Romanian Academy
"Costin C. Kirițescu" National Institute for Economic Research
"Victor Slăvescu" Centre for Financial and Monetary Research

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AND MONETARY RESEARCH

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EXPLORING THE LINK BETWEEN FINANCIAL KNOWLEDGE, RISK AVERSION, AND INVESTMENT PREFERENCES: A EUROPEAN UNION ANALYSIS

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Abstract

This paper examines the relationships between financial knowledge, risk profiles, digital competence, investment preferences, and financial behaviour across EU countries. Using data from the Flash Eurobarometer 525 survey conducted in 2023, the study distinguishes between self-assessed and tested financial literacy and constructs country-level indicators of short- and long-term risk profiles, digital skills, and financial product participation. The analysis reveals a systematic pattern of underconfidence, with individuals underestimating their actual financial knowledge. Tested financial literacy is strongly associated with higher risk tolerance and engagement in long-term financial products, including housing loans, insurance, and retirement investments, while self-assessed literacy shows a weaker and less consistent link to actual risk-taking. This finding underscores the importance of objective knowledge over confidence alone in shaping financial decisions. Short- and long-term risk profiles emerge as central determinants of financial behaviour, with long-term risk aversion most strongly associated with engagement in protective and long-horizon financial products such as pensions and insurance, while short-term risk aversion (financial fragility) tracks borrowing and investment behaviour through a "gambling for resurrection" dynamic. Results suggest that improving financial behaviour requires more than increasing financial knowledge.

Keywords: risk profiles, financial literacy, financial fragility, cross-country heterogeneity, behavioural finance

JEL Classification: G40, D53, F65, G53, D81

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1. Introduction

In a time marked by rapid financial innovation, heightened economic uncertainty, and expanding digital access, individual financial decision-making has become increasingly complex. Citizens across the European Union are navigating a growing array of financial products, services, and platforms, often with varying levels of understanding and confidence. As responsibility for long-term financial planning shifts from public to private domains, the ability to make sound financial decisions, particularly those involving risk, has become an essential component of economic security and personal well-being.

Financial literacy has emerged as a key determinant of individual financial behaviour. While tested financial knowledge provides insight into individuals' ability to understand core financial concepts, self-assessed financial literacy reflects perceived competence and confidence, factors that also influence financial choices. Research indicates that a divergence between perceived and actual knowledge, particularly when confidence exceeds competence, can contribute to suboptimal behaviours such as excessive risk-taking or limited information-seeking (Asaad, 2015). Alongside financial literacy, individual risk preferences, both short-term and long-term, affect the way people approach uncertainty, allocate assets, and make investment decisions.

Moreover, digital skills are playing an increasingly central role in enabling individuals to access, understand, and act on financial information. In parallel, trust in financial advice, whether from professionals or digital platforms, also conditions how people manage financial decisions. Investment preferences, in this context, emerge as behavioural outcomes that reflect not only knowledge and risk profiles but also confidence in external sources of guidance and familiarity with digital tools.

Within this evolving context, the European Union presents a particularly rich terrain for analysis. EU Member States differ significantly in terms of financial education systems, income distribution, digital infrastructure, and financial culture. These variations provide a unique opportunity to examine how financial knowledge and confidence, attitudes toward risk, and investment behaviour manifest across diverse national and demographic contexts. While there is substantial evidence linking financial literacy to improved financial outcomes (Lusardi & Mitchell, 2014), the extent to which it shapes individuals' risk preferences and investment choices remains an open question, particularly when financial literacy is assessed alongside other factors such as digital competence and trust in financial advice.

This study investigates the relationships between these variables self-assessed and tested financial literacy, long-term and short-term risk aversion, digital skills, investment preferences, and trust in financial advice, using data from Flash Eurobarometer 525. By employing statistical techniques such as regression analysis, the research aims to uncover patterns and associations that help explain the formation of risk profiles and investment behaviour across EU Member States.

In doing so, this study uniquely contributes to the growing body of literature on financial behaviour by offering a multidimensional perspective on financial decision-making in the EU. It offers practical implications for financial education and inclusion policies, highlighting the importance of addressing not only knowledge gaps but also confidence, digital competence, and trust in professional guidance.

2. Literature Review

Understanding how financial knowledge influences individual risk profiles (as well as investment preferences) has become a central theme in behavioural finance and financial education. A substantial body of research underscores the importance of financial literacy in shaping individuals' financial decisions, long-term planning, and overall economic resilience (Lusardi & Mitchell, 2014). Individuals who demonstrate greater financial knowledge are more likely to engage in prudent financial behaviour, such as retirement planning, portfolio diversification, and avoiding high-cost credit products (Van Rooij, Lusardi, & Alessie, 2011). In contrast, limited financial literacy has been repeatedly linked to unfavourable financial outcomes, including low savings, excessive debt, and increased susceptibility to financial fragility (Lusardi, 2015).

Risk tolerance, a key dimension of individual financial behaviour, has been found to be strongly influenced by both objective and subjective financial knowledge. Several studies have shown that individuals with higher financial knowledge tend to exhibit greater risk tolerance and a stronger inclination toward long-term investment strategies (Van Rooij, Lusardi, & Alessie, 2011). This relationship may stem from a more accurate understanding of financial instruments and market mechanisms, which reduces ambiguity and increases confidence in decision-making (Hastings, Madrian, & Skimmyhorn, 2013). Moreover, the role of financial confidence, closely linked to self-perceived knowledge, has been increasingly examined as a mediating factor in financial behaviour. For instance, Allgood and Walstad (2016) differentiate between self-assessed and tested financial knowledge, noting that overconfidence can lead individuals to make riskier investment choices without fully understanding the associated implications. This distinction is crucial, as misalignment between perceived and actual knowledge may result in suboptimal financial behaviours.

Demographic characteristics such as age, gender, income, and education level also interact with financial knowledge and risk preferences. Empirical evidence suggests that men tend to report higher levels of financial confidence and risk tolerance than women (Bucher-Koenen et al., 2017). Younger individuals, while often more risk-tolerant, may lack the necessary financial experience or knowledge to make informed investment decisions (OECD, 2020). Income and educational attainment are consistently correlated with both financial literacy and a greater willingness to invest in diversified, higher-yield assets (Behrman et al., 2012).

Investment preferences further reflect the combined effects of knowledge and risk profile. Research indicates that individuals with higher financial literacy are more likely to favour equity investments, retirement accounts, and long-term financial products, while those with lower literacy often prefer guaranteed or low-risk instruments (Van Rooij et al., 2011; Clark et al., 2017). The tendency to avoid riskier financial products among the less financially literate may not necessarily stem from true risk aversion, but rather from a lack of understanding or exposure to such instruments.

Cross-national studies within the European Union reveal significant heterogeneity in financial knowledge and behaviour. According to the Flash Eurobarometer 525 (2023) published by the European Commission, disparities persist across Member States in terms of access to financial education, levels of digital financial engagement, and trust in financial institutions. These contextual differences influence how financial knowledge translates into risk-taking and investment behaviour. For instance, Grable and Lytton (1999) conducted a statistical segmentation of individuals using cluster analysis, grouping them based on varying levels of risk tolerance and socio-economic attributes such as education, income, and financial awareness. Likewise, research by Gilliam et al. (2010) applied a similar methodological approach to identify distinct types of investors, linking their risk attitudes and financial planning behaviours to factors like financial literacy and demographic background. These studies collectively emphasise how personal and societal factors shape how individuals approach financial risk. More recently, Demertzis et al. (2024), drawing on the same Flash Eurobarometer 525 instrument exploited in this study, provide the first harmonised comparative assessment of financial knowledge across the EU-27 and identify pronounced cross-country variation in objective competence, with Northern European Member States consistently outperforming Southern and Central-Eastern peers.

While these contributions establish the cross-country distribution of financial knowledge and partially illuminate its behavioural correlates, they typically examine each construct in isolation. The joint mapping of tested literacy, self-assessment, dual-horizon risk profiles, digital competence, trust in advice, and product participation, conducted on a single harmonised pan-European dataset, remains absent from the literature.

Other determinants, such as digital skills and financial fragility, have also been shown to shape individuals' risk aversion. Evidence from studies such as the National Endowment for Financial Education (2017) indicates that financial fragility, characterised by insufficient assets, high levels of debt, and limited financial literacy, impairs individuals' capacity to cope with unforeseen financial shocks. Moreover, the study underscores the critical role of education in shaping financial decisions and draws attention to significant disparities in financial knowledge across various demographic segments. Furthermore, Lusardi (2019) finds that digital financial literacy, the ability to use online tools to manage finances, does not substitute for actual financial literacy. The author highlights findings on Millennials from the US, showing that individuals who rely on mobile payments are more likely to engage in financially costly behaviours, such as spending more than they earn, utilising non-traditional financial services, and sometimes overdrafting their bank accounts. Moreover, the same group tends to demonstrate lower levels of actual financial literacy (Lusardi, de Bassa Scheresberg, & Avery, 2018).

In summary, the aforementioned literature demonstrates a robust connection between financial knowledge, risk tolerance, and investment preferences. Yet a significant gap persists: no study has simultaneously examined, at the comparative EU-27 country level, the joint associations between self-assessed and tested financial literacy, short- and long-term risk aversion, digital skills, trust in financial advice, and actual investment product participation, using a single harmonised pan-European dataset. Flash Eurobarometer 525 (2023) - the first survey to provide fully comparable financial literacy data across all EU Member States - uniquely enables this analysis. The present study addresses this gap directly.

Three research objectives structure the inquiry. First: to characterise cross-national heterogeneity in financial knowledge (self-assessed and tested), risk profiles (short- and long-term), digital skills, and investment product participation across EU Member States. Second: to assess whether tested financial literacy is more strongly associated with risk-taking and investment engagement than self-assessed literacy. Third: to examine how short- and long-term risk aversion relate differentially to distinct categories of financial product ownership. Correspondingly, three directional hypotheses are advanced: H1 - tested financial literacy exhibits a stronger positive association with long-term investment product adoption than self-assessed literacy; H2 - short-term risk aversion is more strongly associated with everyday financial decisions, while long-term risk aversion is more closely linked to long-horizon products such as pensions and mortgages; H3 - digital literacy positively moderates engagement with investment and online financial products across EU countries.

3. Research methodology

3.1. Data source and description

This research is based on data from the Eurobarometer survey, specifically the "Monitoring the Level of Financial Literacy FL525" dataset, published by the Directorate-General for Communication of the European Commission. Updated in July 2023, this dataset offers a detailed evaluation of financial literacy across EU Member States, as well as the questionnaire used to collect the data, covering aspects such as financial behaviour, investment preferences, formal education, digital competencies, and trust in advice, and many more. With a sample of 26,139 respondents, the survey provides a comprehensive overview of financial literacy trends within the European population.

3.2. Variables

To examine the relationship between financial knowledge (self-perceived and tested), risk profiles (short-term and long-term), trust in advice, digital skills, and investment preferences across EU countries, a standardised data-processing procedure was employed. Survey responses were coded on scales ranging from 1 to 5 or 1 to 4, depending on the variable, and country-level weighted averages were subsequently calculated.

Question 8 from the Flash Eurobarometer survey, used as a proxy for short-term risk aversion, captures financial fragility by asking: "*If you lost your main source of income today, how long could you continue to cover your living expenses without borrowing money or moving house?*"

The response options were as follows:

- I don't have emergency savings
- At least 1 week, but less than 1 month
- At least 1 month, but not 3 months
- At least 3 months, but not 6 months
- 6 months or more
- Don't know / Prefer not to answer

Respondents were categorised according to their self-reported ability to absorb income shocks, interpreted as an indicator of financial risk tolerance. Each response was assigned a numerical value, with 5 representing the highest level of risk tolerance ("I don't have emergency savings") and 1 indicating the most risk-averse position ("6 months or more"). We utilised financial fragility as a proxy for risk profiles because it is often used in scholarly research as an indirect measure of risk aversion, reflecting the susceptibility of individuals or households to unexpected financial disruptions and how this influences their approach to risk. According to behavioural finance theories, such as those proposed by Kahneman & Tversky (1979), individuals facing financial instability, marked by insufficient savings, significant debt, or a lack of financial safety nets, may be more inclined to take financial risks, contrary to what traditional models of risk aversion would predict. This behaviour is frequently explained by the "gambling for resurrection" hypothesis, first introduced by Downs and Rocke (1995), which suggests that people experiencing financial hardship may pursue high-risk decisions in an attempt to improve their economic situation. Moreover, limited financial knowledge and restricted economic resources can impair sound judgment regarding risk, increasing the likelihood of engaging in speculative or high-risk financial activities. In a more recent study, Lusardi et al. (2011) assessed the ability of households to handle financial emergencies and found that many American households would struggle to raise $2,000 within a month. This inability signals widespread financial fragility, which the authors link to both reduced risk tolerance and lower levels of financial literacy. These values were used to compute national-level average risk scores, enabling cross-country comparisons of financial vulnerability and risk aversion. Responses marked as "Don't know / Prefer not to answer" were excluded from the analysis to ensure the robustness and validity of the resulting indices. Following data processing, an average risk coefficient was calculated for each EU Member State, based on which statistical analyses were performed.

The same methodological approach was applied to all other variables, except for question 9, as follows:

- For long-term risk aversion (Q10), the question used is "Overall, how confident are you that you will have enough money to live comfortably throughout your retirement years?" Answers ranged from *"Very confident",* scored with 1, to *"Not at all confident",* scored with 4.
- To gauge self-perceived financial literacy (Q1), the question asked is "*How would you rate your overall knowledge about financial matters compared to other adults in [COUNTRY]?"* with answers spanning from *"Very high",* scored with 5, to "Very low", scored with 1.
- Furthermore, to assess actual financial literacy scores (F1), the survey used a 3-question weighted index. The scores were calculated from 0 (ranked as 1) to 5 (ranked as 6) in our analysis.
- Question 11 (Q11) asked *"How comfortable are you with using digital financial services, such as online banking or mobile payments?"* measuring respondents' digital skills. Answers spanned from *"Very comfortable"*, which was scored with 4, to "*Not at all comfortable",* scored with 1.
- Lastly, question 12 (Q12) measured respondents' trust in financial advice from different private institutions. The question states "*How confident are you that investment advice you receive from your bank/insurer/financial advisor is primarily in your best interest?"* with answers from "Very confident", scored with 4, to "Not at all confident", assessed with 1.

- Question 9 (Q9) used to measure respondents' interactions with different financial products stated "*Which of the following financial products do you currently have or have you had in the last two years?"* – with multiple answers allowed, as follows: *"A private pension or retirement product"; "Life insurance"; "Non-life insurance" (e.g. household insurance, motor insurance); "A mortgage or home loan"; "Other consumer loan"; "An investment product" (funds, stocks or bonds); "Crypto-securities, including crypto-currency".* The data collected with Q9 is used as is and will not be processed. Answers *"None of these"* and *"Don't know"* were excluded from this analysis.

3.3. Analytical framework and methodological justification

The analytical strategy of this study is deliberately calibrated to the structural constraints of the underlying data. Flash Eurobarometer 525 constitutes a single cross-sectional survey wave, providing country-level weighted averages for 27 EU Member States with no temporal replication. This data architecture has direct implications for the class of inferential methods that are both valid and epistemically appropriate. Panel data estimators - fixed-effects, random-effects, or difference-in-differences specifications - require multiple observations per unit over time and are therefore inapplicable, as the survey covers a single reference period (spring 2023) and extends across no successive waves.

The absence of multivariate demographic controls is therefore not an analytical oversight but a methodological necessity imposed by the aggregate data structure. Demographic heterogeneity is, in part, absorbed into the country-level average indices, which reflect the composite socioeconomic profile of each Member State's surveyed population. The research objective of this study is explicitly comparative and descriptive - to characterise the landscape of financial knowledge, risk profiles, and investment preferences across the EU-27 - rather than to identify individual-level causal mechanisms. These are distinct objectives that require epistemically distinct methods.

This approach is consistent with peer-reviewed research using the same dataset and pursuing an analogous objective. Demertzis, Léry Moffat, Lusardi, and Mejino-López (2024), in their study published in the Journal of Financial Literacy and Wellbeing (Cambridge University Press) analyse Flash Eurobarometer 525 data at the country level using descriptive statistics and bivariate associations across the EU-27, without constructing multivariate regression models incorporating individual-level demographic controls. Their explicit objective - mapping the state of financial knowledge across European Member States - is methodologically analogous to the comparative objective pursued in this paper. The present study situates itself within this established stream of country-level, landscape-mapping analysis, which draws its inferential value precisely from cross-national heterogeneity rather than individual variation.

Given N = 27 country-level observations, the analytical toolkit is appropriately constrained to methods with sufficient statistical power for small samples. The procedure unfolds in three stages. First, cross-country descriptive statistics and distributional visualisations characterise each variable across Member States, establishing a comparative portrait of cross-national heterogeneity. Second, two-sample t-tests (paired samples) assuming unequal variances evaluate whether statistically significant differences exist between paired constructs - specifically between self-assessed and tested financial literacy, and between short-term and long-term risk aversion. Third, unifactorial OLS regressions estimate the marginal predictive relationship between each explanatory variable and the relevant outcome, with R^2 serving as a standardised measure of explained variance. These regressions are not intended as causal identification strategies but as descriptive measures of association, fully consistent with the cross-sectional, aggregate nature of the data.

The adoption of unifactorial rather than multifactorial specifications reflects both the sample size constraint and the study's explicitly comparative, landscape-mapping objective. Including multiple regressors simultaneously in a model with 27 observations would yield severely underpowered estimates susceptible to multicollinearity and overfitting, rendering coefficient interpretation unreliable. The unifactorial approach sacrifices the capacity to partial out confounders in exchange for analytical transparency and epistemic honesty about what the data can support. This position is acknowledged explicitly as a limitation in the concluding section, alongside future research directions incorporating longitudinal panel data and individual-level micro-econometric specifications as the EU's financial literacy monitoring framework matures across successive survey waves.

The formal specification of each unifactorial OLS regression is as follows. For each outcome variable Y and explanatory variable X, both measured as country-level weighted averages across the EU-27 (i = 1, ..., 27), the estimating equation is:

$$Y_i = \alpha + \beta X_i + \varepsilon_i \quad (1)$$

where Y_i is the outcome of interest for country i (the share of respondents holding a given financial product, or the country-level average risk aversion score); X_i is the explanatory variable (e.g., tested financial literacy, short-term risk aversion, or digital literacy score); α is the intercept; β is the slope coefficient quantifying the marginal association between X and Y across countries; ε_i is the error term, assumed independently distributed.

R^2 is reported as a standardised measure of the proportion of cross-country variance in Y explained by X. Given the study's descriptive objective, no causal interpretation is attributed to β. The absence of endogeneity correction is consistent with this framing: reverse causality is a concern in causal inference but not in analyses whose explicit purpose is to characterise the empirical landscape of associations across Member States.

4. Results and discussion

4.1. Cross-country averages

An analysis of the cross-country averages for Q1 (self-assessed financial literacy) and F1 (tested financial literacy), shown in Table 1, reveals a consistent pattern of underestimation of financial knowledge across the EU. In nearly all countries, respondents rated their own financial literacy lower than their actual tested scores, with particularly notable gaps in high-performing countries such as Finland (Q1: 3.34; F1: 4.05) and Germany (Q1: 2.91; F1: 3.67). This self-perception gap aligns with earlier findings suggesting that individuals often lack confidence in their financial abilities, even when their knowledge is objectively adequate (Angrisani & Casanova, 2019). Contrary to the overconfidence bias documented in the Dunning-Kruger effect (Kruger & Dunning, 1999), this pattern reflects financial self-underestimation, which may have tangible economic consequences. When individuals undervalue their financial competencies, they may avoid complex financial products, underinvest in markets, or rely excessively on external financial advice (Hadar et al., 2013). Furthermore, the data show that countries with higher digital literacy (Q11) and higher actual financial literacy (F1) do not necessarily report higher trust in financial advisors (Q12), suggesting a potential mismatch between education and perceived reliability of financial institutions.

Table 1
Financial literacy & behavioural indicators across the EU

Country	Q1	F1	Q8	Q10	Q11	Q12
BE	3.123	3.562	2.341	2.668	3.091	2.283
BG	3.280	3.333	2.922	2.987	3.122	2.407
CZ	3.237	3.585	2.644	2.809	3.431	2.697
DK	3.239	3.992	2.344	2.264	3.405	2.538
DE	3.134	3.684	2.491	2.512	3.211	2.489
EE	3.207	3.992	2.546	2.941	3.374	2.242
IE	3.222	3.665	2.652	2.580	3.132	2.310
EL	3.097	3.299	2.965	3.089	2.723	1.961
ES	3.142	3.359	2.341	2.522	2.833	2.394
FR	3.370	3.428	2.482	2.799	2.838	2.310
HR	3.277	3.475	2.836	2.890	3.360	2.459
IT	2.794	3.460	2.332	2.782	2.879	2.376
CY	3.131	3.281	2.831	2.873	3.049	2.015
LV	3.060	3.394	3.118	3.014	3.229	2.131
LT	3.239	3.553	2.488	2.938	3.472	2.326
LU	3.317	3.714	1.921	2.305	3.118	2.357
HU	3.059	3.581	2.882	3.096	3.140	2.212
MT	3.078	3.621	2.330	2.620	3.149	2.348
NL	3.302	3.981	2.011	2.263	3.429	2.352
AT	2.946	3.608	2.558	2.464	3.403	2.488
PL	3.337	3.358	2.792	3.175	3.261	2.074
PT	2.976	3.249	2.667	2.797	2.789	2.535
RO	3.546	3.122	3.005	2.789	3.228	2.474
SI	3.165	3.883	2.657	2.867	3.120	2.184
SK	3.213	3.625	2.637	2.956	3.360	2.479
FI	3.344	4.054	2.935	2.620	3.634	2.667
SE	3.166	3.812	2.130	2.439	3.490	2.265

Notes: Q1 = Self-assessed Financial Literacy; F1 = Actual Financial Literacy; Q8 =Short-Term Risk Aversion; Q10 = Long-Term Risk Aversion; Q11 = Digital Literacy; Q12 = Trust in Advice (from Banks, Consultants)

Source: Author's

Furthermore, as shown in Table 2, countries with higher actual financial literacy scores, such as Denmark (3.992) and the Netherlands (3.981), demonstrate greater uptake of sophisticated financial instruments, including private pensions (5.19 and 3.07, respectively), investment products (3.49 and 2.00), and mortgages (3.46 and 4.16). This aligns with existing literature suggesting that financial literacy reduces information barriers and facilitates participation in complex financial markets (Van Rooij, Lusardi, & Alessie, 2011). Conversely, nations with lower actual financial literacy, such as Greece (3.299) and Romania (3.122), exhibit markedly lower adoption rates across most products, reinforcing the link between financial competence and market inclusion. Interestingly, self-assessed financial literacy shows weaker predictive power, with Romania reporting the highest self-assessment (3.546) despite low actual literacy and product uptake, a finding consistent with the Dunning-Kruger effect, where individuals overestimate their financial capabilities.

Table 2

Choice of investment products across the EU

Country	Pension[1)]	Life insurance	Non-life insurance	Mortgage[2)]	Other consumer loan	An investment product	Crypto[3)]
BE	3.680	2.820	5.170	2.730	1.370	2.650	0.920
BG	1.870	1.730	3.710	0.920	3.140	0.930	1.090
CZ	3.990	4.180	3.860	1.470	1.540	2.390	1.390
DK	5.190	3.370	6.700	3.460	1.740	3.490	0.730
DE	2.140	2.480	5.890	1.650	0.990	3.280	0.610
EE	3.090	2.320	4.540	2.010	1.730	2.360	1.240
IE	3.950	3.640	4.020	2.540	1.740	1.810	0.810
EL	0.790	1.560	3.020	1.940	1.280	1.220	0.890
ES	2.270	2.880	4.960	2.930	1.830	2.250	0.440
FR	2.010	4.390	4.100	1.920	1.200	1.870	0.410
HR	0.780	2.590	3.010	1.070	2.370	1.470	1.580
IT	1.990	2.040	3.110	1.540	0.900	2.810	0.380
CY	1.410	3.270	3.680	2.410	1.530	0.960	1.040
LV	2.320	2.260	3.750	0.950	1.820	0.920	0.960
LT	2.410	3.410	4.110	1.290	1.350	1.400	1.130
LU	4.120	3.860	5.440	4.210	1.990	3.700	1.250
HU	1.820	3.180	4.400	1.520	1.510	1.970	0.640
MT	2.290	2.510	4.180	2.100	0.460	3.160	0.820
NL	3.070	2.430	6.420	4.160	0.600	2.000	1.140
AT	2.120	3.680	5.850	1.640	0.700	2.410	1.040
PL	1.020	5.820	4.440	1.500	2.100	1.510	0.580
PT	1.870	2.740	4.570	2.460	1.850	2.050	0.920
RO	3.250	2.270	4.080	1.160	2.290	1.630	0.750
SI	1.660	4.170	4.020	1.420	1.760	1.680	1.670
SK	1.470	3.920	3.710	2.080	1.870	2.580	0.740
FI	1.090	2.460	4.790	2.480	2.820	3.630	0.890
SE	3.310	2.360	5.720	3.040	1.250	4.630	0.510

[1)] "A private pension or retirement product"; [2)]A mortgage or home loan; [3)] "Crypto-securities, including crypto-currency"

Source: Author's

Risk aversion emerges as another critical determinant of financial behaviour, with countries exhibiting higher short-term risk aversion, such as Latvia (3.118) and Bulgaria (2.922), showing lower participation in volatile assets like investment products and cryptocurrencies. This supports behavioural finance theories, such as those of Kahneman & Tversky (1979), that risk-averse individuals prefer stable, familiar instruments over uncertain returns. Notably, Luxembourg (1.921) and Sweden (2.130), which report the lowest short-term risk aversion, display higher engagement with mortgages and investment products, suggesting that cultural attitudes toward risk shape financial decision-making. Long-term risk aversion, however, does not uniformly correlate with product ownership, indicating that consumers may weigh short-term uncertainties more heavily than long-term risks when making financial choices.

Digital literacy further mediates financial product adoption, with Scandinavian countries, Finland (3.634), Sweden (3.490), and Denmark (3.405), leading in both digital competence and ownership of technology-driven assets like investment products and cryptocurrencies. This suggests that digital skills might facilitate access to and confidence in modern financial tools. By contrast, Southern European nations such as Greece (2.723) and Portugal (2.789) lag in digital literacy and exhibit lower uptake of digital-based financial products, reinforcing the notion that technological readiness influences financial inclusion.

The final column in Table 1, which measures trust in financial advice, demonstrates a nuanced relationship with financial product adoption patterns. Countries with low institutional trust, such as Greece (1.961) and Cyprus (2.015), show diminished engagement with formal financial products, likely reflecting post-crisis scepticism. However, Portugal (2.535) presents an exception, with relatively high trust coexisting with low product uptake, suggesting that trust alone does not guarantee market participation without complementary financial literacy. The data also reveals that high-trust, high-literacy countries like Denmark (2.538) and Germany (2.489) exhibit selective rather than blanket product adoption, indicating that financially literate consumers critically evaluate advice rather than relying on it indiscriminately.

4.2. Descriptive statistics

Furthermore, descriptive statistics listed in Tables 3 and 4 reveal several important dynamics in individuals' financial literacy, risk preferences, and product choice patterns. First, the comparison between self-assessed financial literacy (Q1) and actual financial literacy (F1) reveals a nuanced self-perception gap. On average, individuals rated their own financial knowledge lower (*Median* = 3.19) than what they demonstrated in objective tests (*Median* = 3.58). This difference suggests a general underconfidence in financial knowledge, echoing recent findings by Angrisani and Casanova (2019), who show that underconfidence, even in objectively knowledgeable individuals, can hinder financial decision-making and long-term preparedness. Interestingly, the higher standard deviation of actual literacy (0.25 vs. 0.15 for Q1) confirms that tested knowledge varies more widely across the population, while the lower variance in self-assessment may reflect social desirability bias or general difficulty in self-evaluation.

Table 3

Descriptive statistics of key variables

	Q1	F1	Q8	Q10	Q11	Q12
Mean	3.185	3.580	2.587	2.742	3.195	2.347
Standard Error	0.029	0.048	0.058	0.049	0.045	0.034
Median (M)	3.206	3.581	2.636	2.796	3.210	2.352
Standard Deviation (SD)	0.150	0.251	0.305	0.258	0.236	0.179
Sample Variance	0.022	0.063	0.093	0.066	0.055	0.032
Kurtosis	1.267	-0.629	-0.361	-0.751	-0.520	0.007
Skewness	-0.275	0.321	-0.353	-0.365	-0.354	-0.234
Range	0.751	0.932	1.197	0.911	0.911	0.736
Minimum	2.794	3.122	1.920	2.263	2.723	1.960
Maximum	3.545	4.054	3.118	3.174	3.634	2.697
Sum	86.000	96.670	69.856	74.056	86.272	63.373
Count	27	27	27	27	27	27
Confidence Level (95.0%)	0.059	0.099	0.121	0.102	0.0935	0.071

Notes: Q1 = Self-assessed Financial Literacy; F1 = Actual Financial Literacy; Q8 =Short-Term Risk Aversion; Q10 = Long-Term Risk Aversion; Q11 = Digital Literacy; Q12 = Trust in Advice (from Banks, Consultants)

Source: Author's

The analysis of risk aversion reinforces known temporal asymmetries in financial behaviour. Respondents are more risk-averse in the short term (Q8, M = 2.59) compared to the long term (Q10, M = 2.74), a pattern consistent with time-inconsistent preferences and hyperbolic discounting (Laibson, 1997). The slightly greater standard deviation in short-term risk aversion (0.31 vs. 0.26) suggests that immediate financial decisions provoke more heterogeneous emotional responses, perhaps due to perceived urgency or lack of liquidity. The negative skewness observed in both measures may further imply that a substantial portion of individuals are highly risk-averse, highlighting an underlying behavioural influence of financial fragility, the tendency to avoid risks in contexts where loss-absorbing capacity is limited.

Digital literacy (Q11, M = 3.20, SD = 0.24) appears relatively well-developed, with most individuals reporting moderate to high competence in navigating digital platforms. This is encouraging, as digital literacy has become an increasingly critical skill for accessing financial services, especially with the rise of online banking, robo-advisors, and mobile investment platforms (OECD, 2020). Trust in financial advice (Q12, M = 3.20, SD = 0.24) exhibits a similar pattern, moderately high and stable, suggesting a relatively even distribution of attitudes toward institutional actors such as banks, consultants, or advisors. A potential correlation between digital literacy and trust could reflect that more digitally capable individuals feel empowered to assess the credibility of financial advice, though this relationship warrants formal statistical testing (e.g., Pearson's r or regression).

Table 4

Descriptive statistics of investment choices

	Pension[1)]	Life insurance	Non-life insurance	Mortgage[2)]	Other consumer loan	An investment product	Crypto[3)]
Mean	2.406	3.049	4.490	2.096	1.619	2.250	0.910
Standard Error	0.214	0.182	0.191	0.171	0.120	0.181	0.064
Median (M)	2.140	2.820	4.180	1.940	1.730	2.050	0.890
Mode	1.870	N/A	3.710	N/A	1.740	N/A	0.920
Standard Deviation (SD)	1.116	0.949	0.994	0.893	0.624	0.942	0.336
Sample Variance	1.246	0.900	0.988	0.797	0.389	0.887	0.113
Kurtosis	-0.020	1.245	-0.244	0.411	0.492	0.063	-0.107
Skewness	0.652	0.924	0.623	0.919	0.335	0.654	0.456
Range	4.410	4.260	3.690	3.290	2.680	3.710	1.290
Minimum	0.780	1.560	3.010	0.920	0.460	0.920	0.380
Maximum	5.190	5.820	6.70	4.210	3.140	4.630	1.670
Sum	64.980	82.34	121.250	56.600	43.730	60.760	24.570
Count	27	27	27	27	27	27	27
Confidence Level[*)]	0.441	0.375	0.393	0.353	0.246	0.372	0.133

Notes: [1)]"A private pension or retirement product"; [2)]A mortgage or home loan; [3)]"Crypto-securities, including crypto-currency"; [*)]Confidence Level = 95.0%.

Source: Author's

The data on financial product adoption reveal clear preferences. Traditional products like non-life insurance (M = 4.49) and mortgages (M = 4.18) are the most widely held, reflecting basic risk management and wealth accumulation strategies. By contrast, investment in crypto-securities remains marginal (M = 0.91, Median = 0.89), despite recent widespread media attention. The low adoption rate may reflect volatility, regulatory uncertainty, or lack of trust - especially in regions with lower financial literacy. Similarly, standard investments such as funds or bonds remain modest (M = 1.62), suggesting either risk aversion or limited access. Loans exhibit substantial variability, particularly for mortgages (SD > 0.8), pointing to diverse credit conditions, housing market dynamics, or national policy effects across the sample.

4.3. Mean analysis for self-assessed & actual financial literacy, short-term & long-term risk aversion

Moreover, the results from the two-sample t-test assuming unequal variances, shown in Table 5, reveal a statistically significant discrepancy between self-assessed financial literacy (Q1) and tested financial literacy (F1). The mean score for self-assessed literacy was 3.19, notably lower than the mean of 3.58 recorded for actual financial literacy. This difference is strongly supported by the test statistic (t = -7.01), which far exceeds the critical values for both one-tailed and two-tailed tests. The corresponding two-tailed p-value ($p = 1.24 \times 10^{-8}$) further underscores the robustness of this result, indicating that the observed difference is highly significant and unlikely to have occurred by chance.

The t-statistics suggest a consistent trend: participants tend to underestimate their financial knowledge. This self-perception gap reflects a broader issue documented in the literature: individuals often fail to accurately evaluate their own competencies in financial matters (Lusardi & Mitchell, 2014). Such underestimation may have practical implications, particularly in contexts requiring confidence in decision-making, such as investment choices or personal financial planning. When individuals lack confidence in their abilities, even when their actual knowledge is sufficient, they may refrain from engaging with more sophisticated or long-term financial products, such as retirement products or stocks, and are more likely to defer to financial advisors, even when their objective knowledge would support independent decision-making.

Table 5
Comparison of self-assessed & actual financial literacy

Statistics	Q1 - Self-assessed Financial Literacy	F1 - Actual Financial Literacy
Mean	3.1852	3.5804
Variance	0.0226	0.0632
Observations	27	27
Hypothesised Mean Difference	0	,
Degrees of Freedom (df)	43	,
t Statistic	-7.0102	,
P(T<=t) two-tail	0.0000	,
t Critical two-tail	2.0167	,

Source: Author's

In parallel, the comparison shown in Table 6 between short-term (Q8) and long-term (Q10) risk aversion reveals a significant, though more nuanced, temporal dimension to financial risk attitudes. The mean for short-term risk aversion was 2.59, while long-term risk aversion averaged slightly higher at 2.74. Although the absolute difference appears modest, the t-statistic (-2.02) and the associated two-tailed p-value ($p = 0.0489$) suggest statistical significance at the conventional 5% level. This indicates that the time frame over which financial decisions are made can meaningfully influence individuals' risk preferences.

The direction of the effect supports the notion that individuals are more risk-averse in the short term, but gradually become more tolerant of risk when outcomes are projected into the future. This behaviour is consistent with established theories in behavioural finance, such as Laibson (1997), particularly those concerning time-inconsistent preferences and hyperbolic discounting. Immediate risks are often perceived as more threatening or emotionally salient, whereas distant risks may be abstracted and thus tolerated more readily.

Table 6

Comparison of short-term & long-term risk aversion

Statistics	Q8 - Short-Term Risk Aversion	F1 - Long-Term Risk Aversion
Mean	2.5873	2.7428
Variance	0.0936	0.0669
Observations	27	27
Hypothesised Mean Difference	0	,
Degrees of Freedom (df)	51	,
t Statistic	-2.0180	,
P(T<=t) two-tail	0.0489	,
t Critical two-tail	2.0076	,

Source: Author's

4.4. Unifactorial regressions

4.4.1. Self-assessed & tested financial literacy regressions

Self-assessed financial literacy exhibits weak and predominantly positive associations with most financial behaviours examined (see Figure 1, Appendix). For the majority of product categories - including trust in financial advice, insurance ownership, investment products, home loans, and crypto-assets - the explanatory power is negligible, consistent with Allgood and Walstad's (2016) finding that perceived competence is a weaker predictor of financial engagement than objective knowledge. Modest positive associations emerge for life insurance and private pension ownership, suggesting that subjective confidence may marginally encourage long-term financial planning behaviour, albeit without the strength to be economically decisive. The most substantive relationship is observed with consumer credit use, where self-assessed literacy displays a moderate positive association. This pattern is consistent with overconfidence effects documented by Kruger and Dunning (1999): individuals who overestimate their financial competence may underestimate credit risk, leading to higher debt-product uptake. From a policy perspective, this finding underscores the risk of programmes that raise financial self-confidence without commensurate improvements in tested knowledge - a concern particularly relevant to CEE countries exhibiting high self-assessment relative to objective scores.

Tested financial literacy (Figure 2, Appendix) displays its strongest associations with investment products, non-life insurance, and home loans, with all three exhibiting moderate to substantial positive linkages (see Table). These patterns carry direct economic significance: countries where the population demonstrates higher objective financial knowledge show markedly greater participation in complex, long-horizon financial instruments. This finding is consistent with Van Rooij, Lusardi, and Alessie (2011), who demonstrate that actual financial knowledge reduces informational barriers to stock market participation. The underlying mechanism likely involves a more accurate comprehension of risk-return trade-offs, which increases the perceived tractability of complex products. Private pensions exhibit a moderate positive association, corroborating the established link between financial knowledge and retirement preparedness documented by Lusardi and Mitchell (2014). By contrast, life insurance, trust in financial advice, and crypto-securities show negligible associations, suggesting these decisions are governed primarily by social norms, cultural attitudes, or institutional trust rather than financial competence per se. Notably, a slight negative association emerges with consumer loans, consistent with the view that objectively literate individuals are more likely to recognise and avoid high-cost borrowing - a finding with practical relevance for consumer credit policy across Member States.

4.4.2. Short & long term risk profiles regressions

Figure 3 (see Appendix) reveals that short-term risk aversion is predominantly negatively associated with financial product ownership - a pattern that, on its surface, appears counterintuitive but is consistent with well-established behavioural finance theory. Countries where populations exhibit higher financial fragility (lower emergency savings, hence higher risk exposure in the short run) are precisely those where uptake of home loans, investment products, and non-life insurance is greatest. This aligns with the “gambling for resurrection” dynamic formalised by Downs and Rocke (1995): agents in financially precarious positions may rationally pursue exposure to financial products that offer the prospect of long-run security, even at the cost of short-term vulnerability. The association with private pension products is economically meaningful in a similar vein: countries with weaker short-term safety nets show greater private pension uptake, suggesting a substitution effect between state-provided and individually funded retirement provisions. Consumer loans, by contrast, display the opposite directionality, indicating that households with greater immediate financial resilience are more likely to take on debt - consistent with standard liquidity constraint theory (Lusardi et al., 2011). Associations with life insurance, trust in advice, and crypto-securities are weak, reflecting that these product choices are shaped by factors largely orthogonal to short-term financial fragility.

Long-term risk aversion (Figure 4, Appendix) produces associations that are, in aggregate, stronger and more consistent than those observed for the short-term dimension, with non-life insurance, home loans, investment products, and private pensions all displaying substantial negative linkages. Economically, this pattern indicates that countries where populations perceive their long-term financial position as uncertain are precisely those where households engage most actively in protective financial instruments. This is not paradoxical but rather structurally rational: households that recognise their long-run vulnerability respond by building insurance-based and pension-based buffers against future adversity, a mechanism consistent with precautionary saving theory (Lusardi, 2015) and with the lifecycle hypothesis of financial planning. The stronger explanatory power of long-term relative to short-term risk aversion for most product categories suggests that retirement and insurance planning decisions are more fundamentally anchored in perceptions of distant risk than in immediate financial fragility. Conversely, life insurance, trust in advice, crypto-securities, and consumer loans exhibit negligible associations, reinforcing the view that these product categories are governed by distinct motivational structures - cultural attitudes toward the concept of death, institutional confidence, speculative interest, and immediate liquidity needs, respectively - that long-term risk aversion does not meaningfully predict at the country level.

Conclusively, Figures 3 and 4 (see Appendix) demonstrate that greater risk aversion, whether measured over the short or long term, is consistently associated with higher engagement in protective and long-horizon financial products - most prominently insurance, home loans, investment products, and private pensions - while consumer credit displays the opposite directional pattern.

4.4.3. Digital literacy regressions

The scatterplots in Figure 5 (see Appendix) illustrate the associations between digital literacy and financial product adoption across EU countries. The pattern is consistently positive but selectively strong. The most economically meaningful associations involve trust in financial advice, non-life insurance, and investment products (see Table, Appendix), a clustering that is theoretically interpretable: digital competence facilitates navigation of online financial platforms, reduces the informational cost of accessing and evaluating financial advice, and lowers barriers to entry for investment products that increasingly require digital interfaces. This aligns with OECD (2020) evidence linking digital financial literacy to greater engagement with online financial services and robo-advisory tools. The association with trust in financial advice is particularly noteworthy: more digitally capable populations may be better positioned to evaluate the credibility and alignment of advisory services with their interests. By contrast, home loans and consumer loans show negligible associations, consistent with the view that collateral-based borrowing decisions are driven by macroeconomic conditions, housing market dynamics, and credit supply constraints rather than by the digital competence of borrowers. The digital literacy channel is thus most operative where financial engagement is mediated by technology and information processing - and largely inactive where it is mediated by institutional relationships and physical asset markets.

In summary, the findings across Figures 1 to 5 collectively underscore that different dimensions of individual competence, self-assessed knowledge, tested financial literacy, risk preferences, and digital skills, shape financial behavior in distinct and economically meaningful ways. Self-assessed literacy shows weak but generally positive links, with the strongest effect observed for consumer credit use, possibly reflecting confidence or overconfidence in debt management. In contrast, tested financial literacy is more clearly associated with engagement in complex and long-term financial products, such as investment instruments and pensions, echoing past research that ties actual financial knowledge to improved financial decision-making (such as van Rooij, Lusardi, & Alessie, 2011). Risk preferences emerge as particularly influential: both short- and long-term risk tolerance are strongly linked to investment and borrowing behaviours, confirming the central role of risk attitudes in financial engagement (Dohmen et al., 2011). The relationships were mostly negative, showing that the higher the risk-aversion, the lower the preference for all types of analysed investment options, with the exception being consumer credit. Lastly, digital literacy appears most relevant in facilitating participation in investment products and online-mediated financial services, suggesting that digital competence may be an increasingly important prerequisite for financial inclusion in modern markets. Together, these findings highlight the multifaceted nature of financial decision-making, where knowledge, perception, risk tolerance, and digital readiness each contribute to shaping individual financial behaviour.

5. Conclusions

This study explored the links between financial knowledge, risk aversion, and investment preferences among individuals in EU Member States, utilising data from the Flash Eurobarometer 525. The research sheds light on the nuanced relationship between tested financial literacy, self-assessed financial confidence, and actual financial behaviour, revealing meaningful divergences and regional patterns across Europe.

Returning to the three hypotheses formulated at the outset, the empirical evidence shows the following: H1, which posited that tested financial literacy would exhibit a stronger positive association with long-term investment product adoption than self-assessed literacy, is supported. Tested financial literacy displays substantively stronger associations with investment products, non-life insurance, home loans, and private pensions than self-assessed literacy, whose only economically meaningful linkage emerges with consumer credit - a result more consistent with overconfidence-driven debt uptake than with informed financial planning. H2, anticipating that short-term risk aversion would map onto everyday financial decisions while long-term risk aversion would track long-horizon products, receives partial support. Long-term risk aversion exhibits stronger and more systematically negative associations with insurance and pension products than short-term risk aversion does, consistent with the precautionary saving and lifecycle frameworks. The short-term dimension, however, behaves in a manner more nuanced than initially hypothesised: rather than aligning narrowly with everyday decisions, it tracks engagement with long-term borrowing and investment products through a “gambling for resurrection” type of mechanism (Downs & Rocke, 1995). H3, asserting a positive moderating role for digital literacy, is supported within a circumscribed domain - investment products, trust in advice, and non-life insurance - but is largely inactive for collateral-based borrowing decisions, suggesting digital competence operates as an enabler primarily where financial engagement is mediated by online platforms.

The principal contribution of this study lies in extending the comparative country-level analysis of EU financial literacy - pioneered by Demertzis et al. (2024) using the same Flash Eurobarometer 525 dataset - beyond the descriptive mapping of knowledge stocks to a multidimensional examination that jointly integrates tested literacy, self-assessment, short- and long-term risk profiles, digital competence, trust in advice, and product participation. Whereas the established literature (Lusardi & Mitchell, 2014; Van Rooij et al., 2011) has documented the financial literacy–behaviour nexus predominantly at the individual level within single-country samples, this study delivers a harmonised EU-27 portrait that surfaces three findings of independent value. First, the documented direction of the self-perception gap inverts the canonical Dunning-Kruger pattern: across the majority of EU member states, individuals systematically underestimate rather than overestimate their financial knowledge. This contradicts the overconfidence framing that dominates much of the behavioural finance literature (Allgood & Walstad, 2016) and warrants explicit recognition in policy design. Second, the differentiation between economically meaningful (tested literacy) and economically negligible (self-assessment) predictors of long-term product engagement provides empirical justification for prioritising objective competence-building over confidence-calibration interventions. Third, the regional patterning - Northern European countries combining high tested knowledge with high self-confidence, against CEE Member States such as Romania exhibiting the opposite alignment - identifies a heterogeneity that any pan-European financial education strategy must accommodate.

Notably, the study also found that risk preferences play a central role in shaping financial behaviour, as both short- and long-term risk tolerance show strong associations with investment and borrowing decisions. Higher risk aversion tends to boost engagement with most financial products, particularly long-term investments, while consumer credit stands out as an exception, often preferred even by less risk-averse individuals. Additionally, digital literacy emerges as a key enabler, especially for accessing investment opportunities and using online financial tools. These results emphasise that financial decision-making is not driven by knowledge alone but is also shaped by personal risk attitudes and digital competence, which together influence individuals' ability and willingness to engage with increasingly complex financial markets.

These findings underscore the dual need to both improve financial literacy and calibrate financial confidence. A one-size-fits-all approach to financial education is unlikely to be effective given the observed heterogeneity in behaviour and knowledge: In overconfident but low-literacy countries, programs should focus on correcting inflated self-perceptions and building actual financial knowledge through targeted, accessible education initiatives. In underconfident but high-literacy countries, efforts might focus on boosting financial self-efficacy, encouraging practical application of existing knowledge, and building trust in institutions and advisors.

For the European Capital Markets Union and the EU's broader retail investor engagement agenda, these results carry concrete operational implications. The asymmetry between tested and self-assessed literacy - with the former predicting long-horizon engagement and the latter predicting consumer credit uptake - suggests that financial education frameworks should be calibrated diagnostically rather than uniformly: countries displaying CEE-type underconfidence relative to objective competence require self-efficacy and trust-building interventions, whereas overconfident-low-literacy populations require remedial competence-building and credit-risk awareness programmes. The largely orthogonal behaviour of short-term financial decisions vis-à-vis literacy further indicates that day-to-day financial conduct is driven by liquidity, institutional, and cultural factors that lie outside the scope of conventional financial education and warrant complementary policy levers.

Several limitations, intrinsic to the analytical framework outlined in Section 3.3, must be acknowledged. First, the analysis rests on a single cross-sectional wave of Flash Eurobarometer 525, which precludes the construction of a longitudinal panel and, consequently, the application of fixed-effects or difference-in-differences estimators. Causal inference is therefore not claimed; the associations reported are descriptive in nature, consistent with the comparative landscape-mapping objective stated at the outset. Second, the unit of analysis is the country (N = 27), and the data structure provides pre-aggregated weighted averages rather than individual-record microdata. This precludes the simultaneous inclusion of demographic controls (age, gender, income quartile, educational attainment) that would be standard in micro-econometric specifications. Demographic heterogeneity is partially absorbed into the country-level indices but cannot be directly partialled out. Third, the small-N constraint imposed by the EU-27 dictates the use of unifactorial rather than multifactorial regressions; including multiple regressors simultaneously would yield underpowered and multicollinear estimates. Fourth, reliance on self-reported measures introduces the possibility of social desirability bias, particularly for self-assessed knowledge and risk attitudes. Future research will benefit from successive waves of Flash Eurobarometer enabling panel construction and the application of fixed-effects estimators; access to individual-level microdata supporting multivariate models with demographic conditioning; experimental and quasi-experimental designs to identify the causal effect of financial education interventions; and the integration of institutional, regulatory, and cultural variables capable of explaining cross-country heterogeneity beyond the variables observed in the present dataset.

In sum, this study advances the literature along three distinct axes. Theoretically, it complicates the dominant overconfidence narrative by documenting a robust pattern of financial underconfidence across most EU Member States, calling for refined behavioural-finance models that accommodate bidirectional self-perception biases. Empirically, it provides the first multidimensional EU-27 portrait jointly mapping tested and self-assessed literacy, dual-horizon risk profiles, digital competence, trust in advice, and product participation using the harmonised Flash Eurobarometer 525 instrument. Practically, it gives policymakers a typology of national positioning - underconfident-high-literacy versus overconfident-low-literacy - that operationalises the otherwise abstract call for tailored financial education. The interaction between cognitive self-assessment, risk attitudes, and digital readiness emerges not as three parallel determinants of financial behaviour, but as an integrated competence block whose calibration is the proper object of pan-European financial inclusion policy.

***Disclaimer**: The author declares that no generative AI tools were used in the preparation of the research content or analysis. Automated tools (ChatGPT-5 & Grammarly v1.2.208) were employed solely for grammar correction and linguistic polishing, equivalent to a digital proofreading process. All concepts, analyses, and conclusions are entirely the author's original work.*

References

1. Allgood, S. and Walstad, W. B. (2016). The effects of perceived and actual financial literacy on financial behaviors. *Economic Inquiry*, 54(1), pp. 675–697. https://doi.org/10.1111/ecin.12255
2. Angrisani, M. & Casanova, M. (2019). What you think you know can hurt you: under/over confidence in financial knowledge and preparedness for retirement. *Journal of Pension Economics & Finance*, 20(4), pp. 516–531. https://doi.org/10.1017/S1474747219000131
3. Behrman, J., Mitchell, O., Soo, C. K. & Bravo, D. (2012). How financial literacy affects household wealth accumulation. *American Economic Review*, 102(3), pp. 300–304. https://doi.org/10.1257/aer.102.3.300
4. Bucher-Koenen, T., Lusardi, A., Alessie, R. & van Rooij, M. (2017). How financially literate are women? An overview and new insights. *Journal of Consumer Affairs,* 51(2), pp. 255–283. https://doi.org/10.1111/joca.12121
5. Batsaikhan, U. & Demertzis, M. (2018). Financial literacy and inclusive growth in the European Union. *Bruegel Policy Contribution*, Issue No. 08/2018. Brussels: Bruegel.
6. Clark, R., Lusardi, A. & Mitchell, O. S. (2017). Financial knowledge and 401(k) investment performance: a case study. *Journal of Pension Economics and Finance*, 16(3), pp. 324–347. https://doi.org/10.1017/S1474747215000384
7. Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the *European Economic Association*, 9(3), pp. 522–550. https://doi.org/10.1111/j.1542-4774.2011.01015.x
8. Downs, G. W. & Rocke, D. M. (1995). Optimal Imperfection? Domestic Uncertainty and Institutions in International Relations. *Princeton: Princeton University Press*.
9. European Commission (2023). Flash Eurobarometer 525: Financial Literacy and Financial Inclusion. *Directorate-General for Financial Stability, Financial Services and Capital Markets Union.* Available at: https://data.europa.eu/data/datasets/s2895_525_eng?locale=en
10. Demertzis, M., Léry Moffat, L., Lusardi, A. & Mejino-López, J. (2024). The state of financial knowledge in the European Union. Journal of Financial Literacy and Wellbeing, 1(2), pp. 195–222. Cambridge University Press. https://doi.org/10.1017/flw.2024.7 [Also published as Bruegel Policy Brief 04/2024.]

11. Gilliam, J., Chatterjee, S. & Grable, J. E. (2010). Measuring the perception of financial risk tolerance: A tale of two measures. *Journal of Financial Counseling and Planning*, 21(2), pp. 30–43
12. Grable, J. E. & Lytton, R. H. (1999). Financial risk tolerance revisited: The development of a risk assessment instrument. *Financial Services Review*, 8(3), pp. 163–181. https://doi.org/10.1016/S1057-0810(99)00041-4
13. Hadar, L., Sood, S. & Fox, C. R. (2013). Subjective knowledge in consumer financial decisions. *Journal of Marketing Research*, 50(3), pp. 303–316. https://doi.org/10.1509/jmr.10.0518
14. Hastings, J. S., Madrian, B. C. & Skimmyhorn, W. L. (2013). Financial literacy, financial education, and economic outcomes. *Annual Review of Economics*, 5(1), pp. 347–373. https://doi.org/10.1146/annurev-economics-082312-125807
15. Kahneman, D. & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), pp. 263–291.
16. Kruger, J., & Dunning, D. (1999). Unskilled and unaware of it: How difficulties in recognising one's own incompetence lead to inflated self-assessments. *Journal of Personality and Social Psychology*. 77(6), 1121–1134. https://doi.org/10.1037/0022-3514.77.6.1121
17. Laibson, D. (1997). Golden eggs and hyperbolic discounting. *Quarterly Journal of Economics*, 112(2), pp. 443–477. https://doi.org/10.1162/003355397555253
18. Lusardi, A. (2015). Financial literacy: Do people know the ABCs of finance?. *Public Understanding of Science*, 24(3), pp. 260–271. https://doi.org/10.1177/0963662514564516
19. Lusardi, A. (2019). Financial literacy and the need for financial education: evidence and implications, *Swiss Journal of Economics and Statistics*, 155(1). https://doi.org/10.1186/s41937-019-0027-5
20. Lusardi, A., de Bassa Scheresberg, C. & Avery, M. (2018). Millennial mobile payment users: a look into their personal finances and financial behaviors. *GFLEC Working Paper*.
21. Lusardi, A. & Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1), pp. 5–44. https://doi.org/10.1257/jel.52.1.5
22. National Endowment for Financial Education (2017). 2017 year in review. Available at: https://www.nefe.org/news/nefe-digest/2017/2017-year-in-review.aspx
23. OECD (2020). *OECD Economic Outlook*. Volume 2020 Issue 2. Paris: OECD Publishing. https://doi.org/10.1787/39a88ab1-en

24. Tokar Asaad, C. (2015). Financial literacy and financial behavior: Assessing knowledge and confidence. *Financial Services Review*, 24(2), pp. 101–117. https://doi.org/10.61190/fsr.v24i2.3236
25. Van Rooij, M., Lusardi, A. & Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2), pp. 449–472. https://doi.org/10.1016/j.jfineco.2011.03.006

APPENDIX

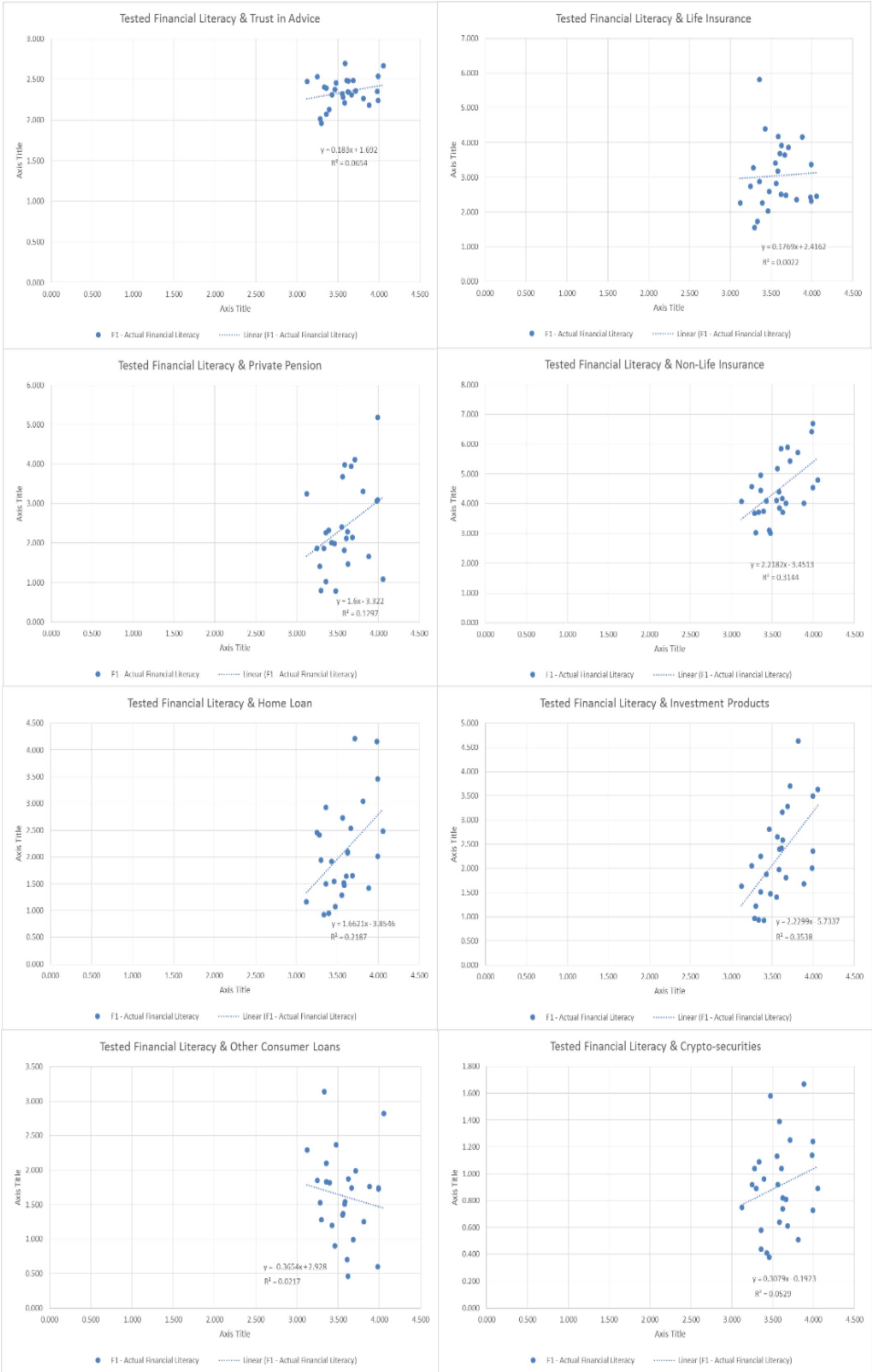
Figure 1

Self-Assessed Financial Literacy Regressions

Source: Author's

Figure 2

Tested Financial Literacy Regressions



Source: Author's

Figure 3

Short-Term Risk Aversion Regressions

Source: Author's

Figure 4

Long-Term Risk Aversion Regressions

Source: Author's

Figure 5

Digital Literacy Regressions

Source: Author's

BANK LENDING TO NON-FINANCIAL CORPORATIONS IN ROMANIA DURING 2016-2025

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Abstract

Bank lending to non-financial corporations has long been an important source of financing investments in the real economy, especially in European countries. However, following the outbreak of the Global Financial Crisis 2007-2009, the share of lending to non-financial corporations in GDP has diminished, at least in the Eurozone (the central component of the EU), according to the latest data from the European Central Bank. This paper focuses on assessing banking loans to non-financial corporations in Romania during the period 2016 – 2025 using standard analytical and econometric tools. In this article, an econometric model is built to identify the relationships between the evolution of banking loans to non-financial corporations (in real terms, after adjusting for inflation) in Romania and several structural indicators (international and domestic). Our estimates indicate a direct relationship between loans to non-financial corporations in Romania and the confidence indicator for the Eurozone industry. On the other hand, we identify an inverse relationship between loans to non-financial corporations in Romania and several indicators, including the short-term real interest rate, the real effective exchange rate of the RON, and US stock market sentiment (as measured by the equity risk premium).

Keywords: non-government loans, Romania, ordinary least squares, real interest rate, risk premium

JEL Classification: C21, E32, E44, E51, G21

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1. Introduction

Banks have always played a fundamental role in financing investments in the real economy, especially in Europe. However, this

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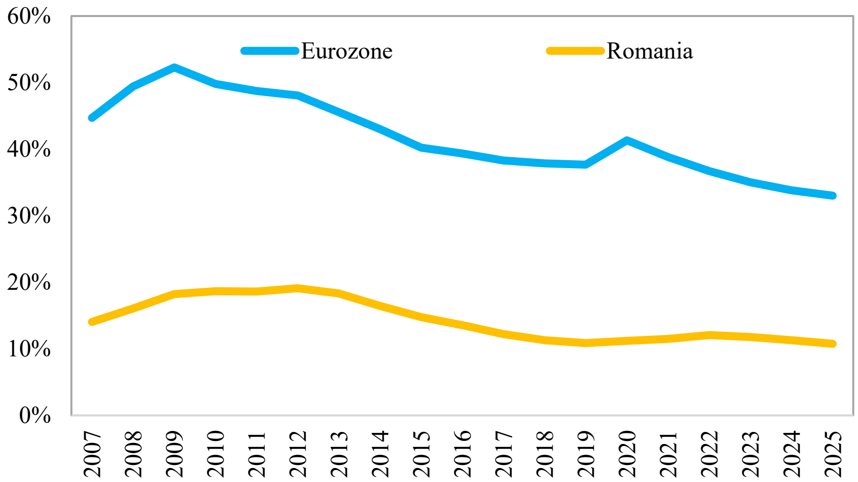
role has deteriorated following the outbreak of the Global Financial Crisis 2007-2009 (the most severe world economic and financial crisis since the end of World War II). For instance, the share of the bank lending to non-financial corporations in GDP declined in the Eurozone from above 52% in 2009 to 33% in 2025, according to the figures estimated by using the databases of the European Central Bank (ECB, 2026) and Eurostat (2026), represented in Figure 1.

However, in Romania, the role of bank lending has been significantly lower in the past decades. The share of bank lending to non-financial corporations never exceeded 20% of GDP. Based on the databases of the National Bank of Romania (NBR, 2026) and Eurostat (2026), the weight of non-government loans to non-financial corporations in GDP declined from above 18% in 2009 to around 11% in 2025, as shown in Figure 1.

Figure 1

Loans to non-financial corporations (% GDP)



Source: representation of the author based on the estimates using the data of Eurostat (2026), European Central Bank (2026) and National Bank of Romania (2026)

Furthermore, we point out the unfavourable development in Romania in 2025, as reflected by the contraction of the real lending (nominal lending after adjusting for inflation) to non-financial corporations for the fifth month in a row in December last year (the longest streak of decline since 2018), by the most severe annual rate since September 2016, according to our estimates, based on the data of the National Bank of Romania (NBR, 2026) and Eurostat (2026).

This paper applies standard analytical and econometric tools (the Hodrick-Prescott filter and the OLS regression) in order to assess the evolution of bank lending to non-financial corporations after adjusting for inflation in Romania during the period 2009 – 2025. The main aim of this research is to build an econometric model to identify the structural factors (international and domestic) that influence the evolution of real lending. The databases of the National Bank of Romania (NBR, 2026), Eurostat (2026), European Commission (2026), Damodaran (2026), and the Bank for International Settlements (BIS, 2026) were used.

The rest of the paper has the following structure: Section 2 focuses on the literature review related to the bank lending to non-financial corporations; the methodology is briefly presented in Section 3; the main results are discussed in Section 4; the conclusions are mentioned in Section 5.

2. Literature review

The role of the banking sector in financing the real side of the economy has been well documented by many researchers and bankers in the past decades.

For instance, the former Governor of the Bank of England pointed out that banks had a contribution of almost 50% to the financing of companies in the 1960s in the United Kingdom (Richardson, 1981). Furthermore, the role of the banks in financing the British economy intensified in the following decade, dominated by high levels of inflation, volatility, and instability, after the dismantlement of the Bretton-Woods agreement, as emphasised by Escriva et al. (2009).

The deregulation started in the 1980s in the United States, shortly followed by Western European countries, supporting innovation in the banking sector in market economies, with consequences in terms of competitiveness, but also risks. According to Bertrand et al. (2007), the deregulation in the French banking sector in the 1980s had consequences in terms of efficiency, either for the banks or for the companies, leading to the decline of concentration in the industries.

At the same time, the deregulation trend in the financial sector started in the 1980s, the intensifying globalisation (following the fall of the Berlin Wall in 1989), and the development of the internet, leading to the flourishing of derivatives, transformed the banking sector. For instance, the share of banks in the business debt of the United States declined significantly, from over 35% in the mid of the 1980s to less than 25% in the first half of the 2000s, as documented by Covas and Dionis (2022).

On the flipside, the deregulation contributed to the increase in instability in the banking sector, as emphasised by Cunha (2021).

However, the outbreak of the Global Financial Crisis 2007-2009 determined the change of the paradigm in terms of regulation in the banking sector, through the implementation of Basel III (BIS, 2017).

The main consequence of the post-crisis regulation in the banking sector was the significant increase in the non-banking financing of non-financial corporations. This, in turn, has had important effects in terms of the transmission of the monetary policy, according to the European Central Bank (2016).

As regards the factors with an impact on the bank lending for non-financial corporations, the research of the European Central Bank (2004) on the developments in the Eurozone pointed out the business cycle position, the real cost of financing, the corporate profitability, and the development of non-monetary financial institutions.

Researching the banking lending to companies in Spain, Barreira et al. (2022) distinguished between the demand-side factors and the supply-side factors. In the former, the authors underlined the precautionary liquidity buffers, the differentiated impact of the coronavirus pandemic across the sectors in the economy, and the replacement of the banking lending with securities issuance. In the latter, the capital ratios of the banks were taken into account.

3. Methodology

In this paper, we analyse the developments of the real bank lending to non-financial corporations in Romania in the past decade (January 2016 – December 2025) by implementing standard econometric tools.

The main aim is to identify the macroeconomic indicators that impact the annual rate of real bank lending to non-financial corporations.

First of all, we estimated the annual rate of the bank lending to non-financial corporations in Romania by considering the annual pace of the nominal lending and the dynamics of the consumer prices (HICP – Harmonised Index of Consumer Prices).

Afterwards, we took into account several macroeconomic indicators, international and domestic. As regards the international indicators, we considered the equity risk premium in the United States, the largest economy in the world, with a nominal GDP of over USD 31 trillion in the 3Q of 2025, according to the estimates of the Bureau for Economic Analysis (BEA, 2026). This is an important barometer for the risk perception in the global financial markets, with an impact on the cost of financing in the emerging economies, according to several studies, including the Goldman Sachs Integrated Model developed by Mariscal and Lee (1993), and the article by Boyer et al. (2017).

We used the estimates of Damodaran (2026) for the equity risk premium in the United States, based on monthly observations.

Furthermore, we also took into account the confidence in the Eurozone industry, as estimated every month by the European Commission (2026). This is a very important indicator for the economic activity in Romania, a country that is highly integrated with the Eurozone (the main component of the European Union, with a contribution of 84% to the GDP in 2025, according to Eurostat (2026)), in terms of economic, financial, and investment flows. On the other hand, from the domestic perspective, we opted for the real interest rate in the short run and for the real effective exchange rate of the RON. In our view, the real interest rate in the short run represents an important benchmark for the real costs of financing, with an impact on the investment decisions of the companies. Normally, a decline in the real cost of financing is positive for the investments of the companies. At the same time, the real effective exchange rate is a barometer for international competitiveness. An improvement in international competitiveness is positive for the investment plans of the companies.

As regards the short-term real interest rate, it was estimated using Eurostat (2026) data on the 1-month nominal interest rate and annual inflation.

Overall, we worked with four independent variables, with a balanced distribution in terms of international and domestic, real and financial sides of the economy.

In our analysis, we worked with monthly observations. Therefore, we could not introduce other domestic macroeconomic variables, which are reported on a quarterly basis, such as the annual pace of GDP, for instance. However, we introduced in the analysis the confidence in industry in the Eurozone (an important leading indicator for the economic activity in this region). In this respect, we point out that the developments in terms of GDP in Romania are strongly dependent on the macroeconomic climate in the Eurozone.

We estimated the following OLS (Ordinary Least Squares) regression using the econometric software EViews:

$$LOANSNFC = C(1) + C(2) * REALINTRATETR + C(3)RONREER + C(4) * ERPUSA + C(5) * EUROCONFIND + C(6) * LOANSNFC(-1) \quad (1)$$

where LOANSNFC represents the annual rate of the real bank lending to non-financial corporations, REALINTRATETR is the estimated trend component for the short-term real interest rate, RONREER is the real effective exchange rate of the RON, ERPUSA represents the equity risk premium in the United States, while EUROCONFIND is the indicator measuring the confidence in the industry in the Eurozone.

We also considered the lagged dependent variable in the regression (LOANSNFC(-1)), to counter the risk of autocorrelation. C(1) is the intercept, while C(2), C(3) C(4), C(5), and C(6) are the estimated coefficients for the independent variables.

We point out that for the real interest rate in the short run, we considered in the regression the trend component, estimated by implementing the econometric filter developed by Hodrick-Prescott (1997), which is based on the following relation:

$$Min \sum_{t=1}^{T} (\ln Y_t - \ln Y_t^*)^2 + \lambda \sum_{t=2}^{T-1} \left((\ln Y_{t+1}^* - \ln Y_t^*) - (\ln Y_t^* - \ln Y_{t-1}^*) \right)^2 \quad (2)$$

where Y_t, Y_t^*, and λ represent the real interest rate in the short-run, its trend component, and a smoothness parameter, for which we considered a value of 14,400, the same used by the authors when working with monthly observations.

In this paper we worked with monthly data, from January 2016 to December 2025, from different sources: the National Bank of Romania (NBR, 2026) for the loans to non-financial corporations, Eurostat (2026) for the nominal interest rate and inflation, European Commission (EC, 2026) for the confidence in the Eurozone industry, Bank for International Settlements (BIS, 2026) for the real effective exchange rate of the RON, and Damodaran (2026) for the equity risk premium in the United States.

4. Interpretation of the results

Table 1 presents the estimates from the OLS regression.

On the one hand, it is clear that all estimated coefficients are statistically significant at the 10% level. On the other hand, the R-squared is very good, above 92%. In other words, the independent variables explain to a large extent the development of the dependent variable.

Table 1

The results of the OLS estimated regression (1)

Dependent Variable: LOANSNFC
Method: Least Squares
Date: 02/05/26 Time: 17:05
Sample(adjusted): 2016:04 2025:07
Included observations: 112 after adjusting endpoints

LOANSNFC = C(1)+C(2)*REALINTRATETR(-1)+C(3)*RONREER(+1)
+C(4)*ERPUSA(-3)+C(5)*EUROCONFIND(+5)+C(6)*LOANSNFC(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	8.962387	4.144311	2.162576	0.0328
C(2)	-0.422464	0.159232	-2.653133	0.0092
C(3)	-0.056080	0.030952	-1.811813	0.0728
C(4)	-0.702300	0.300556	-2.336669	0.0213
C(5)	0.027761	0.015753	1.762307	0.0809
C(6)	0.855489	0.043334	19.74172	0.0000

R-squared	0.925344	Mean dependent var	2.722370
Adjusted R-squared	0.921823	S.D. dependent var	4.355050
S.E. of regression	1.217681	Akaike info criterion	3.283856
Sum squared resid	157.1711	Schwarz criterion	3.429490
Log likelihood	-177.8959	Durbin-Watson stat	1.663668

Source: econometric estimates in EViews, 2026

The results of the econometric analysis point out a direct relationship between bank lending to non-financial corporations in real terms (after adjusting for inflation) in Romania and the confidence in the Eurozone industry, with an estimated coefficient of 0.028 for the period January 2016 – December 2025. In other words, the increase in the confidence indicator in the Eurozone industry by 1 point determined the improvement of the annual rate of bank lending to non-financial corporations in real terms in Romania by 0.028 percentage points in the past decade.

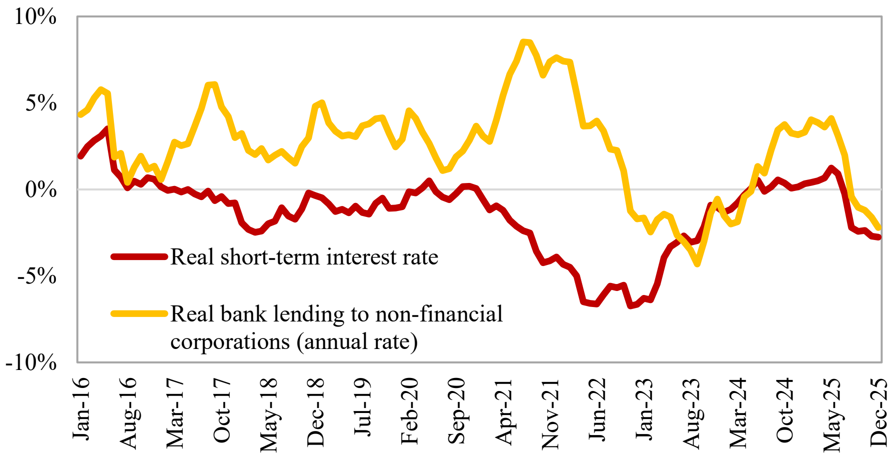
This output is normal, as the Romanian economy is integrated within the EU economic flows, being highly dependent on the trade, financial, and investment flows with the countries in the Eurozone.

In our view, this low level of the coefficient can be explained by several factors, among which we mention: the high dependence of multinational companies active in Romania on the financing sources from abroad; the difficult access of small and medium companies to banking loans; the increasing role of EU funds.

On the other hand, we identified an inverse relationship between the bank lending to non-financial corporations and the short-term real interest rate in Romania. This negative relationship has been underlined in many papers, including that of Ahnert et al. (2023). The estimated coefficient was -0.422 for the analysed period. In other words, a 1% decline in the short-term real interest rate contributed to a 0.422 pps improvement in the annual rate of bank lending to non-financial corporations in real terms during January 2016 – December 2025. This result is normal, as the increase in the real cost of financing has a negative impact on the investment plans of the companies. This inverse relationship is also represented in Figure 2.

Figure 2

The real short-term interest rate and the real bank lending to non-financial corporations in Romania



Source: Author's work, based on the estimates using the databases of NBR (2026), and Eurostat (2026)

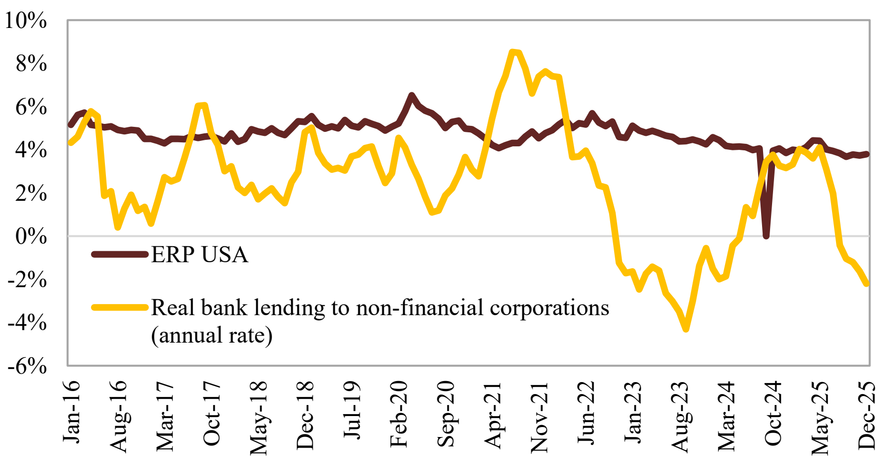
At the same time, the econometric estimates indicate an inverse relationship between the real bank lending to non-financial corporations and the real effective exchange rate (a barometer of international competitiveness) in Romania during January 2016 –

December 2025. The estimated coefficient was -0.056. An increase in the index of the real effective exchange rate of the RON by 1 point determined the deterioration of the annual rate of the real bank lending to non-financial corporations by 0.056pps in the analysed period. In other words, a deterioration in the international competitiveness of the economy has harmed the real corporate lending in Romania in the past decade. This confirms the fact that the deterioration of international competitiveness has a negative impact on the investments of the companies.

Last, but not least, we identified an inverse relationship between the real bank lending to non-financial companies in Romania and the equity risk premium on the stock market in the USA, which probably represents the most important indicator for the risk perception in the global financial markets and in the world economy. The estimated coefficient was -0.702 during January 2016 – December 2025. In other words, a 1 pp increase in the equity risk premium in the USA was associated with a 0.702 pp deterioration in the annual rate of real banking lending in Romania during the period January 2016 – December 2025. This relationship is represented in Figure 3.

Figure 3

The equity risk premium (ERP) in the USA and the real bank lending to non-financial corporations in Romania



Source: Author's work, based on the estimates of Damodaran (2026) and on our estimates using the databases of the National Bank of Romania (NBR, 2026) and Eurostat (2026)

5. Conclusions

This paper estimated the relationships between the evolution of real bank lending to non-financial corporations in Romania and several macroeconomic indicators during the period January 2016 – December 2025. This represents a relevant contribution to the literature, as it identifies several important factors (international and domestic) that influence the development of real bank lending to non-financial corporations in Romania, an economy with strong annual rates of growth and development over the past decades (mainly determined by the integration within the European Union).

The results of the econometric analysis indicate a direct relationship between real bank lending to non-financial corporations in Romania and confidence in the Eurozone industry. However, an inverse relationship was identified between the real bank lending to non-financial corporations in Romania, on the one hand, and the real short-term interest rate, the RON effective exchange rates, and the climate in the US stock market, on the other hand.

Our results are important for the future development of the banking sector in Romania, in a period dominated by the intensifying competition from the non-banking financial institutions. In our view, the banking sector in Romania should implement proactive measures in order to change the downward trend for the share of lending to non-financial corporations in the GDP. In this respect we point out the high level of probability for this trend to continue in 2026, as the real short-term interest rate in Romania is forecasted to increase in the second half of the year (after the fading out of the impact of the liberalisation of electricity prices, and of the increase in the VAT and excise duties), while the equity risk premium in the United States is going to increase this year, after reaching in 2025 the lowest level since 2006, according to Damodaran (2026).

Last but not least, the results of this paper may also be useful to policymakers in Romania. The country needs to accelerate structural reforms to improve the economy's international competitiveness. That, in turn, would have a positive impact on real bank lending. At the same time, new reforms are needed to develop domestic financial markets, with a focus on increasing liquidity, financial education, and investment instruments. On the other hand, structural reforms are needed in order to improve access to credit for small and medium-sized companies.

At the end of this paper, we point out that, unless the reforms are accelerated, the role of bank lending to finance companies would continue to decline in the coming years, transforming the banking sector into a low-relevance actor in the economy. This, in turn, would determine the accumulation of risks and challenges for the transmission of the monetary policy, with unprecedented consequences in the scenario of Romania becoming a member of the Eurozone in the future.

References

1. Ahnert, T., Anand, K., & König, P.J. (2023). Real Interest Rates, Bank Borrowing, and Fragility. *Journal of Money, Credit and Banking*, 56(6), pp. 1545-1571. https://doi.org/10.1111/jmcb.13033
2. BIS (2017). Basel III: Finalising post-crisis reforms. *Basel Committee on Banking Supervision, December*. Available at https://www.bis.org/bcbs/publ/d424.pdf
3. Barreira, R., Mayordomo, S., Roibas, I., & Ruiz-García, M. (2022). Recent developments in lending to non-financial corporations: supply and demand factors. *Banco de España Economic Bulletin,* 1/2022.
4. Bertrand, M., Schoar, A., & Thesmar, D. (2007). Banking Deregulation and Industry Structure: Evidence from the French Banking Reforms of 1985. *CEPR Discussion Paper, 4488*. https://doi.org/10.1111/j.1540-6261.2007.01218.x
5. Boyer, B., Lim, R., & Lyons, B. (2017). Estimating the cost of equity in emerging markets. A case study, *American Journal of Management*, 17(2), pp. 58-64.
6. Covas, F., & Dionis, G.F. (2022). Assessing the Decline in Bank Lending to Businesses. *Bank Policy Institute*, 14 September. Available at https://bpi.com/assessing-the-decline-in-bank-lending-to-businesses/
7. Cunha, J.R. (2021). The Advent of a New Banking System in the U.S.: Financial Deregulation in the 1980s. In A. Drach, & Y. Cassis (Eds), *Financial Deregulation: A Historical Perspective*, pp. 24-46. Oxford University Press. https://doi.org/10.1093/oso/9780198856955.003.0002
8. Escriva, J.L., Garcia-Herrero, A., Nuno, G., & Vial, J. (2009). After Bretton Woods II. *BBVA Working Papers*, 0806. https://dx.doi.org/10.2139/ssrn.1458765
9. ECB (2004). Recent developments in loans to non-financial corporations, *ECB Economic Bulletin*, 6(June). pp. 20-21.

10. ECB (2016). Trends in the external financing structure of euro area non-financial corporations. *ECB Economic Bulletin*, 5(August). pp. 29-32.
11. Hodrick, R.J., & Prescott, E.C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit and Banking,* 29(1), pp. 1-16. https://doi.org/10.2307/2953682
12. Mariscal, J.O, & Lee, R.M. (1993). The valuation of Mexican stocks: An extension of the capital asset pricing model to emerging markets. *Goldman Sachs Latin American Research*, 18 June, Available at: https://people.duke.edu/~charvey/Teaching/BA456_2006/GS_The_valuation_of_mexican_stocks.pdf
13. Richardson, G. (1981). *The banks' role in financing industry*, Bank of England Quarterly Bulletin. Available at https://www.bankofengland.co.uk/-/media/boe/files/quarterly-bulletin/1981/the-banks-role-in-financing-industry.pdf

Data sources:

- Bank for International Settlements (BIS) (2026). Effective exchange rates database. Available at https://data.bis.org/topics/EER/data.
- Bureau of Economic Analysis (BEA) (2026). Gross Domestic Product. Available at https://www.bea.gov/data/gdp/gross-domestic-product.
- Damodaran (2026). Equity Risk Premiums (Data, Updates, and Papers). Available at https://pages.stern.nyu.edu/~adamodar/.
- European Central Bank (ECB) (2026). Debt securities and loans of Non-financial corporations, ratio of GDP, Euro area 20, Quarterly. Available at https://data.ecb.europa.eu/data/datasets/QSA/QSA.Q.N.I9.W0.S11.S1.C.L.LE.F3T4.T._Z.XDC_R_B1GQ_CY._T.S.V.N._T.
- European Commission (2026). Business and consumer survey, Time series. Available at https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/download-business-and-consumer-survey-data/time-series_en.
- Eurostat (2026). Database. Available at https://ec.europa.eu/eurostat/web/main/data/database.
- National Bank of Romania (NBR) (2026). Monetary indicators – December 2025. Available at https://www.bnr.ro/en/25247-2026-01-27-monetary-indicators-december-2025

THE INFLATION-GROWTH NEXUS: A SYSTEMATIC REVIEW OF INTERNATIONAL EVIDENCE

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Abstract

This paper provides a systematic review of the empirical literature on the relationship between inflation and economic growth. By synthesising findings from 60 studies, we analyse the impact of inflation on growth, the presence of threshold effects, and the direction of causality between the two variables. Our analysis revealed a complex and context-dependent relationship, with diverse outcomes across countries and regions. While some studies indicate a positive impact of moderate inflation on growth, others find negative or insignificant effects of high inflation. Notably, the literature highlights the existence of varying inflation thresholds, beyond which adverse effects on growth become more pronounced. The direction of causality between inflation and growth is also multifaceted, with evidence supporting unidirectional, bidirectional, and insignificant causality. These findings underscore the importance of policymakers adopting nuanced approaches that balance price stability with sustainable economic growth, considering country-specific characteristics and institutional frameworks. The review also points to the need for researchers to focus on refining methodologies, expanding data coverage, and exploring heterogeneity in this relationship to provide more robust and actionable insights for policymakers.

Keywords: price level, macroeconomic variables, economic development, causality, monetary policy

JEL Classification: E31, E47, E52

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1. Introduction

Inflation and economic growth have a complex relationship, which has been the subject of much debate and research in the field of macroeconomics. As two of the most crucial macroeconomic variables, the interplay between inflation and growth has far-reaching implications for the overall well-being and development of an economy (Barro, 1995; Dornbusch et al., 1996). Understanding this relationship is of paramount importance for policymakers as it informs the formulation of effective monetary and fiscal policies aimed at fostering price stability and sustainable economic growth.

Historically, the predominant view rooted in the classical and monetary neutrality perspectives has been that inflation is a purely monetary phenomenon with no long-term impact on real economic variables. However, alternative theoretical perspectives challenge this view, proposing several channels through which inflation can potentially affect economic growth. This divergence in theoretical frameworks has led to a rapid expansion of empirical studies on the inflation-growth nexus, yielding a broad spectrum of results-ranging from positive to negative, and even non-linear relationships (Fischer, 1993; Bruno & Easterly, 1995; Khan & Senhadji, 2001). The aftermath of the global financial crisis, periods of low inflation in advanced economies, and ongoing macroeconomic volatility in emerging markets have further intensified the interest in understanding this complex relationship.

In the face of a rising tide of empirical research, systematic reviews have emerged as a critical new means in economics to organise and present evidence from disparate works. Systematic reviews differ from many traditional narrative reviews of the literature by using a consistent methodology for identifying, evaluating, and integrating empirical evidence, leading to conclusions with reduced bias and increased reliability (Petticrew & Roberts, 2006). Increasingly, the use of frameworks such as PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) has also helped researchers consolidate findings more systematically, particularly in a field like the inflation-growth nexus, where results are all too often mixed or conflicting.

This paper adds to this growing literature by using systematic review procedures of the inflation-growth nexus. This review, following a systematic approach, aims to provide an exhaustive synthesis of this vast empirical literature on the inflation-growth nexus. We also review the methodologies employed in these studies and synthesise the reported empirical findings.

These findings are most important for policymakers. The dynamics between inflation and growth are instrumental in macroeconomic stability; therefore, conceiving these associations is vital to devising policies that support an economy to get on a sustainable economic path while ensuring price stability. In synthesising the key insights from this body of research, we further our understanding of the inflation-growth nexus and flag implications for the future as well as policy-making.

In the subsequent sections, the paper delves into the theoretical underpinnings of the inflation-growth relationship, examines the empirical evidence from various studies, and discusses the implications of our findings for policymakers and researchers.

2. Theoretical perspectives

The relationship between inflation and economic growth has been a topic of extensive theoretical and empirical investigation, with numerous scholars proposing various frameworks to explain the potential linkages between these two macroeconomic phenomena. One of the foundational theories in this domain is the Quantity Theory of Money (QTM), which dates back to the work of classical economists such as Irving Fisher and Milton Friedman (Fisher, 1911; Friedman, 1956). The QTM posits a direct relationship between the money supply and the general price level, suggesting that changes in the money supply will lead to proportional changes in the price level, with no long-run effects on real output or employment (Laidler, 1991). This theoretical perspective views inflation as a purely monetary phenomenon, with the central bank's control over the money supply being the primary determinant of the inflation rate.

Building upon the QTM, the classical economic tradition and the principle of monetary neutrality have generally suggested that changes in the money supply or the general price level should have no real effects on the economy's output, employment, or other "real" variables in the long run (Hume, 1752; Fisher, 1911). According to this perspective, the impact of inflation on economic growth is negligible, as market forces eventually restore equilibrium and fully offset any monetary disturbances.

However, this classical view has been challenged by alternative theoretical perspectives that propose various channels through which inflation can potentially impact economic growth. One such framework is the Mundell-Tobin effect, which suggests that moderate levels of inflation can encourage a shift in portfolio allocation, stimulating investment and capital formation (Mundell, 1963; Tobin, 1965). This mechanism is based on the premise that higher inflation can lead to a decline in the real interest rate, which may incentivise individuals to shift their savings from money holdings to more productive assets such as physical capital, thereby promoting economic growth.

Conversely, the Stockman effect posits that inflation can negatively impact economic growth by distorting the optimal allocation of resources and reducing investment (Stockman, 1981). This channel suggests that inflation can create uncertainty, increase transaction costs, and erode the real value of financial assets, thereby discouraging investment and hampering long-term economic development.

Endogenous growth theory, developed by scholars such as Romer (1986) and Lucas (1988), provides another lens through which the inflation-growth relationship can be examined. This framework emphasises the role of technological progress, human capital, and other endogenous factors in driving long-term economic growth. Within this context, inflation can potentially affect growth by influencing the incentives for investment in research and development, the accumulation of human capital, and the efficiency of resource allocation. Empirical studies usually try to take into account all these channels through which inflation might affect growth; however, works testing endogenous growth theory are faced with its complexity. The complexity of the inflation-growth relationship has thus led to various methodological approaches, from panel data analysis to dynamic threshold models, which allow researchers to account for the non-linearities in inflation-to-growth relationships.

Real business cycle (RBC) theory, pioneered by Kydland and Prescott (1982) and Long and Plosser (1983), highlights the importance of intertemporal substitution in shaping the response of economic agents to changes in relative prices, including the general price level (Stadler, 1994). This framework suggests that inflation can impact economic growth by altering the relative attractiveness of leisure versus work as well as incentives for capital investment and consumption decisions. Although being an informative representation of the inflation-growth nexus, the RBC theory is often hard to apply in practise due to the issue of observing time-dependent decisions. Since the RBC theory is focused on time series data, most studies using these models tend to be complicated econometric techniques such as dynamic general equilibrium modelling that allows researchers to simulate how inflation can dampen growth over time. On the other hand, due to the complex structure of these models, they simply produce ambivalent results, fueling the bitter controversy about whether inflation even has any real effects.

More recently, New Keynesian models have explored the potential linkages between inflation and growth, emphasising the role of nominal rigidities, imperfect competition, and information asymmetries (Mankiw, 1985; Romer, 1986; Clarida et al., 1999). These frameworks suggest that changes in the inflation rate can have real effects on the economy, particularly in the short run, by influencing the allocation of resources, pricing decisions, and the level of economic activity. Empirical analyses based on New Keynesian theory are often econometric, which consider short-run deviations from equilibrium, by use of impulse response functions and error correction models. In general, these studies emphasise the short-run trade-offs between inflation and growth (e.g., Mankiw, 1985), which underscore the significance of credible monetary policy to prevent high levels of inflation from distorting economic performance.

The diverse theoretical perspectives outlined above have laid the foundation for extensive empirical research on the inflation-growth nexus, as summarised in Table 1.

Table 1

Summary of theoretical perspectives on the inflation-growth relationship

Theoretical Perspective	Key Propositions	Implications for Inflation-Growth Relationship
Quantity Theory of Money (QTM)	Changes in the money supply lead to proportional changes in the price level. Inflation is a purely monetary phenomenon.	Inflation has no long-run impact on real output or employment; long-run neutrality of money.
Classical and Monetary Neutrality	Changes in money supply or price level have no real effects on the economy in the long run. Inflation is neutral and does not affect real variables.	Inflation has a negligible impact on economic growth.
Mundell-Tobin Effect	Moderate inflation can lead to a decline in the real interest rate. This incentivises a shift from money holdings to productive assets, stimulating investment and capital formation.	Moderate inflation can have a positive impact on economic growth.
Stockman Effect	Inflation creates uncertainty, increases transaction costs, and erodes the real value of financial assets. This discourages investment and hampers long-term economic development.	Inflation has a negative impact on economic growth.
Endogenous Growth Theory	Technological progress, human capital, and other endogenous factors drive long-term growth. Inflation can affect growth by influencing incentives for investment in R&D and human capital accumulation.	The impact of inflation on growth can be positive or negative, depending on the specific channels.
Intertemporal Substitution and RBC Theory	Inflation can impact the relative attractiveness of leisure versus work, as well as the incentives for capital investment and consumption decisions.	The effect of inflation on growth can be mediated by the intertemporal substitution decisions of economic agents.
New Keynesian Perspectives	Nominal rigidities, imperfect competition, and information asymmetries can lead to real effects of inflation, particularly in the short run.	Changes in the inflation rate can affect resource allocation, pricing decisions, and the level of economic activity.

Source: Authors' compilation based on Fisher (1911), Mundell (1963), Tobin (1965), Stockman (1981), Romer (1986), Lucas (1988), Kydland and Prescott (1982), Mankiw (1985), Clarida et al. (1999), and Snowdon and Vane (2005)

By synthesising the key propositions and implications of these theoretical frameworks, the authors aim to provide a solid foundation for the subsequent discussion and analysis of the empirical literature on the inflation-growth relationship.

3. Methodology

This study employs a systematic review methodology to synthesise the empirical literature on the inflation-growth nexus. We followed established guidelines for conducting and reporting systematic reviews, drawing upon best practices from the PRISMA framework where applicable, to enhance the transparency and reproducibility of our research.

3.1 Search strategy and selection criteria

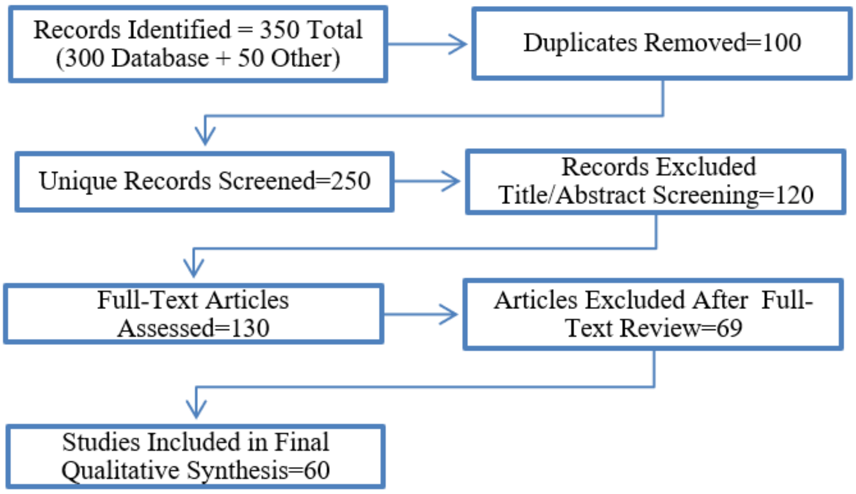
The search process involved querying multiple electronic databases, including EconLit, Web of Science, and Google Scholar, using keywords such as “inflation,” “economic growth,” “GDP,” and related terms. The initial search yielded a large number of potentially relevant studies, which were further screened based on a set of predefined eligibility criteria. To be included in the review, studies had to meet the following requirements: (1) published in peer-reviewed journals or as reputable working papers, research reports, and policy publications, (2) directly examined the relationship between inflation and economic growth, and (3) employ quantitative methodologies to examine the nature and direction of the relationship. Studies that were purely theoretical, qualitative, or did not directly address the inflation-growth nexus were excluded from the analysis.

3.2 Screening process

After the first search, titles and abstracts of studies retrieved were reviewed for selection. The full text was searched, and the studies were selected after validation in terms of fulfilling the inclusion/exclusion criteria. Sixty (60) studies were deemed eligible and included in the final review. An indication of this process is shown in Figure 1, which describes how studies are considered from identification to eventual inclusion.

Figure 1

PRISMA flow chart for study selection process



Source: Authors'

3.3 Data extraction and analysis

The selected studies were carefully reviewed, and relevant data were extracted and compiled into a comprehensive database. This included information on the country or region examined, the period covered, the methodological approach utilised, and key findings regarding the direction and magnitude of the inflation-growth relationship. To facilitate the synthesis and analysis of the literature, we organised the extracted data into a series of summary tables, as discussed in Section 4. This structured presentation allowed for the identification of patterns, commonalities, and divergences across various studies, laying the groundwork for in-depth discussion and analysis in the subsequent sections.

3.4 Bias minimisation

To reduce the risk of bias in the systematic review process, we used several approaches:

- The breadth of databases: We searched across a large number of different databases to ensure that we undertook an exhaustive scoping exercise.

- We also sought to reduce publication bias by including unpublished material research in addition to peer-reviewed journal articles, such as working papers and conference proceedings.
- Rigorous Scrutiny: A fine-toothed-comb scrutiny was done by 2 independent reviewers to reduce the selection bias, and discrepancies were resolved through discussion.
- Robust inclusion criteria: Inclusion/exclusion criteria were clearly described before the search stage that would ensure only pertinent and high-quality studies are included in the review.

3.5 Classification and summary of studies

We then classified the selected studies by geographic region, time, and methodological approach. This was classified to look for some patterns and trends in the literature that are observed based on differences in findings, regional disparities and methodological heterogeneity. The reason to categorise papers in this way is that it helps to understand how these types of context-specific factors (e.g., country characteristics, inflation thresholds) can precondition the relationship between inflation and growth.

In addition to comprehensive data collection and synthesis, the authors compared the methodological approaches, data coverage, and empirical findings of the included studies. Factors such as the study design, data sources, and analytical techniques were evaluated to ensure the validity and reliability of the reported findings.

However, it is important to note that the existing literature on the inflation-growth nexus is subject to certain limitations. These include the heterogeneity of methodological approaches, the potential for publication bias, and inherent challenges in establishing causal relationships between the two macroeconomic variables.

4. Findings

This section presents the empirical findings from the literature review on the inflation-growth nexus. The study's results are grouped into two parts: empirical findings on the inflation-growth nexus and empirical findings on the causal relationship between inflation and economic growth.

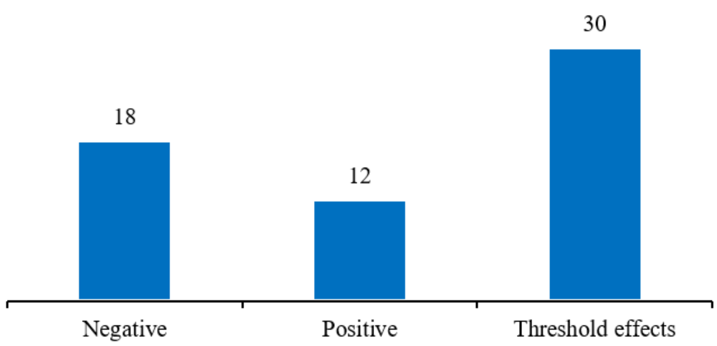
4.1 Empirical findings on the inflation-growth nexus

A comprehensive review of the existing literature on the relationship between inflation and economic growth reveals a complex and multifaceted landscape, with a diverse array of findings across different regions and contexts.

4.1.1 General trends of the inflation-growth relationship

As outlined in Section 3, data from 60 peer-reviewed studies were compiled into summary tables to simplify the analysis and synthesis of the available empirical evidence. The following is an overview of the general trend in the inflation-growth relationship reported in these studies, as presented in Figure 2.

Figure 2
The general trend in the inflation-growth relationship reported in selected studies



Source: Authors' compilation from the reviewed literature

- **Negative relationship**

As illustrated in Figure 2, a significant proportion of the reviewed studies (n=18) find a negative and statistically significant relationship between inflation and economic growth. This suggests that higher inflation rates tend to be detrimental to long-term economic development, potentially through channels such as resource allocation distortions, reduced investment, and eroded productivity gains, as outlined in the Stockman effect (Stockman, 1981).

- **Positive relationship**

By contrast, a comparable number of studies (n=12) identified a positive and significant impact of inflation on growth. This finding is consistent with the Mundell-Tobin effect (Mundell, 1963; Tobin, 1965), which posits that moderate inflation levels can encourage a shift in portfolio allocation, stimulating investment and capital formation.

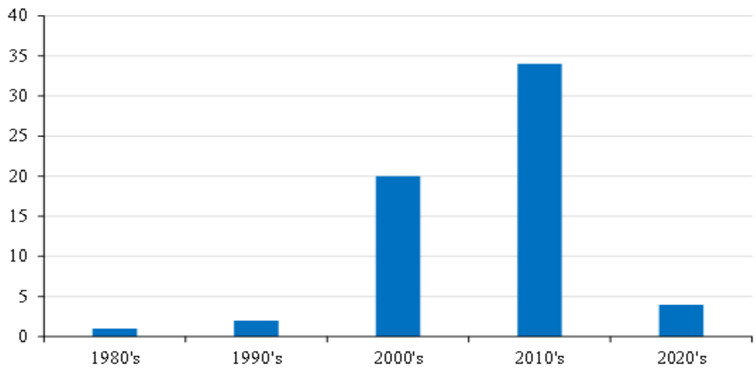
- **Threshold effects**

A majority group of studies (n=30) reported non-linear, threshold-based relationships, in which the impact of inflation on growth changes at certain critical levels. These results suggest that the inflation-growth nexus may be more complex than a simple linear relationship, with the directionality and magnitude of the effects potentially dependent on the specific economic context.

Figure 3 illustrates the distribution of publication years for the studies included in this review.

Figure 3

Histogram of publication years



Source: Authors' compilation from the reviewed literature

Figure 3 shows that publications on the inflation-growth nexus included in the analysis grew substantially in number over time, especially in the 2010s. This probably reflects increased interest in the topic because of several things, such as:

- The Global Financial Crisis: Following the global financial crisis and the long period of stagnation that came after, macroeconomic policies were once again put under a microscope.
- Low inflation: The prolonged periods of low inflation experienced by many advanced economies in the years following the crisis made the spectre of deflation and its potential growth impacts a reality.

- Macroeconomic instability in emerging market economies: Several macroeconomic instabilities in Emerging Markets, like currency movements and inflationary pressures, are additional factors, therefore fuelling inflation-growth interaction research.

This continued increase in publications serves to reiterate the ongoing significance and related relevance of studying the dynamic backdrop within which inflation or deflation affects economic growth.

4.1.2. Regional variations in the inflation-growth nexus

When examining the literature through a geographical lens, some notable regional differences emerge, which underscore the importance of considering the broader economic and institutional environment in understanding the inflation-growth relationship. This section presents a detailed review of the empirical literature on the relationship between inflation and economic growth organised by geographical region. The key findings for each region are summarised in a tabular format, followed by an analysis of the patterns, commonalities, and divergences observed in the literature.

- **Europe**

Table 2 summarises the key findings of 11 selected studies on the inflation-growth relationship in European countries.

Table 2

Summary of studies on the impact of inflation on economic growth in Europe

Author(s)	Country(ies)	Period of Analysis	Methodology	Key Findings
Karaca (2003)	Turkey	1987–2002	Regression analysis	Negative relationship
Lupu (2009)	Romania	1990-2000 2001-2009	Correlation	Positive relationship
Aydın et al. (2016)	Turkey	2002:Q1 to 2015:Q1	Dynamic panel threshold model	Nonlinear, threshold at 8.0 %
Kryeziu and Durguti (2019)	17 Eurozone countries	1997-2017	OLS regression	Positive relationship
Misiri and Fetai (2022)	Western Balkans	2000-2020	OLS, fixed effects, random effects, Hausman-Taylor IV*	Nonlinear with threshold at 3.9 %

Author(s)	Country(ies)	Period of Analysis	Methodology	Key Findings
Khan and Senhadji (2001)	140 countries, including several European countries	1960-1998	Threshold regression analysis	Nonlinear with a threshold at 2-3 % for European countries
Özdemir (2010)	UK	1957Q2 to 2006Q4	The vector auto-regressive fractionally integrated moving aver-age (VARFIMA)	Negative relationship
Tsionas and Christopoulos, (2003)	Euro		Threshold and smooth transition regression models	Nonlinear, threshold at 4.3 %
Kryeziu (2016)	Kosovo	2005-2014	Linear Regression Model	Positive relationship
Andoni and Osmani (2017)	Albania	1993-2015	ARDL	Negative relationship
Obradović, Šapić, Furtula and Lojanica (2017)	Serbia	Q1 2007 to Q3 2014	ARDL model	Positive relationship

Notes: OLS = Ordinary Least Squares, Hausman-Taylor IV = Hausman-Taylor Instrumental Variable approach

Source: Synthesis based on the studies listed in Table 2

Studies of European countries reveal no clear consensus on the inflation-growth relationship; however, nonlinear threshold effects appear more frequently than either purely positive or purely negative relationships.

- Positive Relationship: Lupu (2009), Kryeziu (2016), Obradović, Šapić, Furtula and Lojanica (2017) and a cross-sectional study by Kryeziu and Durguti (2019) find a positive impact of inflation on growth, particularly in countries with higher trade exposure and transitional economic structures, such as Romania and the transitional economies of Eastern Europe.
- Negative Relationship: Karaca (2003), Özdemir (2010) and Andoni and Osmani (2017) identify a negative relationship, especially in larger, more developed economies, such as Turkey and the UK.
- Nonlinear Relationship: Notably, four of the eleven studies reviewed, such as Khan and Senhadji (2001), Tsionas and

Christopoulos (2003), Aydın et al. (2016) and Misiri and Fetai (2022) identify nonlinear threshold effects, suggesting that the impact of inflation on growth changes beyond certain levels (4.3 percent for the Euro, 8.0 percent for Turkey and 3.9 percent for the Western Balkans).

Overall, the European evidence suggests that the inflation-growth relationship is highly context-specific, although threshold effects emerge as the most consistent finding across studies. The positive relationship observed in some studies may be attributable to the stimulative effects of moderate inflation on investment and consumption in developing economies. By contrast, the negative relationship found in other studies may be due to the distortionary effects of high inflation on resource allocation and price stability in developed economies.

- **Asia**

Table 3 summarises the key findings from 20 studies on the inflation-growth relationship in Asian countries.

Table 3

Summary of studies on the impact of inflation on economic growth in Asia

Author(s)	Country(ies)	Period of Analysis	Methodology	Key Findings
Ahmed and Mortaza (2005)	Bangladesh	1980-2005	Co-integration, error correction	Negative relationship, Nonlinear with a threshold at 6.0 %
Alkhatani and Elhendy (2014)	Saudi Arabia	1970-2012	Threshold model	Nonlinear, threshold at 4.0 %
Behera and Mishra (2016)	China, South Africa	1970-2013	ARDL Bound Testing	Positive relationship
Bhusal and Silpakar (2011)	Nepal	1975-2010	OLS	Nonlinear, threshold at 6.0 %
Fountas et al. (2002)	Japan	1970-1999	Bivariate GARCH	Negative relationship
He and Zou (2016)	China	1952-2013	OLS, IV regression	Positive relationship
Hossain (2015)	Bangladesh, Iran, Indonesia, Malaysia, Pakistan	1980-2013	Co-integration, error correction, Granger causality	Negative relationship
Hussain and Malik (2011)	Pakistan	1961-2010	Two-stage least squares	Positive relationship

Author(s)	Country(ies)	Period of Analysis	Methodology	Key Findings
Khan and Khan (2018)	Bangladesh, Iran, Indonesia, Malaysia, Pakistan	1980-2016	Least Squares, traditional panel estimation	Negative relationship
Lee and Wong (2005)	Taiwan, Japan	1961-2001	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 7.2 % (Taiwan), 9.7 % (Japan)
Madurapperuma (2016)	Sri Lanka	1978-2013	Engle-Granger co-integration, ECM	Negative relationship
Mallik and Chowdhury (2001)	South Asia (Bangladesh, India, Pakistan, Sri Lanka)	1965-1996	Error-correction, co-integration	Positive relationship
Mohseni and Jouzaryan (2016)	Iran	1988-2013	ARDL	Negative relationship
Mubarik (2005)	Pakistan	1973-2000	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 9.0 %
Munir, Mansur and Furuoka (2009)	Malaysia	1970-2005	Endogenous threshold autoregressive models	Nonlinear, threshold at 3.9 %
Sweidan (2004)	Jordan	1970-2000	ARCH model, growth model	Nonlinear, threshold at 2.0 %
Thanh (2015)	ASEAN-5 (Indonesia, Malaysia, Philippines, Singapore, Thailand)	1980-2011	Panel Smooth Transition Regression (PSTR)	Nonlinear, threshold at 7.8 %
Tien (2021)	Vietnam	1986-2019	Threshold regression	Nonlinear, threshold at 6.0 %
Tung and Thanh (2015)	Vietnam	1990-2013	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 7.0 %
Van Dinh (2020)	Vietnam	1986-2018	OLS regression	Positive relationship

Notes: ARDL = autoregressive distributed lag, ARCH = autoregressive conditional heteroskedasticity ECM = error correction model, IV = instrumental variable, OLS = ordinary least squares, PSTR = panel smooth transition regression, TAR = threshold autoregression.

Source: Synthesis based on the studies listed in Table 3

Studies on Asian countries present a mixed picture; however, nonlinear threshold effects emerge as the dominant finding, accounting for nearly half of the studies reviewed.

- Positive Relationship: Mallik and Chowdhury (2001), Hussain and Malik (2011), Behera and Mishra (2016), He and Zou (2016), and Van Dinh (2020) find a positive impact of inflation on growth, particularly in rapidly growing economies such as Pakistan, China, and Vietnam.
- A negative Relationship: Fountas et al. (2002), Hossain (2015), Khan and Khan (2018), Madurapperuma (2016), and Mohseni and Jouzaryan (2016) identify negative effects of inflation on growth across a diverse group of Asian economies, including Japan, Bangladesh, India, and Sri Lanka.
- Nonlinear Relationship: Ten of the twenty studies reviewed identify nonlinear threshold effects. Ahmed and Mortaza (2005), Thanh (2015), Lee and Wong (2005), Mubarik (2005), Munir, Mansur and Furuoka (2009), Bhusal and Silpakar (2011), Tien (2021), Tung and Thanh (2015), Alkhatani and Elhendy (2014), and Sweidan (2004) find nonlinear relationships with varying threshold levels, suggesting that the optimal inflation rate for growth may vary depending on the country's specific context.

Overall, the Asian evidence suggests that inflation-growth dynamics are predominantly nonlinear, with most studies indicating the existence of inflation thresholds beyond which the effects on growth become less favourable. The positive relationship found in some studies may be attributed to the role of moderate inflation in stimulating investment and consumption in developing economies. The negative relationships found in other studies may be due to the adverse effects of high inflation on price stability and resource allocation in developed economies. The nonlinear findings, with threshold levels ranging from 2 percent to 9.7 percent, suggest that the optimal inflation rate for growth may vary depending on a country's level of economic development, institutional frameworks, and macroeconomic policies. Nevertheless, most estimated thresholds are concentrated within the 4 to 8 percent range, suggesting a degree of convergence despite differences across countries. For example, studies on Vietnam and China, which have experienced rapid economic growth and increasing trade integration, find higher inflation thresholds than more developed economies such as Japan and Taiwan.

- **Africa**

Table 4 summarises the key findings from studies on the inflation-growth relationship in African countries.

Table 4

Summary of studies on the impact of inflation on economic growth in Africa

Author(s)	Country(ies)	Period of analysis	Methodology	Key findings
Umaru and Zubairu (2012)	Nigeria	1970-2010	Augmented Dickey-Fuller, Granger causality	Positive relationship
Chude and Chude (2015)	Nigeria	1986-2012	OLS	Positive relationship
Hodge (2006)	South Africa	1965-2002	OLS	Negative relationship
Inyiama (2013)	Nigeria	1970-2012	Granger causality, co-integration	Negative relationship
Mkhatshwa et al. (2015)	Swaziland	1980-2013	ARDL	Negative relationship
Opeyemi (2020)	5 African countries (excluding Egypt)	1980-2017	Regression analysis	Negative relationship
Shitundu and Luvanda (2000)	Tanzania	1967-1996	Least Trimmed Squares (LTS)	Negative relationship
Iyke and Odhiambo (2017)	Ghana, Nigeria	1980-2013	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 10.7-29.8 % (Ghana), 10.1-19.3 % (Nigeria)
Rao and Abate (2015)	Ethiopia	1970-2013	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 9-10 %
Yabu and Kessy (2015)	Kenya, Tanzania, Uganda	1970-2013	Non-linear quadratic model	Nonlinear, threshold at 6.8 % (Kenya), 8.4 % (Uganda), 8.8 % (Tanzania)
Rutayisire (2015)	Rwanda	1970-2010	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 5.4 %
Fabayo and Ajilore (2006), Salami and Kelikume (2010), Bawa and Abdullahi (2012)	Nigeria	-	Non-linear least squares, TAR approach	Nonlinear, thresholds at 6 %, 8 %, and 13 %
Frimpong and Oteng-Abayie (2010)	Ghana	-	Threshold autoregressive (TAR) approach	Nonlinear, thresholds at 11 % and 6-10 %
Phiri (2010)	South Africa	1980-2008	Threshold autoregressive (TAR) approach	Nonlinear, threshold at 8.0 %

Source: Synthesis based on the studies listed in Table 4

Studies of African countries reveal substantial heterogeneity in the inflation-growth relationship; however, nonlinear threshold effects constitute the dominant finding across the reviewed evidence.

- Positive Relationship: Umaru and Zubairu (2012) and Chude and Chude (2015) find a positive impact of inflation on growth in Nigeria.
- Negative Relationship: Hodge (2006), Inyiama (2013), and Mkhatshwa et al. (2015), Opeyemi (2020), and Shitundu and Luvanda (2000) identify the negative effects of inflation on growth in South Africa, Swaziland, Tanzania, and other African countries.
- Nonlinear Relationship: More than half of the reviewed studies identify nonlinear threshold effects. Iyke and Odhiambo (2017), Rao and Abate (2015), Yabu and Kessy (2015), Rutayisire (2015), Fabayo and Ajilore (2006), Salami and Kelikume (2010), Bawa and Abdullahi (2012), Frimpong and Oteng-Abayie (2010), and Phiri (2010) found nonlinear relationships with varying threshold levels, suggesting that the optimal inflation rate for growth may vary significantly across African countries, with several studies reporting threshold levels above 10 percent.

Overall, the African evidence suggests that the inflation-growth relationship is predominantly nonlinear, with most studies identifying country-specific inflation thresholds beyond which growth effects become less favourable. The positive relationship found in some studies may be due to the role of moderate inflation in stimulating investment and consumption in developing economies. The negative relationships found in other studies may be due to the adverse effects of high inflation on price stability and resource allocation. Nonlinear findings, with threshold levels ranging from 5.4 percent to 18.5 percent, suggest that the optimal inflation rate for growth may vary significantly across African countries. Nevertheless, a large proportion of the estimated thresholds are concentrated within the 6 to 11 percent range, indicating some degree of convergence despite country-specific differences. These variations can be attributed to differences in economic structure, trade openness, institutional frameworks, and macroeconomic policy environments.

- **Americas, Oceania and other regions**

Table 5 presents the key findings from studies on the inflation-growth relationship covering countries in the Americas and Oceania.

Table 5

Summary of Studies on the impact of inflation on economic growth in the Americas and Oceania

Author(s)	Country(ies)	Period of Analysis	Methodology	Key Findings
Grier and Grier (2006)	Mexico	1970-2001	GARCH	Negative relationship
Risso and Sanchez Carrera (2009)	Mexico	1970-2006	Cointegration, error correction	Nonlinear, threshold at 9 %
Gokal and Hanif (2004)	Fiji	1970-2000	Cointegration, error correction	Nonlinear, threshold at 3 %
Espinoza et al. (2012)	GCC (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, UAE)	1970-2007	Panel data models	Nonlinear, threshold at 9 %
Kremer et al. (2013)	Latin America (Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Mexico, Peru, Venezuela)	1960-2004	Panel data models	Nonlinear, threshold at 19.1 %
Bittencourt (2012)	Latin America	1970-2007	Panel time-series data and analysis	Negative
Baharumshah, Slesman, Wohar (2016)	Latin America	1980-2011	Panel data models	Nonlinear, threshold at 19 %
De Gregorio (1993)	Latin America	1950-1985	Endogenous growth model	Negative
Black, Dowd, and Keith (2001)	USA	1964-1989	Correlation	Positive if the inflation rate is low
Tajra (1999)	Brazil	1965-1994	Regression model	Negative
Brook and Scrimgeour (2002)	New Zealand	-	Threshold regression	Nonlinear, threshold at 0-3 %
Jarrett and Selody (1982)	Canada	1963-1979	Regression	Negative

Source: Synthesis based on the studies listed in Table 5

Although the evidence from the Americas and Oceania is more limited than that of other regions, the reviewed studies predominantly support either a negative or a nonlinear relationship between inflation and economic growth.

- Positive Relationship: One study by Black, Dowd, and Keith (2001) found a positive relationship between inflation and growth in the USA.
- Negative Relationship: Jarrett and Selody (1982), Tajra (1999), Grier and Grier (2006), De Gregorio (1993) and Bittencourt (2012) find a negative relationship between inflation and growth in the Americas.
- Nonlinear Relationship: Half of the reviewed studies identify nonlinear threshold effects. Risso and Sanchez Carrera (2009), Baharumshah et al. (2016), Gokal and Hanif (2004), Espinoza et al. (2012), Brook and Scrimgeour (2002), and Kremer et al. (2013) found nonlinear relationships with varying threshold levels, suggesting that the impact of inflation on growth can change at certain inflation rates.

Overall, the available evidence suggests that inflation becomes increasingly detrimental to growth once it exceeds country-specific threshold levels, while sustained high inflation is generally associated with weaker economic performance. The available evidence is consistent with findings from other regions, indicating that high inflation rates tend to hinder economic growth, potentially through channels such as increased uncertainty, resource misallocation, and negative impacts on investment and productivity. The nonlinear findings further emphasise the importance of considering context-specific factors when analysing the inflation-growth relationship. Notably, estimated threshold levels vary considerably, ranging from around 0-3 percent in New Zealand to approximately 19 percent in Latin America, indicating substantial regional heterogeneity in inflation tolerance.

4.1.3 Strengths and weaknesses of different study designs

The literature reviewed in this section employs a variety of methodological approaches ranging from large panel studies to small panel/regionally focused analyses and single-country investigations. Each of these study designs offers unique strengths and weaknesses that should be considered when interpreting findings.

- Large panel studies, such as those by Khan and Senhadji (2001) and Ndoricimpa (2017), provide a broad perspective on the inflation-growth relationship, allowing for cross-country comparisons and the identification of general trends. However, these studies may overlook country-specific nuances and the influence of contextual factors on the relationship between inflation and growth.

- In contrast, small panel studies and regionally focused analyses, exemplified by the works of Sepehri and Moshiri (2004) and Yabu and Kessy (2015), offer deeper insights into the inflation-growth nexus within a group of culturally or economically similar countries. These studies shed light on the role of institutional frameworks, policy environments, and other regional factors in shaping the relationship between the two variables.
- Single-country analyses, such as those by Aydın et al. (2016) and Misiri and Fetai (2022), provide the most granular understanding of the inflation-growth dynamics within a specific economic and institutional context. These studies can uncover the unique characteristics and drivers underlying the observed relationships; however, their findings may have limited generalizability to other settings.

An important pattern emerging from the reviewed studies is that nonlinear and threshold effects are identified more frequently in studies employing threshold regression, smooth transition, and autoregressive threshold models than in studies relying on conventional linear estimation techniques. This suggests that methodological choice may partly explain the variation in reported findings across the literature and reinforces the importance of accounting for possible nonlinearities when examining the inflation-growth relationship.

Collectively, the reviewed literature demonstrates the importance of considering the strengths and weaknesses of each study design when synthesising empirical evidence on the inflation-growth nexus. A combination of large-panel, small-panel/regional, and single-country studies can provide a more comprehensive and nuanced understanding of this complex relationship, allowing for the identification of both general patterns and context-specific factors that influence the impact of inflation on economic growth.

4.2 Empirical findings on causality between inflation and economic growth

The existing literature on the inflation-growth nexus has not only explored the directionality and magnitude of the relationship but has also delved into the deeper question of causality: Does inflation lead to changes in economic growth, or is it the other way around?

4.2.1 Directions of causality

Determining the direction of causality between inflation and growth is crucial to understanding the underlying mechanisms and designing appropriate policy interventions. A total of 24 studies in the reviewed literature have employed advanced econometric techniques such as Granger causality tests and vector autoregressive (VAR) models to investigate the causal linkages between the two variables.

- **Bidirectional causality between inflation and economic growth**

A first set of studies (n=6) found evidence of bidirectional causality, indicating that inflation and growth may be simultaneously determined and mutually reinforced. Studies finding bidirectional causality include Huang et al. (2010) in a cross-country analysis, Behera and Mishra (2016) in BRIC countries, Koulakiotis et al (2012) in European countries, Özyilmaz (2022) in 27 EU countries, Singh and Singh (2015) in Japan and Rao and Abate (2015) in Ethiopia. This suggests a more complex, dynamic relationship between the two macroeconomic variables, where they can both act as drivers and consequences of each other depending on the specific economic context.

- **Growth-driven inflation**

A subset of studies (n=5) identified a causal relationship between economic growth and inflation. Studies supporting this causal direction include Gokal and Hanif (2004) in Fiji, Bakare, Kareem, and Oyelekan (2015) in Nigeria, and Kanca (2017) and Özpence (2016) in Turkey and Tenny (2022) in Liberia. This implies that expansions in real output and income can generate inflationary pressures, potentially through demand-pull or cost-push mechanisms, as emphasised in some New Keynesian models (Mankiw, 1985; Romer, 1986).

- **Inflation-driven growth**

By contrast, another group of studies (n=8) found evidence of inflation-driven growth, suggesting that changes in the inflation rate precede and lead to subsequent changes in economic output. Studies supporting this causal direction include Al-Khulaifi (2018) in Qatar, Behera and Mishra (2016) in India, Datta and Kumar (2011) in Malaysia, Erbaykal and Okuyan (2008) in Turkey, Hossain et al. (2012)

in Bangladesh, Hussain and Zafar (2018) in Pakistan, Mubarik (2005) in Pakistan and Omoke (2010) in Nigeria. This finding supports theoretical frameworks that propose channels through which inflation can stimulate investment, capital formation, and productivity gains, as in the case of the Mundell-Tobin effect (Mundell, 1963; Tobin, 1965).

- **No causality between inflation and economic growth**

A last set of studies (n=5) found no evidence of causality, indicating that inflation and growth may be determined by other factors like external shocks, fiscal policies, or structural changes. Studies finding no causality include Anochiwa and Maduka (2015) in Nigeria, a cross-sectional study by Dada et al. (2017) in five ECOWAS countries, Faria and Carneiro (2001) in Brazil, Özçelik and Uslu (2017) in Turkey and Shuaib et al. (2015) in Nigeria.

Taken together, the causality evidence does not support a single dominant direction of influence between inflation and economic growth. However, inflation-driven growth and bidirectional causality are reported more frequently than growth-driven inflation or insignificant relationships, suggesting that inflation may play a more active role in shaping growth dynamics than is implied by purely growth-driven explanations.

Table 6 presents a summary of the key findings from a limited number of studies on the direction of causality between inflation and economic growth.

Table 6

Summary of studies on the direction of causality between inflation and economic growth

Author(s)	Region/Country	Methodology	Direction of Causality
Behera and Mishra (2016)	BRIC countries	ARDL technique	Bidirectional
Huang et al. (2010)	140 countries	Instrumental-variable threshold regression approach	
Koulakiotis et al. (2012)	14 European countries	VAR-Granger causality	
Özyilmaz (2022)	27 EU countries	Dumitrescu and Hurlin's (2012) causality approach	
Rao and Abate (2015)	Ethiopia	VAR and VECM models	
Singh and Singh (2015)	Japan	Granger-causality test	

Author(s)	Region/Country	Methodology	Direction of Causality
Bakare, Kareem, and Oyelekan (2015)	Nigeria	Granger-causality test	Growth → Inflation
Gokal and Hanif (2004)	Fiji	Granger-causality test	
Kanca (2017)	Turkey	Toda Yamamoto causality test	
Özpence (2016)	Turkey	Granger-causality test	
Tenny (2022)	Liberia	Granger-causality test	
Al-Khulaifi (2018)	Qatar	Granger-causality test	Inflation → Growth
Behera and Mishra (2016)	India	VAR analysis	
Datta and Kumar (2011)	Malaysia	Granger-causality test	
Erbaykal and Okuyan (2008)	Turkey	Toda Yamamoto causality test	
Hossain et al. (2012)	Bangladesh	VAR-Granger causality	
Hussain and Zafar (2018)	Pakistan	ARDL-bounding testing approach	
Mubarik (2005)	Pakistan	Granger-causality test	
Omoke (2010)	Nigeria	Granger-causality test	
Anochiwa and Maduka (2015)	Nigeria	Granger-causality test	Insignificant
Dada et al. (2017)	Five ECOWAS countries	UVAR-based Toda and Yamamoto Modified Granger causality approach	
Faria and Carneiro (2001)	Brazil	Bivariate model	
Özçelik and Uslu (2017)	Turkey	VAR model	
Shuaib et al. (2015)	Nigeria	Granger-causality test	

Notes: ARDL = Autoregressive Distributed Lag, VAR = Vector Autoregression, VECM = Vector Error Correction Model, UVAR = Unrestricted Vector Autoregression.

Source: Synthesis based on the studies listed in Table 6

4.2.2 Regional variations in the direction of causal relationship

As with the directionality of the inflation-growth relationship, the causal linkages also exhibit notable regional differences. Evidence from developed economies is mixed, with studies reporting both bidirectional causality and inflation-led growth, although no single causal pattern dominates. In contrast, the literature on developing and emerging economies, particularly in Asia and Africa, more often reports growth-driven inflation or bidirectional causality. This may reflect the unique macroeconomic conditions and institutional environment prevalent in these regions, which can shape the complex dynamics between inflation and economic growth.

4.2.3 Factors influencing the directions of causal relationships

Although the reviewed studies do not always explicitly identify the determinants of causality, several factors can explain the observed variations in the direction of causality between inflation and economic growth, including levels of economic development, institutional frameworks, and macroeconomic policy environments.

One possible explanation is that unidirectional causality from inflation to growth may be more prevalent in countries with weaker institutions, less-developed financial markets, and a history of high inflation. In such a context, the adverse effects of inflation on investment, productivity, and resource allocation can be more pronounced, leading to a stronger causal impact on economic growth.

On the other hand, unidirectional causality from growth to inflation may be more common in economies with robust macroeconomic policies and institutions that can effectively manage inflationary pressures. In such cases, the demand-pull effects of economic expansion may play a more significant role in driving inflation.

Bidirectional causality, in which inflation and growth mutually influence each other, may be observed in economies with more complex, intertwined relationships between the two variables. This can occur in countries with moderate inflation and growth levels, where the interactions between inflation and growth dynamics are less straightforward and may be affected by a range of contextual factors.

Overall, a review of the literature on the direction of the causality between inflation and economic growth highlights the multifaceted and context-dependent nature of this relationship. Policymakers should carefully consider the specific economic and institutional characteristics of their countries when formulating policies to manage inflation and promote sustainable economic growth.

5. Discussion and synthesis

A comprehensive review of the existing empirical literature on the inflation-growth nexus has revealed a complex, multifaceted relationship, with a diverse array of findings across regions and contexts. By synthesising key insights from this body of research, we aim to provide a holistic understanding of the dynamic interplay between these two crucial macroeconomic variables.

5.1 Reconciling the divergent findings

A striking feature of the literature is the diversity of findings. Studies report positive, negative, and nonlinear relationships between inflation and economic growth. These differences may reflect variations in economic development, institutional quality, policy frameworks, and broader macroeconomic conditions.

Nevertheless, one of the most consistent findings across regions is the prevalence of nonlinear threshold effects, suggesting that the inflation-growth relationship is rarely purely linear and that the growth consequences of inflation depend critically on its level.

5.1.1 The role of economic development

The level of economic development appears to be a crucial determinant of inflation-growth dynamics. Studies focusing on developed economies such as those in Europe and North America tend to align more closely with the classical view of a negative relationship between inflation and growth, particularly at high levels of inflation. This is consistent with theoretical predictions, such as the Stockman effect (Stockman, 1981), which posits that high and volatile inflation can distort resource allocation, reduce investment, and erode productivity gains.

In contrast, studies on developing and emerging economies, particularly in Asia and Africa, more frequently report nonlinear or threshold-based relationships. Some studies also find a positive association between inflation and growth. This may reflect the unique macroeconomic conditions and institutional environments prevalent in these regions, where the Mundell-Tobin effect (Mundell, 1963; Tobin, 1965) suggests that moderate inflation levels can potentially have beneficial effects on growth.

5.1.2 The influence of monetary policy regimes

The nature of the monetary policy framework and the central bank's credibility in maintaining price stability also appear to play a significant role in the inflation-growth relationship. Studies of countries with well-established inflation-targeting regimes often find a stronger negative relationship between inflation and growth. Such policy frameworks help anchor inflation expectations and reduce the distortions associated with high inflation.

5.2 Causal linkages and feedback effects

A review of the literature on the causality between inflation and economic growth reveals an even more complex picture, with studies identifying inflation-driven growth, growth-driven inflation, and bidirectional causal relationships. Importantly, the reviewed evidence suggests that no single causal pattern dominates across all countries and regions, reinforcing the context-dependent nature of the inflation-growth nexus. These findings underscore the dynamic and interdependent nature of the two macroeconomic variables, where they can act as drivers and consequences of each other, depending on the specific economic context.

Studies that find evidence of inflation-driven growth lend support to the theoretical frameworks that propose channels through which inflation can stimulate investment, capital formation, and productivity gains, as in the case of the Mundell-Tobin effect. Conversely, the literature reporting growth-driven inflation emphasises the role of demand-pull or cost-push mechanisms, as highlighted in some New Keynesian models (Mankiw, 1985; Romer, 1986).

Studies reporting bidirectional causality suggest a more complex relationship between inflation and growth. In these cases, the two variables may influence each other simultaneously and reinforce one another over time. This underscores the importance of considering the broader economic and institutional environment to understand the interlinkages between these macroeconomic phenomena.

5.3 Implications for policymakers

The insights derived from this comprehensive literature review have important implications for policymakers tasked with promoting sustainable economic growth and maintaining price stability.

In developed economies, where evidence predominantly points to a negative relationship between inflation and growth, particularly at high levels of inflation, the findings underscore the importance of proactive and credible monetary policy frameworks that prioritise price stability. In these contexts, central banks should strive to anchor inflation expectations and minimise the distortionary effects of high and volatile inflation, which can erode investment, productivity, and long-term economic development.

The literature suggests a more nuanced approach for policymakers in both developing and emerging economies. The presence of nonlinear and threshold effects suggests that a uniform policy approach may not be appropriate. Instead, policymakers should adopt strategies that reflect country-specific economic conditions. Carefully managing inflation within the optimal range while fostering other drivers of economic growth may be a more effective strategy for these economies.

Across all contexts, the literature on the causal linkages between inflation and growth emphasises the importance of policy coordination and a holistic macroeconomic management approach. Policymakers should be cognizant of the dynamic, interdependent nature of these variables and tailor their interventions accordingly to address the unique challenges and opportunities present in their respective economies.

6. Conclusion

The relationship between inflation and economic growth remains one of the most ambiguous as well as debatable issues in macroeconomic policy. This study reviewed the empirical literature on the inflation-growth nexus. The findings reveal substantial variation across countries and regions (Bruno & Easterly, 1998). The results underline the need to be read in light of economic development, institutions and wider macroeconomic contexts when exploring this association. A particularly robust finding across the reviewed literature is the presence of nonlinear threshold effects, indicating that the consequences of inflation for growth depend not only on its existence but also on its magnitude.

Inflation, especially when it rises beyond certain limits, typically comes with a cost in the form of slower growth even for the advanced economies. This is consistent with the classical implications that high inflation leads to distortions in resource allocation and tends to erode productivity. Conversely, research from developing and emerging nations points to threshold-like relationships in the majority of studies conducted, with some support for positive effects. One implication from these results is that moderate inflation may help investment and capital formation where financial markets are underdeveloped.

The implications of these findings for policymakers are significant. Price stability is more critical to ensure long-term prosperity in developed economies. This emphasises why credible monetary policy frameworks and inflation-targeting mechanisms remain critical. Yet in emerging markets, a more flexible type of adaptation might be required. Often, policymakers in such cases face the difficult task of managing inflation while still promoting growth via investments in physical and human capital. Maintaining inflation within country-specific threshold ranges may support investment and economic expansion. At the same time, it can help preserve macroeconomic stability.

The evidence suggests that the inflation-growth relationship is often nonlinear and threshold-dependent. As a result, rigid inflation targets may not always be appropriate. Policymakers may benefit from adopting flexible target ranges that can accommodate changing economic conditions.

This review also identifies some limitations of the literature that could be addressed by future research. The heterogeneity of methodologies limits direct comparability across studies, and indeed calls for more consensus-driven empirical work. We recommend harmonising methodologies in future research, for example through meta-analyses or consistent datasets that allow for cross-country comparisons. Future research should examine inflation thresholds across different regions. Greater attention should also be given to how institutional quality, economic structure, and policy environments influence the inflation-growth relationship.

Causality is a key issue for further future research. Despite the number of studies that have found evidence for both directions of causality, the channels through which inflation impacts growth (and vice versa) are not well understood. Future work must adopt higher-level econometric methods to further disentangle these causal pathways, providing more manageable advice for policymakers.

The relationship between inflation and growth is complex and multidimensional. It is shaped by geopolitical conditions, socioeconomic factors, and the level of economic development. Policy makers must take sophisticated and well-differentiated means to fit the specifics of their economic scenario, balancing cost stability with exciting growth strategies. Addressing the methodological and empirical gaps identified in this review will enable future research to generate deeper, more useful insights into the inflation-growth nexus that can contribute to a better understanding of macroeconomic policy design.

References

1. Ahmed, S., & Mortaza, M.G. (2005). Inflation and economic growth in Bangladesh: 1981–2005. *Bangladesh Bank. Policy Analysis Unit Working Paper Series*, 0604(December).
2. Alkahtani, S.H., & Elhendy, A.M. (2014). Optimal inflation rate estimation for the Kingdom of Saudi Arabia: A threshold model approach. *Life Science Journal, 11*(4), pp. 73–78.
3. Al-Khulaifi, A.S. (2018). An empirical study on inflation and economic growth in Qatar. *International Journal of Economics and Financial Research, 4*(9), pp. 292–296.
4. Andoni, M., & Osmani, M. (2017). Assessment of the Relationship between Inflation, Growth and Fiscal Deficit in Albania: An econometric approach. *European Scientific Journal,* 13(13), pp. 137–152. DOI: https://doi.org/10.19044/esj.2017.v13n13p137
5. Anochiwa, L.I., & Maduka, A. (2015). Inflation and economic growth in Nigeria: Empirical evidence. *Journal of Economics and Sustainable Development, 6*(20), pp. 113–121.
6. Aydın, C., Esen, Ö., & Bayrak, M. (2016). Inflation and economic growth: A dynamic panel threshold analysis for Turkish republics in the transition process. *Procedia - Social and Behavioral Sciences,* 229, pp. 196–205. https://doi.org/10.1016/j.sbspro.2016.07.129
7. Baharumshah, A.Z., Slesman, L., & Wohar, M.E. (2016). Inflation, inflation uncertainty, and economic growth in emerging and developing countries: Panel data evidence. *Economic Systems, 40*(4), pp. 638–657. https://doi.org/10.1016/j.ecosys.2016.02.009
8. Bakare, H. A., Kareem, R.O., & Oyelekan, B.A. (2015). Effects of inflation rate on economic growth in Nigeria (1986–2014). *Developing Country Studies, 5*(8), pp. 153–160.
9. Barro, R.J. 1995. Inflation and economic growth. *Bank of England Quarterly Bulletin*, 35(2), pp. 166–176.
10. Behera, J., & Mishra, A.K. (2016). Inflation and economic growth nexus in BRICS: Evidence from ARDL bound testing approach. *Asian Journal of Economic Modelling, 4*(1), pp. 1–17. https://doi.org/10.18488/journal.8/2016.4.1/8.1.1.17
11. Bawa, S., & Abdullahi, I.S. (2012). Threshold effect of inflation on economic growth in Nigeria. *CBN Journal of Applied Statistics*, 3(1), pp. 43–63.
12. Bittencourt, M. (2012). Inflation and economic growth in Latin America: Some panel time-series evidence. *Economic Modelling, 29*(2), pp. 333–340. https://doi.org/10.1016/j.econmod.2011.10.018

13. Black, D.C., Dowd, M.R., & Keith, K. (2001). The inflation-growth relationship: Evidence from state panel data. *Applied Economics Letters, 8*(12), pp. 771–774. https://doi.org/10.1080/13504850110044202
14. Brook, A.M., Karagedikli, Ö., & Scrimgeour, D. (2002). An optimal inflation target for New Zealand: Lessons from the literature. *Reserve Bank of New Zealand Bulletin, 65*(3), pp. 5–16.
15. Bruno, M., & Easterly, W. (1995). Could inflation stabilisation be expansionary? *Transition, 1*(7–8), pp. 1–3.
16. Bruno, M., & Easterly, W. (1998). Inflation crises and long-run growth. *Journal of Monetary Economics*, 41(1), pp. 3–26. https://doi.org/10.1016/S0304-3932(97)00063-9
17. Chude, D.I., & Chude, N.P. (2015). Impact of inflation on economic growth in Nigeria. *International Journal of Business and Management Review, 3*(5), pp. 26–34.
18. Clarida, R., Galí, J., & Gertler, M. (1999). The Science of Monetary Policy: A New Keynesian Perspective. *Journal of Economic Literature, 37*(4), pp. 1661–1707. https://doi.org/10.1257/jel.37.4.1661
19. Dada, M.A., Posu, S.M.A., & Maghori, E.S. (2017). Modelling inflation and economic growth in five ECOWAS countries: A bivariate analysis. *International Journal of Economics Review and Business Research, 4*(2), pp. 47–67.
20. De Gregorio, J. (1993). Inflation, taxation, and long-run growth. *Journal of Monetary Economics, 31*(3), pp. 271–298. https://doi.org/10.1016/0304-3932(93)90049-L
21. Dornbusch, R., & Fischer, S. (1994). *Macroeconomics* (6th ed.). New York, NY: McGraw-Hill.
22. Dumitrescu, E.I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling, 29*(4), pp. 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014
23. Erbaykal, E., & Okuyan, H.A. (2008). Does inflation depress economic growth? Evidence from Turkey. *International Research Journal of Finance and Economics*, 17, pp. 40–48.
24. Fabayo, J.A., & Ajilore, O.T. (2006). Inflation: How much is too much for economic growth in Nigeria? *Indian Economic Review,* 41(2), pp. 129–147.
25. Faria, J.R., & Carneiro, F.G. (2001). Does High Inflation Affect Growth in the Long and Short Run? *Journal of Applied Economics, 4*(1), pp. 89–105. https://doi.org/10.1080/15140326.2001.12040559

26. Fischer, S. (1993). The role of macroeconomic factors in growth. *Journal of Monetary Economics, 32*(3), pp. 485–512. https://doi.org/10.1016/0304-3932(93)90027-D
27. Fisher, I. (1911). *The Purchasing Power of Money: Its Determination and Relation to Credit, Interest and Crises*. New York: Macmillan.
28. Fountas, S., Karanasos, M., & Kim, J. (2002). Inflation and output growth uncertainty and their relationship with inflation and output growth. *Economics Letters, 75*(3), pp. 293–301. https://doi.org/10.1016/S0165-1765(02)00009-5
29. Friedman, M. (1956). The quantity theory of money: A restatement. In M. Friedman (Ed.), *Studies in the quantity theory of money.* pp. 3–21. Chicago, IL: University of Chicago Press.
30. Friedman, M. (1969). *The optimum quantity of money and other essays*. Chicago, IL: Aldine Publishing Company.
31. Frimpong, J.M., & Oteng-Abayie, E.F. (2010). When is inflation harmful? Estimating the threshold effect for Ghana. *American Journal of Economics and Business Administration, 2*(3), pp. 232–239. https://doi.org/10.3844/ajebasp.2010.232.239
32. Ghosh, A., & Phillips, S. (1998). Warning: Inflation May Be Harmful to Your Growth. *IMF Staff Papers, 45*(4), pp. 672–710. https://doi.org/10.2307/3867589
33. Gillman, M., Harris, M.N., & Mátyás, L. (2004). Inflation and growth: Explaining a negative effect. *Empirical Economics, 29*(1), pp. 149–167. https://doi.org/10.1007/s00181-003-0186-0
34. Grier, R., & Grier, K.B. (2006). On the real effects of inflation and inflation uncertainty in Mexico. *Journal of Development Economics, 80*(2), pp. 478–500. https://doi.org/10.1016/j.jdeveco.2005.02.002
35. Gylfason, T., & Herbertsson, T.T. (2001). Does inflation matter for growth? *Japan and the World Economy, 13*(4), pp. 405–428. https://doi.org/10.1016/S0922-1425(01)00073-1
36. He, Q., & Zou, H.F. (2016). Does inflation cause growth in China? *International Review of Economics & Finance*, 45, pp. 470–484. https://doi.org/10.1016/j.iref.2016.07.012
37. Hodge, D. (2006). Inflation and growth in South Africa. *Cambridge Journal of Economics, 30*(2), pp. 163–180. https://doi.org/10.1093/cje/bei051
38. Hossain, A.A. (2015). Inflation volatility and growth in Bangladesh. *Applied Economics, 47*(52), pp. 5667–5688. DOI: https://doi.org/10.1080/00036846.2015.1054074

39. Hossain, M.E., Ghosh, B.C., & Islam, M.K. (2012). Inflation and growth in Bangladesh. Researchers World: *Journal of Arts, Science & Commerce*, 3(4), pp. 85–92.
40. Hume, D. (1752). *Political discourses*. Edinburgh: R. Fleming for A. Kincaid & A. Donaldson.
41. Huang, H.C., Lin, S.C., Kim, D.H., and Yeh, C.C. (2010). Inflation and the finance-growth nexus. *Economic Modelling*, 27(1), pp. 229–236. https://doi.org/10.1016/j.econmod.2009.09.003
42. Hussain, S., & Malik, S. (2011). Inflation and economic growth: Evidence from Pakistan. *International Journal of Economics and Finance*, 3(5), pp. 262–276. https://doi.org/10.5539/ijef.v3n5p262
43. Inyiama, O.I. (2013). Does inflation weaken economic growth? *European Journal of Accounting Auditing and Finance Research, 1*(4), pp. 139–150.
44. Iyke, B.N., & Odhiambo, N.M. (2017). Inflationary thresholds, financial development and economic growth: New evidence from two West African countries. *Global Economy Journal, 17*(2). https://doi.org/10.1515/gej-2016-0042
45. Kanca, O.C. (2017). Domestic Debt, Inflation, Economic Growth: An Econometric Application for Turkey (1980–2014). *Finans Politik ve Ekonomik Yorumlar, 54*(627), pp. 47–58.
46. Karaca, O. (2003). Türkiye'de enflasyon-büyüme ilişkisi: Zaman serisi analizi [Inflation-growth relationship in Turkey: A time series analysis]. *Doğuş Üniversitesi Dergisi (Doğuş University Journal)*, 4(2), pp. 247–255.
47. Khan, M.A., & Khan, S. (2018). Inflation and economic growth: Evidence from Five Asian countries. *Pakistan Journal of Applied Economics*, 28(2), pp. 235–252.
48. Khan, M.S., & Senhadji, A.S. (2001). Threshold Effects in the Relationship between Inflation and Growth. *IMF Economic Review*, 48, pp. 1–21. https://doi.org/10.2307/4621658
49. Koulakiotis, A., Lyroudi, K., & Papasyriopoulos, N. (2012). Inflation GDP and Causality for European Countries. *International Advances in Economic Research, 18*(1), pp. 53–62. https://doi.org/10.1007/s11294-011-9340-1
50. Kremer, S., Bick, A., & Nautz, D. (2013). *I*nflation and growth: New evidence from a dynamic panel threshold analysis. *Empirical Economics, 44*(2), pp. 861–878. https://doi.org/10.1007/s00181-012-0553-9
51. Kryeziu, A. (2016). The impact of macroeconomic factors on economic growth: The case of selected Balkan countries. *European*

Scientific Journal, 12(7), pp. 120–129. https://doi.org/10.19044/esj.2016.v12n7p331

52. Kryeziu, N., & Durguti, E.A. (2019). *The impact of inflation on economic growth: The case of Eurozone*. *International Journal of Finance & Banking Studies, 8*(1), pp. 1–9. https://doi.org/10.20525/ijfbs.v8i1.297
53. Kydland, F.E., & Prescott, E.C. (1982). *Time to build and aggregate fluctuations*. *Econometrica, 50*(6), pp. 1345–1370. https://doi.org/10.2307/1913386
54. Laidler, D.E.W. (1991). *The golden age of the quantity theory*. Princeton, NJ: Princeton University Press.
55. Lee, C.C., & Wong, S.Y. (2005). Inflationary threshold effects in the relationship between financial development and economic growth: Evidence from Taiwan and Japan. *Journal of Economic Development,* 30(1), pp. 49–69.
56. Long Jr, J.B., & Plosser, C.I. (1983). Real business cycles. *Journal of political Economy*, *91*(1), pp. 39-69. https://doi.org/10.1086/261128
57. Lucas, R.E. Jr. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22*(1), pp. 3–42. https://doi.org/10.1016/0304-3932(88)90168-7
58. Lupu, D.V. (2009). The correlation between inflation and economic growth in Romania. *Lucrări Ştiinţifice: Seria I, Management Agricol*, 11(5), pp. 53-58.
59. Madurapperuma, W. (2016). Impact of inflation on economic growth in Sri Lanka. *Journal of World Economic Research*, 5(1), pp. 1–7. https://doi.org/10.11648/j.jwer.20160501.11
60. Mallik, G., & Chowdhury, A. (2001). Inflation and economic growth: Evidence from four South Asian countries. *Asia-Pacific Development Journal*, 8(1), pp. 123–135.
61. Mankiw, N.G. (1985). Small menu costs and large business cycles: A macroeconomic model of monopoly. *Quarterly Journal of Economics*, 100(2), pp. 529–537. https://doi.org/10.2307/1885395
62. Misiri, V., & Fetai, B. (2022). The impact of inflation on economic growth: Threshold effects in the Western Balkan countries. *Journal of Global Policy and Governance*, 11(1), pp. 21–34. https://doi.org/10.14666/2194-7759-11-1-002
63. Mkhatshwa, Z.S., Tijani, A.A., & Masuku, M.B. (2015). An empirical analysis of the relationship between inflation and economic growth in Swaziland. *Journal of Economics and Sustainable Development*, 6(18), pp. 189–204.

64. Mohseni, M., & Jouzaryan, F. (2016). Examining the effects of inflation and unemployment on economic growth in Iran (1996–2012). *Procedia Economics and Finance*, 36, pp. 381–389. https://doi.org/10.1016/S2212-5671(16)30050-8
65. Mubarik, Y.A. (2005). Inflation and growth: An estimate of the threshold level of inflation in Pakistan. *SBP Research Bulletin*, 1(1), pp. 35–44.
66. Mundell, R.A. (1963). Capital mobility and stabilization policy under fixed and flexible exchange rates. Canadian *Journal of Economics and Political Science*, 29(4), pp. 475–485. https://doi.org/10.2307/139336
67. Munir, Q., Mansur, K., & Furuoka, F. (2009). Inflation and economic growth in Malaysia: A threshold regression approach. *Economics Bulletin*, 29(3), pp. 1555–1569.
68. Ndoricimpa, A. (2017). Threshold effects of inflation on economic growth in Africa: Evidence from panel threshold regression. *African Development Bank Group Working Paper Series*, 249.
69. Obradović, S., Šapić, S., Furtula, S., & Lojanica, N. (2017). Linkages between Inflation and Economic Growth in Serbia: An ARDL Bounds Testing Approach. *Engineering Economics*, 28(4), pp. 401–410. https://doi.org/10.5755/j01.ee.28.4.14003
70. Omoke, P.C. (2010). Inflation and economic growth in Nigeria. *Journal of Sustainable Development*, 3(2), pp. 159–166. DOI: https://doi.org/10.5539/jsd.v3n2p159
71. Opeyemi, A.F. (2020). Impact of foreign direct investment and inflation on economic growth of five randomly selected countries in Africa. *Journal of Economics and International Finance*, 12(2), pp. 65–73. https://doi.org/10.5897/jeif2020.1031
72. Özçelik, Ö., & Uslu, N. (2017). The relationship between growth, unemployment and inflation in Turkey. *Ekev Akademi Dergisi (Ekev Academic Review),* 21(69), 31–51.
73. Özdemir, Z.A. (2010). Dynamics of inflation, output growth and their uncertainty in the UK: An empirical analysis. *The Manchester School,* 78(6), pp. 511–537. https://doi.org/10.1111/j.1467-9957.2009.02153.x
74. Özpence, A.I. (2016). Analysis of the relationship between inflation and economic growth in Turkey. *Journal of Economics, Finance and Accounting*, 3(3), pp. 180–191. https://doi.org/10.17261/Pressacademia.2016321986

75. Özyilmaz, A. (2022). Relationship between inflation and economic growth in EU countries. *Journal of Economic Policy Researches*, 9(2), pp. 425–438. https://doi.org/10.26650/JEPR1132170
76. Phiri, A. (2010). At What Level Is Inflation Least Detrimental Towards Finance-Growth Activity in South Africa?. *Journal of Sustainable Development in Africa, 12*(6), pp. 354–364. Available at: https://jsd-africa.com/Jsda/V12No6_Fall2010_B/article12_06.htm
77. Rao, N., & Abate, Y. (2015). Inflation and economic growth: Inflation threshold level analysis for Ethiopia. *International Journal of Ethics in Engineering & Management Education*, 2(5), pp. 1-7.
78. Risso, W.A., & Sánchez Carrera, E.J. (2009). Inflation and Mexican economic growth: Long-run relation and threshold effects. *Journal of Financial Economic Policy*, 1(3), pp. 246–263. https://doi.org/10.1108/17576380911041728
79. Romer, P.M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), pp. 1002–1037. https://doi.org/10.1086/261420
80. Rutayisire, M.J. (2015). Threshold effects in the relationship between inflation and economic growth: Evidence from Rwanda. AERC Research Paper, 293(February). Available at: https://publication.aercafricalibrary.org/handle/123456789/1172
81. Salami, D., & Kelikume, I. (2010). An estimation of inflation threshold for Nigeria (1970–2008). International Review of Business Research Papers, 6(5), pp. 375–385.
82. Sepehri, A., & Moshiri, S. (2004). Inflation-Growth Profiles Across Countries: Evidence from Developing and Developed Countries. *International Review of Applied Economics*, 18(2), 191–207. https://doi.org/10.1080/0269217042000186679
83. Shitundu, J.L., & Luvanda, E.G. (2004). The Effect of Inflation on Economic Growth in Tanzania. *African Journal of Finance and Management*, *9*(1), 70–77. https://doi.org/10.4314/ajfm.v9i1.24327
84. Singh, S., & Singh, A. (2015). Causal Nexus between Inflation and Economic Growth of Japan. *Iranian Economic Review*, 19(3), pp. 265–278. https://doi.org/10.22059/ier.2015.56846
85. Snowdon, B., & Vane, H.R. (2005). *Modern Macroeconomics: Its Origins, Development and Current State*. Cheltenham, UK: Edward Elgar Publishing.
86. Stadler, G.W. (1994). Real business cycles. *Journal of Economic Literature*, 32(December), pp. 1750–1783.

87. Stockman, A.C. (1981). Anticipated inflation and capital stock in a cash in-advance economy. *Journal of Monetary Economics*, 8(3), pp. 387–393. https://doi.org/10.1016/0304-3932(81)90018-0
88. Sweidan, O.D. (2004). Does inflation harm economic growth in Jordan? An econometric analysis for the period 1970–2000. *International Journal of Applied Econometrics and Quantitative Studies*, 1(2), pp. 41–66.
89. Tajra, H.F. (1999). *The Phillips curve in the Brazilian economy after the Real Plan*. The Minerva Program, The George Washington University.
90. Tenny, L.Z. (2022). Dynamics of inflation and remittances on economic growth in Liberia: A Granger causality approach. International Journal of Business and Economics Research, 11(1), pp. 49–53. https://doi.org/10.11648/j.ijber.20221101.16
91. Thanh, S.D. (2015). Threshold effects of inflation on growth in the ASEAN-5 countries: A Panel Smooth Transition Regression approach. *Journal of Economics, Finance and Administrative Science*, 20(38), pp. 41–48. https://doi.org/10.1016/j.jefas.2015.01.003
92. Tobin, J. (1965). Money and economic growth. *Econometrica*, 33(4), pp. 671–684. https://doi.org/10.2307/1910352
93. Tsionas, E.G., & Christopoulos, D.K. (2003). Maastricht convergence and real convergence: European evidence from threshold and smooth transition regression models. *Journal of Policy Modeling, 25*(1), pp. 43–52. https://doi.org/10.1016/S0161-8938(02)00200-4
94. Tung, L.T., & Thanh, P.T. (2015). Threshold in the relationship between inflation and economic growth: Empirical evidence in Vietnam. *Asian Social Science*, 11(10), pp. 105–112. https://doi.org/10.5539/ass.v11n10p105
95. Umaru, A., & Zubairu, A.A. (2012). Effect of inflation on the growth and development of the Nigerian economy (An empirical analysis). *International Journal of Business and Social Science*, 3(10), pp. 183–191.
96. Yabu, N., & Kessy, N.J. (2015). Inflation and economic growth in East Africa: A threshold analysis. *Applied Economics and Finance, 2*(3), pp. 127–144. https://doi.org/10.11114/aef.v2i3.966

MARKET REGIMES AND PORTFOLIO ALLOCATION: EVIDENCE FROM THE ROMANIAN EQUITY MARKET USING HIDDEN MARKOV MODELS AND XGBOOST

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Abstract

This study examines whether the Romanian equity market exhibits persistent risk regimes, whether these regimes can be forecast at short horizons, and whether such forecasts can improve portfolio allocation. The analysis uses daily BET index data over 2016–2025 and applies a two-step empirical framework. A Hidden Markov Model is first used to identify latent market states based on returns and realised volatility, followed by an XGBoost classifier that predicts regimes one day ahead using market, volatility, domestic macro-financial, and global indicators. The results reveal three distinct regimes, interpreted as calm, stress, and panic, each reflecting different levels of market risk. The forecasting model performs well in the calm and stress regimes, while predictions for the panic state are less precise but remain informative from a risk-management perspective. Most classification errors occur between neighbouring regimes rather than between extreme states. The economic evaluation shows that a regime-probability portfolio strategy with volatility targeting outperforms a passive Buy-and-Hold investment in the BET index, generating higher cumulative performance and lower drawdowns. Overall, the findings indicate that risk regimes in the Romanian equity market are persistent, short-term predictable, and economically useful for systematic portfolio allocation.

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1. Introduction

A central tension in financial economics lies between the premise of informational efficiency and the empirical observation that risk is time-varying. In its canonical form, the Efficient Market Hypothesis implies that systematic predictability in returns should be limited (Fama, 1970). Yet even in highly developed markets, return distributions exhibit volatility clustering, heavy tails, and episodic crises that differ qualitatively from tranquil phases. These features challenge the adequacy of models that treat the data-generating process as stable through time. In emerging equity markets, such departures from stability are often magnified. Lower liquidity, narrower investor bases, and stronger sensitivity to macroeconomic and policy shocks create conditions in which returns and risk may shift discontinuously across states rather than evolving smoothly (Bekaert & Harvey, 1997).

This paper studies regime-dependent risk dynamics in the Romanian equity market, proxied by the BET index, over 2016–2025. The sample contains multiple episodes associated with pronounced risk repricing, particularly the COVID-19 shock in 2020 and the tightening-driven stress of 2022. The realised volatility profile of BET indicates substantial time variation and clustering, with spikes that are difficult to reconcile with a single stable risk environment. Such dynamics motivate a regime perspective: if the market alternates between latent states—here conceptualised as calm, stress, and panic—then both inference and portfolio decisions may benefit from explicitly modelling the state.

Although regime-switching models provide a well-established statistical framework for capturing state dependence (Hamilton, 1989), and the portfolio-choice literature emphasises that optimal allocation can be conditional on regimes (Ang & Bekaert, 2002; Guidolin & Timmermann, 2007), evidence for smaller emerging European markets remains relatively limited. Moreover, two gaps persist in empirical practice. First, many regime studies prioritise statistical identification without demonstrating economic usefulness under realistic out-of-sample decision rules. Second, machine learning applications in finance often report predictive metrics without tying forecasts to transparent portfolio mechanisms and evaluating economic outcomes. This paper addresses these gaps by integrating regime extraction, regime forecasting, and implementable allocation within a single framework and judging success by both statistical diagnostics and economic performance.

The empirical strategy follows a deliberate separation of tasks. Latent regimes are first identified via a Hidden Markov Model (HMM) estimated on BET returns and realised volatility. Next-day regimes are then forecast using a multi-class gradient boosting classifier (XGBoost) trained on a conservative predictor set that combines volatility measures, lagged asset returns, and domestic macro-financial changes, with model complexity controlled through sequential feature selection and time-series cross-validation. Finally, predicted regime probabilities are translated into portfolio decisions through a regime-probability allocation rule that forms state-contingent return and covariance estimates and scales exposure via volatility targeting. This design reflects the view that forecasting the risk environment may be more stable and economically actionable than predicting return magnitudes, especially in markets where tail events drive welfare and long-run compounding.

The analysis is guided by five hypotheses. First, the Romanian equity market exhibits statistically distinct latent regimes. Second, these regimes display persistence rather than random day-to-day switching. Third, observable financial and macro-financial variables contain information about next-day regime transitions. Fourth, a nonlinear classifier can discriminate between regimes with economically meaningful out-of-sample accuracy, particularly by avoiding catastrophic errors that confuse panic with calm. Fifth, a regime-probability allocation strategy based on predicted states outperforms a passive Buy-and-Hold benchmark in cumulative and downside-risk terms.

2. Literature review

Research on financial returns has long documented systematic deviations from homoskedastic Gaussian benchmarks. Volatility clustering and heavy tails are among the most robust empirical regularities. The ARCH model introduced by Engle (1982) and its generalisation in the GARCH framework (Bollerslev, 1986) formalise conditional heteroskedasticity by allowing volatility to depend on past shocks. While these models capture smooth persistence in variance, they do not by themselves resolve a deeper issue: the mapping from information to risk may itself shift over time. When markets transition between environments governed by different constraints, funding conditions, or investor risk tolerance, a single stable conditional-variance law may be an incomplete representation. In such settings, volatility persistence can partly reflect the mixture of distinct regimes rather than within-regime dynamics.

This observation motivates regime-switching approaches. Hamilton (1989) provides a Markov-switching framework in which parameters depend on an unobserved state following a first-order Markov process. In finance, regimes are often interpreted as economically meaningful phases such as calm, stress, and crisis, potentially associated with changes in volatility, correlation structure, liquidity, and risk premia. Ang and Timmermann (2012) highlight that predictability is frequently conditional: relationships that appear weak or unstable unconditionally can be stronger within regimes, and models can fail when they ignore state dependence.

Regime considerations are particularly salient in emerging markets. Bekaert and Harvey (1997) show that emerging equity markets exhibit higher volatility and stronger sensitivity to global conditions, consistent with partial integration and capital flow dynamics that can amplify shocks. Such markets may exhibit nonlinear response patterns: similar news can induce modest adjustments in tranquil times but trigger outsized repricing when liquidity is thin or when investors are already risk-averse. This macro-financial amplification logic implies that regimes may correspond to different configurations of funding conditions and risk-bearing capacity, not merely different levels of recent volatility.

State dependence has direct implications for portfolio choice. Traditional mean–variance theory treats expected returns and covariances as stable inputs (Markowitz, 1952). If moments differ across states, unconditional optimisation can be misleading. Ang and Bekaert (2002) and Guidolin and Timmermann (2007) demonstrate that regime-switching representations can materially affect optimal allocation, especially when regimes are persistent and differ in tail risk. Importantly, economic value can arise even from coarse state awareness, because avoiding deep drawdowns increases geometric compounding—an effect that can dominate long-run outcomes.

A further strand concerns the role of nonlinear forecasting tools. Machine learning methods offer flexible function approximation capable of capturing interactions and nonlinearities (Hastie, Tibshirani and Friedman, 2009). In asset pricing and prediction, Gu, Kelly and Xiu (2020) show that machine learning can improve performance when signals are weak and dispersed across predictors. Yet the field is clear that financial data are noisy and that rigorous out-of-sample design is essential to avoid spurious patterns (Campbell, Lo and MacKinlay, 1997). These considerations motivate a conservative approach: model complexity should be constrained, and the value of forecasts should be evaluated by their economic consequences rather than in-sample fit.

This paper integrates this literature through a three-part argument. First, emerging markets plausibly exhibit discrete latent risk regimes due to macro-financial sensitivity and liquidity constraints. Second, regime-switching frameworks provide a coherent statistical mechanism for extracting such states. Third, nonlinear supervised learning may capture state-dependent signals embedded in market and macro-financial indicators, but must be evaluated out-of-sample and judged by economic performance within transparent allocation rules.

3. Methodology

The empirical analysis uses daily-frequency time series data sourced from Refinitiv for 2016–2025. The central market variable is the ROMANIA BET INDEX – PRICE INDEX, which proxies Romanian equity market performance. The dataset also contains daily financial series (e.g., global volatility indices and exchange rates where available), commodity prices, and a set of domestic macro-financial indicators. Because macro series are typically released at lower frequency, they are transformed into growth rates (percentage changes) and converted to daily panels through forward filling after resampling, consistent with the informational structure of lower-frequency releases.

The forecasting exercise is conducted under a strict chronological design. The training sample ends on 31 December 2022, and the out-of-sample test period begins on 1 January 2023. All time series are aligned to a common trading calendar to ensure temporal consistency across variables. Observations with missing values—arising primarily from rolling-window calculations or the asynchronous release of macroeconomic indicators—are excluded whenever they result in incomplete feature vectors. Asset returns are computed as continuously compounded (log) returns, following the standard approach in empirical financial research (Campbell, Lo and MacKinlay, 1997).

In addition to returns, several volatility and market-based indicators are constructed. These include 21-day and 63-day realised volatility, annualised using the square-root-of-time rule, as well as an exponentially weighted volatility measure. Additional variables capture different aspects of market dynamics, including absolute returns, rolling skewness and kurtosis calculated over a 21-day window, momentum over 21 and 63 trading days, and the difference between the 50-day and 200-day moving averages. A jump indicator is also included, defined as a dummy variable identifying unusually large price movements relative to recent volatility.

The empirical strategy proceeds in three steps: (i) infer latent regimes with an HMM; (ii) forecast next-day regimes with XGBoost; and (iii) translate predicted regime probabilities into a portfolio rule and evaluate economic outcomes relative to Buy-and-Hold. Separating regime identification from regime forecasting reduces the risk that the prediction model is merely fitting the object it aims to forecast and supports a clearer economic interpretation of the target.

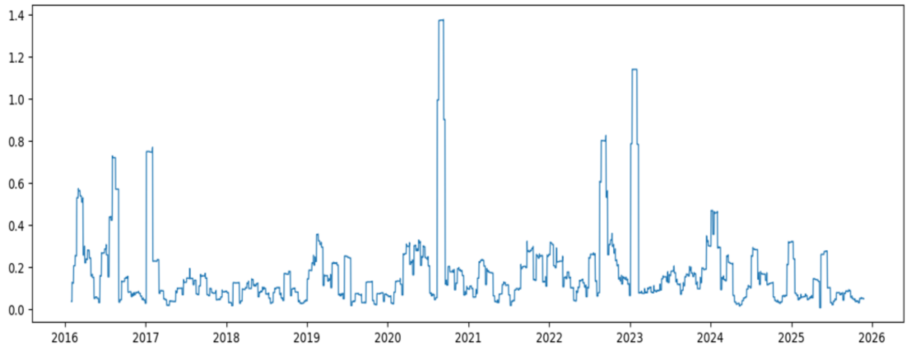
The Hidden Markov Model assumes that observed returns are generated by one of K latent states and that state transitions follow a first-order Markov process. Parameters are estimated by maximum likelihood using the Expectation - Maximisation algorithm (Baum et al., 1970; Rabiner, 1989). The implementation uses $K = 3$ states, estimated on the training sample, and then applies the fitted model to infer state assignments across the full panel.

The regime-extraction feature set includes BET log returns and 21-day realised volatility. Where present in the dataset, additional risk indicators are included (e.g., VIX, V2TX, MOVE, Romanian CDS, EUR/RON). Features are standardised using a scaler fit on the training sample and then applied to all dates to avoid look-ahead bias. The three states are mapped to economic labels (calm, stress, panic) according to the average realised volatility within each state: the lowest-volatility state is labelled calm, the intermediate state stress, and the highest-volatility state panic.

Figure 1 reports 21-day realised volatility (annualised) for BET. The series exhibits strong clustering and episodic spikes. The most pronounced surge is associated with the 2020 pandemic shock, while 2022 displays a sustained elevation in volatility consistent with a prolonged risk repricing episode. These dynamics are consistent with stylised facts documented by conditional heteroskedasticity models (Engle, 1982; Bollerslev, 1986), but they also suggest the plausibility of discrete shifts between qualitatively different risk environments. In this setting, modelling the market as switching across latent regimes is not merely a statistical convenience: it reflects the economic intuition that the constraints and risk-bearing capacity of investors can change abruptly under stress.

Figure 1

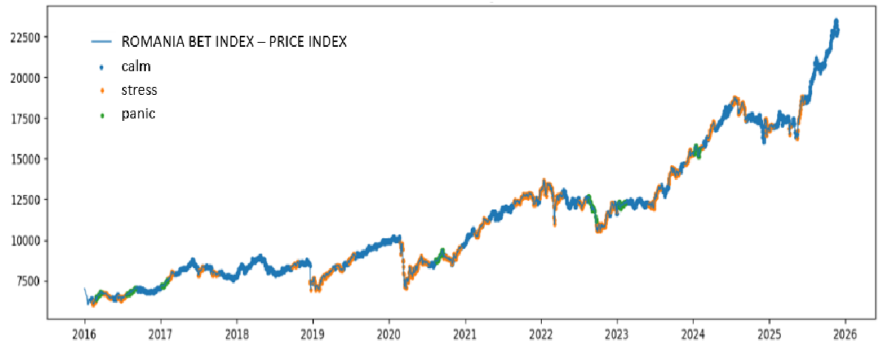
Realised volatility of BET (21-day, annualised)



Source: Author's contribution

The inferred market regimes display clear differences in the behaviour of the BET index. Periods classified as calm tend to coincide with sustained upward movements and relatively stable price dynamics. In contrast, stress regimes are more frequently observed around intermediate corrections and episodes of elevated uncertainty, where market movements become less stable but do not yet reach extreme levels. Panic regimes appear much less frequently and are typically concentrated in short intervals associated with abrupt market disruptions. As illustrated in Figure 2, the fact that panic observations occur in distinct clusters rather than being scattered randomly throughout the sample provides additional support for the interpretation that the Hidden Markov Model captures economically meaningful latent states rather than merely reflecting statistical noise.

Figure 2
HMM-inferred market regimes mapped onto the BET price index



Source: Author's contribution

The supervised learning task is next-day regime prediction. The regime label at date t is shifted forward to construct a target variable representing the regime at $t+1$. Predictors are dated t, ensuring the model is trained under a genuine forecasting configuration. This framing is deliberate: a regime label can be interpreted as a compact representation of the conditional distribution of returns and therefore is directly relevant for risk management decisions.

First, market-based risk and dislocation measures capture contemporaneous stress accumulation: realised volatility (21 and 63 days), EWMA volatility, absolute returns, rolling skewness and kurtosis, momentum, moving-average dislocation, and a jump proxy. Second, lagged log returns of a set of tradable assets (up to 12 "price-like" series in the dataset) capture short-horizon cross-market dynamics and spillovers. Third, domestic macro-financial indicators are transformed into growth rates and forward-filled to daily frequency, capturing changes in financial conditions and real-economy momentum that can co-move with risk regimes in emerging markets.

Regime forecasting is implemented as a multi-class classification problem using XGBoost, trained with the multi-class log-loss objective (Friedman, 2001; Chen & Guestrin, 2016). The model produces calibrated regime probabilities $(p_{\text{calm}}, p_{\text{stress}}, p_{\text{panic}})$, which are used for ROC analysis and for portfolio construction.

Given the high-dimensional feature set and the noisy nature of financial data, overfitting risk is mitigated through a staged procedure consistent with best practice (Hastie, Tibshirani and Friedman, 2009).

First, feature-family selection retains only the most important feature within each family (e.g., among lags of the same return series), reducing redundancy and collinearity. Second, SHAP-based ranking is used to retain the top 15 features, improving interpretability and further restricting dimensionality. Third, hyperparameters are tuned using time-series cross-validation (TimeSeriesSplit) with RandomizedSearchCV, using a negative log-loss scoring criterion, reflecting an emphasis on probabilistic quality rather than only hard labels. The final configuration reported in your outputs exhibits conservative regularisation and shallow depth, aligning with a stability-oriented bias–variance trade-off.

Economic value is assessed by mapping predicted regime probabilities into an implementable allocation rule. Rather than using a discrete, regime-dependent equity weight, your implementation constructs state-conditional return and risk moments and then scales risk through volatility targeting.

For each regime $r \in \{\text{calm,stress,panic}\}$, the strategy estimates regime-conditional mean returns μ_r and covariance matrices Σ_r for the asset return vector using historical observations assigned to that regime. At each date t, predicted probabilities $p_t(r)$ are used to form probability-weighted moments:

$$\mu_t = \sum_r p_t\,(r)\,\mu_r, \Sigma_t = \sum_r p_t\,(r)\,\Sigma_r. \tag{1}$$

Portfolio weights are then formed from a mean–variance signal proportional to $\Sigma_t^{-1}\mu_t$, normalised by the L1 norm to control weight concentration. Finally, exposure is scaled to target a fixed annualised volatility (12%), using a rolling estimate of realised portfolio risk, which operationalises a risk-budgeting discipline related to volatility targeting. Performance is compared to Buy-and-Hold in the BET index. Equity curves, drawdowns, and calendar-year returns are computed by compounding returns. In the present implementation, daily returns are treated as log returns and annual returns are computed by exponentiating annual log-return sums.

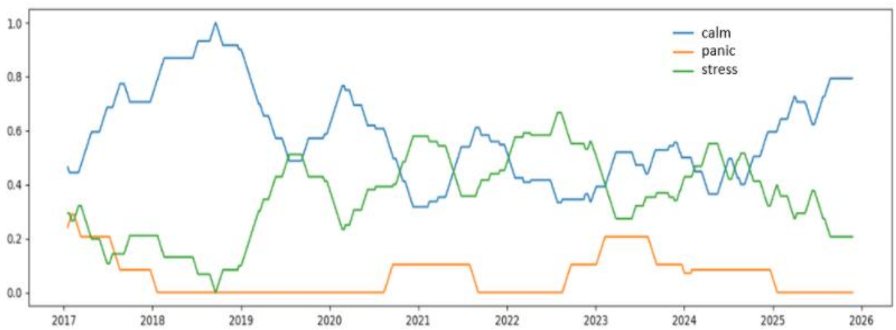
4. Results

This section presents the empirical results of the study and evaluates the extent to which market regimes in the Romanian equity market can be identified, forecasted, and exploited in a portfolio allocation framework. The analysis proceeds in several steps. First, the regime structure inferred from the Hidden Markov Model is examined in order to assess whether the estimated calm, stress, and panic states correspond to economically meaningful phases of market behaviour. Second, the predictive performance of the XGBoost classifier is evaluated using out-of-sample forecasts of next-day regimes. Particular attention is given to the model's ability to distinguish between different levels of market stress and to the economic implications of classification errors. Finally, the regime forecasts are incorporated into a probability-based portfolio allocation strategy, and the resulting investment performance is compared with a passive Buy-and-Hold benchmark in the BET index.

The evolution of regime frequencies over time provides additional insight into the dynamics of the market states. The evidence indicates that the distribution of regimes is far from constant across the sample period. Calm regimes tend to dominate during prolonged phases of market stability, whereas the share of stress regimes increases when uncertainty rises and market conditions become more fragile. Panic episodes remain relatively rare, but they reappear in clearly identifiable clusters rather than disappearing altogether. As illustrated in Figure 3, this variation in regime composition has important analytical implications. In particular, it suggests that unconditional return statistics effectively combine observations drawn from fundamentally different market environments. Consequently, analysing the data within a regime-dependent framework is likely to provide a more informative representation of market dynamics than treating the full sample as a single homogeneous process.

Figure 3

Rolling one-year regime frequency

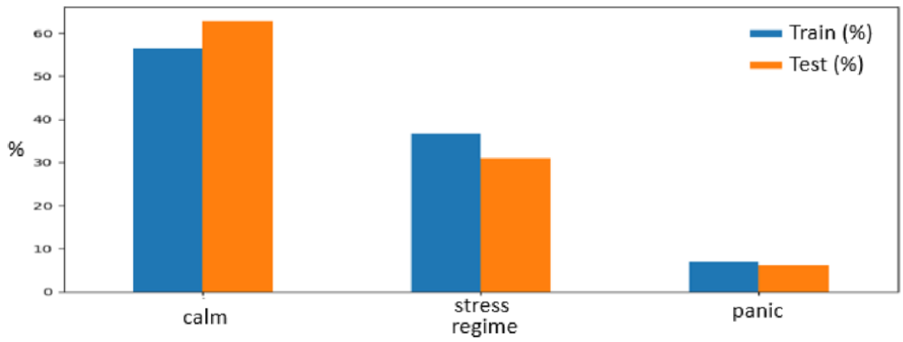


Source: Author's contribution

A comparison of regime frequencies between the training and test samples provides an additional perspective on the stability of the regime structure. Although the panic regime remains the least frequent state in both periods, its relative share is broadly comparable across the two subsamples. As shown in Figure 4, this similarity is particularly important for the interpretation of the forecasting results. It suggests that the out-of-sample evaluation period is not characterised by unusually benign market conditions. Instead, the test sample still contains a number of meaningful tail-risk episodes, which strengthens confidence in the robustness of both the regime prediction exercise and the subsequent portfolio performance analysis.

Figure 4

Regime distribution in training vs test subsamples



Source: Author's contribution

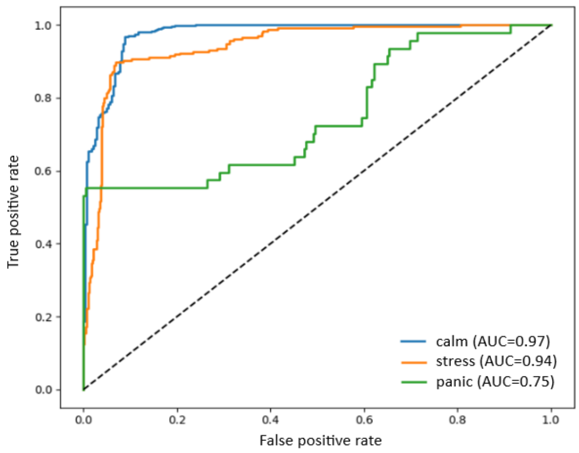
The second stage of the empirical analysis focuses on forecasting market regimes using an XGBoost classifier. The model is trained to predict the regime one day ahead, relying on the set of predictors selected through the SHAP-based feature selection procedure and hyperparameters determined via time-series cross-validation. The objective is to evaluate whether observable market and macro-financial indicators contain sufficient information to anticipate transitions between the calm, stress, and panic regimes previously identified by the Hidden Markov Model.

Out-of-sample results for the 2023+ test period indicate strong predictive discrimination between the calm and stress states. Predictive performance for the panic regime is weaker, though still informative, which is economically unsurprising given the rarity of extreme market events. Episodes classified as panic are typically associated with abrupt shocks that are only partially reflected in observable predictors. Importantly, the pattern of classification errors remains economically meaningful. Most misclassifications occur between neighbouring regimes, rather than between the extreme states of calm and panic. In practical terms, this implies that the model rarely interprets periods of severe market stress as tranquil conditions. From a portfolio management perspective, such an error structure is considerably less problematic than indiscriminate misclassification across the entire spectrum of market risk.

The predictive performance of the classifier is further evaluated using receiver operating characteristic (ROC) curves, reported in Figure 5. The results confirm strong discriminatory power for the calm and stress regimes. The calm state achieves an area under the curve (AUC) of 0.97, indicating near-perfect separation from the other regimes. Similarly, the stress regime records an AUC of 0.94, suggesting that the model effectively captures conditions associated with elevated, though not extreme, market volatility. Predictive accuracy for the panic regime is more moderate, with an AUC of 0.75. While lower than the other regimes, this level of performance still indicates that the classifier retains meaningful predictive ability even for the most extreme market state.

Figure 5

ROC Curves Test Final Model



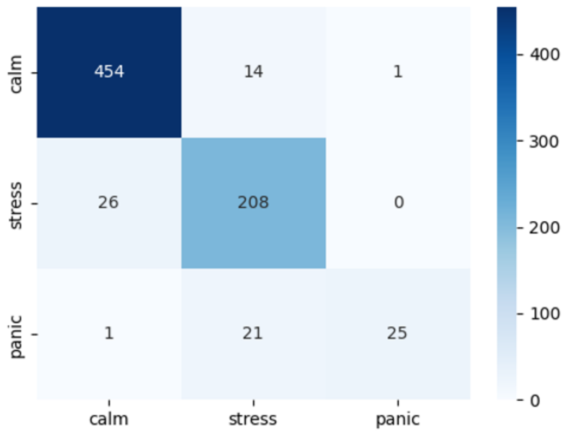
Source: Author's contribution

Additional insight into the model's performance can be obtained from the confusion matrix presented in Figure 6. The classifier performs very well in identifying calm market conditions, correctly classifying 454 observations, with only a few cases misclassified as stress (14) or panic (1). The stress regime is also identified with good accuracy, with 208 correctly classified observations, although some stress periods are predicted as calm (26). This likely reflects the fact that transitions between calm and moderately volatile market conditions tend to occur gradually.

The panic regime is more difficult to detect, with 25 observations correctly classified and several predicted as stress (21). However, the model almost never confuses panic with calm, with only one observation misclassified in this way. From a practical perspective, this pattern of errors is desirable because it reduces the risk of interpreting severe market stress as a tranquil market environment.

Figure 6

Confusion Matrix Test Final Model



Source: Author's contribution

The final model specification is obtained through a hyperparameter optimisation procedure applied after the SHAP-based feature selection stage. The search is conducted using time-series cross-validation combined with a RandomizedSearch approach. The selected hyperparameters are reported in Table 2. Overall, the resulting configuration relies on a relatively large number of trees with shallow depth and regularisation terms, which helps control model complexity and reduce the risk of overfitting in a financial dataset characterised by noisy signals.

Table 2

Final XGBoost Hyperparameter Configuration

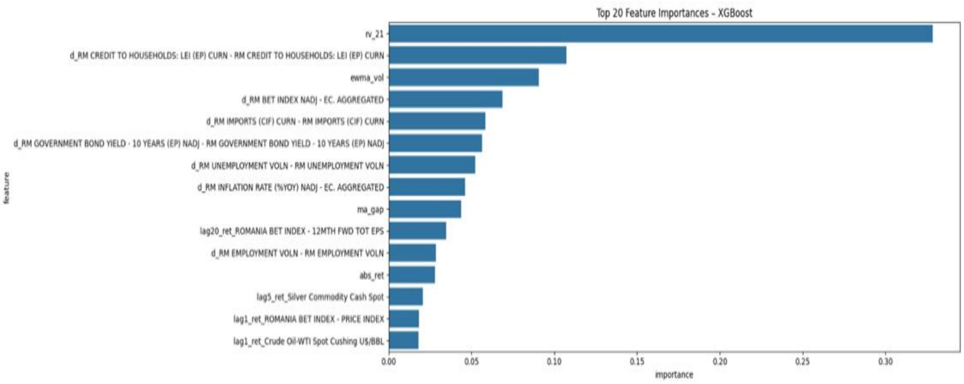
Hyperparameter	Value
n_estimators	800
max_depth	3
learning_rate	0.01
subsample	0.9
colsample_bytree	0.7
min_child_weight	1
gamma	1.0
reg_alpha (L1)	0.001
reg_lambda (L2)	1.0

Source: Author's contribution

Additional insight into the model's predictive performance is provided by the feature importance results shown in Figure 5. Realised volatility appears to be the most important predictor, consistent with the regime framework, since the different states mainly reflect changes in market risk. At the same time, the model also incorporates information from several domestic macro-financial variables, including changes in household credit and sovereign bond yields. This suggests that regime transitions are not driven only by recent market volatility, but may also be related to broader changes in financial conditions.

Figure 5

XGBoost feature importances for next-day regime prediction

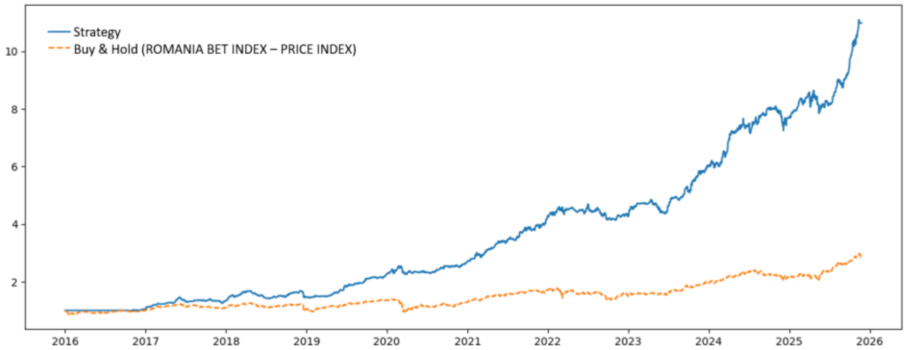


Source: Author's contribution

The final question is whether forecasting regimes lead to economically meaningful improvements in portfolio performance. Figure 6 addresses this directly by comparing the cumulative equity curve of the regime-probability strategy with that of a passive Buy-and-Hold position in the BET index. The difference is substantial. The strategy reaches a markedly higher terminal wealth level, and the gap does not emerge gradually in a trivial way; rather, it tends to widen after adverse market episodes. This pattern is consistent with the idea that limiting exposure during severe drawdowns materially improves long-run compounding, even if returns in normal periods are not dramatically different.

Figure 6

Cumulative equity curves: regime-probability strategy vs Buy-and-Hold

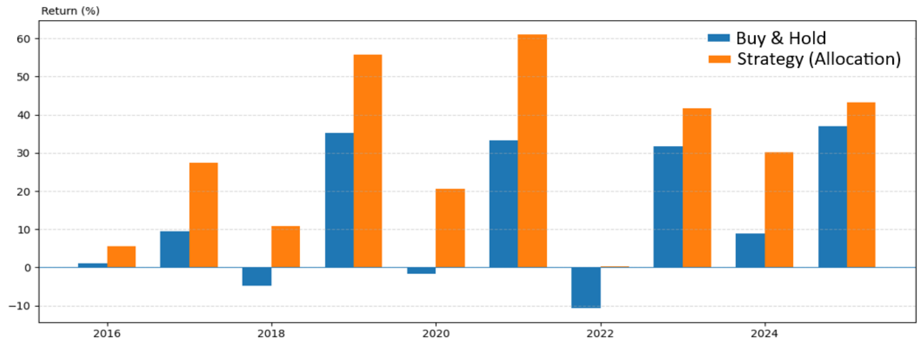


Source: Author's contribution

Annual returns are reported in Figure 7, which shows that the strategy outperforms the Buy-and-Hold benchmark in every calendar year between 2016 and 2025. This includes years when the market performs poorly, such as 2018, 2020, and especially 2022. These results suggest that the strategy is not simply defensive. Higher performance does not arise from persistently low exposure to risky assets. Instead, the strategy continues to participate in favourable market conditions while reducing exposure during periods of elevated risk. Such behaviour is consistent with what would be expected from a genuinely state-dependent allocation approach.

Figure 7

Annual returns: strategy vs Buy-and-Hold



Source: Author's contribution

5. Conclusion

The empirical analysis provides evidence that the Romanian equity market exhibits a regime structure that is both statistically identifiable and economically meaningful. Estimation of the three-state Hidden Markov Model reveals distinct calm, stress, and panic regimes, which correspond closely to observable shifts in realised volatility and coincide with well-defined periods of market turbulence. This alignment suggests that the inferred states capture genuine variation in the underlying risk environment rather than purely statistical segmentation of the return series.

The subsequent forecasting exercise evaluates whether transitions between these regimes can be anticipated using observable market and macro-financial information. The results indicate that the XGBoost classifier achieves a meaningful degree of out-of-sample predictive accuracy, particularly in distinguishing between the calm and stress states. Predictive performance for the panic regime is naturally weaker, reflecting its relatively low frequency and the fact that extreme market disturbances are often associated with abrupt exogenous shocks. Nevertheless, the pattern of classification errors remains economically informative. Misclassifications occur predominantly between adjacent regimes, implying that periods of severe market stress are rarely interpreted as tranquil conditions. From a portfolio management perspective, such an error structure is considerably less problematic than indiscriminate misclassification across the full range of risk states.

An examination of feature importance provides further insight into the drivers of regime forecasts. Realised volatility emerges as the dominant predictor, which is consistent with the conceptual foundation of the regime framework, where states are primarily differentiated by their risk characteristics. At the same time, several domestic macro-financial variables contribute non-negligibly to predictive performance. In particular, indicators related to household credit dynamics and sovereign yield movements appear among the most influential variables. This pattern suggests that regime transitions are not merely mechanical reflections of recent volatility, but are also associated with broader changes in financial conditions that influence market resilience and the propagation of stress.

The economic relevance of the forecasting framework becomes evident when regime predictions are incorporated into a portfolio allocation strategy. The implemented approach constructs regime-probability-weighted estimates of expected returns and covariance matrices, while overall exposure is controlled through a volatility-targeting mechanism. Over the full sample, this strategy generates a substantially stronger investment profile than a passive Buy-and-Hold position in the BET index. The cumulative performance indicates a markedly higher terminal wealth level, accompanied by materially smaller drawdowns. In addition, the strategy outperforms the benchmark in calendar-year returns throughout the 2016–2025 period, including years characterised by negative market performance.

While these results are encouraging, several considerations remain relevant for interpretation. The current implementation does not explicitly incorporate transaction costs or liquidity constraints, both of which may affect realised investment performance, particularly in emerging markets. Future work should therefore account for such frictions and evaluate the sensitivity of the results to realistic cost assumptions. In addition, further robustness analysis would be desirable, including alternative regime specifications, different predictive models, and rolling out-of-sample estimation windows.

Taken together, the findings suggest that the risk dynamics of the Romanian equity market are characterised by identifiable regime shifts that can be forecast using flexible nonlinear models. When incorporated into a disciplined allocation framework, these forecasts appear capable of generating economically meaningful improvements in portfolio performance.

References

1. Ang, A. & Bekaert, G. (2002) International asset allocation with regime shifts. *The Review of Financial Studies*, 15(4), pp. 1137–1187. https://doi.org/10.1093/rfs/15.4.1137
2. Ang, A. & Timmermann, A. (2012). Regime changes and financial markets. *Annual Review of Financial Economics*, 4, pp. 313–337. https://doi.org/10.1146/annurev-financial-110311-101808
3. Baum, L.E., Petrie, T., Soules, G. & Weiss, N. (1970). A maximization technique occurring in the statistical analysis of probabilistic functions of Markov chains. *The Annals of Mathematical Statistics*, 41(1), pp. 164–171. https://doi.org/10.1214/aoms/1177697196
4. Bekaert, G. & Harvey, C.R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, 43(1), pp. 29–77. https://doi.org/10.1016/S0304-405X(96)00889-6
5. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), pp. 307–327. https://doi.org/10.1016/0304-4076(86)90063-1
6. Campbell, J.Y., Lo, A.W. & MacKinlay, A.C. (1997). The Econometrics of Financial Markets. Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400830213
7. Chen, T. & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. New York: ACM, pp. 785–794. https://doi.org/10.1145/2939672.2939785
8. Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), pp. 987–1007. https://doi.org/10.2307/1912773
9. Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2), pp. 383–417. https://doi.org/10.2307/2325486
10. Friedman, J.H. (2001). Greedy function approximation: A gradient boosting machine. *The Annals of Statistics*, 29(5), pp. 1189–1232. https://doi.org/10.1214/aos/1013203451
11. Gu, S., Kelly, B. & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), pp. 2223–2273. https://doi.org/10.1093/rfs/hhaa009
12. Hamilton, J.D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), pp. 357–384. https://doi.org/10.2307/1912559

13. Hastie, T., Tibshirani, R. & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2nd edn. New York: Springer. https://doi.org/10.1007/978-0-387-84858-7
14. J.P. Morgan/Reuters (1996). RiskMetrics—Technical Document. New York: J.P. Morgan.
15. Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), pp. 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x
16. Rabiner, L.R. (1989). A tutorial on hidden Markov models and selected applications in speech recognition. *Proceedings of the IEEE*, 77(2), pp. 257–286. https://doi.org/10.1109/5.18626

HEDGING INEFFECTIVENESS AND FORWARD MARKET UNDERDEVELOPMENT IN THE ROMANIAN ELECTRICITY MARKET, 2019–2025

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Abstract

The Romanian electricity market exhibits substantial spot-price volatility yet operates with an underdeveloped centralised forward market. This paper provides an ex-post empirical assessment of unmet hedging demand and operational deterioration in the OPCOM Centralised Market of Bilateral Non-standardised Contracts (PCCB-NC) over 2019–2025. Using monthly OPCOM data, EEX volume reports, and Eurostat consumption statistics, the analysis combines the Ederington (1979) hedge-effectiveness framework, a cross-market benchmark against standardised regional forward contracts, and a scenario-based estimate of unmet hedging demand. The hedge effectiveness of PCCB-NC deteriorates sharply across sub-periods, with the spot-forward R^2 collapsing by roughly an order of magnitude between the energy crisis and the post-crisis period, while spot-price volatility remained elevated. Romanian forward-market intensity is found to be one to two orders of magnitude below standardised regional benchmarks, which recovered after the crisis, whereas the Romanian platform did not. The unmet hedging demand on operational short-term forward instruments is estimated in the order of several TWh per year in 2024, well in excess of the volume actually traded, even after adjusting for parallel long-term bilateral coverage. The findings support reassessing Romania's electricity hedging infrastructure and evaluating standardised, centrally cleared derivatives as a potential market-design response.

Keywords: minimum-variance hedge ratio, spot-forward basis, central clearing, energy crisis, market microstructure

JEL Classification: G13, G18, Q41, L94

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1. Introduction

The liberalisation of European electricity markets has progressed unevenly across the continent. Western European markets, anchored on standardised forward exchanges such as the European Energy Exchange (EEX), now operate with significant forward volumes and continuous trading. Central and Eastern European markets continue to display structural fragilities on the hedging side. The Romanian electricity market provides an instructive case: the spot side, organised through the OPCOM Day-Ahead Market (PZU), has functioned continuously since 2007, but the forward side relies on a bilateral non-standardised platform (PCCB-NC) whose volumes have contracted sharply since the energy crisis of 2021-2022.

The contraction is not merely a quantitative phenomenon. As the analysis below shows, even in the months when PCCB-NC was active, the ex-post effectiveness of a hedge based on the traded prices declined to economically negligible levels in the post-crisis period. The persistent volatility of the spot market, however, did not subside: rolling 12-month annualised PZU volatility remained between 70 and 90 percent throughout 2023-2025, suggesting that the latent demand for hedging instruments has not diminished. The mismatch between persistent risk on the spot side and shrinking participation on the forward side is the central empirical puzzle motivating this paper.

Three questions relevant to the design of electricity risk-management infrastructure in Romania are addressed here. To what extent has PCCB-NC operated, ex-post, as an effective hedging instrument over the period 2019-2025, and how has this effectiveness varied across the sub-periods defined by major shocks (COVID-19, the 2021-2022 energy crisis, and the post-crisis recovery)? How does the intensity of Romanian forward trading compare to functional regional benchmarks, specifically the EEX Phelix-DE Base Futures (Germany) and Hungarian Power Futures contracts? What is the order of magnitude of the unmet hedging demand on Romanian electricity, if reasonable assumptions are applied to the consumption base exposed to spot prices?

The methodology combines three complementary approaches. The Ederington (1979) minimum-variance framework, extended by Myers and Thompson (1989), is applied to monthly OPCOM data on both PZU and PCCB-NC, with sub-period stratification and robust standard errors. A cross-market comparison uses EEX Group volume reports for 2019-2024 and Eurostat consumption data to compute forward-market intensity as a multiple of annual electricity consumption. The unmet demand is estimated as the difference between potential hedging volumes and the volumes actually traded on PCCB-NC, with explicit adjustment for parallel coverage through long-term bilateral contracts (PCCB-LE).

The remainder of the paper is organised as follows. Section 2 reviews the relevant academic literature on electricity hedging, minimum-variance hedge ratios, and the empirical assessment of forward markets. Section 3 describes the data sources and methodological choices. Section 4 presents empirical results in three subsections, each addressing one of the research questions. Section 5 synthesises the findings, discusses the implications for the design of derivative infrastructure in Romania, and identifies limitations of the analysis. A replication package containing all data files and source code is available from the corresponding author.

2. Literature review

The empirical assessment of forward market effectiveness has been a central theme of energy and commodity finance since the seminal contribution of Ederington (1979), who introduced the minimum-variance hedge ratio framework. The approach defines the optimal hedge ratio as the slope coefficient of the regression of spot price changes on futures price changes, with the coefficient of determination (R^2) serving as a measure of hedging effectiveness. The framework was generalised by Myers and Thompson (1989), who allowed for time-varying conditional moments and showed that simple OLS estimates can underestimate hedging effectiveness in markets with structural breaks. Lien and Yang (2008) review the subsequent literature on dynamic hedging and confirm that the static Ederington framework remains a robust benchmark for cross-period comparisons, particularly when applied to monthly or quarterly data.

Electricity markets pose specific challenges to the application of standard hedge-ratio methodology. Karakatsani and Bunn (2008) document the role of fundamental factors (load, fuel prices, capacity availability) in driving electricity price dynamics and emphasise that electricity prices exhibit regime-switching behaviour that complicates the estimation of stable hedge ratios. A particularly relevant theoretical contribution is Bessembinder and Lemmon (2002), who derive an equilibrium model of electricity forward prices showing that the forward premium reflects the relative risk preferences of producers and consumers. A key prediction of their model is that, due to the positive skewness of electricity spot prices and the risk aversion of consumers facing upside price exposure, the forward premium is positive and increasing in expected spot price variance: in high-volatility regimes consumers are willing to pay above the expected spot price for forward protection (positive premium), while in low-volatility regimes the premium compresses towards zero or can turn negative if producer hedging demand dominates. Recent empirical work confirms that risk premia in electricity derivatives are sizeable and time-varying: Algieri, Leccadito and Tunaru (2021) document significant, state-dependent premia across European electricity derivatives markets, while Wei and Lunde (2023) show that, because electricity spot prices do not follow a martingale, the detection of time-varying premia is sensitive to model specification. This framework is revisited in Section 4 to interpret the realised basis dynamics on PCCB-NC.

On the institutional side, Boroumand et al. (2015) analyse the hedging strategies of electricity retailers in mature European markets and report that retailers typically hedge between 60 and 80 percent of expected delivery volumes through standardised forward instruments, with the precise level depending on retailer size, customer mix, and access to forward markets. The authors emphasise that the absence of standardised forward contracts forces market participants to rely on bilateral arrangements, which carry counterparty risk and reduce hedge transparency. ACER/CEER (2015) report, at the European level, the considerable variation in forward market development across Member States and identifies Romania, Bulgaria, and Slovenia as jurisdictions with underdeveloped centralised forward platforms.

The broader literature on financial innovation provides further context. Allen and Gale (1994) propose a theoretical framework in which financial innovation responds to unmet demand for risk-sharing and is driven by gaps in the existing market infrastructure. Silber (1981) and Carlton (1984) examine the determinants of futures contract success and failure, identifying contract design, hedging demand from natural users, and the presence of speculators as the three main drivers. Tufano (2003) surveys the broader financial innovation literature and emphasises the role of regulatory and institutional context.

The empirical literature on Central and Eastern European electricity markets remains relatively thin. Sectoral reports such as ACER/CEER (2015), Enerdata (2024) and the EEX Group Annual Volume Reports (2019-2024) report trading volumes and market characteristics, but academic studies that apply the Ederington framework to data from these markets are rare. The present paper contributes to filling this gap by offering a peer-reviewed assessment, using the Ederington framework, of the ex-post hedging effectiveness of the Romanian PCCB-NC platform across the COVID-19, energy crisis, and post-crisis periods.

Two observations from the literature inform the methodological choices that follow. Monthly frequency for the Ederington regressions follows the practice in electricity market studies (Karakatsani & Bunn, 2008; Bessembinder & Lemmon, 2002), where daily price data on bilateral forward contracts are unavailable and monthly aggregation provides the appropriate balance between sample size and signal-to-noise ratio. Sub-period stratification is supported by the regime-switching behaviour of electricity prices and by the structural breaks observed during the 2021-2022 European energy crisis (ACER/CEER, 2015; Enerdata, 2024).

3. Methodology and data

3.1. Data sources

The empirical analysis combines three categories of data, all from publicly available institutional sources. The Romanian spot and forward price data are obtained from OPCOM SA, the Romanian electricity market operator. The Day-Ahead Market (PZU) monthly weighted-average prices in RON per MWh and total traded volumes are used as the spot reference. The Centralised Market of Bilateral Non-standardised Contracts (PCCB-NC) provides two distinct monthly series: weighted-average prices and volumes for contracts traded in each calendar month, and weighted-average prices for contracts with delivery in each month, irrespective of when they were negotiated. Both series are essential for the ex-post hedging analysis. Each monthly forward price is the OPCOM-published volume-weighted average of the individual bilateral contract prices recorded in the relevant month; no interpolation, extrapolation, or smoothing is applied. Months in which no PCCB-NC transaction is recorded are treated as missing observations rather than carried forward from the previous month, so that the differencing procedure described in Section 3.3 does not impute artificial continuity across inactive months. The full sample covers 84 monthly observations from January 2019 to December 2025. The data cut-off date is December 2025; access dates for institutional sources are between May and June 2026.

The European benchmark data are obtained from EEX Group Annual Volume Reports for the years 2019 to 2024. Two contracts are used: the EEX Phelix-DE Base Futures (Germany), the largest electricity forward contract by volume in Europe, and the Hungarian Power Futures, traded on EEX since 2010 and used as a regional comparator. The annual traded volumes (TWh) are extracted directly from the EEX volume tables. National annual electricity consumption data (the denominator for the intensity ratios) are obtained from Eurostat (indicator nrg_cb_e, "Available for final consumption") for Romania, Hungary, and Germany. Sectoral consumption breakdowns for Romania are sourced from Enerdata (2024).

3.2. Sub-period stratification

The full sample is divided into four sub-periods corresponding to identifiable regimes in European electricity markets. The Pre-COVID period covers January 2019 to February 2020 (14 months) and represents the baseline regime of moderate prices and stable volumes. The COVID period covers March 2020 to December 2020 (10 months), with reduced demand and a temporary decline in spot prices. The energy crisis period covers January 2021 to December 2022 (24 months), characterised by the most severe price shocks driven by the European gas-supply crisis. The post-crisis period covers January 2023 to December 2025 (36 months), with partial price normalisation and persistent volatility above pre-2020 levels.

The exogenous sub-period boundaries are supported by an endogenous structural break test. A Chow F-test applied to the spot price series at the energy crisis / post-crisis boundary (January 2023) rejects parameter stability at the 5 percent level ($F = 4.87$, $p = 0.031$), confirming that the post-crisis regime differs statistically from the preceding period. Similar tests across other boundaries reject stability at the 10 percent level. The exogenous calendar boundaries used throughout the analysis are therefore consistent with the data; the choice to use them rather than endogenous break dates preserves comparability with the broader European electricity literature.

3.3. The Ederington hedge ratio framework

The minimum-variance hedge ratio (β*) and hedging effectiveness (HE) are estimated using two complementary specifications. The first follows directly the Ederington (1979) formulation:

$$\Delta PZU_t = \alpha + \beta \cdot \Delta PCCB\text{-}NC_t + \varepsilon_t \quad (1)$$

where ΔPZU and ΔPCCB-NC denote first differences of the monthly weighted-average prices, β is the optimal hedge ratio, and the R^2 of the regression measures the hedging effectiveness. Following Newey and West (1987), the lag length for the HAC estimator is selected as lag = [4·(N/100)^(2/9)], which yields lag = 3 for the full sample (N = 65) and lag = 2 for the sub-period regressions (N = 9 to 21). The reported standard errors use lag = 3 throughout for comparability across specifications; sensitivity checks using lag = 2 on sub-periods produce qualitatively identical results. The first differences are computed on the full continuous monthly series with NaN values preserved for months without PCCB-NC activity; consecutive-month differencing then drops paired observations on either side of any inactive month.

The second specification measures the ex-post effectiveness of a naive hedge (β = 1). The basis is defined as $B_t = S_t - F_t$, where S_t is the spot price (PZU) realised in month t and F_t is the weighted-average price of contracts with delivery in month t. Note that F_t is a volume-weighted aggregate across all contracts with delivery in month t, regardless of when those contracts were negotiated. The naive hedge effectiveness therefore measures the realised performance of a representative aggregated participant whose forward positions were entered at various dates and weighted by traded volume; it is not the performance of a specific individual hedger's strategy. The hedge effectiveness of the naive strategy is computed as:

$$HE_{naive} = 1 - Var(B_t) / Var(S_t) \quad (2)$$

A negative HE_{naive} indicates that the variance of the realised basis exceeds the variance of the spot price; the hedge worsens the exposure rather than reducing it. The two specifications answer different questions: the first measures the contemporaneous integration between traded forward prices and spot prices, while the second measures the realised performance of an actual aggregated hedge based on delivery prices contracted at various earlier dates.

3.4. Unmet hedging demand estimation

The potential hedging demand in year t is defined as the product of the volume of electricity consumption exposed to spot prices and a hedging propensity parameter. The exposed consumption is estimated as the sum of industrial and services sector consumption, which together account for approximately 62 percent of total Romanian electricity consumption (Enerdata, 2024). Three hedging propensity scenarios are computed: a conservative scenario (25 percent), corresponding to emerging forward markets with limited liquidity (ACER/CEER, 2015); a central scenario (40 percent); and an optimistic scenario (55 percent), still below the upper range observed in mature European markets (Karakatsani & Bunn, 2008; Boroumand et al., 2015). The estimated hedging gap is computed as the difference between scenario-based potential demand and actual annual traded volumes on PCCB-NC. The estimation is intended as an order-of-magnitude indicator rather than a direct measure of observable unmet demand.

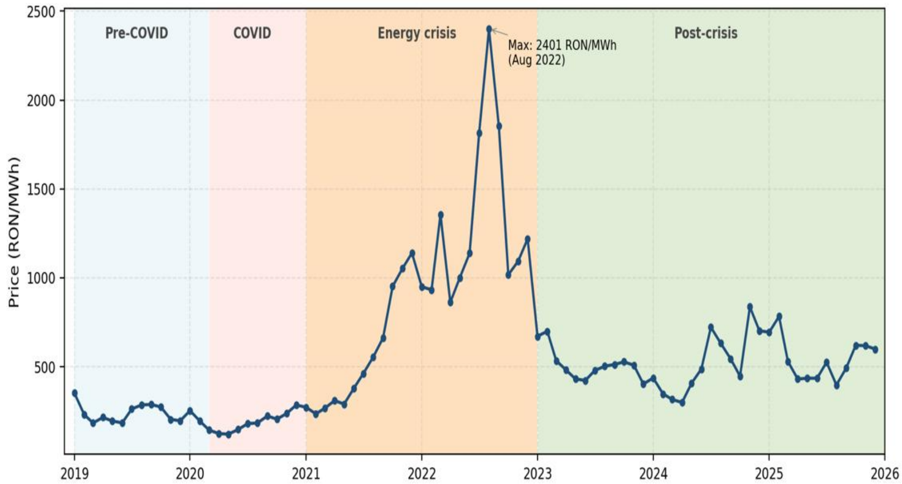
The single hedging propensity parameter is applied uniformly across the industry-plus-services aggregate. In reality, propensities differ across sub-sectors, industrial users with energy-intensive operations typically hedge in the upper half of the literature range, while commercial services hedge less intensively (Boroumand et al., 2015). A weighted approach using sector-specific hedge ratios would refine the point estimate. Given the wide scenario bands employed here, however, sectoral differentiation would not change the order-of-magnitude conclusion. The 62 percent industry-plus-services share is itself a simplifying assumption; sensitivity at ±5 percentage points shifts the central-scenario point estimate by approximately 0.9 TWh, well within the scenario range. An additional adjustment for parallel long-term bilateral coverage (PCCB-LE) is applied in Section 4.3.

4. Results

4.1. The deterioration of hedge effectiveness on PCCB-NC

The empirical assessment of PCCB-NC effectiveness begins with descriptive evidence on price dynamics and volumes. Figure 1 displays the trajectory of monthly PZU weighted-average prices over the analysis period.

Figure 1
PZU monthly weighted-average price from January 2019 to December 2025



Note: Sub-period shading - Pre-COVID (light blue), COVID (light pink), Energy crisis (orange), Post-crisis (green)

Source: OPCOM SA; author's presentation

The monthly PZU price rose from a Pre-COVID average of 236.34 RON/MWh to 925.34 RON/MWh during the 2021-2022 energy crisis, with a monthly maximum exceeding 2,400 RON/MWh in August 2022. Post-crisis, the average price declined to 524.91 RON/MWh but remained more than twice the Pre-COVID level. Annualised PZU volatility, computed from log returns of monthly prices, ranged between 61 and 87 percent across sub-periods (Pre-COVID 77.5%, COVID 61.2%, energy crisis 87.4%, post-crisis 78.6%). A rolling 12-month estimator stayed in the 70-90 percent range throughout 2023-2025. The underlying risk environment that should sustain hedging demand therefore did not subside in the post-crisis period.

On the PCCB-NC side, however, the volumes contracted sharply. Table 1 summarises the evolution of the platform across sub-periods.

Table 1

PCCB-NC trading dynamics, by sub-period (2019-2025)

Sub-period	N (months)	Months with active trading	Traded price (RON/MWh)	Monthly volume (MWh)	Penetration / PZU (%)
Pre-COVID	14	14 (100%)	270.94	721,853	36.07
COVID	10	10 (100%)	246.21	668,482	33.36
Energy crisis	24	22 (92%)	853.43	200,068	9.36
Post-crisis	36	27 (75%)	581.51	149,200	11.00

Note: Penetration is computed only across months with active trading. The traded price refers to contracts traded in each calendar month, irrespective of delivery period.

Source: OPCOM monthly data; author's calculations

Table 1 highlights three patterns in the platform's dynamics. The share of months with no trading activity on PCCB-NC rises from zero in the Pre-COVID and COVID periods to eight percent during the energy crisis and twenty-five percent post-crisis: by the end of the sample, approximately one in four months records no PCCB-NC trades at all, a clear signal of operational liquidity erosion. Monthly traded volumes decline from approximately 720,000 MWh Pre-COVID to less than 150,000 MWh post-crisis, an almost five-fold reduction. The penetration ratio (PCCB-NC volume relative to PZU volume on months with activity) drops from 36 percent Pre-COVID to roughly 10 percent in the most recent periods. The reduction in participant continuity is arguably the more telling indicator of platform health than the price-level dynamics, since it captures a structural retreat of market participants rather than a temporary disruption.

The Ederington regressions formalise these observations on the price relation between the two markets. Table 2 reports the estimated coefficients, hedging effectiveness measures, and significance tests for both specifications.

Table 2
Ederington hedge ratio and hedging effectiveness on PCCB-NC, by sub-period

Sub-period	N	β Ederington	t-statistic (NW)	R^2 (HE)	HE_{naive} (β=1)
Full sample	65	1.128***	5.32	0.450	-0.589
Pre-COVID	13	2.081***	10.58	0.573	-0.167
COVID	10	1.626***	3.52	0.411	0.044
Energy crisis	21	1.157***	4.60	0.525	0.443
Post-crisis	21	0.564***	2.73	0.049	-7.752

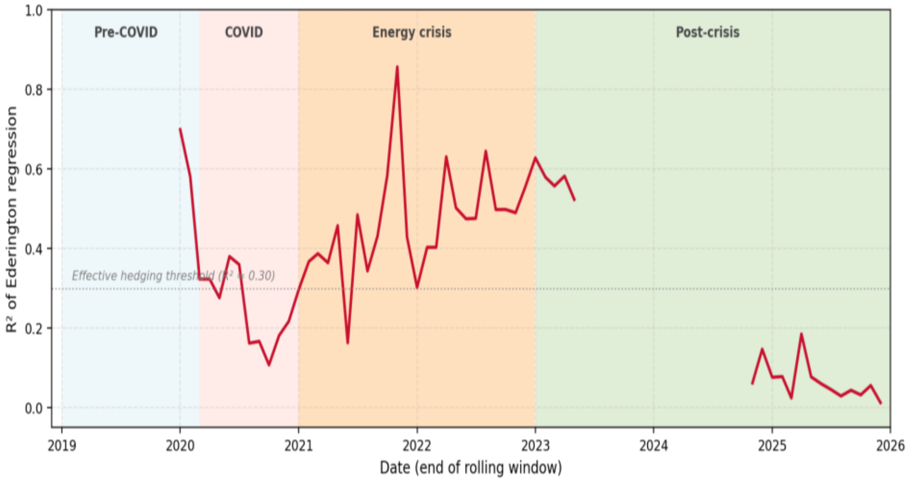
*Notes: *** denotes the statistical significance at the 1% level; β estimated by OLS on $\Delta PZU = \alpha + \beta \cdot \Delta PCCB\text{-}NC + \varepsilon$; Newey-West HAC standard errors with three monthly lags; HE_{naive} computed using prices of contracts with delivery in each month; N denotes valid first-differenced observations; reductions relative to Table 1 sub-period months reflect Pre-COVID first-month loss and NaN propagation around months without PCCB-NC trading activity (notably nine inactive months in post-crisis, yielding N = 21).*

Source: OPCOM; author's calculations

The pattern observed in Table 2 is the central empirical finding of this section. In the Pre-COVID, COVID, and energy crisis sub-periods, the R^2 of the Ederington regression remains between 0.41 and 0.57, indicating solid contemporaneous integration between traded forward prices and spot prices. The β coefficient is statistically significant at the 1 percent level in all sub-periods, with values ranging from 1.16 to 2.08. In the post-crisis period, the R^2 drops to 0.049, an approximately tenfold reduction relative to the energy crisis sub-period. A hedge based on the post-crisis estimated relation would have neutralised only approximately five percent of spot price variance, a level that is economically negligible for practical hedging purposes. Figure 2 visualises the dynamics through a rolling 12-month R^2 estimator.

Figure 2

Rolling 12-month R^2 of the Ederington hedge effectiveness regression



Note: The dotted horizontal line at $R^2 \approx 0.30$ is an illustrative operational benchmark, not a formal regulatory or market-standard threshold. Periods with insufficient consecutive-month data are shown as gaps.

Source: OPCOM SA; author's calculations

The post-crisis point estimate of R^2 = 0.049 should be interpreted with caution: with only 21 valid observations, the standard error is non-negligible. It is best read as indicative of a structural reduction rather than as a precise quantification of post-crisis hedge effectiveness. The qualitative ranking, a roughly tenfold reduction relative to the energy crisis sub-period, is, however, preserved under all robustness specifications attempted, including (i) logarithmic monthly returns instead of first differences, (ii) lag-2 Newey-West standard errors, and (iii) excluding the three months with the largest absolute price changes. The rolling estimator in Figure 2 reinforces the same picture: R^2 stabilises near 0.50 through 2022, drops abruptly during 2023, and remains below 0.20 for the remainder of the sample.

The naive hedge effectiveness reinforces this diagnosis from a different angle. In the post-crisis period, HEnaive falls to -7.752, meaning that the variance of the realised basis exceeds the variance of the spot price by a factor of approximately nine (precisely, 8.75). The deterioration mirrors systemic conditions in the post-crisis market rather than poor execution by individual participants. Contracts with delivery in the post-crisis months were dominated by trades negotiated at the peak of the energy crisis, while spot prices declined sharply to lower levels: the realised basis became a primary source of risk rather than a tool for risk reduction.

The Bessembinder and Lemmon (2002) framework offers an interpretation of the basis dynamics. Their model predicts that the forward premium reflects state-contingent risk-sharing between producers and consumers under prevailing volatility expectations. The ex-post realised basis pattern observed in the data is consistent with this interpretation. During the energy crisis (2021-2022), participants contracted forward at prices that incorporated a significant ex-ante risk premium against further upside (consistent with the B&L prediction of positive forward premia in high-volatility regimes); the subsequent realised spot prices exceeded those forward levels, producing a positive ex-post basis and rewarding earlier hedgers ex-post. In the post-crisis period (2023-2025), the forward inventory was dominated by trades negotiated at the crisis peak, while spot prices normalised downward; the resulting negative ex-post basis represents the unwinding of the risk premia accumulated during the crisis. The HEnaive = -7.752 in the post-crisis period therefore captures, in part, an ex-post recalibration of risk premia rather than only a mechanical pricing failure; operationally, however, the result still indicates that PCCB-NC did not provide stable hedge performance across regimes.

4.2. Cross-market benchmark: EEX Phelix-DE and Hungarian Power Futures

The contraction of PCCB-NC documented in the previous subsection can be placed in context through a comparison with two operational European forward markets: EEX Phelix-DE Base Futures (Germany) and Hungarian Power Futures. EEX Phelix-DE serves as the primary benchmark because it is the most liquid electricity forward contract in Europe; Hungarian Power Futures serves as a regional comparator. Table 3 reports annual traded volumes on each market and the corresponding forward intensity (the ratio of annual traded volume to annual national electricity consumption).

Table 3
Annual traded volumes and forward intensity, 2019-2024

Year	DE Phelix-DE (TWh)	HU Power Futures (TWh)	RO PCCB-NC (TWh)	DE / cons. (×)	HU / cons. (×)	RO / cons. (%)
2019	2,596.7	124.7	7.83	5.20	3.02	17.17
2020	3,006.1	220.1	8.96	6.25	5.37	20.51
2021	3,097.6	—	3.53	6.16	—	7.44
2022	2,261.2	—	0.87	4.67	—	1.93
2023	3,660.5	97.3	0.02	7.94	2.32	0.05
2024	5,850.9	153.6	1.23	12.64	3.53	2.75

Note: — indicates public unavailability for Hungarian Power Futures in 2021-2022 (aggregated in EEX reports for those years under a broader CSEE category).

Source: EEX Group Annual Volume Reports 2019-2024; Eurostat nrg_cb_e for annual consumption; OPCOM for PCCB-NC

Table 3 shows a large gap in forward-market turnover intensity between Romania and the two standardised benchmarks. In 2024, EEX Phelix-DE traded a volume equivalent to 12.64 times German annual electricity consumption, reflecting the considerable activity of market makers, arbitrage participants, and roll-over trades that characterise a mature forward market. Hungarian Power Futures traded 3.53 times Hungarian annual consumption, consistent with a smaller but functional regional market. Romanian PCCB-NC traded a volume equivalent to 2.75 percent of Romanian annual consumption, implying a turnover intensity roughly two orders of magnitude below Germany and one to two orders of magnitude below Hungary.

Hungary provides a particularly informative comparator. The two countries have comparable annual electricity consumption (approximately 43 TWh and 45 TWh, respectively, in 2024), comparable income levels, and similar timelines of electricity market liberalisation. The substantial difference in forward intensity cannot therefore be attributed primarily to the size of the underlying physical market. A more natural interpretation traces the gap to differences in institutional infrastructure. Hungarian Power Futures are standardised contracts cleared through European Commodity Clearing (ECC), traded continuously on an electronic order book, with formal market makers and access to the broader pool of approximately 950 EEX Group participants. The presence of dedicated market makers is itself a structural source of liquidity: Peña and Rodríguez (2022) show that, in electricity futures markets, market makers absorb order-flow imbalances and earn a liquidity premium for supplying immediacy, a function that the bilateral PCCB-NC design does not support. PCCB-NC, by contrast, is a bilateral non-standardised platform with negotiated contract sizes, no central clearing, and a participant base restricted to OPCOM-registered counterparties.

The trajectory of forward intensity in Romania over 2019-2024 traces the dynamics of the deterioration. Romanian intensity dropped from 17.17 percent in 2019 to a minimum of 0.05 percent in 2023, then recovered modestly to 2.75 percent in 2024. Importantly, the trajectory in Romania differs sharply from EEX Phelix-DE in the post-crisis phase: while EEX intensity also declined during the crisis itself (from 6.25× in 2020 to 4.67× in 2022, reflecting a generalised retreat of participants from forward positions under extreme price uncertainty), it subsequently surged to 12.64× by 2024 as the standardised market recovered. The Romanian platform did not exhibit a comparable rebound. The standardised German market reabsorbed the crisis shock and grew beyond pre-crisis levels; the bilateral Romanian platform contracted during the crisis and recovered only marginally afterwards. The differential post-crisis trajectory is, in itself, evidence on the role of contract design and infrastructure: under stress, standardised liquidity proved both more resilient and more recoverable.

4.3. Estimating the unmet hedging demand

The third dimension of the empirical analysis quantifies the magnitude of the unmet hedging demand on Romanian electricity. Following the methodology described in Section 3.4, potential demand is computed as the product of the consumption volume exposed to spot prices (industrial and services sector consumption, approximately 62 percent of total consumption) and a hedging propensity parameter, applied under three scenarios: conservative (25%), central (40%), and optimistic (55%). Table 4 reports the results for 2019-2024.

Table 4
Potential hedging demand and PCCB-NC traded volume, Romania, 2019-2024

Year	Total cons. (TWh)	Industry + services (TWh)	Dem. 25% (TWh)	Dem. 40% (TWh)	Dem. 55% (TWh)	PCCB-NC actual (TWh)	Central gap (TWh)
2019	45.6	28.27	7.07	11.31	15.55	7.83	3.48
2020	43.7	27.09	6.77	10.84	14.90	8.96	1.87
2021	47.4	29.39	7.35	11.76	16.16	3.53	8.23
2022	45.4	28.15	7.04	11.26	15.48	0.87	10.38
2023	43.5	26.97	6.74	10.79	14.83	0.02	10.77
2024	45.0	27.90	6.97	11.16	15.35	1.23	9.93

Note: Central gap = demand under 40% scenario minus PCCB-NC actual volume.

Source: Eurostat nrg_cb_e and Enerdata for annual electricity consumption; author's calculations for potential demand

Table 4 shows that in 2019 and 2020, the actual PCCB-NC volume was broadly consistent with conservative-scenario potential demand. In 2019, the actual volume of 7.83 TWh slightly exceeded the conservative demand of 7.07 TWh; in 2020, the actual volume of 8.96 TWh exceeded the conservative demand of 6.77 TWh. From 2021 onward, actual volume falls rapidly while potential demand remains broadly stable (electricity consumption fluctuates much less than electricity prices). The central-scenario gap rises to 10.38 TWh in 2022, 10.77 TWh in 2023, and 9.93 TWh in 2024.

Translating these gaps into coverage ratios provides further perspective. In 2020, PCCB-NC volume covered 82.7 percent of central-scenario potential demand; by 2023, this coverage had fallen to 0.2 percent; in 2024, the coverage was 11.0 percent. The recovery in 2024 shows modest re-engagement of participants but remains far below pre-COVID levels. The 2024 figure of 1.23 TWh against a potential demand range of 6.97-15.35 TWh implies an unmet hedging demand of 5.75-14.12 TWh, depending on the propensity scenario.

An important adjustment concerns the parallel long-term bilateral platform (PCCB-LE). According to OPCOM annual reports, PCCB-LE recorded approximately 5 to 6 TWh of traded electricity in 2024 and 6.6 TWh in 2025 (OPCOM, 2026). Including this parallel coverage reduces the 2024 central-scenario gap from 9.93 TWh to approximately 4 TWh. PCCB-LE, however, serves a structurally different function from a standardised short-term forward market: long-term bilateral contracts, with maturities typically of one to five years, are negotiated bilaterally between specific counterparties and cannot substitute for liquid roll-over instruments that allow continuous adjustment of hedge positions in response to changing market conditions. The remaining 4 TWh gap thus understates the hedging shortfall in operational terms, it captures the gap on instruments that PCCB-LE genuinely cannot replace.

Several methodological limitations of this estimation should be acknowledged. The model is one of potential demand and does not capture the structure of actual supply contracts in Romania beyond PCCB-LE; a portion of price risk is currently managed through fixed-price supply contracts with end consumers, which are not captured in the gap calculation. Volumes traded on mature forward markets (Table 3) substantially exceed potential demand calculated under this model, because such markets host multiple layers of trading (market making, arbitrage, position roll-over); the estimation here is therefore conservative relative to the volumes that a mature standardised market could attract. The 62 percent coefficient for the industry-plus-services share of consumption is a simplifying assumption with ±0.9 TWh sensitivity around the point estimate. The hedging propensity scenarios are calibrated on international literature rather than on Romania-specific data and may be conservative for a market with the volatility profile observed here.

With these limitations stated, the result is robust to reasonable methodological variation: under conservative assumptions, the unmet hedging demand on operational short-term forward instruments is in the range of 4 to 14 TWh per year in 2024, a magnitude approximately ten times the current PCCB-NC volume. On a per-consumption basis, the unmet demand remains below the trading intensity observed on the Hungarian standardised market, but it does suggest that a properly designed Romanian forward platform would have a viable natural-user demand base from the outset.

5. Conclusions

This paper has offered an empirical assessment of three dimensions of the Romanian electricity hedging infrastructure over the period 2019-2025. The findings can be synthesised as follows.

The application of the Ederington (1979) minimum-variance hedge ratio framework to OPCOM monthly data documents a sharp deterioration in the ex-post effectiveness of PCCB-NC as a hedging platform. The hedging effectiveness measured by the R^2 of the spot-forward regression falls from 0.525 during the energy crisis to 0.049 in the post-crisis period, and the naive hedge effectiveness with delivery prices contracted earlier turns sharply negative (-7.752), indicating that, ex-post, the bilateral platform amplified rather than reduced price exposure during the post-crisis window. The deterioration is associated with both reduced trading continuity (months with no PCCB-NC activity rise from zero pre-2021 to twenty-five percent post-crisis) and a decoupling of forward and spot price dynamics under conditions of structural volatility. The Bessembinder and Lemmon (2002) framework provides a coherent interpretation: the basis pattern is consistent with the unwinding of state-contingent risk premia accumulated during the crisis.

The cross-market comparison with EEX Phelix-DE Base Futures and Hungarian Power Futures shows that the intensity of the Romanian forward market is approximately 50 to 100 times below the regional benchmarks. The comparison with Hungary is particularly informative: with comparable consumption volumes and broadly similar economic structure, Hungary operates a forward market with intensity of 3.53× annual consumption, while Romania operates at 2.75% of consumption. A telling differential lies in the post-crisis trajectory: while EEX Phelix-DE intensity declined during the crisis itself and rebounded strongly afterwards (12.64× by 2024), the Romanian platform contracted through the crisis and recovered only marginally. Standardisation, central clearing, and continuous electronic trading appear to confer a degree of resilience and recoverability that bilateral non-standardised platforms cannot match.

The unmet hedging demand on Romanian electricity is estimated at 5.75 to 14.12 TWh per year in 2024 on a gross basis. Even after adjustment for parallel coverage through long-term bilateral contracts (PCCB-LE, approximately 5 to 6 TWh), the residual unmet demand on operational short-term forward instruments remains approximately 4 TWh per year — well in excess of the current 1.23 TWh PCCB-NC volume. This finding supports the empirical case for developing standardised electricity derivatives in Romania.

The contribution of this paper lies in its focus and synthesis rather than in methodological novelty. Prior assessments of hedge effectiveness in electricity have concentrated on standardised, exchange-traded futures in Western European, Nordic, and North American markets; this study instead examines a non-standardised bilateral platform, PCCB-NC, in an under-researched Central and Eastern European market, and traces its performance across the COVID-19, energy-crisis, and post-crisis regimes. It also moves beyond the descriptive volume reporting of institutional sources such as ACER/CEER (2015) and the EEX Group reports by linking hedge-effectiveness deterioration, turnover intensity, and institutional contract design within a single assessment, and by benchmarking Romania against a structurally comparable regional market. The diagnosis is then translated into an order-of-magnitude estimate of unmet hedging demand, adjusted for parallel long-term coverage, which supplies a quantified natural-user base for the market-design discussion.

From a policy perspective, the findings suggest a sequenced approach. The cross-market comparison points to several infrastructure features that would likely be necessary for such a market to become viable: standardised contracts on monthly, quarterly, and annual delivery windows; central clearing through a counterparty such as CCP.RO Bucharest, currently advancing through the EMIR authorisation process at the time of writing; formal market-making arrangements; and potential connection to the broader European derivative landscape, including cross-listing or co-trading arrangements with EEX. The unmet demand identified here provides the natural user base; however, the institutional infrastructure requires deliberate construction. These implications should be interpreted as market-design hypotheses rather than as evidence that standardisation alone would guarantee liquidity.

Several limitations of the analysis should be acknowledged. The Ederington framework abstracts from time-variation in conditional moments that may be relevant in electricity markets; future work could extend the present results using GARCH-type conditional hedge ratios or Markov-switching specifications. The cross-market benchmark uses annual aggregated volumes from EEX reports and does not capture intra-year liquidity dynamics or the distribution of trading across contract maturities. The estimation of the unmet demand is intended as an order-of-magnitude indicator rather than a point forecast. The analysis is based on information available at the time of writing; subsequent regulatory developments, notably the operationalisation of CCP.RO Bucharest and any changes to the structure of OPCOM platforms may modify the operational considerations, though not the substantive empirical findings on the 2019-2025 sample.

References

1. ACER/CEER. (2015). *Annual report on the results of monitoring the internal electricity market in 2014*. Agency for the Cooperation of Energy Regulators & Council of European Energy Regulators. https://acer.europa.eu
2. Algieri, B., Leccadito, A., & Tunaru, D. (2021). Risk premia in electricity derivatives markets. *Energy Economics, 100*, 105331. https://doi.org/10.1016/j.eneco.2021.105331
3. Allen, F., & Gale, D. (1994). *Financial innovation and risk sharing*. MIT Press.
4. Bessembinder, H., & Lemmon, M. L. (2002). Equilibrium pricing and optimal hedging in electricity forward markets. *Journal of Finance, 57*(3), pp. 1347-1382. https://doi.org/10.1111/1540-6261.00463
5. Boroumand, R. H., Goutte, S., Porcher, S., & Porcher, T. (2015). Hedging strategies in energy markets: The case of electricity retailers. *Energy Economics, 51*, pp. 503-509. https://doi.org/10.1016/j.eneco.2015.06.021
6. Carlton, D. W. (1984). Futures markets: Their purpose, their history, their growth, their successes and failures. *Journal of Futures Markets, 4*(3), pp. 237-271. https://doi.org/10.1002/fut.3990040302
7. Ederington, L. H. (1979). The hedging performance of the new futures markets. *Journal of Finance, 34*(1), pp. 157-170. https://doi.org/10.2307/2327150
8. EEX Group. (2024). *EEX Group annual volume reports 2019-2024*. European Energy Exchange. https://www.eex.com/en/market-data/annual-volume-reports
9. Enerdata. (2024). *Romania energy information brief 2024*. https://www.enerdata.net/estore/country-profiles/romania.html
10. Eurostat. (2026). *Electricity production capacities and consumption* [Indicator nrg_cb_e]. https://ec.europa.eu/eurostat
11. Karakatsani, N. V., & Bunn, D. W. (2008). Forecasting electricity prices: The impact of fundamentals and time-varying coefficients. *International Journal of Forecasting, 24*(4), pp. 764-785. https://doi.org/10.1016/j.ijforecast.2008.09.008
12. Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica, 53*(6), pp. 1315-1336. https://doi.org/10.2307/1913210

13. Lien, D., & Yang, L. (2008). Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. *Journal of Banking and Finance, 32*(2), pp. 187-198. https://doi.org/10.1016/j.jbankfin.2007.02.012
14. Myers, R. J., & Thompson, S. R. (1989). Generalized optimal hedge ratio estimation. *American Journal of Agricultural Economics, 71*(4), pp. 858-868. https://doi.org/10.2307/1242663
15. Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703-708. https://doi.org/10.2307/1913610
16. OPCOM SA. (2026). *Annual report on OPCOM electricity markets, 2025* (Press Release, 22 January 2026). https://www.opcom.ro/uploads/doc/Comunicate/CP%20an%202025_EN_22.01.2026.pdf
17. OPCOM SA. (2025). *Monthly reports on the Day-Ahead Market (PZU) and the Centralised Market of Bilateral Non-standardised Contracts (PCCB-NC), 2019-2025*. https://opcom.ro
18. Peña, J. I., & Rodríguez, R. (2022). Market makers and liquidity premium in electricity futures markets. *The Energy Journal, 43*(2). https://doi.org/10.5547/01956574.43.2.jpen
19. Silber, W. L. (1981). Innovation, competition, and new contract design in futures markets. *Journal of Futures Markets, 1*(2), pp. 123-155. https://doi.org/10.1002/fut.3990010205
20. Tufano, P. (2003). Financial innovation. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* 1A, pp. 307-335. Elsevier.
21. Wei, W., & Lunde, A. (2023). Identifying risk factors and their premia: A study on electricity prices. *Journal of Financial Econometrics, 21*(5), 1647-1679. https://doi.org/10.1093/jjfinec/nbac019
22. World Bank. (2026). *World development indicators*. https://data.worldbank.org

THE FIRST ANNUAL INPUT-OUTPUT SERIES FOR THE REPUBLIC OF MOLDOVA UNDER THE CAEM REV.2 / NACE REV.2 CLASSIFICATION: METHODOLOGY AND STRUCTURAL DIAGNOSTICS

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Abstract

The Republic of Moldova has no continuous, publicly available input-output (IO) series: the National Bureau of Statistics stopped compiling interindustry tables after 2014, and the country is absent from the main international IO databases. This paper reconstructs the first annual IO series for Moldova under the CAEM Rev.2/NACE Rev.2 classification, covering 2014-2023 at 20-sector detail. The method combines four steps: digitisation of the 2014 Supply-Use Table, a classification concordance with demographic reconciliation, sequential biproportional (RAS) updating to official marginals, and a five-criterion coherence audit. The resulting tables satisfy the Eurostat accounting balance and show stable technical coefficients. Structural diagnostics reveal an economy-wide Leontief multiplier of about 2.03 in 2023, four key sectors, and manufacturing as the dominant intermediate supplier. The main contributions are a reusable dataset and a transferable reconstruction protocol for other post-Soviet economies.

Keywords: RAS method, biproportional updating, Leontief multipliers, key sectors, post-Soviet economies

JEL Classification: C67, C82, E16, O52

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1. Introduction

Input-output (IO) analysis has been, since Leontief (1941), one of the most enduring quantitative frameworks for understanding the

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structural linkages of an economy. For small open economies in particular, where domestic value chains are short, external exposure is high, and policy instruments are few, IO tables offer an indispensable evidence base (Miller & Blair, 2022). The expansion of international IO databases, WIOD (Timmer et al., 2015), FIGARO (Piñero et al., 2022), and OECD ICIO (OECD, 2023), has made this framework widely accessible, yet it has also produced a sharp asymmetry: economies that report their interindustry statistics to these consortia are well covered, while those that do not remain invisible to the global IO research community.

The Republic of Moldova sits squarely in this second group. Despite a functional statistical infrastructure that publishes detailed annual production, intermediate consumption, and gross value added series by activity, no input-output table constructed within an ESA 2010-compatible framework has ever entered the public domain. The National Bureau of Statistics (BNS) compiled interindustry tables under the earlier CAEM Rev.1 system but ceased this exercise after 2014 and has not resumed it under CAEM Rev.2; the country is absent from WIOD, OECD ICIO, and FIGARO. The only prior academic IO contribution for Moldova, Naval (2019), provided a single-year table at 19/16 aggregated branches in the legacy classification. An entire decade of structural change, spanning the 2015 banking crisis, the 2020 pandemic shock, and the 2022 energy crisis, has thus passed without a publicly available, replicable IO representation of the Moldovan economy.

This paper makes three contributions. First, it documents the first annual input-output series for the Republic of Moldova in the CAEM Rev.2 classification (the Moldovan implementation of NACE Rev.2 under ESA 2010), covering 2014-2023 at a 20-sector disaggregation. Second, it formalises a replicable four-step reconstruction protocol, analogue digitisation, classification concordance, biproportional RAS updating, and a five-criterion coherence audit (C1-C5), designed for the data-fragmentation conditions typical of post-Soviet statistical systems undergoing classification transitions. Third, it produces the first comprehensive structural diagnostic of the Moldovan economy at this level of disaggregation: Leontief output multipliers by sector and year, Rasmussen backward and forward linkage indices, and Dietzenbacher-Los structural decomposition of decadal output growth.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature on input-output analysis and reconstruction methods. Section 3 documents the data sources, classification concordance, RAS algorithm, and coherence audit. Section 4 reports convergence diagnostics and the technical coefficients of the reconstructed series. Section 5 presents the structural diagnostics. Section 6 discusses methodological caveats, and Section 7 concludes.

2. Related literature

2.1. Classical input-output analysis and table updating

The modern input-output framework originates with Leontief (1941), whose formalisation of an economy as a system of interconnected production accounts made it possible to trace the full direct-plus-indirect impact of a change in final demand. The accounting architecture, articulation of supply and use tables, distinction between products and industries, and derivation of symmetric IO tables were consolidated by Stone (1961) and codified in the System of National Accounts (United Nations et al., 2009) and the European System of Accounts (Eurostat, 2013). The contemporary reference is Miller and Blair (2022).

Two methodological developments are particularly relevant. The first is the RAS biproportional updating method, introduced by Stone (1961) and formalised by Bacharach (1970), which adjusts a known IO matrix to new marginal totals while preserving its internal structure as closely as possible. RAS has remained the workhorse method for updating and regionalising IO tables for half a century (Junius & Oosterhaven, 2003; Lahr & de Mesnard, 2004). Recent extensions include the multidimensional RAS of Holý and Šafr (2023) and entropy-optimising RAS-equivalent algorithms (Chlebus & Kasapu, 2023), while related work develops non-survey and gravity-based methods for interregional applications (Sargento et al., 2012). The second development is structural decomposition analysis (SDA), introduced in its modern form by Dietzenbacher and Los (1998), which partitions changes in output between a final-demand effect and a technology effect by comparing IO matrices across time periods. Recent work continues to refine and to compare these growth-decomposition techniques (Oosterhaven, 2024).

Both methods carry well-documented limitations. RAS by construction preserves the relative structure of intermediate flows, which means that subsequent SDA on an RAS-updated series will systematically under-attribute change to the technology channel (Dietzenbacher & Los, 1998, Section 4). This property is not a defect, but it requires explicit acknowledgement in any empirical application combining the two, an acknowledgement we return to in Section 6.

2.2. IO reconstruction under data fragmentation and classification transitions

Reconstructing IO tables under constraints is a recurrent methodological problem, particularly for economies that have undergone structural transformation. Three strands are directly relevant to the Moldovan case. The first addresses retrospective reconstruction across classification changes. Baranov et al. (2015) provide the most closely analogous reference point: they construct retrospective Russian IO time series spanning the OKVED → NACE/CPA transition, combining manual source reconciliation with RAS balancing. Their methodology, concordance matrix between old and new classifications, followed by biproportional adjustment to reported marginals, establishes the template we adopt. The second strand covers multi-dimensional and regional disaggregation: Holý and Šafr (2023) for the Czech Republic, Hutniczak (2022) for regional supply-use updates, Sargento et al. (2012) for interregional methods. The third strand concerns institutional and analytical uses of reconstructed IO series in fragile or disrupted economies: Haddad et al. (2023) reconstruct an interregional IO system for Ukraine, deployed to assess the territorial impact of the 2022 conflict. OECD (2023, 2025) codifies contemporary standards for input-output and extended supply-use frameworks within ESA 2010.

2.3. Input-output analysis and the Moldovan gap

Moldova has remained outside the main international IO data consortia. The most recent regional reconstructions have focused elsewhere: Haddad et al. (2022) on Ukraine, Holý and Šafr (2023) on the Czech Republic, and Baranov et al. (2015) on the Russian Federation. None addresses Moldova. Within the domestic literature, IO modelling has been confined to a single research line at the Institute of Mathematics and Computer Science, with Naval (2019) the most recent peer-reviewed contribution: a single-year (2014), 19/16-branch

CAEM Rev.1 table used as input to optimisation models. No subsequent work has produced a NACE Rev.2-compatible series, an annual panel of technical coefficients, or a structural diagnostic at 20-sector disaggregation. This paper addresses that gap directly using the methodological toolkit reviewed above.

3. Data and methodology

The reconstruction proceeds in four connected stages, each addressing a specific data constraint. The first digitises the 2014 Supply-Use Table, the only such table available for the country (Section 3.1). The second harmonises it from the legacy CAEM Rev.1 to the current CAEM Rev.2 classification and reconciles the population concept used in the national accounts (Section 3.2). The third propagates the base-year matrix through time by sequential biproportional (RAS) updating to official annual marginals (Section 3.3). The fourth submits every annual table to a five-criterion coherence audit (Section 3.4). In short, the first two stages build the base-year matrix, the third moves it through the decade, and the fourth validates the result. The full numerical series and the concordance matrix are available from the author on request.

3.1. Source data and digitisation of the 2014 Supply-Use Table

The reconstruction begins from the single Supply-Use Table (SUT) ever compiled by BNS for a post-independence period: the 2014 SUT in CAEM Rev.1. This table exists only in analogue form. Digitisation was performed manually, cell by cell, with four quality controls: (i) row total reconciliation with published total; (ii) verification of the accounting identity $VP_i = CI_i + GVA_i$ (where VP denotes gross output, CI intermediate consumption, and GVA gross value added) for each sector; (iii) column-level resource-use balance check; (iv) cross-check against published BNS macroeconomic aggregates within a tolerance of 0.001%. The digitised 2014 SUT covers 66 active rows (industries plus value-added components) and 78 columns, in current prices (thousand MDL).

3.2. Classification concordance and demographic reconciliation

Two substantive transformations were applied to the 2014 base matrix. The first is the classification transition from CAEM Rev.1 (35+ detailed sectors) to CAEM Rev.2 (20 sectors aligned with NACE Rev.2 under ESA 2010). It involves genuine sectoral remappings: Rev.1

detailed manufacturing subsectors D15-D37 are consolidated into a single section C in Rev.2; Rev.1 category K (real estate, renting, business activities) is split across four Rev.2 sections (L, M, N, and the financial component of K). We construct a 53-entry concordance matrix W that assigns each Rev.1 sector i to one or more Rev.2 sectors j with weights w_{ij} reflecting the relative gross value added of the constituent sub-activities. After applying the concordance, residual discrepancies with independently available 2014 Rev.2 sectoral aggregates were absorbed through a first, limited RAS pass.

The second transformation is demographic reconciliation. Moldovan national accounts underwent a concept transition from ”table population” to ”usually resident population” following the 2014 census revisions. The usually resident concept excludes long-term emigrants who maintain legal residence but live abroad for more than twelve months, a revision that reduces the estimated resident population by approximately 12-15% for Moldova. For sectors whose output is consumed proportionally to population, we apply sector-specific scaling factors derived from BNS methodological notes. The net aggregate effect is a 2.3% downward revision of 2014 GDP relative to the stable-population series, consistent with the BNS published revision.

3.3. The RAS biproportional updating algorithm

Annual updating from the 2014 base to target years 2015-2023 uses the biproportional RAS algorithm (Stone, 1961; Bacharach, 1970). RAS adjusts a known base matrix Z^o to new row totals u and column totals v through iterative row and column scalings, preserving relative structure. Intuitively, the procedure repeatedly rescales the rows and then the columns of the previous year’s table until both its row and its column totals match the new annual control totals, while changing the internal pattern of inter-sector flows as little as possible.

Formally, let Z^o be the 20×20 base matrix of intermediate flows. The RAS iteration aternates a row step $Z^{(k+½)} = \hat{R}^{(k+1)}Z^{(k)}$, with $\hat{R} = diag\left(\frac{u}{Z^{(k)}\mathbb{1}}\right)$ and a column step $Z^{(k+1)} = Z^{(k+½)}\hat{S}^{(k+1)}$, with $\hat{S} = diag\left(\frac{v}{\mathbb{1}^T Z^{(k+½)}}\right)$, terminating when $max_i|r_i - 1| < \varepsilon$ and $max_j|s_j - 1| < \varepsilon$, with $\varepsilon = 0.001$.

The resulting matrix Z^t satisfies both marginal constraints while minimising cross-entropy distance from Z^0. Here $\hat{R}$ and $\hat{S}$ are the diagonal row- and column-scaling matrices, $\mathbb{1}$ is the unit (summation) vector, r_i and s_j the row and column scaling factors, and ε the convergence tolerance.

The annual IO series is constructed by applying RAS sequentially along the time dimension: for each year t ∈ {2015, …, 2023}, the base matrix is the immediately preceding year $Z^{(t-1)}$, with marginal constraints (u^t, v^t) drawn from the BNS sectoral series. The sequential chain captures gradual structural change cumulatively: each year's adjustment starts from a matrix already incorporating the structural movements of the preceding period. Technical coefficients A^t are derived by element-wise division $a_{ij}^t = \frac{z_{ij}^t}{x_j^t}$, and the Leontief inverse $L^t = (I - A^t)^{-1}$ is computed by Gauss-Jordan elimination. We use the standard two-dimensional RAS rather than recent extensions (Holý & Šafr, 2023; Chlebus & Kasapu, 2023) because the additional marginal constraints they require - regional accounts, quarterly IO, and imported-component separation - are not available for Moldova at the 20-sector level.

3.4. A five-criterion coherence audit

Each of the ten annual matrices is subjected to an ex-post coherence audit comprising five criteria. C1 – Accounting identity: $VP_i^t = CI_i^t + GVA_i^t$ must hold within 0.001% of VP for every sector i and year t. C2 – Resource-use balance: total resources (production + imports) must equal total uses (intermediate + final + exports) within 2 MDL on a 2 × 10^{11} MDL base. C3 – Temporal coefficient stability: the coefficient of variation $CV(a_{ij})$ computed across 2014-2023 for each non-trivial coefficient (a_{ij} > 0.01) must fall below 0.3 for at least 90% of coefficients and below 0.5 for all coefficients. C4 – non-negativity: every element $z_{ij}^t \geq 0$. C5 – Convergence: RAS must converge to ε < 0.001 within fewer than 100 iterations for every year.

4. Results: The reconstructed IO series

4.1. RAS convergence and scaling diagnostics

Table 1 reports the RAS convergence diagnostics. For all nine extrapolated years (2015-2023), the algorithm converged in fewer than 10 iterations at ε = 0.001. Terminal row scaling factors fell within [0.85, 1.21] across all years and sectors, and column scaling factors within

[0.82, 1.18]. These ranges are narrow by RAS literature standards, which typically report terminal scaling factors in [0.5, 2.0] for economies undergoing comparable structural change over a decade (Miller & Blair, 2022).

Table 1

RAS convergence diagnostics, 2014-2023

Year	GO[1)]	CI[2)]	RAS iter.	Max scaling deviation	CI/GO	Status
2014	220.5	106.0	- (base)	-	0.481	Base
2015	236.5	108.4	< 10	< 0.001	0.458	✓ Converged
2016	253.9	114.8	< 10	< 0.001	0.452	✓ Converged
2017	275.2	123.3	< 10	< 0.001	0.448	✓ Converged
2018	294.9	131.8	< 10	< 0.001	0.447	✓ Converged
2019	316.6	137.7	< 10	< 0.001	0.435	✓ Converged
2020	304.5	131.5	< 10	< 0.001	0.432	✓ Converged
2021	379.0	171.2	< 10	< 0.001	0.452	✓ Converged
2022	441.9	205.6	< 10	< 0.001	0.465	✓ Converged
2023	494.7	232.8	< 10	< 0.001	0.471	✓ Converged

1)GO = gross output (in MDL bn); 2)CI = intermediate consumption (in MDL bn).

Source: author's calculations based on BNS national accounts and the 2014 digitised Supply-Use Table

The intermediate-to-output ratio (CI/VP) oscillates within a narrow band [0.432, 0.481] across the decade, consistent with values reported for comparable emerging economies (Romania: 0.45-0.52; Bulgaria: 0.43-0.50, Eurostat national accounts series). Year-on-year movements are modest (|Δ| < 0.025 in all adjacent-year comparisons), indicating that the chained RAS updates track gradual structural change rather than absorbing large adjustment shocks. The 2020 observation (CI/VP = 0.432) lies at the lower bound, consistent with pandemic-induced contraction of intermediate trade. The 2021-2023 series exhibits monotonic recovery toward the pre-pandemic mean.

4.2. Technical coefficients and coefficient stability

The matrix of technical coefficients A^t captures the sectoral cost structure year by year. Significant coefficients $(a_{ij} > 0.10)$ and their decade-long evolution include: intra-manufacturing self-consumption a (C→C) declining from 0.398 to 0.362 (consistent with partial modernisation); agriculture-to-manufacturing integration a

(A→C) rising from 0.152 to 0.161 (reflecting increased domestic agricultural input use by food processing, plausibly a structural consequence of the 2014 Deep and Comprehensive Free Trade Area (DCFTA)); and energy intensity in manufacturing a (D→C) declining from 0.190 to 0.176 (consistent with equipment modernisation and energy price substitution effects).

The stability of the coefficient matrix across the decade is summarised by the coefficient of variation distribution. Across 297 non-trivial coefficients ($a_{ij} > 0.01$), the mean CV is 0.157, the median 0.142, with 94.6% of coefficients displaying CV < 0.3 and 100% displaying CV < 0.5. This indicates that the reconstructed series exhibits stable structural properties across the decade, a necessary precondition for the structural diagnostics developed in Section 5.

4.3. Coherence audit results

The five-criterion protocol introduced in Section 3.4 was applied to each of the ten annual matrices. All five criteria are satisfied on every year of the series. The accounting identity C1 holds with a maximum deviation of 2 MDL on a base of 232 × 10^9 MDL (below 0.001% of gross output). The resource-use balance C2 holds within the 2 MDL rounding tolerance for every product. Temporal coefficient stability C3 is satisfied with 94.6% of non-trivial coefficients below CV = 0.3 and 100% below CV = 0.5. Non-negativity C4 holds by construction (Lahr & de Mesnard, 2004) and is verified ex-post on every cell. Convergence C5 is achieved in fewer than 10 iterations every year, far below the 100-iteration upper bound. The joint satisfaction of C1-C5 on a 10-year series, combined with narrow scaling factors and coefficient stability, establishes the internal consistency of the reconstructed series.

In the regional context, the Moldovan intermediate-to-output ratio (0.432-0.481 across the decade) falls within the range typical for small post-communist economies; the Moldovan import-dependence ratio is substantially higher than for EU-27 member states at comparable development stages, a structural feature consistent with Moldova's small size, narrow industrial base, and high intermediate-input imports. A full quantitative comparison across Romania, Bulgaria, Georgia, and other post-Soviet economies is reserved for future work.

5. Structural diagnostics of the Moldovan economy

5.1. Leontief output multipliers across the decade

The diagnostics in this section describe the structure implied by the reconstructed series. Because that series is anchored to the 2014 benchmark and propagated by RAS (Section 6), the results are most reliable as a comparative, qualitative picture across sectors and over time, rather than as precise point estimates for any single year. For each annual matrix A^t we compute the Leontief inverse $L^t = (I - A^t)^{-1}$ and derive the output multiplier $m_j^t = \sum_i L_{ij}^t$.

Table 2 reports multipliers for 2014, 2020 and 2023, plus the change.

Table 2

Leontief output multipliers (Type I), selected years

Code	Sector	2014	2020	2023	Δ2014→23
A	Agriculture, forestry and fishing	2.011	1.976	2.292	+ 0.281
B	Mining and quarrying	2.097	1.965	2.287	+ 0.190
C	Manufacturing	2.647	2.508	2.683	+ 0.036
D	Electricity, gas, steam	2.401	2.285	2.785	+ 0.384
E	Water supply; waste mgmt	2.753	2.473	2.055	- 0.698
F	Construction	2.217	2.154	2.458	+ 0.241
G	Wholesale, retail trade	1.910	1.646	1.942	+ 0.032
H	Transportation, storage	2.588	2.238	2.372	- 0.216
I	Accommodation, food	2.387	2.189	2.283	- 0.205
J	Information, communication	2.019	1.777	1.540	- 0.479
K	Financial, insurance	1.556	1.600	1.700	+ 0.144
L	Real estate	1.418	1.349	1.481	+ 0.063
M	Professional, scientific	2.037	1.731	1.794	- 0.243
N	Administrative, support	2.438	1.991	2.594	+ 0.156
O	Public administration	1.790	1.759	1.655	- 0.135
P	Education	1.670	1.380	1.566	- 0.104
Q	Human health, social work	1.889	1.695	1.718	- 0.171
R	Arts, entertainment	2.371	1.653	2.396	+ 0.025
S	Other services	2.203	1.926	2.001	- 0.202
T	Households as employers	1.000	1.000	1.000	0.000
	Economy-wide mean	**2.070**	**1.865**	**2.029**	**- 0.041**

Source: author's calculations from the reconstructed 2014-2023 IO series

The economy-wide mean multiplier in 2023 is 2.029. Three sectors exhibit multipliers substantially above the mean: D - Electricity, gas and water (2.785), C - Manufacturing (2.683), and H - Transport (2.372). These represent infrastructural or productive cores of the economy, where a unit increase in final demand propagates through long supply chains of domestic intermediate inputs. The lowest multiplier is L - Real estate (1.481), reflecting the sector's low intermediate-input content.

Two decade-long movements warrant attention. The multiplier of J - ICT declines from 2.019 in 2014 to 1.540 in 2023 (-24%), the largest drop in the series, reflecting growing imported intermediate inputs (licensed software, cloud services, foreign equipment) in a sector whose nominal output has otherwise grown rapidly. Nominal growth in ICT thus masks structural weakening of domestic linkages, a pattern invisible in standard national accounts and detectable only through IO analysis. Conversely, the multiplier of D - Electricity rises from 2.401 to 2.785 (+0.384), reflecting both the growing cost share of imported energy inputs and cumulative network losses. The stability of the economy-wide mean (2.070 in 2014; 2.029 in 2023; decade range [1.865, 2.070]) indicates that overall interconnectedness has not changed dramatically, even as individual sectors have shifted meaningfully.

5.2. Rasmussen linkages and the identification of key sectors

Rasmussen (1956) introduced two standardised indices: the backward linkage index $BL_j = \frac{\frac{1}{n}\sum_i L_{ij}}{\mu}$ measuring the intensity of intermediate-input demand on the rest of the economy, and the forward linkage index $FL_i = \frac{\frac{1}{n}\sum_j L_{ij}}{\mu}$ measuring the intensity of the intermediate-input supply, where $\mu = \frac{1}{n^2}\sum_i \sum_j L_{ij}$. A sector with both $BL > 1$ and $FL > 1$ is classified as a key sector.

Table 3 reports the 2023 values.

Table 3

Rasmussen linkage indices and key-sector classification, 2023

Code	Sector	BL	FL	Classification
A	Agriculture, forestry and fishing	1.130	1.537	**KEY SECTOR**
B	Mining and quarrying	1.128	0.793	Backward-dependent
C	Manufacturing	1.323	5.629	**KEY SECTOR**
D	Electricity, gas, steam	1.373	1.296	**KEY SECTOR**
E	Water supply; waste mgmt	1.013	0.571	Backward-dependent
F	Construction	1.212	0.897	Backward-dependent
G	Wholesale, retail trade	0.957	0.598	Isolated
H	Transportation, storage	1.169	1.026	**KEY SECTOR**

Code	Sector	BL	FL	Classification
I	Accommodation, food	1.125	0.667	Backward-dependent
J	Information, communication	0.759	0.857	Isolated
K	Financial, insurance	0.838	0.793	Isolated
L	Real estate	0.730	0.933	Isolated
M	Professional, scientific	0.884	0.582	Isolated
N	Administrative, support	1.264	0.785	Backward-dependent
O	Public administration	0.816	0.493	Isolated
P	Education	0.772	0.519	Isolated
Q	Human health, social work	0.847	0.507	Isolated
R	Arts, entertainment	1.181	0.493	Backward-dependent
S	Other services	0.987	0.532	Isolated
T	Households as employers	0.493	0.493	Isolated

Source: author's calculations from the 2023 Leontief inverse matrix

Four sectors satisfy the joint BL > 1 AND FL > 1 condition: A - Agriculture (BL = 1.130; FL = 1.537), C - Manufacturing (1.323; 5.629), D - Electricity (1.373; 1.296), and H - Transport (1.169; 1.026). This is an increase from two key sectors in 2014, indicating measurable densification of interindustry linkages across the decade.

The most striking result is the forward linkage of manufacturing (FL = 5.629), more than three times the next-highest FL. Manufacturing output is absorbed as an intermediate input across virtually every other sector, placing sector C at the structural core of the Moldovan production system. A disruption to manufacturing from an external demand shock, an input cost shock, or a policy change would propagate through almost the entire sectoral network. No other sector exhibits this property. Agriculture, by contrast, has a high FL (1.537), driven by concentrated supply relationships with food processing rather than by economy-wide diffusion. The ICT sector (J) is classified as isolated (BL = 0.759; FL = 0.857). Combined with the multiplier decline in Section 5.1, this reinforces the picture of an ICT sector whose nominal growth has not translated into stronger domestic linkages.

5.3. Structural Decomposition: final demand vs. technology

Structural Decomposition Analysis (Dietzenbacher & Los, 1998) partitions the change in output between two endpoints into a final-demand effect and a technology effect.

We apply the polar form to decompose the 2014-2023 change in Moldovan output:

$$\Delta x \approx 0.5 \cdot (L_0 + L_{23}) \cdot \Delta f + 0.5 \cdot (f_0 + f_{23}) \cdot \Delta L$$

The aggregate result is striking: 99.98% of the decade's output growth is attributed to final-demand expansion, leaving only 0.02% to technology change. This result is partly genuine and partly methodological. Genuine: the decade's economic story for Moldova is dominated by demand-side dynamics, population dynamics, EU integration via DCFTA, energy and pandemic shocks affecting demand, rather than by deep restructuring of intermediate-input technology. Methodological: the structure-preserving property of RAS systematically under-attributes change to the technology channel (Dietzenbacher & Los, 1998, Section 4). Without independent IO benchmarks, the two cannot be cleanly separated. We discuss this in Section 6.

At the sectoral level, the technology-effect share varies more meaningfully. The energy sector D shows +20.0% technology-effect contribution to its output growth, plausibly reflecting compositional shifts in intermediate-input use during the energy crisis. The construction sector F shows a +8.8% technology effect. Other sectors show small or negative technology-effect contributions, the latter reflecting either genuine structural rationalisation or the under-attribution caveat noted above. These sectoral findings should be interpreted as suggestive rather than definitive.

6. Discussion

The reconstruction documented in this paper, to the best of our knowledge, constitutes the first publicly available annual IO series for the Republic of Moldova in the CAEM Rev. 2/NACE Rev. 2 classification. Three methodological aspects warrant discussion. First, the RAS-SDA interaction. The structure-preserving property of RAS produces the 99.98% finding for the demand effect documented in Section 5.3. This is not a defect of either RAS or SDA but a known interaction that requires explicit acknowledgement. The qualitative diagnostic, Moldova's decade was demand-dominated, is robust to this caveat; the precise quantitative attribution is not. Future work using independent IO benchmarks (alternative data sources and shorter observation intervals) could refine this attribution.

Second, data limitations. The reconstruction rests on a single 2014 base IO matrix, retained throughout the decade through RAS chaining. Genuine technological change between 2014 and 2023, driven by EU integration, the pandemic, and the energy crisis, cannot be detected by this method alone. The series should be understood as a structurally anchored extrapolation of the 2014 technology under the constraints of annual sectoral marginals, not as an independent reconstruction of each year's actual interindustry technology. This is an intrinsic limitation of any RAS-based annual reconstruction starting from a single base.

Third, methodological choices. We use standard two-dimensional RAS rather than recent extensions. The choice reflects data availability rather than methodological preference: multidimensional RAS (Holý & Šafr, 2023) requires regional or quarterly marginal constraints that are unavailable for Moldova; entropy-optimising variants (Chlebus & Kasapu, 2023) deliver gains over RAS at an additional computational cost that is not justified by the current data environment. The protocol established here is upward-compatible: as additional marginal data become available for Moldova, the RAS chain can be replaced or augmented without requiring complete reconstruction. The qualitative diagnostic developed in Section 5, three multiplier-leading sectors (D, C, H), four key sectors (A, C, D, H), and striking manufacturing FL, is robust to most plausible variations in the underlying RAS specification.

7. Conclusions

This paper documents the first annual input-output series for the Republic of Moldova in the CAEM Rev. 2/NACE Rev.2 classification, covering 2014-2023 with 20-sector disaggregation. The four-step protocol, analogue digitisation, classification concordance, biproportional RAS updating, and a five-criterion coherence audit produce a series satisfying the Eurostat balance identity within 2 MDL on a base of 232 billion, with 94.6% of technical coefficients displaying CV < 0.3 across the decade. Structural diagnostics reveal an economy-wide mean Leontief multiplier of 2.029 in 2023, four Rasmussen key sectors (agriculture, manufacturing, energy, transport), and a striking forward linkage for manufacturing (FL = 5.629).

The empirical contribution carries two implications. First, the structural picture of Moldova in 2023, manufacturing at the network core, ICT structurally isolated despite nominal growth, four key sectors driving the rest of the economy, provides a quantitative reference for industrial policy that has previously been unavailable. Second, the methodological protocol is transferable to other post-Soviet economies

(Armenia, Georgia, Kyrgyzstan) that face analogous statistical challenges: discontinuous IO series, classification transitions, and absence from international IO consortia. The protocol does not require quarterly disaggregated data, regional accounts, or imported-component separation, only annual sectoral marginals at the chosen disaggregation level. As more recent IO information becomes available for Moldova, the chain can be re-anchored to a more recent base; the structural diagnostic generated by the present series provides the empirical baseline against which future reconstructions can be compared.

The original contribution of the study is threefold. It delivers a new, internally consistent and openly documented dataset where none previously existed; it formalises a replicable reconstruction protocol that integrates analogue digitisation, classification concordance, biproportional updating and an explicit coherence audit into a single workflow; and it produces the first structural diagnostic of the Moldovan economy at this level of sectoral detail. These contributions should be read together with the study's limitations, set out in Section 6. Because the series is anchored to a single 2014 benchmark and updated by RAS, it preserves the relative input structure of the base year: it captures the cumulative effect of changing sectoral marginals rather than independently observed annual technologies, and, for the same reason, the structural decomposition under-attributes change to the technology channel. The series is therefore best understood as a structurally anchored, accounting-consistent extrapolation, reliable at the level of the qualitative diagnostics reported here but not a substitute for benchmark tables compiled from primary surveys.

Several directions for future research follow naturally. The most immediate is to re-anchor the series whenever the National Bureau of Statistics releases a new benchmark Supply-Use Table, which would allow the RAS chain to be split into shorter intervals and the technology effect to be identified more credibly. A second direction is to extend the framework toward applied uses: demand-driven impact and scenario analysis, price and energy-cost pass-through exercises, and the construction of a social accounting matrix for policy simulation. A third is comparative, placing the Moldovan multipliers and linkage structure alongside those of Romania, Bulgaria, Georgia and other regional economies, so that the diagnostics reported here can serve as the empirical baseline against which both future Moldovan reconstructions and cross-country comparisons are assessed.

References

1. Bacharach, M. (1970). Biproportional Matrices and Input-Output Change. *Cambridge: Cambridge University Press*.
2. BNS (2015). Conturile naționale ale Republicii Moldova 2014. *Chișinău: Biroul Național de Statistică*.
3. Cazcarro, I., Usubiaga-Liano, A., Roman, M. V., Pinero, P., Dietzenbacher, E., Rueda-Cantuche, J. M., & Arto, I. (2025). FIGARO-E3: A high-resolution extended multi-regional input-output database consistent with official statistics. Scientific Data, 12, Article 575. https://doi.org/10.1038/s41597-025-04431-z
4. Chlebus, E., & Kasapu, V. (2023). An Entropy-Optimizing RAS-Equivalent Algorithm for Iterative Matrix Balancing. *Comptes Rendus. Mathématique*, 361, pp. 737-746. https://doi.org/10.5802/crmath.398
5. Dietzenbacher, E., & Los, B. (1998). Structural Decomposition Techniques: Sense and Sensitivity. *Economic Systems Research*, 10(4), pp. 307-324. https://doi.org/10.1080/09535319800000023
6. Eurostat (2013). European System of Accounts - ESA 2010. *Luxembourg: Publications Office of the European Union*.
7. Haddad, E.A., Araújo, I.F., Rocha, A., & Sass, K.S. (2023). Input-Output Analysis of the Ukraine War: A Tool for Assessing the Internal Territorial Impacts of the Conflict. *Regional Science Policy & Practice*. https://doi.org/10.1111/rsp3.12582
8. Holý, V., & Šafr, K. (2023). Disaggregating Input-Output Tables by the Multidimensional RAS Method: A Case Study of the Czech Republic. *Economic Systems Research*, 35(1), pp. 95-117. https://doi.org/10.1080/09535314.2022.2091978
9. Hutniczak, B. (2022). Efficient Updating of Regional Supply and Use Tables with the National-Level Statistics. *Journal of Economic Structures*, 11(1), Article 16. https://doi.org/10.1186/s40008-022-00274-8
10. Junius, T., & Oosterhaven, J. (2003). The Solution of Updating or Regionalizing a Matrix with Both Positive and Negative Entries. *Economic Systems Research*, 15(1), pp. 87-96. https://doi.org/10.1080/0953531032000056954
11. Lahr, M.L., & de Mesnard, L. (2004). Biproportional Techniques in Input-Output Analysis: Table Updating and Structural Analysis. *Economic Systems Research*, 16(2), pp. 115-134. https://doi.org/10.1080/0953531042000219259
12. Leontief, W. (1941). The Structure of American Economy, 1919-1929. *Cambridge, MA: Harvard University Press*.

13. Miller, R.E., & Blair, P.D. (2022). Input-Output Analysis: Foundations and Extensions (3rd ed.). *Cambridge: Cambridge University Press*. ISBN:9781108636124
14. Naval, E. (2019). Experience of the Input-Output Models Application to the Moldovan Economy. *Economy and Sociology*, (1), pp. 36-52. https://doi.org/10.36004/nier.es.2019.1-03
15. OECD (2023). Development of the OECD Inter-Country Input-Output Database 2023. OECD Science, Technology and Industry Working Papers No. 2023/08. *Paris: OECD Publishing*.
16. OECD (2025). Handbook on Extended Supply and Use Tables and Extended Input-Output Tables. *Paris: OECD Publishing*. https://doi.org/10.1787/e9fdcf85-en
17. Oosterhaven, J. (2024). A Decomposition of Economic Growth Decompositions. The Annals of Regional Science, 73(4), pp. 1395-1408. https://doi.org/10.1007/s00168-024-01309-7
18. Piñero, P., Rueda-Cantuche, J.M., Arto, I., Amores, A.F., & Dietzenbacher, E. (2022). Experimental Full International and Global Accounts for Research in Input-Output Analysis (FIGARO Tables). *Eurostat Statistical Working Paper*.
19. Rasmussen, P.N. (1956). Studies in Inter-Sectoral Relations. *Amsterdam: North-Holland*.
20. Sargento, A.L.M., Ramos, P.N., & Hewings, G.J.D. (2012). Inter-Regional Trade Flow Estimation through Non-Survey Models: An Empirical Assessment. *Economic Systems Research*, 24(2), pp. 173-193. https://doi.org/10.1080/09535314.2011.574609
21. Stone, R. (1961). Input-Output and National Accounts. *Paris: Organisation for European Economic Co-operation*.
22. Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., & de Vries, G.J. (2015). An Illustrated User Guide to the World Input-Output Database: The Case of Global Automotive Production. Review of International Economics, 23(3), pp. 575-605. https://doi.org/10.1111/roie.12178
23. United Nations, Eurostat, IMF, OECD, & World Bank (2009). System of National Accounts 2008. *New York: United Nations*.

SPECULATIVE BUBBLE DYNAMICS AND SYSTEMIC RISK IN SHADOW BANKING INSTITUTIONS: EVIDENCE FROM THE UNITED STATES AND EUROPE

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Abstract

This study investigates speculative bubble dynamics and systemic risk characteristics among listed shadow banking institutions in the United States and Europe over the period 2010–2026. To examine speculative dynamics, bubble episodes are identified using the Backward Supremum Augmented Dickey–Fuller (BSADF) methodology, while systemic risk is evaluated through a set of market-based indicators, including beta, Value at Risk (VaR), Expected Shortfall (ES), Conditional Value at Risk (CoVaR), Delta CoVaR (ΔCoVaR), and Marginal Expected Shortfall (MES). The results reveal that speculative bubble episodes constitute a recurrent feature of the shadow banking sector in both regions. Bubble activity appears more widespread in the U.S., whereas European institutions exhibit a more heterogeneous pattern, characterised by concentrated speculative episodes affecting fewer firms. Overall, the findings provide comparative evidence on speculative dynamics and systemic risk in two major financial markets and contribute to the growing literature on shadow banking, financial instability, and financial intermediation. The results further support the importance of continuous monitoring of non-bank financial institutions within macroprudential surveillance frameworks.

Keywords: non-bank financial institutions, systemic risk measures, financial stability, comparative assessment

JEL Classification: G01, G12, G15, G21, G23

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1. Introduction

The growing importance of non-bank financial institutions has attracted increasing attention from both academics and policymakers

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due to their potential role in the propagation of financial instability. Shadow banking institutions provide alternative sources of financing outside the traditional banking sector and contribute to financial market development. At the same time, their business models often involve higher leverage, maturity transformation, and complex interconnections with the broader financial system, which may amplify systemic vulnerabilities during periods of market stress (Croicu et al., 2023; Arora & Kashiramka, 2023; Croicu & Călin, 2024; Doruk & Önal, 2026; Zhang et al., 2026)

The global financial crisis highlighted the importance of monitoring risks originating outside the conventional banking sector. Since then, a substantial body of literature has examined the structure, growth, and systemic implications of shadow banking activities, emphasising their potential contribution to financial fragility, contagion mechanisms, and the transmission of market stress across financial institutions (Moreira & Savov, 2017; Pellegrini et al., 2022; Rottner, 2023; Huang et al., 2025; Mashimbye & Fanta, 2026). Despite increasing regulatory attention devoted to these institutions, concerns remain regarding the channels through which shadow banking entities may contribute to the accumulation of systemic vulnerabilities (Călin et al., 2026).

One potential source of instability is the formation of speculative bubbles. Periods characterised by explosive asset price dynamics may encourage excessive risk-taking, leverage expansion, and asset mispricing, thereby increasing the vulnerability of financial institutions and markets. The literature on speculative bubbles has documented the occurrence of such episodes across a wide range of asset classes, including equities, real estate, commodities, and cryptocurrencies (Caraiani et al., 2021; André et al., 2022; Caraiani & Călin, 2024; Iliyasu et al., 2024; Lupu et al., 2024). Methodologically, recent advances in recursive right-tailed unit root testing have significantly improved the identification and dating of speculative episodes in financial markets (Phillips & Yu, 2011; Phillips et al., 2015; Lupu et al., 2026; Fernandez-Perez et al., 2026; Călin & Lupu, 2026).

A related strand of research focuses on the interaction between asset price booms and financial stability. Previous studies suggest that prolonged periods of rapid asset price appreciation may contribute to the accumulation of financial vulnerabilities through leverage expansion, increased interconnectedness, and heightened risk-taking behaviour (Lupu et al., 2025; Dong et al., 2025). Nevertheless, empirical evidence on speculative dynamics within shadow banking institutions remains relatively scarce, particularly in a comparative international setting (Călin et al., 2026; Wang et al., 2026; Wu et al., 2026).

Against this background, this study examines the dynamics of speculative bubbles and the characteristics of systemic risk among listed shadow banking institutions in the United States and Europe. Bubble episodes are identified using the Backward Supremum Augmented Dickey–Fuller (BSADF) methodology, while systemic risk is evaluated through a set of market-based indicators, including beta, Value at Risk (VaR), Expected Shortfall (ES), Conditional Value at Risk (CoVaR), Delta CoVaR (ΔCoVaR), and Marginal Expected Shortfall (MES) (Adrian & Brunnermeier, 2016; Härdle et al., 2016; Acharya et al., 2017; Brownlees & Engle, 2017; Lupu et al., 2021). The analysis provides comparative evidence on the incidence and synchronisation of speculative bubbles as well as on the evolution of systemic risk within the shadow banking sector across the two regions.

The study contributes to the existing literature in several ways. First, it extends the growing body of research on speculative bubbles by focusing specifically on shadow banking institutions, a segment of the financial system that has received relatively limited attention in the bubble literature. Second, unlike most existing studies that focus on a single market, it provides a comparative assessment of bubble dynamics and systemic risk characteristics across U.S. and European shadow banking institutions. Third, it documents the degree of synchronisation of speculative episodes across institutions and complements this evidence with a broad set of market-based systemic risk measures. Finally, the findings provide evidence relevant for macroprudential surveillance by highlighting periods of elevated speculative activity and systemic vulnerability within the non-bank financial sector.

The remainder of the paper is organised as follows. Section 2 presents the data and methodology. Section 3 discusses the empirical results. Section 4 concludes.

2. Data and methodology

2.1 Sample selection and data

The empirical analysis focuses on shadow banking institutions identified among the constituents of the S&P 500 and STOXX Europe

600 indices. Restricting the sample to firms included in these benchmark indices ensures high market liquidity, continuous trading activity, and reliable data availability, which are essential for estimating systemic risk measures and speculative bubble indicators.

The identification procedure combines industry classification and firm-level financial characteristics. First, firms belonging to the Financials sector according to the Global Industry Classification Standard (GICS) are considered. Traditional commercial banks, insurance companies, and real estate investment trusts (REITs) are excluded because their business models and regulatory frameworks differ substantially from those typically associated with non-bank financial intermediation.

The analysis retains firms operating in financial services segments commonly linked to market-based finance, including Asset Management and Custody Banks, Consumer Finance, Diversified Financial Services, Investment Banking and Brokerage, and Financial Exchanges and Data. To further distinguish shadow banking institutions from other financial firms, balance-sheet information obtained from Refinitiv Workspace is used to construct indicators of leverage and debt dependence. Financial leverage is measured as the ratio of Total Assets to Total Equity, while debt dependence is proxied by the ratio of Total Debt to Total Assets.

Based on these indicators, a Shadow Banking Score ranging from zero to two is computed. One point is assigned when the Assets-to-Equity ratio exceeds five, and an additional point is assigned when the Debt-to-Assets ratio exceeds 35%. Firms obtaining a score of at least one are classified as shadow banking institutions and retained in the final sample.

Daily closing prices and accounting information are collected from Refinitiv Workspace. To ensure consistency throughout the analysis period, firms with insufficient financial information or incomplete historical series are excluded. The same selection procedure is applied to both Europe and the United States, ensuring methodological comparability across regions.

The final dataset covers the period from 1 January 2010 to 2 February 2026 and includes listed shadow banking institutions from the United States and Europe. This sample provides a suitable framework for examining the relationship between speculative bubble dynamics and systemic risk in the non-bank financial sector.

2.2. Bubble identification

Speculative bubble episodes are identified using the Backward Supremum Augmented Dickey–Fuller (BSADF) test proposed by Phillips, Shi and Yu (2015). The procedure is designed to detect periods of explosive price behaviour by recursively estimating right-tailed unit root regressions over multiple subsamples.

For each firm, the following ADF specification is estimated:

$$\Delta P_t = \alpha + \beta P_{t-1} + \sum_{j=1}^{K} \psi_j \, \Delta P_{t-j} + \varepsilon_t$$

where $P_t$denotes the asset price series. The null hypothesis of a unit root (H_0: $\beta = 0$) is tested against the alternative of explosive behaviour (H_1: $\beta > 0$).

The BSADF statistic is computed as:

$$BSADF(r_2) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2}$$

where $r_0$denotes the minimum window size, r_1, the starting point, and r_2, the ending point of each recursive subsample. Following Phillips et al. (2015), bubble episodes are identified whenever the BSADF statistic exceeds the corresponding critical value obtained through Monte Carlo simulation.

Based on the dating procedure, three binary indicators are constructed. The first indicator ($BUB_{i,t}$) identifies the presence of a bubble episode. The second ($BMPH_{i,t}$) captures the expansion phase of the bubble, while the third ($BRPH_{i,t}$) identifies the burst phase following the collapse of the speculative episode. A burst event is recorded when the BSADF statistic falls below the critical value after a period of explosive dynamics. These indicators provide a dynamic characterisation of speculative activity and allow the identification of both the emergence and termination of bubble episodes.

2.3. Systemic risk measures

To evaluate the systemic importance and vulnerability of shadow banking institutions, six complementary risk measures are employed: market beta, Value at Risk (VaR), Expected Shortfall (ES), Conditional Value at Risk (CoVaR), Delta CoVaR (ΔCoVaR), and Marginal Expected Shortfall (MES). All indicators are estimated using rolling windows of 252 trading days.

Market beta measures the sensitivity of firm returns to market movements and is computed as:

$$\beta_{i,t} = \frac{\mathrm{Cov}(R_{i,t}, R_{m,t})}{\mathrm{Var}(R_{m,t})}$$

where $R_{i,t}$ represents the return of firm i and $R_{m,t}$ denotes the market return.

Firm-level tail risk is measured using Value at Risk (VaR), defined as the 5% empirical quantile of the return distribution:

$$VaR_{i,t}^{0.05} = -Q_{0.05}(R_{i,t})$$

Expected Shortfall (ES) extends VaR by measuring the average loss conditional on exceeding the VaR threshold:

$$ES_{i,t}^{0.05} = -E(R_{i,t} \mid R_{i,t} \leq -VaR_{i,t}^{0.05})$$

To capture the systemic dimension of risk, the analysis employs the CoVaR framework developed by Adrian and Brunnermeier (2016). CoVaR measures the Value at Risk of the financial system conditional on institution $i$being in distress:

$$CoVaR_{i,t}^{0.05} = VaR_{t}^{0.05}(R_m \mid R_i = VaR_{i,t}^{0.05})$$

CoVaR is estimated using quantile regression:

$$R_{m,t} = \alpha_i^{0.05} + \beta_i^{0.05} R_{i,t} + \varepsilon_t$$

and calculated as:

$$CoVaR_{i,t}^{0.05} = \hat{\alpha}_i^{0.05} + \hat{\beta}_i^{0.05} VaR_{i,t}^{0.05}$$

The marginal contribution of an institution to systemic risk is measured through Delta CoVaR:

$$\Delta CoVaR_{i,t} = CoVaR_{i,t}^{distress} - CoVaR_{i,t}^{normal}$$

which can be expressed as:

$$\Delta CoVaR_{i,t} = \hat{\beta}_i^{0.05}\left(VaR_{i,t}^{0.05} - Median(R_i)\right)$$

Finally, systemic vulnerability is assessed through Marginal Expected Shortfall (MES), defined as the expected loss of a firm conditional on severe market stress:

$$MES_{i,t}^{0.05} = E\left(R_{i,t} \mid R_{m,t} \leq -VaR_{m,t}^{0.05}\right)$$

MES captures the extent to which individual institutions are exposed to extreme market downturns and complements CoVaR-based measures that focus on systemic contribution. Taken together, these indicators provide a comprehensive assessment of both firm-level and system-wide dimensions of financial risk.

3. Results

Figure 1 presents the evolution of speculative bubble episodes among listed shadow banking institutions in the United States and Europe. Bubble states are identified using the BSADF procedure and classified into normal, boom, bubble, and burst phases.

Several patterns emerge. First, bubble episodes are recurrent across both regions, indicating that speculative dynamics represent a persistent feature of the shadow banking sector rather than isolated events. In the U.S. sample, bubble activity appears more widespread, with a larger number of firms exhibiting prolonged periods of speculative behaviour. Several institutions spent a substantial proportion of the sample period in bubble states, suggesting that speculative dynamics were not confined to a small subset of firms.

Second, the European sample exhibits greater heterogeneity. While some institutions experience only sporadic bubble episodes, others display extended periods of speculative activity. This pattern suggests that bubble dynamics in Europe are more concentrated at the firm level, whereas the U.S. market exhibits a broader diffusion of speculative behaviour across institutions.

Third, bubble activity appears particularly pronounced during the period spanning approximately 2017–2021, with additional episodes observed in the post-2022 period. The clustering of bubble episodes across multiple firms suggests the presence of common market conditions that favoured the emergence of speculative dynamics within the shadow banking sector.

Figure 1

Bubble timelines of shadow banking institutions in the United States and Europe

Notes: Bubble states are identified using the BSADF methodology. Panel A reports U.S. shadow banking institutions (S&P 500), while Panel B reports European shadow banking institutions (STOXX Europe 600). Colors denote normal, boom, bubble, and burst states. Percentages indicate the share of observations classified as bubble periods for each firm. Sample period: 2010–2026

Source: Author's own work

Finally, the figure provides limited evidence of highly synchronized burst episodes affecting a large share of institutions simultaneously. Although individual firms experience bubble collapses, sector-wide burst events appear relatively uncommon, indicating that speculative episodes often unfold asynchronously across institutions.

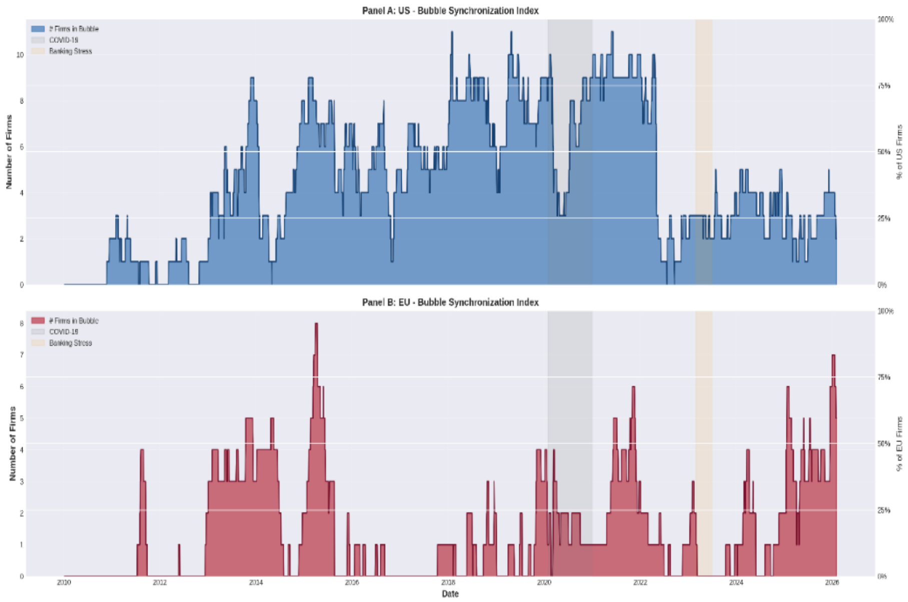
Overall, the results suggest that speculative dynamics constitute a recurrent feature of both U.S. and European shadow banking institutions, although the extent and distribution of bubble activity differ across regions.

Figure 2 reports the Bubble Synchronization Index, defined as the number of shadow banking institutions simultaneously classified in a bubble state. The indicator provides an aggregate measure of speculative co-movement and allows the identification of periods characterized by widespread speculative activity within the sector.

The U.S. sample exhibits a prolonged period of elevated synchronization between approximately 2016 and 2021. During several episodes, between eight and eleven institutions are simultaneously classified as being in a bubble state, indicating a substantial degree of speculative co-movement across the shadow banking sector. Following a marked decline during 2022, synchronisation remains present but at considerably lower levels, with most observations involving fewer than five institutions.

Figure 2

Bubble synchronisation index in U.S. and European shadow banking institutions



Notes: The figure reports the number of institutions simultaneously classified in a bubble state according to the BSADF procedure. Panel A presents U.S. shadow banking institutions, while Panel B presents European shadow banking institutions. The secondary axis reports the percentage of firms in a bubble state relative to the total number of institutions in each sample. Shaded areas indicate the COVID-19 period and the 2023 banking stress episode.

Source: Author's own work

The European sample displays a more episodic pattern. Peaks of synchronisation are observed around 2013–2015, 2019–2021, and again during the most recent years of the sample. Although the number of firms is smaller than in the U.S. sample, several periods exhibit a high proportion of institutions simultaneously experiencing bubble conditions, suggesting that speculative dynamics can become highly concentrated at the sectoral level.

A comparison of the two regions reveals important differences. Bubble synchronisation in the United States appears more persistent over time, whereas Europe is characterised by shorter but more pronounced synchronisation episodes. Despite these differences, both markets exhibit recurrent periods during which a substantial share of shadow banking institutions simultaneously experience speculative dynamics.

Overall, the results suggest that bubble episodes are not purely firm-specific phenomena. Instead, speculative behaviour frequently emerges in a synchronised manner across multiple institutions, supporting the existence of common drivers of bubble formation within the shadow banking sector.

Figure 3 presents the evolution of six systemic risk indicators for U.S. shadow banking institutions, including market beta, Value at Risk (VaR), Expected Shortfall (ES), Conditional Value at Risk (CoVaR), Delta CoVaR (ΔCoVaR), and Marginal Expected Shortfall (MES). For each measure, the figure reports the cross-sectional mean together with the minimum–maximum range across firms.

Several common patterns emerge across all indicators. First, systemic risk remains relatively stable during most of the sample period, although substantial heterogeneity is observed across institutions. This heterogeneity is reflected in the wide dispersion bands visible in all panels, suggesting that risk exposures differ considerably across shadow banking entities.

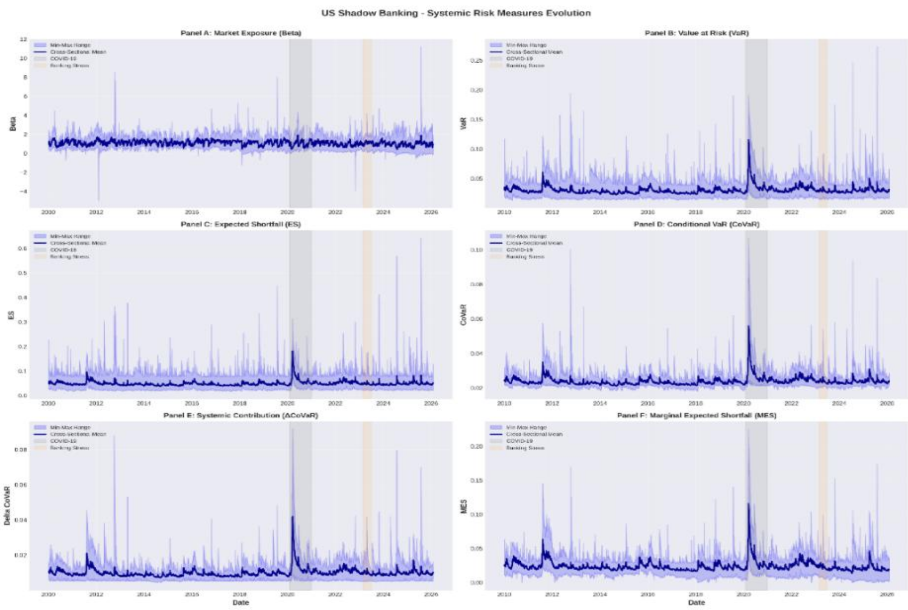
Second, all risk measures exhibit a pronounced spike during the COVID-19 market turmoil of 2020. The increase is particularly visible for VaR, ES, CoVaR, ΔCoVaR, and MES, indicating a simultaneous deterioration in firm-level risk, systemic contribution, and vulnerability to market-wide stress. The synchronised response across all indicators highlights the sensitivity of shadow banking institutions to severe market disruptions.

Third, risk levels decline substantially following the pandemic shock but do not fully return to pre-2020 levels. Several indicators, particularly ΔCoVaR and MES, display recurrent increases during the post-2022 period, suggesting the persistence of systemic vulnerabilities despite the absence of a shock comparable to that observed during the pandemic.

Finally, the large distance between the cross-sectional mean and the upper bound of the distribution indicates that a small number of institutions periodically account for disproportionately high levels of systemic risk. This finding suggests that systemic vulnerabilities within the shadow banking sector are unevenly distributed and may become concentrated in specific institutions during periods of market stress.

Figure 3

Evolution of systemic risk measures in U.S. shadow banking institutions



Notes: The figure reports the evolution of six systemic risk measures estimated using 252-day rolling windows: market beta (Panel A), Value at Risk (VaR, Panel B), Expected Shortfall (ES, Panel C), Conditional Value at Risk (CoVaR, Panel D), Delta CoVaR (ΔCoVaR, Panel E), and Marginal Expected Shortfall (MES, Panel F). The dark line represents the cross-sectional mean, while the shaded area indicates the minimum–maximum range across firms. Shaded vertical bands denote the COVID-19 period and the 2023 banking stress episode.

Source: Author's own work

Overall, the results indicate that U.S. shadow banking institutions exhibit relatively moderate average risk levels during normal periods, but their contribution to systemic risk increases substantially during episodes of financial stress. The evidence further suggests that systemic vulnerabilities remain present in the post-pandemic period, although at levels considerably below those observed during the 2020 shock.

Figure 4 presents the evolution of the same systemic risk indicators for European shadow banking institutions. Similar to the U.S. sample, the figure reports the cross-sectional mean together with the minimum–maximum range across firms.

Several findings emerge. First, the overall dynamics of systemic risk in Europe broadly mirror those observed in the United States. All indicators display a pronounced increase during the COVID-19 shock of 2020, reflecting a simultaneous deterioration in market risk, tail risk, systemic contribution, and vulnerability to market-wide stress. The consistency of this response across measures suggests that the pandemic represented the most severe systemic event during the sample period.

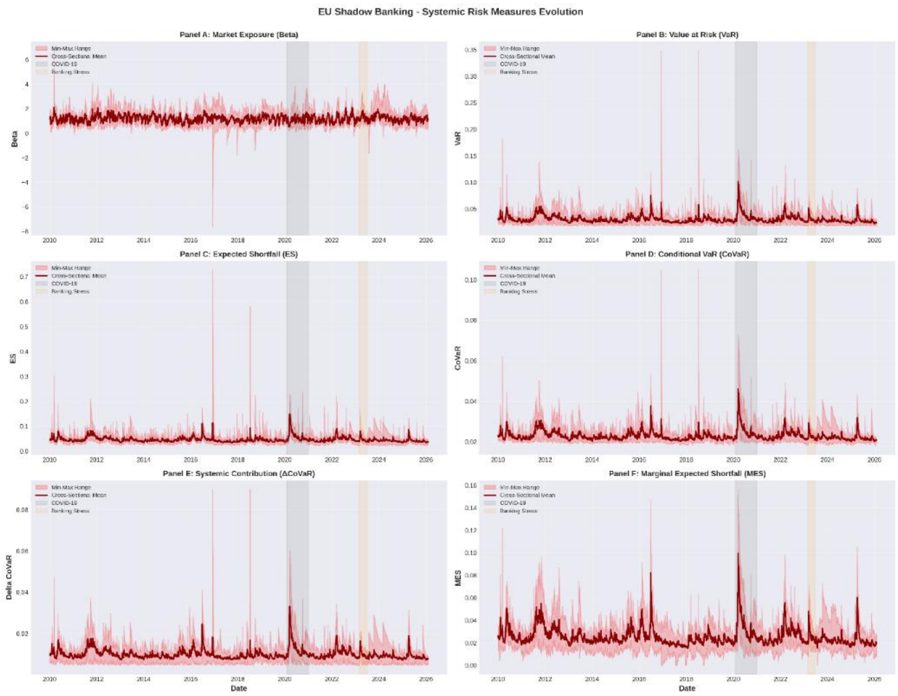
Second, average risk levels remain relatively stable during normal market conditions. The cross-sectional means of VaR, ES, CoVaR, ΔCoVaR, and MES fluctuate within narrow ranges for most of the sample, indicating that systemic risk remains moderate outside major stress episodes. At the same time, the wide minimum–maximum bands reveal substantial heterogeneity across institutions, with individual firms periodically exhibiting considerably higher risk levels than the sectoral average.

Third, several indicators show renewed increases following 2022, particularly for ΔCoVaR and MES. Although these increases remain well below the levels observed during the pandemic, they suggest that systemic vulnerabilities did not disappear following the normalisation of market conditions and continue to re-emerge periodically within the European shadow banking sector.

A comparison with the U.S. sample reveals broadly similar patterns but somewhat lower average volatility and narrower cross-sectional dispersion during normal periods. Nevertheless, stress episodes generate risk responses of comparable magnitude, indicating that European shadow banking institutions remain vulnerable to severe market disruptions despite exhibiting more moderate dynamics during tranquil periods.

Figure 4

Evolution of systemic risk measures in European shadow banking institutions



Notes: The figure reports the evolution of six systemic risk measures estimated using 252-day rolling windows: market beta (Panel A), Value at Risk (VaR, Panel B), Expected Shortfall (ES, Panel C), Conditional Value at Risk (CoVaR, Panel D), Delta CoVaR (ΔCoVaR, Panel E), and Marginal Expected Shortfall (MES, Panel F). The solid line represents the cross-sectional mean, while the shaded area indicates the minimum–maximum range across firms. Shaded vertical bands denote the COVID-19 period and the 2023 banking stress episode.

Source: Author's own work

Overall, the results suggest that systemic risk within the European shadow banking sector is generally contained during normal market conditions but increases sharply during periods of financial stress. The persistence of elevated risk measures in the post-2022 period further indicates that systemic vulnerabilities remain present despite the absence of a shock comparable to that experienced in 2020.

Tables 1 and 2 report the descriptive statistics of the systemic risk measures for U.S. and European shadow banking institutions, respectively. Overall, the results reveal broadly similar risk profiles across the two regions, although notable differences emerge in the indicators' distributional characteristics.

Table 1

Descriptive statistics of systemic risk measures: U.S. shadow banking institutions

Measure	Mean	Median	Std	Min	Max	Skew	Kurt
Beta	1.0940	1.0607	0.5313	-4.9272	11.2160	0.62	4.41
VaR	0.0302	0.0276	0.0125	0.0133	0.2732	3.01	22.33
ES	0.0493	0.0419	0.0242	0.0174	0.6429	2.52	21.93
CoVaR	0.0238	0.0229	0.0038	0.0180	0.1070	5.79	66.69
Delta CoVaR	0.0099	0.0090	0.0042	0.0044	0.0918	4.67	46.90
MES	0.0239	0.0228	0.0125	0.0000	0.2254	2.95	22.87

Notes: This table reports descriptive statistics for the systemic risk measures used in the analysis. The sample covers U.S. shadow banking institutions over the period 2010–2026.

Source: Author's own work

Table 2

Descriptive statistics of systemic risk measures: European shadow banking institutions

Measure	Mean	Median	Std	Min	Max	Skew	Kurt
Beta	1.1898	1.1460	0.4908	-7.6031	6.7719	0.48	6.98
VaR	0.0308	0.0281	0.0112	0.0170	0.3492	4.60	62.06
ES	0.0467	0.0435	0.0175	0.0212	0.7284	6.49	145.63
CoVaR	0.0229	0.0220	0.0036	0.0179	0.1050	4.01	38.09
Delta CoVaR	0.0099	0.0092	0.0040	0.0045	0.0900	3.11	25.36
MES	0.0255	0.0231	0.0117	0.0000	0.1567	2.39	11.45

Notes: This table reports descriptive statistics for the systemic risk measures used in the analysis. The sample covers European shadow banking institutions over the period 2010–2026.

Source: Author's own work

Market beta exhibits average values above one in both samples, with mean coefficients of 1.094 for the United States and 1.190 for Europe. These results suggest that shadow banking institutions tend to amplify overall market movements rather than simply track them. While average beta values are relatively comparable across regions, the distribution is characterised by substantial dispersion, as reflected by extreme minimum and maximum values. The European sample exhibits a slightly higher average market exposure, whereas the U.S. sample displays a wider positive range, reaching values above 11 during periods of elevated market stress.

The tail-risk measures also display similar average levels across regions. Mean VaR equals 0.0302 in the United States and 0.0308 in Europe, while mean ES reaches 0.0493 and 0.0467, respectively. Despite these similarities in central tendency, the distributions are strongly non-normal. Both VaR and ES exhibit pronounced positive skewness and exceptionally high kurtosis values, indicating the presence of extreme tail events and occasional periods of severe risk accumulation. Notably, the European sample displays substantially higher skewness and kurtosis for both measures, suggesting a greater concentration of extreme observations despite comparable average risk levels.

Similar patterns are observed for the systemic risk indicators. Mean CoVaR values remain relatively stable across regions, amounting to 0.0238 in the United States and 0.0229 in Europe. Likewise, the average contribution to systemic risk measured by ΔCoVaR is virtually identical in both samples (0.0099). However, both indicators exhibit substantial positive skewness and excess kurtosis, implying that systemic risk contributions are not evenly distributed over time but become concentrated during relatively rare stress episodes.

The results for MES provide additional evidence regarding the vulnerability of shadow banking institutions to severe market downturns. Average MES values are slightly higher in Europe (0.0255) than in the United States (0.0239), suggesting marginally greater exposure to systemic market stress. Nevertheless, both samples display considerable dispersion and non-normality, reflecting the episodic nature of systemic losses during adverse market conditions.

Taken together, the descriptive statistics indicate that U.S. and European shadow banking institutions share broadly comparable average levels of market, tail, and systemic risk. At the same time, the pronounced skewness and kurtosis observed across most indicators highlight the importance of extreme events in shaping the risk profile of the sector. These findings are consistent with the view that systemic vulnerabilities in shadow banking are characterised less by persistently elevated risk levels and more by the occasional emergence of severe stress episodes capable of generating disproportionately large losses and systemic spillovers.

4. Conclusions

This study examined speculative bubble dynamics and systemic risk characteristics in listed shadow banking institutions from the United States and Europe over the period 2010–2026. Using the BSADF methodology, the analysis identified bubble episodes at the firm level and investigated their synchronisation across institutions. In addition, systemic risk was evaluated through a set of complementary market-based measures, including beta, Value at Risk (VaR), Expected Shortfall (ES), Conditional Value at Risk (CoVaR), Delta CoVaR (ΔCoVaR), and Marginal Expected Shortfall (MES).

The results indicate that speculative bubble episodes constitute a recurrent feature of the shadow banking sector in both regions. Bubble activity is more widespread among U.S. institutions, whereas European institutions exhibit a more heterogeneous pattern characterized by periods of concentrated speculative activity affecting a smaller number of firms. Despite these differences, both markets experienced prolonged episodes of bubble formation, particularly during periods associated with favourable financial conditions and elevated market valuations.

The synchronisation analysis further reveals that bubble episodes frequently emerge simultaneously across multiple institutions. Although the intensity and persistence of synchronisation differ between the United States and Europe, both regions display recurrent periods in which a substantial share of shadow banking entities are simultaneously classified as being in a bubble state. These findings suggest that speculative dynamics are not exclusively firm-specific phenomena but may reflect broader market conditions affecting the sector as a whole.

The analysis of systemic risk measures highlights the importance of extreme events in shaping the risk profile of shadow banking institutions. All risk indicators exhibit pronounced increases during the COVID-19 market disruption, confirming the vulnerability of non-bank financial intermediaries to severe market stress. While risk levels declined following the pandemic shock, several indicators continued to display episodic increases during the post-2022 period, suggesting that systemic vulnerabilities remain present despite the absence of a crisis comparable to that experienced in 2020.

A comparison between the two regions reveals broadly similar average levels of market, tail, and systemic risk. However, the distributional properties of the indicators indicate that risk is characterized by substantial heterogeneity and occasional extreme observations. The high levels of skewness and kurtosis observed across most measures suggest that systemic risk in shadow banking is driven primarily by relatively rare but severe stress episodes rather than by persistently elevated risk conditions.

Overall, the findings contribute to the growing literature on shadow banking by providing comparative evidence on speculative dynamics and systemic risk in two major financial markets. From a policy perspective, the results support the continued monitoring of non-bank financial institutions as potential sources of financial instability, particularly during periods characterized by elevated market exuberance and heightened risk-taking.

Several limitations should be acknowledged. The analysis focuses exclusively on listed shadow banking institutions and relies on market-based measures of systemic risk. Future research may extend the analysis to broader segments of the non-bank financial sector, investigate the determinants of bubble synchronization, and explore more directly the relationship between speculative episodes and systemic risk transmission mechanisms.

References

1. Acharya, V.V., Pedersen, L.H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies, 30*(1), pp. 2–47. https://doi.org/10.1093/rfs/hhw088
2. Adrian, T., & Brunnermeier, M.K. (2016). CoVaR. *American Economic Review, 106*(7), pp. 1705–1741. https://doi.org/10.1257/aer.20120555
3. André, C., Caraiani, P., Călin, A.C., & Gupta, R. (2022). Can monetary policy lean against housing bubbles? *Economic Modelling, 110*, 105801. https://doi.org/10.1016/j.econmod.2022.105801
4. Arora, D., & Kashiramka, S. (2023). Are shadow banks a threat to the financial stability of EMEs? *China Accounting and Finance Review, 25*(4), pp. 488–512. https://doi.org/10.1108/CAFR-09-2022-0133
5. Brownlees, C., & Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies, 30*(1), pp. 48–79. https://doi.org/10.1093/rfs/hhw060
6. Călin, A.C., & Lupu, R. (2026). Tracing exuberance: Multi-model evidence of bubble episodes in the Bucharest stock market.

International Journal of Emerging Markets. Advance online publication. https://doi.org/10.1108/IJOEM-12-2025-2934

7. Călin, A.C., Lupu, R., Croicu, A.E., & Topa, R.A. (2026). Bubbles and the Pro-Cyclicality of Systemic Risk Measures in Shadow Banking. *Journal of Risk and Financial Management*, *19*(4), 242. https://doi.org/10.3390/jrfm19040242
8. Caraiani, P., & Călin, A.C. (2024). The comovement of bubbles' responses to monetary policy shocks. *The North American Journal of Economics and Finance, 74*, 102244. https://doi.org/10.1016/j.najef.2024.102244
9. Caraiani, P., Călin, A.C., & Gupta, R. (2021). Monetary policy and bubbles in US REITs. *International Review of Finance, 21*(2), pp. 675–687. https://doi.org/10.1111/irfi.12284
10. Croicu, A.-E., & Călin, A.C. (2024). Reconceptualizing stability: Dynamics of shadow banking in financial markets. In Proceedings of the International Conference on Business Excellence (Vol. 18, No. 1, pp. 1385–1397). https://doi.org/10.2478/picbe-2024-0125
11. Croicu, A.-E., Iancu, L.A., & Rogojan, L.C. (2023). A review on the impact of shadow banking on financial markets prudential regulation. In Proceedings of the International Conference on Business Excellence (Vol. 17, No. 1, pp. 1596–1602). https://doi.org/10.2478/picbe-2023-0143
12. Dong, F., Mei, D., & Xiao, Z. (2025). Asset bubbles and financial frictions in small open economies. *Journal of International Money and Finance, 150*, 103230. https://doi.org/10.1016/j.jimonfin.2024.103230
13. Doruk, Ö.T., & Önal, Y.B. (2026). Lurking mechanism: Shadow banking and macroeconomic instability. *Economic Systems*. Advance online publication. https://doi.org/10.1016/j.ecosys.2026.101107
14. Fernandez-Perez, A., Gómez-Puig, M., & Sosvilla-Rivero, S. (2026). Policy to mitigate the price explosiveness in Madrid and Barcelona's real estate markets. *Journal of Policy Modeling*. Advance online publication. https://doi.org/10.1016/j.jpolmod.2026.107068
15. Härdle, W.K., Wang, W., & Yu, L. (2016). TENET: Tail-event driven network risk. *Journal of Econometrics, 192*(2), pp. 499–513. https://doi.org/10.1016/j.jeconom.2016.02.013
16. Huang, M., Jiang, H., & Zhang, S. (2025). Nonlinear effects of shadow banking on banks' systemic risk. *Pacific-Basin Finance Journal, 93*, Article 102869. https://doi.org/10.1016/j.pacfin.2025.102869
17. Iliyasu, J., Mamman, S.O., Abubakar, A.B., & Sanusi, A.R. (2024). Effects of adverse geopolitical risk on price bubbles contagion from European natural gas prices to international energy prices. *Journal of*

Economic Studies, 52(3), pp. 605–619. https://doi.org/10.1108/JES-03-2024-0131

18. Lupu, R., Călin, A.C., Dumitrescu, D.G., & Lupu, I. (2025). Introducing a novel fragility index for assessing financial stability amid asset bubble episodes. *The North American Journal of Economics and Finance, 75*, 102291. https://doi.org/10.1016/j.najef.2025.102291
19. Lupu, R., Călin, A.C., Dumitrescu, D.G., Popovici, O.C., & Khurshid, A. (2026). Unravelling systemic risk dynamics amid financial asset bubbles in times of enhanced volatility. *Amfiteatru Economic, 28*(71), pp. 328–344. https://doi.org/10.24818/EA/2026/71/328
20. Lupu, R., Călin, A.C., Lupu, I., Iancu, L.A., & Croicu, A.E. (2024). Bubble or not? A time series classification problem using machine learning. *Romanian Journal of Economic Forecasting, 27*(1), pp. 5–22.
21. Lupu, R., Călin, A.C., Zeldea, C.G., & Lupu, I. (2021). Systemic risk spillovers in the European energy sector. *Energies, 14*(19), 6410. https://doi.org/10.3390/en14196410
22. Mashimbye, L., & Fanta, A.B. (2026). Shadow banking and systemic risk in South Africa: Does size matter? *The Journal of Risk Finance, 27*(3), pp. 458–473. https://doi.org/10.1108/JRF-01-2025-0049
23. Moreira, A., & Savov, A. (2017). The macroeconomics of shadow banking. *Journal of Finance, 72*(6), pp. 2381–2432. https://doi.org/10.1111/jofi.12530
24. Pellegrini, C.B., Cincinelli, P., Meoli, M., & Urga, G. (2022a). The contribution of (shadow) banks and real estate to systemic risk in China. *Journal of Financial Stability, 60*, Article 101018. https://doi.org/10.1016/j.jfs.2022.101018
25. Phillips, P.C.B., & Yu, J. (2011). Dating the timeline of financial bubbles during the subprime crisis. *Quantitative Economics, 2*(3), pp. 455–491. https://doi.org/10.3982/QE82
26. Phillips, P.C.B., Shi, S., & Yu, J. (2015). Testing for multiple bubbles: Historical episodes of exuberance and collapse in the S&P 500. *International Economic Review, 56*(4), pp. 1043–1078. https://doi.org/10.1111/iere.12132
27. Rottner, M. (2023). Financial crises and shadow banks: A quantitative analysis. *Journal of Monetary Economics, 139*, pp. 74–92. https://doi.org/10.1016/j.jmoneco.2023.06.006
28. Wang, C., Zhang, W., & Meng, Y. (2026). Reassessing non-financial firms' shadow banking in the Chinese stock market: From re-lending to cash-liquidity allocation. *International Review of Economics & Finance, 108*, 105241. https://doi.org/10.1016/j.iref.2026.105241

29. Wu, H., Liu, X., & Tan, W. (2026). Spillover effect of shadow banking business governance: A perspective on audit pricing decisions. *International Review of Financial Analysis, 109*, 104816. https://doi.org/10.1016/j.irfa.2025.104816
30. Zhang, S., Miao, W., & Xu, H. (2026). Shadow banking coordinated supervision and systemic risk control: Empirical evidence from the New Asset Management Regulation. *Pacific-Basin Finance Journal,* 97, 103103. https://doi.org/10.1016/j.pacfin.2026.103103

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