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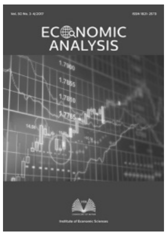

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ORIGINAL SCIENTIFIC PAPER

Imports versus Domestic Production and the Food Security Dilemma in the Arab World: Evidence from a Panel CS-ARDL Approach

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ABSTRACT
This study examines the determinants of food security in a panel of eleven Arab countries over the period 2000–2023 using the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) approach. The aim is to explore both short-run dynamics and long-run equilibrium relationships affecting food self-sufficiency. The results indicate that per capita income exerts a negative effect in the short run, reflecting changing consumption patterns and greater reliance on food imports, while agricultural production emerges as the most consistent positive driver of food self-sufficiency. Short-run dynamics also confirm a rapid adjustment process, with the error correction term (ECT = –1.3569, p < 0.01) indicating strong and more-than-complete convergence toward equilibrium. In the long run, agricultural value added is the only variable with a robust and significant influence, underscoring the strategic importance of the agricultural sector for sustainable food security. These findings highlight the structural vulnerability of food systems reliant on imports and call for policies aimed at enhancing agricultural productivity, promoting self-reliance, and reducing exposure to volatile international food markets.

Keywords: *food security, food self-sufficiency, ariculture, imports, CS-ARDL approach, Arab countries*

JEL Classification: C33, O13, Q17, Q18

INTRODUCTION

Food insecurity, famine, and malnutrition remain persistent global challenges, with profound implications for human health, productivity, and long-term development outcomes. FAO, IFAD, UNICEF, WFP, & WHO (2023) note that chronic undernutrition weakens human capital formation, reduces labor productivity, and perpetuates cycles of poverty and vulnerability. In this context, the concept of food security has gradually evolved from a narrow focus on food availability to a multidimensional framework encompassing availability, economic and physical access, utilization, and stability over time. Countries differ markedly in how these dimensions are

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achieved and balanced, depending on resource endowments, demographic pressures, and exposure to external shocks.

Agricultural development is widely recognized as a cornerstone for improving food security and nutrition (FSN), not only by expanding the quantity and diversity of food supply but also by serving as a driver of structural transformation and inclusive economic growth. HLPE (2016) highlights that agriculture continues to represent the primary source of income for the majority of rural populations, particularly the 1.3 billion people who depend on it directly for their livelihoods, thereby linking agricultural performance directly to food security outcomes. Christiaensen, Demery, & Kuhl (2011) and Kidane, Maetz, & Dardel (2006) emphasize that agriculture can serve as an engine of sustained economic growth, especially in the early phases of development. More recent studies reinforce this perspective, with FAO (2021) and World Bank (2022) noting that investments in agricultural productivity, resilience, and value chains are fundamental not only for achieving Sustainable Development Goal 2 ("Zero Hunger") but also for ensuring broader economic transformation in developing regions.

At the same time, many countries increasingly rely on food imports to close the gap between domestic demand and local production. Imports can play a positive role by compensating for structural constraints such as land and water scarcity, by smoothing domestic supply in the face of climatic shocks, and by enabling consumers to access a more diversified food basket. For resource-rich or highly open economies, food imports may also be a rational strategy to reallocate scarce factors of production toward sectors with higher comparative advantage. However, heavy dependence on imports exposes countries to world market volatility, exchange rate fluctuations, export restrictions from trading partners, and rising geopolitical risks. In periods of global crises, international markets may not always serve as a reliable buffer, thereby amplifying domestic food insecurity.

By contrast, domestic agricultural production contributes to food security through multiple channels: it increases local availability, supports rural incomes, and can strengthen national resilience to external shocks. Yet, in many developing regions, including the Arab world, raising domestic production is constrained by biophysical limits (arid climate, water scarcity, limited arable land), institutional weaknesses, and underinvestment in rural infrastructure and agricultural R&D. As a result, most countries face a food security dilemma: "How do food imports and domestic agricultural production jointly affect food security in Arab countries, and what are the short-run and long-run implications for food self-sufficiency?"

United Nations (2022) project that the global population will surpass 9 billion by 2050, with the most pronounced demographic expansion occurring in developing countries across Africa and Asia. For the Arab world, this demographic pressure is compounded by structural food deficits, rapid urbanization, high unemployment, and acute water scarcity. Meeting the resulting demand for food requires not only faster growth in total supplies but also careful management of the balance between imports and domestic production in order to prevent further tightening of global and regional food markets. Herrmann (2009) notes, however, that food insecurity is often not prioritized adequately in policy agendas, partly because emergency food aid and international trade are assumed to offset short-term shortages, and partly because food security is a multidimensional concept that is inherently difficult to measure and to incorporate into coherent policies. Boussard, Gérard, & Piketty (2006) argue that this has frequently relegated agriculture to a secondary role in national development strategies, especially in oil-exporting or import-dependent economies.

The Arab world provides a particularly relevant setting for examining this trade-off between imports and domestic production. On the one hand, many Arab countries are among the most food-import-dependent economies in the world, especially for cereals and other staple foods. On the other hand, the region is characterized by severe natural resource constraints, high exposure to climate change, and recurrent political and economic shocks. These shared structural features justify treating the Arab world as a meaningful analytical group, while the heterogeneity in income levels, resource endowments, and policy choices across the countries included in our sample offers sufficient variation to identify the differential roles of imports and domestic production in shaping food security outcomes.

Against this background, the present paper, titled “Imports versus Domestic Production and the Food Security Dilemma in the Arab World: Evidence from a Panel CS-ARDL Approach”, seeks to empirically assess how food imports and domestic agricultural production jointly affect food security in a panel of Arab countries. Using a cross-sectionally augmented ARDL (CS-ARDL) framework, we investigate both the short-run and long-run impacts of these two channels on food security indicators, while explicitly accounting for cross-sectional dependence and heterogeneity across countries. By doing so, the study aims to provide evidence-based insights into how Arab countries can navigate the imports–production trade-off in order to enhance their food security in an increasingly uncertain global environment.

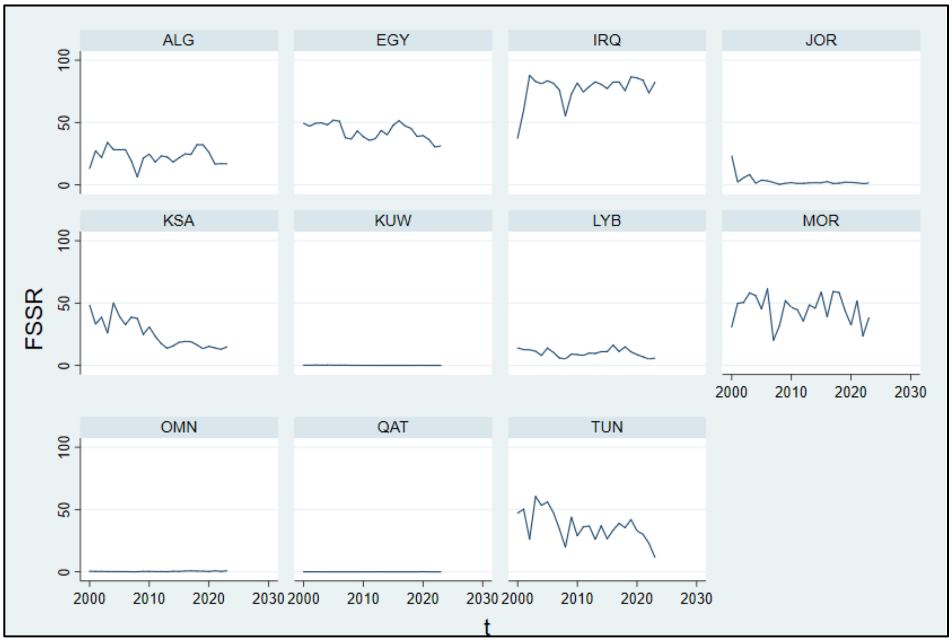

Figure 1. Evolution of Wheat Self-Sufficiency in Arab Countries (2000–2023)

Source: Stata 15 software output

As shown in Figure 1, the analysis of Food self-sufficiency ratios (Wheat FSSR) in eleven Arab countries during the period 2000–2023 reveals clear structural differences between agrarian and resource-dependent economies. Morocco and Algeria achieved relatively higher wheat self-sufficiency levels, often exceeding 40% in several years (e.g., Morocco 61.4% in 2006; Algeria 33.9% in 2003), reflecting the stronger role of domestic agriculture in meeting wheat demand. By contrast, Gulf economies such as Kuwait and Qatar remained almost entirely import-dependent, with Wheat FSSR values close to zero (below 0.3% throughout the period), highlighting the structural constraints of local production under severe water and land scarcity. Egypt and Tunisia, despite their agricultural traditions, experienced downward trends: Egypt’s Wheat FSSR declined from about 49% in 2000 to nearly 31% in 2023, while Tunisia fell sharply from above 50% in the early 2000s to only 11.7% in 2023, reflecting demographic pressures and insufficient agricultural investment. Saudi Arabia clearly illustrates the income–import nexus, as its Wheat FSSR dropped from 48% in 2000 to below 15% after 2020, driven by rising incomes and a shift in demand toward higher-value imported food products. Iraq, on the other hand, maintained relatively high levels often above 75% despite conflict and instability, due to its strong reliance on wheat as a staple crop. Overall, these patterns underscore that wheat production capacity remains the cornerstone of sustainable food security in some Arab states, while rising incomes, demographic expansion, and resource dependence systematically erode self-sufficiency and leave the region highly exposed to volatility in global wheat markets.

LITERATURE REVIEW

A growing body of literature highlights the complex interlinkages between food security, agricultural development, and economic performance in developing countries. Using a dynamic panel of 75 dryland economies between 1970 and 2016, Manap & Ismail (2019) applied the Generalized Method of Moments (GMM) and found that improvements in food security significantly stimulate economic growth, both directly and indirectly, through higher life expectancy, greater employment opportunities, and poverty reduction. Their findings confirm that food security contributes not only to human capital accumulation but also to macroeconomic performance. Sun & Zhang (2021), using panel data for Central Asian countries from 2001 to 2018 and employing the four pillars of food security, examined the impact of trade openness and other determinants on food security using a fixed-effects model, supported by robustness tests through pooled LS and dynamic panel GMM approaches. The findings indicate a U-shaped relationship between trade openness and food security, suggesting that food security improves once trade openness surpasses a certain threshold. The study also shows that GDP per capita, GDP growth, and agricultural productivity positively enhance food security, whereas agricultural employment, arable land constraints, freshwater withdrawals, population growth, natural disasters, and inflation exert negative effects. Overall, the evidence confirms that trade policy reforms contribute to strengthening food security in Central Asia, while maintaining reasonable levels of food self-sufficiency remains crucial due to potential risks associated with global trade dependence. Dekkiche, Saidi, & Cherayett (2025) investigate food security in developing Arab and African countries from 1990 to 2023 using the Panel-ARDL model. The findings show that despite having significant agricultural labor and arable land, food production remains insufficient due to rapid population growth, forcing many countries to rely on food imports and exposing them to global price and supply shocks, especially during crises such as the Russia–Ukraine conflict. The study recommends strengthening the agricultural sector through increased investment, promoting regional trade, and adopting modern technologies such as digital agriculture, artificial intelligence, and smart irrigation. It further highlights the need for regional and global cooperation to ensure stable access to essential food resources. Ngassam, Douanla, & Asongu (2025) analyze the impact of natural resources on food import dependence across 38 sub-Saharan African countries from 2000 to 2020. The findings indicate that resource-dependent countries tend to over-rely on food imports, with oil and gas rents increasing dependence while mineral rents reduce it. Importantly, liberal, egalitarian, deliberative, and electoral democracies can mitigate the effect of natural resources on food import dependence. The study highlights the need for African governments to rethink food policy strategies, suggesting that revenues from natural resources be invested in agricultural infrastructure and that democratic institutions be strengthened to reduce reliance on imported food.

Also, Akramov & Shreedhar (2012) examined Tajikistan in the aftermath of global food and economic crises and documented how macroeconomic shocks and price volatility undermined both national and household food security. Their study stressed the importance of policy instruments to mitigate the effects of external shocks, including sectoral diversification and social protection systems. Similarly, Herrmann (2009) emphasized that although high food prices could potentially stimulate agricultural development, market imperfections and weak transmission of international prices to local producers often prevent such benefits from materializing. This underscores the need for complementary measures such as credit access, infrastructure, and input support to enable producers to respond effectively to price signals .Rezgar and Almojel (2025) analyze the income and price elasticities of imported food demand across Arab countries using the static Almost Ideal Demand System (AIDS) model and find that most essential food imports exhibit inelastic demand, implying that consumption remains relatively stable despite price fluctuations. However, this structural dependence on imports increases exposure to external shocks, prompting the need for government interventions such as subsidies and taxation to stabilize domestic markets.

Building on this import-dependence perspective, recent panel evidence suggests that vulnerability extends beyond consumption behavior to broader structural price dynamics. Dardeer and Shaheen (2025) show that higher food import dependence and urbanization significantly intensify food price volatility in GCC countries, whereas improvements in domestic agricultural productivity and employment contribute to greater price stability and enhanced food security. Similarly, Fan et al. (2024) demonstrate that although agricultural trade openness may improve food availability in the short run, excessive reliance on imports undermines long-term food security by increasing exposure to external price and supply shocks, while stronger domestic production capacity enhances resilience.

Beyond this import–production dichotomy, a growing strand of literature highlights the importance of supply diversification and systemic risk management. Deteix, Salou, and Loiseau (2024) develop food supply risk indicators that integrate both domestic production capacity and the diversity of import sources. Their cross-country analysis shows that countries dependent on a limited number of suppliers face greater vulnerability to disruptions, and that food self-sufficiency alone does not necessarily reduce risk. Instead, resilient food systems require a balanced strategy combining strengthened local production with diversified and stable trade linkages.

Research on sub-Saharan Africa also provides valuable insights. Ofana, Charles, & Eko (2016), using time series econometrics for Nigeria (1970–2010), identified rainfall, exchange rates, and lagged food exports as positive drivers of agricultural output, while food imports, diversion of agricultural funds, and limited technology diffusion acted as major constraints. In the same context, Agwu, Dimelu, & Madukwe (2008) argued for stronger institutional support for agricultural innovation, recommending that governments create incentive structures and extension systems that align research outputs with farmers' realities. Evidence from Gauchan (2008) in Nepal further illustrates the contribution of agriculture to food security, poverty reduction, and overall economic growth, while also highlighting challenges in trade integration, distribution systems, and structural weaknesses that limit the sector's transformative role. Barel Shaked & Buda (2025) examine food self-sufficiency ratios (SSR) in 38 OECD countries from 2010 to 2021, analyzing their relationship with economic growth and external dependencies. Using FAO data and a stratified sampling approach, countries were classified into six typologies based on SSR and GDP per capita, and statistical analyses, including mean comparisons and T-tests, were applied. The findings reveal that wealthier European nations tend to have lower SSRs and rely heavily on food imports, while less affluent countries exhibit higher self-sufficiency, prioritizing local production as a resilience strategy. By focusing on food categories rather than aggregate SSRs, the study offers a nuanced understanding of self-sufficiency trends and highlights areas of high external dependency. The research underscores the importance of economic and agricultural policy reforms to enhance national resilience and reduce vulnerabilities in global food markets, despite limitations related to data coverage and the exclusion of recent global disruptions.

More recent contributions have extended this debate by linking food security to climate change, demographic dynamics, and the water–energy–food nexus. For example, Derouez & Adel (2024) examined five Arab countries spanning 1990–2022 and demonstrated that population growth and climate change pressures necessitate integrated policy frameworks combining renewable energy, desalination, and sustainable agricultural practices. Similarly, a recent panel study in West Africa Frimpong, Mintodê, & Tony (2024) show no significant link between CO2 emissions and economic growth, while agriculture plays a key role, and food availability has mixed effects. Segbefia et al. (2023) investigated the impact of carbon emissions, population growth, economic growth, and human capital on food security across five African countries (Nigeria, Ghana, Kenya, Zimbabwe, and Tanzania) using panel data from 1990 to 2021. It also assessed the moderating role of human capital in the relationship between carbon emissions and food security. Preliminary tests confirmed cross-country interdependence, stationarity, and cointegration among the variables. Using the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model, the study found that carbon emissions and population growth negatively affect food security, while human capital and economic growth enhance it. Additionally, the results showed that human capital moderates the relationship between carbon emissions and food security, indicating that strengthening human capital can mitigate the adverse effects of emissions on food security. Causality analysis revealed a unidirectional relationship running from economic growth, population growth, and human capital to food security, along with a bidirectional causal link between carbon emissions and food security. Overall, the findings contribute new evidence to the literature on the food security–environment nexus and highlight the importance of investing in human capital to reinforce the interaction between carbon emissions and food security in African countries. Ceesay & Ndiaye (2022) aimed to examine the impact of climate change on food security, along with other key variables such as economic growth, population growth, and the agricultural sector, using annual data for the period 1971–2020. The authors employed several modern econometric techniques, including the Vector Autoregressive (VAR) model, Granger Causality tests, the Autoregressive Distributed Lag (ARDL) model, and the Error Correction Model (ECM). The empirical findings revealed that food security growth is strongly and positively correlated with the agricultural sector, while it shows a negative relationship with rainfall variability. In addition, the results indicated that population growth has a significant negative effect on food security in the short run, whereas its long-run effect is negative but statistically insignificant.

The findings underscore the importance of sustainable agriculture and food security in promoting economic resilience in West Africa, offering insights for policymakers. The FAO, IFAD, UNICEF, WFP, & WHO (2023) SOFI report also confirms that progress toward "Zero Hunger" is stagnating globally, with the affordability of healthy diets deteriorating, thereby reinforcing the urgency of productivity, resilience, and value-chain–oriented policies. Taken together, these studies converge on the conclusion that food security is both a driver and an outcome of sustainable economic development. While short-term shocks and external dependencies undermine stability, long-run improvements hinge on agricultural productivity, institutional capacity, and integrated strategies that address the multidimensional nature of food systems.

DATA AND METHODOLOGY

Econometric Approach and Estimation Strategy

This section covers the empirical approach, potential problems with the estimating processes, and our solutions to these problems. To know the impact of food security determinants in the Arab region, we employ panel data. There are well-established advantages to researching this topic with panel data. One significant benefit is that the degrees of freedom increase when both time and unit components are included, and the outcomes are less susceptible to changes in the model specification. Furthermore, the large sample properties linked to panel data contribute to better model estimates, and problems related to measurement error, reverse causality, endogeneity, and omitted variables are considerably minimized. where the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) approach, proposed by Chudik and Pesaran (2015), belongs to the second generation of panel econometric methods. Unlike traditional ARDL models, Pesaran & Smith (1995), CS-ARDL accounts for cross-sectional dependence and slope heterogeneity by incorporating cross-sectional averages of the variables in the estimation. This framework makes it robust in dealing with common shocks and interdependencies across units, such as countries in a panel dataset Chudik & Pesaran (2015). The theoretical foundation begins with the standard Panel ARDL framework, which provides the basis for modeling both short-run dynamics and long-run equilibrium relationships in heterogeneous panels. Building on this, the analysis extends to the more advanced Panel CS-ARDL approach, which augments the traditional specification to account for cross-sectional dependence through cross-sectional averages, thereby offering more consistent and reliable estimates in the presence of common shocks. This method is particularly suitable for food security studies in the Arab region, where shocks in one country often spill over to others due to economic, social, and trade linkages. More specifically, the cross-sectionally augmented ARDL regressions are given by:

Before presenting the cross-sectionally augmented ARDL in detail, it is useful to recall the original Panel ARDL specification introduced by Pesaran & Smith (1995) and further developed by Pesaran et al. (1997). The general formulation of the Panel ARDL model (p, q) was as follows:

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \grave{\delta}_{ij} x_{i,t-j} + \mu_i + \varepsilon_{it} \quad (1)$$

Where Xit (k X 1) is a vector of explanatory variables, which varies across both time periods and cross-sectional units. The value of T should be sufficiently large to allow for estimating the model for each group. However, it is not necessary for T to be the same for each group. For the sake of simplicity in notation, we will assume a common value for T. It is also straightforward to allow for different lag orders on the different variables in Xit. The coefficients of the lagged dependent variables, ⅄_ij, are scalars, and δ`_ij is K X 1 vectors of unknown parameters.

It is convenient to work with the following re-parameterization (1): Blackburne & Frank (2007)

$$\Delta y_{it} = \theta_i\left(y_{i,t-1} - \grave{\theta}_i X_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=1}^{q-1} \grave{\delta}_{ij}^{*} \Delta X_{i,t-j} + \mu_i + \varepsilon_{it} \quad (2)$$

The parameter $\theta_i = -1 - \sum_{j=1}^{p} \lambda_{ij}$ is the error-correcting speed of adjustment term. It should be less than zero (θ<0); and if θ = 0, then there would be no evidence for a long-run relationship. This parameter is expected to be significantly negative under the prior assumption that the variables show a return to long run equilibrium. The vector θ`_i ′ contains the long run relationship of the variables Shuaibu & Popoola (2016).

But if the errors ε_{it} contain unobserved common factors with heterogeneous loadings, standard ARDL estimators become biased and inconsistent. This problem arises in panels with global shocks, regional spillovers, or strong interdependencies across cross-sections. Pesaran (2004, 2006) proposed the CD test to detect (2004) such dependence and developed the Common Correlated Effects (CCE) estimator to account for unobserved common factors. The expanded form of the traditional model can include extra lags (r) to the ARDL specification as follows.

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \grave{\delta}_{ij} x_{i,t-j} + \sum_{j=0}^{r} \beta_{ij} \theta\, \overline{M}_{t-1} + \mu_i + \varepsilon_{it} \quad (3)$$

Where $\overline{M}_{t-1} = (\,\overline{X}_{i,t-k},\, \overline{Y}_{i,t-k})$ is the cross-section average of regressed, and it eliminates cross-section dependencies. We can transform Equation (3) to an ECM to decompose short and long-run effects. At that, we come up with the following CS-ARDL specification.

$$\Delta y_{it} = \theta_i\left(y_{i,t-1} - \grave{\theta}_i X_{it}\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta y_{i,t-1} + \sum_{j=1}^{q-1} \grave{\delta}_{ij}^{*} \Delta X_{i,t-j} + \sum_{j=0}^{r} \beta_{ij}\, \overline{M}_t + \mu_i + \varepsilon_{it} \quad (4)$$

Equation (4) indicates the ECM presentation of the Panel CS-ARDL approach. Δ is the difference operator with an optimal lag order, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}\ (j = 1,2, \ldots . p-1)$and $\grave{\delta}_{ij}^{*} = -\sum_{m=j+1}^{q} \lambda_{im}\ (j = 1,2, \ldots q-1)$ are the short run coefficients, $\theta_i = -(1 - \sum_{j=1}^{P} \lambda_{ij})$is the errorcorrection term. This term indicates the speed of adjustment toward long run equilibrium after a shock to the system. This term should be statistically significant and negative to support the long-run equilibrium. $\grave{\theta}_i = (\sum_{j=0}^{q} \beta_{1i}) / \theta_i$ is the long run coefficient. For the calculation of the variance/covariance matrix of the individual long-run coefficients θi the delta method used the vector of the long run coefficient . $\bar{M}_t$ the cross-sectional averages of the dependent variable and the explanatory variables at time t .Yilmaz (2024).

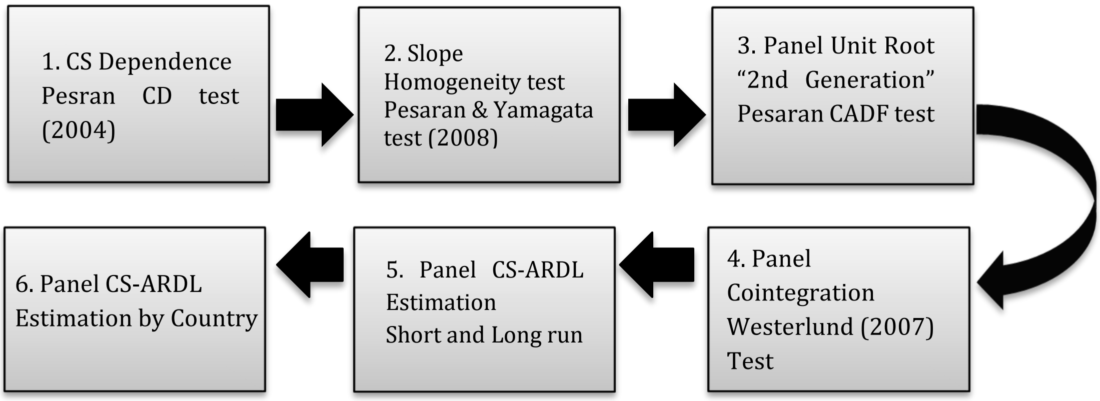

Figure 2. Steps in econometric approach

Source: Authors' elaboration

Empirical Model

As illustrated in Figure 2, this study aims to analyze the determinants of food security in 11 Arab countries over the period 2000–2023 using the Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) approach, which distinguishes between short-run dynamics and long-run relationships in panel data while explicitly accounting for cross-sectional dependence. The sample comprises Jordan, Algeria, Morocco, Oman, Egypt, Saudi Arabia, Kuwait, Iraq, Tunisia, Qatar, and Libya.

Food self-sufficiency ratio (FSSR), sourced from FAO, serves as the dependent variable, while the independent variables include agricultural production (VAGR), GDP per capita (GDPPC), population (POP), and food imports (FIG). The baseline model for the variables in the study may be noted as follows:

$$FSSR = f(VAGR, POP, GDPPC, FIG) \quad (5)$$

Data Sources, Variables and Measurement

Data were collected from FAO and WDI. For consistency and econometric robustness, the natural logarithm (ln) transformation was applied to all continuous independent variables, whereas FSSR remains expressed as a percentage.

Table 1. Variables, source and measurement

Variable	Code	Measurement	Source
Food Security (dependent)	FSSR	Food Self-Sufficiency Ratio (%)	FAO
Agricultural Production	VAGR	Natural log value added in the agricultural sector (constant US$)	WDI
GDP per capita	GDPPC	Natural log of GDP per capita (constant US$)	WDI
Population	POP	Natural log of total population	WDI
Food Imports	FIG	Natural log of food imports value (constant US$)	FAO

Source: Authors' elaboration

Descriptive Statistics of the Study Variables

Table 2 presents the descriptive statistics for the core variables examined in this study, covering 11 Arab countries during the period 2000–2023. The statistics include the mean, standard deviation, minimum and maximum values, and the number of observations. This descriptive analysis provides a preliminary understanding of the distribution and variation of the dataset before proceeding with advanced econometric modeling using the Panel CS-ARDL approach.

Table 2. Descriptive Statistics

Statistic	FSSR	VAGR	POP	FIG	GDPPC
Mean	23.93	21.74	15.98	15.45	3.88
Standard Deviation	24.79	1.67	2.05	0.74	0.50
Minimum	0	17.72	6.39	14.08	2.91
Maximum	87.83	24.67	18.29	17.10	5.03
Observations (N)	264	262	264	264	264

Source: Stata 15 software output

The descriptive results highlight substantial variation across countries and variables. The food self-sufficiency ratio (FSSR) shows a low average of 23.93 with a high dispersion, signifying large disparities in reliance on domestic production. Agricultural production (VAGR) averages 21.75, with relatively low variability, suggesting more stability in this sector. Population (POP) exhibits wide differences, reflecting demographic diversity among Arab countries. Food imports (FIG) also display consistent reliance on external sources, while GDP per capita (GDPPC) indicates heterogeneous income levels, spanning from low- to high-income economies. These descriptive insights underscore the structural differences within the region and set the stage for deeper econometric analysis using Panel CS-ARDL.

Cross-Sectional Dependence Test Results

Before conducting panel data estimations, it is crucial to verify whether the variables exhibit cross-sectional dependence. Cross-sectional dependence implies that shocks affecting one country may also influence others, which is common in regional studies where countries are interconnected economically, socially, and politically. Ignoring such dependence can lead to biased and inconsistent results in panel data models.

Table 3 presents the results of Pesaran's (2004) CD test for cross-sectional dependence. This test examines the null hypothesis of cross-sectional independence against the alternative of cross-sectional dependence. The test statistic follows an asymptotic standard normal distribution. Significant test results (p-value < 0.05) indicate the presence of cross-sectional dependence. Pesaran (2004).

Table 3. Pesaran (2004) Cross-Sectional Dependence Test

Variable	CD-test	p-value	corr	abs(corr)
FSSR	6.15	0.00	0.16	0.30
VAGR	28.20	0.00	0.77	0.77
POP	35.28	0.00	0.97	0.97
FIG	33.45	0.00	0.92	0.92
GDPPC	28.67	0.00	0.78	0.78

Source: Stata 15 software output

The Pesaran (2004) CD test results clearly reject the null hypothesis of cross-sectional independence for all variables under study (p-values = 0.00). This indicates that cross-sectional dependence exists among the 11 Arab countries across the period 2000–2023.

- For FSSR, the CD statistic (6.15) and moderate correlation (0.16) suggest some dependence in food self-sufficiency trends.
- For VAGR, POP, FIG, and GDPPC, the very high-test statistics (ranging from 28.20 to 35.28) and strong correlations (above 0.77, and as high as 0.97 for population) indicate substantial interdependence. This implies that changes in agricultural production, population growth, food imports, and income levels in one country are strongly linked to developments in others.
- These results confirm the existence of strong regional spillovers in food security determinants across Arab countries. Accordingly, the presence of cross-sectional dependence highlights the necessity of employing second-generation econometric methods, such as CS-ARDL, to obtain robust and unbiased results.

Slope Homogeneity Test Results

Table 4 reports the results of the slope homogeneity test developed by Pesaran and Yamagata (2008). The null hypothesis assumes that slope coefficients are homogeneous across cross-sectional units, while the alternative indicates heterogeneity. Rejecting the null implies that the relationship between variables differs significantly across countries, which has important implications for econometric modeling (Yamagata & Pesaran, 2008).

Table 4. Slope homogeneity test

Statistic	Value	p-value
Delta	9.37	0.00
Adj. Delta	10.83	0.00

Source: Stata 15 software output

The test strongly rejects the null hypothesis of slope homogeneity at the 1% significance level. This indicates that the slope coefficients are heterogeneous across the Arab countries in the sample. The result highlights the necessity of using econometric methods, such as CS-ARDL, that account for both cross-sectional dependence and heterogeneous slope parameters. This ensures that country-specific dynamics are appropriately captured rather than imposing a uniform relationship across all panels.

Second-Generation Unit Root Test Results (Pesaran CADF)

To test the stationarity properties of the panel series under cross-sectional dependence, Pesaran's (2007) Cross-sectionally Augmented Dickey-Fuller (CADF) test is applied. This second-generation unit root test augments the standard ADF regression with cross-sectional averages to control for common factors across countries. The null hypothesis assumes non-stationarity (unit root), while the alternative suggests stationarity. The test is conducted at levels and first differences Pesaran (2007) .

Table 5. Pesaran CADF Unit Root Test Results

Variable	Level (p-value)	First Difference (p-value)
FSSR	0.00 (trend); 0.00 (constant)	Stationary at level
VAGR	0.41 (trend); 0.24 (constant)	0.00 (trend); 0.00 (constant) → Stationary after first difference
GDPPC	0.00 (trend); 0.00 (constant)	Stationary at level
FIG	0.00 (trend); 0.00 (constant)	Stationary at level
POP	0.00 (trend); 0.00 (constant)	Stationary at level

Source: Stata 15 software output

All variables are integrated of order I(0) except for agricultural production (VAGR), which is I(1). This combination of stationary and non-stationary variables justifies the application of panel cointegration techniques, such as Westerlund (2007) and dynamic estimators like CS-ARDL, to analyze long-run relationships among food security determinants.

Westerlund (2007) Panel Cointegration Test Results

In the presence of cross-sectional dependence, traditional cointegration tests may lead to biased results. To overcome this limitation, Westerlund (2007) proposed error-correction based panel cointegration tests that are robust to cross-sectional dependence through the use of bootstrapping procedures. These tests examine the null hypothesis of no cointegration against the alternative that the variables are cointegrated. Four test statistics are provided: Gt and Ga (group-mean statistics), and Pt and Pa (panel statistics).

Table 6. Westerlund (2007) Panel Cointegration Test

Statistic	Value	P-value
Gt	-5.03	0.00
Ga	-10.99	0.30
Pt	-10.30	0.00
Pa	-4.89	0.71

Source: Stata 15 software output

The Westerlund (2007) cointegration test results provide mixed evidence regarding the existence of a long-run equilibrium relationship among food self-sufficiency (FSSR), agricultural production (VAGR), population (POP), food imports (FIG), and GDP per capita (GDPPC) across the 11 Arab countries.

- The group-mean test Gt is highly significant (p-value = 0.00), strongly rejecting the null of no cointegration. This indicates that at least some countries in the sample exhibit long-run relationships among the studied variables.
- The group-mean test Ga is insignificant (p-value = 0.30), suggesting weaker evidence of cointegration when using this statistic.
- The panel statistic Pt is also highly significant (p-value = 0.00), confirming the existence of cointegration at the panel level.
- The panel statistic Pa is insignificant (p-value = 0.71), which does not support cointegration according to this measure.

Overall, the results imply that there is strong evidence of cointegration when using the Gt and Pt statistics, indicating that food security determinants and food self-sufficiency share a long-run equilibrium relationship in the Arab region. However, the insignificance of Ga and Pa suggests that the evidence is not uniform across all tests. Thus, while cointegration is present, it may vary in strength and consistency across different countries.

CS-ARDL Estimation Results

This section focuses on a panel of 11 Arab countries in order to examine the determinants of food security over the period 2000–2023. The cross-sectionally augmented autoregressive distributed lag (CS-ARDL) Chudik & Pesaran (2015) approach is employed to capture both the short-run dynamics and long-run equilibrium relationships between the key variables affecting food self-sufficiency. Table 7 presents the empirical estimation results of this model, highlighting the role of the main drivers of food security across the selected countries. The estimation results presented here are based on a PANEL CS-ARDL model, which is a Cross-Sectionally Augmented Autoregressive Distributed Lag model. In this model:

The dependent variable (food self-sufficiency) is expressed in percentage terms.

The independent variables (agricultural production, GDP per capita, population, food imports) are expressed in natural logs.

This setup implies that the model is a lin-log specification (linear-logarithmic). Therefore, each coefficient reflects the absolute change in the dependent variable (food self-sufficiency) for a 1% change in the independent variable.

Table 7. CS-ARDL Estimation Results for Food Security (FSSR)

Variable	**Coef.**	**Std. Err.**	**z**	**p-value**	**Variable**	**Coef.**	**Std. Err.**	**z**	**p-value**
Short-run Estimates					**Long-run Estimates**				
L.FSSR	-0.35	0.12	-2.85	0.00	**lr_FIG**	20.01	17.49	1.14	0.25
GDPPC	-74.38	35.84	-2.07	0.03	**lr_GDPPC**	-80.66	54.71	-1.4	0.14
POP	60932.66	50686.18	1.20	0.22	**lr_POP**	711.21	470	1.51	0.13
FIG	-0.21	8.17	-0.03	0.97	**lr_VAGR**	32.09	15.58	2.06	0.03
ΔVAGR	22.39	10.64	2.10	0.03	**ECT (lr_FSSR)**	-1.35	0.12	-10.8	0.00
L.ΔVAGR	9.75	4.84	2.01	0.04	**R^2 (MG)**	0.74			
L.GDPPC	9.62	17.16	0.56	0.57	**N of obs**	229			
L.POP	-60225.1	50189.51	-1.20	0.23	**N of Grps**	11			
L.FIG	14.37	7.98	1.80	0.07					

Source: Stata 15 software output

The CS-ARDL estimations provide robust evidence on the determinants of food self-sufficiency, shedding light on both short-run dynamics and long-run structural relationships.

Short-Run Dynamics:

Error Correction Term (ECT):

The ECT = -1.35 ($p < 0.01$) is highly significant, indicating a rapid and stable adjustment process in the short run. The large negative value means that deviations from equilibrium are corrected by more than 100% in the subsequent period. This strong convergence indicates that the food security system is resilient to short-term shocks.

GDP per Capita (GDPPC):

The coefficient GDPPC = -74.38 ($p < 0.05$) shows a negative and statistically significant effect on food self-sufficiency in the short run. This suggests that higher income leads to greater dependence on food imports, thereby reducing domestic food production and eroding self-reliance.

Agricultural Production (ΔVAGR, L.ΔVAGR):

ΔVAGR = 22.39 ($p < 0.05$): A 1% increase in agricultural production leads to a 22.39 percentage points increase in food self-sufficiency, reflecting a positive and significant contribution of agricultural production to food security in the short run.

L.ΔVAGR = 9.75 ($p < 0.05$): Similarly, lagged agricultural production changes have a positive and significant effect. This indicates that past agricultural performance continues to impact food self-sufficiency in the short run.

Food Imports (L.FIG):

L.FIG = 14.37 ($p \approx 0.07$) shows a marginally significant effect in the short run. This suggests a substitution mechanism between food imports and domestic agricultural output, although the effect does not persist in the long run.

Long-Run Equilibrium:

Agricultural Value Added (lr_VAGR):

The long-run coefficient for agricultural value added (lr_VAGR = 32.09, $p < 0.05$) is positive and statistically significant, reinforcing the importance of agriculture in sustaining food security. This means that in the long run, agricultural growth is the key driver of food self-sufficiency.

GDP per Capita (lr_GDPPC):

The coefficient for GDPPC (lr_GDPPC = -80.66, $p > 0.05$) is not statistically significant in the long run. This suggests that, while higher incomes may influence short-term fluctuations, they do not affect food self-sufficiency in the long run.

Population (lr_POP):

lr_POP = 711.21 ($p > 0.05$) also shows no long-term statistical significance. This implies that while demographic factors may contribute to short-term variability, they do not fundamentally affect long-term food security outcomes.

Food Imports (lr_FIG):

The coefficient for lr_FIG = 20.01 ($p > 0.05$) does not achieve significance, indicating that food imports do not have a long-term effect on food self-sufficiency in the selected countries.

CS-ARDL Results by Country (Short-Run and Long-Run)

This table summarizes the CS-ARDL estimation results for each country in the sample. The reported coefficients are rounded to one decimal place, and only statistically significant variables are highlighted with an asterisk (*). The table distinguishes between short-run and long-run effects.

This means that the dependent variable (food self-sufficiency ratio, FSSR) is expressed in percentage terms, while the independent variables (agricultural production, GDP per capita, population, food imports) are expressed in natural logs. This implies that each coefficient reflects the absolute change in the dependent variable for a 1% change in the independent variable.

Table 8. CS-ARDL Estimation Results by Country

Country	Short-run Significant Effects	Long-run Significant Effects
JOR	L.FSSR -1.1*, POP -57.0*, D. VAGR 44.7*, 118.0*, LD. VAGR 35.4*, L. GDPPC 0.3*, L.FIG 87.2*	lr_GDPPC 0.5*, lr_VAGR 48.2*, lr_FIG -0.9*
ALG	FIG -61.2*, D. VAGR 44.7*, LD. VAGR 35.4*	lr_VAGR 48.2*
MOR	D.VAGR 118.0*, LD. VAGR 45.5*	lr_VAGR 163.1*
OMN	No significant short-run effects	No significant long-run effects
EGY	FIG -22.4*	No significant long-run effects
KSA	L.GDPPC -100.1*, L.FIG 87.2*	No significant long-run effects
KUW	No significant short-run effects	No significant long-run effects
IRQ	LD. VAGR 10.0*	No significant long-run effects
TUN	No significant short-run effects	No significant long-run effects
QAT	POP -0.1*, D. VAGR -0.2*, LD. VAGR -1.1*, L. GDPPC 0.3*, L.POP 0.01*, L.FIG -0.4*	lr_GDPPC 0.5*, lr_VAGR -1.1*
LYB	No significant short-run effects	No significant long-run effects

Source: Stata 15 software output

The CS-ARDL estimation results reveal that the determinants of food security, measured by the food self-sufficiency ratio (FSSR), vary substantially across the Arab world, reflecting structural differences between agrarian and resource-dependent economies. In Jordan, food security is negatively affected in the short run by population growth (POP = –57.0), while agricultural activity exerts a strong positive influence (D. VAGR = 44.7; LD. VAGR = 35.4).

Food imports contribute positively in the short run (L.FIG = 87.2), but their effect turns negative in the long run (lr_FIG = –0.9), indicating that reliance on imports may temporarily fill supply gaps but undermines sustainable self-sufficiency. In Algeria, food imports strongly reduce food security in the short run (FIG = –61.2), while agriculture exerts a significant positive effect both immediately (D. VAGR = 44.7; LD. VAGR = 35.4) and in the long term (lr_VAGR = 48.2), underscoring the centrality of domestic production in strengthening food security.

In Morocco, agriculture emerges as the most powerful driver of food security, with very strong positive effects in the short run (D. VAGR = 118.0; LD. VAGR = 45.5) and an even larger impact in the long run (lr_VAGR = 163.1). By contrast, in Egypt, food imports reduce self-sufficiency in the short run (FIG = –22.4), while no significant long-run determinants emerge, highlighting the persistent vulnerability of its food system. In Saudi Arabia, lagged income per capita negatively affects food self-sufficiency (L. GDPPC = –100.1), whereas food imports provide short-term relief (L.FIG = 87.2). However, the absence of long-run effects suggests that structural dependence on oil revenues continues to constrain sustainable improvements in food security.

The case of Qatar illustrates a different pattern, where population pressure (POP = –0.1), weak agricultural performance (D. VAGR = –0.2; LD. VAGR = –1.1), and food imports (L.FIG = –0.4) all undermine food self-sufficiency in the short run. Income per capita remains the only positive contributor (L. GDPPC = 0.3), yet agriculture continues to exert a negative effect even in the long run (lr_VAGR = –1.1). For Iraq, agriculture contributes modestly in the short run (LD.VAGR = 10.0) but without long-run sustainability. In the remaining countries (Kuwait, Oman, Tunisia, and Libya), no significant determinants are identified in either the short or long run, reflecting a structural reliance on food imports and resource rents rather than domestic agricultural capacity.

Overall, the results demonstrate that agriculture is the most consistent and sustainable determinant of food security in countries such as Morocco (lr_VAGR = 163.1), Algeria (lr_VAGR = 48.2), and Jordan (lr_VAGR = 48.2). By contrast, food imports systematically undermine self-sufficiency in the long run (e.g., Jordan –0.9, Algeria –61.2, Egypt –22.4, Qatar –0.4), reinforcing the structural vulnerability of food systems dependent on global markets. Population growth and unbalanced economic expansion further exacerbate these challenges, particularly in rentier economies, where food security remains highly exposed to external shocks. These findings highlight the urgent need for more effective agricultural and investment policies to reduce import dependency and build sustainable food security across the region.

CONCLUSION

The findings of this study provide robust empirical evidence that agriculture remains the cornerstone of food security in the Arab world. The CS-ARDL estimations demonstrate that while rising incomes and food imports tend to weaken food self-sufficiency in the short run, agricultural production consistently enhances resilience and strengthens long-term sustainability. Although import dependence may sometimes help bridge short-term supply gaps, it undermines structural self-reliance when sustained over time, leaving economies increasingly vulnerable to external shocks and volatile international markets.

The negative short-run effect of per capita income on self-sufficiency reflects a structural imbalance between consumption and production: as household incomes rise, demand shifts toward more diverse and higher-value food products (meat, dairy, processed goods) that domestic agriculture cannot supply at the required scale or quality. This pattern is particularly evident in the case of Saudi Arabia, where results show that higher income per capita negatively affects food self-sufficiency. This outcome reflects the increased reliance on relatively cheap food imports, illustrating the “Dutch disease” effect typically associated with resource-dependent economies.

Country-level results further confirm the heterogeneity of food security determinants across the Arab world: agrarian economies such as Morocco, Algeria, and Jordan achieve sustainable gains through agricultural expansion, while resource-dependent economies such as Qatar, Kuwait, and Saudi Arabia remain constrained by structural reliance on imports and demographic pressures. These patterns emphasize that food security cannot be decoupled from investment in agriculture, technological modernization, and stronger regional cooperation.

In sum, this study highlights the urgent policy imperative of strengthening agricultural productivity and domestic self-reliance, not only as a short-term stabilization tool but as a long-term strategy to reduce vulnerability, enhance resilience, and ensure sustainable food security across the Arab world.

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ORIGINAL SCIENTIFIC PAPER

Human Capital and Equity-Adjusted Income: A BMA-Based Decomposition Approach

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ABSTRACT

This paper utilizes the Bayesian Model Averaging (BMA) methodological approach to explore how human capital affects equity-adjusted income and its growth rate, commonly described as inclusive growth and defined as income growth adjusted for changes in income distribution. The equity-adjusted income measure that we use is broken down into real GDP per capita and the income equity index (IEI) as its component parts. Framed in this way, the measure is designed to capture how fairly different levels and changes in national income are shaped. In this paper, we study how the preferred measure responds to human capital, a factor widely established as a major driver of both higher income growth and greater equity. We proxy human capital using variables for education and health and, alongside a set of standard growth determinants as controls, incorporate them into a BMA estimation setting. In this context, the main objective of the paper is to determine whether human capital contributes to equity-adjusted income mainly by increasing real GDP per capita or by improving income distribution. Put differently, the paper asks which of these two dimensions accounts more for the overall link between human capital and equity-adjusted income. The estimation results indicate that human capital variables do not exhibit robust effects on inclusive growth rates as originally defined. However, both education and health show robust and positive effects on the level of equity-adjusted income in logarithmic form. The structural decomposition we perform further suggests that the GDP per capita channel is materially more important, although education also retains a meaningful role through the income equity component. This outcome holds regardless of which proxy is included in the estimation.

Keywords: *inclusive growth, GDP growth, human capital, income inequality*

JEL Classification: I3, O1, O4

INTRODUCTION

In their influential paper, Anand, Mishra, and Peiris (2013) defined inclusive growth as a composite variable comprising two components: the growth of real gross domestic product (GDP) per capita and the growth of a specially derived income equity index (IEI). In this framework, inclusive growth may also be viewed as the growth rate of equity-adjusted income, while equity-adjusted income itself represents the underlying level variable that combines income growth and income distribution. Using a stochastic panel model specification with both country and period effects, Anand et al. (2013) explored the influence of a variety of variables on inclusive growth. Education, measured as mean years of schooling, was one of the variables included in the model. This is particularly noteworthy, since this variable represents one of the main proxies for human

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capital and has been consistently shown to significantly affect the economic growth rate in panel studies (Lucas, 1988; Mankiw et al., 1992; Barro & Lee, 1994; Benhabib & Spiegel, 1994). Education has also been identified as one of the main drivers of the income inequality component of inclusive growth, typically measured by an income inequality index (De Gregorio & Lee, 2002; Goldin & Katz, 2008; Lustig et al., 2013). Education and health, as key proxies for human capital, have also been found to be statistically significant determinants of inclusive growth in other studies (Raheem et al., 2018).

There are also important theoretical arguments suggesting that human capital may strongly affect not only the overall level of economic development, as proposed in neoclassical (Mankiw et al., 1992) and endogenous growth theories (Lucas, 1988; Romer, 1990), but also the degree of its inclusiveness. In this context, particularly relevant is the discussion of compression effects, whereby the education premium declines as the share of individuals with higher levels of human capital increases (Knight & Sabot, 1983).

Even though the potential effect of human capital on inclusive growth may operate through both components, none of the earlier studies has explicitly examined how this effect is transmitted to inclusive growth. More specifically, the existing literature has not established whether human capital contributes more to equity-adjusted income through higher real GDP per capita or through improvements in income distribution, nor has it clarified whether such effects are more clearly detectable in the level of equity-adjusted income than in inclusive growth rates themselves. This gap is important because identifying the dominant pathway can help clarify how human capital shapes inclusive development.

Against this background, this paper addresses two main research questions. First, does human capital exert a statistically meaningful effect on inclusive growth, on equity-adjusted income as its underlying level variable, and on their underlying components? Second, if such an effect exists, is it transmitted primarily through the real GDP per capita component or through the income equity component? Accordingly, the main objective of the study is to determine which of these two channels accounts more for the overall link between human capital and equity-adjusted income, while also assessing whether human capital exerts robust effects on inclusive growth rates as originally defined.

To address this issue, we adopt the following strategy in this paper. Considering a sample of countries between 2009 and 2021, we take both education, measured by mean years of schooling, and health, proxied by life expectancy at birth, as the human capital variables of interest. As a set of possible controls, we restrict ourselves to the variables identified by Mirestean and Tsangarides (2009) as robust determinants of economic growth. To obtain robust estimates of the effect of human capital on inclusive growth, on equity-adjusted income, and on their components, we employ the Bayesian Model Averaging (BMA) approach. This approach helps address the issue of model uncertainty, which may affect many of the inclusive growth studies conducted so far. In this way, it may significantly reduce the risk of making statistical inferences based on inadequately specified model formulations (Hoeting et al., 1999).

The expected contribution of this paper is threefold. First, it adds to the literature on inclusive growth by moving beyond the identification of determinants and explicitly examining the pathway through which human capital affects equity-adjusted income and, more broadly, inclusive growth. Second, it contributes methodologically by applying the BMA framework to this question, thereby addressing model uncertainty in a more systematic manner. Third, by decomposing the overall effect of human capital into GDP per capita and income-equity components, the paper provides evidence on the relative importance of these two channels. In doing so, it offers a clearer understanding of whether human capital matters primarily as a driver of economic expansion, as a driver of distributional improvement, or both. This contribution is especially relevant in light of the paper's findings, which suggest that the GDP per capita channel is materially more important and that the more robust results relate to equity-adjusted income rather than to inclusive growth rates themselves.

The remainder of the paper is structured as follows. Section 1 reviews the relevant literature. Section 2 presents the sample, the variables, and the data sources used in the empirical analysis. Section 3 outlines the methodological framework. Section 4 reports the estimation results and the structural decomposition findings. The final section concludes.

LITERATURE REVIEW

Inclusive growth has been conceptually discussed in a number of studies (Ianchovichina & Lundström, 2009; Klasen, 2010; McKinley, 2010). These studies cover multidimensional aspects that are thought to be associated with inclusive growth. However, the most concrete steps toward the development of a clear and measurable concept were taken by Anand, Mishra, and Peiris (2013). These authors defined inclusive growth as a composite index constructed as the sum of two components, in the following manner (Anand et al., 2013):

$$\frac{d\bar{y}^*}{\bar{y}^*} = \frac{d\bar{y}}{\bar{y}} + \frac{d\omega}{\omega} \tag{1}$$

Equation (1) identifies the inclusive growth rate, $(\frac{d\bar{y}^*}{\bar{y}^*})$, as the sum of the real GDP per capita growth rate, $(\frac{d\bar{y}}{\bar{y}})$, and the growth rate of the income equity index (IEI). Anand and colleagues (2013) define IEI as the ratio between what they call "the social mobility index" ($\bar{y}^*$) and real GDP per capita ($\bar{y}$):

$$\omega = \frac{\bar{y}^*}{\bar{y}} \tag{2}$$

Constructed in this way, the IEI can be viewed as a measure of the deviation of the actual income distribution from one in which everyone has the same income. To obtain a measure of the IEI, however, the values of the social mobility index, or what we refer to as equity-adjusted income, are required. Anand and colleagues (2013) calculate this index by integrating the average income of the bottom *i* percent of the population across percentiles ($\bar{y}_i$):

$$\bar{y}^* = \int_0^{100} \bar{y}_i di \tag{3}$$

Anand et al. (2013) used this measure to estimate how different variables affect inclusive growth. They employed a heavily unbalanced panel dataset covering 143 countries over the period from 1980 to 2010. Anand and colleagues (2013) also chose a stochastic model specification with both country and period effects. Their estimation results indicate that several variables have a statistically significant effect on inclusive growth across different model specifications. Among the variables showing the most consistent effects were lagged GDP per capita and inflation, both of which had negative effects, and trade openness and education, both of which had positive effects on the rate of inclusive growth.

Subsequent studies have produced similarly important findings. A number of different variables have thus been identified as significant determinants of inclusive growth. These include fiscal redistribution (Aoyagi & Ganelli, 2015), higher productivity growth (Alekhina & Ganelli, 2023), lower unemployment rates (Aoyagi & Ganelli, 2015), institutional quality (Aslam et al., 2021), ease of doing business (Asongu & Odhiambo, 2019), social, financial, and digital inclusion (Aslam et al., 2021; Cui et al., 2022), public spending (Angulo-Bustinza et al., 2023), and the savings rate (Alekhina & Ganelli, 2023), among other variables. It is worth noting that some of these studies explicitly used the measure developed by Anand and colleagues (Anand et al., 2013; Alekhina & Ganelli, 2023; Aoyagi & Ganelli, 2015; Aslam et al., 2021), while others relied on less complex proxies (Angulo-Bustinza et al., 2023; Asongu & Odhiambo, 2019; Cui et al., 2022; Raheem et al., 2018).

Yet, considering this body of literature as a whole, variables commonly viewed as components of human capital have repeatedly been shown to exert a positive influence on inclusive growth. Starting from the finding of Anand et al. (2013), who estimated the coefficient on education to range between 0.12 and 0.78, multiple other studies have reached similar conclusions. Raheem et al. (2018), for instance, found that public expenditure on both education and health may have a positive impact on inclusive growth. The coefficient on the former was estimated at around 0.08, while the coefficient on the latter was estimated at around 0.11. Tella and Alimi (2016) supported these claims with respect to health expenditure.

These findings are not surprising, given that human capital variables have been identified by many researchers as important drivers of both components of inclusive growth. As for the first of these components, the real GDP per capita growth rate, its relationship with the development of human capital has been emphasized by some of the most influential scholars in the economic growth literature. On a theoretical level, particularly notable is the work of Robert Lucas (1988), who advanced an endogenous growth framework that assigns a central role to human capital accumulation. According to Lucas (1988), human capital can primarily be accumulated in two ways: through schooling and through learning by doing. These two mechanisms play a complementary role in enabling human capital to enhance GDP per capita growth.

Notably, the importance of human capital as a driver of economic growth, proxied by education variables, has been empirically confirmed by studies such as Mankiw et al. (1992), Hanushek and Kimko (2000), Bassanini and Scarpetta (2002), and Hanushek and Woessmann (2012), among many others.[1] Health variables, such as life expectancy at birth, which are also viewed as important proxies for human capital, have similarly been identified as drivers of growth in empirical studies (Barro, 2013; Bloom et al., 2004). Human capital variables have also been investigated within the context of the BMA approach, albeit with mixed results in terms of robustness (Dima & Dima, 2018; Mirestean & Tsangarides, 2009; Moral-Benito, 2012).

With regard to income distribution, Knight and Sabot (1983) discussed what they termed the composition and compression effects. As the share of educated individuals in the total population increases, the composition effect is hypothesized to initially raise income inequality, but eventually to reduce it once that share becomes sufficiently large. Knight and Sabot (1983) placed particular emphasis on the compression effect, under which inequality declines as the education premium falls with an increase in the number of educated individuals. Moreover, numerous empirical studies have identified a significant effect of human capital on income inequality. As expected, this effect has been found to be predominantly negative. The variables used to capture the effect of human capital have been based even more heavily on education. These measures include indicators primarily related to education quality (Blau & Kahn, 2005; Checchi & van der Werfhorst, 2014) as well as average years of schooling (Barro, 2000; De Gregorio & Lee, 2002).

In light of these findings, it is not unreasonable to expect human capital to have a significant effect on equity-adjusted income, likely through both of its components. However, although human capital has been consistently identified as a major determinant of both components separately, no study on inclusive growth has explicitly examined the relative contribution of each component channel to the overall effect of human capital on inclusive growth. The primary aim of this study is to fill this research gap. Accordingly, the following sections explore which of these two channels primarily transmits the effect of human capital on inclusive growth and equity-adjusted income, if such an effect exists at all.

[1] It is important to note that some studies fail to find a positive relationship between education-based human capital and economic growth (Bils & Klenow, 2000; Nedić et al., 2020; Szécsi & Szunomár, 2024).

DATA AND METHODOLOGY

Like previous studies that cover the empirical determinants of inclusive growth, our research is based on panel data. Our sample is primarily determined by the availability of data on income percentile distributions. By browsing the World Bank Poverty and Inequality Platform (World Bank, 2025a), one of the main sources of income distribution data, we identified 50 countries with relatively extensive coverage of income percentile distributions over time. This set of countries constitutes our basic sample. Given the established data-collection rules, these countries are mostly concentrated in Europe and the Americas. The first column of Table 1 lists these countries in alphabetical order.

Table 1. Countries in the sample

Countries in the basic sample (income-based distribution measure)	Countries added in the upgraded sample (consumption-based distribution sample)
Austria, Belgium, Bolivia, Brazil, Bulgaria, Canada, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, El Salvador, Estonia, Finland, France, Germany, Greece, Honduras, Hungary, Iceland, Ireland, Israel, Italy, Korea Republic, Latvia, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Panama, Paraguay, Peru, Poland, Portugal, Romania, Serbia, Slovenia, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay	Albania, Armenia, Belarus, China, Georgia, Indonesia, Iran, Kazakhstan, Kyrgyz Republic, Moldova, Russian Federation, Thailand, Turkey, Ukraine

Source: World Bank (2025a).

When it comes to the time dimension of our sample, we focus on the period from 2009 to 2021. We chose this time range in order to obtain the largest possible sample, given the availability of data across countries. The same time frame applies to the countries listed in the second column of Table 1, which we add in order to create our upgraded sample. Due to the established data-collection rules, these countries only have distribution data based on consumption.

Augmenting our sample with a consumption-based inclusive growth measure benefits us in two ways. First, it increases the number of possible observations in our sample from 650 to 832, which is not insignificant. Second, it helps us assess whether our estimated parameter values remain stable under different measurement rules. Data on income and consumption distributions provide the inputs that we include in equation (3) to obtain the relevant equity-adjusted income data for each country in a given year. The corresponding integration is carried out using Simpson's rule. Inclusive growth rates are then obtained by first-differencing the relevant log values of equity-adjusted income. Because inclusive growth in this framework is defined as the growth rate of equity-adjusted income, the latter remains the underlying level variable of conceptual interest throughout the analysis. For this reason, in addition to estimating models for inclusive growth rates, we also consider whether the explanatory variables display a clearer relationship with the level of equity-adjusted income itself. This allows us to distinguish between effects on the rate of change of equity-adjusted income and effects on its level.

The above discussion leaves us with the question of which variables should be chosen as independent variables, either as human capital proxies or as control variables. Given the limited scope of this paper, our choice of independent variables is guided by the results of the study by Mirestean and Tsangarides (2009). This study provides a valid benchmark, as it identifies robust growth determinants. These results are based on the implementation of the Limited Information Bayesian Model Averaging (LIBMA) approach, which is characterized by the inclusion of moment conditions in a more general Bayesian framework to account for a variety of issues, including dynamics and endogeneity. The variables identified as robust in that study, and which we therefore include in our analysis, are listed in Table 2.

Table 2. Independent variables

Human capital proxy variables	Control variables
Log(years of schooling) Life expectancy at birth (total)	Log(initial equity-adjusted income) Log[fixed capital formation (% of GDP)] Log(population growth) Log(inflation) Central government debt (% of GDP) Trade openness (% of GDP)

Source: Mirestean and Tsangarides (2009).

As can be seen, one of the variables identified as robust by Mirestean and Tsangarides (2009) is life expectancy at birth (total), which serves as our proxy for the health dimension of human capital. Another human capital proxy used by Mirestean and Tsangarides (2009) is mean years of schooling. Although it was not identified as robust by these authors, it is included in our study as the proxy for the education dimension of human capital. The other variables listed as robust growth determinants in Table 2 are incorporated as control variables. These include fixed capital formation (as a percentage of GDP), population growth, inflation, central government debt, and trade openness (Mirestean & Tsangarides, 2009). To account for the fact that our study deals with inclusive growth rather than standard GDP per capita growth, we include initial equity-adjusted income instead of initial GDP per capita that was identified as a robust growth determinant by Mirestean and Tsangarides (2009). This substitution is intended to preserve the logic of standard convergence specifications while adapting it to the Anand et al. (2013) framework: just as initial GDP per capita is used when the dependent variable is GDP per capita growth, initial equity-adjusted income is more appropriate when the dependent variable is inclusive growth, understood as the growth rate of equity-adjusted income. In other words, equity-adjusted income is the underlying level variable whose growth is being explained in our framework, and its initial value therefore plays the same conceptual role that initial GDP per capita plays in conventional growth regressions. This choice also ensures consistency between the definition of the dependent variable and the initial-condition variable used in the model, as relying on initial GDP per capita alone would capture only one dimension of the broader concept embodied in inclusive growth. We also follow Mirestean and Tsangarides (2009) in deciding which independent variables to transform into logarithmic form.

Unlike equity-adjusted income and its growth rate, data for each of our independent variables are readily and fully available from established data sources. The main source is the well-known World Development Indicators database (World Bank, 2025b), from which most of the data are drawn. The main exception is central government debt, for which the data are drawn from the International Monetary Fund's Global Debt Database (IMF, 2025a) and World Economic Outlook (IMF, 2025b). Data on mean years of schooling are taken from the United Nations Development Programme's Human Development Reports data center (United Nations Development Programme, n.d.).

Our goal in this paper is to make our coefficient estimates as robust as possible in light of model uncertainty. To do so, we employ the Bayesian Model Averaging (BMA) methodology. This approach considers a variety of models that may adequately capture the relationship between the dependent variable and the variables that affect it, thus addressing the issue of whether any particular specification chosen by researchers is in fact adequate (Hoeting et al., 1999; Koop, 2003).

The BMA approach is not based on simple averaging. Its building blocks are grounded in the Bayesian framework. This means that the starting point of any estimation is the choice of relevant priors. Since the approach is extended to explore different models, the prior choices include not only those for the coefficients of interest, but also those for the model space itself. In this paper, we opt for the following priors for the model and coefficient space, respectively:

1. **Uniform prior for model selection.** This prior assumes an equal probability for each possible model specification. Even though some proposals suggest penalizing specifications with a larger set of variables, our decision to limit the model space to a relatively small set of variables whose robustness has been established earlier prevents us from considering models with a very large number of regressors.
2. **Zellner's g-prior for coefficient estimation.** Besides mirroring decisions made in the earlier literature (Fernández et al., 2001; Ley & Steel, 2009; Moral-Benito, 2012), this prior choice allows us to vary and control several properties of the coefficients, including the level of prior informativeness.

These prior choices are the first step toward obtaining the estimates that we wish to report. Since we average across models, the situation is somewhat more complex. Having only eight potential regressors makes it much easier to resort to exhaustive enumeration instead of using sampling procedures such as the commonly used MC^3 algorithm.[2] Yet, there are other complex steps that need to be taken. One of the main ones is the calculation of the posterior inclusion probability (PIP_k) for each potential regressor in the model. The way to obtain it can be summarized by the following equation:

$$PIP_k = \sum_{j=1}^{J} \omega_j I_k(M_j) \tag{4}$$

Clearly, PIP_k represents a sum of posterior model probabilities (ω_j) weighted by the inclusion indicators $I_k(M_j)$ that are dummy variables taking the value 1 if the variable whose posterior inclusion probability is being considered is included in the given model. To obtain the relevant posterior model probabilities, we need to use the aforementioned model-selection prior and to calculate the relevant marginal model likelihoods. The calculation of the former requires us to obtain the within-model posterior coefficient distribution. This is achieved by applying Bayes' formula, which combines the coefficient priors with the corresponding marginal likelihoods of the coefficients. The final and crucial step involves calculating the model-averaged posterior mean and posterior standard deviation estimates using the following equations:

$$\bar{\beta}_k = \sum_{j=1}^{J} \omega_j \, \mu_{k|j} \tag{5}$$

$$\sqrt{V[\beta_k \mid \mathrm{y}]} = \sqrt{\sum_j \omega_j v_{k|j} + \sum_j \omega_j (\mu_{k|j} - \bar{\beta}_k)^2} \tag{6}$$

Equation (5) shows that the BMA posterior coefficient mean estimate ($\bar{\beta}_k$) equals the within-model posterior coefficient means averaged by the posterior model probabilities. Equation (6), on the other hand, identifies the BMA posterior coefficient standard deviation (which is the square root of the total variance) with the square root of the sum of the averaged within-model ($\sum_j \omega_j v_{k|j}$) and between-model variances ($\sum_j \omega_j (\mu_{k|j} - \bar{\beta}_k)^2$).

Our work in this paper does not end with the calculation of the BMA posterior coefficient mean and standard deviation estimates. The final step is the exploration of the two channels through

[2] More on this type of algorithm and its specific application to BMA can be found in Madigan & York (1995).

which human capital affects inclusive growth and equity-adjusted income. To do so, we first obtain the BMA posterior coefficient mean estimates of the effect of human capital on each of the two components of inclusive growth and equity-adjusted income, using the same set of independent variables listed in Table 2. We then proceed by applying the following type of structural channel decomposition, inspired by the growth-accounting approach (Barro & Sala-i-Martin, 2003):

$$\alpha = \frac{\bar{\beta}_{gdppcg}}{\bar{\beta}_{ig}}; \quad 1 - \alpha = \frac{\bar{\beta}_{ieig}}{\bar{\beta}_{ig}} \tag{7}$$

Clearly, $\bar{\beta}_{gdppcg}$, $\bar{\beta}_{ieig}$ and $\bar{\beta}_{ig}$ stand for the BMA posterior coefficient mean estimates of the effects of human capital on GDP per capita growth, income equity index growth, and their sum, respectively. The parameters α and $1-\alpha$, on the other hand, refer to the relative importance weights of the effect of human capital on two inclusive growth components. Even though they are not directly observable, these parameters are somewhat analogous to factor income shares in the growth-accounting approach. Their role is to reveal how the relevant channels transmit the effect of human capital to inclusive growth.

RESULTS AND DISCUSSION

Consider now what emerges when we apply the above methodology to our data. Before proceeding with the BMA estimation, we compute Pearson correlation coefficients for the variables included in our modeling procedure. The results of the correlation analysis for both the basic and the upgraded samples are reported in Table 3.

Table 3. Pearson correlation analysis for both samples

Variables	**Inclu-sive growth**	**Log(initial soc mob index)**	**Log(fixed cap form)**	**Log (yrs of schooling)**	**Life expectancy at birth**	**Log (pop growth)**	**Log (inflation)**	**Central government debt**	**Trade open-ness**
					Basic sample				
Inclusive growth	1								
Log(initi soc mob index)	-0.17	1							
Log(fixed cap form)	0.14	0.06	1						
Log(yrs of schooling)	-0.06	**0.79**	0.19	1					
Life expectancy at birth	-0.19	**0.83**	-0.01	0.53	1				
Log(pop growth)	-0.09	-0.02	0.11	-0.18	0.21	1			
Log(inflation)	0.08	-0.36	0.04	-0.33	-0.36	0.07			
Central government debt	-0.13	0.20	-0.52	-0.003	0.32	-0.09	-0.21	1	
Trade openness	0.10	0.37	0.13	0.33	0.16	0.01	-0.19	-0.16	1

Variables	**Inclu-sive growth**	**Log(initial soc mob index)**	**Log(fixed cap form)**	**Log (yrs of schooling)**	**Life expectancy at birth**	**Log (pop growth)**	**Log (inflation)**	**Central government debt**	**Trade open-ness**
Upgraded sample									
Inclusive growth	1								
Log(initial soc mob index)	-0.16	1							
Log(fixed cap form)	0.13	-0.11	1						
Log(yrs of schooling)	-0.07	**0.72**	0.04	1					
Life expectancy at birth	-0.175	**0.79**	-0.20	0.43	1				
Log(population growth)	-0.10	-0.05	0.18	-0.20	0.15	1			
Log(inflation)	0.03	-0.35	0.23	-0.22	0.45	0.07	1		
Central government debt	-0.14	0.24	-0.50	0.03	0.39	-0.09	-0.26	1	
Trade openness	0.09	0.37	0.05	0.32	0.20	-0.02	-0.20	-0.09	1

Source: Author`s calculations using Stata 19.

It is clear that the correlation coefficients are broadly similar across the two samples. This suggests that there should not be substantial parameter instability in the estimates. The main finding from the correlation analysis, however, concerns the existence of high pairwise correlations between initial equity-adjusted income and both of our human capital proxies. This means that including all three variables in the same specification would likely produce unreliable results. To avoid this issue, we perform auxiliary ordinary least squares (OLS) regressions of each human capital proxy on initial equity-adjusted income. The residuals from these regressions, which we use in our subsequent modeling, provide the variation in education or health that is not explained by initial equity-adjusted income. Interestingly, both regressions show significant effects of initial equity-adjusted income on both human capital proxies (full results are available upon request). The other independent variables do not warrant any modification, as they do not exhibit strong correlation patterns.

Table 4 reports the BMA results for both the basic and the upgraded sample. In both cases, a uniform model prior has been selected, along with Zellner's g-prior for the coefficient estimates. All calculations were performed using the Stata 19 software package. As some observations had to be discarded due to missing data, the last row reports the effective sample size, which is lower than the initial sample size in both samples.

Table 4. BMA estimation results on both samples (inclusive growth)

Dependent variable: inclusive growth	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP$_k$**	**Mean**	**St. dev.**	**PIP$_k$**
Log(initial soc mob index)	-1.343	0.255	0.99991	-1.145	0.228	0.99972
Log(fixed cap form)	3.122	1.600	0.86906	2.371	1.328	0.83661
Log(yrs of schooling) res	0.669	1.514	0.2098	0.023	0.307	0.043253
Life expectancy at birth res	0.001	0.026	0.050855	-0.000	0.016	0.4207
Log(population growth)	-1.071	1.070	0.57244	-1.891	0.882	0.89626
Log(inflation)	0.028	0.208	0.052996	-0.02	0.146	0.054621
Central government debt	0.000	0.002	0.0513	-0.001	0.003	0.084135
Trade openness	0.013	0.004	0.98407	0.012	0.004	0.98462
Constant	5.650	5.056	1	7.195	4.595	1
Effective sample size	546			667		

Source: Author`s calculations using Stata 19.

As expected, initial equity-adjusted income has been identified as the most robust determinant of inclusive growth in both samples. Echoing the convergence findings from economic growth studies, initial equity-adjusted income has been found to negatively affect the rate of inclusive growth. Fixed capital formation is somewhat less robust in terms of PIP, but it has a stronger positive posterior mean coefficient estimate. Among the other variables, only trade openness and population growth have PIP values above 50 percent. With a PIP consistently above 90 percent, trade openness has been identified as a positive determinant of inclusive growth, while population growth has been shown to negatively affect inclusive growth, albeit at a significantly lower level of robustness. Inflation and central government debt fail to show robust effects in either sample.

As for our human capital proxy variables, the BMA estimation does not reveal any robust effects of either the health or the education variable on inclusive growth. Yet, the effect of education is markedly stronger and positive in both samples, even surpassing a PIP value of 0.2 in the basic sample. The effect of health, however, hovers around zero in both samples, with strikingly low PIP values.

Even though our analysis does not reveal robust effects of the human capital variables on inclusive growth rates, our earlier correlation and regression analyses of the relationship between initial equity-adjusted income and the human capital proxies suggest that a more meaningful relationship may exist between these variables and equity-adjusted income in levels or logs. Because inclusive growth is defined in our framework as the growth rate of equity-adjusted income, examining the log of equity-adjusted income should be viewed as a complementary step within the same conceptual framework rather than as a departure from it. This allows us to assess whether human capital is more strongly associated with cross-country differences in the level of equity-adjusted income than with variation in its growth rate. For these reasons, we perform a BMA analysis using the log of equity-adjusted income as the dependent variable and the variables from Table 2, excluding initial equity-adjusted income, as the independent variables. The estimation results from this analysis are presented in Table 5.

Table 5. BMA estimation results on both samples (log of equity-adjusted income)

Dependent variable: log(equity-adjusted income)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.003	0.020	0.056983	0.000	0.014	0.040848
Log(yrs of schooling)	1.776	0.069	1	1.766	0.070	1
Log(life expectancy at birth)	7.589	0.266	1	7.194	0.282	1
Log(population growth)	-0.002	0.014	0.057241	-0.001	0.012	0.041163
Log(inflation)	0.051	0.062	0.4672	0.015	0.034	0.20716
Central government debt	0.000	0.000	0.056967	-0.000	0.000	0.35386
Trade openness	0.002	0.000	1	0.002	0.000	1
Constant	-27.879	1.152	1	-26.000	1.183	1
Effective sample size	596			748		

Source: Author`s calculations using Stata 19.

It is now quite clear that the BMA estimates for both samples show highly robust effects of both human capital proxies on the log of equity-adjusted income. Both proxies exhibit an almost certain probability of inclusion, as well as strong positive effects. Besides these, a robust positive effect is identified only in the case of trade openness. The other variables have PIP values below 50 percent, suggesting a lack of robustness. These findings generally indicate that the human capital variables have more of a long-term effect, particularly in explaining what distinguishes countries with high levels of equity-adjusted income from those with lower levels.

It is important to note that, in the above regression, we transformed the health variable into logarithmic form in order to obtain a comparable elasticity-based interpretation for both variables. This enables a more adequate structural channel decomposition of the effects of the different proxies. To perform such a decomposition, we first need to obtain coefficient estimates for the two variables that constitute equity-adjusted income. In Table 6, we begin with the log of GDP per capita as the first component of equity-adjusted income. To ensure comparability of results, we keep the same explanatory variables, in the same form, as those used in the BMA estimation reported in Table 5.

Table 6. BMA estimation results on both samples (log of GDP per capita)

Dependent variable: log(GDP per capita)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.001	0.013	0.04383	-0.258	0.062	0.9965
Log(yrs of schooling)	1.340	0.062	1	1.277	0.066	1
Log(life expectancy at birth)	7.011	0.237	1	7.512	0.247	1
Log(population growth)	0.002	0.014	0.060784	0.002	0.013	0.046286
Log(inflation)	0.096	0.058	0.81099	0.002	0.012	0.057401
Central government debt	-0.000	0.000	0.046447	-0.002	0.000	0.99959
Trade openness	0.002	0.000	1	0.001	0.000	0.99989
Constant	-23.693	1.026	1	-24.611	1.016	1
Effective sample size	616			780		

Source: Author`s calculations using Stata 19.

In line with other empirical growth studies (Barro, 2013; Bloom et al., 2004; Mankiw et al., 1992; Hanushek & Kimko, 2000), our findings reveal that the effects of both human capital proxy variables are positive, strong, and highly robust in both samples. The estimated effects of both human capital proxies are broadly similar to those from the equity-adjusted income analysis, suggesting that the effects of both variables on equity-adjusted income are transmitted primarily through the GDP per capita channel. This conclusion is further supported by the results of the BMA estimation using the log of the income equity index as the dependent variable. These results are reported in Table 7.

Table 7. BMA estimation results on both samples (log of income equity index)

Dependent variable: log(income equity index)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.085	0.028	0.96923	0.183	0.020	1
Log(yrs of schooling)	0.391	0.025	1	0.461	0.021	1
Log(life expectancy at birth)	0.696	0.097	1	-0.002	0.022	0.042766
Log(population growth)	-0.082	0.016	0.99997	-0.054	0.017	0.97189
Log(inflation)	-0.001	0.006	0.068702	0.040	0.011	0.98602
Central government debt	0.001	0.000	0.99751	0.001	0.000	1
Trade openness	0.001	0.000	1	0.001	0.000	1
Constant	-4.879	0.384	1	-2.409	0.126	1
Effective sample size	596			748		

Source: Author`s calculations using Stata 19.

Mirroring the results from the previous BMA analyses, these findings mostly show robust and positive effects of the human capital proxies on the income equity index. While the BMA analysis for GDP per capita revealed a much stronger effect of the health variable in both samples, the results for the income equity index are less unambiguous. The analysis performed on the basic sample reveals somewhat stronger effects of health, whereas the effects of health are virtually non-existent in the upgraded sample. Education, however, exhibits significantly more consistent estimation results across samples.

Given that we observed robust and positive effects of the human capital proxies in log rather than in growth regressions, we modify the structural channel decomposition equation (7) so that it refers to equity-adjusted income, GDP per capita, and the income equity index in the following manner:

$$\alpha = \frac{\bar{\beta}_{gdppc}}{\bar{\beta}_{eai}};\ 1 - \alpha = \frac{\bar{\beta}_{iei}}{\bar{\beta}_{eai}} \quad (8)$$

Here, $\bar{\beta}_{gdppc}$ and $\bar{\beta}_{iei}$ now stand for the BMA posterior coefficient mean estimates for the GDP per capita and the income equity index, respectively. $\bar{\beta}_{eai}$, by contrast, denotes the effect of the human capital proxies on equity-adjusted income, obtained by summing the effects of human capital on the two component variables. The parameters α and $1 - \alpha$ still refer to the relative importance weights of the effects of human capital on the two components of equity-adjusted income. Performing the structural channel decomposition using this formula yields the findings displayed in Table 8.

Table 8. Structural channel decomposition of human capital proxy effects

Proxies	Growth channels	Basic sample	Upgraded sample
Health	GDP per capita	90.97%	100%
	Income equity index	9.03%	0%
Education	GDP per capita	77.41%	73.48%
	Income equity index	22.59%	26.52%

Source: Author`s calculations using Stata 14.

The structural channel decomposition analysis unambiguously shows that the effect of human capital on equity-adjusted income is transmitted mostly through the GDP per capita channel, regardless of the proxy variable or sample chosen. The disproportionate nature of this transmission is much more evident in the case of the health proxy. In the basic sample, more than 90 percent of the effect of health on equity-adjusted income is transmitted through the GDP per capita channel. In the upgraded sample, this share rises to 100 percent, given that the effect of the health variable is not identified as robust in that case. Even though the estimated effects of the education variable are more nuanced, the GDP per capita channel dominates there as well. Its contribution ranges from around 73.5 percent in the upgraded sample to above 77 percent in the basic sample. This, however, still leaves some room for the redistributive effects of education, confirming the findings of earlier studies (Barro, 2000; De Gregorio & Lee, 2002).

It must be noted that the estimated total effects of the human capital proxies on equity-adjusted income reported in Table 5 do not exactly match the effects obtained by summing the separate estimates of their effects on GDP per capita and on the income equity index. These differences in estimates are shown in Table 9.

Table 9. Differences in estimated effects on the equity-adjusted income (absolute values)

Proxies	Basic sample	Upgraded sample
Health	0.118	0.318
Education	0.045	0.028

Source: Author`s calculations.

It can be seen that these differences are not large in magnitude, particularly in the case of the education proxy. In the case of both proxies, they may arise from a variety of factors, including noise resulting from differences in sample size and composition (Wooldridge, 2002). The larger absolute difference in the case of the health variable may be related to specific factors pertaining to health measurement in some countries, particularly the less developed ones included in the upgraded sample. The same factors may also explain the unexpectedly estimated zero effect of health on the income equity index in the upgraded sample. Investigating these issues is beyond the scope of this paper and represents a topic for further research.

CONCLUSION

In this paper, we furthered the empirical assessment of the determinants of inclusive growth using the concept developed by Anand and colleagues (2013). More specifically, we focused on estimating the effect of human capital proxies, namely the education and health dimensions, on inclusive growth, understood as the growth rate of equity-adjusted income, as well as on equity-adjusted income itself as the underlying level variable. This focus is reasonable, given that at least some human capital proxies have been found to be statistically significant contributors to both components of equity-adjusted income: real GDP per capita growth and income equity growth. To do so, we employed the Bayesian Model Averaging (BMA) approach.

Our findings show that both education and health exhibit robust and positive effects on equity-adjusted income as a log variable, while having no robust effect on inclusive growth rates as originally defined. Moreover, we conducted a structural decomposition of the effect of human capital on these two components in order to identify the primary transmission channel of that effect. We found that both human capital proxy variables primarily affect equity-adjusted income through the GDP per capita channel. In the case of health, the relative contribution rises above 90 percent, while in the case of education, it lies around 70–80 percent. This suggests that education also exerts a meaningful influence through the income equity index channel.

In this way, the paper addresses a specific gap in the literature. Although earlier research has identified human capital as an important determinant of inclusive growth, as well as of its growth and distributional components considered separately, it has not explicitly examined through which of these two channels the overall effect of human capital on equity-adjusted income is primarily transmitted. Nor has it clearly distinguished between effects on inclusive growth rates and effects on the underlying level variable itself. The main contribution of this study is therefore to provide such an assessment within a BMA framework, while also complementing it with a structural decomposition of effects. In doing so, the paper adds to the existing literature by showing that the influence of human capital on equity-adjusted income operates predominantly through the GDP per capita channel, while also indicating that education retains a non-negligible role through the income equity channel.

Even though our paper has produced interesting and insightful results, there are significant shortcomings and avenues for further research that should be pointed out. First of all, our measure of inclusive growth, championed by Anand et al. (2013), may need to be modified, particularly in order to account for certain normative considerations. In its current form, this measure allows morally problematic outcomes to be counted as instances of inclusive growth. A good example would be a case in which the two or three highest income deciles experience relatively significant gains, while some of the lowest deciles lose a relatively small amount of income. To address this issue, it may be necessary to refine the measure proposed by Anand et al. (2013) into a rank-weighted metric, as Donaldson and Weymark (1980) did for income inequality indices. It would be particularly relevant to examine whether the relative contribution values change as a result of introducing such rank-weighted metrics.

Furthermore, there is a need for a much more extensive treatment of model uncertainty, endogeneity, and dynamics. Even though the incorporation of the BMA approach addresses model uncertainty to a certain extent, a much wider set of variables, made feasible by model-sampling techniques, should be considered in order to confront model-uncertainty issues more fully. In the context of endogeneity and dynamics, it would be preferable to apply the LIBMA methodology directly to our chosen set of variables. Resorting to control variables that have been established as robust growth determinants by earlier research is a decent initial step, but more is needed, particularly since inclusive growth is much more than mere GDP per capita growth.

Finally, future research should focus on policies aimed at strengthening those dimensions of human capital that are most conducive to improvements in equity-adjusted income and, more broadly, inclusive growth. One such policy could involve increasing public expenditure on education (Tomić, 2015), while simultaneously placing greater emphasis on the efficient allocation of resources. It is highly likely that, without an appropriately designed and implemented policy framework, the transition toward a high-human-capital environment would become considerably more difficult and uncertain.

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ORIGINA SCIENTIFIC PAPER

An Empirical Analysis of Supply and Demand Determinants of Global Oil Prices: The Role of OPEC

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ABSTRACT

This paper examines the key determinants influencing global oil prices from both supply and demand perspectives, including structural and shock-related factors such as the COVID-19 pandemic. Particular emphasis is placed on the influence of OPEC production quotas, non-OPEC production volumes, trade openness, industrial production, and shock-related factors such as the pandemic and major geopolitical events. The analysis covers the period from 2000 to 2023 and applies multiple linear regression, including OLS, Newey-West, and Bootstrap techniques, to test three primary hypotheses concerning the relationship between oil prices and these explanatory variables. The results reveal that a one percent reduction in OPEC quotas leads to a 1.59 percent increase in global oil prices, confirming the organization's significant influence on the supply side. Additionally, the findings show that a one percent increase in global industrial production results in a 12.06 percent price increase, underscoring the strong link between economic activity and oil demand. Conversely, greater trade openness is associated with lower oil prices; specifically, a one percent increase in openness correlates with a 1.62 percent price decrease, likely due to enhanced competition and greater supply efficiency. The COVID-19 variable was also found to have a statistically significant and negative effect on oil prices during the crisis period. These relationships are statistically significant and robust across all model specifications. In contrast, the variable representing non-OPEC production volumes yields a statistically significant positive effect only in the OLS and Newey-West models, while turning statistically insignificant in both Bootstrap models, highlighting potential sensitivity to distributional assumptions and underlying structural heterogeneity. Additionally, the 2001 geopolitical shift, included as a structural dummy variable, did not show statistical significance, suggesting that global oil markets may have absorbed its impact without lasting price disruption.

Keywords: *OPEC quotas, global oil prices, trade openness, COVID-19 shock, oil market concentration, Herfindahl-Hirschman Index (HHI), oil supply and demand*

JEL Classification: Q41, Q43, Q48, F14

INTRODUCTION

Oil remains one of the most strategically important commodities in the modern global economy, with a historical legacy dating back to the second half of the 19th century. The first commercial oil drilling, conducted in 1859 in Titusville, Pennsylvania (USA), marked the beginning of the modern oil industry. By the turn of the 20th century, Standard Oil, founded by John D. Rockefeller, had established a near-monopoly over oil production, refining, and distribution in the United States, embedding oil deeply within the foundations of industrial and economic development. In the mid-

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20th century, the discovery of vast oil reserves in the Middle East shifted the epicenter of global oil production. In 1960, five major oil-producing countries, Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela, established the Organization of the Petroleum Exporting Countries (OPEC). The aim of OPEC was to coordinate petroleum policies among its member states in order to stabilize markets and secure fair and stable revenues for producers. OPEC's influence became globally visible during the oil crises of the 1970s, when it used production limits as a strategic tool, leading to steep increases in oil prices. As noted by Yergin (1991), "the energy shocks of the 1970s were the first global reminder that the 20th-century economy was still powered by a 19th-century fuel." While the 1970s marked the emergence of oil as a geopolitical instrument, the early 21st century illustrated its deeper integration into global financial systems. During the mid-2000s super-cycle, oil exporters accumulated unprecedented surpluses. Balaban et al. (2013) note that these windfalls were "placed through investment funds," primarily sovereign-wealth vehicles investing in U.S. assets. Such petrodollar recycling amplified global leverage; consequently, when the 2008 financial crisis struck, the reversal in risk appetite collapsed oil demand and prices well ahead of OPEC's announced output curbs. The chain of events confirms that liquidity effects can reinforce, and sometimes outpace, supply-side interventions.

In the contemporary era, oil markets are shaped by the complex interplay of globalized consumption and production. Major consumers like the United States, China, India, and the European Union drive demand, while producers, both inside and outside OPEC, compete to maintain market share. At the same time, the world is increasingly focused on the challenges of climate change and energy transition, promoting the development of renewable energy sources and technologies aimed at reducing carbon emissions. Although oil remains central to the global economy, there is a growing emphasis on sustainability, efficiency, and diversification. Oil price volatility has been further complicated by technological advancements, geopolitical risks, and global economic shocks, most notably the COVID-19 pandemic. The global lockdowns in 2020 triggered an unprecedented collapse in industrial activity and oil demand, resulting in record-low and even negative oil prices. COVID-19 did not merely interrupt supply; it severely hit external demand and prices of export commodities (Bodroža & Lazić, 2021), including crude oil. For economies deeply embedded in global trade networks, the shock was immediate: "Economies with higher levels of trade integration are particularly exposed to reduced global demand and distortions in global supply chains" (Stanceva Gigov, 2020). This explains why the 2020 demand collapse magnified the price impact of OPEC's supply cuts, sending Brent and WTI to historic lows. In April 2020, WTI futures briefly traded below zero, illustrating the severe market imbalance. Amid these dynamics, OPEC and its expanded coalition OPEC+, which includes Russia and other non-member producers (since 2016), continue to play a decisive role in global supply coordination. Their joint production agreements have become crucial mechanisms for stabilizing prices and balancing global supply and demand. Studying OPEC's influence, alongside other economic and structural factors, is essential for policymakers, analysts, and scholars seeking to understand the price-setting mechanisms in global oil markets.

Existing research leaves several critical questions unanswered. Most empirical studies still treat OPEC as a single actor and exclude the post-2016 OPEC plus era, so it remains unclear whether formal quota decisions continue to dominate prices once large non-OPEC producers such as Russia participate in coordinated agreements. Global GDP is commonly used as a proxy for demand, although industrial production is the energy-intensive component most directly linked to oil use; very few papers include an explicit industrial-activity measure, and virtually none test its explanatory power during the shale revolution or the recent expansion of emerging-market consumption. Much of the literature ends in 2019, failing to capture the unprecedented supply-demand decoupling caused by COVID-19 or the episode of negative WTI prices in April 2020. In addition, recent work rarely measures how the competitive landscape among producers has changed; the Herfindahl–Hirschman Index, a standard in competition analysis, has seldom been applied to crude-oil supply in the last decade, leaving the link between shifting market concentration and price dynamics opaque.

This study addresses those gaps by disentangling the influence of formal OPEC quotas from the production behavior of non-OPEC suppliers, incorporating global industrial production, introducing a COVID-19 dummy to isolate the 2020 shock, and calculating the annual Herfindahl-Hirschman Index for crude-oil supply to document changes in market concentration. The HHI is analyzed descriptively rather than entered as a regressor. Together, these elements permit the first unified assessment of coordinated supply actions, competitive production, refined demand pressures, unprecedented shocks, and structural market power across the years 2000 to 2023, a period that captures the shale boom and the pandemic disruption. The main objective of the thesis is to identify and empirically quantify the key determinants of global oil prices over that period, with particular attention to OPEC production quotas, non-OPEC output, industrial activity, trade openness, and major global shocks, including the 2001 geopolitical shift and the COVID-19 pandemic. A multiple linear-regression framework is employed in which the dependent variable is the equally weighted average price of WTI, Brent, and Dubai crude. Explanatory variables comprise OPEC quotas, non-OPEC production, global industrial production (as a share of GDP), oil-trade openness, Global Shock 2001 and a COVID-19 dummy capturing short-term demand-side disruptions in 2001 and 2002. A synthetic variable for the 2008–2009 global financial crisis was deliberately excluded in order to isolate and better observe the statistical significance and magnitude of the COVID-19 shock, which constitutes the primary contemporary disruption under examination in this study. According to Tomić et al. (2021), the economic consequences of the COVID-19 pandemic triggered a global recession whose severity exceeded even that of the two World Wars and the Great Depression of the 20th century. For this reason, the model focuses exclusively on capturing the effects of the COVID-19 crisis through a dedicated dummy variable. Data are drawn from OPEC, the International Energy Agency (IEA), the U.S. Energy Information Administration (EIA), the World Bank, and the Federal Reserve Economic Data (FRED).

This study contributes to the existing literature by combining the effects of OPEC's cartel policies, macroeconomic demand factors, and global disruptions into a unified analytical framework. Additionally, the paper evaluates market concentration through the Herfindahl-Hirschman Index, offering insights into the evolution of competition among oil producers during the studied period.

LITERATURE REVIEW

The analysis of oil prices, as a key global energy resource, presents a complex research challenge due to the multitude of international and macroeconomic determinants influencing them. Previous empirical studies have employed various approaches and methodologies to understand the causes and consequences of oil price fluctuations. One major research direction focuses on the impact of global economic factors. For instance, Albaity and Mustafa (2018) investigated the effect of exchange rates, gold prices, and stock indices on oil prices in GCC countries using panel data methods. Similarly, Alredany (2018) and Chatziantoniou et al. (2021) explored the role of OPEC quotas and financial variables in determining global oil prices.

Production quotas are the primary lever through which the Organization of the Petroleum Exporting Countries shapes the global oil market. Their influence travels along two routes. First, by adjusting current supply, quotas affect the physical balance of the market. Second, they work indirectly through the macro-financial cycles of member states. Behnam (2011) provides evidence for this second channel in a panel study of 21 Middle-Eastern economies, noting that "oil extraction has a positive effect on foreign direct-investment attraction and economic growth." Larger inflows of foreign direct investment and faster GDP growth widen the fiscal space of oil-exporting governments, allowing them to finance the maintenance or expansion of upstream capacity. OPEC quotas, therefore, function not only as an immediate supply switch but also as a seedbed for future production. Because of that dual role, member states regularly revisit their quotas to preserve cartel discipline and stabilize prices (Baumeister and Peersman, 2012). Limiting output helps OPEC defend market share and protect revenue objectives (Mercure et al., 2021). At the same time, the formal quota system raises internal transaction costs, a problem observed since its introduction in 1982 (Smith, 2005). Verleger (1982) underlines the centrality of quotas, showing that spot-market prices serve as the benchmark for official OPEC postings, with quota allocations mediating the pass-through. Several empirical studies sharpen this picture. Alhajji and Huettner (2000), using a structural simultaneous-equations model for 1973–1994, find that OECD income and U.S. price controls push prices up, while higher non-OPEC costs and OPEC user costs pull them down. Bremond, Hache and Joëts (2012) employ cointegration and Granger causality tests covering 1973–2009 and show that OPEC's influence weakened after the counter-oil-shock years, shifting from dominant price setter to price taker. Smith (2005), combining standard and novel statistical tests, still detects cooperative behaviour but again highlights the quota-related transaction-cost burden. Verleger's analysis of 1975–1980 data indicates that Rotterdam spot prices drive official postings with a lag, whereas transport and refining costs have a negative effect. A broader literature supports and refines these findings. Guidi et al. (2006) link OPEC decisions to swings in both oil and equity prices. Bina and Vo (2007) trace the dynamic price response to OPEC policy between 1983 and 2005. Kisswani (2011) examines price formation through extraction volumes, Ibrahim and Omoteso (2022) analyze the effects of quota cheating on price stability, and Horan et al. (2004) investigate volatility transmission to futures markets. Across these studies, exchange rates, financial speculation and geopolitical shocks consistently appear as key price drivers alongside quotas and production costs. Together, the literature confirms that OPEC remains central to price formation, though its influence evolves over time and across economic contexts. Important research gaps persist, including the long-term impact of climate policy and the energy transition, the effect of technological change on demand elasticity and the role of governance in oil-rich states. Addressing these issues would deepen our understanding of how production control, market openness and exogenous shocks jointly shape oil prices in the years ahead.

Methodological approaches in the oil-price literature vary widely, from classical regression and principal-component analysis to more flexible frameworks such as time-varying parameter VAR and ARDL models. Albaity and Mustafa (2018) applied Pedroni cointegration tests and Dumitrescu-Hurlin causality tests to examine the link between oil prices and macroeconomic indicators across GCC countries from 2005 to 2015, reporting significant positive relationships with exchange rates, gold prices and stock indices. Alredany (2018) combined regression analysis with principal-component analysis for the period 1986-2010 and found that both OPEC quotas and the number of active drilling rigs exert a strong upward influence on crude-oil prices, whereas a dummy variable for the Gulf War has the opposite effect. Chatziantoniou et al. (2021) employed a time-varying parameter VAR covering 1990-2019 and concluded that financial factors dominate fundamental ones in explaining oil-price volatility. Chevillon and Rifflart (2009), using an error-correction model for 1989-2005, showed that OPEC quotas push prices higher, while OECD inventories pull them lower. Cologni and Manera (2011) relied on a partial-equilibrium model to study small exporting countries between 1995 and 2010; their results indicate that global oil demand shapes production decisions, whereas real-price changes are statistically insignificant. Diaz-Rainey et al. (2017) investigated speculative activity in physical markets with Bai–Perron structural-break tests, finding that inventories depress prices before a speculative phase and lift them during it. Dutta et al. (2020) employed a DCC-GARCH model during the COVID-19 period to analyse the relationship between oil, gold and Bitcoin, highlighting gold's safe-haven role. Liu et al. (2016), using a structural VAR with sign restrictions, attributed about 70 percent of price variation to demand from China and the United States. Madathil et al. (2021) linked oil prices with governance quality and corruption in oil-rich economies from 2000 to 2019, showing that higher prices coincide with both rising GDP and increased corruption. Ozcan (2015) examined oil demand in twenty OECD countries for 1980-2011 and reported positive income elasticity alongside negative price elasticity. Ben Salem et al. (2022) applied ARDL and NARDL models to daily data for 2003-2021, finding that gold prices and futures support higher oil prices, whereas the US dollar index and COVID-19 case counts push them lower. Collectively, these studies underscore the multifaceted drivers of oil-price dynamics. Exchange rates, OPEC quotas and financial speculation consistently emerge as significant determinants, while political uncertainty and financial-market variables also play an important role. Despite this breadth, the long-run implications of climate policy, renewable-energy transitions and innovation in oil-consuming industries remain understudied. Future research would benefit from examining institutional quality, governance and corruption to gain a fuller understanding of oil-price behaviour in resource-dependent economies.

RESEARCH HYPOTHESES

This study investigates three central hypotheses, focusing on the most recent data from the period 2000 to 2023. The selection of this timeframe was motivated by the aim to base the analysis on up-to-date and policy-relevant insights, including the impact of the COVID-19 pandemic. Employing this contemporary scope enables the examination of the latest trends and structural changes in the global oil market, thereby enhancing the relevance of the findings for decision-makers in the fields of resource management and economic energy policy.

Drawing on a thorough review of the relevant literature, the study formulates three hypotheses addressing key factors that influence global oil prices. The first hypothesis examines the effect of OPEC production quotas on oil price formation. The second hypothesis explores the relationship between growth in industrial production and GDP of leading global economies and oil price dynamics. The third hypothesis assesses whether a higher degree of liberalization in the global oil market contributes to lowering international oil prices. Each hypothesis is elaborated below.

H1: Reductions in production quotas set by OPEC have a statistically significant and positive impact on global oil prices

OPEC's production quotas are a pivotal instrument in shaping global oil prices. Acting as a coordinated supply-side mechanism, quotas allow OPEC to reduce overall market supply, thereby increasing prices in accordance with the law of supply and demand. By restricting output, OPEC mitigates oversupply and price collapses, reinforcing its role as a stabilizing force in the oil market. Historically, decisions to reduce production have often been followed by sharp price increases, while expansions of quotas have resulted in falling prices, confirming the theoretical expectations of cartel behavior in oligopolistic markets. This dynamic underscores the relevance of quota policies not only for OPEC members' fiscal stability but also for broader global energy security. Stable oil prices foster greater certainty in national budget planning and long-term energy investment, particularly in the development of alternative energy sources.

H2: Increases in industrial production and GDP growth in major global economies have a statistically significant and positive impact on global oil prices.

The expansion of industrial output and GDP in major world economies leads to a significant increase in global oil demand, which in turn drives up oil prices. This relationship is rooted in the fact that economic growth amplifies demand for energy across sectors such as manufacturing, transportation, and logistics. In partial equilibrium models, where demand surges against a relatively inelastic short-term oil supply, the result is upward pressure on prices. Industrialized economies, such as the United States, China, and the European Union, which are key global oil consumers, drive this demand, making their economic trajectories crucial for understanding oil price trends. While global GDP includes many smaller economies with limited oil demand, the focus on leading economies is justified by their dominant role in global energy consumption and their disproportionate influence on price formation in international oil markets.

H3: A higher level of liberalization in international oil trade has a statistically significant impact on reducing global oil prices.

The third hypothesis is grounded in the principles of international trade and market competition theory. Greater market openness through the reduction or elimination of trade barriers such as tariffs and quotas facilitates the free flow of oil, increases global supply, and stimulates competition. Liberalized oil markets reduce monopolistic constraints and improve allocation efficiency. As more producers enter the market and barriers are removed, operational and logistical costs decline, leading to more competitive pricing. According to economic theory, an increase in competition and supply should result in lower prices, assuming demand does not outpace the supply increase. Moreover, liberalization curtails the ability of dominant firms or cartels to manipulate market conditions, resulting in more stable and affordable energy prices for consumers and industries, while also encouraging broader economic growth.

To empirically test the proposed hypotheses, the study relies on data from publicly available and authoritative databases. Oil price data were obtained from the U.S. Energy Information Administration and the Federal Reserve Economic Data. Production quotas and market concentration data (measured by the Herfindahl-Hirschman Index) were sourced from the Organization of the Petroleum Exporting Countries. Indicators related to industrial production as a share of GDP, as well as oil trade openness, were collected from the World Bank database. This multi-source approach ensures a comprehensive and reliable dataset for capturing the key drivers of global oil market dynamics.

GLOBAL OIL PRICE MODEL

This section defines the analytical framework used to model global oil prices, aiming to elucidate the complex interactions among supply-side, demand-side, and geopolitical factors that influence price formation in international oil markets. Based on a comprehensive review of existing literature, the study identifies the key variables frequently employed in global oil pricing models and the methodological approaches used to assess their impact. The variables affecting oil prices are commonly categorized into three groups: oil supply, oil demand, and geopolitical factors.

The supply side is primarily shaped by global oil production, which encompasses output from both OPEC and non-OPEC countries. A critical instrument in this context is the set of production quotas imposed by OPEC, which serve as a regulatory mechanism for market supply. Additionally, international trade liberalization can significantly influence the supply side. Higher degrees of trade openness allow for greater oil flow across borders, increasing global supply and potentially reducing prices. The demand side is closely tied to global economic growth, especially the gross domestic product of major economies such as the United States, China, and the European Union. As these economies expand, their demand for energy, including oil, rises due to increased industrial production, transportation needs, and other oil-dependent sectors. Industrial activity, therefore, serves as a strong proxy for global oil demand. Geopolitical factors also exert considerable influence over oil prices. OPEC's decisions on production quotas made during regular meetings can cause immediate shifts in oil prices. These interventions often aim to balance supply and demand and stabilize markets, though they may also lead to price increases depending on whether production is cut or raised.

In this model, the dependent variable is defined as the average global oil price, calculated as the arithmetic mean of three benchmark indices: West Texas Intermediate (WTI), Brent, and Dubai. This composite variable allows for a balanced representation of global price movements while mitigating regional biases inherent in any single index. WTI reflects U.S. market dynamics, Brent is the primary reference for European trade, and Dubai serves as a key price point for Middle Eastern crude. By averaging the three, the model ensures a more comprehensive analysis of global oil pricing trends.

The independent variables are structured to capture both supply-side and demand-side influences. These variables were carefully selected to reflect key macroeconomic, trade-related, and exogenous shocks affecting oil markets. The variables are defined as follows:

1. **OPEC Quotas:** This supply-side variable captures oil production levels of OPEC member states. It is measured in thousands of barrels per day (1,000 b/d), as reported in the official OPEC data. Changes in quotas are expected to have a direct impact on global supply, and thus on oil prices.
2. **Non-OPEC Production:** Also on the supply side, this variable reflects oil production from countries outside of OPEC. It is measured in thousands of barrels per day (1,000 b/d), in line with international energy reporting standards. Variations in their output affect global supply levels and oil price movements.
3. **Industrial Production:** Positioned on the demand side, this variable reflects the level of industrial activity worldwide, measured as industry (including construction), value added as a percentage of GDP. As production rises, so does the demand for energy, exerting upward pressure on prices.
4. **Market Openness:** This supply-side indicator measures oil-market openness, calculated as the sum of crude oil imports and exports, measured in thousands of barrels per day (1,000 b/d), and divided by gross domestic product (in constant 2015 US dollars). A higher ratio signals a more liberalized oil trade regime, widening access to international supply channels and thereby exerting downward pressure on prices.
5. **Global Shock 2001:** This demand-side dummy variable captures the immediate and short-term effects of the geopolitical and economic uncertainty following the 9/11 attacks in 2001. The aftermath of the terrorist attacks led to heightened risk aversion, reduced global economic activity, and disruptions in transportation, all of which negatively influenced oil demand and, consequently, oil prices. The variable takes the value of 1 for the years 2001 and 2002, reflecting the period of greatest economic disruption and uncertainty.
6. **COVID-19 Dummy:** This demand-side variable captures the economic shock caused by the COVID-19 pandemic. The years 2020 and 2021 were marked by steep declines in industrial activity and transportation, resulting in a drastic drop in oil demand and prices. The variable takes the value of 1 for the years 2020 and 2021, and 0 otherwise, to reflect the period of most severe pandemic-induced disruption.

In this study, the Herfindahl-Hirschman Index was calculated for global oil production as a means of assessing market concentration and the degree of competition among oil producers. The HHI is a widely used metric in industrial organization and competition policy, providing a quantitative measure of market structure. A higher HHI value indicates a greater level of concentration and thus lower competition, whereas a lower HHI value reflects more diversified and competitive market conditions. By employing the HHI, the study examines how market concentration influences oil prices and how monopolistic or oligopolistic structures may contribute to price fluctuations. In oil markets, where supply is often dominated by a limited number of key producers, understanding the level of concentration is essential for identifying potential market power and related risks. According to Herfindahl and Hirschman (1950), the HHI is calculated as the sum of the squares of the market shares of all firms within the industry. It is particularly useful in evaluating both structural dominance and competitive balance within sectors such as the oil industry. The HHI ranges from 0 to 10,000: Values closer to 0 indicate a highly competitive and diversified market, and Values closer to 10,000 suggest a highly concentrated market, potentially dominated by a few large producers.

Mathematical Expression of HHI:

$$HHI = \sum_{i=1}^{n} s_i^2 \qquad (1)$$

Where:
- s_i = market share of firm iii (expressed as a decimal or percentage),
- n= total number of firms in the industry.

The application of the HHI in this research provides valuable insights into the structural characteristics of the global oil market and supports the analysis of how concentration levels may affect oil price behavior and volatility, especially under conditions of supply shocks or coordinated production limits by dominant producers such as OPEC.

RESULTS

Before presenting the research results, the following table provides the calculated Herfindahl-Hirschman Index for global oil production, illustrating the level of market concentration and competition among producers.

Table 1. HHI of Global Oil Production

HHI All countries		HHI OPEC		HHI OPEC+	
2000	535.254	2000	1947.556	2000	3754.732
2001	541.127	2001	1542.56	2001	2966.685
2002	541.606	2002	1420.442	2002	2924.852
2003	572.547	2003	1508.964	2003	3062.587
2004	572.176	2004	1623.611	2004	3246.608
2005	582.430	2005	1671.513	2005	3316.055
2006	580.364	2006	1681.548	2006	3384.751
2007	577.493	2007	1655.257	2007	3387.745
2008	579.291	2008	1694.927	2008	3405.609
2009	580.870	2009	1587.89	2009	3345.682
2010	583.394	2010	1590.151	2010	3353.293
2011	622.996	2011	1621.894	2011	3323.527
2012	635.087	2012	1719.196	2012	3409.627
2013	654.289	2013	1664.406	2013	3330.146
2014	681.73	2014	1598.658	2014	3184.756
2015	697.678	2015	1620.556	2015	3155.531
2016	705.596	2016	1708.074	2016	3288.096
2017	708.490	2017	1701.088	2017	3273.853
2018	754.270	2018	1673.056	2018	3182.951
2019	793.731	2019	1603.901	2019	3047.485
2020	799.883	2020	1500.486	2020	2875.607
2021	793.459	2021	1546.35	2021	2954.567
2022	824.385	2022	1615.595	2022	2970.833
2023	822.316	2023	1574.227	2023	2894.855

Source: Author's calculation

The table above presents an overview of the Herfindahl-Hirschman Index for global oil production from 2000 to 2023, with a particular focus on three categories: all countries, OPEC, and OPEC+. The HHI values for all countries show a gradual increase over time, indicating a slight rise in market concentration within the global oil industry. At the beginning of the observed period, the HHI stood at 535.254, rising to 822.316 by 2023. Although this trend suggests a growing concentration, the values remain below the threshold of 1,500, which, according to industry standards, corresponds to a low to moderately concentrated market. In the case of OPEC, the HHI values show a notable decline, dropping from 1,947.556 in 2000 to 1,574.227 in 2023. This decline indicates a reduction in internal concentration within OPEC, suggesting that production may be becoming more evenly distributed among its member states. While OPEC continues to play a pivotal role in the global oil market, these figures imply a less concentrated internal structure over time.

As for OPEC+, the HHI values remain high throughout the entire period, reflecting a more concentrated structure among these countries. Although the concentration decreased from 3,754.732 in 2000 to 2,894.855 in 2023, OPEC+ still exhibits substantially higher levels of concentration compared to the other two categories. This indicates that a small number of leading OPEC+ producers continue to dominate global oil production, maintaining a strong influence over global supply dynamics. The data suggest that the global oil industry remains relatively competitive, despite a mild increase in concentration. The reduction in HHI values within OPEC and OPEC+ also points to the growing role of non-member producers, contributing to a more diverse global oil supply landscape.

These shifts in concentration do more than describe the market; they raise the central empirical question of the study. If production is becoming less concentrated inside OPEC and OPEC+, yet remains moderately concentrated worldwide, can such structural changes, together with other forces on the supply and demand sides, move the average world oil price? To investigate this link, the research puts forward a series of testable hypotheses and estimates a multiple regression model that includes the main explanatory variables. Each hypothesis is evaluated by examining the statistical significance and the sign of its coefficient. Before turning to the results, Table 2 presents descriptive statistics for every variable in the model, showing their means, standard deviations, minima, and maxima; this snapshot clarifies the structure of the data used in the empirical analysis.

Table 2. Descriptive Statistics of Variables

Variable	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Average reference oil price	24	4.068	0.466	3.194	4.653
OPEC quotas	24	10.233	0.072	10.057	10.333
non-OPEC production volumes	24	9.654	0.084	9.406	9.723
Market openness	24	-15.898	0.168	-16.171	-15.639
Industrial production	24	3.297	0.024	3.257	3.334
COVID-19 (dummy variable)	24	0.083	0.282	0	1
Global Shift 2001	24	0.083	0.282	0	1

Source: Author's calculation

The hypotheses formulated in this research were tested using a multiple regression model that incorporates key supply-side and demand-side variables affecting the average global oil price. Hypothesis testing was conducted by evaluating the statistical significance of the regression coefficients and the direction of influence of each independent variable on the dependent variable. Before presenting the detailed hypothesis testing results, the descriptive statistics of the main variables used in the model are provided below. These statistics offer an overview of the data characteristics, including mean, standard deviation, minimum, and maximum values for each variable, thereby enabling a better understanding of the underlying structure and distribution of the dataset used in the empirical analysis.

Logarithmic transformations were applied in the model to establish a more linear relationship between the dependent and independent variables, thereby enhancing the model's interpretability and statistical robustness. This transformation reduces the variability of the data, mitigates the influence of outliers, and allows the estimated coefficients to be interpreted as elasticities, i.e., percentage changes. In doing so, the model provides clearer insights into the nature and strength of relationships between variables, an essential component of sound economic analysis and informed policy-making.

After examining the basic descriptive characteristics of the dataset, the study proceeds with the analysis of a multiple linear regression model. The general form of the model is presented as follows:

$$ln(Average\ Oil\ Price)_t = \alpha + \beta_1 ln(OPECQ_t) + \beta_2 ln(NONOPEC_t) + \beta_3 ln(OPEN_t) + \beta_4 ln(IND_t) + \delta_1 GS2001_t + \delta_2 COVID_t + \varepsilon_t \quad (2)$$

Where:

- $ln(Average\ Oil\ Price)_t$ is the log-transformed dependent variable, representing the average benchmark price based on WTI, Brent, and Dubai indices.
- α is the intercept (constant term).
- $ln(OPECQ_t)$ is natural log of OPEC production quotas (thousands of barrels per day); β_1 is its elasticity.
- $ln(NONOPEC_t)$ is natural log of global crude oil production outside OPEC (thousands of barrels per day); β_2 is the corresponding elasticity.
- $ln(OPEN_t)$ is natural log of the global oil-trade openness ratio, defined as (world crude oil imports + world crude oil exports /world GDP); β_3 is its elasticity.
- $ln(IND_t)$ is natural log of global industrial production, measured as an index of world industrial output; β_4 is its elasticity.
- $GS2001_t$ is dummy variable equal to 1 in 2001–2002, 0 otherwise; δ_1 is its semi-elasticity.
- $COVID_t$ is dummy variable equal to 1 in 2020–2021, 0 otherwise; δ_2 is its semi-elasticity.
- ε_t is error term.

Based on the model specified above, econometric estimation was performed. The estimated coefficients, their standard errors and the tests of overall model significance (F-statistic and robust Wald test) are reported in Table 3.

Table 3. Estimated Regression Model with Oil Price as the Dependent Variable

Dependent Variable: Average Oil Price				
Variables	**OLS**	**Newey-West**	**Bootstrap (Replications 3,070)**	**Bootstrap (Replications 2,314)**
OPEC Quotas	**-1.592* (.762)**	**-1.592* (.729)**	**-1.592* (.804)**	**-1.592* (.804)**
non-OPEC production volumes	**2.308*** (.546)**	**2.308*** (.593)**	2.308 (1.403)	2.308 (1.500)
Market Openness	**-1.625*** (.243)**	**-1.625*** (.339)**	**-1.625*** (.353)**	**-1.625*** (.348)**
Industrial Production	**12.062*** (1.463)**	**12.062*** (1.367)**	**12.062*** (1.648)**	**12.062*** (1.658)**
COVID-19	**-0.369** (.156)**	**-0.369* (.181)**	**-0.369* (.208)**	**-0.369* (.207)**

Dependent Variable: Average Oil Price				
Global Shift 2001	-0.181 (.153)	-0.181 (.140)	-0.181 (.290)	-0.181 (.302)
Number of Observations	**24**	**24**	**24**	**24**
F-statistic	**35.77 (p < 0.001)**	**144.75 (p < 0.001)**	**Wald chi2(6) = 387.94 (p < 0.001)**	**Wald chi2(6) = 371.92 (p < 0.001)**
VIF	**2.12**			

Source: Author's calculation

*Note: Coefficients marked with *** (p < 0.01) are statistically significant at the 1% level, ** (p < 0.05) at the 5% level, and * (p < 0.10) at the 10% level. Standard errors are shown in parentheses.*

To validate the assumptions of the regression model, several diagnostic tests were conducted. The Durbin-Watson test suggested a potential presence of positive autocorrelation (d = 1.27), while the Breusch-Pagan test (p = 0.944) and the Skewness/Kurtosis normality test (p = 0.424) confirmed the absence of heteroskedasticity and non-normality of residuals. In response to the presence of autocorrelation, a Newey-West estimator was employed to obtain robust standard errors. Furthermore, Bootstrap methods with 3,070 and 2,314 replications were used to strengthen the robustness of inference, particularly given the small sample size and to account for possible distributional concerns. The results remained largely consistent across all specifications, confirming the overall stability and robustness of the estimated coefficients. However, it is noteworthy that the coefficient for non-OPEC production volumes, while statistically significant in the OLS and Newey-West models, loses significance under the Bootstrap estimators, which may indicate sensitivity to sampling variability for this particular variable. Accordingly, overall model adequacy is evaluated using the F-statistic and the robust Wald test, both of which indicate strong joint significance. This stability is confirmed across the Ordinary Least Squares, Newey-West adjusted regression, and both bootstrap specifications. The high and statistically significant F-statistics and Wald chi-square values across all versions of the model further reinforce the robustness and reliability of the estimated coefficients. Multicollinearity is not considered a significant concern in this model, as the mean variance inflation factor (VIF) is 2.12, well below the commonly accepted threshold of 5. This indicates that linear dependencies among the explanatory variables are limited and do not materially distort the estimated coefficients.

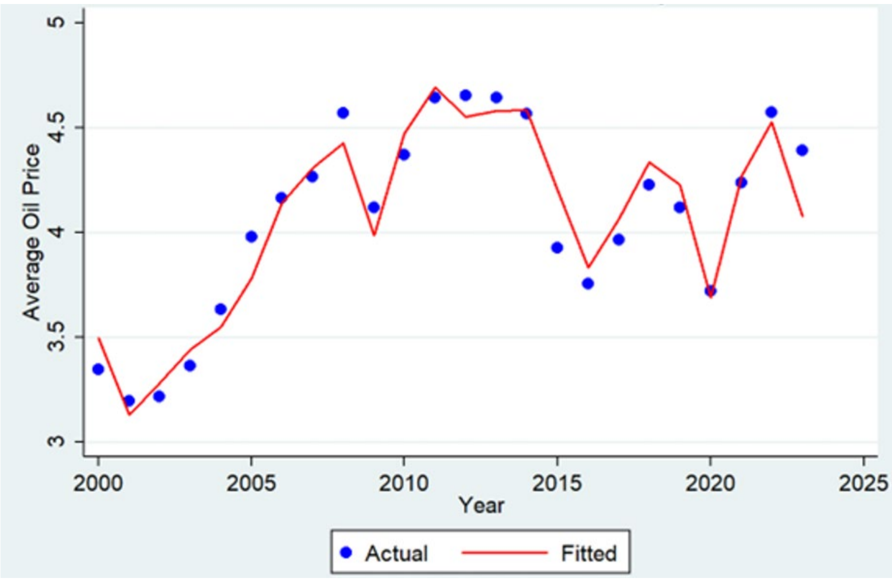

Figure 1. Comparison of actual and predicted values

Source: Author's calculation

To further validate the regression model and visually assess its fit, a comparison between the actual and predicted values of the dependent variable was conducted. The scatter plot of the actual average oil prices and the fitted values derived from the model demonstrate a close alignment, indicating that the model effectively captures the overall trend and fluctuations in the data over time.

As shown in Figure 1, the fitted values closely follow the trajectory of the actual values throughout the observed period, with particularly strong correspondence during periods of major market shifts. Minor discrepancies appear during global shocks, such as the COVID-19 pandemic, underscoring the relevance of incorporating dummy variables to account for such external disturbances. This visual alignment supports the statistical evidence of the model's robustness and its ability to explain variations in the dependent variable.

DISCUSSION

This study analyzed the influence of OPEC-mandated production quotas and other relevant factors on global oil prices. The focus was placed on testing several key hypotheses using a multiple linear regression model and additional statistical tests to assess the significance and impact of these variables.

To validate the key assumptions of the regression model, several diagnostic tests were performed. The Durbin–Watson statistic was used to assess autocorrelation and indicated a potential presence of positive autocorrelation, justifying the application of the Newey–West estimator for robust standard errors. The Breusch–Pagan test confirmed homoskedasticity, while the Skewness/Kurtosis test for normality showed that the residuals follow a normal distribution. These results support the use of OLS and its robust variants in the analysis.

Hypothesis 1 was tested by including the OPEC Quotas variable in the regression model. The results showed a statistically significant negative effect of this variable on global oil prices. Specifically, a one percent increase in OPEC production quotas leads to a 1.59% decrease in the average reference price of oil. Since in the model OPEC quotas are operationalized as actual production volumes (measured in 1,000 barrels per day), the negative coefficient aligns with economic theory: higher quotas increase global supply and reduce oil prices. Therefore, the empirical findings support the expected behavior of a supply-restricting cartel, whereby reductions in quotas lead to upward price pressure. This result was consistently observed across all four model specifications (OLS, Newey-West, and two Bootstrap models), strengthening the robustness of the findings. This finding supports the theoretical framework of supply and demand, where an increase in supply (due to increased quotas) leads to a price decrease. It aligns with numerous previous studies (e.g., Alredany, 2018; Chevillon & Rifflart, 2009; Mercure et al., 2021) that confirm OPEC's influential role in stabilizing oil markets through supply regulation. However, the result contradicts the findings of Colgan (2014), who argued that OPEC's impact on oil prices is statistically insignificant due to the lack of quota compliance among member states. Despite differing interpretations, the significant negative coefficient in this model reaffirms that OPEC quotas remain a critical mechanism for influencing global oil supply and prices. Hence, Hypothesis 1 is confirmed, as reductions in OPEC quotas (i.e., lower production) are associated with higher global oil prices, in line with the stated hypothesis.

Hypothesis 2 was tested by introducing the Industrial Production variable, representing the demand side of the market. This variable reflects the level of economic activity and the need for energy within the industrial sector. The analysis revealed that a one percent increase in industrial production leads to a 12.06% increase in oil prices, indicating a strong and statistically significant positive relationship across all four model specifications (OLS, Newey-West, and both Bootstrap models). This confirms the hypothesis that greater industrial activity boosts demand, subsequently pushing prices higher. The robustness and consistency of this finding underscore the central role of economic activity in shaping oil market dynamics. These results are consistent with theoretical expectations and prior literature (Mercure et al., 2021; Jibril et al., 2020; Yoshino & Victoriia, 2019), which show that demand-side pressures during economic expansion tend to elevate energy prices.

Hypothesis 3 was tested by incorporating the Market Openness variable, approximating the degree of trade liberalization in global oil markets. The regression results show a statistically significant negative relationship between market openness and oil prices across all four model specifications (OLS, Newey-West, and both Bootstrap models). A one percent increase in openness measured by the ratio of oil trade (exports + imports) to GDP results in a 1.62% decrease in the average oil price. This supports the idea that greater trade liberalization and reduced trade barriers increase competition and supply, leading to lower global oil prices. These findings are in line with theoretical models (Jibril et al., 2020; Moshiri & Kheirandish, 2024; Scheitrum & Revoredo-Giha, 2018), which argue that increased global supply without a proportional increase in demand drives prices down due to improved resource allocation and enhanced competition. Therefore, Hypothesis 3 is confirmed.

The variable representing non-OPEC production volumes was included in the model to account for the influence of oil supply from countries outside the OPEC framework. The coefficient for this variable is positive and statistically significant in the OLS and Newey-West models, suggesting that increases in non-OPEC production are associated with higher global oil prices. Specifically, a one percent increase in non-OPEC output corresponds to an average 2.31% rise in the reference oil price, holding other factors constant. However, under the Bootstrap models with 3,070 and 2,314 replications, the coefficient loses statistical significance, indicating a possible sensitivity of this variable to sampling variability and a reduced robustness of this relationship under alternative inference techniques. This may reflect the more fragmented and less coordinated nature of non-OPEC supply behavior, as well as the influence of external shocks and strategic responses that differ by country. Despite this inconsistency, the direction of the coefficient remains the same across all models, which may still suggest some underlying structural relationship between non-OPEC output and price dynamics, albeit less stable than that observed for OPEC quotas or other key demand-side variables.

In addition to the main explanatory variables used to test the three hypotheses, the COVID-19 dummy variable was included in the model to capture the demand-side shock caused by the pandemic. The variable takes the value of 1 for the years 2020 and 2021, reflecting the peak period of global economic disruption. Across all four model specifications (OLS, Newey-West, and both Bootstrap models), the coefficient for COVID-19 is consistently negative and statistically significant, indicating that the pandemic exerted substantial downward pressure on oil prices. Specifically, the presence of COVID-19 is associated with an average decline of approximately 0.369 units in the average oil price. This result confirms the expected impact of the pandemic on global energy demand, particularly through reductions in industrial output, transport, and trade. The finding is consistent with prior research (e.g., Narayan, 2020; Devpura & Narayan, 2020), which documented the severe economic and energy-market repercussions of the COVID-19 crisis. Additionally, the model includes the Global Shift 2001 dummy variable to account for the immediate and short-term market disruptions following the geopolitical and economic instability in 2001. This variable takes the value of 1 for the years 2001 and 2002, reflecting the period of greatest uncertainty. The estimated coefficient is negative across all model specifications, suggesting a reduction in oil prices during that period; however, the result is not statistically significant. This may indicate that while global uncertainty in the early 2000s had an impact on oil markets, the effect was either short-lived or outweighed by other concurrent market factors.

The study also calculated the Herfindahl-Hirschman Index to assess the level of market concentration in global oil production. The HHI values were analyzed descriptively and not included directly in the regression model. Nevertheless, the observed trends provide important structural context. The slight increase in the global HHI over time suggests a growing concentration in oil production at the international level, while internal concentration within

OPEC and OPEC+ shows a moderate decline. These structural changes are relevant when interpreting the regression results. Specifically, the negative and statistically significant coefficient for the Market Openness variable implies that greater trade integration and competitive dynamics tend to reduce oil prices. Although HHI was not used as an explanatory variable, the descriptive trend of rising global concentration helps frame the broader market conditions under which openness exerts its influence. Thus, while the relationship is not modeled directly, the HHI analysis complements the regression findings by offering a structural backdrop against which demand and supply variables operate.

CONCLUSION

The analysis of the impact of the Organization of the Petroleum Exporting Countries and other relevant factors on global oil prices reveals a complex network of interrelated influences that shape the global oil market. Supply and demand forces are fundamental in determining oil prices. Prices respond to supply and demand shocks, economic growth, inflation, and currency fluctuations. Technological advances, such as hydraulic fracturing and horizontal drilling, have significantly increased supply, while economic growth in countries like China and India has driven global demand upward. Geopolitical tensions, conflicts, and sanctions directly affect oil supply and price volatility. For example, sanctions against Iran or political instability in the Middle East often result in price spikes. Additionally, macroeconomic factors, including global GDP growth, inflation, and exchange rate volatility, play an important role in price fluctuations. Technology has made it possible to access previously unreachable reserves, reduce production costs, and improve energy efficiency. These advancements, coupled with the transition toward renewable energy sources, are gradually transforming oil market dynamics.

The empirical findings of this study demonstrate that OPEC production quotas have a statistically significant and negative impact on global oil prices. Specifically, a one percent reduction in quotas leads to a 1.59% increase in oil prices. Based on the descriptive analysis and literature review, OPEC's role as a cartel is central to supply control and price stabilization. The organization operates through coordinated production quota decisions, aiming to balance supply and demand and maintain favorable price levels amid shifting global conditions. The literature review emphasizes several important conclusions: First, geopolitical factors such as crises and conflicts in oil-rich regions significantly affect price volatility. Second, technological progress, particularly among non-OPEC producers, has expanded global supply, reducing dependence on OPEC and increasing competition. The results also show that increased industrial production, especially in the world's largest economies, positively affects demand and price levels. A one percent rise in global industrial output corresponds to a 12.06% increase in oil prices, confirming the strong link between economic activity and oil demand. Moreover, greater market openness contributes to lower oil prices by intensifying competition. An increase in oil trade openness by one percent reduces oil prices by 1.62%, indicating the significant downward pressure that liberalized markets and technological advancement exert on prices. Additionally, the variable representing Non-OPEC production volumes showed a positive and statistically significant coefficient in both the OLS and Newey-West models, indicating that increased output from non-OPEC countries is associated with higher global oil prices. This result may reflect supply-side dynamics where greater production from competitive, non-cartelized sources coincides with rising global demand or anticipatory behavior in futures markets. However, in both Bootstrap models, the coefficient turns negative and statistically insignificant, suggesting that the relationship may be sensitive to distributional assumptions or sampling variability. This inconsistency underscores the heterogeneous nature of non-OPEC producers and the lack of coordinated supply mechanisms, which limits their collective influence on global oil price stabilization.

Synthesis from the literature further highlights the susceptibility of oil markets to economic shocks, geopolitical risks, and technological changes, particularly during the COVID-19 pandemic, which triggered a dramatic decline in global oil demand and a sharp price drop. Furthermore, early 2000s geopolitical and economic shifts did not exhibit a statistically significant effect on global oil prices in the estimated models.

Although this study makes several important contributions, it is not without limitations. The analysis in this study begins in the year 2000 and deliberately excludes the 2008 global financial crisis to allow a focused assessment of more recent structural shifts, particularly the COVID-19 pandemic. While both the COVID-19 and 2001 events are accounted for as structural shocks through dummy variables, the model treats these events as discrete and time-bound. Future research should consider methodologies that allow for a dynamic understanding of such shocks, for example, by employing time-varying parameter models, structural break tests, or rolling regressions to assess how the impact of the pandemic evolves over time, particularly in terms of demand elasticity and supply adjustment. In addition, although this study recognizes the broader relevance of climate policy, renewable energy expansion, and institutional factors, future analyses could benefit from framing these themes into more targeted research questions. For instance: How do long-term decarbonization strategies influence the responsiveness of oil-exporting countries? To what extent does institutional quality mediate the price effects of external shocks? How does the pace of renewable energy adoption reshape expectations in oil futures markets? Addressing such questions would contribute to a more nuanced and policy-relevant understanding of how structural changes interact with traditional market fundamentals in shaping global oil prices.

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REVIEW PAPER

Two Sides of a Digital Coin: Comparison of CBDC and Cryptocurrencies

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ABSTRACT
This paper aims to compare central bank digital currencies (CBDCs) and cryptocurrencies by examining their fundamental differences, with a focus on their implications for financial inclusion, political and corporate influence, and monetary policy effectiveness. The analysis is based on a conceptual and comparative approach, drawing on an extensive literature review and theoretical insights to identify and contrast the key characteristics, advantages, and disadvantages of both CBDCs and cryptocurrencies. The findings highlight that cryptocurrencies offer greater resistance to political and corporate control and support decentralized financial systems, while CBDCs provide enhanced tools for monetary policy implementation and state oversight. Both models have the potential to improve financial inclusion, but their approaches differ: CBDCs rely on institutional infrastructure, whereas cryptocurrencies depend on technological accessibility and user digital literacy. The study also reveals that CBDC could pose risks to personal financial autonomy, while cryptocurrencies may undermine monetary stability in less developed economies. This paper contributes to the understanding of digital money by presenting a structured comparison of two competing models, offering insights into their complementary potentials and long-term implications for the global financial system. Unlike most existing studies, the analysis integrates the perspectives of financial inclusion, political and corporate influence, and monetary policy effectiveness within a single comparative framework. In addition, it emphasizes the relevance of these issues for emerging markets and developing economies, where the introduction of CBDCs or the widespread use of cryptocurrencies could generate distinctive challenges and opportunities. It also highlights how their interaction may shape future developments in financial infrastructure, regulation, and user trust.

Keywords: *digital money, central bank digital currencies, cryptocurrencies, monetary policy, financial inclusion*

JEL Classification: E42, E50, E52, E58

INTRODUCTION

Business entities are increasingly relying on digital technologies to support their operations. E-commerce transforms the way companies interact with their customers and facilitates the execution of transactions. Under the influence of technological innovations, the concept of money has undergone significant changes. Numerous studies indicate that the digital transformation of money is closely intertwined with the emergence of new technologies, which are reshaping the role of traditional financial institutions and facilitating innovation in payment systems (Zhao, Fan

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& Yan, 2016). The digitalization of the economy contributes to a substantial reduction in cash circulation and fosters the implementation of digital technologies in the financial sector (Mischenko & Naumenkova, 2021). This has led to the emergence of new forms of currency that exist exclusively in digital form and are detached from traditional financial systems. One of the key features of digital money is the ability to conduct transactions quickly and efficiently. Compared to traditional bank-based payment systems, where transfers are slow and costly, digital money enables faster transactions with proportionally lower costs. This is particularly important in the context of cross-border payments, where time delays and high fees are common obstacles.

Cryptocurrencies and central bank digital currencies (CBDC) represent two distinct approaches to the development of digital money, each with its own characteristics, advantages, and challenges (Cunha, Melo & Sebastião, 2021). While cryptocurrencies operate on decentralized blockchain networks, offering users greater freedom and pseudonymity, central bank digital currencies are issued by state institutions with primary objectives such as monetary stability and regulatory oversight. In this regard, CBDCs represent centralized and controlled monetary systems (Bindseil, 2020). In the current regulatory vacuum, both national and international institutions face significant challenges in establishing appropriate frameworks for digital currencies (Arner, Auer & Frost, 2020). The fundamental difference in the nature of these forms of digital money also results in differences in their performance and the goals for which they were established. Consequently, their role within the financial system is not identical.

The aim of the paper is to identify the differences in their potential impact on the global financial system through the analysis of the characteristics, advantages, and disadvantages of these two concepts. Understanding these differences is not only relevant for investors and economists, but also for all economic actors aware of the evolving role and functions of money in the digital age.

The first part of the paper will present the fundamental characteristics of cryptocurrencies. The second part will focus on central bank digital currencies. The third part of the paper will provide a key elaboration of how their systemic differences influence their opposing roles and potential within the modern financial system.

CRYPTOCURRENCIES

Although early electronic money systems in the 1990s demonstrated the possibility of developing state-backed digital currencies, governments and central banks showed little to no practical interest in this concept at the time. In reality, it was not until the significant expansion of the cryptocurrency market in the second decade of the 21st century that central banks actively engaged in the development and testing of their own digital currencies. Therefore, cryptocurrencies are, in fact, historically older than the now widely accepted concept of central bank digital currencies.

Cryptocurrencies are generally considered a decentralized form of electronic money, based on distributed database management technology in the form of a ledger, known as blockchain (Narayanan et al., 2016). The basic unit of data entry in the blockchain is a transaction, which represents a change in the state of the system (Iansiti & Lakhani, 2017). In the context of cryptocurrencies, a transaction refers to the transfer of value between the payer and the payee. Transactions are not recorded individually in the ledger but are grouped into blocks that are subsequently embedded into the data chain. Blockchain is a cryptographic technology that, by combining the achievements of asymmetric cryptography, hash functions, Merkle trees, and timestamping with so-called consensus protocols, enables database management in an environment where there is no trust among participants (Scardovi, 2016). The public key of each participant serves as their "current account," i.e., an account to which the cryptocurrency balance is linked. The corresponding private key is used to sign transactions. Since the private key cannot be derived from the public key, while the digital signature created with the private key can be verified, transactions are easy to authenticate but impossible to forge. By applying hash functions to individual transactions and transaction blocks, and by calculating the root of the Merkle tree, data integrity is maintained. Timestamping is used to chronologically sort transactions and the aforementioned blocks.

Consensus protocols play a crucial role in embedding blocks into the blockchain (Bamakan, Motavali & Bondarti, 2020). This means that in the decision-making process, that is, the process of verifying the validity of transactions, any number of participants can be involved, even if they do not know or trust each other. To enable such a system, consensus protocols must ensure that it is impossible to validate unauthenticated transactions (i.e., those not signed by the payer, and therefore most likely falsified) and to prevent the spending of funds that the payer does not actually possess (the double-spending problem inherent to all electronic money systems). Each transaction on the blockchain functions as a micro-program, which, in addition to specifying the amount of cryptocurrency being spent, must digitally sign the transaction on behalf of the payer and provide a reference to a previous transaction that confirms the existence of the funds being spent. In other words, the payer must have previously acquired the funds they intend to spend. Other participants routinely verify the executed transaction by checking the validity of the digital signature and the existence of the funding source. If the transaction is not validly signed, it will be disregarded. Likewise, a transaction will not be considered if no source of funds exists or if the referenced source has already been fully or partially spent, thus preventing additional spending. If all conditions are met, transactions are grouped into blocks according to the rules of the specific consensus protocol. To prevent malicious participants from colluding and attempting to manipulate the system, all protocols are designed to be competitive, meaning that participants (commonly referred to as miners or validators) must invest certain resources that will be forfeited if they fail to comply with the established rules. Protocols reward the participant who is the first to assemble a valid block containing only verified transactions, thereby discouraging malicious behavior by eliminating the opportunity to profit from dishonest actions.

Essentially, cryptocurrencies are self-sustaining systems because they shift maintenance costs to miners, who invest their own resources with the goal of earning rewards by participating in consensus mechanisms. This contributes to system stability and security. Bitcoin, as the first cryptocurrency created in January 2009, remains the most significant and well-known cryptocurrency. According to data from the website coinmarketcap.com, its value exceeded $110,000 per 1 BTC in March 2025, making it primarily an investment asset rather than electronic money held by users for online payments. This leads to the fundamental problem of most cryptocurrencies: they generally do not meet the criteria to function as money because their high price volatility prevents their use as a reliable store of value. Consequently, the majority of users holding Bitcoin and other leading cryptocurrencies do not use them as a medium of exchange but rather hold them primarily for investment purposes (Steinmetz et al., 2021). Cryptocurrencies remain predominantly speculative investment instruments, with their use in payments being sporadic and often associated with misuse, such as payments in illegal activities, rather than legitimate e-commerce transactions. Despite these limitations, cryptocurrencies are increasingly being explored as a means to enhance transaction security and improve the efficiency of financial flows, particularly in sectors that require a high degree of decentralization (Catalini & Gans, 2020). Nevertheless, certain characteristics of cryptocurrencies make them a promising option for the future of electronic money, which will be further elaborated in the third part of this paper.

Beyond Bitcoin, which remains the dominant cryptocurrency, several other digital currencies have gained significant importance in the last decade. Ethereum, launched in 2015, introduced the concept of smart contracts and decentralized applications, thus expanding the use of blockchain beyond simple peer-to-peer payments (Buterin, 2015; Antonopoulos & Wood, 2018). Litecoin, created in 2011, sought to improve on Bitcoin by enabling faster block generation times and lower transaction fees, while Ripple (XRP) targeted the inefficiencies of cross-border payments by offering low-cost and near-instantaneous settlement (Glaser et al., 2014). In addition, the emergence of stablecoins such as Tether (USDT) illustrates an attempt to mitigate one of the key weaknesses of cryptocurrencies – high volatility – by pegging their value to fiat currencies (Lyons & Viswanath-Natraj, 2020; Bullmann, Klemm & Pinna, 2019).

Price volatility is one of the defining features of cryptocurrencies and a major reason why their role as money remains contested. Numerous studies demonstrate that Bitcoin and other cryptocurrencies behave more like speculative assets than stable mediums of exchange (Baur, Hong & Lee, 2018; Yermack, 2015). Bitcoin rose from below USD 500 in 2013 to nearly USD 69,000 in 2021, before undergoing sharp corrections, while Ethereum increased from less than USD 1 in 2016 to over USD 4,800 in 2021, reflecting extreme levels of price fluctuation (Corbet et al., 2019). Such patterns challenge their reliability as a store of value and increase portfolio risks compared to traditional assets (Katsiampa, 2017; Klein, Pham Thu & Walther, 2018). Nevertheless, the high volatility also attracts investors seeking speculative opportunities, contributing to increased trading volumes and liquidity in global financial markets (Urquhart, 2016).

In terms of innovation, Ethereum's architecture, based on programmable smart contracts, has been particularly important for the rise of decentralized finance (DeFi), enabling the creation of new financial instruments and decentralized exchanges that operate without intermediaries (Schär, 2021). These innovations illustrate that, while Bitcoin established the foundation of digital money, subsequent cryptocurrencies have significantly expanded the scope and functionality of blockchain-based finance.

Table 1. Overview of selected cryptocurrencies and their price development (2013–2025)

Cryptocurrency	Launch year	Approx. price 2013	Peak price (USD)	Price 2025
Bitcoin (BTC)	2009	< 500	~69,000 (2021)	~110,000
Ethereum (ETH)	2015	< 1	~4,800 (2021)	~3,500
Ripple (XRP)	2012	< 0.01	~3.84 (2018)	~0.55
Litecoin (LTC	2011	~4	~410 (2021)	~70
Tether (USDT)	2014	~1	~1	~1

Source: CoinMarketCap (2025). Data search. Accessed 27/09/2025 from: https://coinmarketcap.com/

While cryptocurrencies represent a decentralized approach to money creation and governance, central banks have responded by exploring CBDCs as a way to combine digital innovation with monetary control.

CENTRAL BANK DIGITAL CURRENCIES (CBDCS)

With the growth of the cryptocurrency market, the question of adopting this concept by states to reform payment systems has become inevitable. CBDCs are emerging as a response to the need to preserve monetary sovereignty and enhance the efficiency of payment systems in the era of the digital economy (Auer & Böhme, 2020). State-backed digital money emerges not only as a practical necessity due to the digitalization of business operations but also as an opportunity for governments to prevent private cryptocurrency systems from gaining widespread consumer adoption. It should be made clear from the outset that the creation of true blockchain-based cryptocurrencies by states is not only impossible but also undesirable (Stockel, 2025). As previously noted, blockchain is designed for scenarios where a certain number of participants – whether known or unknown in advance – lack mutual trust when making decisions. Participants in reaching consensus have equal voting power. In practice, this would mean that a state would lose its ability to control monetary policy within such a system. It is evident that it would be highly disadvantageous for a state to implement a monetary system that it would subsequently be unable to control. Distributed ledger systems may enhance resilience against cyberattacks; however, blockchain architectures based on proof-of-work mechanisms involve very high energy consumption, which makes them unsuitable for sustainable implementation by central banks and raises broader concerns about efficiency and environmental impact (Sedlmeir et al., 2020).

On the other hand, a digital money system in which the state retains a leading role and makes all decisions would not constitute a true blockchain system. Fortunately, for decades, there has been the possibility of implementing electronic money systems based on blind signatures (Chaum, 1983). CBDC should be viewed in this context – as a form of electronic money developed as early as the 1990s, except that the issuer would now be the central bank instead of private entities (Kiff et al., 2020). In addition to blind signature systems, modern CBDC architectures are increasingly incorporating privacy-enhancing elements through zero-knowledge proofs and tokenisation (Chaum, Grothoff & Moser, 2021).

The literature identifies several motivations or rationales for the introduction of CBDCs. These include the need to support unconventional monetary policy (Bordo & Levin, 2017), the preservation of financial stability, increasing competition in the retail payments sector, and the prevention of criminal activities (Engert & Fung, 2017), as well as enhancing financial inclusion and responding to the emergence of private cryptocurrencies such as Bitcoin (Ozili, 2022). In academic circles and broader societal contexts, there has long been discussion of the so-called Fourth Industrial Revolution and the ways it will transform business operations. One of the main obstacles to the full integration of the Internet of Things and the creation of the so-called Internet of Value is inadequate payment infrastructure (Floros, 2019). CBDC could provide a foundation for faster and cheaper payments, effectively restoring the concept of micropayments to its full significance within payment systems. These motivations are significant, which explains the high percentage of central banks currently engaged in developing operational solutions or conducting testing (Boar & Wehrli, 2021). However, these are highly sensitive projects that will require international coordination among central banks, not only for feasibility but primarily for the acceptability of the project. This refers not only to acceptance by end-users but also by the banking sector, which may be more or less affected depending on the design of the CBDC system. User response will undoubtedly be conditioned by the system's design.

Recent studies emphasise that central banks should adopt a proactive yet cautious approach when considering CBDCs. The International Monetary Fund (IMF) proposes a dynamic decision-making framework that guides central banks through staged exploration, from research and piloting to potential implementation, ensuring that infrastructure, legal frameworks, and institutional capacity are prepared in advance (IMF, 2023). This approach highlights that the feasibility and desirability of CBDCs differ significantly across jurisdictions. Similarly, the Bank for International Settlements (BIS) reports show that more than 90% of central banks are now engaged in CBDC research or pilot projects, with an increasing focus on hybrid systems that combine central bank issuance with private sector distribution (BIS, 2024). Hybrid models are considered particularly promising because they allow central banks to maintain control over monetary liabilities while enabling innovation and efficiency through regulated intermediaries (Auer, Cornelli, & Frost, 2020).

The first scenario involves introducing CBDCs as a complement to the existing payment system. In addition to cash and deposit money, there would be state-issued electronic money. In such circumstances, the burden of adopting CBDC would fall on deposit money, as consumers inclined to use cash could continue to do so. Consequently, commercial banks would be adversely affected because a reduction in demand for deposit money would decrease their lending capacity (Caccia, Tapking & Vlassopoulos, 2024). Moreover, their presence in payment transactions would diminish, leading to a decline in transaction fee revenues. On the other hand, the push towards a fully cashless payment system would significantly impact consumers, as well as banks. The state would gain the ability to monitor consumers permanently and possess a tool for the immediate freezing of all available funds of individuals or enterprises. While this presents significant opportunities in combating terrorism and organized crime, concerns arise that some of these powers could be misused to exert pressure on disloyal individuals (Kaur, 2024).

CBDCs could be stored on cards or mobile applications (a value-based solution), or in dedicated current accounts held at centralized institutions such as central bank departments (an account-based solution) (Bofinger, 2018). These two approaches do not necessarily require a direct replacement of cash and deposit money, as deposit money could continue to function alongside one or both models. In addition to conceptual discussions, practical experiences with CBDCs are already emerging worldwide. The Bahamas launched the Sand Dollar in 2020, aiming to strengthen financial inclusion across remote islands (Central Bank of The Bahamas, 2020). China's e-CNY pilot has been rolled out across multiple provinces, demonstrating large-scale merchant adoption and integration with existing digital ecosystems (Mu, 2021). Nigeria introduced the eNaira in 2021, though adoption has been slower, underlining the importance of trust and adequate user incentives (David-West & Umukoro, 2023). The Eastern Caribbean Central Bank launched DCash as a regional CBDC pilot, providing lessons on cross-border interoperability and governance (ECCB, 2021). Sweden's Riksbank has advanced the e-krona project through technical pilots, though the final policy decision remains open (Riksbank, 2023). These diverse experiences highlight that CBDC design and outcomes vary greatly depending on national objectives, infrastructure readiness, and institutional trust. The question remains whether and how the central bank's role in conducting monetary policy would change.

In a scenario where cash is replaced by CBDC stored directly on devices, no significant changes would occur. Consumers would always be able to withdraw funds onto an application or card, thus keeping them out of the central bank's reach. Demand for transactional deposits could decline due to the possibility of making payments with CBDC via apps. However, a fundamental change would take place with the implementation of CBDC based on some form of current account. Central banks could influence the overall money supply through interest rates, opening new possibilities for monetary policy. In the event of a drop in aggregate demand and the onset of a recession, central banks could implement negative interest rate policies. Without cash and the autonomous holding of CBDC, consumption would become the only way for holders to protect their assets from long-term losses (Tomić, Todorović & Čakajac, 2020). When designing CBDC, central banks must strike a balance between functionality, anonymity, and control, resulting in diverse CBDC models across the globe (Petare et al., 2024).

Given these distinct conceptual foundations, a direct comparison between CBDCs and cryptocurrencies can provide insights into their respective advantages, limitations, and potential complementarities.

COMPARISON OF CRYPTOCURRENCIES AND CBDCS

Both categories analyzed in this paper are highly heterogeneous. "Cryptocurrencies" encompass diverse types, from Bitcoin as a decentralized store of value, to stablecoins designed to reduce volatility, to smart contract platforms such as Ethereum that enable decentralized applications, as well as privacy-oriented coins like Monero and Zcash (Catalini & Gans, 2020; Eichengreen, 2019). Similarly, CBDCs are not a monolithic concept but vary according to design choices: retail versus wholesale, account-based versus token-based, and hybrid or synthetic models that combine public and private sector roles (BIS, 2024; IMF, 2023). Recognizing this heterogeneity is essential for avoiding over-generalization, and the comparison in this paper should therefore be interpreted as a synthesis of main trends rather than a strict equivalence across all subcategories.

The comparative framework applied in this paper does not assume full equivalence between all types of cryptocurrencies and CBDC models. Instead, it synthesizes their most salient characteristics across three analytical dimensions, acknowledging that significant internal variation exists within each group.

Financial Inclusion

Financial inclusion refers to enabling access to financial services for individuals or enterprises (Pesqué-Cela et al., 2021). Although at first glance this may seem a matter of limited interest, it should be noted that financial services tend to be exclusive, especially for individuals (Birkenmaier & Fu, 2018). A large proportion of the population, particularly in developing countries, lacks access even to basic financial services. The network of bank branches does not cover much of the densely populated rural areas, leaving a significant share of the population without access to electronic payments or ATMs. Such users are limited to cash use exclusively, and thus cannot benefit from other, more sophisticated financial services.

Both concepts emphasize their contribution to financial inclusion (Blandin et al., 2020; Tan, 2024). Empirical research suggests that digital currencies can significantly promote financial inclusion in regions with underdeveloped banking infrastructure, enabling vulnerable and marginalized groups to access basic financial services more easily (Tay, Tai & Tan, 2022). As access to the internet and basic computing technologies has become widespread even in developing countries, information technologies can be leveraged to partially overcome this issue. Through electronic payments, users can gain access to a range of other services, such as private pension and life insurance or brokerage services. However, the two concepts do not offer the same degree of financial inclusion. CBDCs must rely on some form of institutional support. Central banks, either independently or with the assistance of the existing banking network, should facilitate the transition from widespread cash use to the distribution of digital money. Cryptocurrencies do not require the involvement of any institution, as their use only requires internet access and appropriate software. Nevertheless, if the user is not engaged in mining, initial possession of cryptocurrency is very likely dependent on a deposit made through the traditional payment system. It can be concluded that neither concept holds a clear advantage in terms of accessibility. Differences across the other two aspects of comparison are more pronounced.

Regarding the level of education, awareness, and digital literacy, it is evident that CBDCs enable a higher degree of inclusion. Apart from technological barriers, a major obstacle to full inclusion is the low level of financial literacy among populations that are already excluded from the system (Demirgüç-Kunt et al., 2022). Regarding the level of education, awareness, and digital literacy, it is evident that CBDCs enable a higher degree of inclusion. Apart from technological barriers, a major obstacle to full inclusion is the low level of financial literacy among populations that are already excluded from the system (Demirgüç-Kunt et al., 2022). In addition, most countries will need to amend existing legislation to grant CBDCs legal tender status and to establish clear regulatory and supervisory frameworks. Appropriate oversight and accountability mechanisms are essential to ensure trust, protect consumers, and prevent misuse of the system, particularly in jurisdictions where institutional capacity is limited (IMF, 2023; BIS, 2024). Thanks to their institutional foundation, CBDCs can establish a clearer and simpler usage system focused on the end user. In contrast, cryptocurrencies appear to be systems that set standards but are not primarily aimed at universal inclusion. In practice, the required level of digital knowledge may vary from case to case, but it can be concluded that the secure use of cryptocurrencies for payments generally demands a higher level of digital literacy. This raises the question of how their usage could contribute to greater inclusion, given that those excluded from traditional financial flows are precisely the individuals lacking advanced digital skills. It goes without saying that the mining process further complicates the situation, as it is an expensive and demanding operation. It remains unclear which individuals can afford mining equipment and participate continuously in this process while lacking access to financial services.

In terms of regulation and legal prerequisites, cryptocurrencies hold an advantage. Within crypto communities, users are relatively equal, so no one's background or legal status affects their access to funds. The situation with CBDCs is somewhat different, considering that even in developed countries, socially marginalized individuals often face difficulties opening current accounts at banks. Individuals with criminal records frequently do not meet the criteria for certain types of financial services, which may discourage them from holding bank accounts altogether. Furthermore, the transition to CBDCs would accelerate the process of freezing and confiscating funds when requested by the state. Thus, while CBDCs enable greater inclusion, they also increase the likelihood of consumer exclusion.

Reduction of Political Influence

One of the characteristics that electronic money must possess, according to Matonis (1995), is the reduction of state influence on monetary value. Building on Hayek's (1976) view that all state-issued money is political money and that every government more or less abuses the monetary system to fulfill its own objectives, Matonis concludes that state influence would undermine trust in private electronic money systems. In other words, for electronic money to succeed, it must operate according to purely economic principles, not political ones. It is clear that CBDCs do not meet this criterion, as they represent a digital extension of traditional state-issued money. All the negative consequences of using monetary policy for political purposes remain present in the case of CBDCs.

While the ideas of Hayek (1976) on the denationalization of money and Matonis's (1995) early criteria for electronic money provide a valuable historical framework, they were developed before the emergence of programmable digital currencies and distributed ledger technology. Contemporary digital currencies – whether in the form of CBDCs or cryptocurrencies – operate under algorithmic governance and programmability, which fundamentally transcends these earlier frameworks (BIS, 2021; Adrian & Mancini-Griffoli, 2019). Therefore, in this paper, the earlier theories are used as a conceptual background, while the main comparative analysis relies on more recent approaches that account for the technological and institutional innovations of blockchain-based systems.

It is important to distinguish between historical forms of money, such as commodity money and early electronic payment systems, and contemporary programmable digital currencies. Commodity money and pre-blockchain systems lacked programmability and algorithmic governance, while both CBDCs and cryptocurrencies are characterized by code-based rules, automated verification, and in many cases smart contract functionality (Böhme et al., 2020; Auer Auer, Cornelli, & Frost, 2020). For this reason, in the present analysis, commodity and early electronic money are referenced only as background, while the main focus remains on the comparison between CBDCs and cryptocurrencies as the two relevant forms of digital money.

Cryptocurrencies, as private money, are free from political influence, precisely in the manner Hayek proposed. Additionally, they possess another significant characteristic – they are not subject to corporate influence either. In early electronic money systems, the reduction of political influence was offset by the rise of corporate control by the issuing company. In practice, corporate influence, despite being a private interest, could be just as detrimental as political interference. Moreover, in decentralized systems, the risk of abuse of power is significantly reduced due to algorithmic transparency and the impossibility of centralized revocation of funds (De Filippi & Wright, 2018). A review of some unsuccessful early electronic money systems shows that all failed due to poor business decisions by the issuers (Guttmann, 2003). Cryptocurrencies are governed by a community of miners regardless of who initiated the project and developed the algorithm. Fully controlled private cryptocurrencies are undesirable and poorly regarded within the crypto community. It can be concluded that cryptocurrencies, at least nominally, strive toward the pure economic model proposed by Hayek. However, in practice, this characteristic is not always desirable, as without mechanisms to mitigate demand shocks, nearly all cryptocurrencies are exposed to high volatility.

Impact on Monetary Stability

Regarding the impact on monetary policy capabilities, CBDCs and cryptocurrencies exhibit significant differences. Earlier, the influence of CBDC implementation modalities on monetary policy was discussed. In contrast, cryptocurrencies as private initiatives potentially reduce policymakers' maneuvering space (He, 2018). The extent of this impact depends on the stability of the national currency and the purposes for which the population uses cryptocurrencies. Developed countries with stable currencies are unlikely to be affected by this issue, even with widespread cryptocurrency adoption. In these countries, the population mainly uses cryptocurrencies for speculative investment purposes. In the long term, cryptocurrencies may emerge as consortium projects by large internet-dependent corporations. This could alter the demand function for cryptocurrencies, not due to distrust in the national currency, but as a means to enable faster and simpler payments within specific internet services. Such cryptocurrency usage would complement the traditional payment system rather than replace it.

Developing countries may face far greater challenges. Studies indicate that the widespread use of cryptocurrencies in countries with weak institutions can undermine the transmission mechanism of monetary policy and reduce the effectiveness of state oversight over capital flows (Davoodalhosseini, 2022). In these contexts, segments of the population turn to cryptocurrencies as alternatives to unstable national currencies that fail to fulfil one of the fundamental functions of money – a store of value. These economies struggle with long-standing high inflation problems. Zimbabwe, for example, was notorious for hyperinflation, which made economic planning and storing value difficult for its population. The cryptocurrency exchange Golix offered a solution by enabling most well-known cryptocurrencies to be purchased directly with the local currency. This created a local alternative for storing value. Since 2018, Golix has been targeted by the central bank, which banned its operations. Although the exchange continued functioning amid legal disputes, users increasingly faced difficulties withdrawing funds, and it is assumed that the founders embezzled part of the assets. While this experiment failed, it demonstrated a way to circumvent poor monetary policy decisions at the local level. Another example is El Salvador, which institutionally relinquished monetary policy by abolishing its national currency and adopting the US dollar and Bitcoin as legal tender (Ward, 2024). Such institutional changes require careful evaluation of their long-term effects on macroeconomic stability and central bank independence (Yermack, 2018). Despite this case, due to high volatility, existing cryptocurrencies are not a suitable solution for a reserve currency role. However, consortium cryptocurrencies developed by large corporations with relatively stable value could serve as financial havens for users in developing countries. Motivations for this include domestic currency volatility, underdeveloped banking networks, the desire for frequent cross-border payments without high fees and currency conversion costs, or evasion of regulatory authorities. The consequence will be the inability of central banks to influence economic developments through monetary policy measures, as these measures will target national currencies used by an insufficient proportion of citizens.

To provide a clearer and more structured understanding of the comparative position of CBDCs and cryptocurrencies, Table 2 summarizes the key advantages and disadvantages of both systems across several dimensions, including monetary control, privacy, efficiency, and financial inclusion. This comparative overview complements the analytical discussion presented earlier by highlighting their practical implications and trade-offs.

Table 2. Overview of selected cryptocurrencies and their price development (2013–2025)

Dimension	CBDCs – Advantages	CBDCs – Disadvantages	Cryptocurrency – Advantages	Cryptocurrency – Disadvantages
Monetary control	Enables effective policy transmission	Potential overreach by central banks	Decentralization ensures autonomy	Lack of monetary stability
Privacy	Regulated data use	Limited anonymity	Pseudonymity protects users	Vulnerable to misuse
Efficiency	Fast domestic payments	Implementation costs	Global reach	High energy use / slow scaling
Financial inclusion	Broad institutional access	Dependence on digital literacy	Peer-to-peer accessibility	Limited trust and volatility

Source: Authors

CONCLUSION

Cryptocurrencies and CBDCs represent two distinct trajectories in the evolution of money, each reflecting broader trends in finance where traditional institutions encounter disruptive innovation. Their development illustrates not only competing visions of money but also opportunities for complementarity.

On the one hand, CBDCs offer clear institutional advantages: they can strengthen monetary policy transmission, improve efficiency in payments, and potentially expand financial inclusion when combined with appropriate regulatory and technological frameworks. They also provide governments with new instruments for oversight and crisis management, which may be crucial in times of financial instability.

On the other hand, cryptocurrencies highlight the benefits of decentralization and reduced dependence on state or corporate control. Their blockchain foundations enable innovation, resilience, and new financial applications, though their high volatility and speculative use remain significant obstacles to their adoption as stable money. Importantly, most cryptocurrencies are not fully anonymous but rather pseudonymous, meaning that transactions are linked to public keys and can often be traced back through network analysis.

Rather than treating CBDCs and cryptocurrencies as mutually exclusive, a balanced view suggests that they may coexist and even complement each other. CBDCs could deliver stability and trust through regulatory backing, while cryptocurrencies could continue to drive technological experimentation and alternative models of finance. This coexistence, however, will depend on careful design choices, regulatory clarity, and the ability to safeguard both efficiency and personal financial autonomy.

Money is a complex institution built on trust and shaped by historical, technological, and social changes. The digitalization of money represents a critical turning point: whether through CBDCs or cryptocurrencies, its acceptance will depend on striking a balance between innovation and stability, as well as between oversight and individual freedom. The future of digital finance is therefore unlikely to be determined by a single model, but rather by the interaction of centralized and decentralized systems, each shaping global financial infrastructure in complementary and sometimes competing ways.

Despite these insights, this paper has certain limitations. It is primarily conceptual and comparative, relying on secondary sources rather than empirical data. Furthermore, while examples of national CBDC projects are referenced, the analysis does not provide an exhaustive country-by-country evaluation. In this sense, the paper should be seen as a contribution that synthesizes dispersed literature by integrating three perspectives—financial inclusion, political and corporate influence, and monetary policy—into a single comparative framework. This integrated approach highlights how both CBDCs and cryptocurrencies may differently affect emerging and developed economies, which has not been systematically addressed in prior studies.

Future research should address these limitations by providing more comprehensive empirical testing of the identified dimensions, comparative case studies of CBDC implementation across jurisdictions, and broader meta-analyses of cryptocurrency adoption patterns. Such work would strengthen the evidence base, clarify causal relationships, and support policymakers in making informed decisions about the design and regulation of digital currencies.

In light of the foregoing, it is clear that CBDCs and cryptocurrencies represent two sides of the same digital coin, and their development and mutual interaction will shape the future of the global financial infrastructure. In the coming years, it can be expected that hybrid models combining elements of both systems will become more prominent, regulatory authorities will strengthen oversight and accountability mechanisms, and privacy and data protection will remain central issues in policy design. At the same time, growing international cooperation is likely to promote the establishment of global standards and interoperability frameworks, while ongoing technological experimentation with programmable money, smart contracts, and tokenization will continue to shape the trajectory of digital finance.

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PRELIMINARY REPORT

Technical Performance and Productive Dynamics in Angolan Maritime Fisheries: An Intertemporal DEA-VRS Approach

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ABSTRACT
The study aims to evaluate the trend of relative technical efficiency within the context of the optimization of productive resources of the seven Decision Making Units. The study encompasses the seven provinces of the Angolan coast. The Data Envelopment Analysis (Variables Returns to Scale model), with an input-oriented approach, was used, adapted to the Angolan production context, which is marked by financial constraints and exchange rate instability. The results show an upward trajectory of mean efficiency across the five analysis windows used, with a moderate positive trend. The results also revealed that intertemporal factors explain, in a differentiated way, a relevant part of the variation in the technical efficiency of the provinces, highlighting Cabinda, Zaire, Bengo, and Kwanza Sul, which showed upward evolution, and, on the other hand, Luanda, Benguela, and Namibe, which showed low performance or decline. Between 2016 and 2023, no province showed full technical efficiency, highlighting gaps in the optimization of available resources. The total fish catch load was a more critical variable, registering high levels of pure technical inefficiency, requiring a sustainable increase in production at the sectoral level. The absence of previous studies on technical efficiency in the Angolan fishing sector reinforces the pioneering nature of this research, which can serve as a basis for future investigations and the formulation of public policies.

Keywords: *Angolan maritime fishing, Intertemporal technical efficiency, DEA-VRS*

JEL Classification: C61; H57; Q22

INTRODUCTION

With the exception of the coastal strip belonging to the province of Cabinda, the coastlines of Angola, Namibia, and South Africa are part of the vast marine ecosystem known as the Benguela Current (BCF), considered one of the richest areas in biodiversity and productivity on the planet (ANGOLA, 2023). This strategic condition gives Angola a competitive advantage for the development of various activities linked to the maritime economy, especially the fishing sector.

A preliminary SWOT analysis of the Angolan fisheries sector, conducted by the United Nations Conference on Trade and Development (UNCTAD) in 2017, resulted in the following diagnosis: strengths such as the existence of technical training centers, support for artisanal fishing, waters rich in biomass, and a well-irrigated interior; weaknesses referring to limited infrastructure for fish processing and transportation, high dependence on the export of primary products, and low levels of maritime security; opportunities involving the development of aquaculture (such as tilapia and catfish), expansion of the supply chain, adding value to fishery products, and creating

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cold chains with synergistic potential for other foods; and threats including the high cost of operation in the sector, inefficient management of fishery resources, and post-harvest losses. Given the above, the following research question is raised: how did the size of the fishing fleet relate to the levels of productive efficiency in the maritime fishing sector in Angola between 2016 and 2023?

Since Data Envelopment Analysis (DEA) is a technique within a non-parametric model of central tendency, it becomes difficult to formulate statistically validated hypotheses around certain mean values (Anderson T. , 2003). Thus, based on the literature on the analysis of fishing efficiency, we expect to observe that provinces with larger fishing fleets exhibit lower levels of productive efficiency, relating the excess of vessels to the inefficiency recorded.

Aiming to achieve results and partially aligned with the problem raised, this study aims to evaluate the trend of relative technical efficiency within the process of optimizing productive resources across the seven DMUs (Decision Making Units), corresponding to the seven provinces that make up the Angolan coast.

DEA is a methodology based on mathematical programming, used to measure the relative efficiency of a set of DMUs in productive resource optimization processes, considering multiple inputs and outputs. Its application has proven effective in evaluating the performance of units with diverse institutional profiles. In this study, the model assuming the variable returns to scale (DEA-VRS) was chosen to capture the heterogeneity between the DMUs, since not all operate on the same scale. An input-oriented approach was adopted, as it is more suitable for the Angolan economic context, characterized by state financial constraints, exchange rate instability, and uncertainties stemming from global financial markets, exacerbated by customs tariffs and the prospects of interest rate hikes by central banks. Thus, this study aims to fill an empirical gap related to the lack of published results on technical performance in the Angolan maritime fisheries sector.

THEORETICAL BACKGROUND

The evaluation of Angolan production units or sectors using DEA models is relatively recent, with the earliest records in the consulted bibliography dating from the 2000s. However, its production has increased in recent years, as evidenced by studies by Santos, Dieke, & Barros (2008), Kirigia, Emrouznejad, Cassoma, Asbu, & Barry (2008), Barros & Assaf (2009), Barros & Managi (2009), Barros, Assaf, & Ibiwoye (2010), Seabra (2011), Dumbo (2011), Barros & Antunes (2013), Barros & Assaf (2009), Barros & Managi (2009), Barros, Liang, & Peypoch (2014), Macanda (2015), Barros, Leão, Macanda, & Mendes (2016), Wanke, Barros, & Emrouznejad (2016), Barros, Wanke, Dumbo, & Manso (2017), (Hadi-Vencheh, Wanke, & Jamshidi (2020), Costa (2020), Silva (2021), (Chávez, Ortega, & Ibarra (2022), (Hadi-Vencheh, Khodadadipour, Tan, Arman, & Roubaud (2024), Pires, Santos, & Silva (2023), Sanches-António (2024), Sanches-António (2025), Sanches-António (2025). Nevertheless, there is no record of studies on evaluating the performance of the fish capture sector, which is the subject of this study.

Literature on the intertemporal evaluation of the relative technical efficiency of DMUs in the fisheries sector, in African countries and the rest of the world, has been widely used, with references to studies by (Mustapha, Aziz, & Hashim, 2013), (Schrobback, Schrobback, Pascoe, McWhinnie, & Hoshino, 2023), and (Ewedji & Dehlor, 2024). Within the scope of evaluating the activity researched using the DEA methodology, the specialized literature frequently presents studies that integrate multiple analytical approaches, particularly those of an economic-environmental nature. Such investigations, as conducted by Vázquez-Rowe, Iribarren, Moreira, & Feijoo (2010) and Martínez-Ibáñez, et al. (2024), serve as examples. This study proposes a broader understanding of productive efficiency, incorporating dimensions that transcend purely economic boundaries. In these studies, the impacts of fishing activity are placed at the heart of the analysis, considering not only the effects on marine ecosystems, but also the repercussions on sectoral productivity, social well-being, and environmental sustainability.

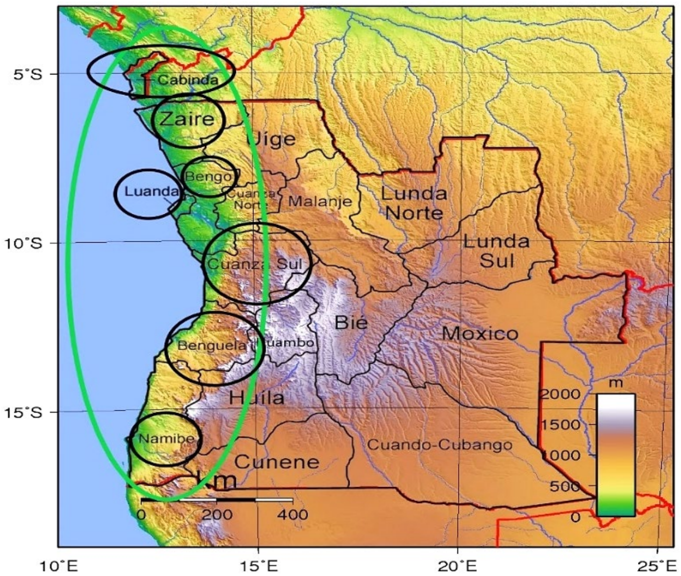

Figure 1. Geographical location of the maritime fishing area

Source: from Plural (2025)

From an economic standpoint, the emphasis is on the fishing sector's capacity to generate added value, optimize resource use, and contribute to the growth of local and national production chains. In the social dimension, the role of fishing as a source of food security is highlighted, especially in coastal communities, where access to high-nutritional-value protein is fundamental for public health and socioeconomic stability. On the other hand, the environmental aspect focuses on analyzing the pressure exerted by fishing activity on marine biomass stocks, addressing issues such as overfishing, habitat distribution, and cumulative effects on ocean biodiversity.

These integrated approaches allow DEA to be applied not only as a tool for measuring technical efficiency, but also as an instrument to support the formulation of public policies, strategic planning, and the sustainable management of fisheries resources. By simultaneously considering economic, social, and environmental variations, the selected studies promote a more holistic understanding of fishing activity and support analyses aligned with the principles of the blue economy, maritime conservation, and sustainable development.

EMPIRICAL APPROACH

Specifications: Model and Analysis Window

In practice, the assumption that the results verified in the context of the optimization of productive resources by DMUs are constant is more likely to be accompanied by their operational reality, considering factors of a difficult and varied nature, exogenous: such as the current economic policy, or the regulation of the markets in which they are inserted; or endogenous related to their heterogeneity. Thus, meeting the validated condition of variable returns to scale, according to Charnes, Cooper, & Rhodes (1978), the DEA-VRS model assumes non-proportionality between inputs and outputs; that is, variations in inputs cause variations in outputs with different magnitudes. In its input-oriented configuration, its formulation appears in (1).

$$Maximize\ h_k = \sum_{r=1}^{m} u_r y_{rk} - u_k$$

subject to:

$$\sum_{i=1}^{m} u_r y_{rj} - \sum_{i=1}^{n} v_i x_{ij} - u_k \leq 0$$

$$\sum_{i=1}^{n} v_i x_{ik} = 1 \tag{1}$$

and

$$u_r, v_i \geq 0$$

where; y: inputs; x: outputs; u e v: weights; r:1,..., m; i:1,..., n; j:1,....., N.

In the DEA literature, there is a consensus that no standard methodology exists for setting analysis windows; however, Cooper, Seiford, & Tone (2007) postulate that the number of DMUs must be at least greater than the sum of the total inputs and the total outputs, a criterion that has been adopted as a standard for the calibration of DEA windows, as shown in (2).

$$n \geq max.\{[(m)(s)]3(m + s)\} \tag{2}$$

where:
- n: number of DMUs;
- m: number of inputs;
- s: number of outputs.

When dealing with multiple time periods, the process of evaluating the efficiency of DMUs presents an increased challenge due to the intertemporal effects inherent in their operational dynamics. This contingency can be confirmed in studies of (Sengupta, 1996), (Řepková, 2014) and (Apan, Alp, & Öztel, 2019).

In this line of thought, studies such as those by Cooper, Seiford, & Tone (2007) and Cooper, Seiford, & Zhu (2011) provide theoretical support for empirical approaches in various research projects related to the efficiency dynamics of DMUs, as presented in the following mathematical formulations, whose practical application is shown in Tables 1 and 2.

$$\begin{aligned} w &= k - p + 1 \\ v &= n(p - 1)(k - 1) \\ z &= (n)(p) \\ h &= (n)(p)(w) \end{aligned} \tag{3}$$

where:
- w: number of windows;
- v: variation in the number of DMUs;
- z: number of DMUs in each window;

- *h*: number of different DMUs;
- *p*: window width (p ≤ k);
- *k* = Periods to which the data refer.

As shown in Table 1, considering the number of DMUs (7) and the number of periods to which the data refers (6 years), a window width of 4 years was selected, since the number of DMUs exceeds that obtained when window widths of 2 and 3 years are used. Thus, with the greater number of different DMUs in each window, the adopted window width allows for greater discriminatory power for obtaining efficiency improvements, thereby validating the efficient DMUs condition with greater reliability.

Table 1. DEA Window calibration

Components	**Formulas**	**p = 4 years**
Number of windows	k – p +1	(8 – 4 + 1) = 5
Number of DMUs in each window	(n) (p)	[(7) (4)] = 28
Number of different DMUs	(n) (p) (w)	[(7) (4) (5)] = 140
Variation in the number of DMUs	n (p – 1) (k – 1)	[(7) (3) (7)] = 147

Source: Author`s calculations in Microsoft Excel (2019)

Based on the procedures adopted for setting the range of the analysis windows, as presented in Table 1, Table 2 shows their configuration in the form of moving means, which, by successively removing the initial year and including the final year immediately afterwards in each period, allows the evaluation process to obtain more reliable results when comparing periods.

Table 2. Window configuration

Periods		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Windows	1	2016	2017	2018	2019				
	2		2017	2018	2019	2020			
	3			2018	2019	2020	2021		
	4				2019	2020	2021	2022	
	5					2020	2021	2022	2023

Source: Author`s calculations in Microsoft Excel (2019)

Methodology and Data

According to Basias and Pollalis (2018), based on measurable and observable data, the statistical method is used to facilitate the development of the assessment through quantitative indicators. Thus, with the objective of capturing changes and levels of efficiency recorded by scientific DMUs, this method employed procedures related to the description, measurement and evaluation of quantitative aspects of scientific reality. Similarly, as part of the adopted procedures, the comparative analysis method was used to examine the phenomenon under study, specifically by identifying trends, differences, and similarities in the performance of the DMUs, over the analyzed period, finding theoretical support in Prodanov and Freitas (2013).

The data supporting the study were obtained from secondary sources, namely official documents from the Angolan Ministry of Fisheries and Marine Resources (MINPERMAR), specifically its statistical yearbooks for (2017), (2022) and (2024), published by the Angolan National Institute of Statistics (INE). Thus, in order to more comprehensively capture the dynamics of the process of optimizing productive resources in the Angolan fishing sector, over the period from 2016 to 2023, data recorded for both industrial and semi-industrial fishing in the provinces of Cabinda, Zaire, Bengo, Luanda, Kwanza Sul, Benguela, and Namibe were considered. The mean values, by variable, for the period 2016-2023, appear in Table 3.

Table 3. Mean values per variable

DMUs	Number of vessels	Population fishing	Captur total
Cabinda	2	17	16984
Zaire	1	9	48193
Bengo	1	8	33801
Luanda	149	2975	162565
Kwanza Sul	8	180	34520
Benguela	53	1107	136914
Namibe	45	773	64738

Source: Author`s calculations in SPSS 26.0 (2019)

Similarly, in order to analyze the longest period permitted by the availability of published data, statistical imputation, specifically the technique of replacing missing data or extreme values with their respective means, was employed. This was achieved by incorporating data for the year 2017 (not published at the time of this study), in order to ensure continuity in the dynamics of the trends observed.

With regard to the statistics included in the model, the results adopted were based on their operational relevance, reflecting the resources used in the Angolan maritime fishing sector (inputs: the fishing fleet comprised of the number of vessels operating in the trained period, representing the sector's installed productive capacity; and the fishing population comprised of the number of workers employed by the sector) and the results (outputs: total catch and marketing revenue, representing the physical indicator of fisheries production).

The descriptive statistics of the sample used in the DEA assessment, presented in Table 4, reveal important structural characteristics of the Angolan maritime fishing sector. The variable number of shipments shows a significant range, with values varying between zero and 184, a mean of 37, and a standard deviation of 51, indicating strong heterogeneity among the DMUs (Detailed Management Units). This high dispersion suggests that some provinces operate with a substantial fishing fleet, while others have no registered vessels during the period. The fishing population variable also shows high variability, with values between 0 and 4,391. Its median of only 115 reveals an asymmetrical distribution, with activity concentrated in a few provinces and a predominance of limited fishing population contingents in most coastal regions. This configuration may reflect regional inequalities in the productive structure and community organization of fishing, directly influencing the levels of efficiency offered, especially in input-oriented models.

The total variable capture, used as the main proxy for productive output, presents a median of 54,423, suggesting a less asymmetrical distribution than the previous variables, although still marked by strong dispersion.

Table 4. Statistics descriptive

Variables	Minimum	Maximum	Median	Media	Std deviation
Number of vessels	0	184	8	37	51
Population fishing	0	4391	115	707	1103
Total capture	2673	225116	54423	68463	53665

Source: Author`s calculations in SPSS 26.0 (2019)

Considering the institutional heterogeneity and statistical limitations observed in the Angolan maritime fishing sector, the sample data did not present a normal distribution, which justified the application of the non-parametric Spearman rank correlation coefficient (ρ^o), suitable for productive contexts with asymmetrical and dispersed variables. Table 5 presents the results of the brightness matrix between the variables considered for inclusion in the DEA model, revealing high and statistically significant coefficients at the 0.01 level (two extremes). The demonstration of ρ^o = 0.971 between the number of vessels and the fishing population stands out, showing a strong structural association between these two inputs, which is consistent with the operational logic of the sector, where the volume of vessels tends to directly reflect the human contingent involved in fishing activity. Despite the demonstrated increase between these variables, it was decided to maintain both in the model due to the limitations of alternative data that could serve as complementary proxies, as well as the greater operational stability and statistical availability of the number of vessels variable. This methodological decision aims to preserve the representativeness of the inputs without compromising the robustness of the model, ensuring that, although correlated, the variables capture distinct dimensions of the productive capacity of the DMUs. As a production variable, the total catch variable was maintained to directly reflect the productive performance of the demonstrated units and to present evident manifestation coefficients with the inputs (ρ^o = 0.723 with vessels and ρ^o = 0.694 with fishing population), reinforcing its suitability as an outcome indicator in the DEA model.

Integrating inspection analysis with the selection of variations allows for greater methodological consistency and contributes to building a technical efficiency model more suited to the specificities of the sector, while respecting the criteria of statistical validity and operational relevance. This approach strengthens the interpretation of results and expands the potential for practical application of the findings, especially in the context of formulating public policies and strategies for optimizing resources in the fisheries sector.

Table 5. Non-parametric correlation matrix between variables

ρ^o	Number of vessels	Population fishing	Capture total
Number of vessels	1,000	0.971 **	0.723 **
Population fishing	0.971 **	1,000	0.694 **
Total capture	0.723 **	0.694 **	1,000
**. The correlation is significant at the 0.01 level (2 tails).			

Source: Author`s calculations in SPSS 26.0 (2019)

RESULTS AND DISCUSSION

Table 6 presents the overall results of efficiency levels for each DMU (province) and in each year. Thus, using the heat map applied to the results, it is possible to see that the DMU with the best mean efficiency record and over the largest number of years were the provinces of Zaire, Bengo and Cabinda respectively, also highlighting the efficiency scores recorded by the provinces of Luanda and Cabinda with a positive trend, despite the high variability (minimum values in 2016 and maximum values in 2023).

The provinces of Kwanza Sul and Namibe showed consistently low performance with little variation, suggesting the prevalence of persistent structural inefficiency in their operational processes. The year 2016 shows results indicating high levels of dispersion among efficiency forecasts for the sector as a whole, i.e., the coexistence of efficient and inefficient DMUs (Daily Management Units) in similar numbers. This contrasts with the period between 2020-2023, which shows a trend of overall improvement and reduced variability. This may indicate the effect of public policies stimulating fishing activity, investments, or operational adjustments in the sector.

The results of the efficiency scores obtained in isolation are consistent with those expected and mentioned in the introduction. They are corroborated in the literature related to the analysis of fishing efficiency. In this regard, studies by Anderson (2002) e Pascoe, Kirkley, Gréboval, & Morrison-Paul (2003), are notable, as they attest to the non-proportionality in the relationship between the size of the fishing fleet and efficiency; in other words, DMUs with larger fleets of vessels tend to be less efficient.

Table 6. Summary of efficiency scores

DMUs	2016	2017	2018	2019	2020	2021	2022	2023	Mean	Std. dev.
Cabinda	0	50	17	75	100	100	100	100	68	41
Zaire	100	50	17	75	100	100	100	100	80	31
Bengo	0	50	33	75	100	100	100	100	70	38
Luanda	15	100	47	53	65	100	61	100	68	31
Kwanza Sul	0	7	9	15	25	25	6	11	12	9
Benguela	100	72	63	24	27	97	91	100	72	32
Namibe	24	10	23	6	2	2	2	2	9	9
Mean	34	48	30	46	60	75	66	73	-	-
Std. dev.	46	33	19	31	42	42	44	46	-	-

Source: Author`s calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)

Figure 1 highlights significant disparities in pure efficiency among the seven provinces tested. The overall mean efficiency, at 54%, serves as a benchmark for evaluating the relative performance of each region. The provinces of Zaire (80%), Benguela (72%), Bengo (70%), Cabinda (68%), and Luanda (68%) stand out positively, all above the national mean. These results suggest greater rationality in the allocation of productive inputs, possibly associated with factors such as consolidated infrastructure, institutional capacity, effective public policies, or greater integration with local production chains. In contrast, Kwanza Sul (12%) and Namibe (9%) present critical levels of efficiency, including underutilization of available resources and possible operational bottlenecks. The poor performance of these regions may reflect structural limitations, lack of targeted investments, weak management, or discontinuity of sectoral policies. These results reinforce the need for specific instructions, such as technical training programs, equipment modernization, institutional strengthening, and encouragement of interprovincial cooperation.

These results are in line with studies by UNCTAD (2022), that explain why disparities in technical efficiency between provinces or fishing regions are not only a reflection of natural conditions, but above all of available infrastructure, institutional capacity, effective public policies and integration with local production chains.

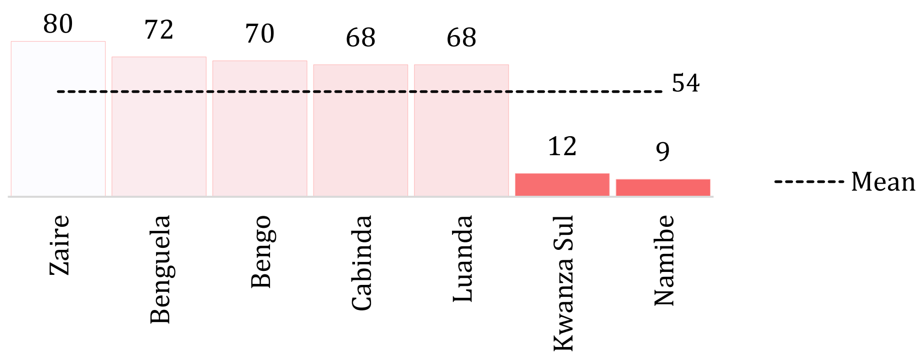

Figure 2. Pure technical efficiency (%)

Source: Author`s calculations in Microsoft Excel (2019)

Figure 3 presents the annual evolution of mean sectoral technical efficiency during the period (2016-2023), revealing a predominantly upward trajectory, albeit marked by occasional fluctuations. In 2016, performance began at 34%, reflecting a scenario of low institutional efficiency. In subsequent years, an alternation between advances and setbacks is observed: in 2017, there is a recovery to 48%, followed by a drop to 30% in 2018, which may indicate operational instability or the absence of structuring policies in the sector.

From 2019 onwards, the trend becomes more consistent, with progressive growth: 46% in 2019, 60% in 2020, and a peak of 75% in 2021. This period suggests the implementation of corrective measures, strategic reorganization, or institutional maturation. Despite a slight decrease to 66% in 2022, performance rises again in 2023, reaching 73%, which reinforces the hypotheses of reported improvements.

The linear trend line fitted to the data shows a coefficient of determination of 76%, indicating that 76% of the variation in mean efficiency can be explained by the annual time progression. This value is statistically robust and confirms the existence of a positive trend over the years. However, the observed fluctuations, especially in 2018 and 2022, suggest the presence of exogenous or non-linear factors, recommending the use of complementary methodological approaches.

Between 2016 and 2023, the mean technical efficiency of the Angolan fishing sector showed a fluctuating, but upward, trajectory, as mentioned. Thus, it was found that the results of the study are aligned with those of MINPERMAR, and consistent with its statistical yearbooks for the years 2017, 2022, and 2024.

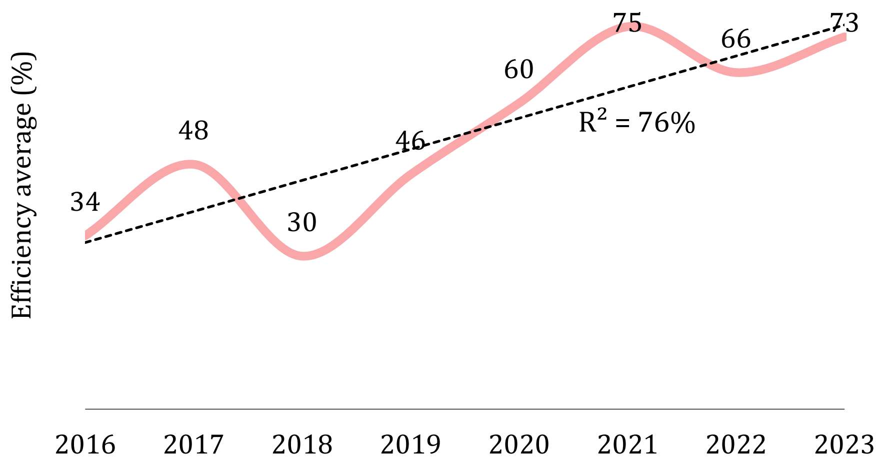

Figure 3. Annual dynamics in sectoral efficiency

Source: Author`s calculations in Microsoft Excel (2019)

Figure 4 shows the evolution of mean efficiency (%) across five analytical windows, revealing an upward trajectory with occasional fluctuations. In the first window, an extremely low efficiency level is observed (18%). From the second window onwards, a significant jump to 64% is seen, indicating the introduction of corrective measures, operational reorganization, or strategic investments.

In the third window, there is a drop to 56%, which may reflect internal configurations, seasonality, or temporary external impacts. However, in the following windows (4 and 5), efficiency returns to the 64% level and reaches 67%, establishing improvements and greater stability in sectoral performance.

The linear trend line has a coefficient of determination R^2 of 58%. This value indicates that 58% of the variation in mean efficiency can be explained by the linear progression between the windows, reinforcing the existence of a moderate positive trend. However, the remaining 42% of variability not captured by the model suggests the influence of non-linear or exogenous factors.

These results, with means smoothed over time, are consistent with the equally increasing trend of catches in African marine areas, including over a much longer period (1975-2023), according to data from (FAO, 2025).

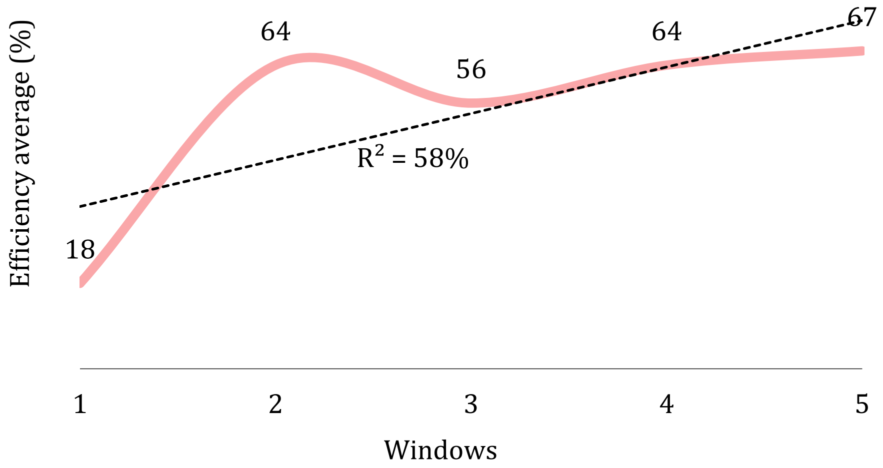

Figure 4. Inter-window dynamics in sectoral efficiency
Source: Author`s calculations in Microsoft Excel (2019)

The information that appears in Figure 5 validates the percentage variation in efficiency rates across the five windows, which is explained by the temporal (linear) trend. Thus, the values obtained for each are R^2 respectively: (Cabinda: the trend in efficiency improvements was 70% upward, i.e., a significant improvement in its levels of productive resource combination, a reduction that intertemporality is a good predictor of improvement, possibly due to investments or institutional reorganization); (Zaire: strong upward trend, having increased consistently, with intertemporality explaining 74% of the observed variation); (Bengo: showed a moderately positive upward trend in efficiency, therefore, intertemporality explains a significant part of the variation that occurred between the analyzed years, namely 63%; however, there are factors that conditioned its performance, and which are not fully explained by technological variations); (Luanda: 15% upward trend: very weak trend. The level of efficiency is low and little influenced by intertemporality. This may indicate stagnation or absence of ineffective management practices); (Kwanza Sul: 70% upward trend, despite low inter-window efficiency rates, these show a tendency to recover or increase efficiency, albeit at levels considered lower); (Benguela: 44% upward trend, weaker compared to those recorded by other provinces, with intertemporal factors explaining less than half of the recorded variation, showing the influence of one-off factors or operational instability) and (Namibe: 29% downward trend, a downward trend in efficiency over time. Intertemporal factors explain little of the recorded variation; however, a possible structural decline or loss of competitiveness in the face of excessive scientific expertise).

Despite the overall upward trend, as mentioned in the discussion of Figure 4, the results for the provinces of Benguela and Namibe, in Figure 5, also show alignment with those obtained in Schrobback, Schrobback, Pascoe, McWhinnie, & Hoshino (2023) and Ewedji & Dehlor (2024), highlighting that, in several fishing regions, mean efficiency remained low over time, revealing a high degree of technical inefficiency and the presence of persistent idle capacity.

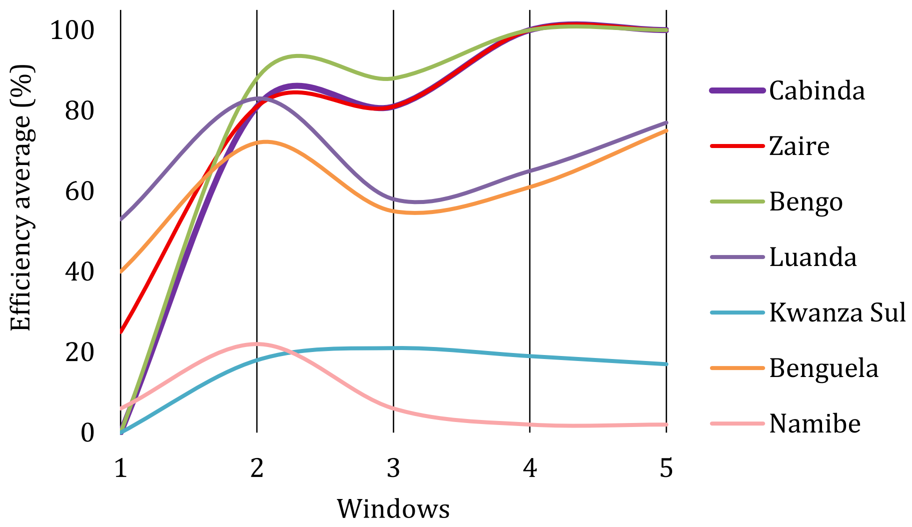

Figure 5. Inter-window dynamics in provincial efficiency
Source: Author`s calculations in Microsoft Excel (2019)

To provide a more comprehensive view of the factors influencing the performance of the provinces shown in their resource optimization process within the context of fishing activity, Table 6 presents the results relating to the mapping of efficiency losses and respective operational slack, by variable. From the results obtained, it is possible to observe that, both in the variable of the number of vessels and in the variable of total catch, the provinces consistently operate below the efficient frontier, without reducing the disproportionate combination of these inputs. These records indicate performance below the optimum, originating from the scale or intensity of their operations.

Although the sources of inefficiency are respected, the greatest attention falls on the total variable catch of the fishery, with a persistent record of maximum inefficiency, within the joint operational scope. From the student provinces. Thus, it can be observed that the corresponding slack periods also show records of high slack.

These results are consistent with studies covering longer time periods, which show that the performance of the African continent as a whole over the last 70 years has recorded inefficiencies equivalent to a loss of 2 million tons of fish production per year, as reported in Ye, Ndiaye, & Al-Husaini (2024). This reflects a trend of degradation in the level of optimization of fisheries resources and fisheries production in Angola and across the continent.

Table 5. Inter-window sectoral inefficiency

Windows	Number of vessels		Population fishing		Total capture	
	Inefficiency (%)	Slack	Inefficiency (%)	Slack	Inefficiency (%)	Slack
1	60	0	36	7	100	43568
2	80	0	20	7	100	5489
3	96	0	4	23	100	5164
4	93	0	7	119	100	5402
5	93	0	7	171	100	6843
Mean	84	0	15	65	100	13293

Source: Author`s calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)

CONCLUSION

The combination of empirical evidence from different contexts confirms patterns already identified in the international literature on fisheries efficiency, such as those of Anderson (2002) and Pascoe et al. (2003), which highlight the non-proportionality between fleet size and efficiency. The Angolan results reinforce this finding, showing that increasing installed capacity does not guarantee efficiency gains.

The growing and relatively stable trajectory of technical efficiency between 2016 and 2023 aligns with studies by UNCTAD (2022) and FAO (2025), which point to the importance of institutional and infrastructural factors in improving fisheries performance. Thus, this study contributes by demonstrating that, in Angola, institutional advances and public policies played a decisive role in the gradual recovery of efficiency, although still far from full optimization.

The critical variable of total fish catch load confirms findings by Schrobback et al. (2023) and Ewedji & Dehlor (2024), which highlight the persistence of idle capacity and technical inefficiency in several fishing regions. The unique contribution of this study lies in showing, with recent and specific data from Angola, how this limitation compromises the exploitation of the potential of the marine ecosystem and requires sustainable growth strategies.

From a political point of view, the results corroborate the literature on fisheries governance (Ye, Ndiaye & Al-Husaini, 2024), which emphasizes significant production losses due to technical inefficiency. The novelty here is the application of interprovincial benchmarking, which allows the identification of good local practices (as in Zaire) and specific bottlenecks (as in Luanda), offering a practical tool to guide structural and operational reforms.

Institutional and community capacity building, already advocated in regional studies by FAO and UNCTAD, gains an applied dimension in this work for the Angolan context, highlighting that the integration of coastal communities in resource management is a necessary condition to reduce waste and increase productivity.

In summary, this study not only confirms trends already documented in the international literature on fisheries efficiency, but also offers a unique contribution: a detailed analysis of Angola's trajectory between 2016–2023, with an interprovincial focus, which highlights both institutional advances and persistent operational challenges. This approach provides original input for national and regional public policies by integrating internal benchmarking with international comparisons, broadening the debate on efficiency and sustainability in the African fisheries sector.

The study, although relevant, has limitations that compromise its scope and robustness. This is the case with the high level of standard deviations recorded in provinces such as Cabinda and Kwanza Sul, which weakens the reliability of the efficiency scores obtained from DEA models, while the centrality of the catch load as the main variable reduces the analytical dimension by excluding institutional and environmental factors. Furthermore, the time frame from 2016 to 2023 does not contemplate long-term cycles, limiting the understanding of the dynamics of structural efficiency. Therefore, it is recommended to incorporate additional variables, expand the historical series, and use complementary methodologies, such as polynomial regressions and stochastic frontier analysis, capable of offering greater sensitivity and analytical consistency.

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APPENDIX

Inter-window sectoral efficiency

DMUs	2016	2017	2018	2019	2020	2021	2022	2023	Mean	Std. dev.
	0	0	0	0					0	0
		100	25	100	100				81	38
Cabinda			25	100	100	100			81	38
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	0	50	17	75	100	100	100	100	68	41
	100	0	0	0					25	50
		100	25	100	100				81	38
Zaire			25	100	100	100			81	38
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	100	50	17	75	100	100	100	100	80	31
	0	0	0	0					0	0
		100	50	100	100				88	25
Bengo			50	100	100	100			88	25
				100	100	100	100		100	0
					100	100	100	100	100	0
Mean	0	50	33	75	100	100	100	100	70	38
	15	100	46	51					53	35
		100	60	73	100				83	20
Luanda			35	44	54	100			58	29
				44	54	100	63		65	24
					50	100	59	100	77	27
Mean	15	100	47	53	65	100	61	100	68	31
	0	0	0	0					0	0
		13	13	20	25				18	6
Kwanza Sul			13	20	25	25			21	6
				20	25	25	6		19	9
					25	25	6	11	17	10
Mean	0	7	9	15	25	25	6	11	12	9
	100	44	16	0					40	44
		100	100	46	41				72	33
Benguela			72	25	23	100			55	38
				25	23	100	95		61	42
					21	91	87	100	75	36
Mean	100	72	63	24	27	97	91	100	72	32
	24	0	0	0					6	12
		20	51	16	2				22	21
Namibe			18	3	2	2			6	8
				3	2	2	2		2	0
					2	2	2	2	2	0
Mean	24	10	23	6	2	2	2	2	9	9
General mean	34	48	30	46	60	75	66	73	-	-
General Std. dev.	44	35	21	33	44	47	47	50	-	-

Source: Author calculations in EMS 1.3 (Dortmund Patente Nº 1.3, 2000)

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ORIGINAL SCIENTIFIC PAPER

Inflation Dynamics in Southeast Europe: A Panel Econometric Analysis of Monetary Policy Transmission

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ABSTRACT
This paper investigates the relationship between monetary policy and consumer price inflation in nine Southeast European (SEE) economies, with the aim of identifying the key channels through which monetary policy influences inflation dynamics. The analysis is based on an annual panel dataset covering the period 2007–2022. Static panel econometric techniques are applied, combining fixed-effects and random-effects estimators with robust standard errors. Model validity is assessed through cross-sectional dependence tests, panel unit-root tests and the Hausman specification test. The model includes lending interest rates, exchange rates and broad money (M3), alongside control variables such as producer price inflation, unemployment, adjusted net income per capita, domestic credit and foreign direct investment. The results indicate that lending interest rates exert a strong positive and statistically significant effect on inflation, consistent with Neo-Fisherian dynamics under uncertainty. Producer price inflation, domestic credit and foreign direct investment also show positive and significant effects, while broad money (M3) displays a negative coefficient, reflecting structural characteristics and high collinearity with credit aggregates in SEE financial systems. By providing a harmonized multi-country dataset and a comprehensive panel diagnostic framework, the study contributes new empirical evidence on the non-standard transmission of monetary policy in transition economies and offers policy-relevant insights for countries aligning their monetary frameworks with European Central Bank practices.

Keywords: *monetary policy transmission, inflation dynamics, panel data econometrics, Southeast Europe, Neo-Fisherian effect, interest rate channel, credit channel, transition economies*

JEL Classification: E31, E52, C23, E58

INTRODUCTION

This study analyzes how monetary policy affects inflation. Monetary policy, a set of instruments used by central banks to influence liquidity and interest rates, plays a central role in shaping inflation dynamics. The relationship between monetary policy and inflation is highly complex and a subject of ongoing debate among economists. The link between monetary policy and inflation is influenced by various factors, economic conditions, and contextual elements. According to some views, inflation is a monetary phenomenon directly determined by changes in the money supply. This suggests that when the money supply grows faster than the economy itself, it leads to

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inflationary pressure or an increase in the inflation rate. In addition to this perspective, there is another view of inflation based on the excess demand model, which takes into account cost-related factors such as prices or wages. Proponents of this model argue that demand-side factors in labor or goods markets provide a better explanation of inflation than monetary variables.

Monetary policy effects are regime-dependent, producing only short-lived price responses at low inflation but stronger and more persistent impacts on both inflation and real activity when inflation is elevated (Gargiulo, Matthes, & Petrova, 2025). The relationship between monetary policy and inflation can be observed and analyzed through various economic variables, that is, elements of macroeconomic dynamics. If we understand macroeconomic dynamics as a set of changes and movements in economic variables at the level of the entire economy, then inflation can be tracked through the movement of monetary aggregates, production, unemployment and similar indicators.

Economists see economic growth as the main manifestation of macroeconomic dynamics (Stefanović, 2014), which primarily refers to the increase in the production of goods and services within the economy. Economic growth can be measured by changes in Gross Domestic Product (GDP) over time, most commonly expressed as a percentage. Inflation is a negative factor influencing the economy, as it reduces the value of the domestic currency in the short-term and, in the long term, hampers economic growth and adversely affects investment activity (Marcu, 2013). If inflation is viewed as a monetary phenomenon, that is, as a consequence of an increase in the money supply, then it is necessary to determine the role of the central bank in this process, given that it is responsible for controlling the money supply.

Monetary authorities may deliberately stimulate economic activity by increasing the money supply. This can also arise from challenges in managing public finances, where additional money is spent to cover budget deficits. Precisely this issue has highlighted the need for the independence and effective functioning of central banks in relation to the executive branch. In a broader economic context, technological innovations contribute to strengthening business performance and the development of sustainability initiatives (Velichkovska, Mitić, & Kojić, 2025), thereby supporting overall economic growth and reinforcing the conditions necessary for stable macroeconomic development. Within this broader framework, empirical evidence suggests that economic growth plays a significant role in stimulating the production of scientific knowledge, while no corresponding effect in the opposite direction has been identified (Vasilić & Veselinović, 2024).

Price increases can be caused by various factors, ranging from higher taxes, reduced inventories of raw materials, increased demand and so on. However, persistent and long-term inflation is most often associated with expansionary fiscal policy, a lack of monetary instruments, governments that are unable to effectively manage public finances or dysfunctional central banks that are subject to political pressures (Jørgensen & Ravn, 2022). What is certain is that economies with high inflation rates and fixed exchange rates are not competitive; in other words, they face slow economic growth. Furthermore, inflation leads to increased speculative activity in financial markets, where alternatives to actual business operations are sought.

Another characteristic of inflation is the spillover effect, where an increase in the price of one product leads to price increases in other products, which can, in turn, cause inflationary effects to spill over from one economy to another. The problem is not stable and controlled inflation, for which various monetary policy measures and instruments are developed and applied. The real issue is high and uncontrolled inflation, the intensity and direction of which cannot be predicted.

This research covers nine SEE countries[1]. Their selection is rooted in their shared geographic location, a region characterized by diverse institutional frameworks and exchange-rate regimes. The legacy of socialist governance followed by a post-conflict transition in many of these countries

[1] Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Hungary, Montenegro, North Macedonia, Romania, and Serbia

provides essential background for interpreting their current economic and monetary policy frameworks.

A key element of this study is the distinction between countries that are already members of the EU and those still on the path to accession. This distinction introduces a layered dynamic in which EU members tend to follow harmonized monetary policy frameworks, while candidate countries often undertake structural reforms to align with EU accession requirements. The gradual convergence of monetary strategies among these states reflects their shared objective of achieving institutional and policy compatibility with EU norms.

Beyond formal monetary frameworks, these countries engage in broader regional cooperation through various initiatives and organizations, facilitating coordinated responses to mutual economic challenges. Such collaboration fosters a climate of policy alignment and regional stability. Moreover, their active participation in global institutions such as the International Monetary Fund (IMF) and the World Bank provides both technical support and access to financial resources that further shape monetary policy decision-making. The analysis covers 2007–2022, a period marked by major global and regional disruptions, including the 2008 global financial crisis and the effects of the COVID-19 pandemic (Grabowski, Janus, & Stawasz-Grabowska, 2023). These episodes offer salient benchmarks for interpreting variation in monetary policy stances and macroeconomic outcomes.

The variable set operationalizes key monetary policy channels and standard controls within a panel framework. We estimate the model on data for SEE economies to quantify the extent to which monetary policy shapes inflation.

This article offers several novelties compared to prior research. First, it assembles a harmonized panel dataset, providing broader coverage than earlier studies, which typically focused on single countries or shorter time spans. Second, it incorporates an extended set of explanatory variables, including lending interest rates, exchange rates, broad money (M3), producer price inflation, unemployment, net income, domestic credit and foreign direct investment. Third, the empirical strategy applies panel FE and RE estimators, supported by a full set of diagnostic tests, ensuring robustness of the results. Finally, the study places its findings within the specific institutional and structural context of SEE, highlighting the non-standard transmission of monetary policy in small open transition economies. The results show that lending interest rates, producer price inflation and foreign direct investment exert positive and significant effects on consumer price inflation, whereas broad money (M3) enters with a negative coefficient, reflecting structural heterogeneity and high collinearity with domestic credit.

THEORETICAL BACKGROUND

This study draws on sources across economics, finance, and monetary economics; in addition to peer-reviewed journals, it uses books, reports, working papers, and government and international publications to provide a comprehensive, multidimensional evidence base.

The literature search imposed no temporal limits, allowing the inclusion of classic works to anchor the theoretical framework. Recent contributions were likewise incorporated to capture current trends and innovations in monetary policy. Selection proceeded through a carefully structured, multi-step approach. Only studies directly relevant to the research question were retained, yielding a comprehensive view of monetary policy's impact in the contemporary economic context.

A large body of research has clarified the mechanisms and transmission channels of monetary policy, providing a foundation for sound economic policymaking. Initial research efforts were primarily concerned with identifying the aims, tools and functions of monetary policy, particularly instruments like interest rates and open market operations and assessing their influence on liquidity and capital flows within the economy.

Research has extensively examined this interaction, yielding insights into price dynamics, inflation expectations and strategies for maintaining price stability.

Among the most transformative figures in economic thought was British economist John Maynard Keynes, whose 1936 work fundamentally reshaped modern economic theory. Challenging the prevailing classical paradigms of the time, Keynes emphasized the central role of interest rates and investment in stimulating economic growth (Keynes, 1936). His contributions provided the intellectual foundation for Keynesian economics and have had a lasting influence on both theoretical and practical aspects of monetary policy.

This review of the literature illustrates the progression of thought surrounding monetary policy, emphasizing its evolving role in guiding economic cycles and ensuring macroeconomic stability in the modern era.

Central banks employ various instruments and strategies to control inflation within an economy. There is a substantial body of literature dedicated to the study of monetary policy and inflation, indicating that this area of economics remains a subject of broad and ongoing research interest. Extensive research investigates how monetary policy relates to inflation in both theoretical and empirical work.

Recent theoretical and empirical work shows that when policy-rate increases are perceived as permanent, inflation tends to rise even in the short run, the so-called neo-Fisher effect (Williamson, 2018), (Uribe, 2022). Vector Autoregression (VAR)-based identification confirms short-run co-movement of nominal interest rates and inflation in the United States (US) data.

Inflation volatility, viewed through the lens of exchange rate fluctuations and output gap volatility (Özer, Grubišić, & Küçüksakarya, 2023) highlights the importance of implementing appropriate monetary policy. Central bank independence is discussed in a section of the book (Agoba, Fiador, Sarpong-Kumankoma, & Sa-Aadu, 2022), which focuses on price stability management in Africa.

Further empirical studies also identify a negative and statistically significant relationship between the perceived tone of monetary policy communication and expected inflation (Carotta, Mello, & Ponce, 2023), using panel data regression analysis. The study on fiscal backing for central banks (Del Negro & Sims, 2015) argues that such support would benefit banks with large balance sheets composed of long-duration nominal assets, such as long-term bonds or time deposits, thereby enhancing their ability to control inflation.

Research on the transmission of monetary policy shocks using relevant economic and financial variables (Gertler & Karadi, 2015) demonstrates that small changes in short-term interest rates can lead to large movements in credit costs. Additionally, this research shows that output and inflation are affected by shocks resulting from frequent surprises in policy announcements. A study conducted in the US since 1979 (Eleftheriou & Kouretas, 2023) reveals patterns in monetary policy characterized by a strong response to inflation and effective management of its fluctuations.

Another study (Flaccadoro & Landi, 2025), which included 27 developing countries, showed that inflation in these countries is dependent on US monetary policy. This suggests that the monetary policy of major economies can significantly influence inflationary trends in less developed countries, posing a challenge for monetary authorities in emerging markets.

Recent empirical advances have emphasized the importance of disentangling the nature of monetary policy shocks. Jarociński and Karadi (2020) show that policy surprises often conflate genuine monetary shocks with information effects, underscoring the need for precise identification strategies. Complementing this perspective, Boissay et al. (2025) examine how the effects of monetary tightening depend on whether inflationary pressures are supply or demand-driven, highlighting that policy transmission can differ substantially across contexts. Together, these studies provide a state-of-the-art framework for understanding the complex and heterogeneous responses of inflation to monetary interventions, which is particularly relevant for economies in SEE.

While global contributions have clarified the transmission of monetary policy across advanced economies, evidence from SEE remains relatively limited. Recent studies increasingly emphasize the unique institutional and structural features of the region. For instance, Jakšić (2022) employs a Global Vector Autoregressive (GVAR) model to show that inflation in Central, Eastern and Southeastern Europe (CESEE) countries is strongly affected by international shocks, but with heterogeneous responses depending on EU membership status. Similarly, Čaklovica and Efendić (2020), using a dynamic panel framework for 28 European transition economies, identify unemployment, wage dynamics and external shocks as key drivers of inflation, underscoring the sensitivity of transition economies to both domestic and global factors.

Focusing more narrowly on the Western Balkans, Minasyan et al. (2023) apply an augmented Phillips curve and structural VAR approach, finding that inflation in the subregion is predominantly driven by demand shocks and that convergence with euro area inflation is limited. Complementing this, Durguti et al. (2021) employ panel Generalized Method of Moments (GMM) techniques to analyze Western Balkan economies and report that GDP growth, remittances, and Foreign Direct Investments (FDI) exert a significant influence on inflation dynamics. Together, these studies demonstrate that SEE countries face distinct inflationary mechanisms, reflecting their post-transition development trajectories and partial integration into EU monetary structures.

Inflation expectations are a critical factor to consider in the conduct of monetary policy. A significant survey explored consumers' willingness to increase spending in relation to their anticipated inflation expectations (Breitenlechner, Geiger, & Scharler, 2024), also taking into account monetary policy shocks. The role of monetary policy in the context of inflation is examined in the work (John, Kumar, & Patra, 2022), who argue that fighting inflation must be pursued through monetary policy instruments regardless of the nature of inflationary pressures.

The study (Rangarajan & Nachane, 2021), which explores the role of monetary aggregates in various macroeconomic theories, challenges the view that monetary aggregates generally cannot explain inflation, except when inflation is linked to the output gap. Additionally, the literature includes works that explain the measures undertaken by central banks of major global economies in response to rising or high inflation (Shapran & Britchenko, 2022).

Recent studies, such as Lukmanova and Rabitsch (2023), which distinguish between interest rate shocks and inflation target shocks and Bouakez and Kano (2024), which propose an alternative empirical identification of the Neo-Fisher effect without assuming cointegration, expand the methodological toolkit used in this literature. These works highlight that the Neo-Fisher effect may manifest differently depending on how permanent shocks are defined and identified.

Building on these findings, the present paper advances the literature by a) extending the sample to nine SEE economies over 2007–2022; b) incorporating a broader set of explanatory variables, including foreign direct investment and adjusted net income; c) applying comprehensive panel diagnostics (unit root, cross-sectional dependence, and Hausman testing), and d) explicitly distinguishing between EU member states and accession countries. This approach allows for a more nuanced assessment of monetary policy's role in shaping inflationary outcomes in a heterogeneous regional setting.

Data and Methodology

A rigorous assessment of monetary policy transmission requires both reliable data and an appropriate methodological design. The empirical analysis is therefore grounded in carefully selected materials and supported by econometric techniques that ensure validity and robustness of the results.

Empirical Settings

The empirical setting reflects the specific structural and institutional features of SEE economies, which shape the transmission of monetary policy to consumer prices. In this context, the dataset captures the interaction between financial variables and inflation dynamics over time, ensuring that the analysis accounts for both cross-country diversity and regional commonalities.

The model specification draws on previous studies but adapts them to the context of SEE. For instance, Coibion and Gorodnichenko (2025) emphasize the role of expectations and interest rates in shaping inflation dynamics, while Salunkhe and Patnaik (2017) incorporate growth considerations in the analysis of inflation control. Other research, such as Roberts (2006) highlighted the role of unemployment and output volatility, whereas Cioran (2014) applied regression methods to explore the relationship between inflation, unemployment and interest rates. Building on this literature, the present study selects variables not only for their theoretical relevance but also for their data availability and suitability for econometric modeling. By combining demand-side and supply-side indicators, the model provides a balanced framework for analyzing inflation dynamics in transition economies.

A recurring limitation in the cited literature is the lack of standardization in terms of country coverage, sectoral scope, variable definitions and sample periods, which often leads to inconsistent or even conflicting results. Methodological diversity further complicates comparisons, ranging from qualitative approaches to various quantitative techniques. Moreover, many studies overlook soft institutional factors such as expectations formation, regime stability, institutional capacity, rule-of-law quality and trust in authorities, all of which influence the effectiveness of monetary policy. Recognizing these limitations is instructive, as it motivates improvements in research design and the construction of richer empirical frameworks.

Against this backdrop, the present study assembles a panel of nine SEE economies observed annually over sixteen years. This multi-country longitudinal dataset provides distinct advantages: it increases variability, reduces collinearity among variables and enhances the degrees of freedom available for estimation. It also enables the analysis of both temporal dynamics and country-specific effects, thus offering a more nuanced perspective than purely cross-sectional or purely time-series approaches. The dataset was compiled primarily from internationally recognized sources such as the World Bank, IMF and Eurostat, and was supplemented by national central bank statistics and official country publications. In cases where no consistent series were available, observations were omitted, resulting in an unbalanced panel. No artificial interpolation or smoothing was applied, preserving comparability and reliability across countries. Details of variable definitions, series codes and data sources are presented in the Appendix.

The use of annual data was dictated by availability and cross-country comparability. While higher-frequency data (quarterly or monthly) could, in principle, allow for more precise identification of monetary policy shocks, such series are incomplete or inconsistent across the SEE sample, limiting their feasibility in a panel setting.

The study period is particularly instructive, spanning the global financial crisis, the recovery phase and the COVID-19 shock, all of which significantly influenced monetary frameworks. During this time, SEE economies also underwent important political and economic transformations, including EU accession progress and institutional reforms. Financial stability, increasingly recognized as a central concern in the formulation of monetary policy since the global financial crisis, further underscores the importance of analyzing SEE economies under heterogeneous conditions. These developments provide a valuable context for assessing monetary policy effectiveness, thereby enriching the understanding of its role in safeguarding stability and supporting long-term development.

Empirical Strategy

The econometric approach is designed to capture both the time-series and cross-sectional dimensions of the dataset while addressing potential challenges such as non-stationarity, cross-sectional dependence and heterogeneity across countries. To this end, the analysis employs panel estimation techniques that allow for valid inference in the presence of unobserved country-specific effects and ensure the robustness of results through a sequence of diagnostic tests and specification checks. In addition to unobserved heterogeneity, institutional differences, such as whether a country is an EU member or an accession candidate, may also shape the transmission of monetary policy. While this study does not explicitly incorporate EU membership as a dummy or interaction term, acknowledging such distinctions highlights an important avenue for future research (Obradović, 2024)[2].

Panel methods are applied to data covering nine economies over a sixteen-year horizon. Using a longitudinal design with repeated country observations, we follow the same economies across years. Formally, the baseline panel specification is given by Baltagi (2021), Hsiao (2015) and Greene (2012):

$$y_{\{it\}} = \alpha_{\{i\}} + X'_{\{it\}}\beta + \varepsilon_{\{it\}}, i = 1, \dots N; t = 1, \dots T \quad (1)$$

Here, $y_{\{it\}}$ denotes the dependent variable (consumer price inflation), $X'_{\{it\}}$ is a K-dimensional vector of explanatory variables, β the parameter vector of interest, $\alpha_{\{i\}}$ unobserved country-specific heterogeneity, and $\varepsilon_{\{it\}}$the idiosyncratic error term. In this study, N=9 and T=16. This structure increases variability, reduces collinearity among regressors and improves the degrees of freedom relative to pure time-series or cross-sectional.

Estimation results in such settings are sensitive to the properties of the data-generating process. Unaddressed heteroskedasticity, autocorrelation or cross-sectional dependence may compromise inference. Therefore, a sequence of diagnostic tests was implemented prior to estimation: a) Pesaran-type tests to detect cross-sectional dependence across countries (Pesaran, 2021); b) panel unit-root tests to establish the stationarity of the variables (Levin, Lin, & Chu, 2002) and c) specification tests to decide between FE and RE estimators, with the Hausman test serving as the criterion (Hausman, 1978). The Hausman specification test evaluates whether the coefficient vectors estimated under FE and RE differ systematically. The test statistic is given by:

$$H = (\{^\wedge\beta\}_{\{FE\}} - \{^\wedge\beta\}_{\{RE\}})^T \left[Var(\{^\wedge\beta\}_{\{FE\}}) - Var(\{^\wedge\beta\}_{\{RE\}}) \right]^{\{-1\}} (\{^\wedge\beta\}_{\{FE\}} - \{^\wedge\beta\}_{\{RE\}});\ H \sim \chi^{2(k)} \quad (2)$$

In this expression $\{^\wedge\beta\}_{\{FE\}}$ and $\{^\wedge\beta\}_{\{RE\}}$ denote the coefficient vectors estimated using the fixed effects and random effects models, respectively, while $Var(\{^\wedge\beta\}_{\{FE\}})$ and $Var(\{^\wedge\beta\}_{\{RE\}})$ represent the corresponding covariance matrices. The superscript T indicates vector transposition and (k) denotes the number of parameters being tested. Under the null hypothesis, the RE estimator is both consistent and efficient, whereas the FE estimator is consistent but inefficient. Rejection of the null hypothesis suggests that the regressors are correlated with the unobserved individual effects, in which case the FE estimator should be preferred. It should be noted that the static FE and RE estimators employed here do not allow for explicit identification of exogenous monetary policy shocks. The focus is therefore on describing associations between monetary variables and inflation, with causal identification beyond the scope of the present econometric design.

[2] Part of the dataset and preliminary empirical analyses are derived from the author's doctoral dissertation (Obradović, 2024), while the present study extends the analysis through discussion of the results.

To quantify the effect of monetary policy on inflation, we estimate a RE panel model and report robust (clustered by country) standard errors. All estimations and diagnostics were performed in Stata.

We distinguish the following types of panel datasets (Beck & Katz, 1995), cross-section–dominant designs (CSTS - Cross Sectional Time Series, N > T) contrast with time-series–dominant designs (TSCS - Time Series Cross Sectional, T > N). Our sample falls into the latter. In such settings, pooled Ordinary Least Squares (OLS) is rarely defensible: country-specific unobservables confound coefficient estimates, regressors may not be exogenous and series often display non-stationary behavior. These departures from the classical assumptions motivate the use of FE/RE estimators with robust inference.

While the focus of this study is on static panel estimators, it is important to note that dynamic specifications, such as VAR; ARDL or System GMM, could in principle address endogeneity and capture richer dynamics. However, the relatively short time dimension of the dataset constrains their applicability. Future research may extend the analysis using these approaches as longer time series become available.

RESULTS AND DISCUSSION

The choice of interest rates, exchange rates and the broad money (M3) supply as proxies for the impact of monetary policy on inflation is firmly grounded in the central role these variables play in shaping price dynamics. Interest rates remain the primary instrument through which central banks influence inflation, consumption and investment: lower rates encourage borrowing and stimulate aggregate demand, while higher rates restrain credit activity, moderating spending and investment to prevent overheating.

The exchange rate, reflecting the relative value of domestic currency against others, directly affects trade flows, capital movements and ultimately consumer prices. An appreciating currency reduces the cost of imports and exerts downward pressure on inflation, but it can simultaneously weaken export competitiveness, whereas a depreciating currency has the opposite effect, boosting exports while increasing import prices and inflationary pressures. In parallel, the broad money (M3) supply captures the liquidity available in the economy and serves as an important barometer of monetary conditions, linking monetary expansion or contraction to inflationary trends. Taken together, these indicators provide a comprehensive lens through which the effectiveness of monetary policy in influencing inflation, particularly in open and financially integrated economies, can be assessed with greater accuracy.

The broad money (M3) supply serves as a comprehensive indicator of the volume of liquid assets circulating within the economy and reflects the broader stance of monetary policy. An expansion in broad money (M3) signals an increase in liquidity, which typically stimulates consumption and investment, thereby exerting upward pressure on inflation. In contrast, a contraction in broad money (M3) reduces the flow of money and credit, helping to cool an overheated economy and contain rising prices.

By analyzing the interactions between broad money (M3), interest rates and exchange rates, this study captures the concrete channels through which monetary policy shapes inflationary dynamics. This framework not only underscores the appropriateness of these indicators but also provides a more nuanced understanding of the complex mechanisms by which monetary policy influences both price stability and the broader contours of economic performance.

Sample Characteristics and Composition

The descriptive statistics presented in Table 1 reveal that the dataset is unbalanced, as shown in the observation column. The dataset takes the form of an unbalanced panel, as certain time series are not available for all countries and years under observation. Such gaps are common in studies covering transition economies over longer time horizons.

Nevertheless, this structure does not undermine the reliability of the findings, since modern panel econometric methods allow for valid estimation under these conditions. Missing values relate to the variable adjusted net national income per capita.

Table 3. Descriptive statistics

Variable	Observations	Mean	Std. deviation	Min	Max
ICP	144	3.326	3.639	-1.584	15.325
OER	144	56.907	81.609	0.679	372.596
BM	144	114.164	155.191	32.248	647.638
PPI	144	4.127	7.464	-7.233	44.710
LIR	144	7.754	3.377	1.471	17.572
UnE	144	14.278	7.714	3.420	35.230
AdjNIpc	135	3.139	4.837	-14.821	16.387
DCPS	144	92.149	132.645	24.623	524.515
EI	144	-6.285	7.827	-49.647	4.552
FDI	144	7.493	13.509	-40.086	106.594

Source: Authors based on Obradović (2024)

The values of these descriptive statistics, especially considering the minimum and maximum values, indicate that the sample includes economies at different levels of development. The sample consists mainly of developing countries but also includes developed economies. The wide range of minimum and maximum values for certain variables, alongside the covered research period, is influenced by the varying levels of development of the observed economies.

Fluctuations are particularly pronounced in broad money (M3) supply (ranging from 32.24 to 647.64), producer price inflation (from -7.23 to 44.71), domestic credit to the private sector (from 24.62 to 524.52) and foreign direct investment (from -40.08 to 106.59).

The standard deviation, as an indicator of dispersion, reflects the extent to which data values deviate from the mean. Larger values of the standard deviation signify higher variability within the dataset, whereas smaller values denote greater concentration around the average. Among the variables under consideration, the highest degree of variability is recorded for domestic credit to the private sector (132.64), followed by broad money (M3) (155.19) and the official exchange rate (81.61), underscoring the pronounced fluctuations in these dimensions of monetary and financial activity.

Statistical Examination

Using panel data regression analysis with both FE and RE models, an empirical study was carried out to investigate how monetary policy influences economic growth across nine countries in SEE. The estimation results indicate that monetary policy variables play a decisive role in shaping consumer price inflation in SEE. Lending interest rates show a strong and statistically significant positive effect, with a coefficient of 0.442 ($p < 0.01$), suggesting that higher borrowing costs are systematically associated with rising consumer prices. Producer price inflation is also positively related to consumer price inflation (0.077, $p = 0.036$), confirming the relevance of cost-push channels. Similarly, domestic credit to the private sector (0.073, $p = 0.005$) and adjusted national income per capita (0.139, $p = 0.012$) exert statistically significant positive effects, while foreign direct investment, though relatively modest in magnitude, is also positive and significant (0.033, $p = 0.018$). In contrast, broad money (M3) enters with a negative and statistically significant coefficient (−0.033, $p = 0.044$), reflecting its high collinearity with domestic credit and the structural features of SEE financial systems. Other variables, such as the exchange rate and employment index, are not statistically significant at conventional levels, while unemployment shows a positive but insignificant association with inflation.

The robustness of these findings is reinforced by the results reported in Table 2, where the coefficients across FE and RE specifications remain similar in magnitude and direction, thereby justifying the choice of the RE estimator based on the Hausman test $\chi^2 = (b - B)^T[Var(b) - Var(B)]^{-1}(b - B) = 2.40$, $p - value = 0.9835$. Taken together, these results confirm that the main transmission mechanisms of monetary policy in the region operate through interest rates, producer prices and domestic credit, while highlighting the structural complexities associated with broad money (M3) and capital inflows.

The results also underscore the importance of considering specific economic conditions and extraordinary events that characterized the period under review. This consideration enables a more precise interpretation of monetary policy impacts and sheds light on the possible shortcomings of traditional modeling approaches. Furthermore, acknowledging these unique circumstances supports the creation of more flexible and robust policy frameworks moving forward.

Empirical Evidence from Panel Regression Analysis

To assess the stationarity properties of the dataset, both the Im, Pesaran, and Shin (IPS) and the Cross-sectionally Augmented IPS (CIPS) tests were applied, with specifications that included and excluded a deterministic trend (Appendix). The inclusion of a trend accounts for systematic upward or downward movements in the series, whereas the specification without a trend assumes the absence of such long-term deterministic components. Evidence of stationarity in the presence of a trend indicates that, despite underlying directional movements, the series fluctuates within bounded limits around its trend path, rather than exhibiting unrestrained growth or decline.

Conversely, non-stationarity in the presence of a trend indicates persistent movements in the data, reflecting potential long-term shifts or systematic increases and decreases over time. Results from the first-generation IPS test revealed that only three variables, adjusted net income per capita, the export-to-import ratio and foreign direct investment, could be considered stationary. The remaining variables exhibited unit roots, which required appropriate transformations, such as differencing, to ensure validity in subsequent estimation. Nevertheless, the final assessment of stationarity relied on the second-generation CIPS test, which provides more robust evidence by accounting for cross-sectional dependence within the panel. To address the issue of non-stationarity, the affected variables were transformed through differencing, yielding stationary series suitable for empirical analysis. Once stationarity was confirmed, panel estimation techniques were applied to account for unobserved heterogeneity across countries, specifically the FE and RE models.

The Hausman specification test produced a probability value of 0.9835, suggesting no systematic differences between the two estimators and thereby supporting the use of the RE specification. Nevertheless, Table 2 also reports the FE results. Although coefficient magnitudes vary slightly, the overall direction and statistical significance of the key variables remain consistent across both estimators. Notably, lending interest rates and producer price inflation retain their positive and significant influence on consumer price inflation under both FE and RE, underscoring the robustness of the findings.

Thus, while the Hausman test favors the RE model, presenting the FE estimates enhances comparability and confirms that the main conclusions are not dependent on estimator choice.

While techniques such as Autoregressive Distributed Lag (ARDL) or its panel variants, Pooled Mean Group Autoregressive Distributed Lag (PMG-ARDL) could, in principle, help address dynamic interactions and potential endogeneity, the relatively short time dimension of the dataset (annual frequency, 2007–2022) constrains their applicability. For this reason, the paper relies on static panel estimators, but acknowledges that future research could employ ARDL or System GMM approaches as more data become available.

Table 4. Analysis of individual effects (Hausman test)

Variable	**(b)**	**(B)**	**(b-B)**	$\sqrt{\mathbf{diag}(\mathbf{v_b} - \mathbf{v_B})}$
	fixed	random	difference	S.E.
ICP				
dOER	-0.029	0.009	-0.038	.
dBM	-0.032	-0.033	0.001	.
dPPI	0.064	0.077	-0.013	.
LIR	0.469	0.442	0.027	0.009
dUnE	0.162	0.173	-0.011	.
AdjNIpc	0.149	0.139	0.011	.
dDCPS	0.072	0.073	-0.001	.
dEI	-0.070	-0.075	0.005	.
FDI	0.028	0.033	-0.005	.

[1] Ho: difference in coefficients not systematic. $\chi^2 = (b - B)^T[Var(b) - Var(B)]^{-1}(b - B) = 2.40$, $p - value = 0.9835$; When the p-value is greater than 0.05, we fail to reject the null hypothesis that the FE model is more appropriate and accept the alternative hypothesis. Given the result and the p-value, we accept the hypothesis that the RE model is suitable.

Source: Authors based on Obradović (2024)

Based on the mentioned Hausman test result, the model is explained using the RE method (Table 3).

Table 5. Random effect model

ICP	**Coefficient**	**Std. error**	**z**	**P>z**	**(95% confidence interval)**	
	dependent variable					
OER	0.009	0.026	0.360	0.719	-0.042	0.061
dBM	-0.033	0.016	-2.010	0.044	-0.064	-0.001
dPPI	0.077	0.0368	2.100	0.036	0.005	0.149
LIR	0.442	0.062	7.190	0.000	0.322	0.563
dUnE	0.173	0.136	1.270	0.204	-0.094	0.439
AdjNIpc	0.139	0.055	2.520	0.012	0.031	0.247
dDCPS	0.073	0.026	2.810	0.005	0.022	0.125
dEI	-0.075	0.053	-1.410	0.158	-0.179	0.029
FDI	0.033	0.014	2.370	0.018	0.006	0.061
_cons	-1.276	0.572	-2.230	0.026	-2.397	-0.156

[2] $R^2 = 0.4705$; ICP =-1.276-0.033dBM+0.077dPPI+0.442LIR+0.139AdjNNIpc+0.073dDCPS+0.033FDI.

Source: Authors based on Obradović (2024)

The RE estimation identified several variables as statistically significant determinants of inflation. The first difference of broad money (M3) was significant at the 5% level, with a coefficient of –0.032, while consumer price inflation, also differenced, showed significance at the same level with a positive coefficient of 0.077. The interest rate on loans emerged as the strongest predictor, statistically significant at the 1% level, with a coefficient of 0.442. In addition, adjusted net national income per capita proved significant at the 5% level, with a coefficient of 0.139. The first difference of the ratio of domestic credits to deposits in the banking sector was significant at the 1% level, carrying a coefficient of 0.073, and foreign direct investment also contributed positively, significant at the 5% level, with a coefficient of 0.033.

Overall, the RE model produced an R^2 value of 0.4487, indicating that approximately 44.87% of the variation in inflation can be explained by the included variables. This relatively high explanatory power, combined with the statistical significance of the estimated coefficients, confirms that the selected independent variables capture important aspects of the dynamics of inflation and are relevant for understanding its variability.

Changes in these independent variables have a significant impact on inflation, which can be useful for forecasting inflationary trends. However, it is important to note that R^2 does not guarantee that all relevant factors have been included in the model or that the independent variables are described in sufficient detail. Therefore, while R^2 provides valuable insight, additional research and analysis are necessary to gain a deeper understanding of the drivers of inflation and improve the accuracy of inflation forecasting.

Discussion

In this study, we note several findings regarding how monetary policy affects inflation. First, the official exchange rate shows no statistically significant influence on inflation in the nine SEE economies over the 2007-2022 sample period. Several factors may explain this. Most of the countries maintained relatively stable exchange-rate regimes, so the limited variability in that variable muted its impact. Moreover, other forces appear to have exerted a stronger pull on prices, especially given that the period 2007-2022 spans disparate business cycles, crises and policy shifts. Hence, any exchange-rate effect is highly contingent on the prevailing economic environment; in this particular sample and period, it is simply not detectable.

Second, the estimated signs on the loan interest rate and on the first difference of broad money (M3) run counter to what standard textbooks predict. The negative coefficient of broad money (M3) observed in the RE model is contrary to theoretical expectations. This anomaly is primarily explained by the strong overlap between broad money (M3) and domestic credit, which are almost perfectly correlated in the SEE sample, and by structural heterogeneity across countries. In several cases, monetary expansion coincided with stabilization measures and foreign exchange interventions, which muted the expected inflationary effect. The data transformation into first differences further reduced variation in broad money (M3), reinforcing this outcome. Thus, the negative sign should not be interpreted as evidence of a causal inverse relationship, but rather as a statistical artifact arising from multicollinearity and country-specific monetary regimes.

A setting in which higher policy rates are followed by higher inflation contradicts conventional monetarist intuition but is consistent with Neo-Fisherian monetary theory. Our results show a strong and positive coefficient for lending interest rates, which is in line with the Neo-Fisher hypothesis as explored in Lukmanova and Rabitsch (2023), who find that shocks to the inflation target or persistent changes in nominal rates can lead to short-run positive co-movement with inflation. Similarly, Airaudo and Hajdini (2023) argue that under certain wealth or markup configurations, such co-movements are more likely, suggesting that contextual institutional and market structure differences in SEE may explain the magnitude of the effect in our estimates.

In the very short run, tighter money can even push prices upward. Markets that already expect inflation may react to a rate hike by front-loading price increases. Long-term and fixed-rate contracts slow the pass-through of higher financing costs; firms and consumers face adjustment costs that temporarily raise prices while the economy adapts.

Similarly, Airaudo and Hajdini (2023) argue that under certain wealth or markup configurations, such co-movements are more likely, suggesting that contextual institutional and market structure differences in SEE may explain the magnitude of the effect in our estimates.

Near-zero policy rates and large-scale quantitative easing, deployed after both the 2008 and 2020 shocks, may have weakened or reversed the usual relationships between interest rates, liquidity and inflation. Investment demand remained tepid and broad-money (M3) surges met slack aggregate demand. Non-linear effects and atypical economic dynamics common in crisis periods can lead standard models astray.

Producer price inflation cannot be ignored either. Higher input costs cascade through the supply chain to consumers, a pass-through visible in the positive link we find between the producer-price index and consumer price inflation. Monetary policy can influence these costs indirectly through several channels. Taken together, the results underscore the need for additional work to untangle the precise mechanisms at play. Future research might explore shifts in market structure, the behavior of firms and households and the specific unconventional measures adopted by central banks during turbulent periods, all of which shape the inflation process.

It should be emphasized that the static panel estimators applied in this study capture correlations rather than strict causal effects. Establishing causality would require isolating exogenous monetary policy shocks. One standard approach is the use of panel VAR models, where each variable is regressed on its own lags and the lags of other variables, thereby capturing dynamic interactions. To identify exogenous shocks within such a framework, researchers often impose timing assumptions through Cholesky restrictions (Love & Zicchino, 2006), which assume that some variables react contemporaneously to shocks, while others respond with a lag. Although such techniques are beyond the scope of this paper, they represent a promising avenue for future research aimed at disentangling the causal transmission channels of monetary policy in SEE.

Based on the empirical results, several policy implications can be drawn for stakeholders in SEE economies. First, the significant impact of lending interest rates and producer price inflation on consumer prices highlights the need for central banks to carefully calibrate monetary tightening, as abrupt increases in borrowing costs may amplify rather than dampen inflationary pressures. Second, the positive role of domestic credit underscores the importance of strengthening banking sector supervision and macroprudential tools to mitigate excessive credit growth while ensuring financial stability. Third, the negative effect of broad money (M3), largely driven by its collinearity with domestic credit, suggests that policymakers should place greater emphasis on credit aggregates rather than traditional monetary aggregates when designing policy frameworks. Furthermore, the evidence of inflationary effects from foreign direct investment points to the necessity of aligning investment promotion policies with macroeconomic stabilization goals, ensuring that capital inflows foster sustainable growth without generating excessive demand-side pressures. Collectively, these insights emphasize the importance of coordinated monetary, fiscal, and financial sector policies in enhancing price stability and supporting long-term development in the region.

CONCLUSION

This paper examined the transmission of monetary policy to consumer price inflation in nine SEE countries over the period 2007–2022 using panel econometric techniques. The empirical results provide several important insights. Lending interest rates display a strong and statistically significant positive association with inflation, a result that diverges from conventional monetary theory but aligns with correlations highlighted in the Neo-Fisherian perspective. Producer price inflation emerges as a robust determinant of consumer price dynamics, confirming the importance of cost-push channels. In addition, foreign direct investment and domestic credit exhibit positive and statistically significant effects, indicating that financial intermediation and capital inflows play a notable role in shaping inflation dynamics in transition economies. By contrast, broad money (M3) shows a negative coefficient, which should be interpreted with caution as it mainly reflects multicollinearity with domestic credit and structural heterogeneity across countries.

These findings carry several policy implications. Monetary authorities in SEE should carefully assess the potential inflationary consequences of interest rate adjustments, particularly in environments characterized by structural rigidities and evolving financial markets. Strengthening monetary credibility, institutional quality and the coordination between fiscal and monetary policies is therefore essential for effective inflation control. The strong pass-through from producer to consumer prices highlights the need to monitor production costs as leading indicators of inflationary pressures. Furthermore, the observed role of domestic credit highlights the importance of maintaining financial sector stability and prudent lending practices, while the positive relationship between foreign direct investment and inflation underscores the need to coordinate investment policies with broader macroeconomic stabilization objectives.

Despite these contributions, several limitations should be acknowledged. First, the analysis relies on annual data covering the period 2007–2022, which restricts the ability to capture short-term dynamics and rapid monetary policy adjustments that may occur within shorter time intervals. Second, the relatively small cross-sectional dimension of the panel limits the application of more complex dynamic estimators. Third, the static panel framework employed in this study identifies statistical associations rather than strictly causal relationships, as it does not isolate exogenous monetary policy shocks.

While static FE and RE models provide consistent evidence, they cannot isolate exogenous monetary policy shocks; as such, the findings should be interpreted as correlations rather than strict causal effects. Future research could address these limitations by expanding the dataset to include quarterly or monthly observations, which would allow for a more precise examination of short-term monetary transmission mechanisms. In addition, the application of dynamic econometric approaches, such as panel VAR, GMM, ARDL or PMG-ARDL models, could provide deeper insights into causal relationships and endogeneity issues. Further research could also explore the role of institutional factors, monetary policy credibility, and financial market development in shaping inflation dynamics across Southeast European economies.

Overall, the paper contributes to the literature by offering new empirical evidence on the non-standard transmission of monetary policy in SEE, a region where institutional fragility and external vulnerabilities challenge conventional theories. By combining empirical results with theoretical debates and outlining directions for future research, the study provides a nuanced perspective on inflation dynamics in transition economies.

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APPENDIX

The model measuring the impact of monetary policy on inflation includes one dependent and nine independent variables (Table 4.).

Table 6. Variable explanation

Variable Name	Abbreviation	Variable Explanation	Unit of measure	Source
Inflation, consumer prices	ICP	Annual change in the cost of goods and services purchased by the consumer (annual change in consumer spending costs or annual change in consumer prices).	Percentage	World Bank, national publications
Official exchange rate	OER	The exchange rate determined by national authorities or the rate established on a legally authorized foreign exchange market.	Local currency against the US dollar	World Bank, Eurostat
Broad money (M3)	BM	The sum of currency outside banks; demand deposits excluding those of the central government; time, savings, and foreign currency deposits of the resident sector excluding the central government; bank and traveler's checks; and other securities such as certificates of deposit and commercial papers.	Percentage	World Bank
Producer price inflation	PPI	Annual change in the prices of raw materials, intermediate goods, and other costs relevant to the production of goods or the provision of services.	Percentage	World Bank, IMF, national publications
Lending interest rate	LIR	The standard loan rate charged on credit extended to the private sector for short- to medium-term purposes.	Percentage	World Bank, national publications
Unemployment	UnE	The proportion of the labor force that remains without employment while being available for work and actively engaged in job search.	Percentage of total workforce	World Bank
Adjusted net income per capita	AdjNIpc	Gross national income minus consumption of fixed capital and depletion of natural resources.	Annual growth rate	World Bank
Domestic credit to private sector by banks	DCPS	Financial resources provided by banks to the private sector, such as loans, purchases of non-government securities, and trade credits and other accounts receivable that establish a claim for repayment.	Percentage of GDP	World Bank
Export-Import	EI	The ratio of the value of exports to imports of goods and services, essentially representing the trade balance.	Percentage of GDP	World Bank
Foreign direct investment	FDI	The balance of inward investment flows designed to secure long-term managerial influence, typically represented by holdings of 10 percent	Percentage of GDP	World Bank

Variable Name	Abbreviation	Variable Explanation	Unit of measure	Source
		or more of voting equity, in firms located outside the investor's domestic economy.		

Source: Authors based on Obradović (2024)

Preliminary analysis (Table 5) reveals a strong correlation between inflation (measured by consumer prices) and producer price inflation (0.7787), with statistical significance at the 1% level. A somewhat weaker correlation is found between inflation and the lending interest rate (0.2454), also statistically significant at the 1% level, followed by the correlation between inflation and the trade balance (–0.2943), with the same level of significance as the previous two. All other correlations between explanatory variables and the dependent variable do not exhibit satisfactory statistical significance.

From the preliminary analysis of the correlation matrix, it can also be observed that domestic credit to the private sector is highly correlated with broad money (M3) (0.9762), and to a lesser extent with the official exchange rate (–0.32434). The high correlation between domestic credit to the private sector and the broad money (M3) aggregate (0.976) is not the result of a methodological error, but rather reflects the structural characteristics of SEE financial systems, where bank lending constitutes the dominant component of the money supply.

Despite their interrelation, both variables were retained in the model as they capture different aspects of the monetary policy transmission mechanism: broad money (M3) reflects overall liquidity in the economy, while domestic credit measures the intensity of banking intermediation.

Table 7. Correlation coefficients

Variable	ICP	OER	BM	PPI	LIR	UnE	AdjNIpc	DCPS	EI	FDI
ICP	1.000									
p value										
OER	0.102	1.000								
p value	0.223									
BM	-0.118	-0.208	1.000							
p value	0.161	0.012								
PPI	0.779	0.054	-0.610	1.000						
p value	0.000	0.523	0.468							
LIR	0.245	-0.185	-0.119	0.033	1.000					
p value	0.003	0.026	0.155	0.691						
UnE	-0.197	-0.244	-0.156	-0.196	0.213	1.000				
p value	0.170	0.003	0.061	0.018	0.010					
AdjNIpc	0.116	-0.098	-0.091	0.286	-0.122	-0.083	1.000			
p value	0.180	0.258	0.294	0.001	0.158	0.341				
DCPS	-0.117	-0.324	0.976	-0.084	-0.036	0.099	-0.123	1.000		
p value	0.163	0.003	0.000	0.316	0.668	0.283	0.154			
EI	-0.294	0.202	0.255	-0.125	-0.373	-0.211	-0.067	0.202	1.000	
p value	0.000	0.015	0.002	0.136	0.000	0.011	0.441	0.015		
FDI	0.098	0.243	-0.097	-0.039	-0.045	-0.105	-0.049	-0.092	-0.254	1.000
p value	0.245	0.003	0.246	0.636	0.591	0.213	0.567	0.273	0.002	

Source: Authors based on Obradović (2024)

If the data are found to be stationary without the presence of a trend, it means there is no systematic change in the data level over time. However, if a trend is included in the model, it suggests that the mean of the time series may vary over time. Stationarity testing in this manner is used to assess whether the data exhibit stable fluctuations around a trend. If the data are found to be stationary with a trend, it indicates that there is a systematic change in the level of the data over time, but that the fluctuations around that trend are stable.

The shaded variables in Table 6 indicate non-stationarity. However, to make an appropriate decision regarding data transformation, a second-generation stationarity test (the CIPS test) was applied (Table 7).

Table 8. IPS test

Variable	without trend		with trend	
	ADF	**t-statistics**	**ADF**	**t-statistics**
ICP	-0.151	0.440	5.946	1.000
OER	0.853	0.803	-1.085	0.139
BM	-0.461	0.322	-1.911	0.028
PPI	-1.155	0.124	3.163	0.999
LIR	1.109	0.866	-0.659	0.255
UnE	1.342	0.910	-3.980	0.000
AdjNIpc	-4.032	0.000	-3.672	0.000
DCPS	0.276	0.609	0.224	0.589
EI	-7.373	0.000	-4.253	0.000
FDI	-10.022	0.000	-8.829	0.000

Source: Authors based on Obradović (2024)

Table 9. CIPS test

Variable	without trend		with trend		significance
	CIPS	**Critical values**	**CIPS**	**Critical values**	
ICP	-3.316	-2.150	-3.842	-2.730	10%
		-2.290		-2.890	5%
		-2.560		-3.200	1%
OER	-0.466	-2.180	-1.265	-2.820	10%
		-2.330		-3.020	5%
		-2.640		-3.460	1%
BM	-1.189	-2.180	-2.635	-2.820	10%
		-2.330		-3.020	5%
		-2.640		-3.460	1%
PPI	-1.946	-2.180	-2.680	-2.730	10%
		-2.330		-2.890	5%
		-2.640		-3.200	1%
LIR	-2.831	-2.180	-4.129	-2.730	10%
		-2.330		-2.890	5%
		-2.640		-3.200	1%
UnE	-2.017	-2.180	-2.693	-2.820	10%
		-2.330		-3.020	5%

Variable	without trend		with trend		significance
	CIPS	Critical values	CIPS	Critical values	
		-2.640		-3.460	1%
AdjNIpc	-3.273	-2.220	-3.709	-2.890	10%
		-2.400		-3.110	5%
		-2.760		-3.610	1%
DCPS	-1.607	-2.180	-2.228	-2.820	10%
		-2.330		-3.020	5%
		-2.640		-3.460	1%
EI	-1.921	-2.180	-2.948	-2.820	10%
		-2.330		-3.020	5%
		-2.640		-3.460	1%
FDI	-3.882	-2.150	-3.454	-2.820	10%
		-2.290		-3.020	5%
		-2.560		-3.460	1%

[3] Consequently, differencing of the non-stationary variables is applied as a common method of data transformation when non-stationarity is identified in the panel. After re-testing, no further modification of the variables is necessary.

Source: Authors based on Obradović (2024)

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ORIGINAL SCIENTIFIC PAPER

Factors Affecting Investment Funds Investing in Different Asset Classes

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ABSTRACT

This paper examines how global financial and macroeconomic factors transmit shock and volatility spillovers to investment funds investing in different asset classes. Using daily data from January 2015 to December 2025, the authors analyse three U.S. funds representing bond, commodity, and equity exposures (PIMCO, USCI, and XLK) and five global factors: 1-month and 10-year U.S. interest rates, the S&P 500, Brent crude oil, and gold. The asymmetric TGARCH models are first estimated to obtain standardized residuals and conditional variances, after which a two-regime Markov switching framework is applied to capture the differences between high- and low-volatility periods. The results show strong regime- and fund-specific spillovers. S&P 500 shocks strongly affect XLK in both regimes, while oil and gold shocks dominate USCI during turbulent periods. Volatility spillovers are most pronounced for USCI and XLK, whereas PIMCO remains relatively insulated. These findings provide regime-aware implications for investors and fund managers.

Keywords: Investment funds, spillover effects, macro factors, regime dependence

JEL Classification: C24, D53, E44

INTRODUCTION

Global financial and macroeconomic factors significantly influence the investment decisions and performance of investment funds. Macroeconomic conditions such as global economic growth, inflation trends, and business cycle dynamics shape expectations about future returns and risks across asset classes (Bali et al., 2014; Leite, 2024). Financial factors, including global interest rates, equity market performance, and commodity prices, directly affect asset valuations and portfolio rebalancing decisions (Assefa et al., 2017). Monetary policy actions by major central banks influence global liquidity and risk-taking behaviour, while exchange rate movements and capital flow dynamics affect international investment exposure. Moreover, heightened financial integration and interconnected markets amplify the transmission of global shocks, increasing the sensitivity of investment funds to changes in global economic and financial conditions.

More specifically, interest rates, commodity prices, and equity market performance are key global factors influencing the behaviour of investment funds (Lee et al., 2015; Babalos and Balcilar, 2017; Pinto-Ávalos et al., 2024). Changes in global interest rates affect discount rates, borrowing costs, and portfolio reallocation between fixed-income and riskier assets. Gold prices are often viewed as a hedge against inflation and financial uncertainty, leading investment funds to increase

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exposure during periods of heightened market stress or declining real interest rates. Oil prices play a dual role, reflecting both global economic activity and supply-side shocks, thereby influencing inflation expectations and sectoral equity returns (Alsubaiei et al., 2023). Meanwhile, the S&P 500 serves as a benchmark for global equity market conditions and investor sentiment, with its movements shaping risk appetite and capital flows across international investment funds (Alexakis et al., 2005). Together, these factors interact to determine asset allocation, risk management, and return dynamics in global investment portfolios (Musawa and Mwaanga, 2017).

Understanding the role of global financial and macroeconomic factors in shaping investment fund behaviour is important for several key stakeholders. For investors, it helps improve portfolio allocation decisions, risk assessment, and diversification strategies (Đekić et al., 2017; Korenak and Stakić, 2021), especially in periods of heightened global uncertainty. For fund managers, insights into how interest rates, equity markets, and macroeconomic conditions interact enable more effective risk management, timing, and asset rebalancing. For policymakers and regulators, recognizing the sensitivity of investment funds to global shocks is essential for monitoring systemic risk and financial stability. Finally, for academics and researchers, analysing these global drivers contributes to a deeper understanding of market integration and the transmission of macro-financial shocks across asset classes and regions.

The goal of the paper is to investigate the shock and volatility effects of five global financial and macroeconomic factors, 1m interest rate, 10Y interest rate, Brent oil, gold and the S&P 500 index, on three American investment funds that invest in different asset classes – PINCO, USCI and XLK. PIMCO funds primarily focus on fixed-income markets, investing in government and corporate bonds, mortgage-backed securities, and other interest-rate–sensitive instruments, making them closely linked to global monetary policy and interest rate dynamics (Koo and Muslu, 2023). In contrast, USCI provides exposure to commodity markets through futures contracts on energy, metals, and agricultural commodities, and is commonly used for diversification and inflation hedging. XLK, on the other hand, is an equity-based ETF concentrated on the U.S. technology sector (Krause and Tse, 2013), investing in large-cap technology firms and closely tracking developments in the S&P 500 and global equity market sentiment. Together, these funds capture bond, commodity, and equity market exposures, making them useful proxies for analysing how global financial and macroeconomic factors affect investment funds across different asset classes.

According to the authors' knowledge, the existing literature has not jointly analyzed the influence of these five determinants on investment funds. Prior studies have typically focused on narrower or more specific dimensions of fund behavior. For example, Ciarlone and Miceli (2016) explore the macroeconomic drivers of Sovereign Wealth Funds' (SWFs) investment decisions, paying particular attention to how these funds adjust their activity in response to financial crises in host economies. In a different context, Jiang et al. (2026) analyze the transmission of financial uncertainty shocks to global bond funds, emphasizing four major sources of uncertainty: equity market volatility (VIX), bond market volatility (MOVE), central bank digital currency uncertainty (CBDCU), and geopolitical risk (GPR). Meanwhile, Wu (2025) investigates the role of cultural heterogeneity in shaping the investment choices of institutional investors.

This paper analyses a relatively long time period, from January 2015 to December 2025, that is permeated with numerous global turbulences, such as the COVID-19 pandemic (2020–2022), the global inflation surge (2021–2023), the global energy crisis (2021–2023) and the Russia–Ukraine War (2022 onward). From this aspect, the authors use the Markov switching (MS) model as a working horse to examine the effect on the factors on the investment funds. Using the MS model is appropriate in this context because the period 2015–2025 is characterized by repeated global turbulences that caused abrupt changes in financial market behaviour and investment fund dynamics. In other words, global financial and macroeconomic shocks – such as the COVID-19 pandemic, the inflation surge, geopolitical conflicts, and rapid interest-rate tightening – tend to generate regime changes rather than smooth, linear adjustments. Investment fund returns, volatilities, and correlations often behave very differently during normal (low-volatility) periods compared to crisis or stress (high-volatility) periods. The Markov switching model explicitly captures these unobserved regimes and allows key parameters to vary across them (Valadkhani and Marashdeh, 2026). In addition, the model does not require ex-ante identification of crisis dates. Instead, it endogenously detects regime shifts based on the data (Wu et al., 2024), which is crucial in a sample containing overlapping and evolving global shocks. This makes it well-suited for analysing how investment funds react to changing global conditions without imposing arbitrary breakpoints. Finally, the Markov switching models provide estimates of regime probabilities and transition dynamics (Çepni et al., 2023), offering insights into the persistence of turbulent periods and the likelihood of moving between regimes. This is valuable for investors, fund managers, and policymakers, as it enhances understanding of risk dynamics, improves portfolio and hedging strategies, and supports more effective monitoring of systemic risk under different global financial and macroeconomic environments.

This paper provides a comprehensive analysis of how key global financial and macroeconomic factors, such as interest rates, commodity prices, and equity market indices, transmit shock and volatility spillovers to investment funds across different asset classes. By combining asymmetric TGARCH and Markov switching models over a turbulent 2015–2025 period, it identifies regime-dependent and fund-specific spillover dynamics, highlighting the heterogeneous responses of bond, commodity, and equity funds. This approach advances the literature by linking theoretical modeling with practical implications for portfolio management and risk assessment under varying market conditions. As far as the authors are aware, this is among the first papers to attempt this type of research, and this is where the authors find the motivation for the research.

LITERATURE REVIEW

This section concisely presents papers that researched factors affecting investment funds. For instance, Shah et al. (2025) investigate how the S&P 500 index funds interact with key real-time markets, namely gold and WTI, amid periods of crisis such as the COVID-19 pandemic and the Russia-Ukraine conflict. By applying a time-varying parameter vector autoregression (TVP-VAR) framework, they identify notable interdependencies and heightened connectedness among these markets during both events. Liu and Hu (2025) examine how the COVID-19 pandemic influenced the investment outcomes of sovereign wealth funds (SWFs) across different regions and fund types. Employing empirical techniques, they assess the overall effects of pandemic-induced shocks on SWF returns and explore how variations in investment strategies and geographic allocations shaped performance. Their results show that the pandemic had a generally negative impact on returns, but funds with a greater focus on cross-border investments tended to fare better, highlighting the role of diversification and international exposure in weathering systemic shocks. Jiang et al. (2026) examine how various forms of financial uncertainty influence returns and volatility in global bond funds. Using advanced models such as TVP-SV VAR, MGARCH, and wavelet quantile regressions on weekly data from 2015-2024, they show that funds respond differently to equity, bond, geopolitical, and digital currency uncertainties. Some funds act as temporary safe havens, while others are more sensitive to specific risks, highlighting the need for tailored risk management strategies.

Dekker et al. (2024) investigate the role of liquidity buffers in open-end corporate bond funds during the COVID-19 market turmoil, focusing on how these buffers influence fund behaviour and market procyclicality. They find that higher liquidity buffers did not reduce investor outflows at the peak of the crisis but did help fund managers meet redemption requests with cash instead of selling less liquid assets, thereby mitigating procyclical fire-sale pressures. Their results suggest that liquidity buffers can support more resilient liquidity management strategies in stressed conditions. Fiszeder et al. (2023) investigate how investor attention to oil prices, measured using Google search data, affects returns, volatility, and covariances among exchange-traded funds representing oil, gold, and the stock market. They develop a new multivariate volatility model that incorporates investor attention and find that search activity can help explain and forecast the covariance dynamics between these asset markets. The results suggest that online investor interest plays a meaningful role in the co-movement of major financial and commodity markets. Amar et al. (2019) analyse how national-level factors shape the investment decisions of sovereign wealth funds, focusing on both the choice to invest and the size of those investments. Using a two-tiered dynamic Tobit panel model, they find that political stability encourages entry into a country, while less democratic but more financially open economies attract larger investment amounts, and that funds are more likely to invest repeatedly in countries where they have previously invested. Their results highlight that sovereign wealth funds' location decisions are influenced differently by country characteristics depending on whether the concern is initial entry or investment scale.

RESEARCH METHODOLOGIES

TGARCH Model

The paper uses the asymmetric threshold GARCH (TGARCH) model to create the time series of standardized residuals and conditional volatilities. Each TGARCH model consists of two equations, a mean equation and a conditional variance equation (Ausloos et al., 2020). The mean equation, given in (1), has a first-order autoregressive AR(1) form, where r_t denotes the time series of logarithmic returns. On the other hand, conditional variance, shown in equation (2), is a variance that depends on past information and changes over time. Past information is captured by the first lags of variance h_{t-1} and residuals ε_{t-1}^2. Therefore, the variance in the GARCH framework is referred to as "conditional".

$$r_t = C + r_{t-1} + \varepsilon_t, \qquad \varepsilon_t = z_t\sqrt{h_t}, \tag{1}$$

where C is a constant term in the mean equation and r_{t-1} is the autoregressive component. $z_t \sim i.i.d.(0,1)$ denotes normally distributed residuals.

The conditional variance h_t in the TGARCH(1,1) model is given by:

$$h_t = c + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{\varepsilon_{t-1}<0} + \beta h_{t-1}, \tag{2}$$

where $c > 0$ is the constant term, $\alpha \geq 0$ measures the impact of past shocks (ARCH effect), while $\beta \geq 0$ measures volatility persistence (GARCH effect). γ captures the asymmetric effect, i.e., the additional impact of shocks on conditional variance. If $\gamma > 0$, negative shocks have a larger impact on conditional variance than positive shocks; if $\gamma < 0$, positive shocks have a larger impact on conditional variance than negative shocks. $I_{\varepsilon_{t-1}<0}$is an indicator function that equals 1 if $\varepsilon_{t-1} < 0$, and 0 otherwise. To ensure that the variance is positive and the model is covariance-stationary, it is commonly required that $\alpha \geq 0$and $\beta \geq 0$.

GARCH models are useful for modelling empirical time series because they address the problems of autocorrelation and heteroskedasticity that commonly arise in most daily financial time series (Sabiruzzaman et al., 2010). In other words, including the lagged dependent variable, AR(1), in the mean equation mitigates autocorrelation, while the lagged variance term h_{t-1} addresses heteroskedasticity.

Markov Switching Model

After constructing the time series of standardized residuals and conditional variances for all variables, these variables are incorporated into the Markov switching model, where the effects of shocks and volatility of five factors are estimated on each investment fund. In other words, the six Markov switching models are estimated.

The Markov switching models are based on the assumption that the behaviour of an economic or financial time series changes over time depending on different regimes, such as periods of low and high volatility, expansions and recessions, or tranquil and crisis periods. These regimes are not directly observed. Instead, they are latent and change stochastically over time (Zhang and Zhang, 2022), i.e., regime changes occur randomly with certain probabilities, rather than deterministically or according to a known rule. The key idea of MS models is that model parameters depend on the current regime, which allows for discrete shifts in the dynamics of the series.

Regime switching in MS models is described by a Markov chain (Qian et al., 2022), where the probability of transitioning to a given regime at time (t) depends solely on the regime in the previous period. These transition probabilities are organized in a transition matrix, whose diagonal elements measure the persistence of each regime. High diagonal values indicate long-lasting regimes, whereas low values imply frequent regime changes.

Due to the latent nature of regimes, their identification relies on estimating the probability of being in a particular regime at each point in time. These probabilities are obtained using filtering and smoothing algorithms (Shi, 2022) and are often used for graphical interpretation of stable and unstable periods. This feature makes MS models particularly useful for analysing structural changes and nonlinear dynamics in macroeconomic and financial time series.

The specifications of the six MS models are given by the following equations:

$$PIMCO_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{3}$$

$$USCI_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{4}$$

$$XLK_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{5}$$

$$PIMCO_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{6}$$

$$USCI_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{7}$$

$$XLK_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{8}$$

where notations "log" and "var" indicate that the model estimates standardized residuals or conditional variances, respectively. $\omega_{0,st}$ is the regime changing intercept in all models, while $\omega_{n,st}$ parameters capture the effects of the explanatory factors on the dependent variables, i.e., the investment funds. The vector $\mathbb{Z}'_n$ contains the five explanatory variables, where $n = 1 \dots 5$. The subscript st indicates that the parameters vary depending on the regime. All MS models are specified with two regimes or states (st): crisis and tranquil states. Specifically, regime $st(1)$ denotes the crisis period, while regime $st(2)$ denotes the tranquil period.

The transition probability matrix between regimes is presented in expression (9). The transition matrix provides the probabilities of moving between different regimes from one period to the next (Stützle, 2020). It describes how stable regimes are and how frequently they change. The matrix is interpreted such that diagonal elements (p_{11} and p_{22}) represent the probability that the system remains in the same regime. High values indicate that the regime is persistent (long-lasting). On the other hand, off-diagonal elements (p_{12} and p_{21}) represent the probability of switching to the other regime. Higher values imply more frequent regime changes.

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}, \quad \sum\nolimits_j p_{ij} = 1 \tag{9}$$

DATASET AND DESCRIPTIVE STATISTICS

The data used in this study consist of the daily prices of three U.S. investment funds (PIMCO, USCI, and XLK), as well as five macroeconomic and financial factors (1-month U.S. bonds, 10-year U.S. bonds, the S&P 500 index, Brent crude oil, and gold). The sample period spans from January 2015 to December 2025. In other words, it covers both a turbulent period, including the COVID-19 pandemic and the war in Ukraine, as well as a relatively tranquil period prior to these crises. All time series were obtained from the website "Investing.com", and all factor series were synchronized with the available observations of the investment funds. This results in a total of 2,396 observations. Table 1 reports the descriptive statistics for all time series. Before estimating the TGARCH models, the authors transform all empirical price series into logarithmic returns according to the following equation: $r_{i,t} = 100 \times log(P_{i,t}/P_{i,t-1})$, where P denotes the daily price of a given asset. Figure 1 shows the empirical dynamics of the three funds. It is obvious that they experience different patterns, and the objective of this paper is to identify which factors had the greatest impact on the three investment funds.

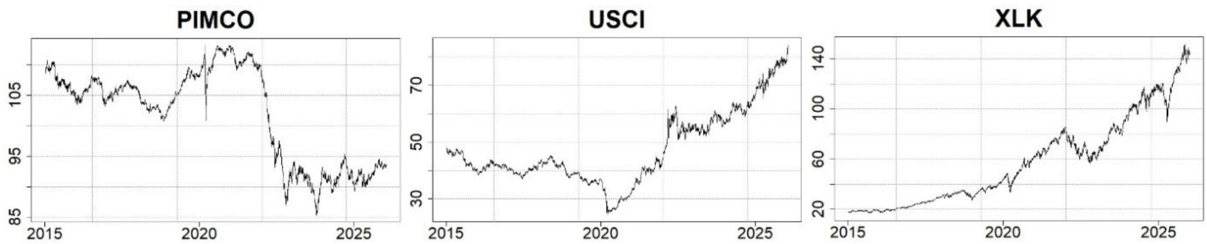

Figure 1. Empirical dynamics of three investment funds

Source: Author's own work.

Table 1. Descriptive statistics of the selected variables

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q²)	ADF
PIMCO	-0.002	0.140	-1.333	20.784	37256.5	0.000	0.000	-50.929
USCI	0.008	0.413	-1.222	17.875	26179.6	0.000	0.000	-49.372
XLK	0.033	0.650	-0.304	12.819	11149.9	0.000	0.000	-17.243
1m bonds	-0.122	9.176	-0.594	26.469	55126.6	0.000	0.000	-24.851
10Y bonds	0.010	1.331	0.238	32.368	86126.0	0.000	0.000	-20.779
S&P 500	0.017	0.495	-0.615	20.293	30006.4	0.000	0.000	-17.641
Brent	-0.004	1.118	-0.932	18.258	23589.4	0.061	0.000	-47.516
Gold	0.027	0.444	-0.133	6.477	1213.9	0.384	0.000	-49.180

Note: JB denotes the Jarque–Bera statistic for normality, while LB(Q) and LB(Q^2) refer to the p-values of the Ljung–Box Q-statistic for the levels and squared log-returns, respectively, using 10 lags. The 1% and 5% critical values for the ADF unit root test with 10 lags, assuming only a constant term, are −3.433 and −2.863, respectively.

Source: Author's calculation.

Table 1 presents the descriptive statistics of the log-returns of the analysed financial instruments for the entire sample period. The average returns are generally small, which is consistent with expectations for daily (or high-frequency) data. The highest mean return is recorded for the XLK fund, while negative mean values are observed for the PIMCO fund, Brent crude oil, and 1-month bonds. These results indicate that, in the long run, returns do not deviate substantially from zero, which is typical for financial time series.

The standard deviation reveals considerable differences in volatility across the examined series. The lowest volatility is observed for the PIMCO fund and gold, whereas the XLK fund, the

USCI index, and particularly 1-month bonds exhibit substantially higher volatility. The high standard deviation of short-term bonds may be related to their sensitivity to monetary policy and changes in interest rates, while the increased volatility of equity and commodity instruments reflects market shocks and cyclical movements.

All analysed log-returns exhibit pronounced asymmetry, with most series showing negative skewness, indicating a greater intensity of negative extreme events compared to positive ones. This result is particularly strong for the PIMCO and USCI funds. In addition, kurtosis values are significantly higher than those characteristic of a normal distribution, indicating the presence of fat tails and extreme return realizations. This leptokurtosis is especially pronounced for bond instruments and equity indices.

The Jarque–Bera test results strongly reject the null hypothesis of normality for almost all series, confirming that return distributions deviate substantially from the normal distribution. This finding is consistent with previous empirical research on financial markets and further justifies the use of models that allow for nonlinearities and time-varying volatility, such as GARCH and Markov switching models.

Ljung–Box tests on the levels of log-returns indicate significant autocorrelation in the mean equation in most cases, with the exception of gold. On the other hand, Ljung–Box tests on squared returns strongly indicate the presence of autocorrelation in the variance for all series, providing clear evidence of conditional heteroskedasticity. This implies that the use of an asymmetric AR(1)–TGARCH model is justified, as it should adequately capture the stylized facts observed in financial time series.

Finally, the Augmented Dickey–Fuller (ADF) unit root test results clearly show that all analysed series are stationary, as the test statistics are substantially lower than the critical values at the 1% significance level. This confirms that log-returns are suitable for further econometric analysis within the TGARCH framework.

RESEARCH RESULTS

TGARCH Findings

This subsection presents the results of the estimated TGARCH models. The TGARCH model is used to generate standardized residuals and conditional volatility time series, which are then used to examine shock and volatility spillover effects. Shock spillovers refer to the transmission of unexpected changes in returns from one market or financial asset to another, with effects manifested through movements in the mean and typically being short-term in nature (Xu et al., 2024). In contrast, volatility spillovers represent the transmission of uncertainty and risk across markets (Boubaker et al., 2023), which does not necessarily affect the direction of returns but rather their variability, and is most often more persistent. While shock spillovers indicate a direct market reaction to new information, volatility spillovers reflect the spread of instability and heightened risk, even in the absence of significant price changes.

Shock spillover effects are assessed using the standardized residuals ($z_t = \varepsilon_t / \sqrt{h_t}$) from the asymmetric TGARCH model, while volatility spillovers are evaluated using the conditional variances from the same model. Standardized residuals are preferred to raw log-returns because they isolate the unexpected innovation from time-varying volatility. In financial time series, returns are usually heteroskedastic and volatility clusters over time, meaning that large returns may reflect high-volatility regimes rather than genuinely large shocks. By scaling the residuals by the conditional standard deviation from the TGARCH model, standardized residuals are approximately homoskedastic and more comparable across time, capturing the relative magnitude of shocks in a consistent way. This makes them particularly suitable for shock spillover analysis, while volatility spillovers can be examined separately using the conditional variance series.

Table 2 contains the findings of the estimated TGARCH models. Panel A reports the estimated TGARCH parameters. The parameter α is positive and statistically significant for all instruments, indicating that past shocks affect current volatility. The largest α values are observed for 1-month bonds and the USCI fund, implying that short-run shocks are particularly influential for these instruments. The parameter β is also positive and high across all series (0.806–0.933), which suggests strong volatility persistence, i.e., periods of high or low volatility tend to persist over time. The highest β is recorded for 10-year bonds, indicating especially long-lasting volatility in this market segment. The parameter γ (the so-called leverage effect) reveals interesting differences: a positive and statistically significant γ is found for XLK, 1-month bonds, 10-year bonds, the S&P 500, and Brent oil, suggesting that negative shocks increase volatility more than positive shocks of the same magnitude. For USCI and gold, γ is negative and statistically insignificant, indicating that asymmetry is either absent or weak for these instruments.

Table 2. Results of the estimated TGARCH models

	PIMCO	**USCI**	**XLK**	**1m bonds**	**10Y bonds**	**S&P 500**	**Brent**	**Gold**
Panel A: T-GARCH parameters								
α	0.071***	0.118***	0.041***	0.142***	0.045***	0.052***	0.072***	0.081***
β	0.911***	0.862***	0.861***	0.810***	0.933***	0.806***	0.852***	0.904***
γ	0.023**	-0.017	0.137***	0.250***	0.044***	0.211***	0.086***	-0.063***
Panel B: Diagnostic tests								
LB(Q)	0.266	0.920	0.266	0.064	0.389	0.390	0.367	0.758
LB(Q^2)	0.835	0.848	0.835	0.601	0.106	0.686	0.784	0.717

Note: The values of LB(Q) and LB(Q^2) represent p-values. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculation.

Panel B presents the Ljung–Box (LB) diagnostic tests for the residuals and squared residuals. All p-values are relatively high (>0.05), implying that there is no significant serial dependence in either the residuals or the squared residuals after applying the TGARCH model. This result confirms that the model successfully captures autocorrelation and conditional heteroskedasticity, effectively removing them from the residuals.

The high β parameters, combined with positive α and γ for most instruments, confirm the typical stylized facts of financial time series: strong volatility persistence and asymmetric shock effects. The estimated TGARCH models are used for generating both standardized residuals and conditional volatilities.

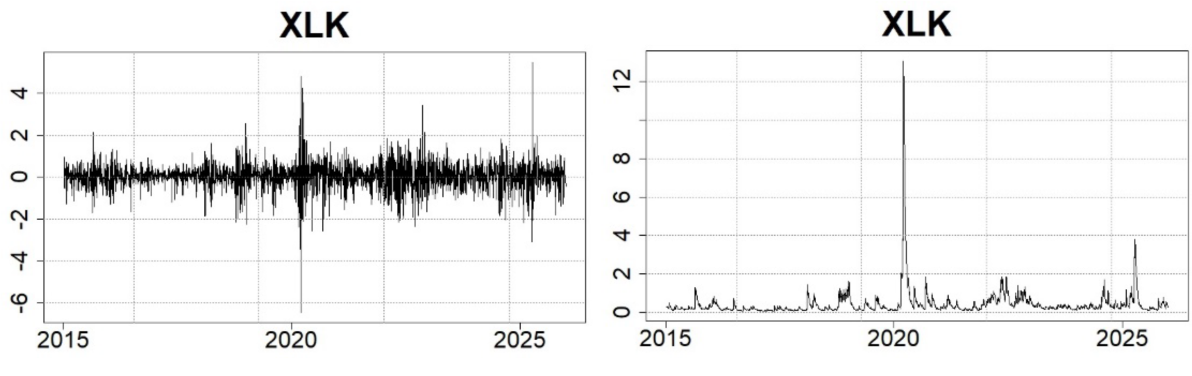

Figure 2. Estimated standardized residuals and conditional volatility of the XLK fund

Source: Author's own work.

For the sake of parsimony, Figure 2 presents only the estimated standardized residuals and conditional volatility of the XLK fund. The plots for all other instruments are available upon request.

Markow Switching Findings – Shock Spillover Effect

This subsection presents the findings of the shock spillover effect, and Table 3 presents the results. In the case of the PIMCO fund, it can be seen that only the S&P 500 has a relatively high shock spillover effect (0.344) in the low volatility regime, while all other factors have a negligible effect. This finding is in line with Jiang et al. (2026), who claimed that bond funds display heterogeneous responses to equity-market, bond-market, geopolitical, and cryptocurrency uncertainty. This might be because PIMCO funds are not purely fixed-income, i.e., they often hold credit-sensitive bonds (corporate, high-yield, emerging market debt). These bonds react to equity market sentiment because equities and corporate bonds share economic and credit risk factors. Therefore, a shock in the S&P 500 can spill over to PIMCO through these credit-sensitive components. In addition, spillovers are higher in the low-volatility regime, probably because market conditions are stable during calm periods, and correlations are relatively predictable. In that sense, a positive or negative shock in equities (S&P 500) can propagate clearly to bond prices and the fund's returns because other risk factors (credit, liquidity, volatility spikes) are small. Therefore, the relative influence of the S&P 500 shock is magnified. On the other hand, in high-volatility (crisis) periods, many shocks occur simultaneously (credit spreads widen, liquidity dries up, yields spike). These dominate fund returns, so the marginal effect of S&P 500 shocks is diluted, reducing spillover.

In the case of the USCI fund, Brent oil (0.361) and gold (0.251) have a relatively high shock spillover effect on the USCI fund in the high-volatility regime. This concurs with Shah et al. (2025), who reported strong cross-market linkages and increased connectedness between investment funds and oil and gold. On the other hand, the S&P 500 has a relatively high effect (0.147) in the low-volatility regime. High-volatility periods are often triggered by commodity shocks, geopolitical crises, or inflation spikes, so in these periods, Brent oil and gold exhibit large price swings. Since USCI is commodity-linked, these shocks directly impact its returns, producing relatively high shock spillover. On the other hand, equity shocks (S&P 500) are less influential because the main holdings of USCI are not equities. In calm periods, S&P 500 returns are a bigger driver of USCI returns than commodities because commodities are relatively stable in low-volatility periods. This means that shocks in oil and gold are small, which leads to a lower shock spillover effect.

Table 3 indicates that only the S&P 500 has a strong shock spillover effect on the XLK fund in both regimes, while all other factors have no effect. This is because XLK is basically a concentrated slice of the S&P 500, and the shock channel mainly captures new information hitting prices immediately. The shock spillover is higher in the low-volatility regime, which may look counterintuitive, but it actually makes sense econometrically and financially. In low volatility periods, XLK movements are usually cleaner and more systematic. Therefore, when the S&P 500 has a shock, it becomes a dominant driver of XLK standardized residuals. On the other hand, in high-volatility regimes, XLK is affected by many additional shocks (earnings surprises, rate shocks, sector rotations, liquidity events). That means the S&P 500 shock still remains, but it becomes less dominant relative to everything else happening.

Panel B of Table 3, as well as Figure 3, describe the regime-switching properties. In other words, Panel B presents the estimated regime transition probabilities (P_{ij}) and the expected duration of each regime for the selected instruments.

Table 3. Markov switching results of the shock spillover effect

			PIMCO	USCI	XLK
	Regimes	**Parameters**	**Panel A: Estimated MS parameters**		
1m U.S. bonds	**1**	$\boldsymbol{\omega 1_1^{log}}$	**0.000**	**0.000**	**-0.001***
	2	$\omega 1_2^{log}$	-0.001	-0.001*	0.003**
10Y U.S. bonds	1	$\omega 2_1^{log}$	-0.069***	0.002	-0.016***
	2	$\omega 2_2^{log}$	-0.097***	0.014**	-0.009
S&P 500	1	$\omega 3_1^{log}$	0.031***	0.116***	1.146***
	2	$\omega 3_2^{log}$	0.344***	0.147***	1.462***
Brent	1	$\omega 4_1^{log}$	0.003	0.361***	-0.033***
	2	$\omega 4_2^{log}$	0.010	0.098***	-0.015
Gold	1	$\omega 5_1^{log}$	0.016***	0.251***	-0.004
	2	$\omega 5_2^{log}$	0.043**	0.174***	0.019
			Panel B: Regime properties		
P11	–	–	0.667	0.996	0.989
P12	–	–	0.333	0.003	0.010
P21	–	–	0.046	0.004	0.013
P22	–	–	0.954	0.996	0.987
Expected duration – 1	–	–	3.0	269.1	95.7
Expected duration – 2	–	–	21.8	228.7	79.4

Note: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Regime 1 corresponds to the high-volatility (crisis) period, while Regime 2 corresponds to the low-volatility (tranquil) period.

Source: Author's calculation.

For the PIMCO fund, the diagonal elements of the transition matrix are relatively high ($P_{11} = 0.667$, $P_{22} = 0.954$), suggesting that both regimes tend to persist for several periods. Regime 1 has an expected duration of 3 days, while Regime 2 is considerably longer-lasting (21.8 days), implying that short-term shocks are quickly replaced by a more stable state.

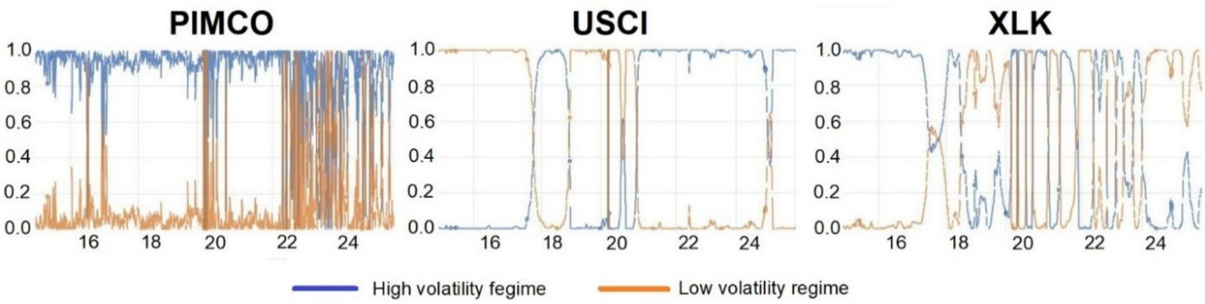

Figure 3. Dynamic regime probabilities of shock spillover effect

Source: Author's own work

For the USCI fund, the diagonal elements are extremely high ($P_{11} = 0.996$, $P_{22} = 0.996$), while the off-diagonal elements are very small, implying that the regimes are highly stable and that transitions are almost nonexistent. The expected durations are in the hundreds of days (269.1 and 228.7), meaning that the series effectively remains in the same regime for large portions of the sample. Such dynamics indicate that USCI fund volatility is not prone to abrupt regime shifts, and that the market tends to remain in the same state (calm or turbulent) for extended periods.

For the XLK fund, a similar pattern emerges: the diagonal elements are high ($P_{11} = 0.989$, $P_{22} = 0.987$)and the off-diagonal elements are low, showing that the regimes are also highly persistent. The expected duration of Regime 1 is 95.7 days, while Regime 2 lasts 79.4 days on average. This suggests that XLK fund volatility also remains within the same regime over longer time horizons, and that abrupt changes are relatively rare.

Markow Switching Findings – Volatility Spillover Effect

This subsection presents the results of the volatility spillover effects between the factors and the three funds. Table 4 contains these results. It can be seen that neither factor has an economically significant volatility spillover effect on the PIMCO fund in either regime. This may be because the PIMCO returns are largely determined by its diversified fixed-income portfolio and active duration and risk management. Consequently, even when external factors experience large volatility shocks, PIMCO's own volatility remains relatively stable, rendering spillovers from these factors negligible across both regimes.

In the case of the USCI fund, the 10-year bonds, the S&P 500 and Brent have a relatively high volatility spillover effect on the USCI fund in the low-volatility regime. In calm periods, commodity markets tend to be driven mainly by macro-financial conditions and growth expectations: The S&P 500 volatility reflects changes in global risk appetite. Even in calm regimes, shifts in equity sentiment often spill over to broad commodity exposure through portfolio rebalancing and "risk-on/risk-off" positioning. The 10-year bond volatility captures changes in interest-rate expectations and discount rates. In stable regimes, rates move mostly due to macro news (inflation/growth), which also affects commodity demand expectations and futures pricing. Finally, the Brent volatility matters strongly because energy is usually a large weight in broad commodity indices. Oil is also highly sensitive to global demand and geopolitical news, so it transmits volatility easily into USCI.

Table 4. Markov switching results of the volatility spillover effect

			PIMCO	USCI	XLK
	Regimes	Parameters	Panel A: Estimated MS parameters		
1m U.S. bonds	1	$\omega1_1^{vol}$	0.000***	0.000	-0.000*
	2	$\omega1_2^{vol}$	0.000***	-0.001***	-0.000***
10Y U.S. bonds	1	$\omega2_1^{vol}$	0.002***	-0.001	-0.002
	2	$\omega2_2^{vol}$	0.000***	0.407***	-0.034***
S&P 500	1	$\omega3_1^{vol}$	0.042***	0.173***	0.975***
	2	$\omega3_2^{vol}$	0.024***	2.842***	1.245***
Brent	1	$\omega4_1^{vol}$	-0.015***	0.006***	-0.016***
	2	$\omega4_2^{vol}$	-0.001***	0.472***	0.008***
Gold	1	$\omega5_1^{vol}$	0.014***	0.135***	0.491***
	2	$\omega5_2^{vol}$	0.018***	0.597	1.525***
			Panel B: Regime properties		
P11	—	—	0.980	0.984	0.990
P12	—	—	0.020	0.016	0.009
P21	—	—	0.007	0.984	0.047
P22	—	—	0.992	0.016	0.953
Expected duration – 1	—	—	50.0	61.7	105.7
Expected duration – 2	—	—	129.3	1.0	21.3

Note: See Table 3.

Source: Author's calculation.

Only the volatilities of the S&P 500 and gold have a significant volatility spillover effect on the XLK fund in both regimes, but higher in the calm regime. XLK consists almost entirely of technology stocks. Its volatility is naturally driven by equity market risk, so the S&P 500 volatility is a direct and dominant source of uncertainty. On the other hand, XLK is not directly exposed to gold, but gold volatility is often anti-correlated with equity market stability, acting as a risk or uncertainty indicator. Even in calm periods, mild changes in gold volatility may signal shifts in safe-haven demand or macroeconomic uncertainty, which can influence investor sentiment and indirectly affect tech stocks.

Panel B in Table 4 reports regime properties, while Figure 4 shows graphical dynamics of the regimes. The diagonal probabilities of the PIMCO fund are very high ($P_{11} = 0.980$, $P_{22} = 0.992$), indicating strong regime persistence. The expected duration is 50.0 days in regime 1 and 129.3 days in regime 2, suggesting that the fund spends long periods in each state and that regime shifts are relatively rare.

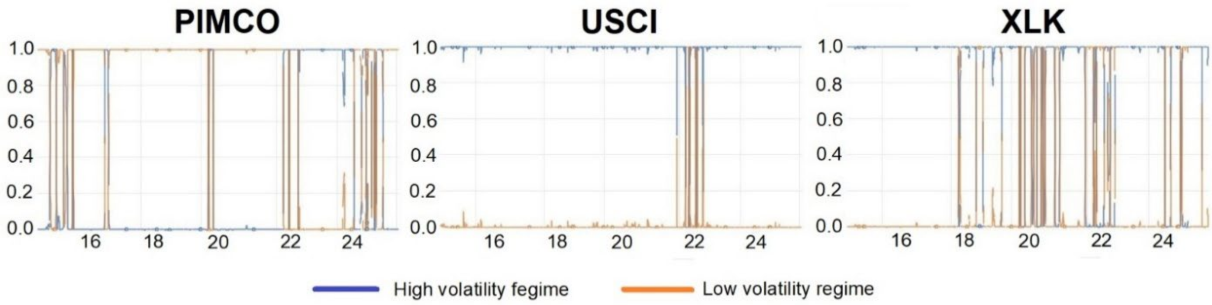

Figure 4. Dynamic regime probabilities of volatility spillover effect

Source: Author's own work

For the USCI fund, regime 1 appears highly persistent ($P_{11} = 0.984$) with an expected duration of 61.7 days, while regime 2 is extremely short-lived, with an expected duration of only 1.0 day. This pattern implies that volatility spikes are mostly transitory and that the series quickly reverts back to the dominant regime.

For the XLK fund, both regimes are also persistent ($P_{11} = 0.990$, $P_{22} = 0.953$). The expected duration is 105.7 days for regime 1 and 21.3 days for regime 2, indicating that the fund typically remains in the calm state for extended periods, while the high-volatility regime is shorter but still meaningfully persistent.

DISCUSSION

The paper reveals heterogeneous shock and volatility spillover results that may have different implications for fund managers and investors. For instance, the S&P 500 shocks transmit to PIMCO, especially in the low-volatility regime. This means that even bond-oriented funds may remain sensitive to equity-market innovations through credit-sensitive holdings and changes in risk sentiment. For fund managers, this implies that equity-market shocks should not be ignored in fixed-income strategies, especially during tranquil periods when cross-market linkages are cleaner and more visible. On the other hand,

The PIMCO fund is only weakly exposed to external volatility transmission from the selected global factors. This implies that PIMCO volatility is primarily shaped by internal portfolio structure, active duration management, credit allocation, and liquidity positioning. For investors, this suggests that PIMCO may provide a relatively stable risk profile across regimes and can serve as a defensive component in diversified portfolios.

For the USCI fund, Brent oil and gold dominate in the high-volatility regime, while the S&P 500 plays a larger role in the low-volatility regime. This implies that in crisis periods, USCI behaves as a commodity-driven instrument, where shocks in key commodity benchmarks transmit quickly into fund returns. For investors, this confirms that commodity-linked funds tend to react most strongly to commodity-specific turbulence, which typically occurs in high-volatility states.

At the same time, the volatility spillover results show that in tranquil regimes, macro-financial volatility from the S&P 500 and long-term interest rates becomes highly relevant for USCI. This indicates that even when commodity prices appear stable, the fund's risk can still be driven by changes in global risk appetite and interest-rate expectations. This means that fund managers should treat equity-market volatility and long-term bond market uncertainty as key drivers of commodity fund volatility. This is especially true during calm periods when portfolio rebalancing and global macro positioning dominate commodity pricing.

The XLK fund is strongly exposed to S&P 500 shocks in both regimes, and the magnitude is even higher in the low-volatility regime. This implies that XLK is not an independent equity segment, but rather a concentrated representation of the broader U.S. equity market. For investors, this means that holding XLK alongside broad market ETFs offers limited diversification benefits and may increase overall portfolio sensitivity to market-wide surprises.

In terms of volatility spillovers, XLK is significantly affected by S&P 500 volatility and gold volatility in both regimes, with stronger effects in the calm regime. This has two key interpretations. First, equity-market uncertainty is naturally the dominant volatility driver for technology-sector portfolios, reinforcing the importance of systematic risk management. Second, gold volatility appears to function as an uncertainty or risk-sentiment proxy, indicating that safe-haven dynamics indirectly influence technology-sector risk even without direct exposure. For fund managers, these findings imply that index-based hedging (S&P 500 futures and options) should be central to XLK risk control, especially during tranquil regimes when spillovers are strongest and hedging effectiveness is likely higher.

CONCLUSION

This paper investigated how key global financial and macroeconomic factors affect investment funds investing in different asset classes. Specifically, the authors examined the transmission of both shock and volatility spillovers from five global factors—1-month interest rates, 10-year interest rates, Brent crude oil, gold, and the S&P 500 index—into three U.S. investment funds representing bond, commodity, and equity market exposures (PIMCO, USCI, and XLK). The authors employ an asymmetric TGARCH model to construct standardized residuals and conditional variances, and subsequently estimated Markov switching models with two regimes representing high- and low-volatility market conditions.

The empirical results reveal that spillover effects are strongly fund-specific and depend on the market regime. In the shock spillover channel, the PIMCO fund is primarily influenced by shocks from the S&P 500, particularly in the low-volatility regime. For the USCI fund, the shock spillovers are regime-dependent: Brent crude oil and gold exert strong effects during high-volatility periods, while the S&P 500 becomes more influential during tranquil periods. In the case of XLK, the results show that only the S&P 500 has a strong and statistically significant shock spillover effect in both regimes, with the effect being even stronger in the low-volatility regime.

The volatility spillover findings provide additional insights. For the PIMCO fund, none of the factors generate economically meaningful volatility spillovers across regimes, indicating that the fund's volatility is largely determined by its internal portfolio structure and active risk management. For USCI, volatility spillovers from the S&P 500, 10-year interest rates, and Brent oil are particularly strong in the low-volatility regime. This suggests that macro-financial uncertainty and risk appetite are important drivers of commodity fund volatility in tranquil periods. For XLK, volatility spillovers from the S&P 500 and gold are significant in both regimes, with stronger effects in calm periods. This indicates that equity-market uncertainty is the dominant volatility driver while gold volatility acts as an indirect proxy for shifts in risk sentiment and safe-haven demand.

The results of this paper could be interesting for investors in funds and fund managers. In other words, investors should recognize that XLK offers limited diversification against U.S. equity shocks, USCI provides commodity-driven exposure that becomes highly sensitive to oil and gold shocks in crises, and PIMCO remains relatively stable in terms of volatility spillovers but is still affected by equity-market shocks through credit and sentiment channels. For fund managers, the results highlight the importance of regime-aware risk management and the need to monitor systematic equity risk, commodity-specific shocks, and interest-rate uncertainty depending on the fund asset-class exposure and the prevailing volatility state.

The analysis is restricted to PIMCO, USCI, and XLK and only five global factors, limiting generalizability and omitting other relevant variables. The TGARCH and Markov switching models rely on historical data, which may not fully capture structural breaks or unprecedented shocks, and the findings from 2015–2025 may not extend to other markets or periods. Future research could expand the fund sample, incorporate additional macro-financial variables, explore alternative econometric approaches, and compare different regions and crisis periods to improve robustness and insight.

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