 (0.004)	-0.002 (0.003)
DEBT RATIO	-0.002 (0.012)	0.000 (0.012)	0.005 (0.011)
CASH RATIO	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
AR(1) p-value	0.000	0.000	0.001
AR(2) p-value	0.462	0.383	0.236
Hansen p-value	0.687	0.844	0.897

Notes: Coefficients reported with robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Two-step Difference GMM (Arellano–Bond) with year dummies included. Dependent variable: ESG Score.

Source: authors' elaboration

The Hansen test of overidentifying restrictions yields extremely favourable evidence for instrument validity, with p-values of 0.687, 0.844, and 0.897, which fail to reject the null hypothesis of instrument exogeneity, and thus concludes that the instruments are valid, not correlated with the error term, the model does not suffer from instrument proliferation, or endogeneity bias, and therefore the estimated coefficients are reliable, providing evidence that the Difference GMM results are robust in capturing the relationship between board diversity, cultural masculinity, and ESG performance. The non-significant AR(2) test confirms the absence of second-order serial correlation and supports the validity of the model specification.

5. CONCLUSIONS

This study provides a new and comprehensive framework to understand the interaction between board gender diversity and national cultural values on ESG performance in Europe. The analysis uses a dynamic panel of 31 European countries for the 2014-2024 period and the Difference Generalized Method of Moments (Difference GMM) estimator (Arellano and Bond, 1991) to address endogeneity, unobserved heterogeneity, and dynamic persistence in ESG behaviour.

This additional empirical evidence provides support for the moderating effect of cultural context on effective gender-diverse boards in promoting sustainability and makes its substantive theoretical contribution to theory development with a shift from seeing diversity as an internal governance attribute toward being considered more affected by societal norms and institutional frameworks (Hofstede, 2001; Ringov and Zollo, 2007).

The results empirically confirm that board gender diversity improves ESG performance and that this positive relationship is moderated by Hofstede's MAS index (more cooperation, empathy, and social responsibility strengthen the positive effects of diversity, while more competition and assertiveness weaken them), which is a novel finding that has been overlooked in previous literature and expands the prior governance–culture frameworks (Li and Zahra, 2012; Krüger *et al.*, 2021) into.

Conceptually, this study contributes to the knowledge on how micro-level governance mechanisms and macro-level cultural institutions interact to influence corporate sustainability outcomes, bridging gaps between corporate governance theory, institutional theory, and cross-cultural management, providing a more contextually sensitive explanation of ESG performance, as opposed to much of the existing literature that treats cultural or gender variables as exogenous determinants rather than interdependent forces.

The paper also offers practical and policy-relevant insights. The findings indicate that gender-diverse boards may be a lever that corporate boards and executives can utilize to improve sustainability performance in collaborative, social welfare-oriented environments, and that investors need to take cultural context into account in ESG assessments because the same governance structure may lead to different sustainability results due to differences in national value systems. These insights can also be used to inform policymakers, especially in the European context, to design culturally adaptive governance regulations, such as gender balance directives (European Commission, 2022) which are more effective when culturally synchronized.

However, this study also highlights several limitations: ESG scores are standardized but may differ in depth of disclosure across countries and industries, and cultural dimensions, such as masculinity, are measured at the national level, which may ignore heterogeneity within countries and sectoral subcultures. Multi-level modelling, alternative cultural frameworks, or longitudinal event analyses that capture evolving corporate and societal dynamics could all be used to address these limitations in future research.

Overall, this research shows that board gender diversity is contingent on the national cultural context and the link between board gender diversity and corporate sustainability is moderated by the socio-institutional fabric of each country, suggesting that governance reforms should be embedded in the socio-institutional fabric of each country, which can be further advanced by jointly modelling culture, gender, and sustainability through a dynamic econometric framework, which extends existing theory, introduces a cross-level interaction previously unexplored in the ESG literature, and provides actionable implications for boards, investors, and regulators.

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Determinants of Human Capital: An Empirical Analysis Using System GMM

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Abstract: This paper examines the key factors shaping human capital in OECD countries, highlighting its multidimensional nature and the interplay between economic, educational, health, and social influences. Covering the period 2000–2024, the study applies the System GMM approach to account for persistence, endogeneity, and country-specific characteristics. Human capital is measured using two indicators – the Human Capital Index and life expectancy – while determinants are grouped into four categories: economic, educational, health-related, and social factors. The results show that economic, educational, and social conditions jointly shape human capital and life expectancy. Economic growth is positively associated with health outcomes, while fiscal variables display limited immediate effects. Education is a key driver, as increases in upper-secondary attainment and a more advanced-educated labor force significantly strengthens human capital. Health expenditure shows mixed results, pointing to possible efficiency issues. Among social factors, female labor force participation consistently improves both human capital and life expectancy, whereas remittances, corruption, and R&D expenditure have weak or context-dependent effects, suggesting that institutional quality and household structure condition their impact. By adopting a multidimensional and dynamic framework, this paper demonstrates that sustainable human capital formation requires integrated policies that simultaneously promote education, health, gender inclusion, and innovation.

Keywords: Human Capital; Life Expectancy; System GMM.

JEL classification: O15; I25; J24; O40; C33.

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1. INTRODUCTION

Human capital is usually defined as the stock of knowledge, skills, health, and productive capacities embodied in individuals and a central factor of modern growth theory as defined by Lucas (1988) or Becker (1966).

This paper aims to examine the determinants of human capital measured through two complementary proxies: the human capital index (The World Bank, 2018) and life expectancy. The analysis is conducted from economic, educational, health, and social perspectives, with the aim of filling a gap in literature by offering a multidimensional and dynamic assessment that accounts for complementarities and persistence. Specifically, our objectives are to analyze how these four categories of determinants shape human capital and life expectancy and to evaluate which dimensions exert the strongest influence.

This paper contributes to the literature by proving a broader viewpoint of what was researched until now. Even though the connection between growth and human capital has been extensively researched by Becker (1966) or Lucas(1988), most of the studies adopt a more limited approach by focusing on specific healthcare inputs, years of education like Affandi *et al.* (2019) or Teixeira and Fortuna (2004), or on education spending like Raheem *et al.* (2018). We consider that these approaches may overlook the multidimensional nature of human capital, which in our view is shaped by various factors. However, recent studies highlight that human capital also interacts with innovation, labor markets, and institutional quality, suggesting a wider set of channels through which productivity improvements occur (Rahim *et al.*, 2021). In this context, conceptualizing human capital as a multidimensional construction allows a broader understanding of how economic, social and fiscal environments shape skills, health, and long-term growth potential. For example, a growing strand of research emphasizes that skills, innovation, and knowledge accumulation also depend on technological capabilities and research activity. For instance, Pop-Silaghi *et al.* (2014) show that both public and private Research & Development (R&D) expenditures significantly contribute to economic growth in Central and Eastern European countries, over the period 1998–2008, suggesting that human capital formation interacts closely with innovation capacity. The authors employ panel cointegration techniques and error correction models for a panel of 10 Central and Eastern European economies. Since private R&D is found to have a positive and statistically significant impact on economic growth in the analyzed countries, one essential conclusion of this paper is that if public R&D – currently insignificant in isolation – would be paired with private R&D investment alongside skilled human capital, one could expect positive spillovers, stronger knowledge diffusion, and higher innovation-driven growth.

Building on this evidence, our study conceptualizes human capital as a multidimensional construct shaped not only by education and health, but also by economic, social, and institutional factors. Therefore, we take into consideration different elements that shape human capital and we use a dynamic panel technique (System GMM) that takes persistence, reverse causality, and cross-country heterogeneity into account, producing a more thorough and reliable evaluation.

The structure of the paper reflects these objectives. Section 2 comprises the literature review where we synthesize existing research and classify determinants into the four perspectives. The methodology section (Section 3) presents the variables, their sources and how we used the System GMM estimator to address persistence and endogeneity. In the empirical analysis we present the models for human capital and life expectancy within each perspective (Section 4). Additionally, we also construct a mixed specification that incorporates the most pertinent determinants from each of the four distinct perspectives with the aim of determining if the impacts found in individual viewpoints are still significant when considered together, serving as a robustness check (Section 5). Finally, the paper concludes with policy implications, limits and further research (Section 6).

2. LITERATURE REVIEW

Human capital refers to the skills, knowledge, health, and productive capacities embodied in individuals, which contribute to economic growth and social development. It also represents a central dimension of intellectual capital, encompassing the knowledge, skills, and competencies that contribute to productivity and innovation. Recent research emphasizes that the development of intellectual capital significantly enhances organizational and economic performance, highlighting the strategic importance of human capital accumulation (Mubarik *et al.*, 2022).

Despite its recognized importance since Adam Smith (1776), national accounts still treat education and health spending largely as consumption rather than investment. This has motivated the development of different approaches to measure human capital. For example, Abraham and Mallatt (2022) define three approaches for measuring human capital: indicator approach, cost approach and income approach. The first one is the simplest to use and offers cross-country comparability but on the other side ignores differences in quality. In this approach we find proxies such as school enrollment rates, literacy, or average years of schooling like the Barro and Lee dataset (1996), composite indices like the World Economic Forum's Global Human Capital Index (2017) which integrates enrollment, attainment, labor participation, and skills deployment. In our study we also use this approach as it is the most suitable for cross-country growth studies. We include Human Capital Index (HCI) (2018), which uses health and education national indicators to annually measure, on a scale from 0 to 1 the amount of productivity that a child born today can expect by their 18th birthday. For example, 0.7 means that in 18 years the productivity of the country will reach only 70% of the total potential. The composite index combines data regarding child survival, school enrollment, quality of enrolment, healthy growth and adult survival. This index is included by Rahim *et al.* (2021) to examine how the Next Eleven nation's economies have grown between 1990 and 2019 in relation to their access to natural resources, financial development, human capital, industrialization, international trade and technological progress (Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, the Philippines, South Korea, Turkey, and Vietnam). Using the Dumitrescu and Hurlin (2012) method to test causality, the authors demonstrate that higher levels of natural resources hinder economic growth in the countries studied. The other variables included in the model are found to positively impact economic progress. The study also reveals that human capital could mitigate the resources course initially assumed and confirmed. Therefore, human capital positively affects the growth of the N-11 nations and lessens the inhibiting effects associated with high levels of natural resources. The cost approach measures human capital by summing education and training expenditures, including both direct spending and the value of students' and parents' time. Originally introduced by Kendrick (1976) and further developed by Eisner (1978, 1985) this method has been applied in more recent studies such as Gu and Wong (2015) for Canada, as discussed in Abraham and Mallatt (2022).

Its main advantage is compatibility with national accounts, since it treats education as an investment and provides a monetary valuation of human capital. However, the approach requires extensive data, it is highly sensitive to assumptions about depreciation and reflects resources regarding education input rather than actual productive outcomes. The last approach, meaning the income or lifetime earnings approach, first introduced by Jorgenson and Fraumeni (1989, 1992), values human capital as the present value of expected future earnings, differentiated by age, sex, and education. Later refinements by (2010, 2014) expand the method to include both market and non-market returns. The advantage of this approach lies in its focus on productive outcomes. However, it is very sensitive to assumptions regarding discount rates, economic growth, and educational completion probabilities, which can significantly affect results.

In our study, besides the Human Capital Index (HCI), we also employ life expectancy (LE) as an additional proxy for human capital. The use of this indicator is well grounded in the literature, which shows that longevity increases the incentives to invest in education and skills, thereby expanding the stock of human capital.

Life expectancy is frequently used as a proxy for the health dimension of human capital. By including both HCI and LE in separate empirical specifications, the analysis captures complementary dimensions of human capital formation. While HCI reflects a broader composite measure that integrates education and health outcomes affecting future productivity, life expectancy provides a more direct measure of the health component of human capital. This dual approach allows the study to examine whether the determinants under investigation influence different representations of human capital in a similar or different way, thereby offering a more nuanced perspective on human capital development.

For instance, Bloom *et al.* (2004), in their cross-country growth regressions, also estimate that a 10% increase in life expectancy raises economic growth rates by about 0.3–0.4% per year, reflecting the indirect contribution of longevity to human capital and productivity. Jayachandran and Lleras-Muney (2009) show the interdependence between health improvements and human capital formation. They use variation in maternal mortality as an exogenous shock to life expectancy on a panel of 97 countries over 1960–1990 to show that declines in maternal mortality significantly increase girls' years of schooling. Similarly, Cervellati and Sunde (2011) developed a growth model on cross-country data for more than 100 countries, for the period 1940-1980 and show that improvements in life expectancy lower the effective cost of education and foster human capital accumulation. Herzer (2017) also analyze a panel of 14 countries over the period 1870–2010 with panel cointegration techniques and found that life expectancy exerts a positive long-term effect on educational attainment and human capital investment. Higher life expectancy encourages individuals to invest more in education and skill acquisition because the expected returns to education increase over a longer working life. Empirical studies show that improvements in life expectancy contribute significantly to human capital accumulation and economic development (2022) .

Therefore, by combining HCI and LE, this study provides a richer a more comprehensive analysis, capturing both composite and health-based aspects of human capital.

When it comes to human capital accumulation, recent research has increasingly focused on the macroeconomic and institutional determinants. For example, Le Clech (2025) investigates the factors shaping human capital wealth using cross-country data and applies an econometric approach based on instrumental variables in order to address potential endogeneity issues. The analysis identifies three key pillars influencing human capital accumulation: physical capital deepening, economic modernization driven by digitalization and technological development and the quality of economic institutions and policies. The results suggest that economies characterized by stronger investment dynamics, greater integration into modern economic structures, and higher institutional quality tend to exhibit higher levels of human capital wealth.

For example, Cuevas Ahumada and Calderón (2020) highlight the joint contribution of physical and human capital to growth but note that the strength of human capital depends on the level of development. Using a balanced panel of 52 countries observed over 2002–2014, the authors group economies by their Inequality-adjusted Human Development Index (IHDI) into six categories (very high, high, medium, low, very-high+high, and medium+low) to ensure greater homogeneity within samples. They also estimate 12 dynamic panel models (with and without period fixed effects) using the Arellano-Bond Generalized Method of Moments (GMM) technique (Arellano and Bover, 1995), which accounts for endogeneity and unobserved heterogeneity. Their results indicate that, while physical capital, human capital, and total factor productivity are the main drivers of growth across all groups, the responsiveness differs by development stage. Human capital formation and Total Factor Productivity (TFP) have the strongest positive effects in low-IHDI economies, suggesting these countries gain the most from investing in education, training, and technology absorption, whereas very high-IHDI countries display the largest elasticity of growth with respect to physical capital accumulation. The study further finds that institutional development supports growth mainly in medium-to-high IHDI countries, but its effect is negligible in the poorest group, where reforms must reach a threshold to become effective.

These findings suggest that the mechanisms underlying human capital formation and its contribution to growth are heterogeneous across countries and depend on broader economic, technological, and institutional conditions. Therefore, our study also examines the determinants of human capital from a multidimensional perspective by considering economic, educational, health, and social factors within a dynamic panel framework.

The economic perspective emphasizes the role of growth, productivity, and fiscal capacity in shaping investments in people. The educational dimension underscores the importance of schooling and skills for long-term development. The health perspective highlights the direct impact of population health on labor market participation and individual potential, while the social dimension captures factors such as female labor force participation and institutional or cultural contexts. Together, these categories provide a comprehensive framework for understanding the multifaceted nature of human capital and life expectancy.

2.1. Economic determinants

Human capital is most often analyzed in relation to economic growth, with the bulk of the literature emphasizing a causal link from human capital to productivity and income.

Education and skills accumulation are considered engines of growth in the endogenous growth theory described by Lucas (1988), and cross-country studies such as the ones of Barro (1991); Hanushek and Woessmann (2008); Pelinescu (2015) confirm that higher educational attainment and healthier populations accelerate long-run economic performance. Recent studies such as the one of Sultana *et al.* (2022) reinforce this view, namely that human capital positively drives growth in developing economies. At the same time, the literature also acknowledges reverse causality: higher levels of income can foster the accumulation of human capital. Wealthier economies have greater fiscal capacity to finance education and healthcare, and households are better able to invest in their children's schooling and health. Khan *et al.* (2022) analyze the relationship between human capital and economic performance in the region of Jammu and Kashmir from South Asia using time-series data covering the period 2000–2019. The authors estimate regression models and complement them with Granger causality tests to explore the direction of the relationship between the variables. Their results suggest that improvements in human capital are associated with stronger economic performance, while the causality analysis indicates dynamic interactions between the two processes. The study also emphasizes the role of policy interventions, particularly public investment aimed at developing human capital, as an important driver of regional economic development. These findings highlight that economic conditions and policy choices may influence both the accumulation and the effectiveness of human capital.

Taxation represents a crucial macroeconomic instrument with direct implications for human capital accumulation. As Tanzi and Zee (1997) argue, fiscal policy influences long-run growth not only through physical capital formation, but also via incentives that shape educational attainment and skill acquisition. Based on a theoretical synthesis of endogenous growth models and cross-country evidence from previous empirical studies, they show that taxes on income and capital can reduce incentives to invest in both physical and human capital. According to them, tax revenues provide governments with stable resources that can be redirected toward productive public spending such as education, vocational training, and health care. When such expenditures reduce the private cost of schooling, improve educational infrastructure, enhance teacher quality, and strengthen health outcomes, they increase the stock of human capital and the productivity of the labor force. From an endogenous growth perspective, higher human capital stimulates innovation, accelerates the diffusion and absorption of new technologies, and improves the economy's capacity to generate sustained growth. In addition, public investment in human capital generates positive externalities that the private sector alone cannot fully internalize. A more educated and healthier workforce attracts domestic and foreign investment, raises total factor productivity, and enhances institutional capacity. Therefore, although distortionary taxation can potentially discourage private investment in physical capital, a well-designed tax structure paired with efficient expenditure allocation yields net long-term gains.

Consistent with this argument, Baldacci *et al.* (2008) demonstrate, based on panel data for 118 developing and transition economies, that tax-financed public spending on education and health significantly improves both human capital and economic growth, particularly under conditions of strong governance. Good institutional quality ensures that tax revenues are not diverted towards unproductive uses, and that fiscal resources are allocated to programs generating high social returns rather than to consumption-oriented or military spending. Nevertheless, the impact of taxation is not universally positive. Excessive tax burdens, poorly designed tax systems, or low transparency in public administration may discourage investment, stimulate informality, or result in misallocation of resources. In such contexts, higher revenues do not automatically translate into improved human capital if they are absorbed by corruption, inefficiency, or politically motivated expenditures. Thus, the literature emphasizes that the composition and quality of public spending matter more than the tax level itself, reinforcing the idea that fiscal policy can enhance human capital only when supported by sound institutions and governance.

When it comes to the structure of taxation, Arnold (2008) investigates the impact of tax systems on growth using annual panel data for 21 OECD countries over 1971–2004. Applying an error-correction model with pooled mean group estimators, the study finds that income taxes, especially corporate income taxes, are the most harmful to long-run GDP per capita, while consumption taxes are less distortionary and recurrent property taxes are the most growth-friendly. In their study, human capital is measured as average years of schooling, and the results show that one additional year of education increases economic output per capita by 5–7%. These findings can be explained through efficiency arguments rooted in the public finance literature. Income and corporate taxes are considered distortionary taxes, as described by Harberger (1964) because they change the relative returns to work and investment, discouraging firms from expanding productive capacity and individuals from increasing their labor supply or investing in education and skills. In contrast, taxes such as consumption or recurrent property taxes tend to be less distortionary, as they have a smaller impact on decisions related to labor, savings, and investment. Therefore, when the tax burden shifts away from highly distortionary income and corporate taxes toward less distortionary bases, households and firms face fewer disincentives to invest, which facilitates the accumulation of both physical and human capital.

Gupta (2018) further analyzes how fiscal policy shapes income inequality and human capital outcomes in developing countries, providing empirical evidence for the period 1985–2015. The study finds that, unlike advanced economies where taxes and transfers substantially reduce inequality, the redistributive impact in developing countries remains limited due to narrow tax bases, high informality, and weaker administrative capacity. Education and health spending are identified as key drivers of human capital and social mobility, yet their effectiveness is often weakened by inefficiencies and governance problems. Gupta argues that expanding progressive taxation – particularly recurrent property taxes, which are harder to evade – and improving the targeting and efficiency of social spending are essential for strengthening human capital formation and achieving inclusive growth. In this sense, it is not only the level of taxation that matters, but also the structure of the tax system and the quality of public expenditure.

The research of Heckman *et al.* (1998) is also crucial in showing how taxes can generate economic growth. He analyzes micro econometric data from the United States and demonstrates that tax-funded early childhood interventions and job training programs generate the highest social returns. Their analysis also includes longitudinal surveys that track individuals' schooling, skills acquisition, and labor market outcomes. Using program evaluation techniques and structural micro econometric models, they estimate the causal impact of public investments in education and training on individual productivity and earnings. These findings highlight that publicly financed human capital policies, particularly in early childhood and targeted training, yield substantial long-term gains in productivity and social welfare, emphasizing their role as growth-enhancing fiscal policy. Also, Alataş and Çakir (2016) enhance the importance of economic factors so that human capital can positively impact growth. They showed that, while education and health enhance growth in developing countries, limited fiscal capacity in less-developed economies may constrain the impact of health investments. Their analysis is based on a balanced panel of 65 countries over the period 1967–2011, using Gross Domestic Product (GDP) per capita as a proxy for economic growth and employing education and infant mortality as indicators of human capital. By applying panel data regression techniques and grouping countries, in developed and developing economies, they find that education and health significantly enhance growth in developing countries, but the effectiveness of health-related investments is limited in less-developed economies due to limited fiscal capacity. This evidence highlights the importance of economic conditions in strengthening the impact of human capital on growth and provides justification for including taxation indicators in the empirical analysis. Building on this theoretical and empirical foundation, the present study incorporates taxation as an explanatory determinant of human capital, testing whether economies with higher and more efficiently allocated tax revenues exhibit superior educational and health outcomes. By estimating a panel model for OECD countries, 2000-2024, the analysis evaluates whether the positive mechanism suggested by Tanzi and Zee (1997) and confirmed by Baldacci *et al.* (2008) holds across European economies and whether governance quality conditions the effectiveness of taxation in fostering human capital development.

Inflation is another economic indicator analyzed in relation with human capital and therefore included in our empirical model. For example, Heylen *et al.* (2004) examine the relationship between increasing rates of inflation and human capital formation. Building on an overlapping generations (OLG) model for a small open economy, they argue that episodes of high inflation reduce total factor productivity, thereby lowering the returns to work and physical capital accumulation. When these shocks are expected to be temporary, young individuals may respond through a phenomenon called intertemporal substitution between labor and education. This means that instead of working in a period where real wages and productivity are reduced, they allocate more time to schooling. This temporarily reduces output but leads to stronger growth once economic conditions normalize. Using GMM estimators for a panel of 86 countries over 1975–2000, the authors find that moderate-to-high inflation episodes (above 25–40%) significantly increase schooling by about 0.3 years on average over a five-year period, while extremely high inflation (above 100%) no longer has this beneficial effect. Their findings also show that the positive impact is stronger when public spending on education increases and in more open economies.

By contrast, He (2018) extends the literature by introducing a cash-in-advance (CIA) constraint on education spending within a Schumpeterian growth model. In his framework, human capital accumulation requires upfront monetary resources, so higher nominal interest rates (and therefore higher inflation) increase the opportunity cost of holding money for educational purposes relative to consumption. This mechanism reduces human capital investment, effective labor supply in both production and R&D sectors, and ultimately long-run growth and welfare. According to his simulations, reducing the nominal interest rate from 9.9% (the U.S. average during 1960–2014) to zero would increase annual per capita growth by 0.61%.

Taken together, these studies reveal contrasting mechanisms. In the model built by Heylen *et al.* (2004), temporary inflationary episodes encourage young individuals to stay in school longer because working during periods of low wages and productivity is less attractive. As a result, human capital rises, and growth strengthens once the economy recovers. By contrast, in He (2018), persistent inflation operates through a liquidity-constraint channel, where higher nominal interest rates make it more expensive to finance education and therefore discourage human capital investment. This reduces effective labor supply in production and innovation and slows long-run growth. Therefore, the effect of inflation on human capital depends on both its duration and the institutional and financial environment: short-lived inflation can push individuals to remain in education, whereas sustained inflation and high interest rates limit access to schooling and hinder long-term economic performance.

Turning to another indicator, namely government debt, Reinhart and Rogoff (2010) provide one of the most comprehensive analyses of the macroeconomic consequences of public debt, as their data covers 44 economies over a two-century period, meaning more than 3,700 annual observations. They showed that when public debt levels remain below 90 percent of GDP, the link with growth is weak, but once debt surpasses this threshold, median growth falls by about 1 percentage point and mean growth drops by several points. In emerging markets, external debt thresholds are even lower, with growth deteriorating once external debt exceeds 60 percent of GDP, and high debt is also associated with higher inflation and financial instability. These results imply that debt accumulation is not only a macroeconomic concern but also a human capital issue. According to them, slower growth reduces fiscal revenues, constraining governments' ability to finance education and health. Rising debt creates budgetary pressure that replaces social spending. Moreover, macroeconomic instability lowers household incomes, discouraging private investment in schooling and health. Therefore, high debt can indirectly hinder human capital accumulation by shrinking fiscal space and lowering the economic stability needed for long-term investments. However, this paper must be observed with caution, since there were found mistakes in data which were recognized and corrected later by the authors themselves. So even if the general concern about the macroeconomic risks of excessive debt remains relevant in the literature, the size of the "90 percent" threshold and the magnitude of the implied growth effects are debated. For this reason, debt should be considered an important determinant in empirical models, but its impact is likely to be context-dependent and sensitive to fiscal institutions, debt composition, and the efficiency of public spending.

Overall, the literature suggests that the relationship between human capital and economic growth is strongly mediated by macroeconomic and fiscal factors such as taxation, inflation, government debt, and the budget balance. Taxes influence incentives and the capacity of governments to finance education and health, inflation shapes the costs and returns to schooling depending on its persistence, debt accumulation constrains fiscal space for social investment, while budget balance signals fiscal discipline that can sustain long-term human capital formation. Building on these findings, our empirical analysis incorporates the following variables: GDP per capita, inflation, government debt, taxes, and budget balance to capture the broader economic environment that conditions the accumulation of human capital and improvements in life expectancy.

2.2. Education proxies for human capital

In the literature, education-related indicators referring to human capital are most frequently examined in connection with economic growth, reflecting the idea that schooling and skills accumulation serve as key engines of development. Proxies such as average years of schooling, literacy rates, and enrollment ratios at different levels of education have long been employed as tangible measures of human capital, as for example done by Maitra and Chakraborty (2021) or Mohamed Sghaier (2022)**.** Primary enrollment, while less commonly used due to its limited explanatory power, has nonetheless been tested in country-specific analyses, as for example by Dada *et al.* (2022), often with mixed results. By contrast, secondary enrollment emerges as a widely adopted proxy, with studies such as the ones of Garza-Rodriguez *et al.* (2020) and Nouira and Saafi (2022) showing a strong positive and sometimes bidirectional relationship with growth. Similarly, tertiary enrollment and education spending are consistently linked to growth in both time-series and panel studies, particularly in the context of foreign capital inflows and innovation capacity, like done by Abdouli and Omri (2021) or Rahman *et al.* (2023).

Beyond enrollment, the average years of schooling has been a classic indicator of human capital, repeatedly found to exert positive effects on productivity and long-run economic performance by researchers as Teixeira and Fortuna (2004); Ljungberg (2024) and Affandi *et al.* (2019). Finally, some scholars extend the concept by incorporating cognitive skills and intelligence into human capital measurement, with Jones and Schneider (2006) demonstrating that national IQ levels predict GDP growth even more strongly than traditional education proxies. Hanushek and Woessmann (2008), also highlight the decisive role of education quality in driving growth and development. Their analysis of 51 countries during 1960-2000 showed that test-based measures of cognitive skills are much stronger predictors of economic performance than schooling duration alone. Using GDP per capita as the dependent variable, they demonstrate that educational attainment does not yield the same economic benefits as cognitive skills. This perspective shifts the literature toward prioritizing learning outcomes and skill acquisition, rather than enrollment or attainment alone, as the pivotal link between education, human capital, and long-run development. Reflecting this shift, recent indices such as the World Bank's Human Capital Index (2018) combine schooling years with harmonized test scores to better capture the full impact of education on human capital formation and long-term health outcomes and this is one of the reasons why we chose to use it as a proxy for human capital.

Public expenditure on education represents one of the key channels through which governments support human capital formation and long-term economic performance(Bal, 2024). Higher levels of educational investment improve access to schooling, increase the quality of educational infrastructure, and enhance learning outcomes. Empirical evidence suggests that countries allocating a larger share of public resources to education tend to achieve higher levels of human capital and productivity Rahman *et al.* (2023).

Building on this evidence, the present study focuses on a set of indicators capturing both educational investment and educational attainment. In particular, the empirical analysis includes public expenditure on education, upper-secondary attainment, and the share of the labor force with advanced education. These variables capture key dimensions of human capital accumulation by reflecting both the resources allocated to education systems and the stock of skills within the population.

2.3. Human capital and health

Health is also shown to impact economic growth through human capital. Health-related proxies have increasingly been incorporated into the measurement of human capital, often alongside educational indicators.

Health expenditure as a share of GDP is a common measure, reflecting the resources allocated to improving population health. Islam and Alam (2022) used an Autoregressive Distributed Lags Model (ARDL) model for Bangladesh and found that health spending has a consistent long-run effect on growth but not an immediate impact, underscoring the cumulative nature of health investments. Some comparative studies emphasize that education and health are not substitutes but they represent complementary dimensions of human capital. For example, Ogundari and Awokuse (2018), employed System Generalized Method of

Moments (SGMM) for 35 countries over 1980–2008, showing that both education and health positively affect growth, with health indicators contributing more strongly in their sample. Similarly, Sultana *et al.* (2022), in a panel of 141 countries, combined health (per capita health expenditure, life expectancy) and education (average years of schooling, pupil–teacher ratio) to demonstrate that human capital accumulation requires both dimensions, though in developed economies longer life expectancy may exert negative effects due to aging populations. The empirical evidence from Aka and Dumont (2008) for the U.S. (1929–1997) and Dhrifi *et al.* (2021) for 108 countries also highlights bidirectional causality between education, health, and economic growth, suggesting deep complementarities between these variables. At the micro level, Ross and Wu (1995) argue that education enhances health by equipping individuals with skills and behaviors that promote well-being, while good health, in turn, raises productivity and the ability to capitalize on acquired education. Also, Bloom and Canning (2003) emphasize the dual role of health as both a consumption good and a form of human capital that enhances productivity and economic performance. They show that public investments in clean water, sanitation, and vaccination are highly effective in improving health outcomes, particularly in developing countries. Improved longevity raises the return to education, as individuals are more willing to invest in schooling when they expect a longer productive life. Overall, their analysis highlights the two-way relationship between health and income, where economic prosperity fosters better health, and health improvements accelerate human capital accumulation and growth. Analyzed together, these findings confirm that health indicators such as life expectancy, fertility, and health spending are integral comprehensive human capital proxies to human capital, and that the interaction between education and health is essential for capturing its full effect. In our empirical analysis, health determinants are captured through expenditure on healthcare, fertility rates, and the ratio of hospital beds to medical doctors.

2.4. Socio-demographic determinants

Beyond economic, educational, and health-related factors, a growing strand of literature highlights the importance of social and institutional determinants in shaping human capital formation and outcomes. Variables such as corruption, remittances, female labor force participation, and research and development (R&D) capture broader socio-cultural and governance dimensions that condition both the level and effectiveness of human capital investments.

Corruption, is broadly defined as the misuse of public authority for private gain. Mauro (1995) used a cross-sectional dataset of around 70 countries and applying regression analysis to demonstrate that corruption reduces growth by lowering investment rates and skewing public expenditure toward unproductive uses. The high level of corruption is also dangerous for healthy economic growth, especially in low-income countries with limited human capital stocks, where talented people could orientate towards high income industries which are not productive just for receiving incentives. For example, Murphy *et al.* (1991), uses a theoretical model based on cross-country evidence on the occupational choices of graduates to show that when high-skilled people are concentrated in rent-seeking activities (e.g., law, lobbying) instead of productive sectors (e.g., engineering), growth slows as incentives to invest in skills decline. Ehrlich and Lui (1999) also build a theoretical framework to argue that corruption magnifies development gaps by reducing incentives for skill investment. The forms of corruption range from large corruption at the political level to bureaucratic and judicial corruption, which shape everyday interactions between citizens and officials. Andvig and Fjeldstad (2001), through a comprehensive review of many contemporary case studies and theoretical approaches, conclude that corruption systematically erodes state capacity, diverts resources and reduces the quality of governance. The empirical evidence further confirms its economic costs. For example, Treisman (2000), based on a large panel of over 100 countries and employing cross-national econometric analysis, finds that higher corruption is associated with weaker political stability, reduced openness, and slower long-run growth. Olson *et al.* (2000), use a cross-country panel dataset of around 70 countries over the period 1970–1990 to evaluate how institutional quality can impact economic growth. Their results show that corruption reduces the efficiency of government spending and erodes institutional capacity, thereby weakening the channels through which human capital contributes to long-run development. Freckleton *et al.* (2012) analyze a panel of 42 developed and developing countries during 1995-2007 with dynamic panel data models (Generalized Method of Moments- GMM estimators) and demonstrate that corruption significantly lowers the productivity of human capital. According to their analysis, this effect appears as the returns to education and the incentives for training and skills acquisition are reduced. Their findings underline that governance quality is a crucial moderator of the human capital–growth relationship. Corruption is shown by Aslam (2020), using cross-country panel data and econometric modeling, to undermine both, economic performance and human capital accumulation by weakening institutions and distorting incentives. These insights provide a strong rationale for including corruption in our empirical analysis as a social determinant of human capital, given its potential to condition not only the scale but also the effectiveness of educational and health-related investments.

Recent studies highlight that migration patterns may significantly influence human capital accumulation. In particular, the emigration of highly skilled workers may reduce the domestic stock of human capital and weaken long-term growth prospects in the countries of origin, a phenomenon commonly referred to as brain drain (Akyıldız *et al.*, 2025). Migration not only implies the movement of skills but also generates financial flows in the form of remittances. Migrant workers often send money back to their home countries, and these remittances can significantly shape educational and health investments at the household level. Although remittances provide additional financial resources to households, their origin lies in international migration and family networks, making them a social rather than purely economic phenomenon. Moreover, the share of income that migrants transfer back home depends largely on social factors—such as family ties, cultural norms and household composition—rather than on earnings alone. For these reasons, we consider remittances in this study as a social factor influencing human capital formation. Empirical evidence suggests that remittances may finance education by alleviating household credit constraints. For instance, Kugler (2006) uses household-level survey data on Colombia for the period 1997-2003 and employs econometric models of household expenditure to show that remittances significantly increase investments in schooling by relaxing liquidity constraints. Similarly, Gyimah-Brempong and Asiedu (2015), employs cross-sectional household survey data from Ghana with probit and instrumental variable estimations to confirm that remittances raise the probability of school enrollment. Amuedo-Dorantes and Pozo (2013) carry nationally representative household survey data from the Dominican Republic (1997–2004) and apply regression analysis to estimate that a 10% increase in remittances raises school attendance by roughly 3%. These findings support the “brain gain” hypothesis described by Docquier and Rapoport (2011), whereby migration prospects and remittances encourage greater household investment in education. However, the evidence is not uniformly positive.

Gao *et al.* (2021) uses panel data from household and school surveys in the Kyrgyztan Republic in his econometric analysis to demonstrate that remittances may reduce school enrollment. The explanation would be that adult migration leaves children without adequate supervision. A similar pattern is documented by Bucheli *et al.* (2018), who analyze household survey data from Ecuador from 2010 and show that the effect of remittances varies with family arrangements. When one parent migrates and sends remittances while the children remain under the care of the other parent, grandparents, or other guardians, school attendance tends to increase because supervision and support for education are preserved. However, when both parents migrate and children are left without close parental monitoring, the positive income effect of remittances is offset by weaker supervision, which can reduce school attendance. Thus, the presence or absence of effective caregivers determines whether remittances reinforce or hinder human capital formation. Therefore, remittances may finance human capital accumulation, but it seems that their impact is highly context-dependent, shaped by household structures, labor market opportunities, and institutional frameworks. As we intend to test their relevance and better understand how international financial flows interact with human capital formation, we include remittances in our empirical analysis for OECD countries.

Another important dimension of human capital emphasized recently in the literature is gender inclusion, with female labor force participation (FLFP) widely regarded as an indicator of human capital quality. Research highlights that FLFP is not only a driver of women’s empowerment but also a catalyst for human capital accumulation and long-term development. Using a comprehensive cross-country literature review, Heath *et al.* (2024) synthesize empirical evidence showing that policies expanding childcare availability, enhancing workplace flexibility, and strengthening women’s bargaining power consistently increase female labour force participation. The review further highlights that higher female labour supply translates into greater investments in children’s schooling and health.

At the micro level, Jensen (2012) provides experimental evidence from rural India. In 160 villages, recruiters linked young women (ages 15–21) to positions in the business process outsourcing (BPO) industry in a randomized controlled study. These women were 5–6 percentage points less likely to marry or have children, 4.6 percentage points more likely to work in BPO), and more likely to invest in computer and English training throughout a three-year period. Crucially, even younger girls in these homes demonstrated better nutrition (as indicated by their body mass index BMI) and increased school enrollment, indicating intergenerational human capital spillovers. These findings support Goldin’s (1994) U-shaped trajectory, whereby FLFP initially declines during industrial transitions but rebounds with rising education and white-collar opportunities.

At the same time, Kleven *et al.* (2019) document persistent barriers such as motherhood “penalties’’, cultural constraints, and limited childcare, which continue to suppress women’s full labor market potential. Addressing these barriers becomes therefore essential, as increasing female participation not only narrows gender gaps but also amplifies long-term human capital formation and economic growth. Given this evidence, we include female labor force participation in our empirical analysis as a social determinant of human capital.

In addition to the traditional educational measures, the literature also emphasizes the role of research and development (R&D) expenditure as a driver of human capital formation and productivity. In our view, unlike direct educational inputs such as attainment or enrollment, R&D reflects the institutional and innovation environment that sustains knowledge creation and diffusion, making it a broader socio-institutional determinant rather than a purely educational one. Empirical evidence confirms its multifaceted contribution. Giyasova *et al.* (2025), used Hong Kong data for 1998–2022 and Granger causality tests and found that R&D spending and researcher growth increase GDP per capita and vice versa, suggesting a reinforcing two-way relationship. Similarly, Diakodimitriou *et al.* (2025) showed through dynamic panel models that R&D acts as a key channel through which education expenditure translates into higher per-capita GDP, highlighting its magnifying effect on human capital investments. However, the findings are not uniformly positive. Pop-Silaghi *et al.* (2014) examine annual data for Central and Eastern European economies over 1998–2008 using a dynamic panel GMM estimator. Their results show that business R&D expenditure has a positive and statistically significant impact on economic growth, both in the short and long run. By contrast, public R&D expenditure is generally found to be statistically insignificant in the baseline specification. When human capital is added to the model, the effect of business R&D remains significant but weakens, suggesting that innovation outcomes depend not only on investment but also on the availability of skilled human capital. Fayyaz and Bartha (2025), apply structural equation modeling on data for 32 lower-middle-income countries, showing that while R&D fosters innovation, this does not automatically translate into growth due to institutional and structural weaknesses. Männasoo *et al.* (2018), analyzing data during 1995-2015 for 99 European regions with panel dynamic techniques, find that human capital has a stronger direct effect on productivity than R&D. This implies that R&D has a positive effect on economic growth only when the human capital is already skilled. Together, these studies underscore that R&D enhances human capital not by expanding basic educational attainment, but by developing already existing innovation capacity. As we want to test the influence of R&D on a developed sample of countries which would also have high-skilled population, we include R&D expenditure as a social determinant of human capital in our analysis.

Another important factor that may be considered in relationship with human capital accumulation and economic growth is urbanization. For example, Arouri *et al.* (2014) study the effects of urbanization in Africa by applying Granger causality` tests and dynamic regressions and their results proved that urbanization is impacting human capital variables, such as enrollment rates and health variables. When it comes to the effects on economic development, this study also confirms what other researchers stated, meaning that there is an inverted U-shape relationship between urbanization and economic development. The explanation would be that in the early stage of development, urbanization supports economic growth, but at later stages it turns negative, as the high or fast rhythm may boost infrastructure and hinder the economy. Also, Jemiluyi and Jeke (2024) use annual macroeconomic data for Nigeria covering 1991–2022, including GDP, urbanization, capital formation, labour and trade openness, and employ an ARDL–ECM framework to demonstrate that urbanization alone does not foster economic growth without supportive productive and structural conditions. Urbanization has a positive effect only when interacting with human capital, emphasizing that education and health investments can mitigate the adverse impacts of rapid urbanization and generate other benefits. Therefore, since urbanization seems to capture a broader series of socio-demographic factors that influence both human capital and life expectancy, we include it as a variable in our study.

2.5. Some gaps in existing research

Most of the existing studies on human capital and development like the ones of Bloom and Canning (2003); Teixeira and Fortuna (2004); Affandi *et al.* (2019) rely on cross-sectional or static panel techniques such as Ordinary Least Squares (OLS), fixed effects, or random effects. Only a limited number of studies like for examples the ones of Baldacci *et al.* (2008); Giyasova *et al.* (2025)or Rahim *et al.* (2021) employ dynamic methods like System GMM to address endogeneity and persistence. Furthermore, literature rarely compares human capital and life expectancy as complementary indicators, even though they are closely connected. The contribution of this study is threefold: first, it adopts a multi-perspective approach, examining economic, educational, health, and social determinants of human capital and life expectancy. Second, it explicitly compares the two indicators highlighting their complementarities and differences; and third, it relies on recent data and a dynamic panel methodology (System GMM), which allows for a more robust assessment of causality and persistence than static models.

The contribution of this study is twofold. First, the paper provides a comprehensive analysis of the determinants of human capital by examining a broad set of socio-economic, educational, and macroeconomic factors. Second, the analysis adopts a dual empirical perspective on human capital measurement, using both the Human Capital Index (HCI) and life expectancy (LE) as alternative dependent variables estimated in separate model specifications. This approach allows us to assess whether the determinants of human capital formation affect a composite measure of human capital (HCI) and a health-based proxy (LE) in a similar or different manner, thereby providing a more nuanced understanding of the mechanisms underlying human capital development. Importantly, the two indicators are not included simultaneously in the same regression equation, but are analyzed in separate models in order to capture complementary dimensions of human capital.

3. DATA AND METHODOLOGY

3.1. Methodological approach

The empirical analysis is based on a panel dataset of the 38 OECD countries covering the period 2000–2024. Due to missing observations for several variables across countries and years, the dataset forms an unbalanced panel. The empirical analysis therefore employs the System GMM estimator, which is particularly suitable for dynamic panel models with potential endogeneity and unbalanced data structures.

The sample consists of annual observations for a wide range of economic, educational, health, and social indicators collected from the World Bank and OECD databank. Human capital is proxied by two alternative indicators: the World Bank Human Capital Index (2018) and life expectancy at birth, which capture different aspects of human capital development related to productivity and population health. The explanatory variables are grouped into four categories: economic (GDP per capita, government debt, taxation, budget balance, inflation), educational (expenditure on education, upper-secondary and share of advanced-educated labor), health-related (health expenditure, fertility and a proxy based on the number of beds and doctors available per 1000 residents) and social (urbanization, corruption indices, remittances, female labor force participation and R&D expenditure,). This structure allows for a multidimensional assessment of the determinants of human capital and life expectancy across advanced economies over nearly a quarter century.

To analyze the determinants of human capital and life expectancy, this study employs dynamic panel models, which are particularly well-suited for capturing persistence effects and accounting for the fact that current levels of human capital are influenced by their past values. Moreover, many explanatory variables—such as education expenditure, female labor force participation, or fiscal indicators—are likely to be endogenous, either because of reverse causality or omitted variable bias. System GMM as described by Arellano and Bover (1995) provides a robust solution by using internal instruments derived from lagged values of the variables, thereby addressing endogeneity. In addition, the method accommodates heterogeneity across countries, which is crucial in a cross-national setting where institutional structures, development levels, and policy frameworks differ significantly. For all these reasons, System GMM is an appropriate methodology for identifying the causal impact of economic, educational, health, and social determinants on human capital dynamics.

3.2. Data and Variables

In this study, human capital is analyzed using two complementary dependent variables: the Human Capital Index (HCI) and life expectancy at birth (LE). Although HCI includes a health-related component associated with survival probability, it is primarily a composite indicator capturing the productivity potential of future workers by combining education quantity, education quality, and health conditions. In contrast, life expectancy reflects broader population health outcomes and demographic conditions as it is shaped by institutional quality, economic development, public health systems and the overall macroeconomic environment in which individuals live. Therefore, the use of both indicators allows the analysis to capture complementary dimensions of human capital development.

The economic determinants included in the analysis are GDP per capita, taxes (calculated as the average of taxes on income, profits, and capital gains and taxes on goods and services) government debt, budget balance, and inflation with data collected from the World Bank. Higher GDP per capita (lnGDP) is expected to positively influence both human capital and life expectancy, as greater income levels improve access to education, healthcare, and overall living conditions. Government debt (GovDebt) is expected to have a negative long-run effect on both indicators, because when a country owes large amounts of money, fewer public resources remain available for education, healthcare, and other social investments. High debt also creates pressure to cut spending or raise taxes in the future, which can further limit support for human capital. By contrast, a stronger budget balance (Budget), meaning that revenues and expenditures are under control, allows governments to invest more steadily in schools, hospitals, and social programs. In this way, government debt is expected to reduce human capital and life expectancy in the long run. Taxation (Taxes) measured through a composite indicator (average of taxes on income, profits, and capital gains, and taxes on goods and services), captures governments' reliance on fiscal revenues. On the public side, higher tax revenues provide governments with the resources needed to finance education, health, and social programs, which should enhance human capital and longevity. On the private side, however, higher taxes on income and profits may reduce incentives for households and firms to invest in skills, training, and innovation. Therefore, the net effect of taxation on human capital is theoretically ambiguous and ultimately depends on the efficiency of public spending and the structure of the tax system. Inflation (Inflation) is generally seen as detrimental since it erodes purchasing power and reduces access to essential goods. However, in certain contexts, moderate inflation may also exert a positive effect, as it may be associated with economic growth, wage adjustments, and increased fiscal revenues that are to be redirected toward education and healthcare.

The level of education is the basis of performant human capital, as it determines both the accumulation of knowledge and the development of skills required in modern economies. Public expenditure on education (EdExp) reflects the resources allocated to improving access, quality, and infrastructure in the education system and it is therefore expected to have a positive impact on human capital. The share of the population with upper secondary education (Upper) captures the stock of advanced skills and qualifications in the society and we anticipate it will enhance human capital through higher productivity, innovation, and adaptability. The share of the labor force with advanced education (LaborAdvance) directly measures the availability of skilled workers and it is expected to increase human capital. All education-related variables should facilitate the comprehension of medical information and the adoption of healthier lifestyles, therefore expecting a positive effect also on life expectancy, not only on human capital.

The health-related variables are closely linked to the formation and accumulation of human capital, since a healthier population is able to learn better, work, and contribute productively. The Public health expenditure (HealthExp) is expected to positively affect human capital and life expectancy, as it improves access to medical services. Fertility rates (**Fertility**) are expected to be also positively linked with the dependent variables as we are working on data from developed countries. Finally, the ratio of hospital beds to doctors (BedsDoctors) reflects the availability of medical infrastructure and personnel and we generally expect a positive relationship with the dependent variables, although in contexts where infrastructure expands faster than qualified staff, the effect may be ambiguous.

Social and institutional factors also play an essential role in shaping both human capital (HC) and life expectancy (LE). Urbanization (UrbanPop) may foster HC by providing improved access to schools, universities, and infrastructure, while for LE it can enhance access to healthcare and services. The level of corruption (Corruption) given by the Corruption Perceptions Index is anticipated to reduce HC by undermining the efficiency of public spending on education and health, and we also assume it would lower LE by weakening institutional quality and diverting resources away from essential social services. Remittances (Remittances) may positively affect HC by financing education, training, or health-related investments, and they can also raise LE by improving household access to private healthcare, nutrition, and better living conditions. Female labor force participation (FemaleLabor) is expected to positively influence HC by increasing household income, stimulating greater investment in children’s education, and promoting gender equality in skills development. We also expect an increased LE caused by FLFP as it would facilitate access to healthcare and better intergenerational outcomes. Finally, R&D expenditure (RDExp) is expected to contribute positively to HC by fostering innovation, knowledge creation, and advanced skills, while for LE it can improve health outcomes through medical advances, new treatments, and enhanced healthcare efficiency.

For clarity, the full description, measurement, and sources of all variables included in the analysis are reported in Annex, Table no. A1.

3.3. Preliminary Analysis

Prior to estimation, the dataset was organized as a country–year panel of OECD economies. Descriptive statistics, correlation analysis, and panel unit root tests were conducted to examine the statistical properties of the variables and their stationarity. Missing observations were addressed selectively using linear interpolation for several variables, including government debt, education expenditure, upper-secondary attainment, advanced-educated labor and R&D expenditure. In the case of education expenditure, limited forward and backward filling was also applied to complete isolated gaps in the time series.

For variables exhibiting non-stationarity, first differences were generated and used in the empirical analysis where appropriate. Additionally, logarithmic transformations were tested for selected macroeconomic indicators such as GDP and health expenditure in alternative specifications. Potential outliers were examined through descriptive statistics and distributional measures; however, extreme values were retained as they reflect genuine cross-country heterogeneity among OECD economies. As missing observations differ across indicators and countries, the resulting dataset constitutes an unbalanced panel, which is compatible with the System GMM estimation framework employed in the study.

Table no. 1 – Descriptive Statistics

	Mean	Median	SD	Min	Max	N
HCI	.626	.669	0.235	0	1	839
Life	78.93	79.61	3.191	69.75	84.56	840
GDP	32767.752	31611.293	21636.023	4016.81	112417.88	874
GovDebt	78.865	67.308	46.323	3.814	249.366	433
Taxes	28.22	27.372	4.874	18.079	48.122	779
Budget	-1.992	-2.115	4.423	-32.098	26.301	800
Inflation	3.474	2.44	5.426	-4.448	72.309	875
EdExp	5.196	5.016	1.153	2.614	8.584	735
Upper	67.285	74.807	19.336	15.77	95.289	622
LaborAdvance	79.368	79.405	4.523	65.702	94.867	793
HealthExp	8.345	8.136	2.250	3.703	18.813	823
Fertility	1.651	1.59	0.374	.721	3.11	840
BedsDoctors	4.089	3.838	1.750	1.224	14.61	777
UrbanPop	75.559	76.92	11.404	50.754	98.224	875
Corruption	1	1.015	0.909	-1.703	2.459	805
Remittances	.955	.492	1.059	0	6.176	873
FemaleLabor	52.381	53.062	7.710	23.114	73.42	875
RDExp	1.775	1.594	1.082	.131	6.019	782

Source: authors computation using Stata 18.00

Table no. 1 presents the descriptive statistics for the variables used in the empirical analysis. The comparison between mean and median values provides a first indication of the distributional characteristics of the data. For most variables, the mean and median are relatively close, suggesting moderate symmetry in their distributions. However, for some macroeconomic indicators, particularly GDP per capita and inflation, larger differences between the mean and median indicate the presence of asymmetric distributions across countries, reflecting the heterogeneity of OECD economies. The dispersion measures further reveal substantial variability in several variables. GDP per capita displays the widest range, highlighting significant differences in economic development levels across the sample. Fiscal indicators such as government debt and budget balance also show considerable variation, reflecting heterogeneous fiscal conditions among OECD countries.

To further assess the distributional properties of the variables, Table no. 2 reports the skewness and kurtosis coefficients. These statistics provide additional information on the degree of asymmetry and the presence of heavy tails in the distributions. In particular, inflation shows extremely high skewness and kurtosis, suggesting the presence of significant outliers. Similar patterns, though less pronounced, are observed for budget balance and the beds-to-doctors ratio. These results indicate that the dataset contains extreme observations, which are typical in cross-country macroeconomic data and reflect structural heterogeneity across OECD economies rather than measurement errors.

Table no. 2 – Skewness and Kurtosis

	Skewness	Kurtosis
HCI	-.657	2.672
Life	-.709	2.689
GDP	1.196	4.803
GovDebt	1.006	3.909
Taxes	.811	3.558
Budget	.676	10.473
Inflation	7.202	73.23
EdExp	.619	3.013
Upper	-.855	2.541
LaborAdvance	.259	3.53
HealthExp	.913	4.959
Fertility	1.401	5.921
BedsDoctors	2.094	12.689
UrbanPop	-.155	2.237
Corruption	-.501	2.796
Remittances	1.687	5.969
FemaleLabor	-.614	4.72
RDExp	.695	3.18

Source: authors computation using Stata 18.00

To further investigate the presence of extreme observations, percentile statistics were also computed. The detailed percentile distributions are reported in Table no. A2. The comparison between lower and upper percentiles confirms the presence of wider dispersion for several macroeconomic indicators, particularly GDP per capita and inflation. These results indicate that some variables contain extreme values; however, these observations reflect the substantial heterogeneity across OECD economies rather than data inconsistencies.

Prior to the estimation, panel unit root tests were conducted in order to determine the order of integration of the variables. Specifically, the Im–Pesaran–Shin and Fisher-type panel unit root tests were employed, and the results are reported in Table no. 3.

Table no. 3 – Unit root test

Variables	Im-Pesaran-Shin/ Fisher - Level	Im-Pesaran-Shin/ Fisher - First Difference	Status
HCI	-2.5494***	-	I(0)
Life	3.2303	14.6426***	I(1)
GDP	-2.0384**	-	I(0)
GovDebt	31.1310	210.1972***(Fisher)	I(1)
Taxes	-1.0106	-9.7300***	I(1)
Budget	-4.3239***	-	I(0)
Inflation	-7.7823***	-	I(0)
EdExp	96.9673**	-	I(0)
Upper	43.8080	291.1575***(Fisher)	I(1)
LabourAdvance	79.6483	334.3051***(Fisher)	I(1)
HealthExp	-0.5037	14.5956***	I(1)
Fertility	6.9787	-3.4501***	I(1)
BedsDoctors	1.8081	-4.9542***	I(1)
UrbanPop	-29.8340***	-	I(0)
Corruption	1.8998	11.9786***	I(1)
Remittances	-1.7707**	-	I(0)
FemaleLabour	-0.1527	11.1709***	I(1)
RDExp	-9.0532***	-	I(0)

Note: IPS test performed with lags (1), with trend. Panel: OECD (N=38)
Source: authors computation using Stata 18.00

The optimal number of lags was selected automatically based on the Schwarz Information Criterion (BIC), as implemented in Stata. The results indicate that the variables exhibit mixed orders of integration. Several variables, including HC, GDP, Inflation, Budget balance, Urbanization, Remittances, and R&D expenditure, are stationary in levels, indicating an integration order of I(0). In contrast, variables such as Life expectancy, Government debt, Taxes, Upper-secondary attainment, Advanced labor, Health expenditure, Fertility, Beds per doctor, Corruption, and Female labor force participation are non-stationary in levels but become stationary after first differencing, indicating that they are integrated of order one, I(1). The presence of both I(0) and I(1) variables supports the use of dynamic panel estimation techniques such as System GMM (Arellano and Bond, 1991). In addition, several variables (e.g., health expenditure, fertility and female labor force participation) are potentially endogenous due to reverse causality, so system GMM is therefore appropriate, as it controls for unobserved heterogeneity and mitigates potential endogeneity as described by Arellano and Bover (1995) and by Blundell and Bond (1998).

4. EMPIRICAL ANALYSIS

The theoretical foundation of the human capital models presented in this study is based on the framework proposed by Baldacci *et al.* (2008), who examined the channels through which public social spending affects human capital formation and economic growth. *Their model integrates education, health, and growth equations within a dynamic panel framework* for 120 developing countries between 1975 and 2000. The framework emphasizes the role of public policies and macroeconomic conditions in shaping the accumulation of human capital.

In simplified form, the growth equation proposed by Baldacci *et al.* (2008) can be written as:

$$Growth_{it} = f\left(\ln y_{i,t-1}, Investment_{it}, Education_{it}, Health_{it}, \Delta Education_{it}, \Delta Health_{it}, Z_{it}\right) \quad (1)$$

where $Growth_{it}$ denotes real GDP per capita growth in country i at time t, while $\ln y_{i,t-1}$ represents the lagged level of income capturing convergence effects. $Investment_{it}$ reflects the investment rate and therefore the accumulation of physical capital. $Education_{it}$ and $Health_{it}$ represent the stocks of education and health capital, respectively, while $\Delta Education_{it}$ and $\Delta Health_{it}$ capture changes in these dimensions of human capital. Finally, Z_{it} is a vector of macroeconomic and institutional control variables, including trade openness, terms of trade shocks, fiscal balance, inflation, and governance indicators.

In this framework, economic growth is influenced by both physical investment and human capital accumulation. Education and health represent the two main dimensions of human capital, while macroeconomic stability and institutional conditions shape the environment in which these factors contribute to growth.

Although the present study does not estimate a separate growth equation, this conceptual structure provides the theoretical background for our empirical analysis. In particular, it highlights the central role of education and health in the accumulation of human capital, which motivates our focus on the determinants of human capital and life expectancy in OECD economies.

In addition to the growth equation, Baldacci *et al.* (2008) also specify an investment equation describing the macroeconomic and human capital factors that influence physical capital accumulation. In simplified form, the investment equation proposed by Baldacci *et al.* (2008) can be written as:

$$Investment_{it} = f\left(\ln y_{i,t-1}, PopulationGrowth_{it}, Education_{it}, Health_{it}, FiscalBalance_{it}, Inflation_{it}, Governance_{it}\right) \quad (2)$$

where $Investment_{it}$ denotes the investment ratio measured as gross capital formation as a percentage of GDP. The variable $\ln y_{i,t-1}$ represents the lagged level of income and captures convergence effects across countries. $PopulationGrowth_{it}$ reflects demographic dynamics that influence savings and investment decisions. $Education_{it}$ represents the stock of education capital, proxied in the Baldacci framework by the composite primary and secondary school enrollment rate, while $Health_{it}$ captures the stock of health capital, proxied by the logarithm of under-five child mortality. These variables reflect the idea that higher levels of human capital increase productivity and therefore stimulate investment. Macroeconomic stability is captured through fiscal and monetary indicators. In particular, the fiscal balance variable reflects the sustainability of public finances, while inflation captures macroeconomic instability that may discourage investment. Governance indicators are also included in order to account for institutional conditions that affect the efficiency of investment and economic activity. Although the present study does not estimate a separate investment equation, this mechanism is reflected in our empirical framework through the inclusion of macroeconomic variables such as GDP per capita, inflation, government debt, taxation, and budget balance, which capture the broader economic environment in which human capital is accumulated.

In the framework proposed by Emanuele Baldacci *et al.* (2008), human capital is modeled as the outcome of the interaction between education and health, both influenced by public expenditure and macroeconomic conditions. In their empirical specification, education and health represent the two main components of human capital and are determined not only by public spending but also by a set of broader contextual variables.

Education and health jointly determine the stock of human capital, which in turn contributes to economic growth. Public spending on education and health therefore influences growth both directly and indirectly through improvements in human capital outcomes. In simplified form, the education equation proposed by Baldacci *et al.* (2008) can be written as:

$$Education_{it} = f(\ln y_{it}, Popu15_{it}, Health_{it}, Urban_{it}, Quality_{it}, EduSpending_{it}, Governance_{it}, Female_{it}) \quad (3)$$

where $Education_{it}$ represents the stock of education capital, proxied by the composite primary and secondary school enrollment rate. The variable $\ln y_{it}$ captures the level of economic development, reflecting the idea that higher income increases the demand for education. Demographic pressure on the education system is captured by $Popu15_{it}$, which represents the share of population below 15 years of age. $Health_{it}$ captures the stock of health capital, proxied by the under-five child mortality rate, reflecting the idea that a healthier population is more likely to invest in education. Additional variables reflect broader socio-institutional conditions affecting education outcomes. Urbanization ($Urban_{it}$) captures access to educational infrastructure, while education quality ($Quality_{it}$) is proxied by the school repetition rate. Public education expenditure ($EduSpending_{it}$) measures government spending on education as a percentage of GDP and is included both in current and lagged form in order to capture delayed effects of spending on education outcomes. Governance conditions ($Governance_{it}$) reflect institutional quality affecting the efficiency of public spending, while gender equality ($Female_{it}$) is captured through the share of female students in primary and secondary education. In the Baldacci framework, this equation highlights that education outcomes are determined by a combination of economic development, demographic pressure, health conditions, institutional quality, and public spending.

In the present study, the education dimension is represented through indicators of educational attainment and skills formation, including education expenditure, upper secondary attainment, literacy rates, and the share of labor force with advanced education.

In simplified form, the health equation proposed by Baldacci *et al.* (2008) can be written as:

$$Health_{it} = f(\ln y_{it}, Fertility_{it}, Urban_{it}, HealthSpending_{it}, Governance_{it}, Female_{it}) \quad (4)$$

where $Health_{it}$ represents the stock of health capital, proxied by the logarithm of the under-five child mortality rate. The variable $\ln y_{it}$ captures the level of economic development, reflecting the idea that higher income levels improve access to healthcare services and living conditions. Demographic factors are captured by $Fertility_{it}$, which reflects population dynamics affecting health outcomes and healthcare demand. Urbanization ($Urban_{it}$) captures access to healthcare infrastructure and services, as urban populations generally benefit from better medical facilities and public health conditions. Public health expenditure ($HealthSpending_{it}$) measures government spending on health as a percentage of GDP and captures the role of public investment in improving health outcomes. Governance conditions ($Governance_{it}$) are included to account for the institutional environment influencing the efficiency of healthcare spending, while gender-related factors ($Female_{it}$) reflect the role of female education and gender equality in improving health outcomes. In the Baldacci framework, this equation highlights that health outcomes are determined by a combination of economic development, demographic dynamics, institutional conditions, and public spending.

In the present study, the health dimension is captured through variables such as public health expenditure, fertility rates, and healthcare capacity (proxied by the ratio of hospital beds and physicians), while life expectancy is used as a direct indicator of health outcomes and human capital accumulation.

Building on this framework, the present study extends the set of determinants in order to capture a broader range of factors influencing human capital formation in advanced economies. While Baldacci et al. focus primarily on social spending and macroeconomic stability, our analysis incorporates a wider group of variables reflecting economic, educational, health-related and socio-institutional conditions. In particular, the social dimension is represented through variables such as urbanization, corruption perceptions, remittances, female labor force participation, and research and development expenditure, while demographic dynamics are captured mainly through fertility rates. This broader specification allows for a more detailed assessment of the mechanisms through which macroeconomic conditions, institutional environments, and social structures influence human capital and life expectancy across OECD countries.

Therefore, the general dynamic panel specification for human capital is:

$$HC_{it} = \alpha HC_{it-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

$$LE_{it} = \alpha LE_{it-1} + \beta X_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

where:

- $\mathrm{HC_{it}}$ and $\mathrm{LE_{it}}$ represents human capital (or life expectancy) for country i in year t;
- $\mathrm{HC_{it-1}}$ and $\mathrm{LE_{it-1}}$ are the lagged dependent variable, capturing persistence;
- $\mathrm{X_{it}}$ is a vector of explanatory variables (specific to each perspective: economic, educational, health, social);
- μ_i denotes country-specific effects;
- $\varepsilon_{\mathrm{it}}$ is the error term.

The empirical analysis employs the System GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), which is well-suited for dynamic panel models where the dependent variable depends on its lagged values and regressors may be endogenous. The estimator combines equations in first differences with equations in levels, using lagged levels as instruments for the differenced equation and lagged differences as instruments for the levels equation. This framework addresses key econometric concerns by correcting the dynamic bias introduced by lagged dependent variables, mitigating endogeneity arising from variables such as GDP, health expenditure, or education, and controlling for unobserved country-specific heterogeneity through differencing. To enhance efficiency and inference, the analysis applies the two-step robust estimator with Windmeijer's finite-sample correction, which improves the reliability of standard errors compared to the one-step procedure. To ensure the robustness of the dynamic panel estimates, several specification tests were conducted, including the Arellano-Bond test for serial correlation (where AR(1) is expected and AR(2) should be absent), the Hansen and Sargan tests for instrument validity as their exogeneity, and check for instrument proliferation, which are addressed by collapsing the instrument matrix and restricting lag depth.

The validity of the dynamic panel estimations was assessed through a series of specification tests commonly used in the System GMM framework. In particular, the Arellano–Bond tests for serial correlation were applied to the differenced residuals, where the presence of first-order autocorrelation (AR(1)) and the absence of second-order autocorrelation (AR(2)) represent the expected pattern. In addition, the Hansen and Sargan tests of overidentifying restrictions were used to evaluate the validity and exogeneity of the instruments employed in the estimation. To further ensure the reliability of the instrument set and to avoid instrument proliferation, the instrument matrix was collapsed and the lag depth was restricted following standard practice in the System GMM literature.

Multicollinearity was assessed through the Variance Inflation Factor (VIF) tests in preliminary OLS estimations. All VIF values were below the conventional threshold of 5, indicating no critical collinearity concerns among the explanatory variables included in the System GMM specifications.

4.1. Economic Perspective

For human capital index (HCI), the specification includes GDP, inflation and the budget balance because fiscal sustainability affects investments in education and social protection more directly than debt stock. The baseline economic specification (model 7) for Human Capital (HC) is:

$$HCI_{it} = \alpha HCI_{it-1} + \beta_1 \, lnGDP_{it} + \beta_2 \, Budget_{it} + \beta_3 \, Inflation_{it} + \varepsilon_{it} \tag{7}$$

where $\mathrm{HCi}_{\mathrm{it}}$ represents the Human Capital Index for country i in year t, $\mathrm{HCI}_{\mathrm{it}-1}$is the lagged dependent variable capturing persistence effects, $\mathrm{lnGDP}_{\mathrm{it}}$denotes the logarithm of GDP per capita, $\mathrm{Budget}_{\mathrm{it}}$represents the fiscal balance, $\mathrm{Inflation}_{\mathrm{it}}$is the inflation rate, and $\varepsilon_{\mathrm{it}}$is the error term.

For HCI, the lagged dependent variable is positive and highly significant, indicating strong persistence in human capital accumulation. GDP per capita does not exhibit a statistically significant relationship with human capital once persistence effects are taken into account. Inflation shows a small but statistically significant positive coefficient, suggesting that moderate inflation may be associated with periods of economic dynamism rather than macroeconomic instability. Fiscal variables do not display robust short-term associations with human capital in this specification.

For life expectancy, the economic specification is extended to include government debt and taxation, in addition to GDP per capita, inflation, and the fiscal balance. The logic behind is that health outcomes are more sensitive to long-term fiscal pressures and structural budget conditions than to short-run economic fluctuations. Government debt may influence life expectancy indirectly through its impact on future public healthcare spending and infrastructure maintenance. High debt levels may constrain fiscal space over time, leading to postponed investment in health systems. Taxation may affect the affordability of healthcare services and the financing of public health programs. The model estimated is therefore:

$$\mathrm{LE_{it}} = \alpha \mathrm{LE_{it-1}} + \beta_1 \ln \mathrm{GDP_{it}} + \beta_2 \mathrm{GovDebt_{it}} + \beta_3 \mathrm{Taxes_{it}} + \beta_4 \mathrm{Inflation_{it}} + \beta_5 \mathrm{Budget_{it}} + \varepsilon_{it} \quad (8)$$

where $\mathrm{LE_{it}}$ denotes life expectancy at birth for country i in year t, $\mathrm{LE_{it-1}}$ is the lagged dependent variable, $\mathrm{lnGDP_{it}}$ represents the logarithm of GDP per capita, $\mathrm{GovDebt_{it}}$ denotes government debt, $\mathrm{Taxes_{it}}$ represents the composite taxation indicator, $\mathrm{Inflation_{it}}$ is the inflation rate, $\mathrm{Budget_{it}}$ denotes the fiscal balance, and ε_{it} is the error term.

Table no. 4 – Economic Determinants of HCI and LE - System GMM, OECD, 2000-2024

	(7) HCI	(8) Life
L.HCI / L.Life	0.981***	0.699***
	(0.021)	(0.141)
lnGDP	-0.001	2.455**
	(0.006)	(1.143)
GovDebt	-	0.002
		(0.002)
Taxes	-	-0.057*
		(0.030)
Budget	0.001	-0.010
	(0.001)	(0.010)
Inflation	0.001***	0.063**
	(0.000)	(0.025)
Constant	0.045	0.000
	(0.046)	(.)
Observations	767	388
AR(1) p-value	0.001	0.000
AR(2) p-value	0.186	0.362
Hansen p-value	0.323	0.997
Sargan p-value	0.205	0.956

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Source: authors computation using Stata 18.00

The results confirm that for life expectancy, persistence remains strong, as indicated by the significant lagged term. GDP per capita shows a positive and statistically significant association, consistent with higher income levels being linked to improved living conditions. Inflation also displays a positive and significant association. Government debt and budget balance are not statistically significant, while taxation shows a small negative but significant coefficient. This suggests that income conditions are more strongly associated with life expectancy than short-term fiscal adjustments. For both HCI and LE models, diagnostic tests indicate the validity of the specifications, as the AR(2) test does not indicate second-order serial correlation and both Hansen and Sargan tests suggest acceptable instrument validity.

For both models, diagnostic tests (AR (2) > 0.1, Hansen > 0.2) confirm model validity.

4.2. Educational Perspective

This perspective distinguishes between educational inputs, educational attainment, and the effective integration of skills into the labour market. Education expenditure (EdExp) captures financial investment in the education system. While expenditure and attainment capture educational inputs and schooling levels, human capital formation depends on whether those skills are absorbed into productive employment. If education is not effectively utilized, increases in schooling or spending do not immediately raise the stock of human capital.

For education, the HCI specification of model 9 is:

$$HCI_{it} = \alpha HCI_{it-1} + \beta_1 \, EdEXp_{it} + \beta_2 \, Upper_{it} + \beta_3 \, LaborAdvance_{it} + \varepsilon_{it} \quad (9)$$

where $\mathrm{HCI_{it}}$represents the Human Capital Index for country i in year t, $\mathrm{HCI_{it-1}}$is the lagged dependent variable capturing persistence effects, $\mathrm{EdExp_{it}}$denotes public expenditure on education, $\mathrm{Upper_{it}}$represents the share of the population with upper secondary education, $\mathrm{LaborAdvance_{it}}$denotes the share of the labor force with advanced education and was included as differences as it became stationary only after first differentiated and $\varepsilon_{it}$is the error term.

For life expectancy (LE), the specification is as follows:

$$LE_{it} = \alpha LE_{it-1} + \beta_1 \, EdExp_{it} + \varepsilon_{it} \quad (10)$$

where $\mathrm{LE_{it}}$denotes life expectancy at birth for country i in year t, $\mathrm{LE_{it-1}}$is the lagged dependent variable capturing persistence in life expectancy, $\mathrm{EdExp_{it}}$represents public expenditure on education.

For HCI the lagged dependent variable is positive and highly significant (1.17, $p < 0.01$), confirming strong persistence in human capital. Among the education variables, only upper secondary attainment (Upper_diff) is weakly significant ($p < 0.1$), indicating that increases in the share of individuals completing upper secondary education are associated with small improvements in human capital. By contrast, education expenditure and the share of advanced labour force are not statistically significant. Their coefficients remain close to zero, which suggests that these factors do not produce immediate changes in the HCI within the estimation window, although they may matter through slower channels not captured in short-run dynamics.

Table no. 5 – Educational Determinants of HC and LE - System GMM, OECD, 2000-2024

	(9) **HCI**	**(10)** **LE**
L.HCI / L.Life	1.172***	1.297***
	(0.160)	(0.147)
EdExp	-0.011	-0.099
	(0.009)	(0.129)
Upper	0.001*	-
	(0.001)	
LaborAdvance	0.000	-
	(0.001)	
Constant	-0.105	-24.203**
	(0.075)	(11.415)
Observations	615	702
AR(1) p-value	0.000	0.000
AR(2) p-value	0.385	0.263
Hansen p-value	0.301	0.699
Sargan p-value	0.212	0.003

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors computation using Stata 18.00

Life expectancy also exhibits strong persistence in model 10. Education expenditure is again not statistically significant, meaning that no direct short-run association can be identified in this specification. This does not rule out long-run effects but it indicates that, within the structure of the model and sample period, changes in education spending are not immediately reflected in life expectancy. The estimated constant varies across model specifications and in some cases may appear relatively large (e.g., in model 10). This is not unusual in dynamic System GMM models. Since the lagged dependent variable captures most of the persistence, the intercept absorbs remaining level effects and unobserved factors not explicitly included in the model. In addition, differences in variable scaling and sample composition across specifications may contribute to variation in the estimated constant.

Model diagnostics support the statistical validity of both specifications. The AR(1) test shows the expected first-order serial correlation, while the AR(2) test fails to reject the null of no second-order autocorrelation ($p > 0.1$), confirming that the moment conditions are correctly specified. The Hansen test indicates valid instruments ($p > 0.2$). The Sargan test is borderline for Model 10 ($p = 0.003$), which suggests caution in interpreting the strength of the instruments for this specification, although the Hansen statistic—more robust in the presence of heteroskedasticity – still supports overall instrument validity.

4.3. Health Perspective

This perspective examines how health system inputs and demographic factors influence human capital. The aim is to isolate the health channel of development, focusing on the resources and structural conditions that shape population health rather than on education or macroeconomic factors. Health expenditure (HealthExp) captures the financial resources allocated to the healthcare system. Fertility changes (Fertility) reflect demographic dynamics that affect the age structure of the population and long-term human capital formation. Medical infrastructure (BedsDoctors) measures the capacity of the healthcare system, proxied by the availability of hospital beds and medical personnel. The last two variables (Fertility and BedsDoctors) were included in both equations as differences as they became stationary only after first differentiated. The equation of the model for HCI is:

$$HCI_{it} = \alpha HCI_{it-1} + \beta_1 \, HealthEXp_{it} + \beta_2 \, Fertility_{it} + \beta_3 \, BedsDoctors_{it} + \varepsilon_{it} \quad (11)$$

where $\mathrm{HC_{it}}$represents the Human Capital Index for country i in year t, $\mathrm{HC_{it-1}}$is the lagged dependent variable capturing persistence in human capital, $\mathrm{HealthExp_{it}}$denotes public health expenditure, $\mathrm{Fertility_{it}}$represents the fertility rate, $\mathrm{BedsDoctors_{it}}$denotes the composite indicator of healthcare capacity (average number of physicians and hospital beds), and $\varepsilon_{\mathrm{it}}$is the error term.

While for LE as follows:

$$LE_{it} = \alpha LE_{it-1} + \beta_1 \, HealthEXp_{it} + \beta_2 \, Fertility_{it} + \beta_3 \, BedsDoctors_{it} + \beta_4 \, Trend_t + \varepsilon_{it} \quad (12)$$

where $\mathrm{LE_{it}}$denotes life expectancy at birth for country i in year t, $\mathrm{LE_{it-1}}$is the lagged dependent variable capturing persistence effects, $\mathrm{HealthExp_{it}}$represents public health expenditure, $\mathrm{Fertility_{it}}$denotes the fertility rate, $\mathrm{BedsDoctors_{it}}$represents the composite indicator of healthcare capacity, $\mathrm{Trend_t}$is a time trend capturing the general upward evolution in life expectancy over time, and $\varepsilon_{\mathrm{it}}$is the error term.

A linear time trend is included only in the life expectancy specification within the health perspective. Life expectancy displays a well-documented secular upward trajectory across OECD countries, largely driven by long-term improvements in medical technology, public health systems, and living standards. Because these broad structural developments are not fully captured by the health variables included in the model (such as health expenditure, fertility, or the BedsDoctors ratio), the trend term is introduced to control for this common temporal evolution. In contrast, the other model specifications focus on socio-economic and institutional determinants whose dynamics already reflect gradual structural changes over time, making an additional deterministic trend unnecessary.

Table no. 6 – Health Determinants of HC and LE - System GMM, OECD, 2000-2024

	(11) HCI	(12) LE
L.HCI / L.LE	0.878^{***}	1.082^{***}
	(0.039)	(0.126)
HealthExp	0.004	-0.081
	(0.006)	(0.050)
Fertility	0.054^{**}	-0.130
	(0.025)	(1.856)
BedsDoctors	0.001	-0.009^{**}
	(0.001)	(0.004)
Trend		-0.036
		(0.025)
Constant	0.061^{*}	67.485
	(0.030)	(40.677)
Observations	742	742
AR(1) p-value	0.004	0.000
AR(2) p-value	0.978	0.559
Hansen p-value	0.130	0.731
Sargan p-value	0.000	0.576

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors computation using Stata 18.00

Human capital shows again strong persistence, as indicated by the highly significant lagged dependent variable ($p < 0.01$). Among the health covariates, fertility has a positive and statistically significant coefficient, suggesting that demographic dynamics play a role in shaping human capital outcomes within the panel. By contrast, health expenditure and healthcare capacity (BedsDoctors) are not statistically significant, meaning that within the estimated specification their direct association with human capital cannot be identified. The AR(2) and Hansen tests support overall model validity, although the Sargan test indicates some misspecification, so the results should be interpreted with caution. A more complete interpretation of the BedsDoctors indicator would require joint consideration of medical personnel per capita, which can be incorporated in future extensions of the analysis.

Life expectancy also displays high persistence, as shown by the positive and highly significant lagged term ($p < 0.01$). The coefficient on BedsDoctors is negative and significant, which may reflect efficiency issues in healthcare systems where the number of beds grows faster than medical personnel capacity. In such cases, a higher beds-to-doctor ratio can signal pressure on medical staff and lower productivity per physician. Health expenditure and fertility are not statistically significant in this specification. The diagnostics tests confirm models' validity.

4.4. Social Perspective

Our social determinants are urbanization, perceived corruption, remittances, female labour force participation and R&D expenditure. The HCI specification includes R&D expenditure and female labour participation because human capital reflects productive capacity, which depends on labour market inclusion and the knowledge environment. Female labour force participation captures social inclusion and the utilization of human potential, while R&D expenditure reflects the innovation context that supports skill development and knowledge accumulation. All the variables in this sub-chapter were included in both equations as differences as they became stationary only after first differentiated.

Therefore, for HCI the model has the following equation:

$$HCI_{it} = \alpha HCI_{it-1} + \beta_1\ FemaleLabor + \beta_2\ RDExp_{it_{it}} + \varepsilon_{it} \tag{13}$$

where $\mathrm{HC_{it}}$represents the Human Capital Index for country i in year t, $\mathrm{HC_{it-1}}$is the lagged dependent variable, $\mathrm{FemaleLabor_{it}}$represents female labor force participation, $\mathrm{RDExp_{it}}$ denotes research and development expenditure, and $\varepsilon_{\mathrm{it}}$is the error term.

The life expectancy model includes urbanization, corruption, remittances, female labour participation, and R&D expenditure because longevity is influenced by living conditions, institutional quality, household financial capacity, and technological progress. These variables capture access to services, governance quality, and the socio-economic environment that affects health outcomes. The life expectancy model estimated is:

$$\begin{aligned} LE_{it} = \alpha LE_{it-1} + \beta_1\ UrbanPop_{it} + \beta_2\ Corruption_{it} + \beta_3\ Remittances_{it} \\ +\ \beta_4\ FemaleLabor_{it} + \beta_5\ RDExp_{it} + \varepsilon_{it} \end{aligned} \tag{14}$$

where $\mathrm{LE_{it}}$ denotes life expectancy at birth for country i in year t, $\mathrm{LE_{it-1}}$is the lagged dependent variable capturing persistence effects, $\mathrm{UrbanPop_{it}}$represents the urban population share, $\mathrm{Corruption_{it}}$denotes the corruption perception index, $\mathrm{Remittances_{it}}$represent remittance inflows, $\mathrm{FemaleLabor_{it}}$denotes female labor force participation, $\mathrm{RDExp_{it}}$represents research and development expenditure, and $\varepsilon_{\mathrm{it}}$is the error term.

In both models, model 13 and model 14, human capital is highly persistent, as indicated by the strong significance of the lagged dependent variable. Among the social variables, female labor force participation shows a consistent positive and statistically significant effect, indicating that greater female involvement in the labor market is associated with higher levels of human capital. This result aligns with the literature linking gender inclusion to improved household resources, education, and health outcomes. By contrast, urbanization, corruption, remittances, and R&D expenditure do not show statistically significant coefficients in these specifications. The diagnostics confirm model validity.

Table no. 7 – Social Determinants of HCI and LE - System GMM, OECD, 2000-2024

	(13) HCI	(14) LE
L.HCI / L.LE	0.939***	0.927***
	(0.031)	(0.041)
UrbanPop	-	-0.029
		(0.166)
Corruption	-	-0.274
		(0.300)
Remittances	-	0.364
		(0.372)
FemaleLabor	0.006***	0.687***
	(0.002)	(0.251)
RDExp	-0.012	-0.212
	(0.014)	(0.163)
Constant	0.058***	5.846*
	(0.020)	(3.232)
Observations	738	679
AR(1) p-value	0.001	0.001
AR(2) p-value	0.241	0.151
Hansen p-value	0.504	0.644
Sargan p-value	0.313	0.006

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors computation using Stata 18.00

Diagnostic tests support model validity for the HCI equation. For the life expectancy model, AR (2) and Hansen statistics are acceptable, although the Sargan test indicates some instrument sensitivity, so results should be interpreted with caution.

5. ROBUSTNESS

The mixed models combine determinants identified in the separate perspectives (education, social, and health) in order to assess their joint contribution to human capital. These specifications serve as robustness checks rather than alternative structural models. The economic factors are excluded as they mainly capture the broader economic environment and our focus lies instead on the structural mechanisms through which human capital is accumulated. All variables in this sub-chapter, with the exception of health expenditure, are included in first differences, as they are non-stationary in levels and become stationary only after first differencing. For HCI, the integrated model includes the effective integration of advanced-educated labour (LabourAdvance), demographic dynamics (Fertility), female labour participation (FemaleLabour), and health expenditure (HealthExp). This specification captures the interaction between education utilization, social inclusion, demographic structure, and health conditions in shaping productive capacity.

$$HCI_{it} = \alpha HCI_{it-1} + \beta_1\, LaborAdvance_{it} + \beta_2\, Fertility_{it} + \beta_3\, FemaleLabor_{it} + \beta_4\, HealthExp_{it} + \varepsilon_{it} \quad (15)$$

where $\mathrm{HC_{it}}$represents the Human Capital Index for country i in year t, $\mathrm{HC_{it-1}}$is the lagged dependent variable capturing persistence in human capital, $\mathrm{LaborAdvance_{it}}$denotes the share of the labor force with advanced education, $\mathrm{Fertility_{it}}$ represents the fertility rate, $\mathrm{FemaleLabor_{it}}$ denotes female labor force participation, $\mathrm{HealthExp_{it}}$ represents public health expenditure, and ε_{it} is the error term.

For life expectancy, the integrated specification focuses on skill structure (LabourAdvance), urbanization (UrbanPop), and remittances (Remittances), which reflect the socio-economic environment influencing health outcomes. These variables represent the social and human capital context through which longevity evolves. Therefore, model nr 16 has the following equation:

$$LE_{it} = \alpha LE_{it-1} + \beta_1\, LaborAdvance_{it} + \beta_2 UrbanPop_{it} + \beta_3\, Remittances_{it} + \varepsilon_{it} \quad (16)$$

where $\mathrm{LE_{it}}$ denotes life expectancy at birth for country i in year t, $\mathrm{LE_{it-1}}$ is the lagged dependent variable capturing persistence in life expectancy, $\mathrm{LaborAdvance_{it}}$ represents the share of the labor force with advanced education, $\mathrm{UrbanPop_{it}}$ denotes the urban population share, $\mathrm{Remittances_{it}}$ represents remittance inflows, and ε_{it} is the error term.

Table no. 8 – Mixed Determinants of HCI and LE - System GMM, OECD, 2000-2024

	(15) **HCI**	**(16)** **LE**
L.HCI / L.LE	0.989***	1.131***
	(0.026)	(0.032)
LaborAdvance	0.002	0.069**
	(0.002)	(0.033)
Fertility	0.044*	-
	(0.024)	
UrbanPop		-0.218
		(0.216)
Remittances		0.166
		(0.126)
FemaleLabor	0.004***	-
	(0.002)	
HealthExp	-0.003**	-
	(0.001)	
Constant	0.055***	-10.025***
	(0.012)	(2.508)
Observations	756.000	772.000
AR(1) p-value	0.001	0.000
AR(2) p-value	0.218	0.176
Hansen p-value	0.553	0.057
Sargan p-value	0.417	0.310

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors computation using Stata 18.00

Persistence remains the dominant feature. For HCI, fertility and female labour force participation display positive and statistically significant association. Health expenditure shows a small but statistically significant negative coefficient, while the remaining variables do not exhibit statistically significant contemporaneous effects in the combined specification.

These results indicate that demographic dynamics and social inclusion are more strongly associated with human capital accumulation than the other controls in this framework.

For LE (eq. 16), the skill structure of the labour force, proxied by the share of advanced-educated workers (LabourAdvance), shows a positive and statistically significant association. Urbanization and remittances do not display statistically significant effects in the integrated model. This suggests that the composition of the labour force is more strongly associated with longevity than the other included socio-economic controls in this specification. Diagnostic tests broadly support model validity. The AR (2) tests do not indicate second-order serial correlation, and Sargan statistics are acceptable. The Hansen statistic in the life expectancy equation is borderline, so results should be interpreted as robustness evidence rather than definitive structural relationships.

6. CONCLUSION

This paper contributes to the literature by examining the determinants of human capital and life expectancy in OECD countries through a multidimensional dynamic panel framework. Using annual data for the period 2000–2024 and applying the System GMM estimator, the analysis provides a comprehensive assessment of the economic, educational, health, and social factors shaping human capital development. By employing two complementary proxies – the Human Capital Index (HCI) and life expectancy (LE) – the study offers a broader perspective on human capital formation, capturing both skill accumulation and long-term health outcomes.

The empirical results reveal strong persistence in both human capital and life expectancy, indicating that these indicators evolve gradually and exhibit pronounced path dependence. This finding suggests that improvements in human capital are the result of long-term accumulation processes rather than short-term policy interventions. Countries with stronger human capital foundations tend to maintain their advantages over time, while those starting from lower levels require sustained and consistent policy efforts in order to close the gap.

The analysis also highlights important differences across the economic, educational, health, and social dimensions considered in the empirical models. Economic growth, measured through GDP per capita, shows a positive and significant relationship with life expectancy, confirming the well-established link between higher income levels and improved health outcomes. In contrast, fiscal variables such as government debt, taxation, and fiscal balance display limited short-term effects once the dynamic persistence of the dependent variables is accounted for. These results suggest that while fiscal conditions shape the macroeconomic environment, their direct influence on human capital outcomes may operate primarily through longer-term channels.

Education-related indicators emerge as important drivers of human capital accumulation. In particular, upper-secondary attainment and the share of the advanced-educated labor force are positively associated with human capital outcomes, highlighting the crucial role of investments in education and skill formation for long-term economic development. At the same time, the relatively weak short-run effects of education expenditure suggest that the benefits of educational investments materialize gradually and require sustained policy commitment over time. Expanding access to education and improving educational quality therefore remain essential for strengthening human capital in advanced economies.

Health-related determinants display more complex patterns. Health expenditure and healthcare infrastructure indicators show mixed effects across the estimated models, suggesting that the efficiency and allocation of healthcare resources may be more important than the overall level of spending. In addition, demographic variables such as fertility appear to influence human capital outcomes indirectly, highlighting the importance of demographic dynamics in shaping long-term development trajectories. These results underline the need for balanced health policies that focus not only on the volume of spending but also on the efficiency and effectiveness of healthcare systems.

Among the social determinants, female labor force participation emerges as one of the most robust and consistent drivers of both human capital accumulation and life expectancy. This finding emphasizes the central role of gender inclusion in fostering economic productivity and human capital development. Policies that promote equal opportunities, flexible working arrangements, and improved work–life balance can therefore contribute significantly to strengthening the human capital base of modern economies. In contrast, other social variables such as remittances, corruption, urbanization, and R&D expenditure show weaker or context-dependent effects, suggesting that their influence may depend on institutional quality or may materialize over longer time horizons.

Taken together, the results highlight the strong interdependence between education, health, and social inclusion in shaping human capital outcomes. Human capital formation should therefore be understood as a multidimensional process that requires coordinated policy strategies across several domains. Governments aiming to strengthen their human capital base should prioritize improving education quality and skills relevance, ensuring a better alignment between education systems and labor market needs. In the health sector, the focus should shift from the volume of spending toward efficiency, including better allocation of medical personnel and reducing disparities in access to healthcare services. In addition, policies supporting female labor force participation – such as access to childcare and flexible work arrangements – can further enhance human capital accumulation.

This study contributes to the literature by providing a comprehensive empirical assessment of the determinants of human capital using a broad set of socio-economic indicators and by comparing two complementary measures of human capital within a unified econometric framework. By distinguishing between economic, educational, health, and social determinants, the analysis offers a more nuanced understanding of the mechanisms that shape human capital development in advanced economies.

Despite the contributions of this study, several avenues remain open for future research. First, the present analysis focuses on OECD countries, which are characterized by relatively high levels of institutional development and human capital accumulation. Extending the analysis to developing and emerging economies could provide valuable insights into whether the determinants of human capital formation operate differently across stages of economic development. Comparative studies between advanced and developing economies may help identify structural differences in the relative importance of economic, educational, health, and social factors.

Second, while the System GMM estimator is appropriate for addressing endogeneity and dynamic persistence in panel data, future research could explore potential non-linear relationships between human capital determinants and development outcomes. In particular, panel threshold models or non-linear dynamic panel techniques could be used to identify critical levels of education, health expenditure, or economic development beyond which their impact on human capital or life expectancy becomes more pronounced.

Thirdly, future studies could therefore complement macroeconomic analyses with micro-level or household-level data in order to better understand how individual socio-economic characteristics, such as income, education, labor market participation, and demographic conditions, shape human capital accumulation and health outcomes.

Finally, further research could incorporate additional structural determinants that are becoming increasingly relevant in modern economies, such as technological progress, digitalization, institutional quality and innovation capacity. Understanding how these factors interact with traditional drivers of human capital formation, including education systems, healthcare infrastructure and labor market participation, may provide a more comprehensive picture of the long-term mechanisms shaping human capital development.

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ANNEX

Table no. A1 – Variables and Data Sources

Variables	Notation	Description (defined by the issuer)	Data source
Dependent variables			
Human Capital Index	HC	The amount of human capital a child born today can expect to attain by age 18, given the risks of poor education and health.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Life Expectancy At Birth, total (years)	LE	The number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Independent variables			
Gdp Per Capita (constant US$)	GDP	The gross domestic product (GDP) divided by mid-year population, adjusted for inflation to a base year (e.g., 2015).	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Consumer Price Index (annual %)	Inflation	The yearly percentage change in the cost of a basket of goods and services to the average consumer.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Central Government Debt (% of GDP)	GovDebt	The entire stock of direct government fixed-term contractual obligations to others outstanding on a particular date.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Central Government Budget Balance (% of GDP)	Budget	Current and capital revenue and official grants received, less total expenditure and lending minus repayments.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Distortionary Vs. Consumption Tax Mix (%)	Taxes	Average of: (i) taxes on income, profits, and capital gains (% of revenue), and (ii) taxes on goods and services (% of revenue).	Constructed variable based on - The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Public Expenditure On Education (% of GDP).	EdExp	General government expenditure on education.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Share Of Population With Upper Secondary Education (%).	Upper	The percentage of population ages 25 and over that attained or completed upper secondary education.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Share Of Labour Force With Advanced Education (%)	Labour Advance	The percentage of the working age population with an advanced level of education* who are in the labour force.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Public health expenditure (% of GDP).	HealthExp	The sum of public and private health expenditure.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Medical Infrastructure	BedsDoctors	Average between the number of doctors and number of beds per 1000 inhabitants.	Constructed variable based on The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)

Variables	Notation	Description (defined by the issuer)	Data source
Fertility Rate, Total (births per woman)	Fertility	The number of children that would be born to a woman if she were to live to the end of her childbearing years.	The World Bank - Worldwide Governance Indicators (http://info.worldbank.org/governance/wgi/)
Labour Force, Female (% of total labour force)	FemaleLaborur	Female labour force participation rate (% of female population ages 15+).	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Urban Population	Urban	The share of the total population living in areas defined as urban.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Corruption Perceptions Index	Corruption	It scores and ranks countries by their perceived levels of public sector corruption	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Personal remittances received (% of GDP).	Remittances	Personal transfers and compensation of employees—household income from foreign economies sent by migrants.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)
Research and development expenditure (%)	RDRxp	The gross domestic expenditures on research and development.	The World Bank - World Development Indicators (WDI)(http://info.worldbank.org/governance/wgi/)

Note: * Advanced education comprises short-cycle tertiary education, a bachelor's degree or equivalent education level, a master's degree or equivalent education level, or doctoral degree or equivalent education level according to the International Standard Classification of Education 2011 (ISCED 2011).
Source: Authors' processing.

Table no. A1 – Percentile Distribution of the Variables

	1st Perc.	p5	p25	Median	p75	p95	99th Perc.	Min	Max
HCI	0	.155	0.469	.669	.824	.933	.963	0	1
Life	70.9	72.7	76.9	79.6	81.41	83.007	83.883	69.75	84.56
GDP	5046.9	7915.5	14703.6	31611.2	44391.4	74729.7	106544.0	4016.8	112417.8
GovDebt	4.8	14.7	45.4	67.3	101.5	186.7	215.8	3.8	249.3
Taxes	19.0	21.7	25.0	27.3	30.1	38.8	41.5	18.0	48.1
Budget	-12.8	-8.3	-4.1	-2.1	.07	4.4	14.1	-32.1	26.3
Inflation	-.92	-.18	1.2	2.4	3.8	9.6	19.5	-4.4	72.3
EdExp	3.2	3.5	4.3	5.0	5.7	7.5	8.2	2.6	8.5
Upper	21.0	30.2	52.8	74.8	82.1	88.7	91.1	15.7	95.2
LaborAdvance	68.4	72.7	76.2	79.4	82.1	86.8	91.3	65.7	94.8
HealthExp	4.3	5.23	6.7	8.1	9.7	11.4	16.2	3.7	18.8
Fertility	1.1	1.2	1.3	1.6	1.8	2.3	3.0	.72	3.1
BedsDoctors	1.3	1.6	3.2	3.8	4.9	6.	13.1	1.2	14.6
UrbanPop	52.2	55.5	67.8	76.9	83.6	93.1	97.9	50.7	98.2
Corruption	-1.5	-.44	0.37	1.01	1.79	2.24	2.39	-1.70	2.45
Remittances	.01	.034	0.21	.49	1.37	3.03	4.56	0	6.17
FemaleLabor	27.1	38.6	49.1	53.1	56.9	62.1	71.6	23.1	73.4
RDExp	.18	.35	0.91	1.59	2.52	3.58	4.79	.13	6.01

Table no. A2 – Simple Correlations between the economic variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) HC	1.000						
(2) Life	0.855	1.000					
	(0.000)						
(3) GDP	0.559	0.602	1.000				
	(0.000)	(0.000)					
(4) Inflation	-0.288	-0.291	-0.221	1.000			
	(0.000)	(0.000)	(0.000)				
(5) GovDebt	0.281	0.358	-0.008	-0.164	1.000		
	(0.000)	(0.000)	(0.852)	(0.000)			
(6) Taxes	0.146	0.165	0.249	0.012	-0.151	1.000	
	(0.000)	(0.000)	(0.000)	(0.732)	(0.001)		
(7) Budget	0.148	0.090	0.339	-0.008	-0.482	0.137	1.000
	(0.000)	(0.008)	(0.000)	(0.818)	(0.000)	(0.000)	

Table no. A3 – Pairwise correlations between the education-related variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) HC	1.000							
(2) Life	0.855	1.000						
	(0.000)							
(3) EdExp	0.245	0.166	1.000					
	(0.000)	(0.000)						
(4) Doctoral	0.289	0.331	0.052	1.000				
	(0.000)	(0.000)	(0.295)					
(5) Master	0.254	0.140	-0.054	0.635	1.000			
	(0.000)	(0.003)	(0.284)	(0.000)				
(6) Upper	0.464	0.194	0.182	0.335	0.442	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(7) LaborAdvance	0.013	0.019	0.280	-0.007	-0.001	-0.118	1.000	
	(0.711)	(0.588)	(0.000)	(0.882)	(0.988)	(0.003)		
(8) Literacy	0.071	0.022	0.397	0.000	-0.060	-0.036	-0.136	1.000
	(0.471)	(0.826)	(0.000)	(0.999)	(0.651)	(0.724)	(0.176)	

Table no. A4 – Pairwise correlations between the health variables

Variables	(1)	(2)	(3)	(4)	(5)
(1) HC	1.000				
(2) Life	0.855	1.000			
	(0.000)				
(3) HealthExp	0.418	0.529	1.000		
	(0.000)	(0.000)			
(4) Fertility	-0.146	-0.042	-0.057	1.000	
	(0.000)	(0.202)	(0.087)		
(5) BedsDoctors	0.191	0.146	0.097	-0.455	1.000
	(0.000)	(0.000)	(0.005)	(0.000)	

Table no. A5 – Pairwise correlations between the social variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) HC	1.000						
(2) Life	0.855	1.000					
	(0.000)						
(3) UrbanPop	0.189	0.162	1.000				
	(0.000)	(0.000)					
(4) Corruption	0.045	0.100	0.463	1.000			
	(0.189)	(0.003)	(0.000)				
(5) Remittances	-0.225	-0.502	-0.037	-0.205	1.000		
	(0.000)	(0.000)	(0.253)	(0.000)			
(6) FemaleLabor	0.531	0.373	0.256	0.163	-0.169	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(7) RDExp	0.523	0.581	0.255	0.097	-0.388	0.421	1.000
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	

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Asymmetric Shocks and Long-Memory Volatility: An Egarch Approach to Global Oil and Local Import Dynamics

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Abstract: This study investigates the volatility dynamics of commodity import prices in Republic of Moldova and global Brent crude oil prices, employing advanced econometric models to enhance understanding of risk in small open economies and energy markets. Utilizing monthly data from 1992 to 2025 for Republic of Moldova's Commodity Import Price Index and from January 1990 to May 2025 for Brent oil, the analysis confirms that both series are integrated of order one, with no significant structural breaks in the mean, supporting constant-parameter modelling. For Republic of Moldova's Commodity Import Price Index, an AR (1)-GARCH (1,1) specification effectively captures high volatility persistence and symmetric shock responses, indicating long-memory effects without asymmetry. In contrast, Brent oil exhibits leverage effects, where negative shocks amplify volatility more than positive ones, best demonstrated via AR(1)-EGARCH(1,1,1). Comprehensive diagnostics, including ADF tests, Bai-Perron structural break analysis, ARCH-LM, Ljung-Box, and Nyblom stability tests, validate model adequacy, confirming residual whiteness and structural stability. These findings underscore the need for symmetric risk management in Republic of Moldova's import sector and asymmetric hedging in oil markets, with implications for macroeconomic stability and policy formulation. Research gaps highlight opportunities for multivariate spillover analysis and regime-switching models to address cross-market dependencies.

Keywords: volatility modeling; GARCH; EGARCH; commodity import price index, structural breaks, leverage effects, small open economies.

JEL classification: C22; C58; Q02; Q41; Q43; F41.

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1. INTRODUCTION

Commodity markets play a pivotal role in the global economy, influencing everything from energy prices to agricultural outputs and, by extension, the macroeconomic stability of nations. Volatility in these markets – characterized by sudden and unpredictable price fluctuations – poses significant challenges for policymakers, investors, and businesses, particularly in small open economies like Republic of Moldova that rely heavily on imports. This research delves into the intricate dynamics of commodity price volatility, with a specific focus on Republic of Moldova's *Commodity Import Price Index, Individual Commodities Weighted by Ratio of Imports to GDP with Recent Fixed Weights (CIPI)* and *global Brent crude oil prices*.

We use the full monthly histories available at the time of the study, data are from the IMF's Primary Commodity Price System (IMF, 2025), 1992–2025 for the Republic of Moldova's Commodity Import Price Index (CIPI) and January 1990 - May 2025 for Brent oil – because these spans maximize information, improve statistical power, and ensure the analysis reflects all major commodity and energy price regimes observed to date. The CIPI begins in 1992 due to data availability following Republic of Moldova's statehood; Brent is available earlier, so we retain its pre-1992 observations to better characterize its own dynamics and volatility. Employing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques – standard GARCH and Exponential GARCH (EGARCH) – we uncover high persistence, symmetric shock responses for import prices, and pronounced asymmetry with leverage effects in oil markets. These insights enhance understanding of risk transmission to vulnerable economies and inform hedging, policy design, and resilience strategies.

Commodity prices exhibit clustering, long-memory effects, and differential responses to shocks – phenomena theorized by Engle's (1982) ARCH and Bollerslev's (1986) GARCH. For the Republic of Moldova, a landlocked nation dependent on imported energy and raw materials, import price volatility directly impacts inflation, trade balances, and fiscal stability. Our empirical investigation (1992–2025) reveals Moldova's CIPI series is integrated of order one (I(1)), displaying symmetric volatility with near-unit-root persistence ($\alpha + \beta \approx 0.97$), implying a volatility half-life of approximately two years. This symmetry indicates positive and negative shocks affect volatility equally, without leverage effects seen in financialized assets. Comprehensive diagnostics – Augmented Dickey-Fuller (ADF) for stationarity, Bai-Perron for structural breaks (none detected in mean), HEGY for seasonality (absent), and post-estimation ARCH-LM, Ljung-Box, and Nyblom stability tests – confirm AR(1)-GARCH(1,1) model robustness. Conversely, Brent oil exhibits asymmetric dynamics where negative shocks amplify volatility more than positive ones (leverage effect), captured by AR(1)-EGARCH(1,1) with shorter half-life (~1.6 months), highlighting faster mean reversion in highly traded commodities.

Volatility modeling has proven essential across energy, agriculture, and metals sectors. In developing economies, fluctuations exacerbate external vulnerabilities, as seen in Moldova's exposure to global supply shocks, geopolitical tensions, and currency risks. Bridging theory with evidence, the present paper is deliberately univariate in scope: it estimates and diagnoses conditional-volatility models for the two series individually – AR(1)-GARCH(1,1) for CIPI and AR(1)-EGARCH(1,1) for Brent – and compares their persistence, asymmetry and stability properties within a common methodological frame. Extensions that fall outside this scope – multivariate spillover analyses quantifying cross-market volatility transmission and regime-switching frameworks accommodating dynamic parameter shifts – are identified as directions for future research and are not claimed as contributions of the present study. Findings underscore tailored risk management –diversification for symmetric, persistent import basket volatilities and asymmetric hedging for oil-driven asymmetries – contributing to macro-stability and sustainable development in small open economies. This introduction sets the stage for detailed exploration of methodologies, results, and policy implications, building on rigorous diagnostics to provide actionable insights for stakeholders navigating an increasingly volatile global landscape.

Current state of research. The literature on commodity-price volatility has developed along four broad pillars that together define the current state of the art. The first pillar is methodological: Engle's (1982) ARCH and Bollerslev's (1986) GARCH frameworks established the baseline for modelling time-varying conditional variance, and Nelson (1991)'s EGARCH and Zakoïan's (1994) TGARCH/TARCH extensions introduced the asymmetric responses to positive and negative shocks that have since become a defining stylised fact of financial and commodity series. The second pillar consists of single-commodity empirical applications, predominantly on energy: Sadorsky (2006) and Kang *et al.* (2009) documented strong volatility clustering, persistence and leverage effects in crude oil; Wei *et al.* (2010) and Hung *et al.* (2018) showed that asymmetric specifications systematically outperform symmetric GARCH in forecasting oil volatility; and more recent work by Mușetescu *et al.* (2022) and Merabet *et al.* (2021) has applied AR–EGARCH and ARIMA–EGARCH frameworks to Brent and WTI with a forecasting focus. The third pillar broadens the empirical base to non-energy commodities and to the long-run record: Pindyck and Rotemberg (1990), Karali and Power (2013) and Jacks *et al.* (2011) established that volatility clustering, long memory and time-varying co-movement are pervasive across agricultural, metals and aggregate commodity series, while Bai and Perron (1998, 2003), Hammoudeh and Li (2008) and Aloui and Jammazi (2009) developed and applied structural-break and regime-switching tools that have become standard preliminaries to any GARCH-family estimation. The fourth pillar addresses transmission to small open and import-dependent economies, emphasising how global commodity volatility passes through to domestic inflation, trade balances and fiscal stability; this strand remains dominated by large emerging markets and resource exporters, with relatively few studies of diversified import baskets in post-transition landlocked economies. The present study sits at the intersection of the second and fourth pillars: it brings the asymmetric-GARCH toolkit developed for single-commodity oil markets and the structural-break and seasonality diagnostics developed for commodity time series to a small open economy – the Republic of Moldova – and, by estimating both an aggregated import-price index and Brent oil within the same methodological frame, delivers a direct comparison of persistence and asymmetry across levels of aggregation that the existing literature does not provide.

The remainder of this Introduction states, in order, the rationale for analysing these two indicators in parallel, the specific objectives of the study, its contributions to the literature, and its novelty relative to prior GARCH-family work on oil and commodity prices.

Rationale for the parallel analysis. The two indicators are studied side by side for four related reasons. First, they are economically linked rather than independently chosen: Brent is the dominant global price signal for the energy complex and, through direct fuel imports and indirect pass-through into the prices of transported, processed and petroleum-intensive goods, is a primary external driver of the Republic of Moldova's import bill. Any framework aimed at informing Moldovan stabilisation policy must therefore characterise both the upstream benchmark and the downstream aggregate. Second, the two series sit at deliberately different levels of aggregation – a single globally-traded commodity versus a diversified, GDP-weighted import basket – which allows us to test whether the stylised facts established for individual commodities (volatility clustering, asymmetric leverage, rapid mean reversion) survive aggregation into a national import index, or whether diversification reshapes them. Third, estimating both series with the same preliminary tests (ADF, Bai-Perron, HEGY) and the same GARCH-family toolkit, and subjecting both models to the same post-estimation diagnostics (ARCH-LM, Ljung-Box, Nyblom), yields an apples-to-apples comparison of persistence, asymmetry and stability that neither series could deliver on its own. Fourth, this comparison is directly policy-relevant for a small open economy: the horizon over which shocks dissipate, and the sign-dependence of the volatility response, differ sharply between the external benchmark and the domestic aggregate, implying that hedging strategies calibrated to oil dynamics cannot be transplanted to the management of the wider import basket. The empirical contrast that emerges – short-horizon, asymmetric volatility in Brent versus long-horizon, symmetric volatility in CIPI – is therefore not an incidental by-product of the analysis but its central finding, and it is available only because the two indicators are modelled jointly within a common methodological frame.

Objectives. Against this backdrop, the present study pursues four explicit objectives. First, it characterizes and models the conditional volatility of the Republic of Moldova's Commodity Import Price Index (CIPI) over the period 1992–2025 using an AR(1)-GARCH(1,1) specification, uncovering the degree of volatility persistence and the symmetric nature of shock responses in an aggregated import-price basket. Second, it models global Brent crude oil price volatility (January 1990–March 2025) through an AR(1)-EGARCH(1,1) framework, documenting asymmetric leverage effects and estimating the speed of mean reversion. Third, it subjects both models to a comprehensive battery of diagnostics–Augmented Dickey-Fuller unit-root tests, Bai-Perron structural-break detection, HEGY seasonality tests, post-estimation ARCH-LM and Ljung-Box residual tests, and Nyblom parameter-stability tests–to ensure statistical robustness and model adequacy. Fourth, it translates the empirical findings into actionable risk-management and policy recommendations tailored to small open economies exposed to commodity-price uncertainty.

Contributions. This paper makes several additions to a well-developed literature. It addresses a recognized gap by applying rigorous univariate volatility modeling to a diversified commodity import-price index for a post-transition, landlocked small open economy–a context largely absent from the existing GARCH literature, which has concentrated on individual energy commodities or large emerging markets. It demonstrates empirically that the symmetric GARCH specification is the appropriate model for an aggregated import-price basket, in contrast to the asymmetric EGARCH model required for a single energy commodity, thereby clarifying the modeling choice for researchers working with composite price indices. It further establishes that Moldova's import-price volatility carries a half-life of approximately two years, implying that standard short-horizon stabilization policies are insufficient to absorb persistent external price shocks, a finding with direct fiscal and monetary-policy implications. Finally, the study provides a replicable methodological template–integrating stationarity testing, structural-break detection, seasonality testing, and

GARCH-family estimation with full diagnostics–that can be applied to other small open economies seeking to quantify and manage commodity-price risk.

Novelty relative to the literature. The novelty of the present study is twofold. First, prior GARCH-family applications to oil have focused overwhelmingly on individual benchmarks and have been conducted on developed-market or large emerging-market perspectives: Sadorsky (2006) and Kang *et al.* (2009) established asymmetric leverage effects in WTI and Brent returns; Mușetescu *et al.* (2022) estimated AR–EGARCH dynamics on Brent with a forecasting focus; and Merabet *et al.* (2021) documented ARIMA–EGARCH forecast performance on daily oil data. Our Brent estimates (AR(1)-EGARCH(1,1,1), 1990m01–2025m05, leverage coefficient γ statistically significant and negative, volatility half-life ≈ 1.6 months) are directionally consistent with the asymmetry and clustering documented in these studies, while extending the sample to the full post-2020 period that incorporates the pandemic and post-pandemic regimes not available to earlier work. Second, and more substantively, we document that these oil-market stylized facts do not carry over mechanically to an aggregated import-price basket: our CIPI estimates (AR(1)-GARCH(1,1), $\alpha + \beta \approx 0.97$, no leverage effect in TARCH specification, volatility half-life ≈ 23 months) show that diversification across commodities in an import basket damps the asymmetric response observed in single-commodity oil studies while preserving–indeed amplifying–the persistence. To our knowledge, this contrast has not previously been documented for a post-transition, landlocked small open economy, and it carries direct implications for the design of stabilization policies, which we develop in §4.5.

Key Concepts and Theoretical Underpinnings

- **Volatility Clustering and Persistence**: Commodity prices often show periods of high volatility followed by calm, with effects lingering over time, as modeled by GARCH parameters where the sum of α (arch effect) and β (garch effect) approaches unity, indicating long-memory processes.
- **Asymmetry and Leverage Effects**: In assets like oil, negative news (e.g., supply disruptions) disproportionately increases uncertainty, a feature EGARCH models by incorporating the sign and magnitude of shocks.
- **Structural Stability**: The absence of significant breaks in our series supports constant-parameter modeling, validated against tests for regime changes, ensuring reliable forecasts for policy applications.

This synthesis draws from extensive empirical validation, establishing a foundation for understanding how global commodity dynamics ripple into local economies like Republic of Moldova's, with implications extending to risk assessment, portfolio optimization, and economic forecasting.

Structure of the paper. The remainder of the paper is organised as follows. Section 2 presents a comprehensive literature review of volatility modelling in commodity markets, covering the GARCH-family methodological foundations, single-commodity empirical evidence from energy and agricultural markets, stylised facts and modelling challenges specific to commodity series, and applications to small open economies and import-price dynamics. Section 3 describes the methodological framework, including the data sources (IMF (2025) Primary Commodity Price System for Brent, and the Republic of Moldova's Commodity Import Price Index), the preliminary testing strategy (Augmented Dickey-Fuller unit-root tests, Bai-Perron structural-break detection and HEGY seasonality tests), and the specification of the AR(1)-GARCH(1,1) and AR(1)-EGARCH(1,1) models. Section 4 reports the empirical results for both series, including parameter estimates, the full battery of post-estimation diagnostics (ARCH-LM, Ljung-Box and Nyblom tests), a comparative discussion of persistence, asymmetry and mean reversion across the two models, and the implications for risk management and public policy in small open economies (Section 4.5). Section 5 concludes, summarising the main findings and outlining directions for future research. Supporting tables – correlograms, full diagnostic output and auxiliary test statistics – are provided in the Annex.

2. VOLATILITY MODELING IN COMMODITY MARKETS: A COMPREHENSIVE LITERATURE REVIEW

Synthesis, Controversies and Research Gaps. The GARCH-family literature on commodity volatility has converged on a small set of stylised facts and an equally small set of persistent controversies. Four points of broad consensus can be identified.

(i) Commodity prices exhibit time-varying conditional variance with pronounced clustering and long memory, documented across energy, agricultural and metals markets Sadorsky (2006), Kang *et al.* (2009), Karali and Power (2013), Jacks *et al.* (2011).

(ii) Single-commodity series, and crude oil in particular, display statistically significant asymmetric leverage effects, with negative shocks amplifying volatility more than positive shocks of equal magnitude Nelson (1991), Wei *et al.* (2010), Hung *et al.* (2018), Olanrewaju and Oseni (2021).

(iii) Preliminary testing for unit roots, structural breaks and seasonality is a necessary precondition for GARCH estimation on commodity series Hylleberg *et al.* (1990), Bai and Perron (1998, 2003), Hammoudeh and Li (2008).

(iv) Global commodity volatility transmits to domestic economies through import costs, exchange rates and input-output linkages, with particular intensity in small, open and import-dependent economies (Cashin *et al.*, 2000; Raddatz, 2007; van der Ploeg and Poelhekke, 2009; Frankel, 2012).

Against these points of consensus three active controversies remain. First, whether parsimonious GARCH(1,1) is adequate or whether higher-order and mixed-data-sampling alternatives deliver material forecasting gains – Hansen and Lunde (2005) argue that little beats GARCH(1,1), whereas Wang *et al.* (2023) and Lin *et al.* (2020) document improvements from regime-switching and MIDAS extensions. Second, whether the appropriate framework for commodity-market shocks is a stable asymmetric GARCH specification or a regime-switching / structural-break model with time-varying parameters Aloui and Jammazi (2009), Lin *et al.* (2020) – an unresolved question directly relevant to any study that must decide whether to impose constant parameters. Third, whether asymmetric leverage effects established for individual energy commodities survive aggregation into a diversified commodity basket: Pindyck and Rotemberg (1990) and Creti *et al.* (2013) suggest that composition and diversification effects can dampen or even eliminate the asymmetry observed at the single-commodity level, but the empirical evidence on aggregate import-price indices is thin.

These controversies open three research gaps that frame the present study. First, the GARCH-family literature is dominated by applications to individual commodities – especially oil – and by large emerging markets; rigorous univariate modelling of a diversified national import-price index in a post-transition, landlocked small open economy remains largely absent. Second, there is no direct comparison, within a single methodological frame and common diagnostic battery, of the persistence and asymmetry properties of a global single-commodity benchmark against those of an aggregated import basket that includes that benchmark among its drivers. Third, the literature offers limited guidance on whether the short-horizon hedging strategies calibrated to oil-market asymmetry are appropriate for managing the risk of a diversified import basket in a small open economy with limited monetary-policy space. The present study is designed to address these three gaps directly.

The volatility of commodity prices presents a fundamental challenge for policymakers and researchers analyzing international trade and economic stability. Since Engle (1982) and Bollerslev (1986), sophisticated econometric models for time-varying volatility have revolutionized understanding of financial and commodity markets. Early applications of these frameworks to commodity markets quickly confirmed their relevance: Pindyck and Rotemberg (1990) documented pronounced time-varying co-movement and volatility in a broad cross-section of commodity prices, while Sadorsky (2006) and Kang *et al.* (2009) provided seminal GARCH- and EGARCH-based evidence of volatility clustering, persistence and asymmetric leverage effects in crude oil markets. These studies established that conditional-variance models originally devised for inflation and equity returns are equally – and in some respects more – informative for commodity prices, where supply disruptions, inventory shocks and speculative pressures generate the very volatility dynamics that standard homoskedastic models fail to capture. GARCH models and their extensions now provide powerful tools for analyzing commodity price movements.

This literature review examines volatility modeling in commodity markets, emphasizing GARCH family models' application and performance across sectors and contexts. It synthesizes theoretical developments, empirical findings, and applications spanning four decades, from foundational volatility clustering work to contemporary machine learning and regime-switching advances.

Commodity price volatility profoundly impacts economic policy, risk management, and development, particularly in small open economies dependent on commodity imports. Stylized facts – volatility clustering, asymmetric shock responses, and long memory properties – present unique modeling challenges distinct from traditional financial market research.

Beginning with theoretical foundations from Engle (1982), Bollerslev (1986), and Nelson (1991) – namely the ARCH, GARCH and EGARCH specifications, respectively – we trace symmetric and asymmetric GARCH specifications adapted to commodity markets. We examine empirical literature across energy, agricultural, and metal sectors, noting that asymmetric models consistently outperform symmetric specifications in capturing commodity price volatility.

The review emphasizes applications for small open economies, examining how global commodity price volatility transmits domestically through import prices and exchange rates. We analyze the growing multivariate GARCH and volatility spillover literature, increasingly important as markets become interconnected and financialized.

Contemporary developments – machine learning integration, structural breaks and regime change modeling, and high-frequency data incorporation – are examined for theoretical and forecasting contributions. We focus on policy implications, particularly for developing and import-dependent countries.

The synthesis reveals consistent patterns: asymmetric volatility models' superiority, heavy-tailed error distributions' importance, volatility shock persistence, and increasing global commodity market interconnectedness. Significant gaps remain in understanding diversified commodity import basket dynamics, transmission mechanisms between global commodity volatility and domestic conditions, and global supply chain structural changes' impact on volatility.

This review provides researchers, policymakers, and practitioners comprehensive understanding of current knowledge in commodity volatility modeling while identifying research directions addressing challenges in an increasingly complex global commodity market environment.

2.1. Modeling Commodity Price Volatility: Foundations, Developments, and Applications in Small Open Economies

2.1.1. Commodity Price Volatility: Theoretical Foundations and Modeling Approaches

The volatility of commodity prices represents one of the most significant sources of economic uncertainty for small open economies, particularly those heavily dependent on commodity imports. The development of sophisticated econometric models to capture, predict, and manage this volatility has become increasingly critical for policymakers and risk managers. This literature review examines the extensive body of research on volatility modeling in commodity markets, with particular emphasis on GARCH family models, their extensions, and applications to import price dynamics in emerging and small open economies.

The theoretical foundations of volatility modeling in commodity markets have evolved substantially since the pioneering work of Engle (1982) on Autoregressive Conditional Heteroskedasticity (ARCH) models and the subsequent generalization by Bollerslev (1986) into GARCH specifications. These developments emerged from the recognition that traditional econometric models, which assume constant variance, fail to capture the distinctive stylized facts observed in commodity price series: volatility clustering, leptokurtosis, and time-varying conditional variance. The adaptation of these models to commodity markets has revealed unique characteristics that distinguish commodity price volatility from traditional financial asset volatility. Empirical applications of these frameworks to commodity data quickly validated their relevance: Sadorsky (2006) documented strong volatility clustering and persistence in petroleum futures, Kang *et al.* (2009) confirmed the same stylized facts for crude oil across multiple GARCH specifications, Karali and Power (2013) demonstrated long-memory volatility in agricultural commodities, and Jacks *et al.* (2011) showed that these volatility features have characterized commodity prices over more than a century. Together, these studies provide the empirical foundation on which subsequent commodity-specific volatility modeling has been built.

2.1.2. Evolution of GARCH Models in Commodity Market Analysis

The standard GARCH(1,1) model, while foundational, has proven insufficient for capturing the full complexity of commodity price dynamics. Nelson (1991) introduced the EGARCH model to address the asymmetric response of volatility to positive and negative shocks, a phenomenon initially observed in equity markets but subsequently documented in various commodity markets. The EGARCH specification allows for leverage effects, where negative price shocks generate disproportionately larger volatility responses than positive shocks of equal magnitude. This asymmetry has particular relevance for energy commodities, where supply disruptions and geopolitical events often manifest as sharp price increases accompanied by heightened uncertainty.

Threshold GARCH (TARCH) models, developed by Zakoïan (1994) provide an alternative framework for modeling asymmetric volatility responses. These models partition the impact of innovations based on their sign, allowing for different volatility responses to positive and negative shocks while maintaining the computational simplicity of the original GARCH framework. The choice between EGARCH and TARCH specifications often depends on the specific commodity market under investigation and the nature of the asymmetric effects present in the data. Empirical applications across commodity markets have generally favoured the asymmetric specifications: Wei *et al.* (2010) find that EGARCH and TGARCH outperform symmetric GARCH in forecasting crude oil volatility, Hung *et al.* (2018) identify EGARCH(1,1) with Student-t errors as the preferred model for world oil prices, Olanrewaju and Oseni (2021) document significant leverage effects in Nigerian crude oil price volatility, and Dinku and Worku (2022) report that EGARCH and TGARCH provide the best fit across major agricultural commodities in Ethiopia. These studies establish empirically that asymmetric responses to positive and negative shocks are a pervasive feature of commodity price data rather than a purely theoretical possibility.

2.1.3. Commodity Market Stylized Facts and Modeling Challenges

Commodity markets exhibit several distinctive characteristics that differentiate them from traditional financial markets and create unique modeling challenges. First, commodity prices often display pronounced seasonality patterns, particularly for agricultural products, which necessitate careful treatment of deterministic seasonal components before applying volatility models Hylleberg *et al.* (1990), Canova and Hansen (1995). Second, commodity markets frequently experience structural breaks associated with policy changes, technological innovations, or shifts in global supply and demand patterns, as documented by Bai and Perron (1998, 2003) and Hammoudeh and Li (2008). These breaks can significantly affect volatility persistence and require sophisticated modeling approaches such as regime-switching GARCH models or models with time-varying parameters Aloui and Jammazi (2009), Lin *et al.* (2020).

The concept of convenience yield, unique to commodity markets, introduces additional complexity to volatility modeling. Unlike financial assets, commodities provide utility through their physical properties and storage characteristics, creating non-monetary benefits that affect price dynamics and volatility patterns Yang *et al.* (2001), Pindyck and Rotemberg (1990). This convenience yield can vary substantially over time, particularly during periods of supply stress, leading to complex volatility dynamics that challenge standard GARCH specifications Sadorsky (2006), Wei *et al.* (2010).

2.1.4. Applications to Small Open Economies and Import Price Dynamics

For small open economies, commodity price volatility poses distinctive challenges that have attracted increasing research attention Raddatz (2007), van der Ploeg and Poelhekke (2009). These economies typically face price-taking behavior in international commodity markets, making them vulnerable to external price shocks without the ability to influence global price formation Cashin *et al.* (2000), Frankel (2012). The transmission of international commodity price volatility to domestic economies occurs through multiple channels: direct import costs, exchange rate effects, and second-order impacts through input-output linkages across sectors Abdulkareem and Abdulkareem (2016).

Research on import price volatility in small open economies has revealed several important empirical regularities. Import price indices often exhibit higher volatility persistence than individual commodity prices due to aggregation effects across multiple commodities and the influence of domestic factors such as exchange rate fluctuations and trade policies Cashin *et al.* (2000), Jacks *et al.* (2011). The volatility of aggregate import price indices may also display different asymmetric properties compared to individual commodity prices, as the composition effects and domestic economic conditions can dampen or amplify external shocks in complex ways Pindyck and Rotemberg (1990), Creti *et al.* (2013).

2.1.5. Methodological Considerations and Model Selection

The application of GARCH models to commodity markets requires careful attention to model specification, diagnostic testing, and parameter interpretation Hansen and Lunde (2005), Patton (2011). The choice between symmetric and asymmetric GARCH models should be guided by formal testing procedures, including likelihood ratio tests and information criteria, rather than a priori assumptions about market behavior Laurent *et al.* (2012). Diagnostic tests for remaining heteroskedasticity, normality of standardized residuals, and parameter stability are essential for ensuring model adequacy Nyblom (1989), Hansen (1990).

Methodological advances have emphasized the importance of robust estimation procedures and finite-sample properties of GARCH estimators, particularly relevant for commodity price series that may contain outliers or structural breaks Brooks *et al.* (2001), Hammoudeh and Li (2008). The development of quasi-maximum likelihood estimation and robust standard errors has improved the reliability of inference in GARCH models applied to commodity data Bollerslev (1986), Hansen and Lunde (2005).

2.1.6. Contemporary Research Frontiers

Current research in commodity price volatility modeling is expanding along several dimensions, including multivariate volatility spillovers Diebold and Yilmaz (2012), high-frequency and mixed-data-sampling approaches Wang *et al.* (2023), and the integration of fundamental macroeconomic and weather variables into volatility models Karali and Power (2013). Multivariate GARCH models increasingly examine volatility spillovers between related commodity markets and transmission mechanisms across the global commodity complex Diebold and Yilmaz (2012), Silvennoinen and Thorp (2013), Chevallier and Ielpo (2013). These models are particularly valuable for analyzing interconnections between energy and agricultural markets, where biofuel policies and climate considerations create complex linkages Serra (2011), Nomikos and Pouliasis (2011).

High-frequency volatility modeling, utilizing intraday price data, represents another active research area Liu and Wan (2012). Availability of real-time commodity price data has enabled application of realized volatility measures and mixed-data sampling (MIDAS) approaches, providing more accurate volatility forecasts and better understanding of intraday volatility patterns in commodity markets Wang *et al.* (2023).

Integration of fundamental variables into volatility models constitutes a third frontier, where researchers link commodity price volatility to underlying supply and demand factors, weather conditions, inventory levels, and macroeconomic variables Karali and Power (2013), Wang *et al.* (2023). These structural approaches promise to improve both explanatory power and forecasting performance of volatility models while providing deeper insights into economic drivers of commodity price uncertainty Kristjanpoller and Minutolo (2015), Ramos-Pérez *et al.* (2019).

2.2. Theoretical Foundations of Volatility Modeling

The canonical references for the methods operationalised in this study are already standard in the specialised literature and are therefore summarised here only to the extent needed to signpost the research approach; for a fuller treatment the reader is referred to Section 2.1 above and to the original sources. The GARCH-family apparatus adopted below rests on three foundational contributions: Engle (1982), who introduced ARCH and established that conditional variance is time-varying and predictable; Bollerslev (1986), who generalised ARCH to the parsimonious GARCH(p,q) specification that has since become the workhorse for volatility analysis; and the asymmetric extensions of Nelson (1991) and Zakoïan (1994), which admit leverage effects and thereby accommodate the differential impact of positive and negative innovations documented in the empirical commodity-market literature reviewed in Section 2.1.2.

2.3. GARCH Applications in Commodity Markets

2.3.1. Energy Markets and Oil Price Volatility

The application of GARCH models to commodity markets has been extensive, with energy markets receiving particular attention due to their economic importance and volatility characteristics. Kang *et al.* (2009) conducted a comprehensive study of oil price volatility using various GARCH specifications, finding that the EGARCH model outperformed standard GARCH models in capturing asymmetric volatility patterns in crude oil markets. Their research demonstrated that negative oil price shocks generate higher volatility than positive shocks, confirming leverage effects in energy markets. This has important implications for risk management, suggesting that downside risk measures should receive greater attention in portfolio optimization and hedging strategies.

Recent empirical evidence has further strengthened the case for asymmetric volatility models in oil markets. Al-Sharoot and Al-Rashide (2024) compared GARCH, EGARCH, and ARMA-GARCH models for OPEC oil prices, finding that EGARCH(1,1) with Student's t-distributed errors best predicts oil price fluctuations as indicated by information criteria (AIC, SIC, H-QIC). This supports using EGARCH for capturing asymmetric and leptokurtic nature of oil price volatility.

Hung *et al.* (2018) provided additional confirmation by forecasting world oil price volatility using GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models under various error distributions. Their findings demonstrated that EGARCH(1,1) with Student's t-distribution provides the most accurate forecasts, emphasizing the importance of modeling asymmetry and heavy tails in oil price returns. Importantly, their study noted that past volatility is a strong predictor of future volatility, while price shocks have relatively minor direct impact.

The COVID-19 pandemic provided a unique natural experiment for testing volatility models under extreme market conditions. Amiri and Remita (2022) investigated crude oil price volatility during this period using the GARCH(1,2) model for WTI oil prices. Interestingly, while EGARCH and TGARCH models are theoretically superior at capturing volatility asymmetry, their analysis demonstrated that GARCH(1,2) outperformed them in forecasting accuracy for the pandemic period, with predicted and actual values closely aligning. This highlights the importance of model validation under different market conditions and suggests that forecasting performance may vary significantly during crisis periods.

Sadorsky (2006) examined volatility dynamics of petroleum futures using various GARCH models, providing evidence that energy futures volatility exhibits both clustering and asymmetric responses to market shocks, highlighting the importance of accurately modeling and forecasting volatility in these key markets for developing investment and hedging strategies.

Wei *et al.* (2010) investigated crude oil price volatility using a comprehensive set of GARCH family models, including standard GARCH, EGARCH, and threshold GARCH (TGARCH) specifications. Their comparative analysis revealed that while all models successfully captured volatility clustering, the asymmetric models (EGARCH and TGARCH) provided superior forecasting performance, particularly for short-term horizons, reinforcing the importance of accounting for asymmetric volatility effects in commodity price modeling.

2.3.2. Advanced Modeling Approaches for Oil Markets

Recent research has explored more sophisticated approaches to modeling oil price volatility. Wang *et al.* (2023) proposed an augmented EGARCH-MIDAS model to incorporate the effects of extreme shocks (such as wars and financial crises) on oil price volatility. Their results demonstrated that extreme shocks significantly increase volatility, with negative shocks having a larger effect than positive ones. The EGARCH-MIDAS-ES model, which accounts for asymmetry and long-term shock effects, outperformed conventional GARCH-MIDAS models in both in-sample and out-of-sample forecasts.

Lin *et al.* (2020) compared uni-regime GARCH-type models and hidden Markov regime-switching models for WTI and Daqing crude oil markets. The HM-EGARCH model outperformed all competitors, effectively capturing different volatility states and providing superior forecasting performance in both developed and emerging markets. This research highlights the importance of considering regime changes and structural breaks in oil market volatility modeling.

Mușetescu *et al.* (2022) estimated and forecasted Brent crude oil volatility using GARCH(1,1), GARCH-M(1,1), and EGARCH(1,1) models. They found that EGARCH(1,1) is preferred for measuring conditional variance due to its ability to capture negative reactions to market shocks. However, for forecasting purposes, the symmetric GARCH-M(1,1) model proved most efficient over their analyzed period, suggesting that the choice between symmetric and asymmetric models may depend on the specific application and time period.

Merabet *et al.* (2021) applied ARIMA-GARCH and EGARCH models to daily oil price data, concluding that the ARIMA(3,1,1) + EGARCH(1,2) model provides the best forecasts, with predicted and actual values closely matching. This underscores the value of combining ARIMA for mean dynamics with EGARCH for volatility modeling.

Nomikos and Pouliasis (2011) analyzed the volatility spillover effects between crude oil and refined product markets using multivariate GARCH models. Their research documented significant volatility transmission mechanisms across the petroleum complex, with implications for integrated oil companies and refiners' risk management strategies. The study demonstrated that understanding cross-market volatility dynamics is crucial for effective hedging in interconnected commodity markets.

2.3.3. Oil Market Applications in Developing Economies

The application of GARCH models to oil markets in developing economies has revealed important insights about volatility patterns and their macroeconomic implications. Abdulkareem and Abdulkareem (2016) analyzed macroeconomic and oil price volatility in Nigeria using GARCH, GARCH-M, EGARCH, and TGARCH models. Their findings highlighted that all macroeconomic variables, including oil price, are highly volatile. Importantly, asymmetric models (EGARCH and TGARCH) outperformed symmetric GARCH models, indicating the significance of accounting for asymmetry in volatility modeling. The study concluded that oil price volatility is a major source of macroeconomic instability in Nigeria and recommended economic diversification to mitigate these effects.

Olanrewaju and Oseni (2021) examined Nigerian crude oil price volatility using GARCH and its variants, finding that GARCH(2,1) best models price volatility, while IGARCH(1,1) is optimal for production and export volatility. The study confirmed that positive and negative shocks have asymmetric effects on volatility, supporting the use of asymmetric models in oil-dependent economies.

Two findings from the non-energy commodity literature bear directly on the analysis of the Republic of Moldova's aggregate import price index, in which food and agricultural goods form a substantial share of the basket. Karali and Power (2013) provide FIGARCH evidence of long-memory volatility in agricultural commodity prices, showing that shocks to agricultural price volatility persist over extended horizons – a property directly relevant to the CIPI persistence hypothesis (H1). Serra (2011) documents significant volatility spillovers from oil to agricultural commodity markets that intensified following the 2007–2008 food crisis, reinforcing the rationale for analysing Brent and a diversified Moldovan import basket within one methodological frame.

2.3.4. Import Price Dynamics and Small Open Economies

The specific application of volatility modeling to import price dynamics in small open economies represents a crucial but relatively understudied area of research. Cashin *et al.* (2000) examined commodity price volatility and its impact on developing countries using a comprehensive dataset spanning multiple decades. Their analysis revealed that commodity price shocks tend to be highly persistent, with half-lives typically exceeding several years. This persistence has significant implications for fiscal and monetary policy in commodity-dependent economies, as it suggests that temporary shocks can have long-lasting effects on government revenues and balance of payments.

Jacks *et al.* (2011) investigated the historical evolution of commodity price volatility over more than a century, finding that while the average level of volatility has remained relatively stable, there have been significant changes in volatility persistence and cross-commodity correlations. Their research suggests that globalization and financialization have altered the nature of commodity price risks, making diversification strategies less effective and increasing the importance of sophisticated risk management techniques.

Pindyck and Rotemberg (1990) examined the co-movement of commodity prices using factor models and found evidence of "excess co-movement" that cannot be explained by common macroeconomic fundamentals alone. Their findings suggest that psychological factors and speculative behavior play important roles in commodity price dynamics, with implications for the effectiveness of traditional hedging strategies based on fundamental analysis.

2.3.5. Asymmetric Volatility Effects and Leverage

The documentation and modeling of asymmetric volatility effects in commodity markets has been a significant focus of recent research. Glosten *et al.* (1993) introduced the TGARCH model, providing an alternative framework for capturing asymmetric volatility responses. Their model allows for different volatility responses to positive and negative innovations of the same magnitude, offering greater flexibility than the standard GARCH specification while maintaining computational tractability.

The empirical evidence consistently supports the superiority of asymmetric models across various commodity markets and time periods. The studies reviewed demonstrate that EGARCH and TGARCH models, which account for asymmetry and leverage effects, generally outperform symmetric GARCH models in modeling and forecasting oil and commodity price volatility. This finding has been confirmed across different commodities, markets, and shock characteristics, making the case for asymmetry modeling particularly robust.

Awartani and Maghyereh (2013) analyzed the dynamic spillovers between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries, finding that these spillovers are significant and have important implications for portfolio diversification in the region.

Chevallier and Ielpo (2013) investigated volatility spillover effects across a range of commodity markets, providing evidence of the interconnectedness of market-specific shocks and highlighting how volatility is transmitted between different assets. Their work demonstrates that volatility effects are not limited to individual markets but are part of a broader system of commodity interdependencies.

2.3.6. Risk Management and Hedging Applications

The practical application of volatility models to risk management and hedging in commodity markets represents a crucial bridge between academic research and industry practice. Ederington and Salas (2008) examined the effectiveness of various hedging strategies for commodity price risk, finding that the choice of volatility model significantly affects hedging performance. Their research highlighted the importance of accurate volatility forecasting for optimal hedge ratio determination and demonstrated that asymmetric models generally produce superior hedging outcomes.

Chang *et al.* (2013) investigated the conditional correlations and volatility spillovers between crude oil markets and stock index returns, finding that the relationship between these markets is time-varying, which has critical implications for investors hedging oil risk with equity instruments.

Brooks *et al.* (2001) examined the statistical accuracy of GARCH model parameter estimation, finding that the choice of estimation technique can significantly impact the reliability of the model's parameters, which is a foundational concern for any subsequent application like forecasting or hedging.

2.3.7. Structural Breaks and Regime Changes

The presence of structural breaks and regime changes in commodity markets has important implications for volatility modeling and forecasting. Hammoudeh and Li (2008) examined sudden structural changes in the volatility of Gulf Arab stock markets using the Bai-Perron methodology, finding multiple break points corresponding to major regional and global economic events. Their research demonstrates the importance of testing for structural stability in volatility models.

Liu and Wan (2012) examined the impact of financialization on commodity market volatility regimes, finding that increased financial market participation has led to more frequent regime switches and higher volatility persistence. Their findings suggest that traditional volatility models may need to be adapted to account for the changing nature of commodity markets in an increasingly financialized global economy.

2.4. Policy Implications and Small Open Economies

The implications of commodity price volatility for small open economies have received increasing attention in the literature, particularly following the commodity price boom and bust cycles of the 2000s and 2010s. Raddatz (2007) examined the impact of commodity price shocks on small open economies using a comprehensive cross-country dataset, finding that these economies are particularly vulnerable to external price shocks due to their limited diversification capabilities and constrained policy space.

Frankel (2012) investigated the resource curse phenomenon and its relationship to commodity price volatility, arguing that the volatility of commodity prices rather than their level may be the primary driver of the resource curse. Frankel's research suggests that volatility management through appropriate fiscal and monetary policies may be more important than traditional concerns about Dutch disease effects.

Van der Ploeg and Poelhekke (2009) examined the impact of commodity price volatility on economic growth in developing countries, finding that volatility has a significant negative effect on growth prospects. Their research highlights the importance of developing institutions and policies that can effectively manage commodity price risks, including the establishment of stabilization funds and the development of domestic financial markets that can provide hedging opportunities.

2.5. Emerging Market Considerations

Volatility modeling in emerging market commodity sectors presents unique challenges due to data limitations, structural changes, and institutional factors. Malik and Hammoudeh (2007) examined volatility spillovers between US and Gulf equity markets in the context of oil price shocks, finding that spillover effects are asymmetric and time-varying. Their research highlights the importance of considering institutional and structural differences when applying volatility models developed in advanced market contexts to emerging markets.

Aloui and Jammazi (2009) investigated crude oil and stock market interactions in emerging markets using a regime-switching approach, finding evidence of non-linear dependence structures that vary with market conditions. Their research suggests that traditional linear correlation measures may be inadequate for capturing the full range of dependencies between commodity and financial markets in emerging economies.

Creti *et al.* (2013) examined the financialization of commodity markets and its impact on emerging market economies, finding that increased financial market participation has altered the traditional relationships between commodity fundamentals and prices. Their research has important implications for emerging market policymakers, as it suggests that traditional commodity market analysis may be less reliable in an increasingly financialized environment.

2.6. From the Literature to the Present Study: Justification and Research Hypotheses

Justification

The literature reviewed above establishes that (a) the GARCH-family toolkit is the standard device for modelling commodity-price volatility, (b) asymmetric specifications are typically needed for individual energy commodities, (c) structural-break and seasonality testing are preconditions for valid inference, and (d) transmission to small open economies operates through multiple channels. Yet the existing evidence has been built almost entirely on single-commodity series and on large emerging or developed markets. The Republic of Moldova – a landlocked, post-transition small open economy whose import bill combines energy, food, metals and manufactures – provides a setting in which the diagnostic and modelling questions raised by the literature can be addressed jointly for a single global benchmark (Brent crude oil) and a diversified national aggregate (the Commodity Import Price Index, CIPI). The present study is therefore not a redundant re-estimation of known oil-market facts but a deliberate test of whether those facts carry over to the aggregate import-price series that actually drives Moldovan external vulnerability. The contrast between the two series is the analytical payoff of the exercise.

Research hypotheses.

Guided by the literature synthesised above, the study tests four hypotheses:

H1: *(persistence in the aggregate basket). The conditional volatility of the Republic of Moldova's CIPI exhibits high persistence in the sense of an AR(1)-GARCH(1,1) specification with $\alpha + \beta$ close to unity, consistent with the long-memory features documented across aggregate commodity indices by* Karali and Power (2013) *and* Jacks *et al.* (2011).

H2: *(symmetry in the aggregate basket). Because diversification across commodities and composition effects dampen individual-commodity asymmetries* (Pindyck and Rotemberg, 1990; Creti *et al.*, 2013), *the CIPI does not exhibit statistically significant leverage effects*

– formally, the asymmetry parameter of a TARCH/EGARCH specification estimated on CIPI is not significantly different from zero.

H3*: (asymmetric leverage in Brent). Global Brent crude oil prices exhibit statistically significant negative leverage effects in an AR(1)-EGARCH(1,1,1) specification, consistent with the body of evidence from* Sadorsky (2006)*,* Kang *et al.* (2009)*,* Wei *et al.* (2010)*,* Hung *et al.* (2018) *and* Olanrewaju and Oseni (2021)*, and extending this evidence to a sample that includes the post-2020 pandemic and post-pandemic regimes.*

H4*: (differential mean reversion). The half-life of a volatility shock is substantially shorter in Brent than in the CIPI, reflecting the difference between a financialised, continuously traded global benchmark and a monthly aggregated national import index – an implication consistent with the market-integration and financialisation evidence of* Tang and Xiong (2012) *and* Büyükşahin and Robe (2014).

These four hypotheses are taken to Sections 3 and 4, where the methodology and estimation results test each one explicitly.

3. METHODOLOGICAL REVIEW

This section presents the empirical framework used to model the conditional volatility of CIPI and Brent. The methods are standard in the specialised literature and are therefore described only to the extent needed to indicate the research approach; fuller expositions are available in the original sources cited below. The framework addresses the four stylised features documented in Section 2 – volatility clustering and long memory Sadorsky (2006), Karali and Power (2013), asymmetric responses to positive and negative innovations (Nelson, 1991; Zakoïan, 1994; Wei *et al.*, 2010), seasonality in monthly commodity series Hylleberg *et al.* (1990), Canova and Hansen (1995), and endogenous structural change Bai and Perron (1998, 2003), Hammoudeh and Li (2008) – through a sequential pipeline that runs preliminary unit-root and seasonality tests on the log-differenced series before any conditional-variance modelling is attempted.

Structural change is detected endogenously via the Bai and Perron (1998, 2003) procedure, which accommodates regime shifts without imposing prior break dates. Conditional variance is then estimated with the GARCH family – GARCH(p,q) (Bollerslev, 1986), EGARCH (Nelson, 1991) and TARCH (Zakoïan, 1994) – with model selection driven by empirical performance and diagnostic adequacy in the manner recommended by Hansen and Lunde (2005) and Laurent *et al.* (2012), rather than by prior assumptions about the sign of asymmetry.

Post-estimation diagnostics assess residual behaviour and parameter stability using the standard battery – ARCH-LM Engle (1982) for remaining conditional heteroskedasticity, Ljung–Box for serial correlation in standardised and squared standardised residuals, and the Nyblom (1989) / Hansen (1990) stability tests for time-invariance of the estimated parameters – and model selection integrates information criteria with economic and forecasting performance along the lines discussed by Patton (2011) and Brooks *et al.* (2001).

The same pipeline is applied to both series, delivering the apples-to-apples comparison of persistence, asymmetry and stability between a global single-commodity benchmark and a diversified national import basket that motivates this study (see Sections 2.6 and 4).

3.1. Analytical Framework and Research Design

This study employs a comprehensive econometric framework to analyze the volatility dynamics of two monthly price series: the Republic of Moldova's Commodity Import Price Index (CIPI, 1992m01–2025m05) and the global Brent crude oil price (1990m01–2025m05). Because both series are non-stationary in levels but stationary in first differences of their logarithms (see Section 4), the object of estimation throughout is the monthly continuously-compounded return $r_t = \Delta\log P_t = \log(P_t) - \log(P_{(-1)})$, denoted dlog(CIPI) and dlog(Oil Brent) respectively. The methodology is structured in three distinct phases: (i) preliminary data analysis including unit-root and seasonality testing on the log-differenced series, (ii) endogenous identification of structural breaks via the Bai–Perron procedure, and (iii) volatility modeling using GARCH-family specifications fitted to r_t. This sequential approach ensures that the statistical properties of r_t are fully characterized before proceeding to conditional-variance modeling, thereby enhancing the reliability and interpretability of the empirical findings.

At each stage, diagnostic test outcomes inform the next modelling choice – a sequencing consistent with best practice in the GARCH-family literature Hansen and Lunde (2005), Patton (2011) – and the monthly sample runs from 1992m01 to 2025m05 for CIPI and from 1990m01 to 2025m05 for Brent.

3.2. Preliminary Data Analysis

3.2.1. Unit Root Testing

The order of integration of each series is established via the Augmented Dickey–Fuller test applied first to the price level log(P t) and then to the log-differenced return r_t; the ADF regression is:

$$\Delta y_{s,t} = \alpha_{0,s} + \alpha_{1,s}\, t + \gamma_s y_{s,t-1} + \sum_{j=1}^{p_s} c_{s,j}\Delta y_{s,t-j} + \varepsilon_{s,t},\ s \in \{CIPI, Brent\},\ t = 1,\dots,T_s \qquad (1)$$

where:

$y_{s,t}$ denotes the series under test for $s \in$ {CIPI, Brent} (either the log-price $\log P_{s,t}$ in levels or the log-return $r_{s,t} = \Delta\log P_{s,t}$);

Δ is the first-difference operator; $\alpha_{0,s}$ is the series-specific intercept;

$\alpha_{1,s} \cdot t$ the deterministic linear trend;

γ_s the unit-root coefficient on the lagged level;

$\{c_{s,j}\}_{j=1}^{p_s}$ the coefficients on the augmenting lagged differences;

p_s the lag length selected by information criterion separately for each series;

$\varepsilon_{s,t}$ a zero-mean white-noise disturbance;

T_s the sample size for series s.

The null hypothesis of a unit root is $H_0: \gamma_s = 0$ against the stationary alternative $H_1: \gamma_s < 0$. Tables 1–2 (CIPI) and the analogous Brent tables in Section 4 confirm that both series are I(1), so that $r_{s,t} = \Delta\log P_{s,t}$ is the stationary variable entering the volatility models.

3.2.2. Seasonality Tests

Because monthly commodity series may display both deterministic and stochastic seasonality, the log-differenced return r_t is subjected to a standard battery of seasonality diagnostics: the Levene test for seasonal heteroskedasticity, the Kruskal–Wallis non-parametric test for seasonal location differences, the Canova and Hansen (1995) test for deterministic-seasonal stability, and the HEGY test for seasonal unit roots at the zero, Nyquist and annual frequencies Hylleberg *et al.* (1990). These tests are standard in the commodity-volatility literature – see, inter alia, Hammoudeh and Li (2008) – and full formal statements are available in the original sources; their joint purpose here is to establish whether any deterministic or stochastic seasonal component must be removed before GARCH estimation. The empirical outcomes for CIPI and Brent are reported in Tables no. 3 and no. 14 of Section 4.

3.3. Structural Break Analysis: Bai–Perron Test

Endogenous breaks in the conditional mean of r_t are identified via the Bai and Perron (1998, 2003) multiple-break procedure, which jointly estimates the break dates and the regime-specific coefficients without imposing prior break locations. The linear regression with m breaks (m+1 regimes) is:

$$y_t = x_t'\beta^{(j)} + u_t \quad \text{for } t = T_{j-1} + 1, \dots, T_j \tag{2}$$

with j = 1,…,m+1,unknown break dates (T_1,…,T_m),T_0 = 0,T_{m+1} = T.The break dates are estimated by minimising the sum of squared residuals:

$$min_{\{\beta^{(j)}\}_{j=1}^{m+1},\{T_j\}_{j=1}^{m}} \sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} \left(y_t - x_t'\beta^{(j)}\right)^2 \tag{3}$$

Model selection uses the SupF(l+1|l) sequential test along with the BIC and LWZ information criteria, subject to the standard minimum segment length restriction of ε = 0.15T (at least 15% of observations per regime). Full formal statements, including break date confidence intervals, are given in Bai and Perron (1998, 2003); their application in commodity volatility studies is illustrated by Hammoudeh and Li (2008).

3.4. Volatility Modeling Framework

Conditional volatility is modelled with the GARCH family (Bollerslev, 1986; Nelson, 1991; Zakoïan, 1994). In the standard GARCH(p,q) specification the variance is driven by past squared innovations (ARCH terms) and past conditional variances (GARCH terms), with covariance stationarity requiring $\alpha + \beta < 1$. We consider three specifications – AR(1)-GARCH(1,1), TARCH (Glosten *et al.*, 1993; Zakoïan, 1994) and EGARCH Nelson (1991) – and select between them on the basis of in-sample diagnostic adequacy and information criteria Hansen and Lunde (2005), Laurent *et al.* (2012). For a fuller formal exposition the reader is referred to the original sources.

3.4.1. AR(1)-GARCH(1,1)

To absorb short-run serial correlation in r_t, the mean equation is augmented with an AR(1) term:

Mean equation:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t \tag{4}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

with $|\phi| < 1$ for mean stationarity, $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ for covariance stationarity. This is the specification estimated for CIPI (Section 4).

3.4.2. TARCH (Threshold ARCH)

The Threshold ARCH specification (Glosten *et al.*, 1993; Zakoïan, 1994) – also known as GJR-GARCH – admits an asymmetric response of volatility to positive and negative innovations by adding an indicator-weighted squared-residual term:

Mean equation:

$$r_t = \mu + \varepsilon_t \tag{6}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

where I_{t-1} = 1 if ε_{t-1} < 0 and 0 otherwise, so that γ captures the leverage effect: $\gamma > 0$ means negative shocks raise volatility more than positive shocks of equal magnitude, $\gamma = 0$ collapses the specification to standard GARCH, and the non-negativity conditions are $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$, $\beta \geq 0$. TARCH is estimated here as a specification check on the symmetric AR(1)-GARCH baseline (Section 4).

3.4.3. EGARCH (Exponential GARCH)

The Exponential GARCH specification of Nelson (1991) models the logarithm of conditional variance, which guarantees a positive σ_t² without parameter restrictions and allows an asymmetric response of volatility to signed innovations:

Mean equation:

$$r_t = \mu + \varepsilon_t \tag{8}$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\ln(\sigma_{t-1}^2) \tag{9}$$

In equation (9) the absolute-value term captures the size effect (the magnitude of shocks, α), the linear term in ε_{t-1}/σ_{t-1} captures the sign effect (γ; a negative γ indicates a leverage effect) and $|\beta| < 1$ delivers persistence of volatility shocks. This is the specification estimated for Brent (Section 4).

3.5. Model Diagnostics and Specification Tests

Post-estimation adequacy is assessed with a standard battery of diagnostics. The ARCH-LM test Engle (1982) is applied to the squared standardised residuals to verify that no residual conditional heteroskedasticity remains; the Ljung–Box portmanteau statistic is computed on both the standardised residuals (to detect uncaptured serial correlation in the mean) and their squares (to detect uncaptured volatility clustering); and the Nyblom (1989) and Hansen (1990) cumulative-score tests assess time-invariance of the estimated parameters. Diagnostic outcomes are reported in Section 4 and are interpreted jointly in the model-selection step below, following the guidance of Patton (2011), Brooks *et al.* (2001) and Hansen and Lunde (2005).

3.6. Model Selection

Model selection among the three GARCH specifications is driven by the Akaike, Bayesian and Hannan–Quinn information criteria, the diagnostic battery of Section 3.5, and – where specifications are non-nested and diagnostics are similar – out-of-sample forecasting performance assessed by mean squared and mean absolute error, along the lines discussed by Hansen and Lunde (2005), Laurent *et al.* (2012) and Patton (2011). Parameter estimates are further required to be economically sensible – in particular, $\alpha + \beta < 1$ in GARCH and $|\beta| < 1$ in EGARCH – before a specification is retained.

4. MODEL AND ESTIMATION

This section conducts a comprehensive econometric assessment of the Republic of Moldova's CIPI to characterize external price pressures on a small, structurally import-dependent economy. Import price evolution is pivotal for domestic inflation, external competitiveness, and macroeconomic stability. The CIPI–constructed by weighting key commodity prices by import-to-GDP ratios–measures how global price fluctuations translate into domestic costs. The analysis spans 1992–2025, from post-Soviet artificial stability to the contemporary polycrisis volatility.

Methodologically, we proceed in three stages. First, we establish the CIPI's stochastic properties via preliminary diagnostics: unit root tests (Augmented Dickey-Fuller), seasonality tests (Levene, Kruskal-Wallis, Canova-Hansen, HEGY), and Bai–Perron procedures to endogenously detect structural breaks in the conditional mean–preventing spurious inference. Second, we estimate GARCH-family models to capture time-varying volatility, including standard GARCH for clustering and TARCH/EGARCH to test for asymmetric leverage effects. Third, the preferred specification undergoes post-estimation checks: ARCH-LM for residual heteroskedasticity, Ljung-Box Q-statistics for serial correlation in standardized residuals, and the Nyblom test for parameter stability–ensuring statistical adequacy.

Results show the Republic of Moldova's import price dynamics exhibit significant short-term momentum, exceptionally persistent volatility clustering, and no asymmetric leverage effects. These findings have direct implications for macroeconomic policy, risk management, and resilience strategies, highlighting how deeper global integration exposes the Republic of Moldova to complex, overlapping external shocks that challenge traditional stabilization approaches.

4.1. Republic of Moldova's Commodity Import Price Index: Econometric Analysis of External Price Pressures and Regime Evolution (1992-2025)

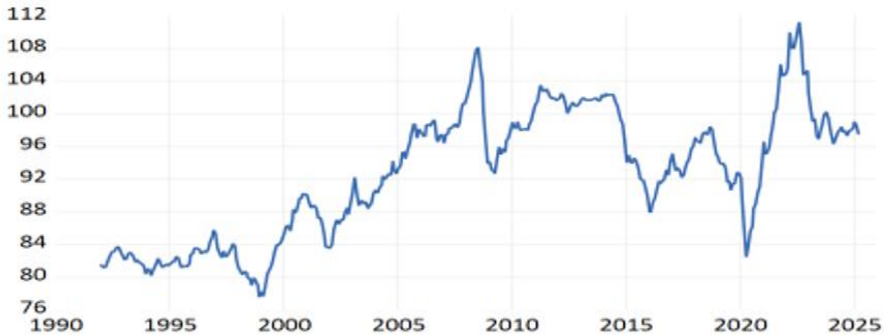
CIPI is a critical macroeconomic indicator of external price pressures in small open economies with structural import dependencies. For the Republic of Moldova–a landlocked economy with limited domestic production and high reliance on imported energy, food, and intermediate goods–import prices fundamentally shape domestic inflation, external competitiveness, and economic stability. CIPI, constructed by weighting commodity prices by import-to-GDP ratios, measures how global price fluctuations translate into pressures within the Republic of Moldova’s trade structure.

This analysis examines CIPI dynamics over 1992–2025, covering the Republic of Moldova’s post-independence trajectory from initial transition to contemporary polycrisis conditions. The temporal scope encompasses six economic regimes with distinct external shocks, institutional arrangements, and integration levels. The import price environment shifted with the Republic of Moldova’s evolving position in global value chains and rising vulnerability to external disruptions.

The methodological approach combines structural regime analysis with advanced time series econometrics. We begin with diagnostics establishing the CIPI’s statistical properties–stationarity, seasonality, and structural breaks–to ensure valid modeling and avoid spurious inference under non-stationarity or instability. Building on these, we estimate GARCH-family models to capture volatility clustering characteristic of commodity prices, with specifications (standard GARCH, TARCH, EGARCH) testing for asymmetric responses to positive versus negative shocks and selecting the most parsimonious volatility representation.

Model adequacy is validated through ARCH-LM tests for residual heteroskedasticity, Ljung-Box statistics for serial correlation, Nyblom tests for parameter stability, and correlogram analyses of standardized and squared residuals, ensuring the specifications capture the data-generating process without systematic residual patterns.

Results show the Republic of Moldova’s import price environment progressed from transition-era administrative stability to extreme volatility and heightened external vulnerability. Econometric findings indicate significant short-term price momentum, high volatility persistence, and no asymmetric effects, with implications for policy design, risk management, and resilience. The regime progression underscores how deeper global integration, while expanding trade opportunities, exposes the Republic of Moldova to complex, overlapping external shocks that challenge traditional macroeconomic stabilization approaches.



Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Figure no. 1 – Evolution of CIPI

The **Post-Independence Stabilization Period (1992-1999)** constitutes the inaugural phase of Republic of Moldova's economic transformation, distinguished by the most subdued average CIPI value (81.96) and remarkably constrained volatility (CV = 1.92%). This temporal framework encompasses the disintegration of Soviet commercial networks, the Transnistrian territorial dispute (1992), and the Asian Financial Crisis (1997). The observed minimal volatility represents a paradoxical phenomenon, reflecting not genuine economic stability but rather the institutional rigidity inherent in a command economy undergoing transformation, wherein administrative pricing mechanisms and constrained market integration attenuated the transmission of external price signals. The moderate compound annual growth rate of 0.47% indicates protracted adaptation to market-oriented mechanisms.

The **Post-Russian Crisis Adjustment Phase (2000-2004)** signifies a fundamental structural transformation subsequent to the 1998 Russian financial default, evidenced by an elevation in mean CIPI to 88.66 and increased volatility to 2.82%. This regime encapsulates Republic of Moldova's compelled diversification from Commonwealth of Independent States (CIS) markets and the inception of enhanced integration with global commodity markets. The accelerated CAGR (1.70%) reflects both economic recuperation from the Russian crisis nadir and escalating exposure to international price signals as commercial barriers diminished and market mechanisms strengthened.

The **Global Commodity Boom Era (2005-2009)** demonstrates the most pronounced volatility among pre-2020 regimes (CV = 3.70%) alongside elevated price levels (98.19), encompassing the extraordinary escalation in global commodity valuations driven by Chinese demand expansion and the financialization of commodity markets. This period, culminating with the Global Financial Crisis, illustrates Republic of Moldova's comprehensive integration into global price dynamics. The regime's volatility captures the oscillatory nature of the 2007-2008 price surge followed by crisis-induced contraction, validating Republic of Moldova's intensified susceptibility to global commodity cycles.

The **Post-Crisis Plateau** (2010-2014) exhibits minimal volatility (CV = 1.52%) despite encompassing the Eurozone crisis and Arab Spring upheavals. The peak mean CIPI (101.02) coupled with negligible growth (CAGR = 0.29%) indicates a period of elevated yet stable pricing, potentially reflecting coordinated global monetary accommodation and relatively subdued commodity markets between crisis episodes. This transitory stability proved ephemeral, concealing accumulating geopolitical tensions.

The **Geopolitical Instability Regime (2015-2020)** captures the dual disruption of Crimean annexation and petroleum price collapse, with mean CIPI declining to 93.44 and the sole negative CAGR (-2.58%) across all regimes. The moderate volatility (CV = 2.91%) underrepresents the regime's characteristic feature: persistent downward pressure on import prices driven by regional conflict, Russian economic sanctions, and the deterioration of remittance flows. This regime starkly demonstrates Republic of Moldova's susceptibility to regional geopolitical disruptions transmitted through energy and remittance channels.

The **Polycrisis Era (2021-2025)** manifests extraordinary volatility (CV = 6.51%), nearly doubling any preceding regime, while recording the highest CAGR (3.78%). This regime encompasses the COVID-19 pandemic, the Ukrainian conflict, global food security crisis, and Middle Eastern tensions–representing a convergence of disruptions that has fundamentally destabilized Republic of Moldova's import price environment. The extreme volatility reflects not merely the multiplicity of crises but their overlapping and synergistic effects: pandemic-induced supply chain disruptions amplified by conflict-driven energy shocks and food security challenges.

The sequential regime evolution reveals a transforming vulnerability profile: from the artificial stability of economic transition, through progressive global integration and commodity boom exposure, to the contemporary polycrisis characterized by extreme volatility. The near-quadrupling of volatility in the current regime relative to the post-crisis plateau of 2010-2014 indicates that the Republic of Moldova's external vulnerability has attained unprecedented magnitudes, propelled by the convergence of geopolitical fragmentation, supply chain disruption, and the instrumentalization of energy and food supplies. This analysis emphasizes the critical necessity for comprehensive resilience strategies addressing Republic of Moldova's structural dependencies on imported energy, food commodities, and remittance flows.

Figure no. 1 plots the evolution of the CIPI level over the full sample period 1992–2025 and motivates the regime-change discussion above. Prior to conducting our main econometric analysis, we must establish the time series properties of CIPI to ensure the validity and reliability of our subsequent modeling efforts. Table no. 1 reports the Augmented Dickey–Fuller test applied to CIPI in levels. Specifically, we begin our empirical investigation by rigorously testing for stationarity in the CIPI series, as non-stationary time series can lead to spurious regression results and invalid statistical inferences. The stationarity assessment is crucial because many econometric techniques, which require the underlying data to exhibit stationary behavior–that is, constant mean, variance, and covariance structure over time. To accomplish this essential diagnostic step, we employ a unit root tests, the Augmented Dickey-Fuller (ADF) test, which will provide robust evidence regarding the stationarity properties of our CIPI time series. This methodical approach to examining the fundamental statistical characteristics of our data ensures that our subsequent analytical framework rests on solid econometric foundations and that our findings will be both statistically sound and economically meaningful.

Table no. 1 – Unit root test of CIPI

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
CIPI	-2.071	0.257	1	Fail to reject H0	Non-stationary at level

Note: Critical values are -3.447 at 1%, -2.869 at 5%, and -2.571 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 2 – Unit root test of dlog (CIPI)

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
DLOG(CIPI)	-14.037	0.000	0	Reject H0	Stationary at first difference

Note: Critical values are -3.447 at 1%, -2.869 at 5%, and -2.571 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Tables no. 1 and no. 2 report the ADF test applied to CIPI in levels and in first log-differences, respectively. The Augmented Dickey-Fuller (ADF) unit root test results reveal that CIPI exhibits non-stationary behavior in levels, with the ADF t-statistic of -2.0714 failing to exceed the 10% critical value of -2.5706 and yielding a p-value of 0.2566, thus failing to reject the null hypothesis of a unit root. Although Figure no. 1 displays an upward drift in the CIPI level series, the constant-only specification was selected because the drift is plausibly stochastic rather than deterministic. As a robustness check, we re-estimated the ADF test with a constant and linear trend, obtaining t = -2.567 and p = 0.2958 – a higher p-value than the constant-only specification – so the unit-root conclusion is unchanged (and, if anything, reinforced) under the alternative specification. However, upon first-differencing, the series becomes stationary, as evidenced by the ADF statistic of -14.0368, which is well below the 1% critical threshold of -3.4466, with a p-value effectively zero (0.0000), decisively rejecting the unit root null hypothesis. These findings confirm that CIPI is integrated of order one, I(1), indicating that while the level series contains a stochastic trend, its first difference (growth rate) is stationary. Consequently, for subsequent econometric analyses including for multiple seasonality tests, Bai-Perron tests for structural break detection and GARCH modeling to examine volatility clustering, the stationary first-differenced series dlog(CIPI) will be employed to ensure valid statistical inference and avoid spurious regression problems associated with non-stationary data.

Table no. 3 – Test for seasonality of dlog CIPI

Test	Null Hypothesis	Test Statistic	P-Value	Decision	Interpretation
Levene Test	Equal variances across months	0.8883	0.552	Fail to reject H_0	No seasonal heteroskedasticity
Kruskal-Wallis Test	Equal medians across months	7.7051	0.7395	Fail to reject H_0	No seasonal differences in medians
Canova-Hansen Test (Joint)	Seasonal stability (no seasonal unit roots)	1.228	0.5924	Fail to reject H_0	No evidence against seasonal stability
HEGY Test (Zero frequency)	Unit root at zero frequency	-5.8058	< 0.001	Reject H_0	No unit root (stationary)
HEGY Test (Nyquist frequency)	Unit root at Nyquist frequency	-6.2307	< 0.001	Reject H_0	No unit root (stationary)
HEGY Test (Seasonal frequencies)	Unit roots at seasonal frequencies	31.1794	< 0.001	Reject H_0	No seasonal unit roots (stationary)
HEGY Test (All frequencies)	Unit roots at all frequencies	47.5659	< 0.001	Reject H_0	No unit roots at any frequency (stationary)

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 3 presents the battery of seasonality tests (Levene, Kruskal–Wallis, HEGY, Canova–Hansen) applied to dlog CIPI. The comprehensive seasonality analysis of the log-differenced Commodity Import Price Index (dlog CIPI) reveals no evidence of seasonal patterns across multiple dimensions. The Levene test for homogeneity of variance yields an F-statistic of 0.8883 ($p = 0.552$), indicating that the null hypothesis of equal variances across months cannot be rejected, thereby confirming the absence of seasonal heteroskedasticity in the series. Similarly, the Kruskal-Wallis non-parametric test produces a chi-squared statistic of 7.7051 ($p = 0.7395$), providing no evidence for seasonal differences in median values across the twelve months. The Canova-Hansen test for seasonal stability, which examines the presence of seasonal unit roots, yields a joint test statistic of 1.228 ($p = 0.5924$), with none of the individual monthly coefficients achieving statistical significance at conventional levels, thus supporting the null hypothesis of seasonal stability. Most conclusively, the HEGY (Hylleberg, Engle, Granger, and Yoo) test comprehensively rejects the presence of unit roots at zero frequency ($t_1 = -5.8058$, $p < 0.001$), Nyquist frequency ($t_2 = -6.2307$, $p < 0.001$), and all seasonal frequencies ($F_{3:4} = 31.1794$, $p < 0.001$), with the joint test across all frequencies ($F_{1:12} = 47.5659$, $p < 0.001$) providing overwhelming evidence of stationarity. Collectively, these findings demonstrate that the dlog CIPI series exhibits neither seasonal variance patterns, seasonal mean shifts, nor seasonal unit root behavior, confirming its suitability for standard time series modeling approaches without the need for seasonal adjustment procedures. The Bai–Perron multiple-break test results for dlog CIPI are reported in Table no. 4.

Table no. 4 – Bai–Perron Multiple-Break Test Results of dlog(CIPI)

Breaks	RSS	BIC	BIC_Rank
0	0.0452	-2473.64	1
1	0.0448	-2465.21	2
2	0.0439	-2461.58	3
3	0.0433	-2455.09	4
4	0.0431	-2444.83	5
5	0.0432	-2432.01	6

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

In applying the Bai–Perron multiple-break procedure to the monthly log-differenced Commodity Import Price Index (dlog CIPI), six competing specifications–ranging from zero to five structural breaks–were evaluated on the basis of residual sum of squares (RSS) and the Bayesian Information Criterion (BIC). Although incremental breaks marginally reduce RSS, the BIC–which penalises over-parameterisation–reaches its minimum at the zero-break model (BIC = -2473.64). Consequently, the optimal specification contains no structural shifts, implying that the mean behaviour of dlog CIPI remains stable throughout the sample. Visual inspection of candidate break dates (1996:12, 1999:02, 2002:01, 2008:07, 2014:06, 2020:04) confirms that, once information-criterion penalties are applied, none of these points provide sufficient explanatory gain. Collectively, these findings indicate that the growth dynamics of CIPI are homogeneous over time, reinforcing earlier evidence of stationarity and supporting the use of conventional, break-free time-series models for subsequent empirical analysis. The dlog(CIPI) series exhibits **no structural breaks**, maintaining a constant mean throughout the entire sample period (1992-2025).

4.2. GARCH Modeling of Import Price Volatility: Specification, Estimation, and Diagnostic Testing of Republic of Moldova's Commodity Import Price Dynamics

Having established the fundamental time series properties of our data through comprehensive diagnostic testing, we now proceed to the construction of a GARCH model using the log-differenced Commodity Import Price Index (dlog CIPI). The Commodity Import Price Index represents individual commodities weighted by the ratio of imports to GDP of the Republic of Moldova, making it a crucial indicator of import price dynamics relative to the country's economic output and a key measure for understanding external price pressures on the Republic of Moldovan economy.

The preceding empirical analysis provides strong justification for this modeling approach: our unit root tests confirmed that CIPI is integrated of order one, I(1), necessitating the use of first differences to achieve stationarity; our comprehensive seasonality testing revealed no seasonal patterns, heteroskedasticity, or unit roots at seasonal frequencies, eliminating the need for seasonal adjustment procedures; and our Bai-Perron structural break analysis identified no significant structural shifts in the mean behavior of dlog CIPI, confirming temporal stability throughout the sample period (1992-2025).

The GARCH framework is particularly well-suited for modeling the dlog CIPI series as it addresses the potential presence of volatility clustering–a phenomenon especially relevant for commodity import prices of small open economies like Republic of Moldova, where external shocks and global commodity market fluctuations can create periods of heightened price volatility followed by periods of relative stability. While our previous tests established that the conditional mean of dlog CIPI remains stable over time, they do not preclude the possibility of time-varying conditional variance, which is particularly important for understanding how external price shocks propagate through Republic of Moldova's import basket.

Table no. 5 presents the baseline GARCH(1,1) estimation results for dlog CIPI. The GARCH specification allows us to model both the conditional mean equation and the conditional variance equation simultaneously, thereby capturing the dynamic volatility patterns inherent in commodity import price movements weighted by their economic significance to Republic of Moldova's GDP. This approach provides more efficient parameter estimates and robust standard errors while offering insights into the persistence and clustering of price volatility in Republic of Moldova's import structure. The logarithmic first-difference transformation ensures that we are modeling percentage changes in the import-weighted commodity price index, providing economically meaningful interpretations as growth rates that reflect the relative impact of import price changes on the Republic of Moldovan economy.

Table no. 5 – Result of GARCH (1,1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000512	0.000422	1.214	0.2247	Not significant
Variance equation: C	0.00000480	0.00000219	2.191	0.0285	Significant
ARCH term, α_1	0.208061	0.042860	4.854	0.0000	Significant
GARCH term, β_1	0.762503	0.044240	17.235	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The GARCH (1,1) model appears to be well-specified for capturing the volatility of Republic of Moldova's commodity import price changes. The results show no significant average monthly price change (drift), but they strongly indicate the presence of **volatility clustering**. This means that periods of high price fluctuation tend to be followed by more high fluctuation, and calm periods are followed by calm. Shocks to volatility are highly persistent, meaning it takes a long time for the market to return to its average level of volatility after a major price event.

The average monthly log-return of the price index is 0.000512 (about 0.051% per month), but since the p-value is 0.2247, this mean is not statistically different from zero, indicating that the series can be considered to have no drift. The R-squared of -0.000031 (effectively zero) confirms that this constant term explains none of the variation in price changes, which is very common for financial and economic return series.

Variance Equation:

$$\sigma\_t\hat{}2 = \omega + \alpha * RESID(-1)\hat{}2 + \beta * GARCH(-1) \quad (10)$$

where:

- **Constant ($\boldsymbol{\omega}$ or C):** 4.80E-06 (or 0.0000048) with a p-value of 0.0285.
- **ARCH Term ($\boldsymbol{\alpha}$ or RESID(-1)^2):** 0.208061 with a p-value of 0.0000.
- **GARCH Term ($\boldsymbol{\beta}$ or GARCH(-1)):** 0.762503 with a p-value of 0.0000.

Constant ($\boldsymbol{\omega}$): This coefficient is positive and statistically significant (p-value < 0.05), which is a necessary condition for a stable model. It represents the baseline, long-run average variance when the effects of past shocks have dissipated. The fact that it is positive and significant indicates that the unconditional (long-run) variance is well defined.

ARCH Term ($\boldsymbol{\alpha}$): The coefficient of 0.208 is highly significant. This term measures the impact of past shocks (squared residuals) on current volatility and confirms the presence of volatility clustering. A large price shock in the previous month leads to higher volatility in the current month. As the "news" coefficient, it implies that 21% of monthly squared shock feeds into today's variance. Its large and highly significant value indicates a strong ARCH effect, meaning volatility responds strongly to new shocks.

GARCH Term ($\boldsymbol{\beta}$): The coefficient of 0.763 is also highly significant. This term measures the persistence of volatility. A high value indicates that past volatility is a strong predictor of current volatility, meaning that volatility shocks are long-lasting. As the "persistence" coefficient, it shows that 76% of monthly variance carries forward to today.

Volatility Persistence ($\boldsymbol{\alpha + \beta}$): The sum of the ARCH and GARCH coefficients is 0.208 + 0.763 = 0.971. This sum is a critical measure of how quickly shocks to volatility dissipate. With a value of 0.97, which is very close to 1, it indicates that volatility shocks are highly persistent–meaning it takes a long time for volatility to return to its long-run average after a significant market event. Because the sum is less than 1, the conditional variance is (weakly) stationary. However, being so close to 1 suggests extremely high volatility persistence, where shocks decay slowly (with a half-life of approximately $\ln(0.5) / \ln(\alpha + \beta) \approx 22$ months).

Unconditional variance: The unconditional variance is calculated as $\omega / (1 - \alpha - \beta) \approx 1.63 \times 10^{-4}$, which corresponds to an unconditional standard deviation of approximately 1.28% per month.

For a GARCH(1,1) model to be stable (stationary), the sum of $\alpha + \beta$ must be less than 1. Since $0.97 < 1$, the model is stable and well-behaved. The high persistence ($\alpha + \beta \approx 0.97$) implies that shocks–such as global commodity price spikes or supply disruptions–have a prolonged impact on Republic of Moldova's import-cost volatility, lasting for roughly two years.

An insignificant drift indicates that the average real change in the import-price index is negligible. As a result, price dynamics are driven primarily by volatility rather than by a sustained trend.

The Durbin-Watson statistic tests for autocorrelation in the residuals of the mean equation, with a value of 2 indicating no autocorrelation. A value of 1.33 suggests potential positive serial correlation in the residuals. While the GARCH model primarily addresses volatility, this result indicates that some predictability in the price changes themselves may remain unaccounted for by the simple constant-mean model. To address this, you might consider adding autoregressive (AR) terms to the mean equation–resulting in an ARMA-GARCH model–to see if this improves the model fit.

We will now add a AR(1) term to fix the autocorrelation problem. The estimation results of the augmented AR(1)-GARCH(1,1) specification are reported in Table no. 6.

Table no. 6 – Result of GARCH (1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000460	0.000558	0.824	0.4100	Not significant
Mean equation: AR(1)	0.303409	0.048208	6.294	0.0000	Significant
Variance equation: C	0.00000407	0.00000192	2.121	0.0340	Significant
ARCH term, α_1	0.183421	0.047313	3.877	0.0001	Significant
GARCH term, β_1	0.785576	0.046808	16.783	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

This AR(1)-GARCH(1,1) model is a **significant improvement** over the previous specification. The inclusion of the AR(1) term has successfully corrected the serial autocorrelation in the residuals, as shown by the Durbin-Watson statistic now being very close to 2.

The model now captures two distinct features of Republic of Moldova's commodity import prices:

1. **Short-term momentum:** The current month's price change is significantly influenced by the previous month's change.
2. **Persistent volatility clustering:** Volatility remains high following market shocks, and this effect takes a long time to dissipate.

Based on the improved diagnostics (R-squared, D-W stat, and information criteria), this is a much more robust and reliable model.

The updated AR (1)-GARCH (1,1) model shows significant improvements in both the mean and variance equations, enhancing its suitability for modeling Republic of Moldova's commodity import price index. In the mean equation, the **AR (1) coefficient is 0.303409 with a p-value below 0.0001,** indicating strong statistical significance. This implies that roughly 30% of the previous month's return carries over to the current month, reflecting a moderate positive autocorrelation and short-term momentum. The constant term remains statistically insignificant, confirming no meaningful long-term drift in prices. Importantly, the AR root is 0.30–well within the unit circle–indicating stationarity and overall model stability. In the variance equation, the ARCH term (α) is 0.183421 and the GARCH term (β) is 0.785576, both highly significant, with a combined persistence of approximately 0.969. This high level of persistence suggests that volatility shocks decay slowly, consistent with volatility clustering and long memory in price volatility. Diagnostics confirm the model's improvement: the Durbin-Watson statistic rose from 1.33 to 1.94, indicating the effective removal of serial correlation. The model fit has also improved, with the R-squared increasing from nearly zero to 0.11, and the log-likelihood rising from 1291.58 to 1304.36. Both the Akaike (AIC) and Schwarz (SC) information criteria decreased, further supporting the superior performance of the revised model. Overall, the enhanced AR(1)-GARCH(1,1) specification offers a statistically robust framework for capturing the dynamic structure of both the conditional mean and variance in Republic of Moldova's commodity import price series.

Table no. 7 – ARCH-LM test for remaining ARCH effects in the AR(1)-GARCH(1,1) model

Statistic	Value	p-value	Conclusion
F-statistic	1.3419	0.2474	No ARCH effect
Obs*R-squared	1.3441	0.2463	No ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

To verify that the estimated specification adequately captures the conditional-variance dynamics, we apply an ARCH-LM test for remaining ARCH effects in the standardized residuals, with the results reported in Table no. 7. The ARCH-LM test results provide strong evidence that the AR (1)-GARCH (1,1) model is correctly specified and has effectively captured the conditional heteroskedasticity present in the data. Specifically, the test was conducted on the standardized residuals–residuals scaled by the model's estimated conditional standard deviations–to determine whether any remaining ARCH effects (volatility clustering) persist. The null hypothesis of the test asserts that there are no remaining ARCH effects, which is the desired outcome, while the alternative suggests that such effects are still present. The results show p-values of 0.2474 (F-test) and 0.2463 (Chi-square), both well above the conventional 0.05 threshold. As a result, we fail to reject the null hypothesis, indicating no statistical evidence of leftover ARCH effects. In practical terms, this means the GARCH (1,1) component of the model has successfully accounted for the time-varying volatility in the series. The standardized residuals now exhibit constant variance, confirming that the model has effectively filtered out volatility clustering–an essential criterion for a well-specified GARCH model.

Next, we will test a TARCH model; the estimation results are reported in Table no. 8. This model is an extension of the standard GARCH model designed specifically to test for **asymmetric effects**, also known as the "leverage effect." The key question it answers is: do negative shocks (bad news) have a different impact on volatility than positive shocks (good news) of the same magnitude?

Table no. 8 – Result of TARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000406	0.000623	0.652	0.5144	Not significant
Mean equation: AR(1)	0.304408	0.051079	5.960	0.0000	Significant
Variance equation: C	0.00000406	0.00000200	2.028	0.0426	Significant
ARCH term, α_1	0.172718	0.074260	2.326	0.0200	Significant
Threshold term, γ_1	0.018279	0.075835	0.241	0.8095	Not significant
GARCH term, β_1	0.786592	0.052355	15.024	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation:

$$DLOG(CIPI) = C + \varphi * DLOG(CIPI)(-1) \tag{11}$$

where:

Constant (C): Insignificant (p-value = 0.5144).

AR (1) Term (φ): Highly significant (p-value = 0.0000).

The mean equation results are virtually identical to the previous model. It confirms the presence of significant short-term momentum (a 0.304 coefficient) and no long-term drift.

Variance Equation:

$$\sigma\_t\hat{}2 = \omega + \alpha * RESID(-1)\hat{}2 + \gamma * RESID(-1)\hat{}2 * (RESID(-1) < 0) + \beta * GARCH(-1) \tag{12}$$

where:

- **Constant (ω or C):** 4.06E-06, significant (p-value = 0.0426).
- **ARCH Term (α or RESID (-1)^2):** 0.172718, significant (p-value = 0.0200). This now represents the impact of a *positive* shock on volatility.
- ***Leverage Term (γ or RESID(-1)^2(RESID(-1)<0)):*** 0.018279, **insignificant** (p-value = 0.8095).
- **GARCH Term (β or GARCH (-1)):** 0.786592, highly significant (p-value = 0.0000).

The interpretation of the leverage effect in the model focuses on the term RESID (-1)²*(RESID(-1)<0), which is designed to capture any asymmetry in how past shocks affect future volatility. Specifically, the coefficient γ, estimated at 0.018279, measures whether negative shocks (price decreases) lead to a different volatility response compared to positive shocks (price increases) of the same magnitude. However, with a p-value of 0.8095, this coefficient is not statistically significant. This indicates **there is no evidence of a leverage effect in Republic of Moldova's commodity import price series**. In other words, the market's reaction to price changes is symmetric–negative and positive shocks have an equal impact on future volatility. Therefore, sudden declines in prices do not generate more volatility than sudden increases, suggesting that the volatility process in this market is not driven by asymmetric news responses.

Next, we will test an EGARCH model; the estimation results are reported in Table no. 9. The primary reason to use an EGARCH model is to test for asymmetric effects, also known as leverage effects, where negative shocks (bad news) might have a different impact on volatility than positive shocks (good news) of the same magnitude.

Table no. 9 – Result of EGARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000551	0.000629	0.875	0.3814	Not significant
Mean equation: AR(1)	0.314515	0.050989	6.168	0.0000	Significant
Variance constant	-0.853144	0.280735	-3.039	0.0024	Significant
Magnitude effect	0.348353	0.077132	4.516	0.0000	Significant
Asymmetry effect	-0.025802	0.042683	-0.605	0.5455	Not significant
Persistence term	0.938195	0.026563	35.320	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation:

$$DLOG(CIPI) = C + \varphi * DLOG(CIPI)(-1) \quad (13)$$

where:

- **Constant (C):** 0.000551 (p-value = 0.3814) indicating an insignificant, no long-term drift.
- **AR (1) Term (φ):** 0.314515 (p-value = 0.0000) indicating a highly significant, confirming short-term price momentum.

The mean equation results are virtually identical to the previous model. It confirms the presence of significant short-term momentum (a 0.31 coefficient) and no long-term drift.

Variance Equation:

$$LOG(\sigma\_t\text{^}2) = \omega + \alpha * |z\_\{t-1\}| + \gamma * z\_\{t-1\} + \beta * LOG(\sigma\_\{t-1\}\text{^}2) \quad (14)$$

where:

- **Constant (ω or $C(3)$):** -0.853144 (p-value = 0.0024). This is the long-run average level of log variance. It is allowed to be negative in an EGARCH model because the actual variance (exp(log(variance))) will always be positive.
- **Magnitude Effect (α or $C(4)$):** 0.348353 (p-value = 0.0000). This is the symmetric effect of a shock. It is positive and highly significant, confirming that the magnitude of a shock (regardless of its sign) increases volatility. This is the standard GARCH effect.
- **Asymmetry/Leverage Effect (γ or $C(5)$):** -0.025802 (p-value = 0.5455). This is the most important new coefficient. It measures the asymmetric impact of shocks. Since its p-value (0.5455) is far above 0.05, this coefficient is not statistically significant. This is strong evidence that there is no leverage effect in Republic of Moldova's commodity import price volatility. Negative shocks do not have a different impact on volatility than positive shocks.
- **Persistence (β or $C(6)$):** 0.938195 (p-value = 0.0000). This is the GARCH persistence term. A value of 0.938 is very high and significant, indicating that volatility shocks are highly persistent, consistent with the previous model's findings.

The EGARCH model confirms the findings of the previous AR(1)-GARCH model: there is significant short-term momentum in price changes and high persistence in volatility. However, the key finding from this model is the **lack of a statistically significant asymmetric (leverage) effect**. Since the more complex EGARCH model does not provide a better fit to the data (as shown by the information criteria) and its main additional feature (the asymmetry term) is insignificant, the previous **AR(1)-GARCH(1,1) model is the preferred and more parsimonious choice**. Both **TARCH** and **EGARCH** reveal **no leverage effect** (no asymmetry in response to positive vs. negative shocks).

Next we will test the GARCH (1,1) AR(1) with ARCH LM TEST with 12 lags; the results are reported in Table no. 10. The goal of this "Heteroskedasticity Test: ARCH" is to check if there are any remaining ARCH effects (i.e., conditional heteroskedasticity or volatility clustering) in the residuals.

Table no. 10 – Result of ARCH LM TEST with 12 lags for Garch (1,1) AR(1)

Statistic	Value	p-value	Conclusion
F-statistic	0.5447	0.8849	No remaining ARCH effect
Obs*R-squared	6.6484	0.8800	No remaining ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The ARCH-LM diagnostic applied to the standardized residuals of the estimated AR(1)–GARCH(1, 1) model finds no evidence of remaining second-moment dependence. With 12 lags, the F-statistic equals 0.545 and the corresponding p-value is 0.885; the alternative χ^2 form of the test (Obs × R^2 = 6.65) delivers an almost identical p-value of 0.880. Both statistics are far above conventional significance thresholds, so the null hypothesis of "no ARCH effects up to order 12" cannot be rejected. Hence the volatility dynamics captured by the GARCH(1, 1) specification appear sufficient: once the conditional mean and variance equations are accounted for, the residuals behave as white noise in both levels and squares. No additional ARCH lags, higher-order GARCH terms, or alternative variance structures are warranted on statistical grounds. The consistency of the diagnostics provides strong evidence that the AR(1)–GARCH(1,1) framework captures the dynamics of import-price volatility without leaving systematic patterns in the residuals–thereby validating subsequent inference and forecasting based on this specification.

Table no. 11 – Result of Nyblom for GARCH (1,1) AR(1)

Test	Statistic	5% Critical Value	Conclusion
Mean equation: C	0.087866	0.470	Stable
Mean equation: AR(1)	0.095681	0.470	Stable
Variance equation: C	0.089699	0.470	Stable
ARCH term, α_1	0.086970	0.470	Stable
GARCH term, β_1	0.070208	0.470	Stable
Joint test	0.597142	1.470	Stable

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Nyblom parameter-stability test results for the AR(1)-GARCH(1,1) specification are reported in Table no. 11. Nyblom cumulative score diagnostics reveal no evidence of structural parameter drift in the AR(1)–GARCH(1,1) specification. For each coefficient in both the mean and variance equations, the test statistic (0.07–0.10) lies well below the 10 % critical threshold of 0.353, while the joint statistic (0.597) remains markedly below even the most lenient critical value of 1.280 Hansen (1990). Hence, the null hypothesis of parameter constancy cannot be rejected at any conventional significance level, indicating that the model's coefficients remain stable throughout the sample. This finding, when combined with earlier ARCH-LM diagnostics showing no residual heteroskedasticity, affirms that the AR(1)–GARCH(1,1) framework not only captures volatility clustering but also does so with time-invariant parameters–thereby strengthening its suitability for inference, forecasting, and policy analysis based on Republic of Moldova's import-price dynamics.

The correlogram of the standardized residuals (Table no. A1) provides no evidence of remaining linear dependence in the conditional-mean equation. All individual autocorrelations lie well inside the approximate 95 % confidence band ($\pm 1.96 / \sqrt{T} \approx \pm 0.11$ for $T \approx 400$), with the largest spike equal to 0.11 in absolute value (lag 23). More formally, the Ljung–Box portmanteau statistics–shown in the Q-Stat column and computed with one degree of freedom deducted to account for the AR(1) term–are insignificant at every horizon. For example, the joint statistic up to lag 12 is 9.73 (p = 0.56), up to lag 24 is 28.62 (p = 0.19), and even at lag 36 it is only 42.87 (p = 0.17), all far above the conventional 5 % threshold. Hence, we fail to reject the null hypothesis that the residuals are white noise at any lag length considered. Taken together with the earlier ARCH-LM results, these findings confirm that the AR(1)–GARCH(1,1) specification has successfully purged both serial correlation and conditional heteroskedasticity, thereby validating its use for inference and forecasting of Republic of Moldova's import-price inflation.

Inspection of the correlogram (Table no. A2) of the standardized residuals (T = 397) confirms that the AR(1)–GARCH(1,1) specification has successfully eliminated serial correlation. All sample autocorrelations lie within the approximate 95 % confidence band of $\pm 1.96/\sqrt{T} \approx \pm 0.10$, with the sole exception of an isolated spike at lag 23 (AC = 0.15; PAC = 0.14), which is not accompanied by a run of adjacent large coefficients and is therefore unlikely to signal systematic misspecification. The Ljung–Box portmanteau statistics, adjusted for the single AR term in the mean equation, are uniformly insignificant across all horizons considered: Q(12) = 6.53 (p = 0.89), Q(24) = 21.52 (p = 0.61), and Q(36) = 27.96 (p = 0.83). Consequently, the null hypothesis that the residuals constitute white noise cannot be rejected at any conventional significance level, indicating the absence of remaining linear dependence. Coupled with earlier ARCH-LM tests that found no residual heteroskedasticity, these results attest to the adequacy of the chosen model for statistical inference and for forecasting Republic of Moldova's import-price dynamics.

4.3. EGARCH Modeling of Brent Oil Price Volatility: Capturing Asymmetric News Effects and Leverage Dynamics in Global Energy Markets

The analysis of Brent crude oil price dynamics constitutes a fundamental component in understanding global commodity market behavior and its transmission mechanisms to small open economies. Brent crude is selected over alternative benchmarks–West Texas Intermediate (WTI), Dubai/Oman, and the OPEC Reference Basket–for three reasons. First, Brent is the pricing reference for approximately two-thirds of internationally traded crude and is the benchmark against which European, African and Asian–Pacific contracts are settled, which makes it the most relevant price signal for a European import-dependent economy such as the Republic of Moldova, whose crude and refined-product imports transit primarily through European supply chains. Second, Brent is a seaborne, waterborne-delivered grade, so its price reflects global supply–demand conditions without the landlocked pipeline and storage constraints that episodically distort WTI (most visibly during the 2011–2014 Cushing bottleneck and the April 2020 negative-price episode), yielding a cleaner measurement of the global oil-price process we seek to characterize. Third, Brent is quoted continuously on ICE Futures Europe and has the longest uninterrupted daily history among liquid international benchmarks, enabling the 1990m01–2025m05 sample that underpins our volatility and leverage estimates. As the primary international benchmark for oil pricing, Brent serves not only as a critical input for energy-intensive sectors but also as a barometric indicator of global economic sentiment, geopolitical tensions, and supply-demand imbalances in international commodity markets. For transition economies like Republic of Moldova, where energy imports constitute a substantial proportion of total import expenditure and exert significant influence on domestic price levels, understanding the stochastic properties and volatility characteristics of international oil prices is essential for both macroeconomic policy formulation and external vulnerability assessment.

The temporal evolution of Brent oil prices over the period 1990-2025 encapsulates multiple episodes of structural transformation in global energy markets, reflecting the interplay of technological innovation, geopolitical developments, financial market evolution, and macroeconomic policy shifts across major economies. From the relative price stability of the 1990s through the dramatic commodity super-cycle of the 2000s, the Global Financial Crisis-induced volatility, the shale oil revolution, and the recent pandemic-induced market disruptions, oil price movements have exhibited complex patterns of persistence, clustering, and asymmetric responses that require sophisticated econometric modeling approaches to adequately capture their underlying dynamics.

The econometric investigation of Brent oil price behavior necessitates careful attention to several distinctive characteristics of commodity financial time series that differentiate them from traditional macroeconomic variables. First, oil prices typically exhibit high-frequency volatility clustering, where periods of large price movements tend to be followed by periods of continued high volatility, while calm periods are succeeded by relative stability. Second, commodity markets frequently display asymmetric volatility responses, commonly referred to as leverage effects, wherein negative price shocks generate disproportionately larger increases in volatility compared to positive shocks of equivalent magnitude. Third, the integration of commodity markets with global financial systems has intensified the role of speculative trading, momentum effects, and news-driven volatility transmission mechanisms.

The empirical framework employed in this analysis addresses these complexities through a systematic examination of the fundamental time series properties of Brent oil prices, beginning with rigorous diagnostic testing to establish stationarity characteristics, seasonal patterns, and structural stability. The methodological approach emphasizes the importance of proper specification testing to avoid spurious inference and ensure that subsequent volatility modeling captures the genuine data-generating process rather than artificial statistical relationships. Unit root testing using the Augmented Dickey-Fuller methodology provides essential evidence regarding the order of integration, while comprehensive seasonality analysis employing multiple complementary approaches–including the Levene test for seasonal heteroskedasticity, the Kruskal-Wallis test for seasonal location differences, the Canova-Hansen test for seasonal stability, and the HEGY test for seasonal unit roots–ensures that any seasonal adjustment requirements are properly identified and addressed.

The structural break analysis using the Bai-Perron methodology represents a critical component of the diagnostic framework, as oil markets have experienced numerous potential regime shifts associated with major geopolitical events, technological disruptions, and policy changes. The absence of statistically significant structural breaks in the log-differenced series, despite the occurrence of major economic shocks, provides important evidence regarding the resilience of the underlying stochastic process governing oil price movements and supports the use of constant-parameter models for volatility analysis.

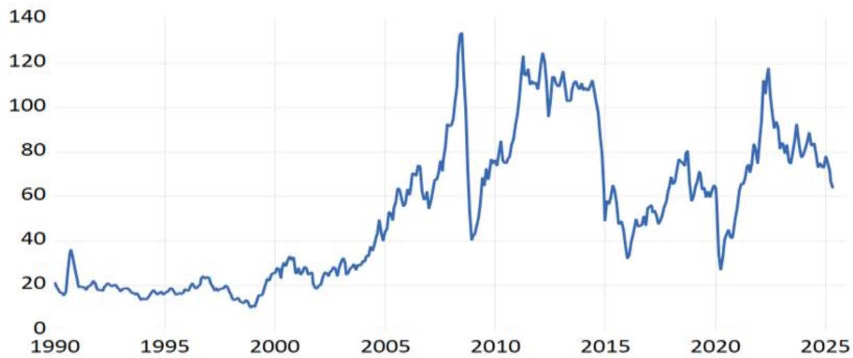
The volatility modeling strategy progresses through multiple specifications to identify the most appropriate framework for capturing the dynamic characteristics of oil price movements. The initial application of standard GARCH methodology reveals fundamental specification issues, particularly the theoretically inconsistent negative persistence parameter that violates the non-negativity constraints essential for valid variance modeling. This finding necessitates the adoption of more sophisticated approaches, specifically the EGARCH framework, which accommodates asymmetric volatility responses while ensuring positive conditional variances through its logarithmic specification.

The incorporation of autoregressive terms in the conditional mean equation addresses the documented presence of short-term momentum effects in oil returns, reflecting the impact of market microstructure factors, information processing delays, and speculative trading strategies that create temporary deviations from random walk behavior. The AR(1)-EGARCH specification thus provides a comprehensive framework for simultaneously modeling both the conditional mean dynamics and the asymmetric volatility clustering characteristic of oil markets.

The empirical results demonstrate the superior performance of the AR(1)-EGARCH(1,1,1) specification in capturing the essential features of Brent oil price dynamics, particularly the statistically significant leverage effect that confirms asymmetric news impacts on volatility. This finding aligns with established theoretical and empirical literature on commodity markets, where negative supply shocks or adverse demand conditions tend to generate greater uncertainty and risk perception compared to positive developments of equivalent magnitude. The comprehensive diagnostic testing–including ARCH-LM tests for residual heteroskedasticity, Ljung-Box statistics for serial correlation, Nyblom tests for parameter stability, and detailed correlogram analysis–provides robust evidence of model adequacy and validates the specification for subsequent inference and forecasting applications.

The successful modeling of Brent oil price volatility has important implications beyond academic interest, providing essential insights for risk management, portfolio optimization, and policy analysis in energy-dependent economies. Understanding the persistence, clustering, and asymmetric characteristics of oil price volatility enables more accurate assessment of external vulnerability, improved design of hedging strategies, and enhanced calibration of macroeconomic models that incorporate energy price shocks as key transmission mechanisms for international economic fluctuations.

4.3.1. Brent Crude Oil Price Evolution and Time Series Properties: Stationarity, Seasonality, and Structural Stability Analysis (1990-2025)



Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Figure no. 2 – Oil brent evolution

The temporal evolution of Brent crude oil prices over the period 1990-2025 reveals distinct phases characterized by varying degrees of volatility and structural shifts driven by fundamental economic, geopolitical, and supply-side factors.

Phase I: Early 1990s Price Stability (1990-2000)

The initial decade was characterized by relatively stable pricing, with quotations predominantly remaining below $20 per barrel. This period of price stability reflected balanced supply-demand fundamentals, with consistent global production patterns and moderate consumption growth. A notable exception occurred circa 1990, when geopolitical tensions associated with the Gulf War generated temporary supply disruptions, resulting in a transient price spike.

Phase II: Demand-Driven Price Appreciation (2000-2008)

The early 2000s marked the onset of a sustained upward price trajectory, attributable to accelerating global demand, particularly from emerging economies experiencing rapid industrialization, notably China and India. This fundamental shift in demand dynamics resulted in a systematic price appreciation, with quotations surpassing $50 per barrel by 2005.

Phase III: Speculative Peak and Financial Crisis Impact (2008-2009)

The period witnessed an extraordinary price escalation, reaching approximately $140 per barrel in 2008, driven by supply–side concerns and heightened speculative activity in commodity markets. However, this peak was followed by a precipitous decline during the global financial crisis, as economic contraction significantly reduced energy demand, with prices retreating below $50 per barrel.

Phase IV: Post-Crisis Recovery and Enhanced Volatility (2009-2014)

The subsequent recovery phase was characterized by price stabilization within the $80−$120 range, supported by global economic recovery and persistent geopolitical uncertainties. This period of relative stability was disrupted by the emergence of unconventional oil production, particularly the U.S. shale revolution circa 2014, which contributed to a substantial price correction.

Phase V: Supply Glut and Market Adjustment (2015-2020)

An extended period of depressed pricing ensued from 2015-2020, reflecting market oversupply conditions resulting from both expanded U.S. shale production and strategic production decisions by OPEC member states. The COVID-19 pandemic in 2020 precipitated an unprecedented demand shock, leading to extreme price volatility, including instances of negative pricing in futures markets.

Phase VI: Post-Pandemic Market Rebalancing (2021-2025)

The most recent period has been characterized by significant price recovery driven by economic reopening and supply chain constraints, though elevated volatility persists. Recent price moderation suggests potential market stabilization as supply chains adjust to evolving global market conditions.

Fundamental Market Drivers

The observed price dynamics reflect the interplay of three primary categories of determinants: (1) geopolitical developments, including regional conflicts and international sanctions regimes; (2) macroeconomic demand fluctuations associated with business cycles and structural economic transitions; and (3) supply-side dynamics, encompassing OPEC production policies and technological innovations in extraction methods, particularly unconventional resource development.

Figure no. 2 plots the evolution of Brent crude oil prices over the sample period January 1990–March 2025 and motivates the discussion of fundamental market drivers above. First, we will conduct the Augmented Dickey-Fuller (ADF) test on Brent. The ADF test results for Brent in levels and in first log-differences are reported in Tables no. 12 and no. 13 respectively.

Table no. 12 – Brent oil unit root test

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
OIL_BRENT	-2.380	0.148	1	Fail to reject H0	Non-stationary at level

Note: Critical values are -3.446 at 1%, -2.868 at 5%, and -2.570 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 13 – dlog (brent oil) unit root test

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
DLOG(OIL_BRENT)	-14.986	0.000	0	Reject H0	Stationary at first difference

Note: Critical values are -3.446 at 1%, -2.868 at 5%, and -2.570 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Augmented Dickey–Fuller (ADF) statistics in Table no. 12 indicate that the Brent crude-oil price series in levels cannot be regarded as stationary, whereas its first log-difference clearly satisfies the stationarity requirement. Specifically, the ADF test statistic for the level series (–2.380) exceeds the 10 % critical value (–2.570) in absolute terms only marginally and falls well short of the 5 % (–2.868) and 1 % (–3.446) thresholds, yielding a p-value of 0.148. Consequently, the null hypothesis of a unit root cannot be rejected, implying the presence of stochastic non-stationarity. In contrast, the ADF statistic for the first log-difference in Table 13 (–14.986) is far below the 1 % critical value, with a p-value effectively equal to zero. This overwhelming evidence leads to the rejection of the unit-root null and confirms that the differenced series is stationary.

Table no. 14 – Test for seasonality of dlog (oil brent)

Test	Null Hypothesis	Test Statistic	P-Value	Decision	Implication
Levene Test	Equal variances across months	F = 0.8086	0.6315	Fail to reject	No seasonal heteroskedasticity
Kruskal-Wallis Test	Equal medians across months	χ^2 = 19.6807	0.0499	Reject (marginal)	Weak evidence of seasonal differences
Canova-Hansen Test	Seasonal stability	Joint = 1.7337	0.5063	Fail to reject	Stable seasonal patterns
HEGY Test (Zero freq)	Unit root at zero frequency	t = -6.0299	< 0.001	Reject	Series is stationary
HEGY Test (Pi freq)	Unit root at pi frequency	t = -5.4128	< 0.001	Reject	Series is stationary
HEGY Test (Seasonal freq)	Unit roots at seasonal frequencies	F = 33.9569	< 0.001	Reject	No seasonal unit roots

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 14 reports the battery of seasonality tests applied to dlog(Oil Brent). The comprehensive seasonality analysis of the log-differenced Brent oil price series (dlog(Oil Brent)) was conducted using four complementary statistical tests, each examining different aspects of seasonal behavior. The Levene test for seasonal heteroskedasticity yielded a test statistic of 0.8086 (p-value = 0.6315), failing to reject the null hypothesis of equal variances across months, thus indicating the absence of seasonal volatility clustering. The Kruskal-Wallis test, which examines differences in location parameters across seasonal periods, produced a chi-squared statistic of 19.6807 (p-value = 0.0499), providing marginal evidence of seasonal differences in medians at the 5% significance level. The Canova-Hansen test for seasonal stability, with a joint test statistic of 1.7337 (p-value = 0.5063), failed to reject the null hypothesis of stable seasonal patterns, suggesting that any seasonal effects present in the series remain constant over time. Most notably, the HEGY (Hylleberg-Engle-Granger-Yoo) test comprehensively rejected the presence of unit roots at all frequencies: zero frequency (t-statistic = -6.0299, p-value = 0), π frequency (t-statistic = -5.4128, p-value = 0), and seasonal frequencies (F-statistic = 33.9569, p-value = 0), confirming that the series is stationary without seasonal unit roots. Collectively, these results indicate that the dlog(Oil Brent) series exhibits weak seasonality at best. While the Kruskal-Wallis test provides borderline evidence of seasonal differences in central tendency, the absence of seasonal heteroskedasticity, the stability of seasonal patterns, and the strong rejection of seasonal unit roots suggest that any seasonal effects are minimal and do not compromise the stationarity properties of the series. This finding implies that seasonal adjustments or seasonal differencing are not necessary for econometric modeling of oil price changes, and that standard time series methods assuming weak or no seasonality are appropriate for this series.

The seasonality testing results provide robust evidence that the log-differenced Brent oil price series does not exhibit economically or statistically significant seasonal patterns. The convergence of evidence across multiple tests–particularly the absence of seasonal heteroskedasticity, the stability of any seasonal patterns, and the comprehensive rejection of seasonal unit roots–supports treating the series as non-seasonal for modeling purposes. This finding aligns with economic intuition, as oil prices are primarily driven by global supply and demand factors, geopolitical events, and market speculation rather than predictable seasonal cycles.

Table no. 15 – Bai-Perron Structural Break Test Results for dlog (oil brent)

Breaks	RSS	BIC	BIC Rank
0	3.4299	-827.13	1
1	3.4147	-816.91	2
2	3.3674	-810.74	3
3	3.3433	-801.68	4
4	3.3555	-788.03	5
5	3.3742	-773.57	6

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 15 reports the Bai–Perron structural-break test results for dlog(Oil Brent). The Bai-Perron structural break test was applied to the log-differenced Brent oil price series (dlog(Oil Brent)) spanning from February 1990 to May 2025, comprising 424 monthly observations. The test evaluated models with zero to five structural breaks, with model selection based on the Bayesian Information Criterion (BIC). The results unequivocally indicate that the model with zero structural breaks minimizes the BIC value (-827.13), suggesting the absence of significant structural changes in the mean of the series. While the residual sum of squares (RSS) exhibits a monotonic decrease from 3.4299 (0 breaks) to 3.3742 (5 breaks), indicating improved fit with additional break points, the BIC criterion appropriately penalizes model complexity. The monotonically increasing BIC values across models with 1 to 5 breaks (-816.91 to -773.57) reinforce the preference for the no-break specification. Although the algorithm identifies potential break dates coinciding with major economic events–notably the 1998 Asian financial crisis, the 2008 global financial crisis, the 2016 oil price collapse, and the 2020 COVID-19 pandemic–these breaks do not achieve statistical significance under the BIC criterion. This finding suggests that despite substantial volatility in oil markets during these periods, the log-differenced series maintains structural stability in its unconditional mean, implying that oil price shocks, while potentially severe, do not fundamentally alter the underlying stochastic process governing oil price changes. This result has important implications for econometric modeling, as it supports the use of constant-parameter models for the dlog(Oil Brent) series without the need for regime-switching specifications or time-varying parameters in the mean equation.

The empirical evidence from the Bai-Perron test strongly supports the conclusion that the log-differenced Brent oil price series does not exhibit structural breaks in its mean, despite experiencing several major economic shocks over the 35-year sample period. This finding is particularly noteworthy given the volatile nature of oil markets and suggests that oil price changes follow a stable stochastic process that is resilient to structural shifts. Thus we are able to run the Garch model without break points.

4.3.2 Volatility Modeling and Leverage Effect Analysis: AR(1)-EGARCH Estimation Results and Diagnostic Validation for Brent Crude Oil Returns

Table no. 16 – Result of GARCH (1,1) model oil brent

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.006671	0.004011	1.663	0.0963	Not significant
Variance equation: C	0.004611	0.000830	5.552	0.0000	Significant
ARCH term, α_1	0.472978	0.064733	7.307	0.0000	Significant
GARCH term, β_1	-0.022411	0.103010	-0.218	0.8278	Not significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation Analysis

Table no. 16 reports the baseline GARCH(1,1) estimation results for dlog(Oil Brent). The mean equation analysis models the monthly return of Brent oil using the first difference of the natural logarithm of the oil price, denoted as DLOG(OIL_BRENT), which is a standard method for calculating continuously compounded monthly returns. The coefficient for the constant term (C) is 0.006671, indicating an average monthly return of approximately 0.67% over the sample period. The associated p-value of 0.0963 suggests that this return is statistically significant at the 10% level, though not at the more conventional 5% threshold, providing weak evidence that the mean return differs from zero. The R-squared value is -0.002016, which implies that the model performs worse than a simple average and confirms that the constant mean offers no predictive power–a common outcome in modeling financial returns, which are inherently difficult to forecast.

Variance Equation Analysis

This is the core of the GARCH model, designed to capture volatility dynamics. The equation is:

$$\sigma\_t^2 = \omega + \alpha * \varepsilon\_\{t-1\}^2 + \beta * \sigma\_\{t-1\}^2 \quad (15)$$

where:

- **C (ω): 0.004611 (p-value = 0.0000):** This is the constant term in the variance equation. It is positive and highly statistically significant, which is good. It represents the baseline or long-run average variance.
- **RESID (-1)^2 (α): 0.472978 (p-value = 0.0000):** This is the ARCH term. It measures how much of a shock in the previous period (the squared residual) affects the current period's variance.

Interpretation: The coefficient is large and highly significant. This indicates the presence of strong volatility clustering. A large price shock last month leads to high volatility this month. This is a typical and expected finding for financial assets like oil.

- **GARCH (-1) (β): -0.022411 (p-value = 0.8278):** This is the GARCH term. It measures the persistence of volatility, i.e., how much of the previous period's variance carries over to the current period.

Interpretation: This coefficient is the model's **critical failure**.

- **Negative Coefficient:** The coefficient is negative. For a variance to be guaranteed non-negative, the GARCH term (β) must be greater than or equal to zero. A negative β is theoretically invalid and makes no economic sense, as it implies that high volatility last month would *reduce* volatility this month, which contradicts the concept of volatility persistence.
- **Insignificant:** The p-value of 0.8278 is extremely high, meaning the coefficient is not statistically different from zero. The model finds no evidence that past variance has any impact on current variance.

Model Diagnostics

- **Volatility Persistence (α + β):** The sum of the ARCH and GARCH coefficients (α + β) measures how quickly volatility shocks fade. Here, 0.473 + (-0.022) = 0.451. A sum less than 1 suggests that the variance process is stationary (it will revert to the mean). However, given that β is invalid, this calculation is meaningless.
- **Durbin-Watson stat (1.386558):** This statistic tests for first-order serial correlation in the residuals. A value close to 2.0 suggests no correlation. A value of 1.39 is low enough to suggest the presence of **positive serial correlation**, meaning the mean equation is misspecified. The model is not fully capturing the dynamics in the returns themselves.

This GARCH (1,1) model is **not a valid or reliable model** for Brent oil price volatility. It has a fundamental theoretical flaw in the variance equation that makes its results unusable for forecasting or interpretation. While it correctly identifies some characteristics of oil returns (like volatility clustering), the model specification is incorrect.

Given what we found we will now estimate an EGARCH with an AR (1) term; the estimation results are reported in Table no. 17.

Table no. 17 – Result of EGARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.001521	0.005247	0.290	0.7720	Not significant
Mean equation: AR(1)	0.251191	0.059501	4.222	0.0000	Significant
Variance constant	-2.167527	0.581412	-3.728	0.0002	Significant
Magnitude effect	0.544868	0.080279	6.787	0.0000	Significant
Asymmetry effect	-0.124211	0.048182	-2.578	0.0099	Significant
Persistence term	0.655834	0.111803	5.866	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation Analysis

$$DLOG(OIL\_BRENT) = C + \varphi * DLOG(OIL\_BRENT)(-1) \tag{16}$$

where:

- **Constant ($\boldsymbol{C}$):** 0.001521 (p-value = 0.7720) -> Statistically insignificant. There is no evidence of a consistent long-term upward or downward drift in monthly oil returns;
- **AR (1) Term ($\boldsymbol{\varphi}$):** 0.251191 (p-value = 0.0000) -> Highly significant. This indicates a positive short-term momentum. About 25% of the previous month's price change (whether positive or negative) carries over into the current month.

Variance Equation (EGARCH):

$$LOG(\sigma\_t\text{^}2) = \omega + \alpha * |z\_\{t-1\}| + \gamma * z\_\{t-1\} + \beta * LOG(\sigma\_\{t-1\}\text{^}2) \tag{17}$$

where:

- **Constant ($\boldsymbol{\omega}$ or $\boldsymbol{C}(\mathbf{3})$):** -2.167527 (p-value = 0.0002) -> The long-run average level of log variance is significant;
- **Magnitude Effect ($\boldsymbol{\alpha}$ or $\boldsymbol{C}(\mathbf{4})$):** 0.544868 (p-value = 0.0000) -> This term is positive and highly significant, confirming the presence of GARCH effects. The magnitude of a shock clearly impacts future volatility;
- **Asymmetry/Leverage Effect ($\boldsymbol{\gamma}$ or $\boldsymbol{C}(\mathbf{5})$):** -0.124211 (p-value = 0.0099) -> **This is the key result.** The coefficient is negative and **statistically significant** (p-value < 0.01). A negative γ coefficient signifies a leverage effect. When there is a negative shock (bad news, RESID (-1) is negative), the term γ * RESID (-1) becomes positive, leading to a larger increase in log variance. Conversely, for a positive shock (good news), the term is negative, dampening the impact on volatility. In simple terms: **bad news about oil prices creates more volatility than good news;**
- **Persistence ($\boldsymbol{\beta}$ or $\boldsymbol{C}(\mathbf{6})$)):** 0.655834 (p-value = 0.0000) -> The GARCH persistence term is highly significant, indicating that volatility shocks have a long-lasting effect on the market.

The application of the AR (1)-EGARCH model to Brent oil prices has yielded an excellent result, revealing a classic and critical feature prevalent in many financial and commodity markets: the leverage effect. The model diagnostics further support its efficacy, with the Durbin-Watson statistic of 1.849347 being reasonably close to 2, indicating that the AR(1) term has effectively mitigated serial correlation in the residuals. In contrast to the general commodity import index for Republic of Moldova, the global Brent oil market demonstrates a clear and significant asymmetric response to news, making the EGARCH model a superior choice over a standard GARCH model for this dataset, as it adeptly captures the leverage effect. Economically, the results align with weak-form market efficiency, as the average monthly return is indistinguishable from zero once autocorrelation is accounted for. Additionally, a 1% unexpected decline in Brent prices triggers a disproportionately larger increase in volatility–approximately 12% more in log-variance–compared to a 1% unexpected rise, highlighting a downside risk sensitivity crucial for risk managers and option pricing. The model also reveals realistic and persistent volatility clustering, with a β value of approximately 0.66, contrasting sharply with the near-zero β observed previously, and aligning with empirical evidence of highly persistent and asymmetric oil-price volatility. Practically, the asymmetric EGARCH model effectively captures the empirically observed "volatility-leverage" in oil markets, where bad news spikes risk more significantly than good news. Furthermore, one-month-ahead volatility forecasts decay rapidly, with a half-life of about 1.6 months, implying that recent shocks influence risk assessments for only one to two months.

Next we will test the EGARCH (1,1,1) AR(1) with ARCH LM TEST with 12 lags; the results are reported in Table no. 18.

Table no. 18 – Result of ARCH LM TEST with 12 lags for EGARCH(1,1,1) AR(1)

Statistic	Value	p-value	Conclusion
F-statistic	0.6197	0.8257	No remaining ARCH effect
Obs*R-squared	7.5390	0.8200	No remaining ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The ARCH-LM diagnostic applied to the standardized residuals of the estimated AR(1)–EGARCH(1,1,1) model reveals no evidence of leftover ARCH structure. With twelve test lags, the F-statistic is 0.620 ($p = 0.826$) and the alternative Obs × R^2 statistic is 7.54 ($p = 0.820$). Both p-values far exceed conventional significance thresholds, so the null hypothesis of "no ARCH effects up to order 12" cannot be rejected. Accordingly, the EGARCH specification appears to have absorbed the conditional heteroskedasticity–including potential leverage or asymmetry–in the monthly Brent-oil returns: once the time-varying variance equation is accounted for, the residuals exhibit no further second-moment dependence. This result supports the adequacy of the chosen EGARCH model for volatility modelling.

The Nyblom parameter-stability test results for the AR(1)-EGARCH(1,1,1) specification are reported in Table no. 19.

Table no. 19 – Nyblom test foe EGARCH (1,1,1) AR (1)

Variable	Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Decision
C	0.106088	0.748	0.470	0.353	Stable
AR(1)	0.131601	0.748	0.470	0.353	Stable
C(3)	0.182266	0.748	0.470	0.353	Stable
C(4)	0.058215	0.748	0.470	0.353	Stable
C(5)	0.211660	0.748	0.470	0.353	Stable
C(6)	0.178952	0.748	0.470	0.353	Stable
Joint	**1.089166**	**2.120**	**1.680**	**1.490**	**Stable**

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Nyblom–Hansen cumulative score test provides strong evidence that the parameter vector of the AR(1)–EGARCH(1,1,1) model for monthly Brent-oil returns is time-invariant over the 1990:02–2025:05 sample. For each coefficient, the test statistic (ranging from 0.06 for the variance constant to 0.21 for the volatility-persistence term) lies well below the 10 % critical threshold of 0.353 reported by Hansen (1990), indicating that none of the individual parameters exhibits statistically significant drift. The joint statistic of 1.09 also falls short of the 10 % critical value (1.49), so the null of overall parameter stability cannot be rejected. Taken together with the absence of residual ARCH effects documented earlier, these results validate the choice of a constant-parameter EGARCH specification: the model successfully captures both the conditional mean and the asymmetric volatility dynamics without evidence of gradual structural change across the three-and-a-half decades examined.

The Ljung–Box portmanteau diagnostics (Table no. A3) applied to the standardized residuals of the AR(1)–EGARCH(1,1,1) model reveal no evidence of remaining linear dependence. Across horizons 1 to 36, all sample autocorrelations and partial autocorrelations are small in magnitude ($|AC| \leq 0.10$) and none is individually significant at conventional levels. More importantly, the sequential Ljung–Box Q-statistics never exceed their corresponding 10 % significance thresholds–the smallest p-value reported is 0.153 at lag 36–so the joint null hypothesis of no residual autocorrelation cannot be rejected at any horizon considered. These results indicate that the conditional mean and variance equations have successfully filtered out serial correlation and volatility clustering, leaving the standardized innovations essentially white-noise. Consequently, the AR(1)–EGARCH(1,1,1) specification appears well-specified in both the first and second moments, reinforcing the earlier conclusions drawn from the ARCH-LM and Nyblom stability tests regarding the model's adequacy for monthly Brent-oil returns.

The Ljung–Box portmanteau (Table no. A4) test applied to the squared standardized innovations of the AR(1)–EGARCH(1,1,1) model strengthens the evidence that the conditional-variance equation has eliminated residual second-moment dependence. Across horizons 1–36 all sample autocorrelations remain extremely small ($|AC| \leq 0.10$) and every Ljung-Box Q-statistic is accompanied by a p-value well above conventional significance thresholds (the minimum p-value is 0.859 at lag 16). Consequently, the joint null hypothesis that the squared standardized residuals are serially uncorrelated cannot be rejected at any lag length considered. Together with the earlier ARCH-LM results, these findings indicate that the EGARCH specification has successfully absorbed volatility clustering, leaving the standardized shocks indistinguishable from independent and identically distributed noise in both the first and second moments.

4.4. Conclusions drawn from the AR(1)-GARCH(1,1) model for Republic of Moldova's CIPI and the AR(1)-EGARCH(1,1) model for Brent Crude Oil.

This sub-chapter synthesises the results obtained from the AR(1)-GARCH(1,1) specification for Republic of Moldova's CIPI and the AR(1)-EGARCH(1,1) specification for Brent crude oil. The discussion is organised around three themes–model adequacy, conditional-mean behaviour, and conditional-variance behaviour–followed by the policy and risk-management implications.

4.4.1. Model Adequacy and Stability

Both series were found to be integrated of order one and free of seasonal unit roots or structural breaks in first differences, justifying the use of constant-parameter GARCH-type models. Diagnostic checks confirm that each selected specification is statistically adequate:

- **Residual whiteness:** Ljung–Box statistics on standardised (and squared) residuals are insignificant up to 36 lags for both models, indicating no remaining serial correlation.
- **Absence of residual ARCH:** ARCH-LM tests with twelve lags report p-values above 0.80, showing that the conditional-variance equations absorb the volatility clustering.
- **Parameter constancy:** Nyblom–Hansen statistics lie well below critical values, so the null of time-invariant parameters cannot be rejected.

Consequently, the AR(1)-GARCH(1,1) for CIPI and the AR(1)-EGARCH(1,1) for Brent constitute parsimonious yet sufficient representations of the underlying data-generating processes. Table no. 20 summarizes the comparative conditional-mean dynamics of the two series.

Table no. 20 – Conditional-Mean Dynamics comparative analysis of CIPI and oil Brent

Statistic	CIPI	Brent Oil
AR(1) coefficient (ϕ)	0.303***	0.251***
Constant (μ)	0.00046 (ns)	0.00152 (ns)

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Both markets exhibit short-run momentum–approximately one-quarter to one-third of the previous month's return carries into the current month–while **long-run drift is statistically indistinguishable from zero**. This outcome is consistent with weak-form market efficiency once low-order autocorrelation is taken into account.

Table no. 21 reports the comparative conditional-variance dynamics of CIPI and Brent.

Table no. 21 – Comparative Conditional-Variance Dynamics of CIPI and Brent Oil

Feature	CIPI – AR-GARCH	Brent Oil – AR-EGARCH	Comparative Insight
ARCH effect α	0.183***	0.545***	Volatility reacts more strongly to new shocks in Brent oil than in CIPI
GARCH/EGARCH persistence β	0.786***	0.656***	The lagged conditional variance effect is higher for CIPI, while Brent's EGARCH persistence is captured directly by β
Symmetry/ asymmetry parameter γ	0.018 ns	-0.124**	No leverage effect is evident in CIPI, whereas Brent oil exhibits a statistically significant asymmetric effect
Persistence measure	$\alpha + \beta \approx 0.97$	$\beta \approx 0.66$	Volatility is substantially more persistent, or "stickier," in the import price index than in Brent oil
Shock half-life	≈ 22 months	≈ 1.6 months	Volatility shocks dissipate much more slowly in CIPI than in Brent oil

Note: For the CIPI AR-GARCH model, volatility persistence is measured by $\alpha + \beta$. For the Brent AR-EGARCH model, persistence is governed by the EGARCH β coefficient. Therefore, $\alpha + \beta$ is not used as the persistence measure for Brent, because adding the EGARCH ARCH coefficient to β is not directly comparable to the GARCH persistence condition.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Key contrasts are therefore twofold:

- **Persistence:** The import-price index displays near-unit-root persistence in variance ($\alpha + \beta \approx 0.97$). Volatility shocks dissipate only gradually, implying that external price surprises translate into prolonged uncertainty for Republic of Moldovan import costs. Brent volatility, although sizeable, reverts roughly an order of magnitude faster.
- **Asymmetry (leverage):** The EGARCH term for Brent is negative and significant, confirming that **negative price shocks amplify volatility more than positive shocks** of the same magnitude. In the CIPI series the corresponding TARCH and EGARCH coefficients are insignificant, indicating **symmetric** volatility responses.

4.4.2 Economic Interpretation

1. **Transmission of global shocks:**
   - The long memory in CIPI volatility suggests that a single global commodity shock (e.g., energy embargo, supply-chain disruption) can affect Republic of Moldovan import-price risk for up to two years, complicating fiscal and monetary planning.
   - Brent volatility, while sensitive to current news, normalises within a quarter; thus, energy traders and policymakers can rely on more frequent re-calibration.
2. **Risk asymmetry:**
   - The leverage effect in Brent confirms market participants' asymmetric reaction to downside risk, consistent with inventory, option-pricing and precautionary-demand theories.
   - The absence of asymmetry in the aggregate CIPI implies that the diversified import basket buffers idiosyncratic commodity-specific leverage effects.
3. **Portfolio hedging:**
   - Hedging Brent exposure alone cannot offset the long-lived variance component embedded in CIPI. A **diversified hedge portfolio**–including futures or options on multiple commodity groups–would better align with the slow-decay property observed.

4.4.3 Policy and Risk-Management Implications

1. **Macro-stabilisation:** Republic of Moldovan authorities should build medium-term fiscal buffers and consider multi-period risk-sharing instruments (e.g., contingent credit lines) to counteract the high persistence of import-price volatility.
2. **Energy-sector strategy:** Given Brent's leverage effect, energy importers should emphasise **downside-risk insurance** (protective puts, collars) and employ dynamic hedging intervals consistent with the 1–2-month volatility half-life.
3. **Forecasting frameworks:** DSGE or VAR models used by the National Bank should incorporate **symmetric shocks for the import basket** and **asymmetric shocks for oil prices**, reflecting the empirical variance structure documented here.

4.5. Model Selection Rationale

The empirical analysis estimated a family of conditional-volatility specifications for each series–GARCH(1,1), AR(1)-GARCH(1,1), AR(1)-TARCH(1,1,1), and AR(1)-EGARCH(1,1,1)–so that the preferred model could be identified from within-sample evidence rather than imposed a priori. The selection criteria applied jointly were: (i) the

Akaike (AIC) and Schwarz (SC) information criteria, which reward in-sample fit while penalising parameter count; (ii) the statistical significance of the asymmetry (leverage) coefficient; (iii) the residual-diagnostic battery (Ljung–Box on standardised and squared standardised residuals, ARCH-LM at 12 lags, Nyblom–Hansen stability); and (iv) parsimony, preferring the simplest specification consistent with the data.

Republic of Moldova's Commodity Import Price Index. Moving from the baseline GARCH(1,1) to the AR(1)-GARCH(1,1) raised the log-likelihood from 1291.58 to 1304.36, increased R^2 from near zero to 0.11, corrected the Durbin-Watson statistic from 1.33 to 1.94, and lowered both AIC and SC–establishing that a first-order autoregressive mean equation is required. Extending further to AR(1)-TARCH(1,1,1) and AR(1)-EGARCH(1,1,1) did not yield a better fit on the information criteria, and in both asymmetric specifications the leverage term was statistically insignificant (EGARCH $\gamma = -0.026$, $p = 0.5455$; the TARCH threshold coefficient likewise non-significant). Because the additional flexibility contributed no empirical content, the more parsimonious AR(1)-GARCH(1,1) was retained for CIPI.

Brent Crude Oil. The picture differs. Relative to a symmetric AR(1)-GARCH(1,1) on Brent returns, the AR(1)-EGARCH(1,1,1) delivered a lower AIC and SC and, critically, an asymmetry coefficient $\gamma = -0.124$ that is statistically significant at the 5% level. The negative and significant γ confirms a textbook leverage effect–downside price shocks amplify conditional variance more than upside shocks of the same magnitude–so a symmetric specification would impose a counter-factual restriction on Brent's data-generating process. Diagnostic tests (Ljung–Box Q and ARCH-LM) clear the AR(1)-EGARCH(1,1,1) residuals of remaining autocorrelation and heteroskedasticity, and the Nyblom–Hansen statistic does not reject parameter stability. The AR(1)-EGARCH(1,1,1) is therefore the empirically and theoretically supported specification for Brent.

The dual selection–symmetric GARCH for the aggregated import basket, asymmetric EGARCH for the single-commodity global benchmark–is itself a substantive finding rather than an arbitrary modelling choice: it reflects that diversification across commodity groups attenuates idiosyncratic leverage, whereas a concentrated financialised market such as Brent preserves it.

4.6. Implications for Public Policy

The empirical results translate directly into differentiated policy prescriptions. The two defining parameters–a variance half-life of roughly 22 months in the CIPI versus 1.6 months in Brent, and the presence of a leverage effect in Brent but not in the import basket–imply that the appropriate policy response depends on which risk is being managed. The following recommendations are organised by policy actor.

Fiscal authority (Ministry of Finance). Because CIPI shocks decay slowly, fiscal buffers must be sized for multi-period drawdowns rather than single-year deficits. Three instruments are indicated by the empirical persistence: (i) a counter-cyclical fiscal rule that targets the structural balance adjusted for a two-year moving average of import-price deviations, so that transitory but long-lived shocks do not mechanically trigger pro-cyclical tightening; (ii) establishment or expansion of a commodity-price stabilisation fund with a calibrated drawdown horizon of at least 24 months, consistent with the estimated shock half-life; and (iii) standby access to contingent credit facilities (IMF FCL/PLL, World Bank Cat-DDO) to bridge the extended adjustment period without recourse to procyclical borrowing.

Central bank (National Bank of Moldova). Symmetric but highly persistent import-price volatility implies that inflation expectations may remain elevated for extended periods after an external shock, even in the absence of domestic demand pressure. Monetary policy should therefore: (i) distinguish between the transitory first-round impact and the persistent second-round component when setting the policy rate, to avoid over-tightening into a slowly-decaying shock; (ii) communicate an explicit medium-term horizon (18–24 months) for the return of inflation to target, aligned with the empirical CIPI half-life; and (iii) strengthen foreign-exchange reserve buffers, since protracted import-cost pressure translates mechanically into current-account strain. Forecasting and DSGE frameworks used for monetary analysis should embed a symmetric high-persistence specification for aggregate import costs.

Energy-sector regulator and state-owned importers. The leverage effect and short half-life in Brent dictate a fundamentally different risk-management posture for the energy segment. Appropriate instruments include: (i) protective put options and collar structures on crude and refined products, whose asymmetric pay-off profile matches the asymmetric volatility process; (ii) short-tenor dynamic hedging programmes (1–3 months) consistent with the 1.6-month half-life, rather than long-dated static hedges that would carry unnecessary basis risk; (iii) strategic petroleum and gas reserves calibrated against tail-loss scenarios from the estimated EGARCH distribution; and (iv) diversification of supply contracts across pricing benchmarks to reduce single-index concentration.

Private sector and development partners. Importers and manufacturers exposed to the broad CIPI should negotiate longer-tenor supplier contracts with price-indexation clauses rather than rely on short-term spot procurement, which would lock in transitory peaks. Development partners financing structural-adjustment programmes should size programme duration and disbursement profiles to the two-year volatility half-life documented here, and condition reforms on the adoption of the counter-cyclical fiscal and monetary frameworks outlined above.

Cross-cutting implication. Because the CIPI and Brent processes are statistically distinct–differing in both persistence and symmetry–policy instruments designed around oil-price benchmarks alone will systematically under-insure the aggregate import-cost risk that ultimately drives domestic inflation, fiscal pressure, and external-balance dynamics in the Republic of Moldova. The empirical evidence thus supports a dual-track risk-management architecture: short, asymmetric instruments for the energy segment and long, symmetric instruments for the import basket as a whole.

5. CONCLUSIONS: UNDERSTANDING REPUBLIC OF MOLDOVA'S ECONOMIC VULNERABILITY THROUGH DUAL-RISK ANALYSIS

This study establishes a dual-risk profile in external price volatility that is central to understanding the Republic of Moldova’s macroeconomic vulnerability. The Commodity Import Price Index exhibits volatility that is persistent and broadly symmetric, whereas Brent crude displays volatility that is asymmetric yet comparatively short-lived. The two price differences match the different market systems because total import costs stem from actual trade activities and various market risks yet Brent operates within a fast-moving financial market that responds to investor emotions and market trading behavior. The identification of these distinct risk structures serves as a fundamental requirement for developing empirical models and designing policies and managing risks.

The CIPI volatility remains active which means market disturbances maintain their impact through multiple periods and this extended market uncertainty makes it difficult to plan budgets and control inflation and select investment choices. The import basket demonstrates symmetrical behavior which means that prices can move up or down unpredictably thus requiring stabilization tools to focus on medium-term risk management instead of short-term market changes. The asymmetrical nature of Brent's leverage causes negative shocks to produce bigger volatility responses which fade away rapidly thus making energy price shocks short-term events that become controllable through fast policy adjustments and sufficient liquidity reserves.

The research findings prove that standard modeling methods fail to work for markets which possess different underlying microeconomic structures. The traditional volatility models show the ongoing symmetrical patterns which exist in aggregate import costs. The analysis of Brent requires EGARCH or related asymmetric forms to model its leverage-like behavior because these specifications allow for sign dependence. The research strategy requires two different approaches because the domestic CIPI functions as the better predictor for domestic results through its ability to show how external elements affect domestic expenses yet worldwide benchmark shocks serve as better tools for detecting structural transmission effects.

The research results produce direct consequences for policy development. The solution for handling long-term vulnerability from steady import-cost fluctuations needs medium-term stabilization through enhanced fiscal reserves and supplier risk-sharing agreements and multiple sourcing options and long-term hedging strategies. The solution to sudden energy price increases needs quick liquidity control together with short-term price stabilization methods and backup plans for power supply. The global energy benchmark remains insufficient for risk management because organizations need to handle both long-term import cost fluctuations and sudden extreme market shocks from worldwide commodity markets.

Several limitations qualify these conclusions and delineate priorities for future research. The first step involves analyzing CIPI and Brent separately by studying their individual characteristics of persistence and symmetry through univariate methods which exclude their mutual interactions and macroeconomic connections and feedback loops. Second, model adequacy is assessed primarily in-sample, leaving open the relative out-of-sample forecasting value of CIPI versus Brent for inflation, output, or external balances. The third point explains how simplifying assumptions limit generalizability because volatility parameters changed throughout three decades of crises which required regime-switching models and Gaussian errors fail to detect tail risk so heavier-tailed distributions should be used and monthly data hides quick policy response transmission.

The research limitations match the basic exploration goal which leads to a concentrated research plan for further studies. The analysis of Brent oil prices requires multivariate forecast-oriented models (e.g., VAR/VECM with GARCH effects, DCC-GARCH, BEKK, or factor structures) to identify spillover effects on CIPI and their subsequent impact on inflation and economic activity. Regime-dependent volatility (e.g., Markov-Switching GARCH) and heavy-tailed error distributions can better capture crisis dynamics and tail risk. Rigorous out-of-sample forecast evaluation should compare CIPI- and Brent-based predictors, potentially leveraging forecast combination and using the model-evaluation frameworks developed by Hansen and Lunde (2005) and Patton (2011). The MIDAS method allows analysts to link fast-moving commodity data with slow-moving monthly economic indicators to create better and faster predictions. Hybrid frameworks that combine the theoretical structure of GARCH-type models with the flexibility of machine-learning techniques – as explored for commodity markets by Kristjanpoller and Minutolo (2015) and Ramos-Pérez *et al.* (2019) – offer a further promising direction, particularly for capturing non-linear dynamics that univariate EGARCH specifications cannot accommodate.

The external vulnerabilities of Moldova exist in various forms which depend on specific market structures. The selection of statistical tools for modeling and policy development depends on the nature of volatility patterns which show persistent symmetric behavior for aggregate import costs yet display asymmetric transient characteristics for global energy prices. Dual-risk assessment implementation through institutionalization enables forecasting and causal identification and policy design to build resilience which addresses both ongoing import price volatility and sudden global commodity market shocks.

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ANNEX

Table no. A1 – Results of the Correlogram Q-Statistics (Ljung–Box Portmanteau Test) for GARCH(1,1) AR(1)

<table>
<tr><td colspan="7">Sample (adjusted): 1992M03 2025M05</td></tr>
<tr><td colspan="7">Q-statistic probabilities adjusted for 1 ARMA term</td></tr>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob*</th></tr>
<tr><td>.|. |</td><td>.|. |</td><td>1</td><td>0.040</td><td>0.040</td><td>0.6418</td><td></td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>2</td><td>0.029</td><td>0.028</td><td>0.9806</td><td>0.322</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>3</td><td>0.012</td><td>0.010</td><td>1.0416</td><td>0.594</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>4</td><td>0.027</td><td>0.026</td><td>1.3377</td><td>0.720</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>5</td><td>-0.003</td><td>-0.006</td><td>1.3415</td><td>0.854</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>6</td><td>0.004</td><td>0.003</td><td>1.3491</td><td>0.930</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>7</td><td>-0.016</td><td>-0.017</td><td>1.4593</td><td>0.962</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>8</td><td>-0.015</td><td>-0.015</td><td>1.5560</td><td>0.980</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>9</td><td>-0.017</td><td>-0.015</td><td>1.6704</td><td>0.990</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>10</td><td>0.106</td><td>0.108</td><td>6.2388</td><td>0.716</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>11</td><td>0.054</td><td>0.048</td><td>7.4246</td><td>0.685</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>12</td><td>-0.075</td><td>-0.085</td><td>9.7269</td><td>0.555</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>13</td><td>-0.080</td><td>-0.080</td><td>12.338</td><td>0.419</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>14</td><td>-0.038</td><td>-0.036</td><td>12.938</td><td>0.453</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>15</td><td>-0.017</td><td>-0.009</td><td>13.056</td><td>0.522</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>16</td><td>0.007</td><td>0.017</td><td>13.078</td><td>0.596</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>17</td><td>-0.055</td><td>-0.048</td><td>14.324</td><td>0.575</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>18</td><td>-0.088</td><td>-0.082</td><td>17.580</td><td>0.416</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>19</td><td>-0.046</td><td>-0.037</td><td>18.483</td><td>0.424</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>20</td><td>0.027</td><td>0.023</td><td>18.792</td><td>0.470</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>21</td><td>-0.007</td><td>-0.017</td><td>18.812</td><td>0.534</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>22</td><td>0.008</td><td>0.022</td><td>18.840</td><td>0.595</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>23</td><td>-0.118</td><td>-0.098</td><td>24.689</td><td>0.312</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>24</td><td>-0.096</td><td>-0.090</td><td>28.617</td><td>0.193</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>25</td><td>0.013</td><td>0.018</td><td>28.691</td><td>0.232</td></tr>
<tr><td>.|. |</td><td>*|. |</td><td>26</td><td>-0.062</td><td>-0.074</td><td>30.323</td><td>0.212</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>27</td><td>-0.014</td><td>-0.006</td><td>30.411</td><td>0.251</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>28</td><td>-0.090</td><td>-0.068</td><td>33.854</td><td>0.170</td></tr>
<tr><td>*|. |</td><td>*|. |</td><td>29</td><td>-0.085</td><td>-0.079</td><td>36.970</td><td>0.120</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>30</td><td>0.004</td><td>-0.011</td><td>36.978</td><td>0.147</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>31</td><td>0.080</td><td>0.063</td><td>39.747</td><td>0.110</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>32</td><td>0.008</td><td>-0.009</td><td>39.776</td><td>0.134</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>33</td><td>-0.010</td><td>-0.004</td><td>39.823</td><td>0.161</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>34</td><td>-0.004</td><td>0.017</td><td>39.830</td><td>0.192</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>35</td><td>0.083</td><td>0.060</td><td>42.849</td><td>0.142</td></tr>
<tr><td>.|. |</td><td>.|. |</td><td>36</td><td>0.007</td><td>-0.026</td><td>42.872</td><td>0.169</td></tr>
<tr><td colspan="7">Note: *Probabilities may not be valid for this equation specification.</td></tr>
</table>

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A2 – Result of Correlogram squared residuals for GARCH (1,1) AR(1)

Sample (adjusted): 1992M03 2025M05
Included observations: 397 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.058	0.058	1.3552	0.244
.|. |	.|. |	2	0.019	0.016	1.5071	0.471
.|. |	.|. |	3	-0.032	-0.034	1.9236	0.588
.|. |	.|. |	4	-0.032	-0.029	2.3452	0.673
.|. |	.|. |	5	0.006	0.010	2.3576	0.798
.|. |	.|. |	6	-0.031	-0.032	2.7388	0.841
.|. |	.|. |	7	-0.030	-0.029	3.1015	0.875
.|. |	.|. |	8	-0.044	-0.041	3.9021	0.866
.|. |	.|. |	9	0.054	0.059	5.0930	0.826
.|. |	.|. |	10	0.036	0.027	5.6120	0.847
.|. |	.|. |	11	-0.047	-0.058	6.5267	0.836
.|. |	.|. |	12	-0.001	0.005	6.5269	0.887
.|. |	.|. |	13	0.027	0.034	6.8168	0.911
.|. |	.|. |	14	0.024	0.015	7.0461	0.933
.|. |	.|. |	15	-0.029	-0.037	7.4055	0.945
.|. |	.|. |	16	-0.054	-0.046	8.6349	0.928
.|. |	.|. |	17	-0.063	-0.049	10.263	0.892
.|. |	.|. |	18	0.033	0.038	10.706	0.906
.|. |	.|. |	19	0.007	-0.007	10.726	0.933
.|. |	.|. |	20	-0.010	-0.012	10.772	0.952
.|. |	.|. |	21	-0.052	-0.047	11.915	0.942
.|. |	.|. |	22	0.011	0.013	11.968	0.958
.|* |	.|* |	23	0.150	0.142	21.472	0.552
.|. |	.|. |	24	0.011	-0.010	21.524	0.608
.|. |	.|. |	25	0.048	0.044	22.507	0.606
.|. |	.|. |	26	-0.053	-0.042	23.688	0.594
.|. |	.|. |	27	-0.050	-0.048	24.755	0.588
.|. |	.|. |	28	-0.031	-0.032	25.159	0.619
.|. |	.|. |	29	-0.059	-0.043	26.653	0.590
.|. |	.|. |	30	0.010	0.029	26.693	0.639
.|. |	.|. |	31	0.039	0.051	27.359	0.654
.|. |	.|. |	32	0.026	-0.013	27.645	0.687
.|. |	.|. |	33	0.021	0.006	27.843	0.722
.|. |	.|. |	34	0.006	0.016	27.861	0.762
.|. |	.|. |	35	0.004	0.005	27.869	0.799
.|. |	.|. |	36	0.014	0.012	27.962	0.829

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A3 – Results of the Correlogram Q-Statistics (Ljung–Box Portmanteau Test) for EGARCH(1,1,1) AR(1)

Sample (adjusted): 1990M03 2025M05
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.030	0.030	0.3806	
.|. |	.|. |	2	-0.046	-0.047	1.2995	0.254
.|. |	.|. |	3	-0.021	-0.018	1.4869	0.475
*|. |	*|. |	4	-0.067	-0.068	3.4031	0.334
.|. |	.|. |	5	-0.014	-0.012	3.4915	0.479
.|. |	.|. |	6	-0.019	-0.025	3.6398	0.602
.|. |	.|. |	7	0.014	0.011	3.7233	0.714
.|. |	.|. |	8	-0.039	-0.047	4.3714	0.736
.|. |	.|. |	9	-0.057	-0.056	5.7726	0.673
.|. |	.|. |	10	0.052	0.049	6.9597	0.641
.|* |	.|* |	11	0.082	0.075	9.9253	0.447
.|. |	.|. |	12	0.014	0.007	10.008	0.530
.|. |	.|. |	13	-0.059	-0.060	11.545	0.483
*|. |	.|. |	14	-0.073	-0.064	13.879	0.382
.|. |	.|. |	15	0.007	0.017	13.901	0.457
.|. |	.|. |	16	-0.022	-0.025	14.109	0.517
.|. |	.|. |	17	0.004	-0.007	14.115	0.590
.|. |	.|. |	18	-0.045	-0.061	15.006	0.595
.|. |	.|. |	19	-0.032	-0.022	15.451	0.631
.|. |	.|. |	20	0.050	0.052	16.552	0.620
.|. |	.|. |	21	0.010	-0.005	16.599	0.679
.|. |	.|. |	22	0.065	0.042	18.497	0.617
.|. |	*|. |	23	-0.054	-0.066	19.814	0.595
*|. |	*|. |	24	-0.095	-0.072	23.878	0.411
.|. |	.|* |	25	0.063	0.078	25.692	0.369
.|. |	.|. |	26	-0.039	-0.048	26.378	0.388
*|. |	*|. |	27	-0.098	-0.120	30.749	0.238
.|. |	.|. |	28	-0.027	-0.036	31.070	0.268
.|. |	.|. |	29	-0.061	-0.055	32.763	0.245
.|. |	.|* |	30	0.073	0.076	35.220	0.197
.|. |	.|. |	31	-0.021	-0.056	35.420	0.228
.|. |	.|. |	32	-0.018	-0.065	35.568	0.262
.|* |	.|. |	33	0.076	0.065	38.224	0.208
.|. |	.|. |	34	-0.051	-0.024	39.448	0.204
.|. |	.|. |	35	0.031	0.039	39.883	0.225
.|* |	.|. |	36	0.089	0.066	43.532	0.153

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A4 – Result of Correlogram squared residuals for EGARCH (1,1,1) AR(1)

Sample (adjusted): 1990M03 2025M05
Included observations: 423 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.006	-0.006	0.0140	0.906
.|. |	.|. |	2	-0.000	-0.000	0.0141	0.993
.|. |	.|. |	3	-0.023	-0.023	0.2469	0.970
.|. |	.|. |	4	-0.017	-0.017	0.3683	0.985
.|. |	.|. |	5	0.019	0.019	0.5204	0.991
.|. |	.|. |	6	-0.018	-0.018	0.6608	0.995
.|. |	.|. |	7	0.024	0.023	0.9135	0.996
.|. |	.|. |	8	-0.003	-0.002	0.9166	0.999
.|. |	.|. |	9	0.035	0.035	1.4379	0.998
.|. |	.|. |	10	0.071	0.072	3.6544	0.962
.|. |	.|. |	11	-0.016	-0.014	3.7673	0.976
.|. |	.|. |	12	-0.042	-0.042	4.5286	0.972
.|. |	.|. |	13	0.008	0.013	4.5543	0.984
.|. |	.|. |	14	-0.022	-0.022	4.7628	0.989
.|. |	.|. |	15	0.045	0.041	5.6594	0.985
.|* |	.|* |	16	0.101	0.103	10.151	0.859
.|. |	.|. |	17	0.006	0.005	10.168	0.896
.|. |	.|. |	18	0.022	0.022	10.383	0.919
.|. |	.|. |	19	0.001	0.006	10.384	0.943
.|. |	.|. |	20	-0.031	-0.036	10.806	0.951
.|. |	.|. |	21	-0.017	-0.012	10.934	0.964
.|. |	.|. |	22	0.009	0.016	10.969	0.975
.|* |	.|* |	23	0.083	0.078	14.101	0.924
.|. |	.|. |	24	0.013	0.014	14.173	0.943
.|. |	.|. |	25	0.023	0.012	14.419	0.954
.|. |	.|. |	26	-0.049	-0.063	15.501	0.947
.|. |	.|. |	27	-0.006	-0.001	15.520	0.961
.|. |	.|. |	28	0.035	0.039	16.084	0.965
*|. |	*|. |	29	-0.070	-0.068	18.298	0.938
.|. |	.|. |	30	0.001	0.006	18.299	0.953
.|. |	.|. |	31	-0.006	-0.009	18.314	0.965
.|. |	.|. |	32	-0.028	-0.056	18.662	0.971
.|. |	.|. |	33	-0.011	-0.029	18.720	0.978
.|. |	.|. |	34	-0.008	-0.011	18.748	0.984
.|. |	.|. |	35	-0.048	-0.049	19.831	0.982
.|. |	.|. |	36	0.031	0.052	20.291	0.984

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

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Subjective Determinants of Attitudes Towards Euro Adoption in Non-Euro Countries. A Machine Learning Approach

Ana-Maria Giurgi*, Carmen Pintilescu**, Ciprian Ionel Turturean***

Abstract: The adoption of the euro is a sensitive topic in the European Union (EU) member states that are not yet part of the Euro Area. Public perceptions and attitudes are influenced not only by objective economic factors, but also by subjective factors, such as the level of trust in institutions, perceptions of prices changes or the mixed feelings about EU. This paper investigates the subjective determinants of attitudes towards euro adoption among EU member states before euro adoption, using an approach based on machine learning algorithms. The analysis is based on Flash Eurobarometer data for 2011–2024 and includes only observations from countries in years before they adopted the euro. The results show that price-related perceptions consistently emerge as the most important predictor of attitudes towards euro adoption, while concerns related to national identity and economic control are also strongly associated with lower levels of support. In addition, self-perceived knowledge about the euro appears to be linked to more favourable attitudes. The study contributes methodologically through the comparative application of machine learning techniques and empirically by identifying the main subjective factors associated with public support for euro adoption in the EU.

Keywords: Euro; machine learning; Eurobarometer; Euro adoption.

JEL classification: E42; E52; E65.

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1. INTRODUCTION

The process of economic integration within the European Union (EU), initiated in 1957, was strengthened by the creation of the Economic and Monetary Union (EMU), which aims to coordinate economic and fiscal policies, implement a common monetary policy, and introduce a single currency, the euro. EMU contributes to macroeconomic stability, fosters sustained economic growth, and generates positive effects on the well-being of European citizens. The Maastricht Treaty (1992) established the convergence criteria necessary for the transition to monetary integration. Since 1999, the euro area has gradually expanded, reaching 21 member states following Croatia's accession in 2023 and Bulgaria's adoption of the euro in 2026.

After the first 11 countries introduced the euro, a substantial amount of literature examined the effects of the euro changeover and highlighted the persistence of public concerns about price increases after adoption. Numerous studies have documented a discrepancy between perceived post-changeover price increases and actual price developments, often labelled the "euro illusion", showing that citizens tend to overestimate price increases after the transition to the euro even when official price indicators show more moderate developments (Gamble *et al.*, 2002; Angelini and Lippi, 2006; Gamble, 2006; Lunn and Duffy, 2010). Given the central role of public perceptions in shaping support for monetary integration, research has increasingly focused on the determinants of perceived post-adoption price increases, trust in institutions, and symbolic concerns such as economic control and national identity.

For countries that have not yet adopted the euro, understanding public attitudes towards euro adoption is particularly relevant in the current context, marked by the COVID-19 crisis, the war in Ukraine, rising prices, and declining purchasing power in Europe. These developments have amplified feelings of uncertainty and contributed to the resurgence of Euroscepticism (Roth et al., 2023). In addition, recent geopolitical developments, including ongoing conflicts in the Middle East and increased global uncertainty regarding energy supply and international security, have further contributed to a volatile economic environment (Zhou, 2024), which may influence public perceptions regarding euro adoption. Identifying the main concerns associated with the adoption of the euro is therefore essential for policymakers, as it can support the design of communication and transition strategies that address citizens' concerns and facilitate the completion of the integration process.

In this study, we analyse citizens' attitudes and perceptions regarding euro adoption in non-euro EU member states. The analysis is based on Flash Eurobarometer surveys covering the period 2011–2024 and includes nine EU countries observed during their non-euro period: Bulgaria, Croatia, the Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania and Sweden. We include Croatia, Latvia and Lithuania, countries that adopted the euro during the analysed period, to capture the dynamics of perceptions prior to adoption. In the empirical analysis, only observations corresponding to the pre-adoption period are considered, ensuring that all data points reflect non-euro contexts. Bulgaria is also included because, during the 2011 - 2024 survey period analysed in this study, it had not yet adopted the euro. Its subsequent accession to the euro area in 2026 makes its pre-adoption experience particularly relevant for understanding attitudes in a late pre-adoption context. Denmark is excluded because it negotiated an opt-out from the obligation to adopt the euro under the Maastricht Treaty (1992), making its public attitudes structurally different from those of countries under mandatory convergence.

As a methodological approach, in the first stage of the analysis we apply two machine learning algorithms, Random Forest and logistic regression, in order to identify and rank the subjective factors associated with attitudes towards euro adoption. The analysis includes five perception-based variables reflecting several dimensions: self-perceived knowledge about the euro, perceptions of price change, concerns about loss of national identity, concerns about loss of control over economic policy, and concerns about price abuses. In the second step of the analysis, we applied the CART algorithm in order to identify the profile of the respondents according to the subjective factors at two points in time, 2016 and 2020. The year 2016 was chosen as representative for the post-crisis recovery period and the year 2020 was chosen as representative for a period of economic uncertainty, following the pandemic crisis. To assess the performance of the models estimated, we used the following indicators: accuracy, balanced accuracy, sensitivity, specificity and AUC.

The paper is structured as follows: in Section 2, we present a survey of the literature on the main economic and institutional framework of euro adoption and the public perception concerning this process. Section 3 describes the data and methodology used to assess the main subjective determinants of attitudes towards euro adoption. Section 4 presents the empirical analysis for non-euro EU member states, while the final section concludes.

2. LITERATURE REVIEW

2.1. The economic and institutional framework of euro adoption

Economic and Monetary Union (EMU) is one of the most important integration projects of the European Union, aiming to strengthen economic convergence and macroeconomic stability. The Maastricht Treaty (1992) established convergence criteria relating to inflation, the budget deficit, public debt, exchange rate and interest rates, intended to ensure the compatibility of the participating economies (Proctor, 2023). The implementation of a common monetary policy, coordinated by the European Central Bank, marked an important stage of economic integration, but also implied a partial loss of national autonomy in economic policymaking. The theoretical foundations of EMU are based on the Optimum Currency Area theory (Mundell, 1961), which emphasizes the advantages of reducing transaction costs, increasing price transparency, and facilitating trade, as well as the costs associated with the loss of monetary and exchange rate flexibility. The efficiency of a monetary union thus depends on the degree of economic convergence and the ability of states to adapt to asymmetric shocks through fiscal policies and labour mobility (Verdun, 2005).

Recent global crises have influenced attitudes toward the euro. The global financial crisis of 2008 - 2009 and the sovereign debt crisis raised questions about the resilience of the euro area (Roth *et al.*, 2015). The COVID-19 pandemic and high inflation in 2020 have renewed concerns about monetary stability and purchasing power (Roth *et al.*, 2024). These events have highlighted that public support for the euro does not depend only on economic indicators, but also on perceptions of security and economic control. For non-euro states in Central and Eastern Europe (CEE), such as Romania, Bulgaria, Poland, Hungary, the Czech Republic or Sweden, adopting the single currency remains a complex political and social decision, even though they are formally expected to adopt the euro, as they do not have an opt-out clause. While Romania and Bulgaria maintain relatively high levels of public support, in countries such as Hungary and Poland concerns related to sovereignty and loss of economic control appear more prominent (Dandashly and Verdun, 2018). Croatia's recent experience provides a useful example of how institutional readiness and social perceptions condition the success of the euro accession process. Bulgaria's accession to the euro area on January 1, 2026, also makes its pre-adoption experience relevant.

2.2. Public attitudes towards the euro, main determinants identified in the literature

Public attitudes towards the adoption of the euro are a central topic in research on European integration, being influenced by a complex combination of economic, political, identity and informational factors. The literature highlights that support for the euro is not only shaped by rational assessments of economic benefits, but also by symbolic perceptions and trust in the institutions managing the integration process (Jonung and Conflitti, 2008; Hobolt and Wratil, 2015).

In the economic framework, support for the euro can be interpreted through the lens of economic voting theory, according to which individuals evaluate economic performance both at a personal level (pocketbook effects) and at a national level (sociotropic effects). For example, research on Greece during the economic crisis highlights that, despite severe austerity measures and economic recessions, support for the euro remained strong due to both personal economic considerations and broader national economic evaluations, with sociotropic evaluations often taking precedence as uncertainty about policy outcomes diminished (Jurado *et al.*, 2020). Positive perceptions of economic growth, income prospects, and price stability favour pro-euro attitudes, while economic uncertainty and high inflation can increase hesitancy. Research based on the Eurobarometer has shown that individuals who perceive the single currency as a guarantee of price stability and economic integration tend to support it more strongly (Jonung and Conflitti, 2008), while those who fear losing control over prices adopt a negative position (Banducci *et al.*, 2009).

The adoption of the euro in CEE countries is associated with issues of national identity and symbolic frameworks. The euro, as a symbol of European integration, challenges traditional national symbols and can be perceived as a threat to national identity and economic sovereignty. This is particularly pronounced in CEE countries, where the process of building a post-transition national identity is recent and fragile. The perception that the adoption of the euro could lead to a "loss of country identity" and a "loss of control over economic policy" reflects concerns about diminishing national autonomy (Parizek, 2011). In these regions, the euro is not just a currency, but an indicator of European identity, which can unify or divide public opinion depending on historical legacies and the success of economic transitions(Allam and Goerres, 2011).

Another important determinant is trust in national and European institutions. Studies suggest that support for the euro tends to be higher among individuals with greater levels of trust in the European Union, the European Central Bank and, to a lesser extent, in the national government (Bergbauer *et al.*, 2020). Trust can act as a mediating factor, so individuals who perceive European institutions as competent and stability-oriented are more likely to support the adoption of the euro. Conversely, where domestic institutions are perceived as corrupt or inefficient, support for monetary integration may be weakened by the fear of losing domestic control over economic decisions (Hobolt and Wratil, 2015; Roth and Jonung, 2022).

In addition, individual information levels and political competence also influence attitudes towards the euro. People who declare themselves informed or who have a higher educational level tend to better understand the economic mechanisms of the single currency and to display pro-European attitudes(Fernández *et al.*, 2023). Media exposure and the quality of public discourse also have an effect; in times of disinformation or excessive politicization, perceptions can be divided, and limited information may increase the likelihood of "Don't know" responses or fear-based opposition (Conflitti, 2011).

Overall, the literature suggests that attitudes towards the euro are the result of an interaction between economic evaluations, identity attachments, trust in institutions and the level of information. These dimensions do not act in isolation, but form a complex framework in which support for the single currency reflects both material interests and symbolic values related to European membership. The factors influencing attitudes towards the euro found in the literature will be presented in more detail below.

Perceptions of price increases after euro adoption are one of the most sensitive dimensions of the public debate on the adoption of the euro, being directly linked to citizens' perceived well-being and trust in national economic policies. Numerous studies have highlighted the existence of a phenomenon known as the "euro illusion", according to which citizens tend to perceive sharper price increases immediately after the introduction of the euro, even when official price indicators show more moderate developments (Gamble *et al.*, 2002; Angelini and Lippi, 2006; Gamble, 2006). This phenomenon is explained by psychological and behavioural effects, the initial difficulty of converting monetary values (Lunn and Duffy, 2010), the rounding up of prices to facilitate payments, and the tendency of consumers to pay disproportionate attention to frequently purchased consumer goods, where visible changes are more common (Cornille and Stragier, 2007). Thus, citizens' perceptions of post-adoption price increases often become more negative than suggested by official price statistics, which affects attitudes towards the single currency and trust in European institutions.

2.3. Conceptualizing subjective determinants of euro adoption

In the literature on public attitudes toward the euro, subjective determinants refer to individual-level perceptions, beliefs, and evaluations that shape preferences beyond of objective economic conditions. These factors are rooted in behavioural and political economy approaches, which emphasize that individuals do not respond only to measurable macroeconomic indicators, but also to perceived realities and cognitive interpretations of economic processes (Hobolt and Wratil, 2015; Roth and Jonung, 2022).

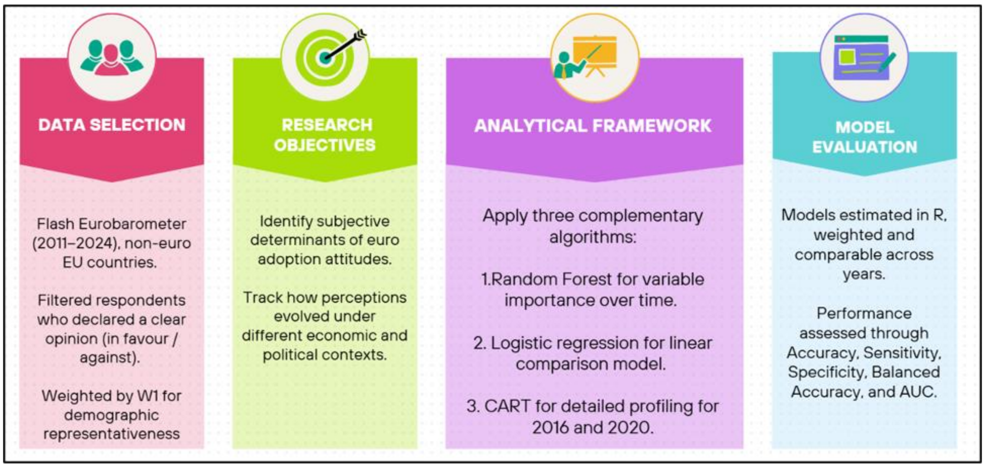
Subjective determinants typically include perceptions of price developments, concerns about economic control and national sovereignty, trust in institutions, and the level of individual information or awareness. These variables are frequently operationalized using survey-based measures, particularly within Eurobarometer datasets, where attitudes are captured through self-reported evaluations rather than objective indicators (Banducci *et al.*, 2009; Fernández *et al.*, 2023).

From a theoretical perspective, these factors can be grouped into three broad dimensions. First, the economic perception dimension captures individuals' expectations regarding price rise, purchasing power, and overall economic stability. Second, the symbolic and identity dimension reflects concerns related to national identity and sovereignty. Third, the cognitive dimension relates to the level of information and understanding of the euro, which may influence the way individuals interpret both economic and symbolic aspects of monetary integration.

This framework supports the selection of the variables used in the empirical analysis, namely price change perceptions, concerns about loss of country identity and economic control, perceived price abuses, and self-reported knowledge about the euro. These variables capture the key subjective dimensions identified in the literature and allow for a structured analysis of how perceptions shape attitudes toward euro adoption.

3. METHODOLOGY

The methodological approach applied in the paper is presented in Figure no. 1.



Source: authors' analysis in Canva

Figure no. 1 – Scheme of the methodology used

To assess the main determinants of public perceptions regarding the adoption of euro, we use the data from the Flash Eurobarometer surveys corresponding to the period 2011–2024. In this study, we perform two analyses. The first focuses on the analysis of variable importance for each year of the analysed period using Random Forest and Logistic Regression algorithms. The second analysis uses the CART algorithm to profile the classes of respondents according to the subjective factors. The analysis is conducted at the country-year level and focuses on observations corresponding to periods in which countries had not yet adopted the euro. For countries that joined the euro area during the analysed period (e.g., Croatia, Latvia, Lithuania), only pre-adoption observations are included in the empirical models.

3.1. Research Hypothesis

Drawing on the literature on public support for the euro and the specific design of the Flash Eurobarometer questionnaires, this study proposes four hypotheses regarding the role of subjective determinants in shaping attitudes towards euro adoption in non-Eurozone countries. All hypotheses refer to expected relationships between self-reported perceptions and the likelihood of supporting euro adoption.

H1: *Price perceptions dominate euro adoption attitudes.*

In line with the literature on the "euro illusion" and the central role of concerns about price increases after euro adoption in public debates, we expect the Price change variable to be strongly associated with support for the euro. Empirically, H1 is assessed by examining whether this variable occupies the top positions in the importance rankings of variables in the Random Forest and logistic regression models and whether it appears as a primary splitting variable in the CART trees. A consistently higher importance weight for price-related variables, compared to identity or information factors, is interpreted as evidence consistent with H1.

H2: *Identity and sovereignty concerns reduce support for euro adoption.*

The literature on euro symbolism suggests that concerns about national identity and sovereignty can generate resistance to monetary integration. Therefore, we expect stronger agreement with statements about the loss of country identity and the loss of control over economic policy to be associated with lower support for euro adoption. The two variables are analysed separately in the empirical models in order to distinguish between symbolic identity concerns and economic-sovereignty concerns.

H3: *Self-perceived knowledge of the euro has a strong influence.*

Previous studies indicate that better-informed individuals tend to have more stable and pro-European attitudes. We therefore hypothesize that higher values of the variable "euro informed" are associated with a higher likelihood of supporting the euro and that information may mitigates the negative impact of fears about prices, loss of identity or loss of control. H3 is tested by examining whether "euro informed" has an effect in the first two models and whether CART splits show that better-informed respondents are more supportive at comparable levels of perceived risks.

H4: *Subjective determinants become more discriminative in periods of heightened uncertainty.*

We expect that subjective perceptions related to prices, identity, and economic control differentiate supporters and opponents of euro adoption more clearly in periods marked by heightened economic and political uncertainty. Given the repeated cross-sectional design, the changing country composition across survey waves, and possible differences in questionnaire wording, H4 is treated as an exploratory expectation rather than a direct causal hypothesis. It is assessed descriptively by comparing variable importance, CART profiles, and classification performance across selected years.

3.2. Data used

To identify the subjective factors influencing perceptions regarding the adoption of the euro, two machine-learning methods were applied to data from the Flash Eurobarometer surveys corresponding to the period 2011–2024. The dataset includes only country-year observations corresponding to periods before euro adoption. Therefore, for countries that joined the euro area during or after the broader period considered, only observations from their pre-adoption years are retained. The analysis is conducted separately for each year, in order to observe the temporal variations in the importance of the explanatory variables. To ensure the national representativeness of each sample included, the weighting variable W1 was used to adjust the sample structure according to demographic distributions (sex, age, NUTS II region and size of the locality) and the size of the population of each country. The comparison of the two methods made it possible to assess the robustness and consistency of the determinants. The codes of the datasets used and the countries included in the analysis, as well as the codes from the target variable questionnaire, can be seen in Table no. A1.

In our analysis, we removed "Don't know" responses and missing values (NA) from the target variable to maintain consistency in the interpretation of the results. These responses do not reflect a clear position on the adoption of the euro and could have introduced ambiguity into the classification algorithms. By excluding them, the analysis focuses only on respondents who expressed an explicit opinion, which allows for a more precise estimate of the true distribution of attitudes and a higher accuracy of the predictive models. The target variable was coded as binary, with 0 indicating opposition to euro adoption and 1 indicating support. After this filtering, the final sample includes 87,669 valid observations out of the initial total of 97,944.

In the first analysis, the data set was not divided into training and test subsets, as the main objective was not to estimate the predictive performance of the models, but to identify and rank the explanatory variables relevant to the attitude towards the adoption of the euro. In both algorithms, the aim was to assess the importance of the variables and to select the factors that contribute to the differentiation of the respondents' attitudes. In this context, using the entire sample ensures a more stable estimate of the relative importance of the predictors and minimizes the loss of information. The Random Forest models were evaluated by the OOB (Out-of-Bag) error, which provides a robust measure of performance without requiring an explicit separation of the data. Similarly, in the LASSO-penalized logistic regression analysis, validation was performed through the cross-validation penalty procedure, which allows for optimal selection of variables. Model performance was evaluated using accuracy, sensitivity, specificity, balanced accuracy, and area under the curve (AUC).

Five variables related to perceptions were included, capturing dimensions such as the degree of information about the euro, the perception of price change, the loss of national identity, the loss of control over economic policies, and the perception of price abuses. Items on the consequences of adopting the euro at the personal and national level are available in the data used but were excluded, as they already express a global judgment on the phenomenon and can absorb a significant proportion of the explained variance, reducing the relevance of the other explanatory factors. The variable used in the analysis, the expected effect of these variables, and the connection with the hypothesis can be seen in Table no. 1.

Table no. 1 – Description of variables and connection with research hypotheses

Variable name	Price change	Loss of country identity	Loss of economic control	Price abuses	Euro informed
Concept measured	Perceived price evolution with euro adoption	Concern about losing national identity	Concern about losing control over national economic policy	Fear of unfair price rounding or manipulation during changeover	Self-perceived knowledge and awareness about the euro
Example question (Flash EB 548, 2024)	"What impact will the introduction of the euro have on prices in your country?"	"Adopting the euro will mean that this country will lose part of its identity."	"Adopting the euro will mean that this country will lose control over its economic policy."	"I am concerned about abusive price setting during the changeover."	"How well informed do you feel about the euro?"
Coding / categories used in the model	Nominal variable: keep prices stable; increase prices; no impact; DK/NA. "Keep prices stable" used as reference category.	Ordinal variable: strongly disagree; rather disagree; rather agree; strongly agree; DK/NA. "Strongly agree" used as reference category.	Nominal/binary recoded variable: disagree; agree; DK/NA. "Agree" used as reference category.	Nominal/binary recoded variable: not concerned/disagree; concerned/agree; DK/NA. "Concerned/agree" used as reference category.	Ordinal variable: not at all informed; not very well informed; rather well informed; very well informed; DK/NA. "Very well informed" used as reference category.
Hypothesis link	**H1** – *Price perceptions dominate attitudes toward the euro*	**H2** – *Identity and sovereignty concerns reduce support for euro adoption*	**H2** – *Identity and sovereignty concerns reduce support for euro adoption*	**H4** – *Subjective determinants become more discriminative in periods of heightened uncertainty*	**H3** – *Knowledge moderates negative perceptions*
Expected effect on support for euro adoption	**Negative** – People who expect prices to rise are less supportive	**Negative** – Stronger identity concern decreases support	**Negative** – Stronger perception of control loss decreases support	**Negative** – Stronger fear of abuses reduces support	**Positive** – Better-informed individuals show higher support

Source: authors' analysis

3.3 Random Forest and logistic regression

The Random Forest method was introduced by Leo Breiman (2001) in his article "Random Forests", published in the journal Machine Learning. This technique is an extension of the idea of "Random Decision Forests" previously proposed by Tin Kam Ho (1995) in 1995, which introduced the random selection of subsets of variables for building decision trees. Breiman combined this approach with the bagging method (bootstrap aggregating), which he had developed in 1996 (Breiman, 1996), obtaining an ensemble learning model that reduces variance and increases the accuracy of predictions by training an ensemble of independent trees on randomly chosen samples and subsets of features. Due to its robustness, high accuracy and interpretability through the analysis of the importance of variables, Random Forest has become one of the most popular machine learning methods applied in economics, medicine and the social sciences.

The Random Forest models in this analysis were built using a standard configuration optimized for binary classification analyses, adapted to the purpose of variable selection and interpretation of their importance. Each model was composed of 1,000 decision trees (in R *num.trees = 1000*), a value chosen to ensure the stability of the results and reduce the variance between successive runs. The importance of the variables was based on the Gini index. This index expresses how much the heterogeneity of the classes (favourable/unfavourable attitudes towards the euro) decreases when a variable is used to divide the nodes in the decision tree. The higher the value of this index, the more consistently the respective variable contributes to the correct separation of observations between the two categories of the dependent variable (Kuyoro *et al.*, 2022). To facilitate within-model interpretation over time, the raw importance values were rescaled into percentages separately for each algorithm. These percentages are not interpreted as directly comparable across algorithms, but only as indicators of the relative contribution of each variable within the same modelling approach. The models were run in a weighted manner, using W1 weights, to reflect the demographic structure and population size of each country included in the sample. In addition, the probability estimation option (probability = TRUE) was enabled to allow the calculation of the area under the ROC curve (AUC), thus providing an additional assessment of the discriminatory power of the models.

The second algorithm used to examine changes in variable importance over time is LASSO-penalized logistic regression. The LASSO (Least Absolute Shrinkage and Selection Operator) method was introduced by Robert Tibshirani in 1996 (Tibshirani, 1996). LASSO is a penalty technique that combines parameter estimation with variable selection by applying an L_1 penalty to the coefficient values. This penalty constrains the sum of the absolute values of the coefficients, causing some of them to become exactly zero, which allows the automatic identification of the most relevant variables in a model. Due to this simultaneous regularization and selection capability, this penalty method has become an important tool in statistics, econometrics, and machine learning, being widely used in contexts with a large number of predictors or with collinearity problems (Mahalani and Rifai, 2022). For this study we estimated the models separately for each year from 2011–2024, using W1 weights, which adjust the sample distribution according to the population structure.

Variable importance was derived from the magnitude of the estimated coefficients after regularization. Specifically, we use the absolute value of the standardized coefficients as an indicator of the relative contribution of each predictor to the model. Variables with coefficients close to zero are considered non-informative, while larger absolute values indicate stronger associations with the dependent variable (Kuhn and Johnson, 2013). To facilitate comparison with the Random Forest results, the coefficient-based importance measures were rescaled into relative percentages, expressing each variable's contribution as a share of the total absolute importance across predictors. It should be noted that these importance measures are not directly equivalent in a strict methodological sense, as Random Forest importance reflects reductions in impurity, while LASSO importance reflects the strength of linear associations. Therefore, the comparison is intended to highlight robust patterns across methods rather than exact quantitative equivalence. The validation process was performed internally by the k-fold cross-validation procedure ($k = 5$), automatically selecting the optimal value of the penalty parameter λ that maximizes the area under the ROC curve (AUC). The performance indicators were calculated in the same way as above for Random Forest.

In addition to the variable importance results, the LASSO-penalized logistic regression models were further examined through the estimated coefficients. This additional interpretation is important because variable importance indicates the relative contribution of each predictor to the classification process, while logistic regression coefficients show how specific response categories are associated with the probability of supporting euro adoption. A synthesis of the average coefficients by variable category is presented in Table no. A5. Since the predictors were categorical and introduced into the models through dummy coding, each coefficient is interpreted relative to the omitted reference category of the corresponding variable. Therefore, the signs of the coefficients should be interpreted as category-specific associations with support for euro adoption.

To compare the predictive performance of the two models over time, we calculated the annual AUC difference between logistic regression and Random Forest models (ΔAUC = AUC Logistic Regression − AUC Random Forest).

3.4. CART algorithm

For the second, profiling analysis, only the years 2016 and 2020 were selected, as they capture two contrasting economic and social contexts, relevant for the analysis of perceptions regarding the adoption of the euro. The year 2016 was chosen as representative of the post-crisis recovery period, when European economies had returned to growth, inflation remained low, and trust in European institutions was being consolidated. At this stage, positive perceptions related to stability and economic convergence had a higher weight (Roth *et al.*, 2022). By contrast, the year 2020 reflects a period of economic tension and uncertainty, marked by accelerated price increases. These conditions amplified concerns about the loss of economic control, depreciation of purchasing power, and the perceived risks of belonging to the euro area (Carella, 2023). The selection of these two moments allows the comparison of attitude profiles in a differentiated framework, between a stage of relative stability and one of inflationary crisis, providing a relevant picture of how the economic context shapes support for the euro.

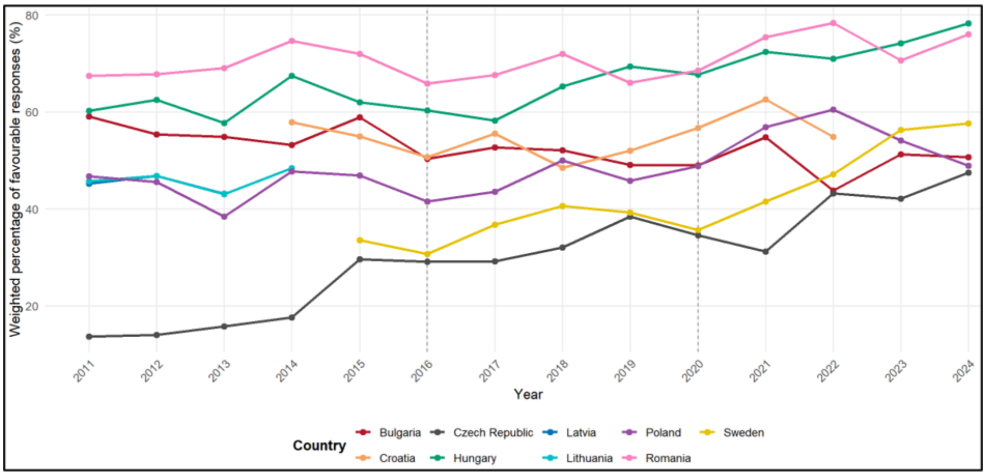
For explainable profiling, we used a CART decision tree, which generates simple and interpretable classification rules. This method provides an intuitive interpretation of the determinants and allows a clear presentation of the identified segments of attitudes. For the year 2016, a calibration of the CART model was carried out, by testing several combinations of parameters (cp, maxdepth, minbucket, minsplit). The first parameter, cp (complexity parameter), controls how much the model penalises each additional split. Larger values of cp produce simpler trees, while smaller values allow the model to grow deeper and capture more detailed patterns. This parameter is used to avoid overfitting, and is typically selected through cross-validation (Breiman, 1996; Therneau *et al.*, 2023). The second parameter, maxdepth, limits the maximum number of levels the tree is allowed to grow. By restricting tree depth, the model avoids creating overly complex decision structures that memorise noise rather than general patterns. Shallow trees tend to be more stable and easier to interpret, a principle widely discussed in introductory texts on statistical learning (James *et al.*, 2013). The minbucket parameter specifies the minimum number of observations required in a terminal node. This constraint ensures that the final leaves of the tree contain enough data to generate reliable predictions. Very small terminal nodes tend to be unstable and sensitive to noise, so increasing minbucket leads to more robust trees (Therneau *et al.*, 2023). Finally, minsplit defines the minimum number of observations needed in a node for the algorithm to attempt a new split. If a node contains fewer observations than the value of minsplit, no further partitioning is allowed. This prevents the model from creating unnecessary or unreliable splits based on very small subsets of data (Quinlan, 1986; Breiman *et al.*, 2017).

The aim of this stage was to achieve a balance between the predictive performance and the interpretability of the model. The selected configuration offered high accuracy, balanced specificity and sensitivity and, at the same time, a clear and readable structure of the tree, which allowed a coherent interpretation of the determinants of support for the adoption of the euro. The configuration was chosen for this year because the period was characterized by relative economic stability, without major shocks, which allowed a "clean" assessment of public perceptions and attitudes in relation to the adoption of the single currency. The CART models were estimated separately for 2016 and 2020, using the same set of parameters to ensure comparability across the two periods, and to assess how the model's performance changed in a different socio-economic context. This approach keeps the technical settings constant, and the variations observed in the indicator's performance differences can be interpreted as reflecting changes in respondents' behaviour and perceptions, rather than differences in model structure.

4. RESULTS AND DISCUSSION

4.1. Dataset description

Figure no. 2 illustrates the weighted evolution of public support for the adoption of the euro in the EU member countries that were not part of the euro area at the time of each survey. The dataset is presented in Table no. A2. Romania stands out as the country with the most constant and high favourable attitude towards the adoption of the euro. The values remained above 65% throughout the period and reached a peak of almost 78% in 2022.



Source: authors' analysis in Rstudio

Figure no. 2 – Weighted evolution of favourable attitudes toward euro adoption across EU member states before euro adoption (2011–2024)

This stability suggests a consolidated positive perception of monetary integration, probably associated with expectations of economic convergence and increased stability (Dragoi *et al.*, 2017). Hungary also records high levels of support, but its evolution is not strictly linear. Support was around 60% in 2011, declined in some years, including 2013 and 2017, and then increased more visibly after 2019, reaching over 78% in 2024. Therefore, Hungary should be interpreted as a case of generally high but fluctuating support, with a stronger upward movement in the most recent years rather than as a country with a constant linear increase. This pattern may be linked to changing domestic and regional economic conditions, as well as to the increased salience of monetary stability in periods of uncertainty (Roth and Jonung, 2022).

In contrast, Bulgaria shows a more volatile and generally declining pattern over the analysed period. Support decreased from approximately 59% in 2011 to a minimum of around 44% in 2022, before partially recovering to about 51% in 2024. However, this recovery did not restore support to its initial level, indicating that Bulgaria's late pre-adoption context was characterized by moderate rather than strongly consolidated public support. This pattern is particularly relevant in light of Bulgaria's subsequent accession to the euro area in 2026 and may reflect persistent uncertainty regarding economic readiness, domestic political instability, and concerns about the expected effects of euro adoption (Todorov, 2023).

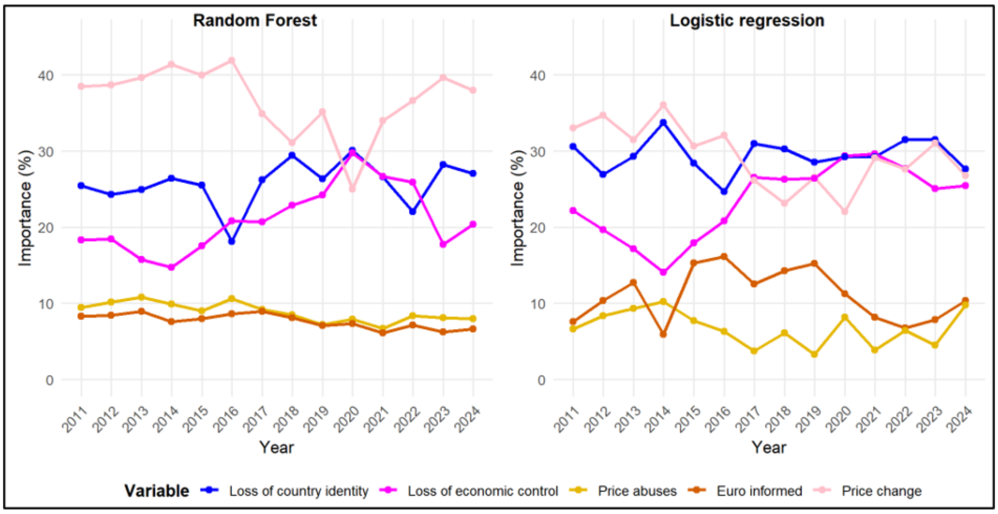
The Czech Republic remains the country with the lowest level of support, even if it gradually rises from 14% in 2011 to almost 47% in 2024, reflecting a historically reserved attitude towards monetary integration and a preference for economic policy independence (Szőcs, 2015). Poland remains in an intermediate zone, with support between 45–60%, reaching a peak in 2022, while Sweden shows a constant increase, from 33% in 2015 to almost 58% in 2024, a sign of a gradual improvement in citizens' attitudes towards the adoption of the euro.

The results indicate an increasing trend in the share of respondents declaring themselves in favour of euro adoption, with clear differences between CEE, where support is higher and more stable, and Northern Europe, where support remains more moderate, but on an upward slope.

4.2. Random Forest and Logistic regression

4.2.1. Variable importance across machine learning models

In Figure no. 3 represent the comparative analysis of the importance of variables obtained through the Random Forest and Logistic regression models for the period 2011–2024. The complete variable importance values are presented in Tables no. A3 and no. A4. The evolution shows several robust patterns and method-specific differences. In both modelling approaches, the variable capturing perceptions of price increases after euro adoption ("Price Change") consistently emerges as the most important predictor of attitudes towards the adoption of the euro. This highlights the relevance of post-adoption price expectations, as widely discussed in the literature on the "euro illusion" (Gamble *et al.*, 2002; Gamble, 2006; Lunn and Duffy, 2010). The pronounced increase in the importance of price perceptions after 2019 - 2020 aligns with the inflationary peak documented in recent studies on the public's reaction to economic uncertainty (Roth *et al.*, 2024).



Source: authors' analysis in Rstudio

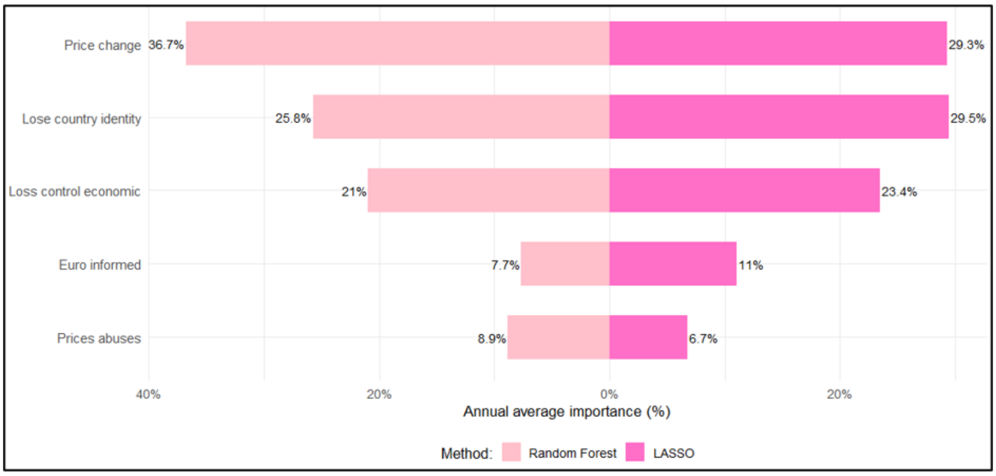
Figure no. 3 – Evolution of variable importance in machine learning algorithms

In the Random Forest models, the importance of price changes increases after 2014. Concerns about national identity and the loss of control over economic policy also gain weight, which is consistent with previous research on symbolic and sovereignty-related considerations in CEE countries (Allam and Goerres, 2011; Parizek, 2011; Dandashly and Verdun, 2018). Although these factors are not more important than price perceptions. Their consistent contribution suggests that opposition to euro adoption combines economic anxieties with identity-based considerations.

In contrast, the logistic regression models attribute a relatively stronger and more stable role to informational factors, in particular self-perceived knowledge about the euro ("Euro informed"). This is consistent with evidence that political information is associated with lower reliance on emotional or identity-based beliefs (Fernández *et al.*, 2023). The higher visibility of the "informed euro" variable in the linear model may reflect the ability of logistic regression to isolate direct effects once collinearity is penalized by regularization (Tibshirani, 1996), whereas in Random Forest these effects are often absorbed in nonlinear interactions (Breiman, 2001; Guo and Lin, 2023). In both approaches, "Price Abuse" presents the weakest and most volatile contribution, consistent with findings that concerns about unfair rounding influence attitudes but remain secondary to broader price-change expectations (Cornille and Stragier, 2007).

These results show that price perceptions consistently emerge as the most important predictors of euro support, strongly reflected in both the economic and behavioural literature, followed by concerns about sovereignty and national identity, while information levels appear to play a moderating role, especially in the linear context. Although the importance measures are not directly comparable across algorithms, both methods identify the same broad hierarchy of relevant predictors, especially the central role of price-related perceptions. This qualitative agreement supports the robustness of the substantive pattern, but not a direct numerical equivalence between the two importance measures. In addition, this aligns with previous empirical work showing that economic perceptions, symbolic attachments, and political information jointly shape public support for monetary integration (Hobolt and Wratil, 2015; Roth and Jonung, 2022).

Figure no. 4 shows the mean importance of each subjective factor over the period 2011–2024, comparing the Random Forest method and logistic regression. In both approaches, price-related perceptions consistently emerge as the most important predictors, suggesting that expectations about price increases after euro adoption play an important role in shaping attitudes toward euro adoption. This pattern is in line with the extensive literature on the "euro illusion", which shows that citizens often tend to overestimate price increases after the euro changeover (Gamble *et al.*, 2002; Angelini and Lippi, 2006; Gamble, 2006; Lunn and Duffy, 2010). A second level of determinants is formed by the loss of country identity and the loss of economic control, the average importance of which is only slightly below price perceptions, especially in the logistic models. This pattern may reflect previous findings that concerns about sovereignty and national identity are central ingredients of scepticism towards monetary integration in CEE countries (Allam and Goerres, 2011; Parizek, 2011; Dandashly and Verdun, 2018).



Source: authors' analysis in Rstudio

Figure no. 4 – Mean of variables for the analysed period, 2011-2024

The "informed euro" variable makes a more modest but not negligible contribution, with higher average weights in logistic than in Random Forest, which is consistent with evidence that political information promotes more stable and pro-European orientations (Conflitti, 2011; Fernández *et al.*, 2023). Finally, price abuses have the lowest average importance in both approaches (non-linear and linear), suggesting that concerns about incorrect rounding or opportunistic pricing matter but are overshadowed by broader expectations regarding price increases after euro adoption and symbolic concerns, as also indicated by post-transition studies of perceived price dynamics (Cornille and Stragier, 2007). The fact that Random Forest (Breiman, 2001) and LASSO-penalized logistic regression (Tibshirani, 1996; Mahalani and Rifai, 2022) converge on this hierarchy of determinants reinforces the robustness of the empirical evidence on the stratified structure of subjective factors of support for the euro.

4.2.2. Interpretation of LASSO-penalized logistic regression coefficients

According to Table no. A5, the coefficient mean confirms that the "price change" variable has the strongest category-level association with attitudes toward euro adoption. The category indicating that euro adoption will increase prices records the highest average coefficient, followed by the category indicating no impact. Since these coefficients are estimated relative to the reference category of the Price change variable, they show that price-related expectations strongly differentiate respondents in terms of support for the single currency. This result should therefore be interpreted as evidence of the strong discriminatory role of post-adoption price expectations rather than as a direct effect of expecting prices to increase. The finding is consistent with the literature on the "euro illusion", which shows that citizens' evaluations of the euro are strongly shaped by expectations and concerns about price increases after the changeover (Gamble *et al.*, 2002; Angelini and Lippi, 2006; Gamble, 2006; Lunn and Duffy, 2010).

For "loss of country identity", the positive coefficients for the disagreement categories indicate that respondents who reject the idea that euro adoption would lead to a loss of national identity are more likely to support euro adoption than respondents in the reference category. In other words, lower identity-related concern is associated with a higher probability of favourable attitudes toward the euro. This result supports the theoretical expectation that symbolic and identity-related fears reduce support for monetary integration. It also aligns with previous research showing that national identity and symbolic attachments are important determinants of euro attitudes, especially in CEE countries (Allam and Goerres, 2011; Parizek, 2011; Dandashly and Verdun, 2018).

A similar interpretation applies to "loss of economic control". The positive coefficients for the disagreement categories show that respondents who do not perceive euro adoption as a threat to national control over economic policy are more likely to support the single currency than respondents in the reference category. This suggests that sovereignty-related concerns are associated with opposition to euro adoption, while the absence of such concerns favours support. This finding is consistent with studies emphasizing the role of economic autonomy, sovereignty, and trust in the institutions managing monetary integration (Hobolt and Wratil, 2015; Bergbauer *et al.*, 2020; Roth and Jonung, 2022).

The *Euro informed* variable shows negative coefficients for the lower information categories, especially for respondents who declare themselves not at all well informed or not very well informed. Since the coefficients are interpreted to the reference category of the variable, this indicates that lower self-perceived information is associated with a lower probability of supporting euro adoption. This result supports the hypothesis that information plays a moderating role in euro adoption attitudes. Respondents who feel better informed are more likely to express favourable views, while limited information may increase uncertainty or vulnerability to negative perceptions. This interpretation is consistent with research emphasizing the role of political knowledge, information, and education in shaping pro-European orientations (Conflitti, 2011; Fernández *et al.*, 2023).

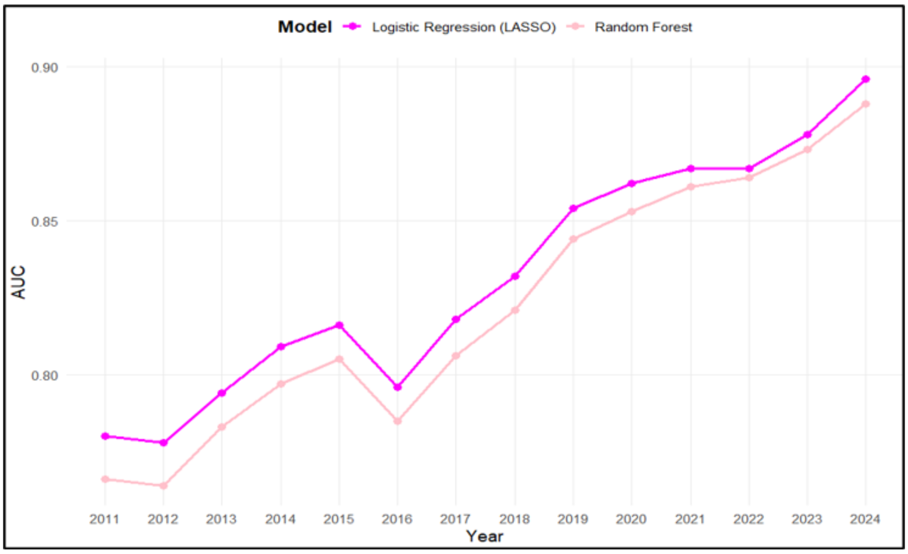
Finally, the *Price abuses* variable has smaller and less stable coefficients compared with the other predictors. The results suggest that categories reflecting lower concern about abusive price setting are generally associated with higher support for euro adoption relative to the reference category, but the magnitude of these coefficients is weaker than in the case of broader price-change expectations, identity, or economic-control variables. This indicates that concerns about abusive price setting matter, but they play a secondary role compared with more general expectations regarding price increases after euro adoption. This finding is consistent with studies showing that fears of unfair rounding and opportunistic pricing may affect public attitudes during euro changeovers, but are often embedded in broader concerns about post-adoption price developments and purchasing power (Cornille and Stragier, 2007).

The logistic regression results complement the Random Forest findings by showing not only which subjective factors are important, but also how specific categories of these factors are associated with support for euro adoption. The results confirm the centrality of price-related expectations, while also highlighting the relevance of identity, sovereignty, and information-related dimensions in shaping attitudes toward the euro.

4.2.3. Temporal evolution of classification performance

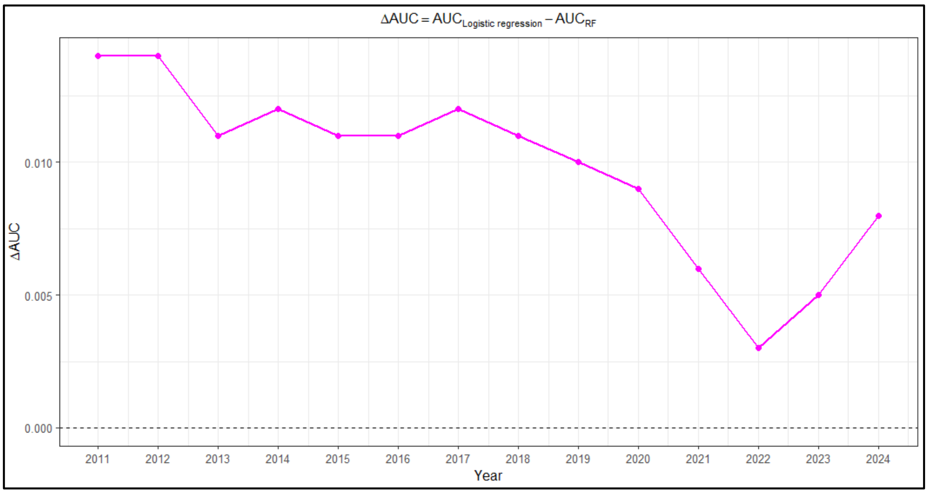
Figure no. 5 shows the evolution of model performance measured by AUC for Random Forest and LASSO-penalized logistic regression over the period 2011–2024. Both algorithms start with AUC values of approximately 0.78–0.80 and show a clear upward trend, with a temporary decrease in 2016 and a significant improvement from 2018 onwards, reaching values close to 0.90 by 2024. The advantage of logistic regression over Random Forest is small but persistent, indicating slightly higher classification performance in terms of AUC. However, this difference should not be interpreted as evidence that the underlying relationships between subjective perceptions and support for euro adoption are linear, since AUC measures classification performance rather than the functional form of associations between variables. The increase in AUC in years associated with crises and increased uncertainty, including the COVID-19 period and the subsequent rise in prices, suggests that subjective factors may become more discriminative predictors of attitudes towards the euro when macroeconomic and geopolitical conditions are turbulent (Roth *et al.*, 2015; Roth *et al.*, 2024). This pattern is consistent with H4, which suggests that subjective factors may matter more during periods of instability. Nevertheless, this interpretation should be treated with caution, as the analysis is based on repeated cross-sectional data and does not fully isolate the effect of economic instability. The observed patterns may also reflect changes in country composition over time, as well as minor variations in questionnaire structure across survey waves. The full performance values are presented in Table no. A6 and no. A7.

The performance differences between the two models (Figure no. 6) show that LASSO-penalized logistic regression consistently outperforms Random Forest over the period 2011–2024, although its advantage is relatively small, generally between 0.01 and 0.015 AUC points in most years. This suggests that, although the two models provide similar predictive results, LASSO-penalized logistic regression achieves slightly higher classification performance for the selected subjective variables in terms of AUC. This comparison refers only to model performance and does not allow conclusions about the linearity or nonlinearity of the underlying relationships between perceptions and support for euro adoption.



Source: authors' analysis in Rstudio

Figure no. 5 – Performance evolution measured with AUC



Source: authors' analysis in Rstudio

Figure no. 6 – Performance evolution measured with AUC

The early part of the period shows the largest advantage for logistic regression, while the differences gradually decrease afterwards, reaching a minimum in 2022, when the two models almost completely converge in performance. This convergence may reflect a context marked by overlapping crises, including the pandemic, rising prices, and economic uncertainty, in which attitudes became more heterogeneous and difficult to classify. In recent years (2023–2024), the differences increase again, suggesting that logistic regression regained a slight predictive advantage. However, these patterns should be interpreted strictly as differences in algorithmic performance over time.

These results indicate that LASSO-penalized logistic regression achieves slightly higher predictive performance than Random Forest in terms of AUC. The LASSO penalty may help stabilize the coefficient estimates and reduce the effect of collinearity between subjective perceptions. AUC evaluates the ability of the model to discriminate between respondents in favour of and against euro adoption, but it does not measure the functional form of the associations between variables. Random Forest remains useful for detecting potential nonlinear patterns and interactions, but in this case it does not lead to higher AUC values.

To complement the visual comparison of yearly AUC values, we performed a one-sample t-test on the annual performance differences (ΔAUC = AUC Logistic Regression − AUC Random Forest). The aim was to assess whether the average difference in classification performance between the two models is statistically different from zero over the period 2011–2024. The results indicate that the mean difference is statistically significant (p-value = 4.642e-08), suggesting that logistic regression tends to achieve slightly higher AUC values on average. Although the yearly differences are relatively small, this result points to a robust pattern in which the regularized logistic model has a modest performance advantage compared to the Random Forest approach.

4.3. Analysis of attitudes profiles towards the euro adoption

Table no. 2 shows that all performance indicators of the CART models, accuracy, balanced accuracy, sensitivity, specificity and AUC, are higher in 2020 than in 2016, both in the training and test samples. This improvement suggests that the structure of subjective perceptions appears more internally consistent in 2020, a year marked by inflationary pressure and heightened economic uncertainty. In such contexts, attitudes toward the euro may be more strongly associated with perceptions related to prices, economic control, and identity, resulting in more clearly differentiated patterns that are easier to classify (Hobolt and Wratil, 2015; Roth *et al.*, 2024).

Table no. 2 – Performance of the CART models

	2016		2020	
	train	test	train	test
Accuracy	0.7295	0.7136	0.7751	0.7650
Balanced accuracy	0.7271	0.7106	0.7775	0.7661
Sensitivity	0.6787	0.6541	0.7392	0.7214
Specificity	0.7755	0.7670	0.8158	0.8108
AUC	0.7700	0.7598	0.8227	0.8123

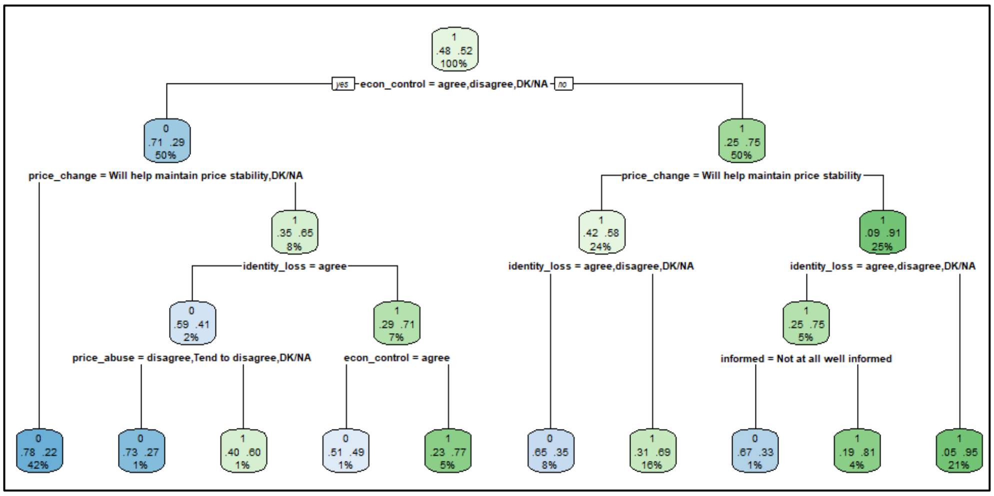
Source: authors' analysis

CART models, which are designed to capture perception-based segmentation, perform better when these beliefs are more polarized. The stronger discriminatory capacity in 2020, reflected in the higher AUC values in both the training and test samples, supports hypothesis H4. This may show that *subjective determinants become more discriminative in periods of heightened uncertainty*, these factors have greater explanatory power during periods of instability, when individuals depend more on affective evaluations and simplified cognitive frames. In contrast, the 2016 model, estimated in a period of relative macroeconomic calm, reflects more diffuse attitudes and weaker separation between supportive and sceptical groups, which naturally lowers the predictive sharpness of the decision tree. The complete structure of the decision rules extracted from the CART models for the years 2016 and 2020 is presented in Tables no. A8 and no. A9, where both the conditions of each branch and the corresponding respondent segments can be seen.

The CART model applied for 2016 (Figure no. 7) illustrates the core mechanisms through which subjective perception's structure support or opposition to euro adoption. The central variable in the root node is Price change, indicating that expectations about prices play a key role in structuring attitudes towards euro adoption. This finding is consistent with the literature on perceived post-adoption price increases and the "euro illusion" (Gamble *et al.*, 2002; Gamble, 2006; Lunn and Duffy, 2010).

The left branch includes respondents who believe that euro adoption will help maintain price stability. Within this group, attitudes vary depending on perceptions of economic sovereignty. Individuals who do not associate the euro with a loss of economic control are more likely to show higher probabilities of supporting the single currency (approx. 77%). This pattern is consistent with findings suggesting that economic evaluations and confidence in institutional capacity are associated with more favourable attitudes toward the euro (Jonung and Conflitti, 2008; Banducci *et al.*, 2009). When respondents perceive potential losses in economic autonomy, support tends to be lower, and this pattern is more pronounced when concerns about loss of national identity are also present, as highlighted in studies emphasizing the symbolic dimension of monetary integration in CEE countries (Allam and Goerres, 2011; Parizek, 2011; Dandashly and Verdun, 2018). At the same time, respondents who report higher levels of information about the euro are more likely to exhibit more favourable attitudes, a finding consistent with evidence that political information is associated with reduced reliance on identity-based concerns (Conflitti, 2011; Fernández *et al.*, 2023).

The right branch of the model includes respondents who do not expect euro adoption to preserve price stability, typically corresponding to more sceptical profiles. Within this group, two main patterns can be observed. One is associated with strong concerns about the loss of economic control, corresponding to relatively low levels of support (approx. 20%). The other relates to perceptions of potential price abuses, a concern consistent with behavioural studies on post-changeover price rounding (Cornille and Stragier, 2007). Respondents who both expect price abuses and report lower levels of information tend to be less supportive overall. Conversely, those who do not expect abusive price setting and report higher levels of information are more likely to exhibit more favourable attitudes, with probabilities between 60% and 70%.



Source: authors' analysis in Rstudio

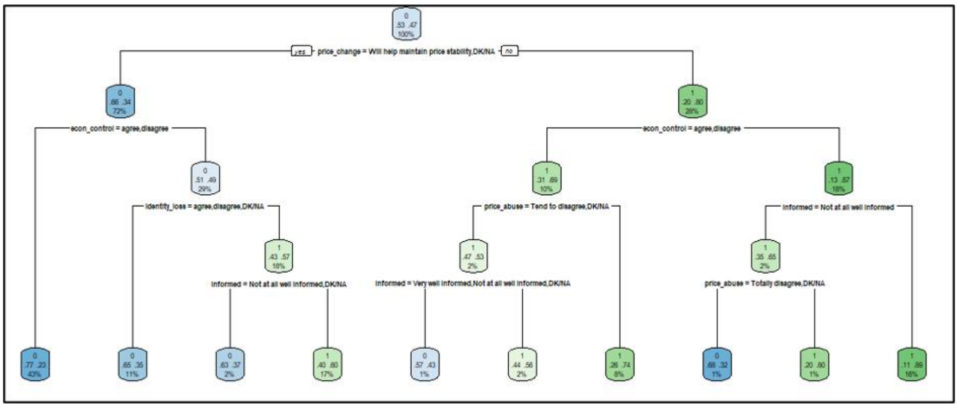
Figure no. 7 – CART tree for 2016 year

Taken together, the model highlights three interdependent dimensions associated with attitudes towards the euro in 2016. First, the economic dimension emerges as particularly important, as perceptions of price change and economic control are among the most influential predictors, reflecting the relevance of price expectations and sovereignty concerns (Hobolt and Wratil, 2015). Second, the cognitive dimension, self-perceived information, acts as a filter that moderates the impact of fears and encourages more rational evaluations of monetary integration (Fernández *et al.*, 2023). Third, the identity dimension, expressed through fears of losing national identity, systematically contributes to oppositional orientations, particularly among individuals with low information levels, confirming the long-established interplay between symbolic attachments and attitudes towards the euro (Allam and Goerres, 2011).

The CART structure highlights a clear polarization between two groups: (1) individuals with favourable economic expectations, sufficient information, and low sovereignty/identity concerns, forming the core group supportive of euro adoption; and (2) respondents marked by distrust in price change, perceived threats to economic autonomy, and low information, forming a consistently sceptical segment. These findings suggest that economic perceptions, information levels, and identity-related concerns are jointly associated with attitudes toward the euro (Roth and Jonung, 2022; Roth *et al.*, 2024), and are broadly consistent with the hypotheses derived from the literature.

The CART model for 2020 suggests that attitudes toward euro adoption are primarily associated with concerns about economic control, price expectations, and national identity. The root node of the tree is the perception that adopting the euro may lead to a loss of economic control. Respondents who do not perceive the euro as reducing national economic autonomy are more likely to be favourable toward the single currency. This pattern is consistent with previous studies indicating that sovereignty concerns are closely linked to euro-scepticism in CEE (Allam and Goerres, 2011; Parizek, 2011; Dandashly and Verdun, 2018). Within this group, support remains high when respondents also expect the euro to help maintain price stability. People who are confident that prices will remain under control have probabilities of support above 70%. This strong effect of price expectations is consistent with the literature on the "euro illusion" and concerns about price increases after euro adoption, which suggests that people often evaluate the euro primarily through price expectations (Gamble *et al.*, 2002; Angelini and Lippi, 2006; Lunn and Duffy, 2010). Even when some respondents' express concerns about identity or economic control, these concerns are partially mitigated when the perceived impact on prices is positive.

The model also highlights the role of national identity. Respondents who express concerns that the euro could lead to a loss of national identity are more likely to be less supportive of the single currency, even when they recognize possible economic advantages. This pattern is consistent with previous research suggesting that symbolic concerns and national identity are associated with lower support for European integration, especially in countries where sovereignty is a sensitive issue (Allam and Goerres, 2011; Dandashly and Verdun, 2018).



Source: authors' analysis in Rstudio

Figure no. 8 – CART tree for 2020 year

Another important element is the level of information. People who report being well informed about the euro tend to have more balanced attitudes and a higher likelihood of support. Information acts as a moderating factor, reducing the emotional impact of fears about price abuse or loss of identity. This is consistent with the broader literature showing that political knowledge and economic information foster more stable and rational evaluations of the euro (Conflitti, 2011; Fernández *et al.*, 2023).

The right-hand side of the tree identifies the most sceptical profile, respondents who do not expect the euro to stabilize prices and who fear losing economic control. Within this group, support for the euro falls to extremely low levels. Perceptions of price abuse further reduce support. This finding aligns with studies documenting how concerns about price abuse have shaped public reactions during previous euro changeovers (Cornille and Stragier, 2007).

One apparently counter-intuitive pattern appears in the 2020 CART model. Respondents who agree that euro adoption may involve a loss of control over economic policy, but who also expect the euro to help maintain price stability, show a very high probability of support. This result should not be interpreted as evidence that sovereignty concerns generally increase support for euro adoption. Rather, it may suggest that, for some respondents, the perceived benefit of price stability outweighs concerns about losing national economic control. In countries where domestic economic performance or policy credibility is questioned, the transfer of monetary control to the euro area may not necessarily be perceived negatively, but rather as an acceptable trade-off associated with greater stability. Therefore, this terminal node can be interpreted as a local CART profile in which expected price stability dominates sovereignty-related concerns. However, the result should be interpreted cautiously, as decision trees may generate local patterns that do not necessarily represent general average effects.

The CART model for 2020 highlights two distinct profiles. Respondents classified as supportive of the euro are more likely to express confidence in price stability, reject the idea of losing economic autonomy, and report at least a moderate level of information. In contrast, less supportive respondents are more often associated with concerns about price stability, fears of losing economic control, and lower levels of information. The tree structure also suggests that these perception-based patterns are more clearly differentiated and easier to classify in 2020, a year marked by inflationary pressure and uncertainty. This finding is consistent with previous research indicating that subjective evaluations may become more salient in periods of crisis (Hobolt and Wratil, 2015; Roth *et al.*, 2024).

5. CONCLUSIONS

The analysis of Flash Eurobarometer data for 2011–2024 indicates a general increase in support for the euro across the EU member states observed before euro adoption, with cross-country differences. Support appears to be relatively high and stable in Romania and Hungary, while the Czech Republic and Sweden remain more cautious. This pattern is consistent with earlier evidence on heterogeneous attitudes toward the euro across Central and Eastern Europe and Northern Europe.

The empirical results are generally consistent with the proposed hypotheses. First, price expectations emerge as the main factor associated with attitudes toward euro adoption (H1, *price perceptions dominate euro adoption attitudes*) as "Price change" is the most important predictor across both Random Forest and logistic models. Second, concerns about loss of country identity and loss of economic control are systematically associated with lower support (H2, *identity and sovereignty concerns reduce support for euro adoption*), forming a second layer of relevant determinants. Third, self-perceived information about the euro appears to act as a moderating factor (H3, s*elf-perceived knowledge of the euro has a strong influence*), as better-informed respondents tend to be more supportive and less influenced by negative perceptions. Finally, subjective determinants appear to become more structured and predictive in periods of instability (H4, *subjective determinants become more discriminative in periods of heightened uncertainty*), as reflected in higher model performance and clearer segmentation patterns in 2020 compared to 2016. These findings should be interpreted as evidence of consistent associations rather than causal effects, given that the empirical strategy is primarily predictive and descriptive.

The results suggest three main priorities for policymakers in EU member states preparing for euro adoption. First, communication should directly target price expectations. Clear messages about actual price developments during previous monetary changes, visible consumer baskets, and transparent price monitoring can help counter the euro illusion and fears of hidden rise of prices. Second, authorities should acknowledge sovereignty and identity concerns rather than ignore them. Framing the euro as compatible with national identity and emphasizing domestic control over key fiscal instruments can reduce resistance, particularly in CEE states, where symbolic politics around sovereignty are strong. Third, targeted information policies are important. Since better-informed respondents tend to be more supportive and less vulnerable to negative narratives, educational campaigns and accessible online tools explaining how the euro works can shape attitudes, especially among younger and less politically informed citizens. Given the heterogeneity of support across countries, these measures could be adapted to national contexts, ranging from consolidation strategies in countries with high support (e.g. Romania) to broader deliberative debates in more sceptical states (e.g. Czech Republic, Sweden).

This study has several limitations. First, it relies on repeated cross-sections rather than panel data, so the models identify associations rather than causal effects, and temporal changes may combine individual dynamics with changes in sample composition. All key variables are self-reported perceptions and may therefore be subject to bias, including the overestimation of price increases after euro adoption or of individual information levels. This is a well-known issue in research on price perceptions after euro changeovers. In addition, the modelling strategy focuses on a narrow set of subjective factors and does not model objective macroeconomic conditions or institutional trust together, even though previous work shows that these dimensions interact; this represents a direction for future research. Methodologically, Random Forest Gini importance can be influenced by the scaling of variables and the number of categories, while logistic regression imposes linear additive effects and may underrepresent complex interactions. Changes in questionnaire wording and the availability of some items only at certain stages also limit comparability over time. Future research could therefore combine the current machine learning approach with multilevel models, including economic and institutional indicators at the country level, and develop country-specific case studies to understand why similar perceptions produce different policy outcomes. This would contribute to a better understanding of how economic expectations, identity attachments, and information together shape the prospects for further euro adoption in the EU. Also, the exclusion of "Don't know" responses from the dependent variable may introduce selection bias. These responses accounted for approximately 10.5% of the initial sample and may reflect a distinct respondent profile, characterized by lower levels of information, uncertainty, or weaker political engagement. Consequently, the findings should be interpreted as applying to respondents with a clear position on euro adoption rather than to the entire population of respondents. Future research could explicitly model "Don't know" responses as a separate category, for example through multinomial classification, or compare the socio-demographic and informational profile of respondents with and without a definite opinion.

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ANNEX

Table no. A1 – Dataset codes used and countries included in the analysis

Flash Eurobarometer number	Data set code	Year	Countries	Target Question code
336	5771	2011		
349	5784	2012	BG, CZ, LV,	
377	5894	2013	LT, HU, PL, RO	Q14
400	5910	2014		
418	6287	2015		
440	6778	2016		
453	6859	2017		
465	6935	2018	BG, CZ, HR,	
479	7559	2019	HU, PL, RO, SE	
487	7638	2020		Q11
492	7769	2021		
508	7884	2022		
527	8758	2023	BG, CZ , HU,	
548	8824	2024	PL, RO, SE	

Source: authors' analysis

Table no. A2 – Percentages of people in favour of adopting the euro by country and year

Year	Bulgaria	Croatia	Czech Republic	Hungary	Latvia	Lithuania	Poland	Romania	Sweden
2011	59.05		13.70	60.22	45.20	45.71	46.77	67.41	
2012	55.33		14.01	62.51	46.79	46.77	45.57	67.82	
2013	54.88		15.75	57.70	43.12	43.05	38.44	69.04	
2014	53.15	57.92	17.59	67.42		48.41	47.77	74.68	
2015	58.93	54.98	29.63	62.01			46.91	71.95	33.55
2016	50.32	50.63	29.14	60.33			41.56	65.82	30.73
2017	52.71	55.50	29.21	58.21			43.54	67.58	36.76
2018	52.10	48.52	32.01	65.28			49.99	72.00	40.64
2019	49.11	52.02	38.45	69.36			45.84	65.99	39.24
2020	48.96	56.69	34.60	67.71			48.83	68.53	35.65
2021	54.78	62.59	31.17	72.40			56.91	75.39	41.50
2022	43.75	54.86	43.22	70.95			60.47	78.33	47.10
2023	51.25		42.14	74.18			54.14	70.67	56.27
2024	50.68		47.45	78.26			48.92	75.98	57.60

Table no. A3 – Variable importance of RF models

year	variable/ importance	Lose country identity	Loss control economic	Prices abuses	Euro informed	Price change
2011	Raw importance	237.59	172.90	101.79	95.48	339.62
2012		204.24	163.85	100.75	89.90	322.99
2013		232.15	150.93	103.96	98.04	359.02
2014		264.99	151.52	103.15	87.36	396.08
2015		262.56	194.90	94.90	76.36	396.41
2016		205.56	235.55	120.08	97.41	473.98
2017		314.81	248.55	110.48	107.38	419.01
2018		376.11	292.09	108.85	103.62	397.52
2019		376.21	346.12	102.79	100.86	502.06
2020		445.72	440.93	117.09	109.15	370.87
2021		383.86	384.57	97.06	87.97	490.45
2022		317.01	372.85	120.29	102.74	527.51
2023		377.29	237.35	108.80	83.64	530.10
2024		371.29	279.87	109.85	91.01	521.52
2011	Percentage importance	18.29	13.31	7.83	7.35	26.14
2012		15.53	12.46	7.66	6.84	24.56
2013		17.77	11.55	7.96	7.50	27.48
2014		19.66	11.24	7.65	6.48	29.38
2015		17.27	12.82	6.24	5.02	26.07
2016		18.15	20.80	10.60	8.60	41.85
2017		26.23	20.71	9.20	8.95	34.91
2018		29.43	22.85	8.52	8.11	31.10
2019		26.34	24.24	7.20	7.06	35.16
2020		30.04	29.72	7.89	7.36	25.00
2021		26.58	26.63	6.72	6.09	33.97
2022		22.01	25.89	8.35	7.13	36.62
2023		28.22	17.75	8.14	6.25	39.64
2024		27.03	20.38	8.00	6.63	37.97

Table no. A4 – Variable importance of logistic regression models

Year	Variable/ Importance	Lose country identity	Loss control economic	Prices abuses	Euro informed	Price change
2011	Raw importance	0.33	0.22	0.05	0.15	0.57
2012		0.31	0.18	0.05	0.15	0.49
2013		0.36	0.18	0.07	0.25	0.53
2014		0.38	0.19	0.09	0.18	0.65
2015		0.45	0.28	0.08	0.10	0.49
2016		0.36	0.31	0.00	0.22	0.51
2017		0.48	0.33	0.08	0.31	0.47
2018		0.53	0.39	0.03	0.33	0.47
2019		0.55	0.43	0.12	0.41	0.51
2020		0.59	0.52	0.10	0.42	0.46
2021		0.58	0.49	0.09	0.29	0.86
2022		0.53	0.44	0.12	0.23	0.63
2023		0.62	0.41	0.13	0.25	0.72
2024		0.58	0.46	0.05	0.35	0.84
2011	Percentage importance	12.31	8.01	1.72	5.55	21.04
2012		11.34	6.64	1.85	5.37	17.87
2013		12.56	6.14	2.54	8.87	18.28
2014		13.10	6.44	3.10	6.19	22.15
2015		13.60	8.40	2.32	3.07	15.03

Year	Variable/ Importance	Lose country identity	Loss control economic	Prices abuses	Euro informed	Price change
2016		25.59	21.89	0.36	15.94	36.23
2017		28.92	19.60	4.66	18.70	28.11
2018		30.23	22.18	1.98	18.98	26.63
2019		27.21	21.13	6.13	20.35	25.18
2020		28.24	24.63	5.01	19.96	22.16
2021		25.02	21.14	3.94	12.48	37.41
2022		27.02	22.53	6.30	11.98	32.17
2023		28.97	19.22	6.03	11.95	33.84
2024		25.36	20.37	2.10	15.25	36.92

Table no. A5 – Yearly summary of LASSO-penalized logistic regression coefficients by variable

Variable	Category	Mean coefficient	Median coefficient
Euro informed	Not at all well informed	-0.7442936	-0.7568885
	DK/NA	-0.3607903	-0.3908045
	Not very well informed	-0.3232927	-0.2792908
	Rather well informed	-0.0714146	0
Loss of country identity	Totally disagree	1.54896022	1.55974263
	Tend to disagree	1.13495144	1.14599778
	DK/NA	0.94045295	0.96496615
	disagree	0.65008435	0.6440838
Loss of economic control	Totally disagree	1.30129096	1.33065915
	Tend to disagree	1.02271179	1.01621809
	DK/NA	0.70665996	0.66685108
	disagree	0.41415857	0.45977409
Price abuses	DK/NA	0.13146433	0.23705797
	disagree	0.28514228	0.28236941
	Totally disagree	-0.0681299	-0.064118
	Tend to disagree	0.14709625	0.17305782
Price change	Will increase prices	1.96756359	1.96913314
	No impact	1.62845504	1.73520887
	DK/NA	0.60247452	0.60627269

Note: Coefficients refer to dummy-coded categories and are interpreted relative to the omitted reference category of each variable. The dependent variable is coded as 0 = against euro adoption and 1 = in favour of euro adoption. Positive coefficients therefore indicate a higher probability of supporting euro adoption relative to the reference category, while negative coefficients indicate a lower probability. Mean coefficients were computed across the annual LASSO-penalized logistic regression models for 2011–2024.

Table no. A6 – Performance of Random Forest models

Year	Sample size	Accuracy	Sensitivity	Specificity	Balanced accuracy	AUC
2011	6591	0.701	0.639	0.758	0.699	0.766
2012	6591	0.705	0.648	0.756	0.702	0.764
2013	6156	0.718	0.611	0.809	0.710	0.783
2014	6194	0.728	0.732	0.724	0.728	0.797
2015	6320	0.742	0.715	0.771	0.743	0.805
2016	6380	0.722	0.653	0.784	0.718	0.785
2017	6321	0.732	0.699	0.765	0.732	0.806
2018	6426	0.737	0.710	0.766	0.738	0.821
2019	6345	0.773	0.757	0.790	0.774	0.844
2020	6440	0.771	0.766	0.775	0.771	0.853
2021	6358	0.785	0.800	0.766	0.783	0.861

Year	Sample size	Accuracy	Sensitivity	Specificity	Balanced accuracy	AUC
2022	6415	0.795	0.800	0.788	0.794	0.864
2023	5529	0.802	0.831	0.759	0.795	0.873
2024	5603	0.820	0.853	0.769	0.811	0.888

Table no. A7 – Performance of Logistic regression models

Year	Sample size	Accuracy	Sensitivity	Specificity	Balanced accuracy	AUC
2011	6591	0.709	0.658	0.755	0.707	0.780
2012	6591	0.712	0.641	0.776	0.709	0.778
2013	6156	0.726	0.636	0.805	0.720	0.794
2014	6194	0.731	0.714	0.750	0.732	0.809
2015	6320	0.742	0.725	0.760	0.743	0.816
2016	6380	0.729	0.653	0.797	0.725	0.796
2017	6321	0.742	0.720	0.763	0.742	0.818
2018	6426	0.751	0.755	0.745	0.750	0.832
2019	6345	0.779	0.782	0.776	0.779	0.854
2020	6440	0.773	0.791	0.754	0.772	0.862
2021	6358	0.787	0.812	0.755	0.784	0.867
2022	6415	0.790	0.827	0.739	0.783	0.867
2023	5529	0.808	0.844	0.756	0.800	0.878
2024	5603	0.822	0.861	0.763	0.812	0.896

Table no. A8 – Decision rules extracted from the 2016 CART model and their interpreted profiles

Rule	Conditions	Support Probability	Interpretation
R1	price_change = "Will help maintain price stability" AND loss_econ_control = "disagree"	**~77%**	Positive economic expectations and no sovereignty concerns → most supportive profile
R2	price_change = "Will help maintain price stability" AND loss_econ_control = "agree" AND loss_identity = "disagree"	**~51%**	Belief in price stability but moderate sovereignty concerns → mixed support
R3	price_change = "Will help maintain price stability" AND loss_econ_control = "agree" AND loss_identity = "agree" AND euro_informed = "high"	**~47%**	Strong identity concerns softened by high information → balanced segment
R4	price_change = "Will help maintain price stability" AND loss_econ_control = "agree" AND loss_identity = "agree" AND euro_informed = "low"	**~26%**	Identity threat and low information → clearly sceptical
R5	price_change = "Will NOT maintain price stability" AND loss_econ_control = "agree"	**~25%**	Negative price expectations and sovereignty concerns → strongly sceptical
R6	price_change = "Will NOT maintain price stability" AND loss_econ_control = "disagree" AND price_abuse = "disagree" AND euro_informed = "high"	**~60–70%**	Reject price-abuse fears and possess high information → unexpectedly favourable
R7	price_change = "Will NOT maintain price stability" AND loss_econ_control = "disagree" AND price_abuse = "agree" AND euro_informed = "low"	**~20%**	Fear of abuses and low information → most sceptical profile

Table no. A9 – Decision rules extracted from the 2020 CART model and their interpreted profiles

Rule	Conditions	Support Probability	Interpretation
R1	loss_econ_control = *disagree* AND price_change = *Will help maintain price stability*	**~85%**	Very confident group: no sovereignty concerns + belief in price stability → strongest support
R2	loss_econ_control = *disagree* AND price_change = *Will NOT help maintain price stability* AND identity_loss = *disagree*	**~31%**	Price sceptics but no identity concerns → moderate but hesitant support
R3	loss_econ_control = *disagree* AND price_change = *Will NOT help maintain price stability* AND identity_loss = *agree* AND euro_informed = *high*	**~67%**	Identity-concerned yet informed → information moderates scepticism
R4	loss_econ_control = *disagree* AND price_change = *Will NOT help maintain price stability* AND identity_loss = *agree* AND euro_informed = *low*	**~20%**	Low information and identity threat → clearly sceptical
R5	loss_econ_control = *agree* AND price_change = *Will help maintain price stability*	**~95%**	Believe in price stability despite sovereignty concerns → surprisingly strong support
R6	loss_econ_control = *agree* AND price_change = *Will NOT help maintain price stability* AND identity_loss = *disagree*	**~42%**	Price sceptics but no identity fears → divided segment
R7	loss_econ_control = *agree* AND price_change = *Will NOT help maintain price stability* AND identity_loss = *agree*	**~29%**	Sovereignty, identity concerns and price pessimism → stable sceptical profile

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Listening at Scale: A Replicable, Low-Cost Pipeline for Collecting and Analyzing Google Business Reviews with SerpApi and VADER

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Abstract: Small and medium-sized enterprises increasingly rely on public review platforms as signals of quality, reputation, and customer experience, yet many owners still lack a practical way to process multilingual review text at regular intervals. This study develops a low-cost and reproducible workflow for collecting Google Business reviews, filtering translated English content, and summarizing sentiment with open analytical tools. The pipeline uses SerpApi to retrieve recent reviews for a known Google Maps place identifier and VADER to classify translated review text into positive, neutral, and negative sentiment. The procedure is demonstrated on 200 Google reviews for an auto-rental location, Klass Wagen Sibiu. Results indicate a strongly positive corpus, with 85% positive, 4% neutral, and 11% negative reviews, a mean VADER compound score of 0.538, and a median of 0.733. The association between VADER scores and star ratings is high, r = 0.83, but it is interpreted as convergent descriptive evidence rather than classification accuracy. The study contributes an applied decision-support blueprint that connects online-review analytics, sentiment analysis, and SME monitoring practice. Its limits remain important: review data are self-selected, platform access is constrained, automatic translation can alter sentiment, and lexicon-based models may miss sarcasm or domain-specific wording.

Keywords: sentiment analysis; VADER; SerpApi; Google Maps review; SMEs.

JEL classification: C88; C55; L86.

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1. INTRODUCTION

Public review platforms, including Google Maps, Yelp, TripAdvisor, and Trustpilot, have become part of the market infrastructure through which local businesses are discovered, compared, and judged. Prior research shows that online reviews can influence demand, revenue, and consumer choice, especially where service quality is difficult to observe before purchase (Chevalier and Mayzlin, 2006; Luca, 2016). For small and medium-sized enterprises, however, the managerial problem is not simply whether reviews matter. The harder issue is how to transform dispersed, multilingual, and unevenly written comments into a repeatable monitoring routine that can inform concrete service decisions.

Existing research offers strong evidence on the economic effects of review ratings and textual feedback, while the technical literature provides many sentiment-analysis tools. A gap remains between these streams. Academic studies often treat online-review analytics as an explanatory instrument, whereas practical scripts and platform documentation rarely connect data collection, sentiment scoring, sampling limits, and managerial interpretation within a reproducible SME-oriented workflow. This paper addresses that gap by positioning review listening as a lightweight business-analytics and decision-support process rather than as a one-off technical exercise.

The proposed workflow automates three tasks: retrieving recent Google Maps reviews for a known business location, retaining translated English text available through platform metadata, and producing reproducible sentiment and text-salience outputs. The empirical demonstration uses Klass Wagen Sibiu, an auto-rental location, and shows how 200 translated Google reviews can be converted into a concise monthly monitoring file. The analysis is not designed to adjudicate the accuracy of individual customer claims. Its purpose is to identify recurring friction points, protect strengths that customers repeatedly mention, and make review monitoring feasible for resource-constrained owners.

The contribution is therefore applied but still academic. It integrates literature on online reviews as market signals, text-rating discrepancy, sentiment analysis, and self-selection bias into a transparent pipeline that can be replicated, audited, and adapted. In doing so, the study clarifies the boundary between a useful managerial pulse and stronger inferential claims that would require validation, benchmarking, or longitudinal evidence.

2. LITERATURE REVIEW

2.1. Reviews as economic signals

Online reviews reduce information asymmetry by making prior customer experience visible to prospective buyers. In early e-commerce, consumer book reviews affected relative sales across online retailers (Chevalier and Mayzlin, 2006). In local services, Yelp ratings have been associated with revenue effects for independent restaurants (Luca, 2016), and discontinuities around rounded ratings can change demand near visible thresholds (Anderson and Magruder, 2012). More recent work also shows that review systems are not neutral mirrors of service quality because text, ratings, platform design, and reviewer self-selection interact. Text-rating review discrepancy is especially relevant for analytics because written comments and numerical stars do not always convey the same evaluation (Almansour *et al.*, 2022).

2.2. Text analytics for user-generated reviews

Sentiment-analysis approaches can be grouped into three broad families: lexicon-based and rule-based methods, traditional supervised machine-learning classifiers, and transformer-based models. Lexicon-based tools score text through dictionaries and handcrafted rules; they are transparent, inexpensive to run, and easy to explain to non-specialists. Supervised machine-learning models can capture richer patterns, but they normally require labelled data, feature engineering, and validation on a relevant domain. Transformer-based models, developed after the attention architecture and language-model pretraining, can deliver stronger contextual representations but add computational, interpretability, and maintenance costs (Vaswani *et al.*, 2017; Devlin *et al.*, 2019; Bordoloi and Biswas, 2023). For SMEs, this trade-off matters. A model that is marginally more accurate but opaque, costly, or difficult to rerun may be less useful for routine monitoring than a transparent baseline.

VADER fits the present purpose because it was designed for short, informal, socially expressed text and produces interpretable scores without labelled training data (Hutto and Gilbert, 2014). Its use here is not a claim that lexicon-based methods are universally superior. Rather, VADER is treated as a low-cost baseline suitable for recurring descriptive monitoring, with the explicit limitation that sarcasm, domain-specific expressions, and translated phrasing may require later validation or comparison with a transformer model.

Recent hospitality and restaurant applications further show that online review text can be converted into service dimensions and sentiment ind icators that support managerial interpretation, provided that the dataset, platform, language choices, and coding rules are made explicit (Nguyen and Dao, 2024).

2.3. Language and translation

Real-world businesses receive reviews in multiple languages. Automatic translation helps create a common analysis layer, but it can alter polarity, weaken idioms, and change affective nuance (Balahur and Turchi, 2014; Mohammad *et al.*, 2016). Using platform-provided translated text is still managerially relevant because this is often the text visible to users browsing in an English interface. The analytical obligation is therefore to document translation provenance and avoid treating translated sentiment as a direct equivalent of the original expression.

2.4. Platforms, access, and sampling

Access pathways also shape what can be analyzed. Google Places API exposes only a limited review sample per request, while aggregator services can support broader collection through paginated public review pages (SerpApi; Google Maps Platform, 2025). Regardless of access path, online reviews are affected by self-selection, polarity, and platform effects. Early or extreme reviewers may not represent the full customer base, and review distributions often overrepresent highly positive or strongly negative experiences (Li and Hitt, 2008; Schoenmueller *et al.*, 2020). Consequently, review analytics should be interpreted as directional evidence for managerial attention, not as an unbiased estimate of population-level satisfaction.

2.5. Visualization

Word clouds remain popular for rapid reconnaissance, but they can encourage superficial interpretation because they discard syntax, negation, and context (Harris, 2011). In this study, the word cloud is used only as an exploratory pointer to recurring vocabulary. It is interpreted together with sentiment labels, star ratings, and representative snippets rather than as independent evidence.

3. METHODOLOGY

The workflow follows the logic of CRISP-DM by linking business understanding, data preparation, modelling, and evaluation, but it is intentionally simplified for a small-business context (Wirth and Hipp, 2000). The pipeline has two scripts: one retrieves translated Google review text for a specific business location, and the other produces sentiment outputs and an exploratory vocabulary visualization. This design prioritizes transparency, repeatability, and low maintenance over methodological complexity.

3.1. Data collection with SerpApi

Data were collected through SerpApi Google Maps Reviews engine for the place identifier associated with Klass Wagen Sibiu. The request used an English interface setting and sorted reviews by recency. Reviews were retained only when the response contained a translated English text field. The collection was capped at 200 translated reviews, a pragmatic threshold chosen to keep the workflow lightweight while still providing enough observations for descriptive monitoring, frequency patterns, and review examples. The cap should not be read as a statistically representative sample of all customers.

The selection criteria were therefore explicit: one business location, recent Google review pages returned by the configured query, translated English text available in the extracted snippet, and a maximum of 200 retained observations. This procedure supports replication because the same place identifier, language setting, sorting rule, and cap can be rerun. It also creates identifiable constraints: untranslated reviews are excluded, the platform ordering and availability rules influence the sample, and the resulting corpus reflects voluntary reviewers rather than all customers.

3.2. Sentiment analysis with VADER

For sentiment scoring, the analysis applies VADER to the translated English text and stores per-review scores, labels, and summary statistics. The standard compound-score thresholds are used: scores of 0.05 or higher are labelled positive, scores of -0.05 or lower are labelled negative, and values between these thresholds are labelled neutral (Hutto and Gilbert, 2014). These thresholds provide a reproducible descriptive baseline. They are not treated as validated classification boundaries for this specific business domain.

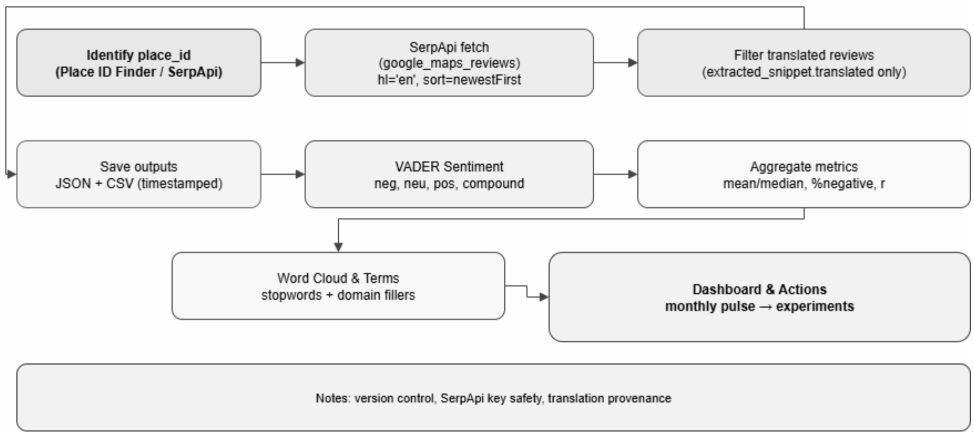
3.3. Word cloud

The word cloud is generated after removing generic stopwords, brand and location terms, and unavoidable industry words such as car, vehicle, and rental. The goal is to surface recurring service and process terms rather than predictable context words. Because the visualization is exploratory, the interpretation remains tied to the sentiment table and manually inspected examples.

3.4. Reproducibility, versions, and environment

The scripts retain fixed inputs, package dependencies, thresholds, and output names to reduce configuration drift between runs. Timestamps are kept as returned by SerpApi, and no stochastic modelling is introduced. This makes the workflow auditable, although it also means that any change in platform access, translation availability, or stopword settings should be documented before comparing monthly outputs.

3.5. Workflow scheme



Source: own creation

Figure no. 1 – Workflow scheme

4. RESULTS

4.1. Dataset overview

The collection script retrieved 200 reviews containing translated English text. Reviews span multiple months and languages of origin, but the analysis is restricted to the translated text stored in the English text field. The business Google summary, provided by SerpApi response at the time of collection, indicated a rating of 4.7 across 1,683 total reviews.

4.2. Sentiment distribution and summary statistics

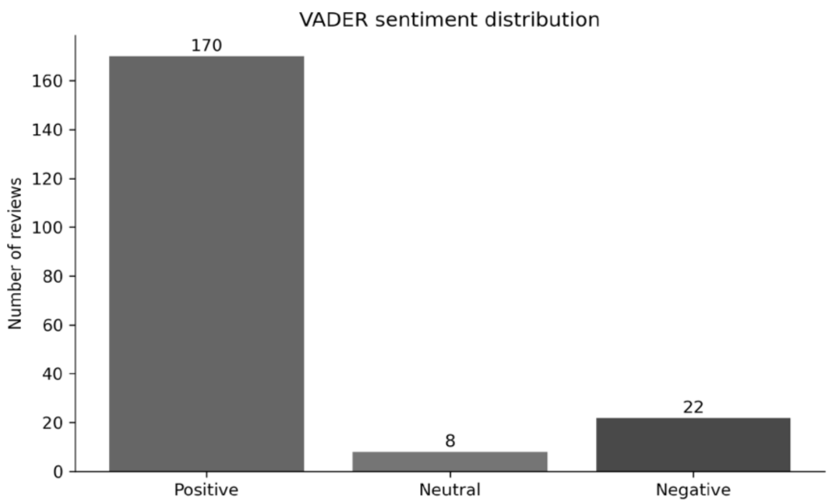
Table no. 1 summarizes the VADER outcomes from sentiment_summary.json.

Table no. 1 – Sentiment summary (translated texts, n = 200)

Metric	Value
Positive (compound ≥ 0.05)	170 (85%)
Neutral (–0.05 < compound < 0.05)	8 (4%)
Negative (compound ≤ –0.05)	22 (11%)
Mean compound	0.5377
Median compound	0.7328
Pearson correlation: star rating vs VADER compound	0.8302

Source: own creation

Two observations stand out. First, the distribution is strongly skewed positive. Second, VADER compound scores are highly associated with numeric ratings, r approximately 0.83. This association should be read cautiously. It suggests that the sentiment scores and star ratings move in a similar direction in this corpus, but it does not demonstrate classification accuracy. A stronger validation claim would require manually coded labels, a confusion matrix, agreement statistics, or a comparison with another sentiment model.



Source: own creation

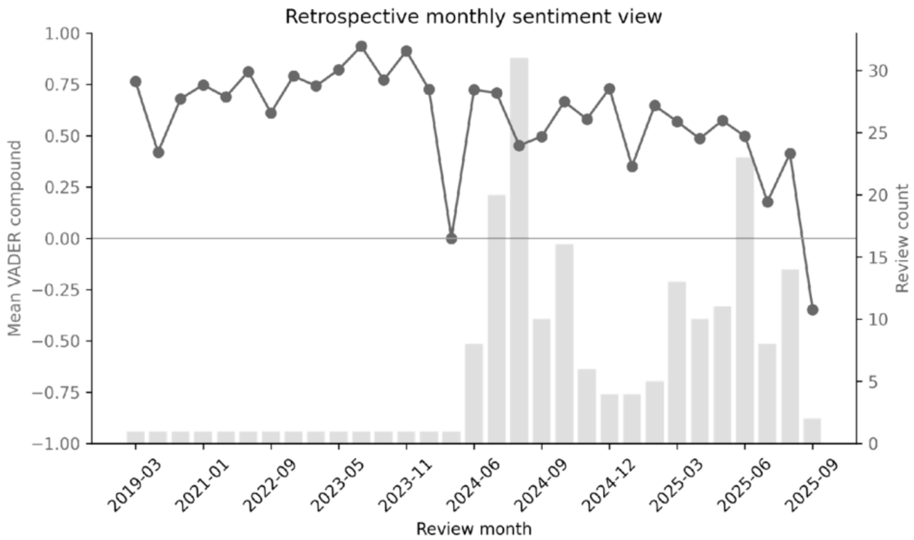
Figure no. 2 – VADER sentiment label distribution

Figure no. 2 presents the distribution of VADER sentiment labels. The skew toward positive reviews is visually clear: 170 reviews are classified as positive, 8 as neutral, and 22 as negative. This distribution supports the descriptive claim that the corpus is broadly favorable, while still leaving a visible minority of negative cases for operational diagnosis.

Source: own creation

Figure no. 3 – Google star rating and VADER compound score

Figure no. 3 plots Google star ratings against VADER compound scores. Most 5-star reviews are located above the positive threshold, while most 1-star reviews fall below the negative threshold. A small number of discordant cases remain, including low-star reviews with non-negative text sentiment and high-star reviews with weaker textual polarity. These cases show why the pipeline should preserve both rating and text indicators.



Source: own creation

Figure no. 4 – Retrospective monthly sentiment view

Figure no. 4 provides a retrospective time view based on the review timestamps. The line reports monthly mean VADER compound scores and the bars report the number of reviews available in each month. This view is descriptive because reviews were not collected prospectively at fixed monthly intervals, but it illustrates how the same workflow can support repeated monitoring once run on a regular schedule.

4.3. What positive and negative reviews discuss

A rapid read of high- and low-score examples helps triangulate the numbers.

- **Positive exemplars** (high compound and 5★): "*I highly recommend, everything was perfect, thanks to the entire team.*" and "*Fast service for pick up and drop off. Everything was easy and hassle free. The staff was very friendly and very helpful.*" Sentiment drivers include *speed (fast), staff (friendly/helpful), cleanliness (clean/new),* and *recommendation intent* ("recommend," "100%").
- **Negative exemplars** (low compound and 1–2★): "*They pressured us to buy very expensive insurance; otherwise a huge deposit and threats of high costs for any small scratch.*" and "*Card 'not working' unless purchasing on-site insurance; return required carwash.*" Here the drivers are *insurance pressure, deposit size/handling, perceived unfairness, card acceptance,* and *carwash/cleaning requirements*.

These themes align with broader literature showing that checkout frictions and uncertainty about liability often dominate negative word-of-mouth in services (Luca, 2016).

4.4. Word cloud

Source: own creation

Figure no. 5 – Word cloud

Our word cloud removes generic vocabulary (the library's stopwords), brand/location words (e.g., *Klasswagen/KW, Sibiu, Romania*), and industry head terms (*car, vehicle, rental*) so that more diagnostic language surfaces. In this rendering, **positive** clusters center on *friendly, helpful, recommend, fast, professional, clean/new*, while **negative** clusters surface *insurance, deposit, credit card, scratch/damage, wash/cleaning*. Because word clouds ignore negation and syntax, we validate these impressions against the per-review sentiment table and spot-read several examples (Mueller; Harris, 2011).

Practical takeaway for owners: the cloud directs attention to recurring friction points that are actionable: (1) how insurance/deposits are explained, (2) clarity about cleaning/return expectations, and (3) card requirements. Conversely, positive themes (*friendly staff, fast pickup/drop-off, transparent process*) are differentiators to protect and standardize.

4.5. Interpretation of the correlation with ratings

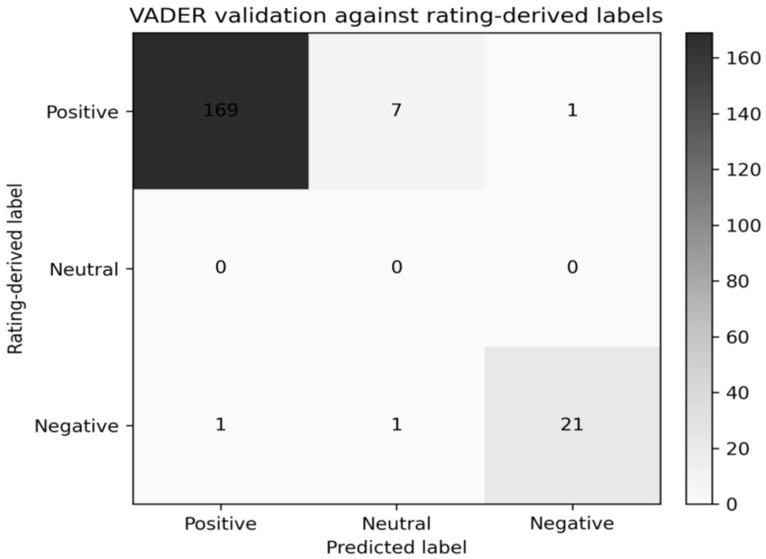
The strong correlation between VADER compound scores and star ratings is consistent with the many clearly positive and negative narratives in the corpus. At the same time, text-rating discrepancy research shows that written comments and numeric scores can diverge, so the correlation is best treated as descriptive convergence rather than proof that the model classifies sentiment correctly (Almansour *et al.*, 2022). Owners should therefore monitor both indicators: star distributions for high-level movement and review text for specific operational signals.

4.6. Rating-derived validation and benchmark comparison

To address the distinction between correlation and classification accuracy, an additional validation check was performed using rating-derived weak labels. Reviews with 4 or 5 stars were coded as positive, reviews with 1 or 2 stars were coded as negative, and 3-star reviews would be coded as neutral. In the present dataset, the rating-derived labels contain 177 positive and 23 negative cases, with no 3-star observations. This validation strategy is weaker than manual annotation, but it offers a transparent triangulation between numerical ratings and text-based sentiment labels.

Against these rating-derived labels, VADER correctly classified 190 of 200 reviews, yielding 95.0% accuracy and a weighted F1 score of 0.969. The confusion matrix shows that 169 positive cases and 21 negative cases were aligned with their rating-derived labels; the remaining disagreements mostly involve neutral VADER outputs for reviews whose star ratings were strongly positive or negative. Figure no. 4 reports this confusion matrix.

As a lightweight benchmark, a TF-IDF logistic-regression classifier was evaluated with stratified 5-fold cross-validation on the same translated review texts and rating-derived labels. This model reached 96.0% accuracy and a weighted F1 score of 0.960. The similarity between VADER and the supervised baseline supports the use of VADER as a transparent monitoring tool in this corpus, although the result should not be generalized beyond the present dataset without manual labels or additional cases.



Source: own creation

Figure no. 6 – VADER confusion matrix against rating-derived labels

4.7. Limitations and validity threats

Translation bias. The study analyzes only reviews with an English translation field. Automatic translation can alter sentiment by changing idioms, intensity, or polarity (Balahur and Turchi, 2014; Mohammad *et al.*, 2016). The translated text remains relevant for managerial monitoring because it approximates what many English-interface users see, but it is not equivalent to expert translation or original-language sentiment analysis.

Sampling and self-selection bias. Google review writers are volunteers, not a random sample of all customers. Customers with unusually positive or negative experiences may be more likely to post, and platform-level polarity can produce review distributions that differ from the underlying customer population (Li and Hitt, 2008; Schoenmueller *et al.*, 2020). The single-location design strengthens operational specificity but limits generalizability.

Platform and access bias. The corpus depends on the reviews made available through the platform interface and on the ordering, language, and pagination choices used during collection. These constraints may affect which reviews enter the dataset. The analysis therefore supports descriptive monitoring and issue detection rather than causal claims about service quality.

Method bias. VADER is a transparent lexicon-based tool, but it can miss sarcasm, domain-specific meanings, mixed sentiment, and complaints written in polite language (Hutto and Gilbert, 2014). Word clouds are similarly limited because they ignore grammar and negation (Harris, 2011). These outputs should trigger closer reading and, where decisions are high stakes, additional validation.

Validation constraint. The validation uses star ratings as weak labels rather than independent human annotation. This approach is useful for checking whether text sentiment and rating-derived polarity broadly align, but it cannot replace manual coding because stars and text may express different aspects of customer experience.

Benchmark constraint. The TF-IDF logistic-regression comparison is a lightweight baseline trained and tested on rating-derived labels. It shows that a simple supervised model performs similarly to VADER on this corpus, but it does not establish superiority over transformer-based models or domain-specific human coding.

5. A REPLICABLE BLUEPRINT FOR ENTREPRENEURS

This section distills the demonstration into a recipe any owner can reuse.

1. **Identify your Google Maps place_id.** You can obtain it via Google's Place ID Finder or SerpApi's tooling. Keep it in a safe configuration file.
2. **Collect reviews monthly.** Run serpapi_klasswagen_reviews.py with your key and place id. Use hl="en" and keep only reviews with extracted_snippet.translated to maintain an English corpus. Save JSON + CSV with a date stamp (e.g., myplace_2025-09_en.json).
3. **Analyze sentiment.** Run analyze_sentiment.py to produce per-review VADER scores and the monthly summary. Append new rows to a long-format store (e.g., a single CSV partitioned by month) to track trends.
4. **Skim the word cloud.** Use it as a pointer to investigate a concrete policy area (e.g., *insurance explanation*), then read 10–20 representative reviews to decide on an action.
5. **Make a small change; measure again next month.** Examples: simplify deposit signage at pickup; add a pre-arrival email explaining credit card requirements; adopt a clearer cleaning policy. Look for a drop in negative share and a shift in word-cloud salience.
6. Document versions and assumptions. Keep package versions, thresholds, stopword changes, anonymized input files, processed outputs, and generated figures in the reproducibility package so a given month can be audited later.

6. TABLES AND EXHIBITS

Table no. 2 – Example positive and negative snippets with VADER outputs

Example (translated)	Stars	VADER compound	Label
"Fast service for pick up and drop off… staff was very friendly and very helpful. Highly recommend."	5	0.93	Positive
"Top-notch company. Very friendly staff, everything quick and easy."	5	0.84	Positive
"They pressured us to buy very expensive insurance… deposit threats for any small scratch."	1	–0.51	Negative
"Card 'not working' unless we bought on-site insurance; return required a carwash."	1	–0.95	Negative

Note: Examples paraphrased from the dataset to preserve privacy and focus on themes.

Source: own creation

Table 3. Operational dashboard metrics an owner can track monthly

Metric	Definition	Why it matters
% Negative	Negative labels ÷ total	Early warning; drill into themes
Mean compound	Average VADER score	High-level tone index
Rating–sentiment r	Pearson r between stars and compound	Checks method stability
Top negative bigrams	E.g., “additional insurance,” “credit card,” “car wash”	Turns themes into actions
Response lag	Average time to owner reply (if tracked)	Service recovery KPI

Source: own creation

7. DISCUSSION

The managerial value of the pipeline lies in a four-step monitoring routine: collect recent reviews, score the translated text, interpret recurring positive and negative themes, and act on a small number of service frictions in the next operating cycle. For the case analyzed here, the most salient negative themes concern insurance explanations, deposits, credit-card requirements, scratches or damage, and return cleaning. The most salient positive themes concern friendly staff, fast pickup and drop-off, clean vehicles, and recommendation intent. This structure turns descriptive analytics into an operational checklist without overstating the precision of the model.

From a research perspective, the study should be read as an applied decision-support blueprint. It does not introduce a new sentiment algorithm and does not claim population-level representativeness. Its contribution is to connect a replicable data-collection routine, a transparent sentiment baseline, and explicit validity boundaries in a format that can be reused by SMEs and audited by researchers. Future extensions can test whether the same workflow remains stable across locations, industries, languages, and monitoring periods.

8. CONCLUSION

The study shows that small firms can transform public review text into a repeatable monitoring routine without building complex analytics infrastructure. By combining SerpApi collection, VADER sentiment scoring, and carefully limited exploratory visualization, the workflow produces a monthly pulse of customer experience that is understandable to non-specialists and reproducible by a single analyst.

The findings support practical attention to recurring service frictions rather than broad causal claims. In the case analyzed, positive reviews emphasize speed, staff helpfulness, cleanliness, and recommendation intent, while negative reviews concentrate around insurance, deposits, credit-card requirements, damage disputes, and cleaning expectations. These patterns can guide targeted operational adjustments, especially clearer pre-arrival communication and more consistent explanation of return conditions.

The boundaries of the pipeline are equally important. It cannot prove that service quality changed, cannot remove self-selection from voluntary reviews, and cannot guarantee sentiment accuracy for translated or ambiguous text. Its value is iterative: run the same workflow regularly, compare the same indicators over time, read representative comments behind the metrics, make small service changes, and reassess whether the negative share and recurring friction vocabulary decline.

DATA AND CODE AVAILABILITY

An anonymized reproducibility package has been uploaded to GitHub and is available at the following repository address: https://github.com/MaraAlexandru/listening-at-scale-google-reviews-vader. The repository contains the translated review input file, sentiment-analysis scripts, processed outputs, validation files, and generated figures. It excludes API keys, direct user identifiers, Google profile links, contributor IDs, review links, thumbnails, and raw API metadata.

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ANNEX A.1 ANALYZE_SENTIMENT.PY

```
#!/usr/bin/env python3
"""
Analyze sentiment on translated Google reviews (VADER) and build a word cloud.

Input (hardcoded):
  klasswagen_translated_only.json
    {
     "place_info": {...},
     "reviews": [
       {
        "extracted_snippet": {
          "original": "...",
          "translated": "ENGLISH TEXT HERE"
        },
        "rating": 5.0,
        "iso_date": "2025-09-01T07:10:48Z",
        "review_id": "..."
       }, ...
     ]
    }

Outputs (hardcoded):
  sentiment_by_review.csv     # one row per review with VADER scores + label
  sentiment_summary.json      # averages + counts
  wordcloud_translated.png    # word cloud from translated text (stopwords removed)
```

```
Install once:
    pip install vaderSentiment wordcloud matplotlib pandas

Note:
    We score sentiment on the English *translated* text only and do NOT filter it with stopwords.
    Stopwords are applied only to the wordcloud (to “ignore filler words” visually).
"""

from __future__ import annotations

import json
import re
from pathlib import Path
from typing import Dict, List

import pandas as pd
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt


# ---------------------------- HARD-CODED PATHS ----------------------------
INPUT_JSON = Path("klasswagen_translated_only.json")
OUT_CSV = Path("sentiment_by_review.csv")
OUT_SUMMARY_JSON = Path("sentiment_summary.json")
OUT_WORDCLOUD = Path("wordcloud_translated.png")


# ---------------------------- HELPERS -------------------------------------
def load_translated_reviews(path: Path) -> List[Dict]:
    data = json.loads(path.read_text(encoding="utf-8"))
    reviews = data.get("reviews", []) or []

    out = []
    for r in reviews:
        ex = r.get("extracted_snippet") or {}
        text_en = ex.get("translated")  # we saved only translated ones earlier
        if isinstance(text_en, str) and text_en.strip():
            out.append(
                {
                    "review_id": r.get("review_id"),
                    "iso_date": r.get("iso_date"),
                    "rating": r.get("rating"),
                    "text_en": text_en.strip(),
                }
            )
    return out


def vader_label(compound: float) -> str:
    # Standard VADER thresholds
```

```
    if compound >= 0.05:
        return "positive"
    elif compound <= -0.05:
        return "negative"
    return "neutral"


def build_wordcloud(texts: List[str], out_path: Path) -> None:
    # Start from WordCloud's built-in STOPWORDS and extend with domain fillers
    extra_stop = {
        # brand / domain-specific fillers that add little meaning to the cloud
        "klasswagen", "klass", "wagen", "kw",
        # recurring codes / tokens
        "sbz", "sbz-", "sbz_", "sbz - ",
        # generic business/location fillers
        "romania", "sibiu", "bucharest", "cluj", "napoca", "airport",
        "company", "team", "services", "service",
        # industry-common words that would dominate the cloud
        "car", "cars", "rental", "rent", "vehicle", "vehicles",
        # politeness fillers
        "hello", "hi", "dear", "thanks", "thank", "please",
    }
    stopwords = STOPWORDS.union(extra_stop)

    # Clean: drop URLs, collapse whitespace. (We keep punctuation; WordCloud tokenizes.)
    cleaned_texts = []
    url_re = re.compile(r"https - ://\S+")
    code_re = re.compile(r"\b( - :sbz)[\w\-]*\b", flags=re.IGNORECASE)
    for t in texts:
        t2 = url_re.sub(" ", t)
        t2 = code_re.sub(" ", t2)
        t2 = re.sub(r"\s+", " ", t2)
        cleaned_texts.append(t2.strip())

    blob = "\n".join(cleaned_texts)

    wc = WordCloud(
        width=1800,
        height=1000,
        background_color="white",
        stopwords=stopwords,
        collocations=True,   # keep meaningful bigrams if frequent
        max_words=400,
    ).generate(blob)

    # Save to disk
    plt.figure(figsize=(18, 10))
    plt.imshow(wc, interpolation="bilinear")
    plt.axis("off")
    plt.tight_layout(pad=0)
    plt.savefig(out_path, dpi=180)
```

```
    plt.close()

# ---------------------------- MAIN ----------------------------------------
def main() -> None:
    if not INPUT_JSON.exists():
        raise SystemExit(f"Input not found: {INPUT_JSON.resolve()}")

    rows = load_translated_reviews(INPUT_JSON)
    if not rows:
        raise SystemExit("No translated reviews found in the input JSON.")
    # VADER sentiment
    analyzer = SentimentIntensityAnalyzer()
    scored = []
    for r in rows:
        s = analyzer.polarity_scores(r["text_en"])
        compound = s["compound"]
        scored.append(
            {
                "review_id": r["review_id"],
                "iso_date": r["iso_date"],
                "rating": r["rating"],
                "text_en": r["text_en"],
                "vader_neg": s["neg"],
                "vader_neu": s["neu"],
                "vader_pos": s["pos"],
                "vader_compound": compound,
                "sentiment_label": vader_label(compound),
            }
        )

    df = pd.DataFrame(scored)
    df.to_csv(OUT_CSV, index=False, encoding="utf-8")

    # Summary
    summary = {
        "n_reviews": int(df.shape[0]),
        "vader_compound_mean": float(df["vader_compound"].mean()),
        "vader_compound_median": float(df["vader_compound"].median()),
        "counts": {
            "positive": int((df["sentiment_label"] == "positive").sum()),
            "neutral": int((df["sentiment_label"] == "neutral").sum()),
            "negative": int((df["sentiment_label"] == "negative").sum()),
        },
        # (Optional) Rating correlation with sentiment if ratings exist
        "rating_vs_compound_correlation": (
            float(df["rating"].corr(df["vader_compound"])) if "rating" in df and
df["rating"].notna().any() else None
        ),
    }
    OUT_SUMMARY_JSON.write_text(json.dumps(summary, indent=2), encoding="utf-8")
```

```
    # Wordcloud from translated text (ignoring stopwords/fillers)
    build_wordcloud(df["text_en"].tolist(), OUT_WORDCLOUD)

    print(f"Done.\n- Wrote {OUT_CSV}\n- Wrote {OUT_SUMMARY_JSON}\n- Wrote
{OUT_WORDCLOUD}")


if __name__ == "__main__":
    main()
```

ANNEX A.2 SERPAPI_KLASSWAGEN_REVIEWS.PY

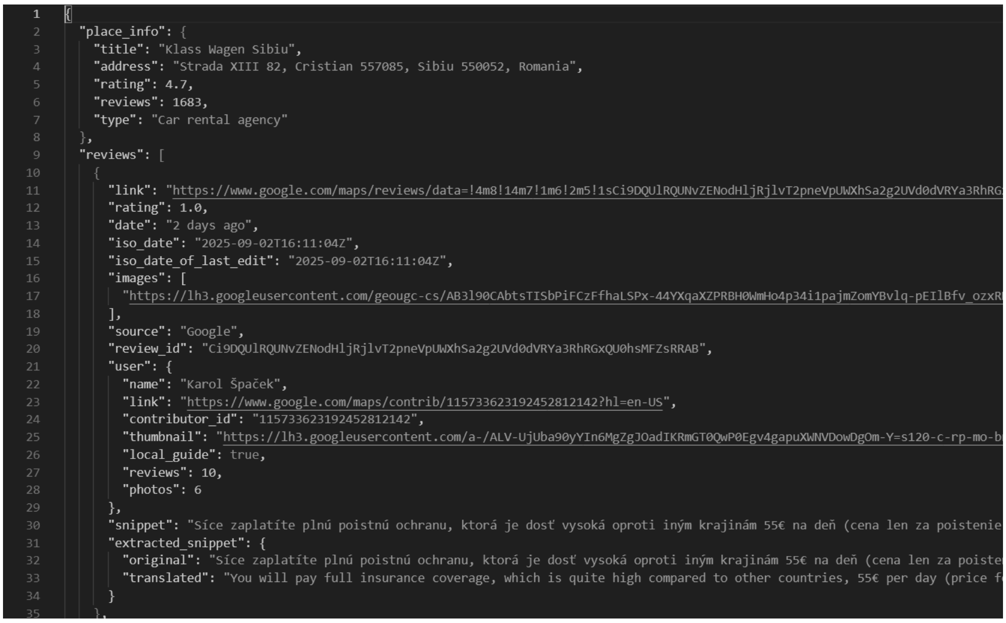
```
#!/usr/bin/env python3
"""
Fetch up to 200 *translated* Google Maps reviews for Klass Wagen via SerpApi
 - ONLY rows that have `extracted_snippet.translated` are saved.

Hardcoded:
- SerpApi API key
- Google Maps place_id
- Output file names
- Sort order and language context

Requirements:
    pip install google-search-results

NOTE: Your API key is embedded in plaintext. Share/commit with care.
"""

from __future__ import annotations

import csv
import json
import time
import os
from typing import Any, Dict, List, Optional

from serpapi import GoogleSearch

# ------------------- HARD-CODED SETTINGS -------------------
API_KEY   = os.getenv("SERPAPI_API_KEY", "REDACTED")  # ← MASKED
PLACE_ID  = "ChIJQbiBR6JCTEcRlIC2V-CB2uI"  # Klass Wagen Sibiu
HL        = "en"              # request English UI/context
SORT_BY   = "newestFirst"       # qualityScore | newestFirst | ratingHigh | ratingLow
MAX_TRANSLATED = 200           # stop once we have this many translated reviews
SLEEP_BETWEEN_PAGES = 0.35      # be polite between page requests
OUT_PREFIX = "klasswagen_translated_only"  # outputs: .json and .csv

# ---------------------------------------------------------
```

```
def fetch_translated_only() -> Dict[str, Any]:
    """
    Use SerpApi Google Maps Reviews API to fetch reviews for PLACE_ID,
    paginate with next_page_token, and keep ONLY those with a translated text
    at review['extracted_snippet']['translated'].
    Returns dict with 'place_info' and 'reviews' (translated-only).
    """
    params = {
        "engine": "google_maps_reviews",
        "api_key": API_KEY,
        "place_id": PLACE_ID,
        "sort_by": SORT_BY,
        "hl": HL,
    }
    search = GoogleSearch(params)

    place_info: Optional[Dict[str, Any]] = None
    translated_reviews: List[Dict[str, Any]] = []
    seen_ids: set[str] = set()

    while len(translated_reviews) < MAX_TRANSLATED:
        result = search.get_dict()

        # Basic error handling
        if "error" in result:
            raise RuntimeError(f"SerpApi error: {result['error']}")

        if place_info is None:
            place_info = result.get("place_info")

        page_reviews = result.get("reviews", []) or []
        for r in page_reviews:
            rid = r.get("review_id")
            if rid and rid in seen_ids:
                continue

            ex = r.get("extracted_snippet") or {}
            translated_text = ex.get("translated")

            # Keep ONLY reviews that have a translated version
            if isinstance(translated_text, str) and translated_text.strip():
                translated_reviews.append(r)
                if rid:
                    seen_ids.add(rid)
                if len(translated_reviews) >= MAX_TRANSLATED:
                    break

        if len(translated_reviews) >= MAX_TRANSLATED:
            break

        # Pagination: use next_page_token for the next batch; request up to 20 after first page
```

```
        serp_pagination = result.get("serpapi_pagination") or {}
        next_token = result.get("next_page_token") or serp_pagination.get("next_page_token")
        if not next_token:
            break  # no more pages available

        search.params_dict.update({
            "next_page_token": next_token,
            "num": 20,  # allowed after the first page
        })
        time.sleep(SLEEP_BETWEEN_PAGES)

    return {
        "place_info": place_info,
        "reviews": translated_reviews[:MAX_TRANSLATED],
    }

def flatten_review_translated(r: Dict[str, Any]) -> Dict[str, Any]:
    """
    Flatten fields for CSV, putting the translated English text into `text_en`.
    Also include `original_text` for reference.
    """
    user = r.get("user") or {}
    ex = r.get("extracted_snippet") or {}
    response = r.get("response") or {}
    rex = response.get("extracted_snippet") or {}

    return {
        "review_id": r.get("review_id"),
        "rating": r.get("rating"),
        "date": r.get("date"),
        "iso_date": r.get("iso_date"),
        "likes": r.get("likes"),
        "text_en": ex.get("translated"),
        "original_text": ex.get("original"),
        "review_link": r.get("link"),
        "user_name": user.get("name"),
        "user_link": user.get("link"),
        "user_contributor_id": user.get("contributor_id"),
        "user_local_guide": user.get("local_guide"),
        "user_reviews_count": user.get("reviews"),
        "user_photos_count": user.get("photos"),
        # Optional: include company reply (translated if present)
        "reply_text_en": rex.get("translated"),
        "reply_original_text": rex.get("original"),
        "reply_iso_date": (response.get("iso_date") or response.get("iso_date_of_last_edit")),
    }

def write_outputs(payload: Dict[str, Any]) -> None:
    """Write JSON + CSV with hardcoded filenames."""
    # JSON (translated-only)
    with open(f"{OUT_PREFIX}.json", "w", encoding="utf-8") as f:
```

```
        json.dump(payload, f, ensure_ascii=False, indent=2)

    # CSV (translated-only)
    rows = [flatten_review_translated(r) for r in (payload.get("reviews") or [])]
    fieldnames = list(rows[0].keys()) if rows else list(flatten_review_translated({}).keys())
    with open(f"{OUT_PREFIX}.csv", "w", newline="", encoding="utf-8") as f:
        writer = csv.DictWriter(f, fieldnames=fieldnames)
        writer.writeheader()
        writer.writerows(rows)

def main() -> None:
    payload = fetch_translated_only()
    write_outputs(payload)

    place = (payload.get("place_info") or {}).get("title")
    print(f"Place: {place or 'Unknown'}")
    print(f"Translated reviews saved: {len(payload.get('reviews', []))}")
    print(f"Wrote: {OUT_PREFIX}.json and {OUT_PREFIX}.csv")

if __name__ == "__main__":
    main()
```

ANNEX A.3 ARTIFACT PLACEHOLDERS (PASTE SCREENSHOTS)



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    "type": "Car rental agency"
  },
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      "date": "2 days ago",
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      ],
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        "contributor_id": "115733623192452812142",
        "thumbnail": "https://lh3.googleusercontent.com/a-/ALV-UjUba90yYIn6MgZgJOadIKRmGT0QwP0Egv4gapuXWNVDowDgOm-Y=s120-c-rp-mo-b
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        "reviews": 10,
        "photos": 6
      },
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        "translated": "You will pay full insurance coverage, which is quite high compared to other countries, 55€ per day (price f
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    },
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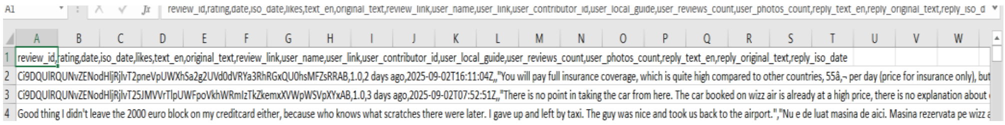
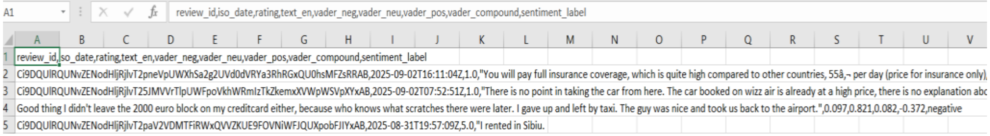
Source: own creation

Figure no. A1 – klasswagen_translated_only.json - place metadata and 200 translated reviews.



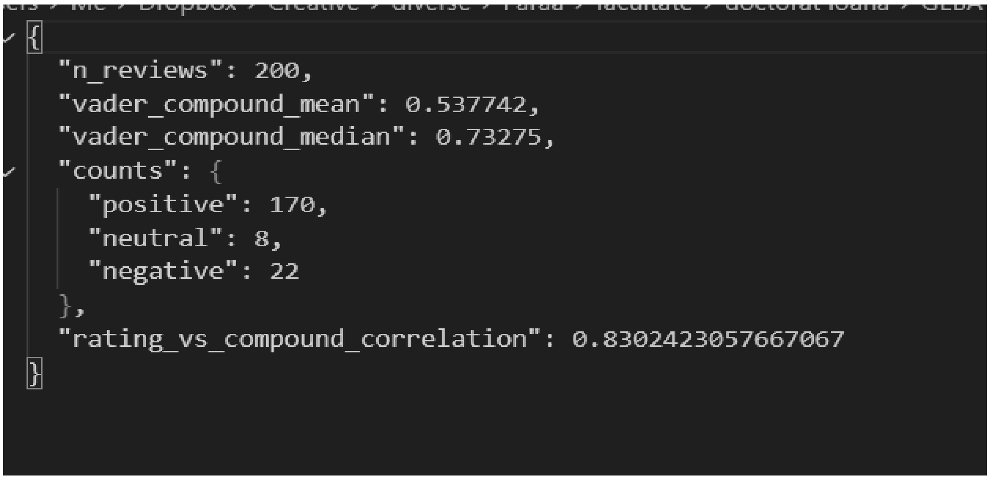
Source: own creation

Figure no. A2 – klasswagen_translated_only.csv - flattened fields including text_en



Source: own creation

Figure no. A3 – sentiment_by_review.csv - per-review VADER scores and labels



Source: own creation

Figure no. A4 – sentiment_summary.json - summary metrics (counts, mean/median, correlation)

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Financial Intermediation and Economic Growth: Empirical Evidence from the EU

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Abstract: Although the relationship between financial intermediation and economic growth has been widely investigated in both theoretical and empirical literature, there is still no consensus regarding its existence, intensity, direction, or functional form (linear vs. nonlinear). This study aims to empirically assess the nexus between financial development and economic growth in the 28 member states of the European Union (EU28) over the period 2000- 2021. Motivated by the recent Draghi Report (2024), which underscores the urgency of building a more integrated and efficient financial system to sustain long-term growth in the EU, our analysis explicitly explores the potential nonlinearity of this link. Using a panel data approach and applying the System Generalized Method of Moments (System GMM), we address endogeneity concerns and account for dynamic effects. Our results reveal a negative impact of the linear component of financial development on economic growth, while the squared term exhibits a positive and statistically significant effect. This U-shaped pattern suggests that the benefits of financial development materialize only after surpassing a certain threshold level. These findings carry important policy implications, particularly in the current context where the EU's financial sector is considered underdeveloped relative to other major global economies, emphasizing the need for structural reforms to enhance its catalytic role in promoting sustainable growth.

Keywords: financial development; economic growth; causality; EU countries.

JEL classification: E44; G21; O11; O16; O43.

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1. INTRODUCTION

It is widely acknowledged that a high standard of living can only be achieved through an increase in the production of goods and services, and thus, through economic growth. Studies on the topic (Hassan *et al.*, 2011; Prochniak and Wasiak, 2017; Afonso and Blanco-Arana, 2022) highlight the existence of several factors that can be considered drivers of economic growth, among which the financial system stands out. The institutional framework of the financial system, as well as its performance, represents a fundamental pillar for macroeconomic performance. Therefore, the vital importance of studying the association between financial development and economic growth is emphasized.

Although the relationship between the level of financial intermediation development and economic growth has been extensively explored, previous research presents mixed and sometimes contradictory results.

Prior to the financial crisis, the literature largely focused on the linear relationship between these variables and almost unanimously highlighted the positive effect of financial development on economic growth (King and Levine, 1993; Beck *et al.*, 2000; Arestis *et al.*, 2001). After the crisis, a new strand of studies (Caporale *et al.*, 2015; Fajeau, 2021) identified not only the absence of an association between the two phenomena but also highlighted that the incidence of financial crises is related to the dampening effect of financial deepening on growth (Rousseau and Wachtel, 2011).

More recently, the first evidence of a nonlinear relationship has emerged. Studies suggest that the effects of financial development on economic growth may depend on the level of development of economies (Arcand *et al.*, 2015), the occurrence of crises (Afonso and Blanco-Arana, 2022) or the structural characteristics of the economies analyzed (Swamy and Dharani, 2019; Tariq *et al.*, 2023; Asteriou *et al.*, 2024).

While previous research, such as that by Swamy and Dharani (2019) and Purewal and Haini (2022), has predominantly identified an inverted U-shaped relationship, especially in highly financially developed economies or earlier analyses of the European Union, the global role of the European financial system has notably diminished in recent years. Institutions that once dominated global financial rankings, including HSBC and BNP Paribas, have ceded leadership to American and Asian banks like JPMorgan Chase, the Industrial and Commercial Bank of China, and the Agricultural Bank of China. This shift signals a transformed global economic environment and underscores the need to reassess the link between financial development and economic growth within the contemporary European context. Thus, our study aims to fill this gap in the literature by empirically reassessing this relationship, focusing on its potential nonlinear form.

It is important to say that the **motivation** for this research comes from the ongoing academic and policy debate about the role of the financial system in promoting economic growth. This relationship remains ambiguous and context dependent in empirical literature. This long-standing debate has received renewed attention from European authorities, particularly through *the report published by Draghi* (2024). The report reconfirms and strongly highlights the current limitations of the European financial system, pointing out persistent imbalances in terms of capital market depth, access to finance, and the efficiency of financial resource allocation. These factors continue to limit economic growth across the European Union. Also, the report calls for institutional and regulatory reforms aimed at fostering financial integration, stimulating capital market development, and improving financial intermediation through diversified channels.

As a result, considering the renewed attention to the analysis of the relationship between financial development and economic growth, our study aims to provide updated empirical evidence, contributing to the academic literature and the current political debate prompted by the *the report published by Draghi* (2024).

In this context, the research question that underpins this paper is: What would be the potential impact of financial intermediation development on economic growth in the European Union member states (EU28)?

The main objective of this study is to investigate the potential nexus between financial intermediation development and macroeconomic performance, with particular attention to the possible linear or nonlinear nature of this linkage. The empirical analysis is conducted using a panel dataset comprising the 28 EU member states over the period 2000–2021. This time interval was deliberately chosen, as it includes the years preceding the global financial crisis, the crisis period itself, and the post-crisis recovery, thus offering a comprehensive perspective on the evolution and dynamics of the association under examination.

The empirical investigation of this nexus, focused on the 28 member states of the European Union over the period from 2000 to 2021, seeks to offer a **twofold contribution**. On the one hand, it aims to extend the theoretical framework on the link between financial intermediation and economic growth by testing the hypothesis of non-linearity. On the other hand, beyond its academic contribution, it also provides empirical findings that can inform policy considerations. For instance, the finding that there is a detrimental impact at early stages but becomes beneficial once a critical institutional and functional maturity threshold is reached implies that policymakers could focus on strengthening the capacity of financial markets to mobilize the resources necessary for sustainable economic growth.

The **novelty of our study** is highlighted by multiple aspects. Primarily, it focuses on the nonlinear relationship between financial development and economic growth, examined in the context of the recent findings of *the report published by Draghi* (2024). As mentioned above, the role of European financial systems has diminished in the past, thus necessitating a review of the relationship between financial development and economic growth in the current European economic context.

Furthermore, the **originality of our research** is reinforced by the comprehensive utilization of the multidimensional indicators from the International Monetary Fund's Financial Development Index database. Previous studies often employed only two well-known proxies of financial development: the credit to GDP ratio and the stock market capitalization to GDP ratio with the aim of emphasizing the financial development. However, financial systems have evolved into much more complex mechanisms that include the other dimensions of financial development (access and efficiency, besides depth), as well as other types of non-bank financial intermediaries (such as pension funds, mutual funds, insurance companies). To reflect this multi-dimensional and complex nature of financial development we used IMF's Financial Development Indexes. These indicators measure financial development in terms of depth, access, and efficiency at both institutional and market levels.

Unlike earlier studies, such as those by Purewal and Haini (2022) and Asteriou *et al.* (2024), which relied on selected indicators, our study employs the complete set of available indices. As previously mentioned, financial systems have evolved into much more complex mechanisms. Consequently, the aggregate effect might mask significant heterogeneity across different dimensions (depth, access, and efficiency) and components of financial systems (institutions or capital markets). To address this specific issue, we employ the full set of indexes, to identify which specific component of financial systems (market vs. institutions) and which facets (depth vs access vs efficiency) positively impact economic growth, and which might not have a direct impact or even a negative one. Rather than reaching a vague conclusion that more finance is better or worse for economic growth, we emphasized which aspects of financial development require attention from policymakers. Additionally, we introduce the **output gap** as an alternative proxy for economic growth alongside the conventional GDP growth rate, *offering novel insights into the cyclical dimension of the relationship.* Unlike the GDP growth rate, which measures gross output changes over time, the output gap reflects the deviation of actual GDP from potential GDP, thereby offering a cyclically adjusted view of how the economy is functioning (European Commission: Directorate-General for *et al.*, 2019). This study employs the output gap because of its essential role in identifying business cycle phases (expansions and recessions), which are relevant for understanding the relationship between financial development and economic performance at different cycle stages. It is worth noting that, to our knowledge, this variable has not yet been widely used in the context of exploring the nexus between financial development and economic growth. However, it has been employed as a proxy for economic growth in other studies (e.g., (Rzonca and Laszek, 2016; Ferreiro *et al.*, 2017)).

The application of the *bias-corrected least squares dummy variable* (LSDVC) *estimator* is novel in the context of analyzing the nexus between financial development and economic growth. Developed by Bruno (2005) based on earlier work of Kiviet (1995), the LSDVC estimator corrects the small-sample bias (Nickell bias) often found in classic LSDV estimates, especially when lagged dependent variables are present. Unlike GMM techniques such as Arellano-Bond or System GMM, which may become biased or inefficient in small-N panels *(*Hansen, 2001*)*, the LSDVC estimator is a reliable alternative for moderately sized panels, as in our study. While there are studies that use this technique in different contexts (Salem *et al.*, 2025; Căpraru *et al.*, 2026), to the best of our knowledge, no studies have employed the LSDVC estimator to analyze the relationship between financial development and economic growth. Therefore, its novel application in our context not only addresses a key methodological challenge but also strengthens the robustness of our findings. It achieves this by providing more precise estimators with lower variance that are less prone to over instrumentation problems.

Through this approach, our study addresses an urgent research need and provides valuable insights that could inform the development of effective economic policies within the European Union.

To achieve the main objective of the research, *our paper is structured as follows:* introduction; the first section is dedicated to the analysis of specialized literature; Section 2 describes the data and variables, Section 3 the research methodology, while Section 4 highlights the empirical results obtained and the corresponding discussions. The general conclusions are presented in the final section.

2. LITERATURE REVIEW

A significant body of both qualitative and quantitative research has focused on identifying the causal relationship between financial development and economic growth.

Seminal studies (e.g., (Levine, 2005; Andrieş, 2009; Méon and Weill, 2010) highlight the theoretical underpinnings of financial intermediation, particularly the *theories of information asymmetry, agency theory, and the modern theory of financial intermediation*. These frameworks emphasize the essential role of financial institutions and markets in mobilizing funds, whether through deposit-taking or insurance issuance, and reallocating them to deficit agents in need of capital for productive activities. The development of financial intermediation is therefore seen as a catalyst for overall financial development, which in turn enhances macroeconomic performance, particularly through increased GDP growth.

Building on these theoretical foundations, researchers have argued that financial intermediaries exist primarily to mitigate information asymmetries and reduce transaction costs arising from technological disparities between surplus and deficit agents. This role is reinforced in the modern theory of financial intermediation, which outlines key channels through which intermediation contributes to productivity and growth: ex-ante evaluation of investments, corporate governance through monitoring, pooling of savings to reduce transaction and information costs, and facilitating the exchange of goods and services. These mechanisms support improved capital allocation, increased firm productivity, and macroeconomic expansion. Nonetheless, while theoretical models emphasize a predominantly positive impact of financial intermediation on economic growth, they tend to overlook potential negative effects or bidirectional causality. This aspect is more thoroughly explored by empirical quantitative studies, which reveal a range of nuanced and often conflicting findings.

Early empirical studies strongly supported this link, finding a robust positive correlation. King and Levine (1993) were the pioneers, demonstrating not only a positive and statistically significant impact on economic growth, but also on the accumulation of physical capital and the improvement of its efficiency. This fundamental finding was reinforced and expanded upon by Beck *et al.* (2000), who used two econometric instruments to demonstrate the existence of a positive relationship between financial development and economic growth.

Over two decades, numerous studies have replicated and refined this basic result. Pradhan *et al.* (2014), for example, examined the link between the development of capital markets, the banking system, economic growth, and four other macroeconomic variables of interest, as follows: foreign direct investment; trade openness, inflation rate, and final consumption expenditure of the government. The analysis focused on the Association of Southeast Asian Nations (ASEAN) and the period between 1961 and 2012. Among the general conclusions of the research was the finding that there is a causal relationship between the development of the banking sector, the development of capital markets, economic growth, and the four key macroeconomic variables. Another conclusion reflected in this study is highlighted by the fact that the development of the banking sector and capital markets, as well as other macroeconomic variables, have a positive long-term impact on economic growth.

These findings are also supported by more recent studies, such as Afonso and Blanco-Arana (2022), which review the relationship between financial development and economic growth, using the example of 31 OECD countries between 1990 and 2016. The authors' overall conclusion is that there is a positive impact of variables representing the financial system (such as domestic credit, stock market capitalization, and the turnover rate of traded shares) on the growth rate of GDP per capita.

Contrasting with this broad consensus, a smaller number of studies have questioned the universality or strength of this link. Caporale *et al.* (2015) analyzed the impact of financial development on economic growth in ten EU countries from the penultimate enlargement phases, during the period 1994–2007, when these countries had underdeveloped financial markets, and thus their contribution to economic growth was minimal. Nevertheless, the authors also showed that a more efficient banking system could lead to accelerated economic growth, implying that a causal relationship could still exist. In a different approach, Fajeau (2021) found that the relationship between financial intermediation and economic growth may not necessarily depend on the level of financial development, but rather on the overall level of economic development. Asteriou *et al.* (2024) demonstrated that during periods free of fiscal stress or crisis, the relationship between financial development and economic growth becomes highly significant. However, in times of crisis, this relationship tends to lose significance.

In contrast, Rousseau and Wachtel (2011), using data for 84 countries over 1960–2004, show that excessive financial deepening and rampant credit growth can cause inflation and weaken the banking system. This can lead to financial crises and inhibit economic growth. This perspective is also supported by (Wen *et al.*, 2022). Their study highlights a positive link between financial development and either inflation or employment growth.

Additionally, there are studies (Méon and Weill, 2010; Breitenlechner *et al.*, 2015; Prochniak and Wasiak, 2017; Ito and Kawai, 2018; Asteriou and Spanos, 2019; An *et al.*, 2025), that demonstrate *both positive and negative effects*, depending on the specific context.

Another dimension of complexity concerns the direction of influence. Several researchers (Demetriades and Hussein, 1996; Greenwood and Smith, 1997; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Čižo *et al.*, 2020) have argued that causality does not operate in a single direction. For example, Demetriades and Hussein (1996), along with Greenwood and Smith (1997), concluded that there is a *bidirectional* causal link between the two phenomena. Similarly, Hassan *et al.* (2011) found evidence of a *unidirectional* relationship from economic growth to financial development in East Asia, the Pacific, and Sub-Saharan Africa, while a *bidirectional* relationship was observed in the remaining regions.

An extensive body of research (King and Levine, 1993; Beck *et al.*, 2000; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Caporale *et al.*, 2015; Asteriou and Spanos, 2019; Ferreira, 2020) has examined the relationship between financial development and economic growth from a **linear perspective**. In contrast, a number of more recent contributions have emphasized the potential **non-linear nature** of this relationship (Arcand *et al.*, 2015; Samargandi *et al.*, 2015; Prochniak and Wasiak, 2017; Benczúr *et al.*, 2019; Swamy and Dharani, 2019; Li and Wei, 2021; Afonso and Blanco-Arana, 2022; Purewal and Haini, 2022; Tariq *et al.*, 2023), suggesting that the effects of financial development on economic growth may vary depending on the level of financial development achieved or the structural characteristics of the economy in question.

Most studies that explore the non-linear dimension of this nexus support the existence of an *inverted U-shaped* curve (Arcand *et al.*, 2015; Swamy and Dharani, 2019), indicating that beyond a certain threshold, excessive financial development may become detrimental to economic growth. This perspective contrasts sharply with the current policy diagnosis of the European Union. In particular, *the report published by Draghi* (2024) states that the EU financial system is not overdeveloped, but fundamentally underdeveloped and fragmented, representing more of a brake on growth than a catalyst. The report, therefore, implies a U-shaped relationship. So, the benefits of financial development may only materialize after a certain level of financial maturity is reached.

The report's findings indicate that the European financial system is characterized by pronounced fragmentation, incomplete market integration, and limited capacity to efficiently mobilize capital. This is evident when compared to other major economies, such as the United

States and China. Draghi points out that, without significant structural reforms, financial development will be unable to sustainably support economic growth or facilitate green and digital transitions. He suggests deepening the Capital Markets Union by establishing common financial infrastructures, harmonizing regulatory frameworks, and reducing excessive reliance on bank-based financing.

Although the inverted U-shape is supported by broad cross-country studies, as mentioned above, the U-shaped hypothesis implied by *the report published by Draghi* (2024) remains an untested assumption in the context of EU member states. This gap in the empirical literature motivates our analysis.

3. METHODOLOGY

The present research is based on a panel dataset, targeting a sample of 28 European Union member countries. The United Kingdom is included in the sample because, for the majority of the analysis period, it was a full member of the European Union. Its inclusion enables a consistent analysis of the relationship between financial development and economic growth among countries subject to common EU-level regulations and economic policies. Excluding the UK solely due to its later withdrawal from the Union could distort the results, as the data corresponding to the period of its membership reflects economic and institutional conditions comparable to those of the other EU member states. The analysis covers 22 years, from 2000 to 2021. The statistical information used includes the GDP growth rate, which characterizes economic growth, a set of variables related to financial development, and a series of control variables. The data sources consist of the *World Bank's World Development Indicators (WDI)* and *Global Financial Development Indicators (GFDI)*, the *International Monetary Fund's Financial Development Index*, and the *AMECO database*.

The dependent variable in this study is the **GDP growth rate**, selected due to its widespread use as a key indicator of economic growth in the existing literature (Samargandi *et al.*, 2015; Swamy and Dharani, 2019; Wen *et al.*, 2022; Montañez-Enríquez *et al.*, 2024). Additionally, in the subsequent analysis conducted to test the robustness of the results, we will use the **output gap** as an alternative dependent variable to the GDP growth rate. This variable measures the difference between actual GDP and potential GDP as a percentage of potential GDP. Although the output gap is often used in the literature (Larch *et al.*, 2023; Căpraru *et al.*, 2025) for fiscal policy analysis, we employ it in this study due to its essential role in identifying business cycle phases (expansions and recessions), which are particularly relevant for understanding the dynamics between financial development and economic performance at different stages of the cycle. In this context, financial development may impact the output gap in the form of influencing the magnitude of the deviation between actual GDP from potential GDP, over different economic cycles. To illustrate this mechanism, consider the role of a higher degree of financial development in an economic expansion phase. Greater financial depth, for instance, which implies a greater degree of investment and consumption, could cause actual economic growth to exceed potential growth, thus increasing the positive output gap. In addition, to control the influence of fiscal policy, we include general government final expenditure as a control variable in the models.

Specifically referring to the variables used to describe financial development, their source is the International Monetary Fund (IMF) database. From the perspective of the indicators used to measure financial development, most empirical literature since the 1970s has assessed financial development using two measures of financial depth: the share of private credit in GDP and the share of stock market capitalization in GDP. Several studies (Pradhan *et al.*, 2014; Prochniak and Wasiak, 2017; Benczúr *et al.*, 2019; Afonso and Blanco-Arana, 2022) use both indicators to show that financial development promotes economic growth. Comparatively, some authors (Fajeau, 2021; Wen *et al.*, 2022) use only one indicator, namely the private credit/GDP ratio. Other authors (Arcand *et al.*, 2015) use the share of credit in GDP to determine the existence of a threshold above which financial development no longer has a positive effect on economic growth.

However, these authors used variables that did not fully address the complex and multidimensional nature of the financial sector. The diversity of financial systems worldwide reflects the need for multiple indicators to assess financial development comprehensively. To overcome the limitations of single indicators, the IMF created the Financial Development Index database proposed by Svirydzenka (2016). These indices capture the development level of financial institutions and markets in terms of depth, access, and efficiency. These are then summarized in a global index of institutional and market development, culminating in an overall financial development index. Although some authors (Purewal and Haini, 2022; Asteriou *et al.*, 2024) have already attempted to analyze the link between financial development and economic growth using certain financial development indicators provided by the IMF, to the best of our knowledge, no study employed the full set of available indicators to assess the impact of financial development in terms of depth, access, and efficiency, across both financial institutions and financial markets.

Table no. 1 – Description of variables

Variable name	Description	Source
	Dependent variables	
GDP growth rate (%)	Annual percentage growth rate of GDP at market prices based on constant local currency.	World Bank's World Development Indicators database
Output gap	Measured as the difference between actual GDP and potential GDP, expressed as a percentage of an economy's potential GDP.	AMECO database
	Financial Development Variables	
Financial Institutions Depth Index	Reflects the depth of financial institutions, calculated based on indicators such as: credit to the private sector/ GDP; pension fund assets/GDP; mutual fund assets/ GDP; and insurance premiums (life and non-life)/GDP	International Monetary Fund's Financial Development Index database
Financial Institutions Access Index	Measures the degree of access to financial institutions, determined by indicators such as: the number of bank branches per 100,000 adults and ATMs per 100,000 adults	
Financial Institutions Efficiency Index	Reflects the efficiency of financial institutions, calculated using indicators such as: the net interest margin, loan-deposit spread, non-interest income/total income, operating costs/total assets, return on assets, and return on equity	
Financial Institutions Index	Includes the Financial Institutions Depth Index, Financial Institutions Access Index, and Financial Institutions Efficiency Index	

Variable name	Description	Source
Financial Markets Depth Index	Reflects the depth of financial markets and was calculated using indicators such as: stock market capitalization/GDP, shares traded/GDP, international government debt securities/GDP, total debt securities of financial companies/GDP, and total debt securities of non-financial corporations/GDP	
Financial Markets Access Index	Measures the degree of access to financial markets and was determined by indicators such as the percentage of market capitalization outside the top 10 largest companies and the total number of debt issuers (domestic and international, non-financial and financial).	
Financial Markets Efficiency Index	Reflects the efficiency of financial markets and was calculated using indicators such as the turnover rate on the stock market (shares traded/capitalization).	
Financial Markets Index	Includes the Financial Markets Depth Index, Financial Markets Access Index, and Financial Markets Efficiency Index.	
Financial Development Index	Includes both the Financial Institutions Index and the Financial Markets Index	
	Control Variables	
Inflation Rate	Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole.	World Bank's World Development Indicators database
General Government Final Consumption Expenditure (% of GDP)	General government final consumption expenditure (formerly general government consumption) includes all government current expenditures for purchases of goods and services (including compensation of employees). It also includes most expenditures on national defense and security, but excludes government military expenditures that are part of government capital formation.	
Unemployment	Unemployment refers to the share of the labor force that is without work but available for and seeking employment.	

It is worth noting that economic growth is influenced not only by financial intermediation development but also by other factors. Therefore, in addition to the aforementioned determinants, the study also includes a set of control variables. From this perspective, we mention that a large number of specialized works (Beck *et al.*, 2000; Kuhry and Weill, 2010; Méon and Weill, 2010; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Arcand *et al.*, 2015; Creel *et al.*, 2015; Asteriou and Spanos, 2019; Raghutla and Chittedi, 2021; Afonso and Blanco-Arana, 2022) have used **inflation rate** as a determinant factor of economic growth.

Therefore, we assert that the majority of studies (Beck *et al.*, 2000; Kuhry and Weill, 2010; Méon and Weill, 2010; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Arcand *et al.*, 2015; Asteriou and Spanos, 2019; Asteriou *et al.*, 2024) have demonstrated a negative impact of inflation rate on economic growth, which, according to some authors (Kuhry and Weill, 2010), can be explained by the distortions induced by inflation, including the fact that high inflation limits available resources for profitable domestic investments. Despite this, there are also studies (Creel *et al.*, 2015; Raghutla and Chittedi, 2021; Afonso and Blanco-Arana, 2022) that have obtained results contrary to this theory, in other words, they found a positive impact of inflation on economic growth. An explanation for this phenomenon may be as follows: when the economy is not operating at its full capacity, meaning when the unemployment rate is quite high, inflation may theoretically favor increased production, so more money would lead to higher spending, which in turn increases the demand for goods and services. Therefore, increased demand would lead to a higher supply, thus higher productivity. This nexus is observed only when the inflation rate is at reasonable levels, meaning it is not excessively high. It is worth noting that Afonso and Blanco-Arana (2022) have demonstrated a negative influence of inflation in OECD countries, while in the EU(21) during the period 1990–2016, the impact is positive. Therefore, the impact of the inflation rate on economic growth cannot be precisely predicted, but we consider there is a higher probability of obtaining a positive effect.

Other authors (Okun, 1962; Ferreira, 2020; Afonso and Blanco-Arana, 2022) use the **unemployment rate** as a factor influencing economic growth. In this regard, we emphasize that all studies reflect a negative impact of the unemployment rate on economic growth. It is worth mentioning that Okun's law (1962) states that a 1% increase in unemployment is usually associated with a 2% decrease in GDP, which can be explained by the fact that economic growth cannot be achieved with a shrinking active workforce, thus a reduced production capacity.

Beck *et al.* (2000) argue that **government spending** also influences GDP growth rates. The same conclusion is reflected in other empirical studies (Méon and Weill, 2010; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Breitenlechner *et al.*, 2015; Prochniak and Wasiak, 2017; Wen *et al.*, 2022), which have shown a negative impact of government spending on GDP growth. This phenomenon is argued by the fact that higher taxes, required to cover a larger volume of public spending, inhibit investment initiatives, as well as by the fact that the government excludes suppliers and is less efficient than they are.

For the aforementioned reasons, in addition to the variables characterizing financial development, as illustrated in Table no. 1, our analysis also includes the unemployment rate, the inflation rate, and government consumption expenditures relative to GDP as control variables. Table no. 2 presents the descriptive statistics of the variables and Table no. A2 shows the correlation matrix.

Within the literature examining the link between financial development and economic growth, a wide range of estimation techniques is employed, including Fixed Effects OLS, the Generalized Method of Moments (GMM), Panel VAR, Barro regressions, the Panel Smooth Transition Regression (PSTR) model, and Threshold regression models. It is worth noting that in our research, the models will be estimated using the **System GMM** method (Blundell and Bond, 1998), a choice justified both by existing literature and by the specific characteristics of the dataset analyzed.

The GMM method is frequently applied in empirical studies that investigate the link between financial development and economic growth (Beck and Levine, 2004; Ferreira, 2020; Cheng *et al.*, 2021; Fajeau, 2021; Wen *et al.*, 2022), due to its ability to effectively address common challenges in panel data analysis, such as endogeneity, unobserved heterogeneity, and serial correlation, which often affect econometric models based on panel structures.

Table no. 2 – Summary statistics for the period (2000–2021)

Variable	Obs	Mean	Std. dev	Min	Max
Dependent variables					
GDP_growth	588	0.025	0.040	-0.160	0.246
Output gap	588	-0.005	0.036	-0.186	0.119
Independent variables					
Fin_inst_dep	588	0.494	0.258	0.042	1.000
Fin_inst_acc	588	0.647	0.218	0.062	1.000
Fin_inst_eff	588	0.575	0.076	0.300	0.830
Fin_inst	588	0.648	0.162	0.139	0.943
Fin_markt_dep	588	0.433	0.312	0.011	0.989
Fin_markt_acc	588	0.435	0.298	0.003	1.000
Fin_markt_eff	588	0.463	0.394	0.000	1.000
Fin_markt	588	0.449	0.265	0.018	0.950
Fin_dev	588	0.560	0.203	0.105	0.956
Control variables					
Gen_gov	588	0.199	0.029	0.117	0.278
Unempl	588	0.085	0.043	0.018	0.277
Infl	588	0.027	0.035	-0.099	0.432

Although the Difference GMM approach, initially proposed by Arellano and Bond (1991), represented a significant step forward in tackling these issues, it has certain limitations, particularly when dealing with variables that display high persistence over time or when working with panels that have a relatively small time dimension. In this context, the **System GMM** technique, later developed by Blundell and Bond (1998), offers additional advantages by simultaneously using the equations in levels and in first differences, thereby improving estimation efficiency and reducing specification bias.

Unlike classical methods such as fixed effects OLS regressions, which may yield biased estimates in the presence of explanatory variables correlated with the error term, the System GMM framework controls simultaneously for specification bias and variable persistence. Our application of System GMM does not explicitly instrument for reverse causality from growth to financial development. This modeling choice is directly influenced by prior causality analysis. Using the Dumitrescu and Hurlin (2012) test (results in Table no. A1), we find no evidence that economic growth drives financial development, while causality runs in the opposite direction.

Despite the various advantages System GMM holds over earlier GMM approaches, it remains seldom employed in the literature on the financial development -economic growth nexus, with a few recent exceptions (Fajeau, 2021; Asteriou *et al.*, 2024).

Therefore, the **baseline models** can be specified as follows:

$$Y_{it} = \beta_0 + \beta_1 * FIN_{DEV_{it}} + \beta 2 * X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (1)$$

where: Y is a proxy for economic growth (gdp growth or output gap); FIN_DEV reflects a matrix of financial development variables which includes nine financial development indices from the IMF Financial Development Index database; $\boldsymbol{X}i,t$ is a vector of country-specific characteristics that are found in the empirical literature to influence GDP growth, i.e., lagged dependent variable, inflation, unemployment rate and government spending; i represents the cross-sectional units (1, 2, ..., 28 countries); t represents the year within the time period 2000-2021; δi reflects the use of country fixed effects; γt are time fixed effects to capture aggregate time shocks; and εit represents the error term.

To test potential non-linearity between financial development and economic growth, we estimate an augmented specification that includes both the linear and the squared term of the financial development indicator. The **model** takes the following form:

$$Y_{it} = \beta_0 + \beta_1 * FIN_{DEV}{}_{it}^2 + \beta_2 * FIN_{DEV_{it}} + \beta 3 * X_{it} + \delta_i + \gamma_t + \varepsilon_{it} \qquad (2)$$

where: Y is a proxy for economic growth (gdp growth or output gap); FIN_DEV^2 is the squared term of financial development, introduced to capture potential non-linearities; FIN_DEV reflects a matrix of financial development variables which includes nine financial development indices from the IMF Financial Development Index database; $\boldsymbol{X}i,t$ is a vector of country-specific characteristics that are found in the empirical literature to influence GDP growth, i.e., lagged dependent variable, inflation, unemployment rate and government spending; i represents the cross-sectional units (1, 2, ..., 28 countries); t represents the year within the time period 2000-2021; δi reflects the use of country fixed effects; γt are time fixed effects to capture aggregate time shocks; and εit represents the error term.

The model specifications were designed to minimize potential multicollinearity arising from the hierarchical structure of financial development indicators, which comprises multiple levels, including composite indices, sub-indices, and more disaggregated sub-subindices. Accordingly, indicators from different hierarchical tiers are not jointly included in the same regression specification.

To manage statistical multicollinearity among conceptually related variables at the same hierarchical level, we consulted the correlation matrix (results in Table no. A2). For example, it revealed a strong positive association between the Financial Market Depth Index and the Financial Institutions Depth Index. Consequently, only one of these two depth measures was included in our regression model.

To limit the influence of extreme values and ensure comparability across variables, a winsorization procedure at the 1st and 99th percentiles was applied. Additionally, to address potential heteroskedasticity and autocorrelation in the residuals, robust standard errors were employed for the System GMM estimations, while bootstrap standard errors were applied in the case of the LSDVC estimator.

4. RESULTS AND DISCUSSION

Baseline model results

The results of our regression analysis, presented in Table no. 4, provide robust evidence that financial development significantly influences economic growth in the EU. The impact is statistically significant for the vast majority of our financial development indicators, except for the overall financial markets index, the squared value of the financial markets development index, and the depth index of financial institutions.

Our main result indicates **a nonlinear**, **U-shaped** relationship between financial development and economic growth in the EU. While the baseline linear specification indicates **a negative** effect of the Composite Financial Development Index (see Table no. 3), this initial finding becomes clearer when non-linearity is considered: the *linear term remains negative* while the *squared term is positive* and highly significant.

This dual influence suggests a nonlinear, U-shaped association: financial development has a detrimental impact at early stages but becomes beneficial once a critical institutional and functional maturity threshold is reached. The effect of financial development on GDP growth varies with its level, being negative initially and positive after a certain maturity point is confirmed. At the current development level, EU28 financial systems are not mature enough to generate beneficial economic outcomes. However, as financial development progresses, it may become supportive of growth.

The negative influence of the linear term can be attributed to the negative influence exerted by both the financial institutions development index and the financial markets development index, both sub-components of the composite indicator. Our findings align with those of other studies that have identified a negative effect of financial development under certain conditions, including analyses using IMF-derived indicators (An *et al.*, 2025) and alternative measures of financial development (Méon and Weill, 2010; Rousseau and Wachtel, 2011; Arcand *et al.*, 2015; Breitenlechner *et al.*, 2015; Prochniak and Wasiak, 2017; Ito and Kawai, 2018; Asteriou and Spanos, 2019; Cheng *et al.*, 2021; Wen *et al.*, 2022; Tariq *et al.*, 2023).

We interpret this negative correlation of the linear term as evidence of insufficient and inefficient financial development within the EU. A fragmented financial sector may create systemic distortions that stifle rather than foster growth. Several observed features of European financial architecture support this view. For instance, high private saving with low productive investment has contributed to the region's current account surplus, excessive reliance on bank debt rather than equity finance hampers innovation, as banks are ill suited for supporting long term, risk taking investments, and a banking sector whose capacity is constrained by low profitability and high costs. These structural deficiencies, highlighted in analyses such as *the report published by Draghi* (2024), suggest that without a more robust and diversified financial system, further development in its current form may continue to hinder economic growth.

Our findings are further confirmed by the analysis of the two main financial pillars: institutions and markets, reveals a clear asymmetry in their nonlinear effects on economic growth. The squared financial institutions development index has a positive and statistically significant effect on growth. In contrast, the squared financial markets index has a positive but not significant effect. Our results are in line with Asteriou *et al.* (2024), who find a nonlinear nexus for financial institutions but a linear one for capital markets. In the linear specifications for both financial institutions and markets (Table no. 3), their respective indices retain a negative effect on growth, indicating that early financial development may be harmful. For financial institutions, however, once maturity and efficiency are achieved, their influence becomes positive and significant.

The negative influence of financial markets is attenuated by a stronger, significant negative effect from financial institutions, underscoring the EU's bank-centric financial structure, where bank intermediation dominates over capital market development. When used separately, both financial institutions and financial markets development indicators also show significant negative impacts on growth. Our findings align with those of other studies (Botev *et al.*, 2019; Ferreira, 2020; Tariq *et al.*, 2023; An *et al.*, 2025).

Table no. 3 – Baseline Model Results

Dependent: GDP_ growth	I	II	(1) III	IV	V	VI	(2) VII	VIII
Fin_dev	**-0.0205***** (0.0042)					**-0.1155***** (0.0356)		
Fin_dev_squared						**0.0883***** (0.0306)		
Fin_inst		-0.0228** (0.0092)	-0.0269*** (0.0064)				-0.1013** (0.0513)	
Fin_inst_squared							0.0639* (0.0382)	
Fin_markt		-0.0038 (0.0053)		-0.0127*** (0.0033)				-0.0279** (0.0123)
Fin_markt_squared								0.0180 (0.0139)
Fin_inst_acc					-0.0093* (0.0048)			
Fin_inst_dep					-0.0025 (0.0059)			
Fin_inst_eff					0.0574*** (0.0091)			
Fin_markt_acc					0.0071* (0.0042)			
Fin_markt_eff					-0.0148*** (0.0038)			
Infl	0.0018 (0.0264)	-0.0003 (0.0308)	-0.0002 (0.0331)	0.0206 (0.0280)	0.1621*** (0.0460)	-0.0248 (0.0424)	0.0701** (0.0289)	0.0055 (0.0323)
Gen_gov	-0.1605*** (0.0277)	-0.1402*** (0.0327)	-0.1391*** (0.0319)	-0.1870*** (0.0257)		-0.0794 (0.0495)	-0.1407** (0.0636)	-0.1782*** (0.0297)
Unempl	-0.0271 (0.0202)	-0.0296 (0.0224)	-0.0236 (0.0229)	-0.0238 (0.0197)		-0.0198 (0.0209)	-0.0267 (0.0310)	-0.0262 (0.0197)
Dependent (t-1)	0.4990*** (0.0707)	0.5248*** (0.1004)	0.5373*** (0.0791)	0.4731*** (0.0756)	0.2959*** (0.0963)	0.5813*** (0.0932)	0.4140*** (0.0940)	0.4930*** (0.0799)
Constant							0.0165 (0.0223)	
Observations	588	588	588	588	588	588	588	588
Countries	28	28	28	28	28	28	28	28
AR (1) test (p-value)	0.001	0.001	0.001	0.000	0.000	0.001	0.000	0.000
AR (2) test (p-value)	0.080	0.086	0.094	0.077	0.086	0.111	0.058	0.077
Hansen J statistic (p-value)	0.640	0.325	0.253	0.822	0.753	0.103	0.572	0.671
Instruments	27	28	27	27	28	28	28	28
CountryFE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the estimation results for the baseline models described in Equation (1) and Equation (2). Robust standard errors are reported in parentheses. *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level.

Source: authors calculation

A granular examination of the sub-components reveals clear evidence of these structural weaknesses: the financial institutions' efficiency index and the financial markets' access index positively affect GDP growth, while the access and depth indices for institutions, and the efficiency index for markets, exhibit negative impacts. These negative effects reflect low structural development. Limited institutional depth and inefficient markets indicate an immature financial system that is unable to allocate resources to productive investments. This observation is supported by the sub-indices' mean values (see Table no. 2), which lie below the mean measurement threshold, confirming insufficient financial development in the sample.

Notably, the lagged dependent variable (GDP growth at t–1) shows a consistently positive and statistically significant effect across all models, highlighting the models' dynamic nature and the persistence of growth over time. A result supported by other authors (Fajeau, 2021; Purewal and Haini, 2022; Asteriou *et al.*, 2024).

Regarding the control variables, our results suggest that inflation rate predominantly has a positive impact on economic growth, though the direction varies slightly between models, aligning with literature (Creel *et al.*, 2015; Raghutla and Chittedi, 2021; Afonso and Blanco-Arana, 2022). One possible explanation is that in economies operating below potential with relatively high unemployment, moderate inflation can stimulate aggregate output; increased money supply may boost consumption and investment, raising demand and output. However, this effect holds only at moderate inflation levels, as extreme inflation may be destabilizing. In our sample, inflation rates fall within reasonable ranges. For the control variable "unemployment rate", all regression models demonstrate a negative impact on GDP growth, consistent with Okun's (1962) law and subsequent studies (Ferreira, 2020; Afonso and Blanco-Arana, 2022).

The ratio of government final consumption expenditure to GDP shows a significant negative impact (at the 1% level, with some exceptions) on economic growth across all models, in line with other studies (Beck *et al.*, 2000; Kuhry and Weill, 2010; Méon and Weill, 2010; Hassan *et al.*, 2011; Pradhan *et al.*, 2014; Breitenlechner *et al.*, 2015; Prochniak and Wasiak, 2017; Diaconașu *et al.*, 2019; Čižo *et al.*, 2020; Wen *et al.*, 2022; An *et al.*, 2025). This effect likely reflects how higher public spending, funded through taxes, can suppress private investment, and governments, being less efficient, may crowd out private providers.

The validity of the estimates is supported by diagnostic tests: the AR(2) test confirms absence of second-order autocorrelation, while the Hansen J test supports the validity of the instruments used, all p-values fall within acceptable econometric thresholds.

Robustness Tests

To test the robustness of the results obtained, we used the output gap as the dependent variable, serving as a proxy for economic growth. The results (Table no. 4) broadly validate our core conclusions but introduce important nuances regarding linear effects and market channels. According to the estimates, financial development continues to exert a negative effect on economic performance, consistent with previous findings obtained when the GDP growth rate was used as the dependent variable. However, a key difference emerges. The coefficient of the linear term is not statistically significant in this specification. This result suggests that at lower levels of financial development, its impact on the output gap is limited or ambiguous. In such contexts, the financial sector may still be underdeveloped, inefficient, or poorly regulated, which restricts its capacity to support effective resource allocation and stabilize economic fluctuations. As a result, financial development does not significantly contribute to closing the gap between actual and potential output, nor does it consistently prevent economic underperformance or overheating.

Nevertheless, our robustness results confirm a central similarity: the persistence of a nonlinear link. The squared term of the financial development index is positive and significant, while the linear relationship remains negative but statistically insignificant (Table no. 4). These results are consistent with the conclusions drawn in the baseline analysis, supporting the existence of a U-shaped nonlinear correlation between financial development and economic growth.

Table no. 4 – Robustness Analysis Results: Different Dependent Variable

Dependent:			**(1)**				**(2)**	
Output_ gap	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Fin_dev	**-0.0112**					**-0.1060*****		
	(0.0101)					(0.0406)		
Fin_dev_squared						**0.0891****		
						(0.0451)		
Fin_inst		-0.0325***	-0.0228***				-0.1417***	
		(0.0085)	(0.0085)				(0.0352)	
Fin_inst_squared							0.1022***	
							(0.0339)	
Fin_markt		0.0099		-0.0023				-0.0248
		(0.0077)		(0.0075)				(0.0256)
Fin_markt_squared								0.0257
								(0.0350)
Fin_inst_acc					-0.0191***			
					(0.0069)			
Fin_inst_dep					-0.0009			
					(0.0073)			
Fin_inst_eff					-0.0639***			
					(0.0134)			
Fin_markt_acc					-0.0030			
					(0.0048)			
Fin_markt_eff					-0.0016			
					(0.0039)			
Infl	-0.0344	-0.0128	-0.0376	-0.0143	0.0349	-0.0236	0.0132	-0.0190
	(0.0964)	(0.0953)	(0.0816)	(0.1028)	(0.0886)	(0.0993)	(0.0893)	(0.1026)
Gen_gov	-0.0700	-0.1528***	-0.1526***	-0.2121***		-0.1110*	-0.0579	-0.1975***
	(0.0541)	(0.0472)	(0.0436)	(0.0455)		(0.0633)	(0.0525)	(0.0545)
Unempl	-0.0578	-0.0577	-0.0632*	-0.0524		-0.0532	-0.0320	-0.0556
	(0.0428)	(0.0415)	(0.0376)	(0.0385)		(0.0440)	(0.0383)	(0.0438)
Dependent (t-1)	0.9268***	0.9285***	0.9281***	0.9260***	0.9355***	0.9279***	0.9291***	0.9268***
	(0.0051)	(0.0046)	(0.0047)	(0.0051)	(0.0033)	(0.0046)	(0.0040)	(0.0050)
Observations	587	587	587	587	587	587	587	587
Countries	28	28	28	28	28	28	28	28
AR (1) test (p-value)	0.314	0.314	0.314	0.314	0.313	0.314	0.314	0.314
AR (2) test (p-value)	0.324	0.324	0.324	0.324	0.325	0.324	0.324	0.324
Hansen J statistic(p-value)	0.269	0.272	0.271	0.270	0.270	0.264	0.271	0.262
Instruments	26	27	26	26	28	27	27	27
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the estimation results for the robustness checks using an alternative dependent variable in Equation (1) and Equation (2). Robust standard errors are reported in parentheses. *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level.

Source: authors calculation

A further difference highlighted by the robustness check concerns the role of financial markets. While the core findings are confirmed, the indicators reflecting financial market development lose their statistical significance in explaining the output gap. This lack of significance might be explained by the fact that the financial markets in the EU28 countries analyzed are underdeveloped or fragmented, such that their effects on cyclical performance (as measured by the output gap) may be weak or delayed. This fact reduces the effectiveness of market signal transmission mechanisms to the real economy and diminishes the potential impact of these markets on the deviation of output from its potential level (output gap). Moreover, as mentioned by Furlanetto *et al.* (2021), financial frictions, such as transaction costs, asymmetric information, and credit constraints, limit the ability of monetary policy to fully stabilize the output gap, making some fluctuations unavoidable and causing the effects of financial development on cyclical economic performance to manifest weakly or with delay.

Thus, the lack of statistical significance for the financial markets development index, compared to the significance of the financial institutions development index, reflects a structural imbalance (also confirmed by the baseline model analysis) between the two financial intermediation channels, exacerbated by market fragmentation and excessive reliance on the banking sector.

To further assess the robustness of our results, we employed a different estimation technique: the Bias-Corrected Least Squares Dummy Variable (LSDVC) estimator for dynamic panel models. We made this choice due to concerns about potential over instrumentation in GMM estimates, even when the number of instruments is formally within acceptable limits. Over instrumentation can lead to efficiency losses and biased estimators. Thus, applying the LSDVC method provides an additional robustness check.

The results obtained from applying LSDVC confirm the robustness of the results obtained in the baseline analysis. In addition, they confirm the consistency of the GMM system estimates, using a method that is less sensitive to specification and instrumentation issues, which increases confidence in the robustness and credibility of our conclusions.

Table no. 5 presents the robustness check results obtained using the Bias-Corrected Least Squares Dummy Variable (LSDVC) estimator, initialized via System GMM. The findings confirm the previously identified patterns, notably the persistent and statistically significant negative impact of financial development on economic performance. The key similarities are confirmed: the linear component of the financial development index continues to point to a negative effect, while the squared term indicates a positive effect. Therefore, the U-shaped relationship is robustly validated.

Our results reconfirm the conclusion from the main analysis that the current level of financial development remains insufficient to effectively support economic growth. Despite this fact, the growing significance of the squared term suggests that once a higher level of development is reached, financial systems may act as growth catalysts. Still, the variables capturing financial market development remain statistically insignificant under LSDVC, reinforcing the idea that, unlike financial institutions, financial markets are not yet functioning as effective channels for fostering economic growth in the EU context.

Table no. 5 – Robustness Analysis Results: Alternative Estimation Instrument (“Bias-corrected LSDV Dynamic Panel Data Estimator”)

Dependent:			(1)				(2)	
GDP_growth	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Fin_dev	**-0.0451**** (0.0186)					**-0.1653***** (0.0596)		
Fin_dev_squared						**0.1138**** (0.0563)		
Fin_inst		-0.0546*** (0.0164)	-0.0527*** (0.0167)				-0.1704** (0.0690)	
Fin_inst_squared							0.0967* (0.0561)	
Fin_markt		-0.0020 (0.0124)		0.0022 (0.0127)				0.0113 (0.0412)
Fin_markt_squared								-0.0105 (0.0452)
Fin_inst_acc					-0.0330*** (0.0097)			
Fin_inst_dep					-0.0160 (0.0174)			
Fin_inst_eff					0.0362** (0.0178)			
Fin_markt_acc					0.0021 (0.0102)			
Fin_markt_eff					0.0032 (0.0078)			
Infl	0.1615*** (0.0566)	0.1552*** (0.0576)	0.1538*** (0.0578)	0.1696*** (0.0556)	0.1424*** (0.0523)	0.1528*** (0.0556)	0.1428** (0.0564)	0.1675*** (0.0568)
Gen_gov	-0.4004*** (0.1076)	-0.3893*** (0.1087)	-0.3880*** (0.1090)	-0.4149*** (0.1083)		-0.4210*** (0.1065)	-0.4192*** (0.1103)	-0.4150*** (0.1090)
Unempl	-0.0106 (0.0357)	-0.0410 (0.0399)	-0.0416 (0.0398)	0.0072 (0.0347)		-0.0228 (0.0356)	-0.0470 (0.0389)	0.0071 (0.0349)
Dependent (t-1)	0.3216*** (0.0366)	0.3069*** (0.0359)	0.3075*** (0.0358)	0.3281*** (0.0370)	0.3454*** (0.0364)	0.3200*** (0.0373)	0.3092*** (0.0368)	0.3286*** (0.0366)
Countries	28	28	28	28	28	28	28	28
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

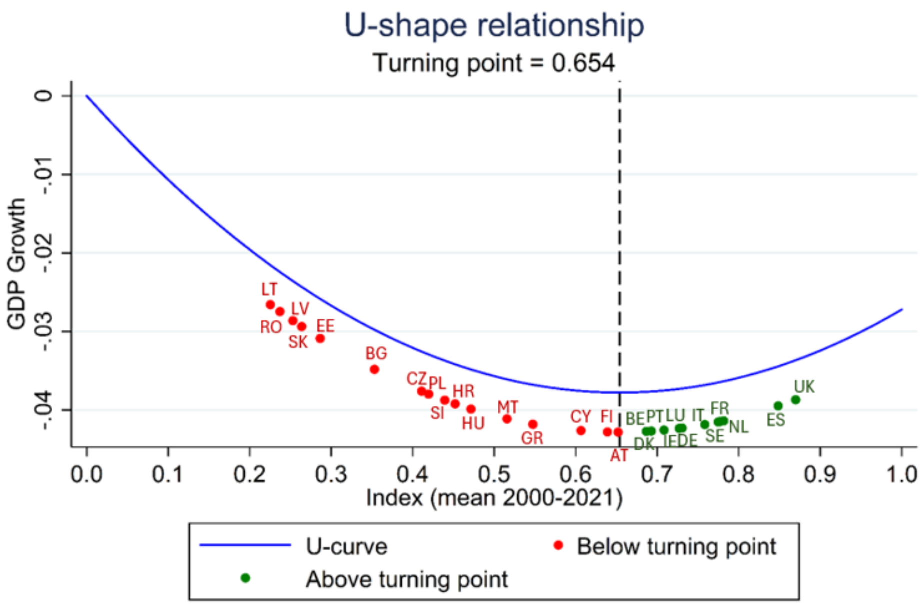
Note: This table presents the results of the robustness checks obtained by using an alternative estimator (“Bias-corrected LSDV dynamic panel data estimator”) for the estimation of Equations (1) and (2). Bootstrap errors are reported in parentheses. *** Statistically significant at the 1% level. ** Statistically significant at the 5% level. * Statistically significant at the 10% level.

Source: authors calculation

Turning Point Analysis

To further investigate the U-shaped relationship between financial development and economic growth, we calculate the turning point based on the estimated coefficients from the baseline model. The turning point is estimated at 0.654, falling within the normalized range of the financial development index [0, 1]. Notably, this value exceeds the sample mean of the financial development index (0.560) reported in Table no. 2, suggesting that the majority of EU countries have not yet reached the threshold beyond which financial development begins to generate beneficial economic outcomes, thus confirming the general conclusion that financial systems in most EU economies are not yet sufficiently mature.

Figure no. 1 illustrates the U-shaped relationship and the position of each EU country relative to the turning point. The results reveal that 16 out of 28 countries analyzed have not yet reached the turning point, being located on the negative side of the curve. These include predominantly new EU member states that joined the Union in 2004 or after, such as Lithuania, Romania, Latvia, Slovakia, Estonia, Bulgaria, Czechia, Poland, Slovenia, Croatia, Hungary, Malta, and Cyprus, but also several older member states, namely Greece, Finland, and Austria. For these economies, the current level of financial development still exerts a negative effect on economic growth, suggesting that financial systems in these countries may not yet be sufficiently mature to generate beneficial economic outcomes. Notably, on the downward slope of the curve, the dispersion across countries is more pronounced, with countries spread across a wide range of index values, reflecting considerable heterogeneity in the level of financial development among economies that have not yet reached the turning point.



Note: Predicted values are calculated based on the estimated coefficients from the baseline model, holding all control variables constant at their sample means for the 2000-2021 period. Red points represent countries positioned below the turning point (downward slope); green points represent countries that have surpassed the turning point (upward slope). Country abbreviations: AT (Austria), BE (Belgium), BG (Bulgaria), CY (Cyprus), CZ (Czechia), DE (Germany), DK (Denmark), EE (Estonia), ES (Spain), FI (Finland), FR (France), GR (Greece), HR (Croatia), HU (Hungary), IE (Ireland), IT (Italy), LT (Lithuania), LU (Luxembourg), LV (Latvia), MT (Malta), NL (Netherlands), PL (Poland), PT (Portugal), RO (Romania), SE (Sweden), SI (Slovenia), SK (Slovakia), UK (United Kingdom).

Source: Authors' own estimations

Figure no. 1 – U-shaped relationship and position of EU countries relative to the turning point of the financial development-growth nexus (2000-2021)

In contrast, 12 countries have surpassed the turning point and are positioned on the positive side of the curve, where further financial development contributes positively to economic growth, including Germany, France, the Netherlands, Belgium, Denmark, Sweden, Luxembourg, Ireland, Portugal, Italy, Spain, and the United Kingdom. These are exclusively older EU member states, suggesting that more established economies tend to exhibit higher levels of financial development. On the upward slope, the vast majority of countries are clustered in close proximity to the threshold, with the notable exceptions of Spain and the United Kingdom, which exhibit considerably higher levels of financial development. This suggests that even for many economies on the upward slope, the transition toward achieving substantial positive effects from financial development is still in its early stages.

Overall, the turning point analysis reveals that the majority of EU countries have not yet reached the threshold level of financial development required to generate positive effects on economic growth.

5. CONCLUSION

Our research shows that most independent variables reflecting financial development have a statistically significant impact on GDP growth. Despite this fact, the financial market index, the squared financial market development index, and the financial institutions' depth index are exceptions. Our results highlight the impact of financial development on economic growth and underscore the relevance of this relationship in the EU context. The general financial development index shows **a negative impact on GDP growth, indicating an inverse relationship**. This may be due to the insufficient level of financial development among EU member states, where a weak and fragmented financial sector hinders growth rather than promoting it. Our interpretation of an underdeveloped system aligns with the structural diagnosis of European financial deficiencies presented in policy documents, such as *the report published by Draghi* (2024).

A key insight from our analysis is the presence of a **U-shaped nonlinear link** between financial development and economic growth. The linear component of the financial development index has a significant negative effect, while the squared term has a significant positive effect, suggesting that financial development initially hinders growth but becomes a catalyst once a critical level of institutional and functional maturity is reached. Our robustness analysis confirms this pattern, thus financial institutions exert a stronger impact on growth than financial markets, reflecting the institutional channel's central role in financial intermediation in the EU.

The results of our paper can serve as a **solid starting point for designing policies** aimed at effectively stimulating financial development, while also strengthening the capacity of financial markets and institutions to mobilize resources in support of sustainable economic growth. For instance, the estimated U-shaped relationship indicates that the growth effects of financial development depend on its level. This suggests that EU-level reforms aimed at advancing financial development may yield growth benefits primarily once higher levels of financial development are attained.

Furthermore, looking more closely at the underlying mechanisms, the analysis highlights several operational priorities. While the efficiency of financial institutions (captured by indicators such as net interest margins, operating costs, and return on assets) has a positive impact on growth, the measures of financial institutions depth, such as private credit and pension fund assets relative to GDP, show no comparable effect.

This finding offers a clear policy message: EU financial reforms should move away from simply expanding bank balance sheets and instead focus on improving efficiency within the sector. Such reforms include fostering greater competition to reduce interest margins and spreads, lowering operational costs in banking, and enhancing profitability through better risk-adjusted returns.

Additionally, the finding that nonlinear, threshold effects are strong for institutions but weak for markets reinforces the idea of a strategic sequence for integration. Completing the Banking Union through a common deposit insurance scheme and harmonized supervision is a direct institutional reform that can improve efficiency and stability. This reform should be prioritized over pushing for deep capital market integration in an environment that is still fragmented and may lack the foundational depth and efficiency of markets.

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ANNEX

Table no. A1 – Results of Dumitrescu and Hurlin (2012) Panel Granger Causality Test

Null Hypothesis	W-Stat	Zbar (tilde)	Prob (p-value)
Economic growth does not Granger-cause financial development	1.19	0.21	0.830
Financial development does not Granger-cause economic growth	2.20	3.20	0.001

Table no. A2 – Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1)Fin_dev	1.000											
(2)Fin_inst	0.887*	1.000										
(3)Fin_markt	0.960*	0.723*	1.000									
(4)Fin_inst_acc	0.453*	0.680*	0.265*	1.000								
(5)Fin_inst_dep	0.856*	0.825*	0.782*	0.164*	1.000							
(6)Fin_inst_eff	0.212*	0.237*	0.174*	-0.094*	0.243*	1.000						
(7)Fin_markt_acc	0.607*	0.500*	0.606*	0.310*	0.477*	-0.091*	1.000					
(8)Fin_markt_dep	0.942*	0.805*	0.923*	0.318*	0.843*	0.237*	0.476*	1.000				
(9)Fin_markt_eff	0.686*	0.393*	0.789*	0.028	0.499*	0.215*	0.078*	0.652*	1.000			
(10)Infl	-0.369*	-0.344*	-0.341*	-0.203*	-0.345*	0.029	-0.229*	-0.331*	-0.237*	1.000		
(11)Gen_gov	0.312*	0.221*	0.332*	-0.193*	0.428*	0.290*	-0.104*	0.377*	0.426*	-0.260*	1.000	
(12)Unempl	-0.179*	-0.226*	-0.133*	0.046	-0.295*	-0.350*	-0.145*	-0.127*	-0.051	-0.208*	0.023	1.000

Note: The table presents the correlation matrix of the winsorized independent variables. * indicates statistical significance at the 10% level.