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How do microfinance and economic development mutually support each other? A Panel VAR approach in developing economies.

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Abstract

This paper explores the relationship between microfinance and economic development using a cross-country dataset of 60 developing countries from 2000-2018. We employ the Panel VAR model, estimated by the generalised method of moments (GMM). Microfinance institutions indicators are categorised into social and financial performance variables. Social performance variables include the number of clients served and the percentage of women borrowers, while financial performance indicators consist of the portfolio at risk, operational self-sufficiency, and operating expenses. Economic development is assessed using the Human Development Index, which integrates economic indicators like Gross National Income per capita with social indicators such as educational attainment and life expectancy at birth. We perform a Granger causality test confirming a Granger causal relationship between microfinance and economic development. Our findings indicate that shocks to social performance variables positively influence economic development, and shocks to financial performance variables significantly impact the human development index.

Keywords: Microfinance, Economic development, Granger causality, Panel VAR, HDI.

1 Introduction

In the space of a few decades, given its promising qualitative and quantitative results, microfinance has taken a predominant role at the international level, mainly in developing countries (Blondeau, 2006), as microfinance was developed to give unbanked populations access to financial services (Morduch, 1999; Blondeau, 2006). The concept of microfinance and microfinance institutions (MFIs) should contribute to economic development by increasing the levels of short-term consumption and savings, encouraging education, professional independence and the creation of new businesses (Morduch, 1999). MFIs are financial intermediaries that combine the characteristics of formal and informal financial systems and improve the quality and accessibility of financial services by helping low-income populations access credit (Kamath, 2009). Responsible for serving people who are generally excluded from the formal banking sector, microfinance providers can be described as social enterprises (Hudon and Périlleux, 2014). Indeed, MFIs are organizations that seek to provide financial services, such as loans, savings and insurance, to people who do not have access to traditional financial services, so they have a dual objective of achieving both social and financial outcomes (Bos and Millone, 2015).

The MFI's financial performance is usually measured by indicators such as loan repayment rate, effective interest rate, cost of operations, quality of the MFIs portfolio and return on assets. The social performance of an MFI is measured by indicators such as the number of clients served, the proportion of poor clients who have no access to the banking system, the proportion of women using financial instruments, and the number of people with access to education and healthcare thanks to microfinance programs. In addition, the indirect social performance of MFIs is also measured and includes raising awareness of financial education among poor clients, empowering women, creating jobs and reducing poverty. According to Rosenberg (2009), indirect performance can be quantified by indicators such as average loan balances, number of borrowers, and percentage of female clients to male clients. It is therefore important for MFIs to measure their performance in both financial and social terms, as this enables them to achieve dual objectives while improving their operations and maximizing their social impact. The social aspirations of MFIs include poverty alleviation, job creation and women's empowerment, which may conflict with their profitability objectives, although MFIs are not technically designed to make a profit for investors. It is recommended for MFIs to achieve financial self-sufficiency, i.e. generate enough income to cover their expenses (Dehejia et al.,

2012; Jackson, 2016; Prior and Argandona, 2009) through interest income and be independent of subsidies (Rosenberg, 2009).

There is a high distinction between financial and social achievements and several papers equate the outreach of MFIs to the poor population, quantified by indicators such as the number of borrowers, the percentage of female borrowers and the average loan balance (Rosenberg, 2009). Moreover, the operational costs of MFIs (Arnone et al., 2012; Dissanayake, 2012; Tchakoute-Tchuigoua, 2010), their size (Hudon and Périlleux, 2014) and their age (Hermes et al., 2011; Koivulehto, 2007) significantly influence their outreach and financial performance. The social and financial performance of MFIs can be influenced by regional factors such as poverty, the density of competition in the microfinance sector, the geographical proximity of commercial banks and other MFIs, the characteristics of the market and competition, and cultural differences.

In general, microfinance generally has a positive impact on economic development by increasing the capital of economies and improving their financial development, as highlighted by researchers such as Armendáriz and Morduch (2010) and Kamath (2009). Existing empirical works admit that MFIs impact indicators such as GDP growth or GNI per capita (Assefa et al., 2013; Vanroose and D'Espallier, 2013). However, an important **shortcoming** of these studies is that they fail to conclusively establish a direction effect, so **the question** that this paper explores is: does any causal relationship exist between MFIs performance and their macroeconomic environment and what are these causal directions? Although some studies have explored this relationship at the national level, there is a **lack of international empirical studies** on this issue. Several studies propose empirical analyses which study the effects of microfinance on the economic environment, but these works are based solely on data from a single country (Anaduaka, 2014; Raihan et al., 2017).

Our main **objective** is to discover a robust statistical causal relationship between microfinance and economic development through new economic development indicators that have been shown to correlate with microfinance. In this respect, **our three contributions are: first**, to provide to the current literature the first, as far as we know, empirical relationship between microfinance and economic development for 60 developing countries, using the Panel VAR model, estimated by the generalised method of moments (GMM). This contribution is all the more important as there is no consensus among practitioners and researchers on the size of the effects of microfinance on economic development. **The second contribution** is to differentiate between the effects of, on the one hand, the social performance and, on the other hand, the financial performance on the economic development variables, as previous research papers that

used macroeconomic aggregations to assess the impact of microfinance on economic development limits the ability to make a distinction between their impact on economic development (Imai et al., 2012; Maksudova, 2010). Our **third contribution** is to establish if there is any Granger causality between our main variables, i.e. microfinance and economic development.

The Granger causality test confirms a Granger causal relationship between microfinance and economic development. Specifically, we observe bidirectional causality between the human development index and the number of clients, as well as between the percentage of women entrepreneurs and the human development index. However, we also identify unidirectional Granger causalities, such as from the human development index to portfolio at risk and operational self-sufficiency, as well as from operating expenses to the human development index.

Our **results** highlight that social performance variables positively affect economic development: as the number of clients and the percentage of women entrepreneurs increases, the development index also rises. Next, we find that shocks to financial indicators namely portfolio at risk, operational self-sufficiency, and operating expenses have a positive and significant impact on the human development index, although this effect diminishes progressively in the long run.

The paper is structured in the following way: we highlight in Section 2 the Trends and Stylized Facts, Section 3 presents the Literature Review, Section 4 describes the Data, and Section 5 outlines the Methodology we adopt for our model. Moreover, Section 6 discusses the Empirical Results obtained, Section 7 exhibits the Robustness and Section 8 displays the Conclusions.

2 Microfinance and economic development: trends and stylized facts

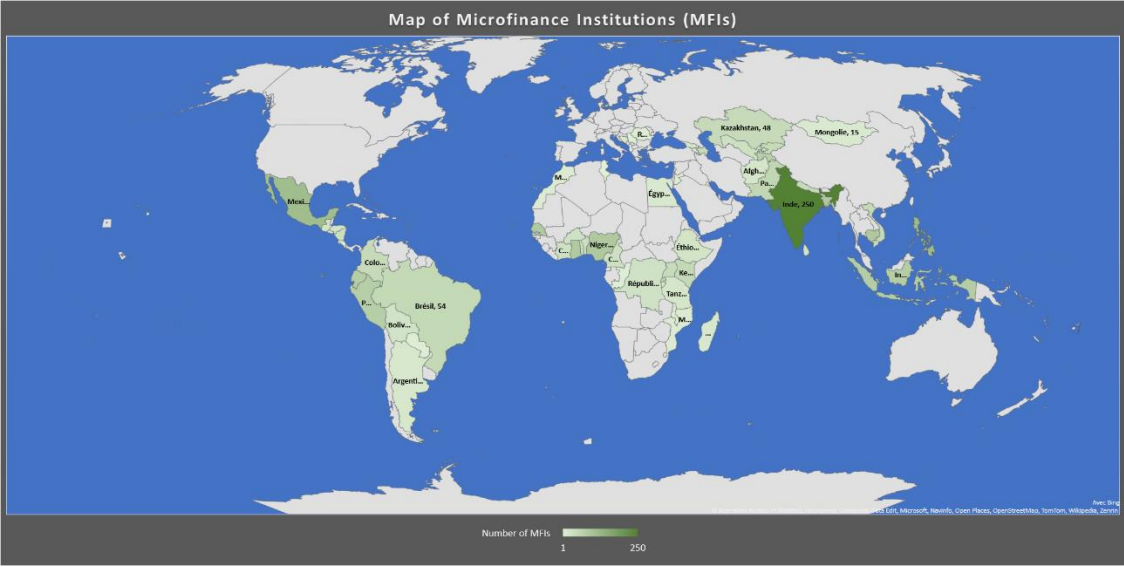
Since the 1970s, microfinance has proliferated to solve economic and social problems in developing countries (poverty, education, health). This considerable development over the last few decades has been reflected in the number of borrowers and the volume of the loan portfolio. Microfinance is a major industry, with more than three thousand¹ microfinance institutions (MFIs) and 139.9 million customers² worldwide. The processes for providing affordable financial services in emerging markets have evolved over the years. More specifically, 2017 offered new opportunities to achieve financial inclusion goals while overcoming obstacles.

¹ Microfinance Barometer 2019

² idem

Indeed, 762 microfinance institutions (MFIs) submitted awareness and financial performance data to the MIX Market. The number of active borrowers grew by 9.8% and the gross loan portfolio increased by 14.3% from one year to the other. The total number of active borrowers increased to 120 million and the gross loan portfolio amounted increased to USD 112 billion at the end of 2017.

Figure 1: Map of Microfinance Institutions (MFIs) worldwide

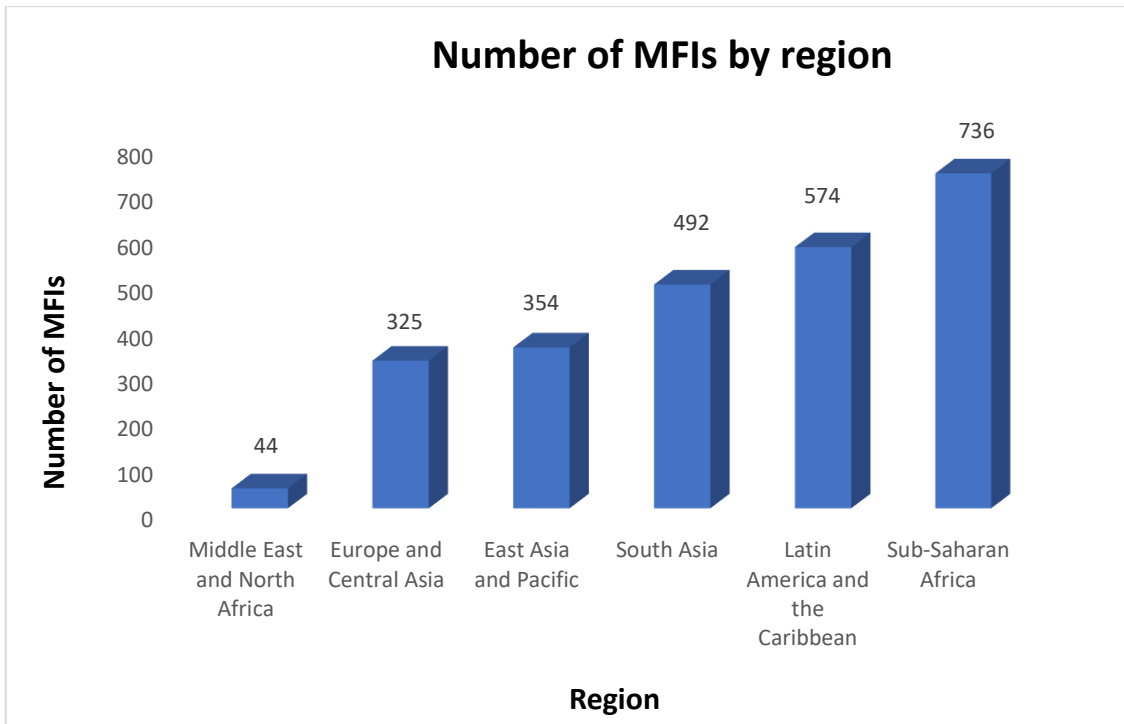


Source: Authors' calculations based on public databases.

In our study, we focus on data from 2525 microfinance institutions around the world. Figure 1 shows that these institutions are mainly present in less developed countries, where poverty levels are generally high. India, the Philippines, Mexico, Cambodia, Nigeria, Bangladesh, Ghana, Senegal, Indonesia and Ecuador are among the top 10 countries in terms of the number of microfinance institutions, with 250 institutions in India and 77 in Ecuador. These institutions are broken down by region, in Sub-Saharan Africa we find 736 institutions, and in Latin America, there are 574 institutions, being the regions with the highest numbers of institutions. However, in the Middle East and North Africa regions, we find the lowest number of institutions (i.e., 44 institutions, as Figure 2 shows).

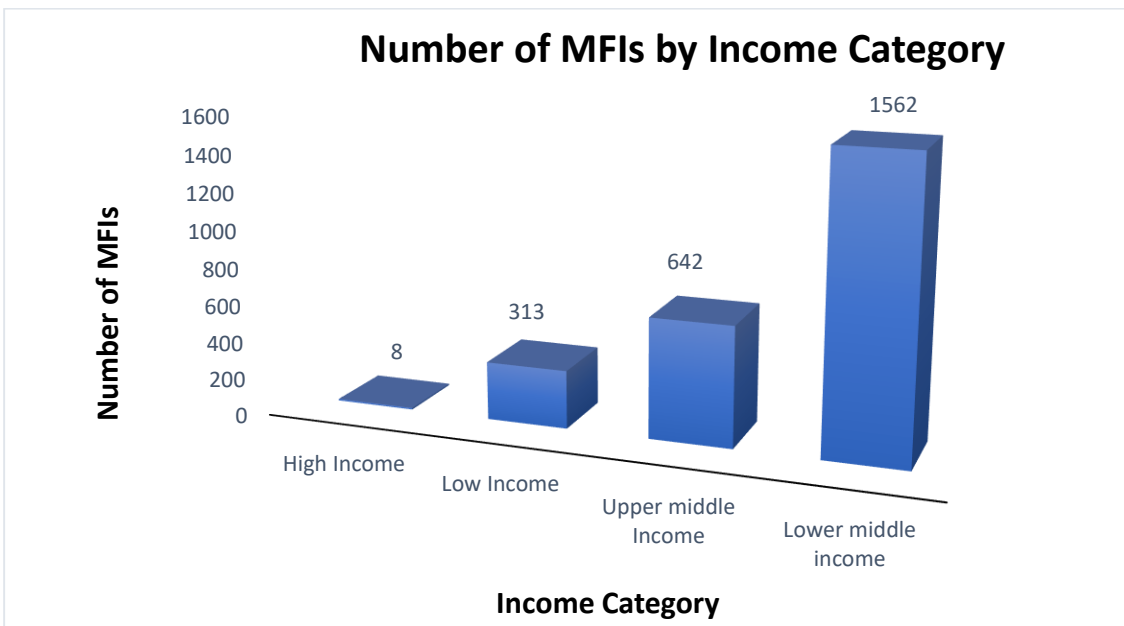
The countries classified as Lower-Middle-Income and Upper-Middle-Income provide the majority of institutions, with 1,562 and 642 respectively, while in Low-Income Countries we get 313 institutions. On the contrary, in High-Income Countries, we find a very limited number of institutions (Figure 3).

Figure 2: Breakdown of Microfinance Institutions (MFIs) by region



Source: Authors' calculations based on public databases.

Figure 3: Distribution of Microfinance Institutions (MFIs) by Revenue



Source: Authors' calculations based on databases.

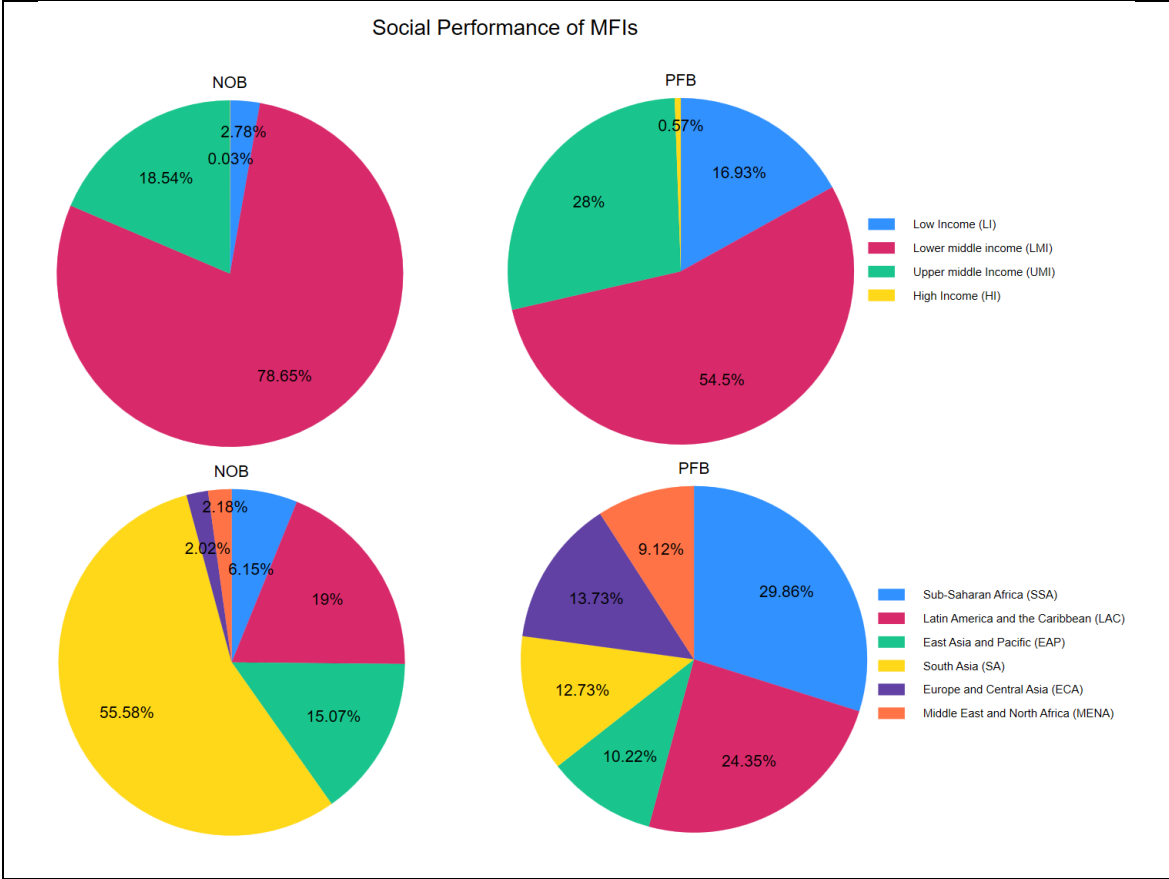
2.1 The Microfinance Institutions' Social Performance.

Figure 4 shows the distribution of MFIs' social performance by income and region. On the left-hand side of Figure 4, the Number of Clients is classified by income, showing that the majority of clients (78.65%) come from the Lower Middle-Income bracket. Upper-middle-income

customer revenues represent the second largest group (18.54%), followed by Lower-Income customer revenues (2.78%). A very low level of income is attributed to customers in the Highest-Income Bracket (0.03%). Below, the dispersion of the Number of Clients by region reveals that the majority of customers (55.58%) are coming from South Asia. Customers in Latin America are in proportion of 19% of the total number, while those in East Asia and the Pacific represent 15.07% of the total number. However, customers in Sub-Saharan Africa, the Middle East and North Africa, and Europe and Central Asia represent 6.15%, 2.18% and 2.02% respectively of the total number of customers.

On the right side of Figure 4, the Number of Women Entrepreneurs is broken down by income, showing a similar pattern to the number of customers. The Lower-Middle-Income group has the highest Number of Women Entrepreneurs per income (54.5%). The next highest income group of women entrepreneurs (28%) is the Upper-Middle-Income group. Women entrepreneurs in the Lowest Income bracket represent the third highest number by income (16.93%), while the Highest Income bracket is attributed to the fourth highest number (0.5%).

Figure 4: Distribution of MFIs' social performance by income and by region.



Authors' calculations based on databases.

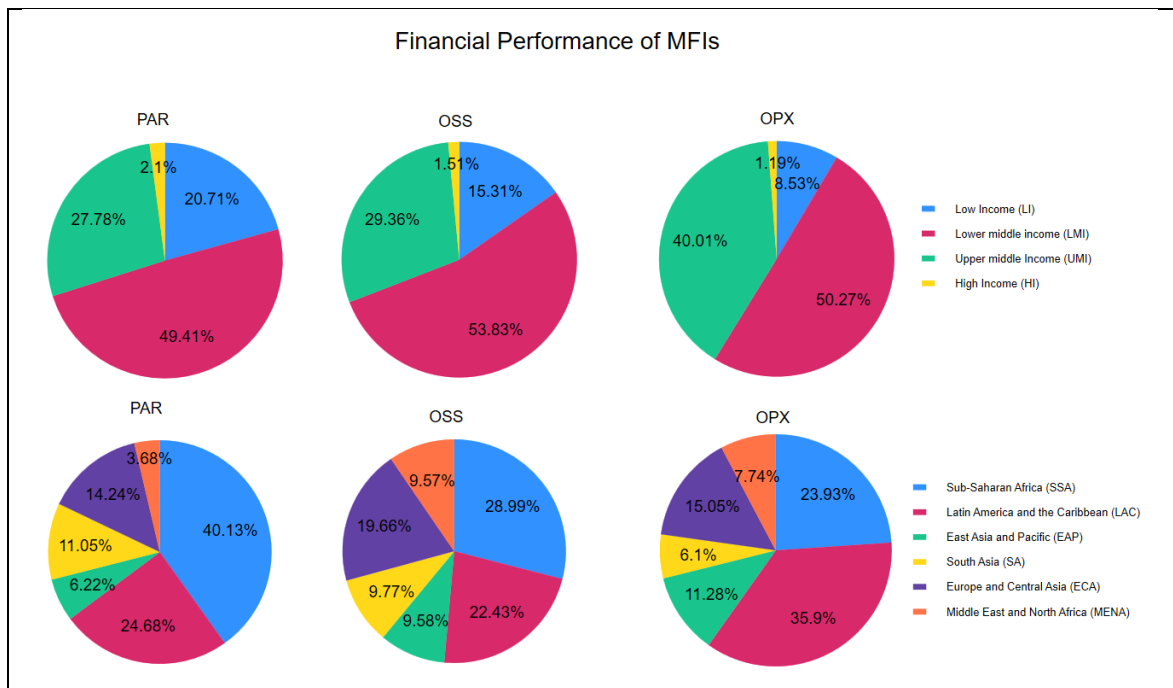
2.2 The Microfinance Institutions' Financial Performance.

Three main indicators are shown in Figure 5, which provides a detailed financial performance analysis of microfinance institutions (MFI): Portfolio at Risk (PAR), Operational Self-Sufficiency (OSS), and Operating Expenses (OPX). On the left-hand side of the figure, we display the distribution of portfolios at risk, by income, which shows that the Lower Middle-Income class has the highest PAR rate (49.41%), followed by the Upper Middle-Income class (27.78%), the Low-Income class (20.71%) and the High-Income Class (2.1%). Analysis by region shows that the highest PAR rates predominate in Sub-Saharan Africa (40.13%), closely followed by Latin America (24.68%) and Europe and Central Asia (14.24%). The remaining regions show lower percentages, namely South Asia represents 11.05%, East Asia and the Pacific represents 6.22%, and the Middle East and North Africa exhibits 3.68%.

In the center of Figure 5, Operational Self-Sufficiency is examined by income, highlighting that the Lower Middle-Income class represents the highest rate (53.83%), followed by the Upper Middle-Income class (29.36%), the low-income class (15.31%) and the high-income class (1.5%). By region, Operational Self-Sufficiency is at the highest rate in sub-Saharan Africa (28.99%), followed by Latin America (22.43%), Europe and Central Asia (19.66%), South Asia (9.77%), East Asia and the Pacific (9.58%), and finally the Middle East and North Africa (9.57%).

On the right-hand side of Figure 5, Operating Expenses are examined by income and by region. The Upper-Middle Income class accounts for the largest share of expenses (50.27%), followed by the Upper-Middle Income class (40.01%) and the Low-Income class (8.53%). The High-Income class represents just 1.19%. By region, Operating Expenses exhibit the highest rate in Latin America (36.9%), followed by sub-Saharan Africa (23.93%) and Europe and Central Asia (15.05%). The Operating Expenses are displayed in the following order: an 11.28% rate for East Asia and the Pacific, a 7.74% rate for the Middle East and North Africa, and a 6.1% rate for South Asia.

Figure 5: Distribution of MFI financial performance by income and region.



Source: Authors' calculations based on databases.

3 Literature review

Attracted by the promise of a win-win solution that benefits poor customers, financial institutions, and ultimately the economy (Morduch, 1999), new institutions enter and develop the microfinance market. These new institutions, known as MFIs, increase loan amounts and expand the potential client base. As part of the concept of sustainable development and the quest for social well-being, MFIs specifically target women (Morduch, 1999). Women in developing countries often lack professional skills and, therefore, cannot provide marketable loan guarantees. MFIs contribute to the empowerment of women by providing them with resources that would otherwise be inaccessible, helping them to start businesses and achieve integrity and equality. Small groups of people can obtain microloans, with members of the group guaranteeing each other. The concept of microfinance also accepts social relationships as collateral for loans. However, according to Schicks (2014), the integrity and financial independence of microfinance clients may be jeopardized by exploitative practices such as high interest rates ranging from 80–100% and insufficient repayment schemes.

Three dominant streams of research can be identified when reviewing the current literature on microfinance. The **first stream** focuses on the **financial performance** of MFI self-

sufficiency. The significance of regional effects on the social and financial performance of MFIs is confirmed by both qualitative and quantitative studies (Vanroose & D'Espallier, 2013). In this respect, D'Espallier et al. (2013) analyze the effects of regional characteristics on the financial performance of MFIs and find that the density of competition in the microfinance sector and the level of financial regulation are important factors. Additionally, Gonzalez (2010) examines the impact of regional culture on MFI performance in Latin America and concludes that cultural differences can affect relationships between clients and lenders. Moreover, Arnone et al. (2012) find that MFIs operating in poorer regions tend to have higher levels of social performance, measured in terms of impact on poverty and financial inclusion. The financial performance of MFIs is analyzed by Lopatta and Tchikov (2017) who examine the impact of regional characteristics on the financial performance of MFIs in Eastern Europe and Central Asia, finding that market characteristics and competition in the microfinance sector play a major role. Additionally, Vanroose and D'Espallier (2013) analyze how geographical proximity to commercial banks affects the MFIs' financial performance in sub-Saharan Africa. They find that MFIs located close to other MFIs tend to have better financial performance, while those located close to commercial banks tend to have worse financial performance. However, competition in the microfinance market seems to negatively affect the reach and performance of MFIs (Assefa et al., 2013).

According to Cull et al. (2007) and Hudon & Périlleux (2014), MFIs' performance and efficiency are also influenced by factors such as age, size, lending practices, and operating expenses. Moreover, El Kharti (2014) studied the main determinants of the financial performance of MFIs in Morocco using a sample of 10 MFIs over the period from 2003 to 2010. The results indicate that the age of the MFIs and the portfolio at risk (PAR) are the most significant factors.

The **second stream of research** focuses on the **macroeconomic impact of microfinance on economic development**. However, analyses based on MFIs often overlook the long-term goals of the microfinance concept—namely poverty reduction, financial system development, and overall economic development. These analyses fail to consider the interdependent effects of economic efficiency, even though these factors are particularly pertinent to MFI practices. In this context, microfinance impacts the development of economic and financial systems through several channels such as capital allocation, encouragement and monitoring investments, and consumption support. Additionally, microfinance promotes entrepreneurship and ultimately enhances productivity. In practice, MFIs provide modest amounts of basic financial services to underemployed and low-income individuals, as well as small-scale informal business owners.

Compared with formal credit, microcredits are smaller, lack typical collateral, and allow for flexible repayments. Since MFIs' clients often lack official financial statements, MFIs use alternative criteria to assess the creditworthiness of borrowers, such as their character, social position, and willingness to repay after having visited them at their places. This last criterion applies a qualitative method to credit risk assessment when no quantitative solution is found.

According to Armendáriz & Morduch, (2010) and Kamath (2009), studies in this area are based on theoretical models of economic development and growth, analyzed through the lens of microfinance and its primary outcome: an increase in capital stock. Achieving sustainable economic growth and developing financial systems are crucial for developing countries, as the two are closely linked: economic growth increases the demand for financial services, which in turn fuels further economic growth (Hassan et al., 2011). However, the precise magnitude of microfinance's benefits on economic growth and poverty alleviation remains a contentious area of study, as evidenced by Rajbanshi et al. (2015). MFIs refocus their support on economic development by reducing costs, increasing profitability, and managing risks (Assefa et al., 2013; Cull et al., 2007). Some works reveal the effects of MFI on developing indicators such as poverty reduction or standard of living. For instance, Nwakanma et al. (2014) examine the impact of microfinance on poverty reduction in Nigeria using a controlled experimental approach. Sharma et al. (2014) explored the impact of microfinance on women's employment and living conditions in India, providing a better understanding of the relationship between microfinance and economic development through precise measures assessing its impact on communities and individuals.

A large number of works use macroeconomic indicators, such as the GDP or the credit-to-GDP ratio. For example, Raihan et al. (2017) studied the macroeconomic impact of microfinance on Bangladesh's GDP through channels such as capital accumulation, productivity improvement, and the reallocation of capital and labor across different sectors. They employ a static computable general equilibrium (CGE) model to capture these mechanisms. According to their estimates, microfinance contributed between 8.9% and 11.9% of the country's GDP, depending on assumptions about the labor market's functioning, with a higher contribution to rural GDP, ranging from 12.6% to 16.6%.

Maksudova (2010) uses averages of the growth rate of MFIs' gross loan portfolios to quantify microfinance by nation and year. Macroeconomic indicators include increases in the ratio of private credit to GDP, the real GDP growth rate, and the money supply growth rate over a year. This study demonstrates that microfinance positively contributes to GDP growth based on a cross-national sample of data from over 1,400 MFIs in 102 countries during 14 years (1995-

2009). However, the effects vary depending on the level of development of the countries involved.

Using a choice model, Ahlin and Jiang (2008) examined the long-term effects of microcredit on development. Their results show that microcredit can either increase or decrease GDP in the long term, while generally reducing inequality and poverty. Specifically, it was shown that microcredit reduces poverty and can contribute to development by positively impacting the lives of the poorest half of the population. Ahlin et al. (2011) examined how the success of MFIs depends on the national context, focusing on macroeconomic and institutional characteristics. By analyzing data from 373 MFIs and merging it with country-level economic and institutional data, they demonstrated that MFI performance is complementary to overall economic performance. MFIs are more likely to cover their costs when the economy is growing stronger, is financially deeper, and has lower default and operating costs, as well as lower interest rates. According to Sharma and Puri (2013), microcredit has a significant impact on GDP. The development of microfinance in India has provided rural poor people with better economic, social, and cultural opportunities, thereby improving their standard of living and quality of life. Additionally, Dwivedi and Sharma (2015) analyzed the relationship between microcredit to self-help groups (SHGs) and GDP. Their study found a positive correlation between microcredit and GDP, indicating that microcredit to SHGs significantly impacts GDP. These findings align with those of other studies on the same topic, such as Khandker et al. (2010).

The third stream of literature refers to studies which count for the **causal relationship** between microfinance and economic development. In this respect, Anaduaka (2014) use MFI loan portfolios as a measure of microfinance and real GDP to quantify economic growth to investigate the Granger causality between microfinance and growth. They examined MFIs in Nigeria using quarterly data collected over 11 years (1992-2012). The results of their Granger causality analysis indicated a unidirectional causal link from microfinance to economic growth. However, they did not find substantial evidence to confirm the significant impact of microfinance on GDP. This finding was supported by Nwakanma et al. (2014), who also analyzed the causality between economic growth and microfinance in Nigeria and could not verify the bidirectional causality between MFI credit volumes and GDP. Additionally, Sharma et al. (2014) found a unidirectional Granger causal relationship between economic development, measured by GDP, and microfinance in India over 20 years (1992-2012). Lopatta & Tchikov (2017) investigated the statistical causality between microfinance and economic development using a cross-country dataset covering 1995-2012. They used MFI performance

indicators as well as economic development indicators measuring not only economic and capital growth but also poverty, income inequality, and labor market participation. They found bidirectional causal interactions between the social and financial performance of MFIs and economic development.

4. Data

To empirically examine the causal relationship between microfinance and economic development, we analyze data from 2000 to 2018, measuring microfinance performance through its social and financial aspects. We consider both quantitative and qualitative aspects of microfinance operations, using MFI performance indicators. This approach builds on earlier empirical research that measured microfinance based on gross loan portfolios or aggregate microcredit volumes (Maksudova, 2010; Nwakanma et al., 2014; Sharma et al., 2014).

From the Microfinance Exchange Market (MIX) database, we gather unique information on financial institutions for 2,525 MFIs across 60 countries³. Following the guidelines of the World Bank's Consultative Group to Assist the Poor (Rosenberg, 2009) and previous literature (e.g., Assefa et al., 2013; Cull et al., 2007), we use the following variables to measure microfinance performance: **Number of Clients Served (NOB)**, **Percentage of Women Borrowers (PFB)**, **Portfolio at Risk (PAR)**, **Operational Self-Sufficiency (OSS)**, and **Operating Expenses (OPX)**. According to Rosenberg (2009), the first two metrics namely NOB and PFB assess MFIs' social success, while the latter three metrics namely PAS, OSS and OPX reflect their financial performance.

To perform reasonable time series tests, we aggregate the MFIs' performance indicators to their annual and national averages (Maksudova, 2010), as well as to totals for the number of customers served, respectively (Imai et al., 2012). MIX database provides data only until 2018, as recent papers claim (Baltas and Liñares-Zegarra, 2024; Adusei, 2021; and Afrifa et al., 2019). Given the interdependence of development parameters, we measure economic development using the **Human Development Index (HDI)**, which combines social and economic indicators such as **Life Expectancy at Birth (LE)** and **Educational Attainment (EDI)**. Previous research studies confirm that the HDI is a meaningful indicator of economic development because HDI incorporates essential factors such as income, education, and life expectancy (e.g., Ahlin et al., 2011; Schicks, 2014; Islam et al., 2015; Lopatta & Tchikov, 2016; Aksentijević, 2018; and Caire and Nivoix, 2019).

³ Table 9 in Appendix present the countries.

Figure 1 shows the three components of the Human Development Index used in the robustness section to validate the results obtained. The United Nations Development Programme (UNDP) and the World Bank's World Development Indicators are the sources of the economic development metrics used in our analysis. Detailed descriptions of all the variables used in our study are presented in Table 1.

Table 1: Description of variables

	Variables	Description
Social performance of MFIs	Number of customers served (NOB)	It represents the total number of people or households to which an MFI provides financial services such as loans, savings accounts, insurance services, etc. This figure is often used as a key indicator of the size and influence of an MFI. This figure is often used as a key indicator of the size and influence of an MFI.
	Percentage of women borrowers (PFB)	A measure of the social performance of Microfinance Institutions (MFIs), particularly those that implement specific programs for the economic empowerment of women. This percentage represents the proportion of borrowing clients who are women about the total number of borrowing clients of the MFI.
Financial performance of MFIs	Portfolio at risk (PAR)	The term "portfolio at risk" refers to the portion of loans granted by the institution that is exposed to a high risk of non-repayment. This includes loans granted to borrowers who may be experiencing financial difficulties, economic challenges or other circumstances that compromise their ability to repay their debts.
	Operational self-sufficiency (OSS)	Average annual operational self-sufficiency as a percentage of the MFI's financial income and its financial costs, impairment and operating expenses. Refers to the institution's ability to cover all of its operating costs from its revenues, without relying on external subsidies in the long term. In other words, an MFI is considered operationally self-sufficient when it can generate sufficient income from its microfinance activities to cover its operating expenses.
	Operating expenses (OPX)	Average annual operating expenses of the MFI's gross loan portfolio. Refers to the costs associated with the day-to-day management and operation of the institution. These costs include various elements required to maintain the MFI's day-to-day operations and provide financial services to its clients. Effective management of these costs is crucial to ensuring the financial viability of the MFI.
Economic development indicators	Human Development Index (HDI)	a composite indicator developed by the United Nations Development Programme (UNDP) to assess the human development of countries. This index measures the average level of human development by taking into account three key dimensions of human well-being: health, education and standard of living. The HDI combines these dimensions

to provide a comprehensive measure of development that goes beyond a simple economic assessment.

Gross national income (GNI) per capita	a measure of the standard of living. It is calculated by adjusting the country's gross national income according to purchasing power parity and dividing it by the total population.
Education Index (EDI)	An indicator that measures the level of education of a population in a given region. This index may vary according to the sources and methodologies used, but it generally includes elements such as the average length of schooling and the expected length of schooling.
Life expectancy at birth (LE)	This is the measure of longevity. It reflects the average lifespan of a person at birth and is used as an indicator of the overall health of the population.

Source: Own Representation.

According to the descriptive statistics presented in Table 2, MFI performance and economic development vary greatly across countries within our sample. Consequently, both our descriptive statistics and the pertinent literature highlight the necessity for representative empirical investigations into the causal relationship between microfinance and economic development on a cross-national and global scale. These findings also demonstrate that results derived from data from a single nation have limited generalizability (Nwakanma et al., 2014; Sharma et al., 2014)⁴.

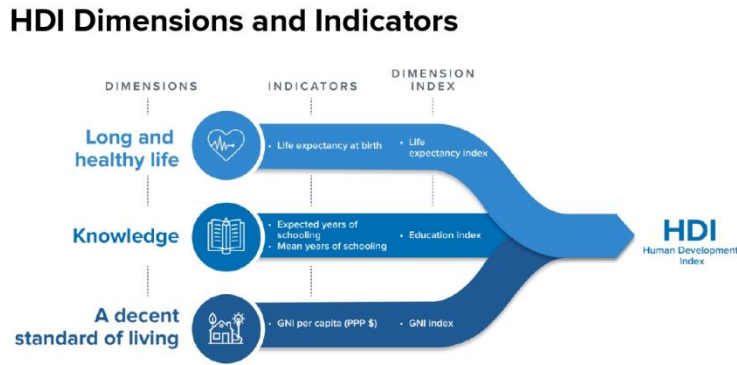
Table 2: Descriptive statistics

	N	Mean	Median	SD	Min	Max
IDH	1132	.607	.632	.128	.287	.851
logGNI	1140	8.488	8.528	.878	6.415	10.239
EDI	1132	.538	.548	.152	.141	.861
logLE	1140	4.195	4.231	.121	3.796	4.379
logNOB	1111	12.1	12.124	1.946	.693	17.492
logPFB	1097	4.054	4.092	.416	-3.912	5.004
logPAR	1097	1.57	1.735	.98	-4.605	4.603
logOSS	1109	4.719	4.725	.266	3.023	6.34
logOPX	1111	14.712	14.801	1.465	8.057	17.966

Source: Authors' calculations based on databases.

⁴ A matrix of correlations is also performed in Table 8 (Appendix) to check the multicollinearity implications.

Figure 6: Component of the Human Development Index HDI.



Source: United Nations Development Programme UNDP

5 Methodology

In this section, we analyse the relationship between economic development and microfinance in order to determine whether microfinance promotes development or vice versa. Our methodological approach is based on the panel VAR methodology. This method, initially developed by Holtz-Eakin et al (1988), combines the classic VAR model of Sims (1980) with the panel data technique. The main advantage of the panel VAR approach is its ability to treat all variables simultaneously as endogenous, thus allowing endogenous interaction between the human development index and the financial and social performance of microfinance institutions.

The panel VAR model takes advantage of the cross-sectional dimension of the sample by including unobserved individual heterogeneity in the form of fixed effects. Formally, the panel VAR model can be represented by the following equation (1):

$$Y_{it} = A_i + B(L)Y_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$i \in \{1, 2, \dots, N\}, t \in \{1, 2, \dots, T\}$$

Where: $Y_{i,t}$ is the vector of endogenous variables for individual unit i and period t , A_i is the vector of constants, B are matrices of parameters to be estimated, L is the lag operator and $\varepsilon_{i,t}$ is the error term.

To estimate this model, we use the methodology of Abrigo and Love (2016), specifically adapted to panel VAR models with many individual units (N) and a small number of periods (T). This method is based on a variant of generalized moment estimation (GMM), optimized for VAR panel data. Unlike the classic GMM methods, Abrigo and Love's approach makes it

possible to deal more effectively with endogenous dynamics between variables within the framework of a VAR model, while exploiting the specificity of panel data.

To assess the dynamic effect of shocks on endogenous variables, we calculate impulse response functions (IRFs) using the Cholesky decomposition of the variance-covariance matrix of residuals. These functions allow us to observe the response of the variables to an exogenous shock to another variable in the model. The IRF values are accompanied by confidence intervals at 5% and 95%, calculated by Monte Carlo simulation with 1,000 replications, providing a better understanding of the dynamics and uncertainty of the responses. To test the validity of the results, we also perform the causality Granger test to verify causal links between variables (see below).

6 Empirical results

Unit root test

Before estimating the panel VAR model, we check the stationarity of our main variables using the Fisher-type unit root test based on the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Fisher-type unit root test based on the Phillips-Perron (PP) test (Phillips and Perron, 1988)⁵. These tests are particularly well-suited to unbalanced panel data, ensuring robust results. Given the wide variability of situations between different countries, unit root tests like the Fisher ADF and Fisher PP are appropriate, as they assume an individual unit root process in each series of cross-sections.

The second test is based on the Phillips-Perron approach. According to Phillips and Perron (1988), the ADF test tends not to reject the null hypothesis when time series are subject to both a structural break caused by an exogenous shock and a deterministic time trend.

The results of both tests are presented in Table 3. The null hypothesis, which posits that all panels contain unit roots, is rejected for both tests. This indicates that the variables are stationary, making them suitable for use in the PVAR analysis.

Table 3: Unit root test.

Variables	Test	Stationarity
IDH	ADF	I (0)
	Phillips-Perron	I (0)
GNI	ADF	I (1)

⁵ The tests' results are shown in Table 10 (Appendix).

	Phillips-Perron	I (1)
EDI	ADF	I (1)
	Phillips-Perron	I (1)
LE	ADF	I (0)
	Phillips-Perron	I (0)
NOB	ADF	I (0)
	Phillips-Perron	I (0)
PFB	ADF	I (0)
	Phillips-Perron	I (0)
PAR	ADF	I (0)
	Phillips-Perron	I (0)
OSS	ADF	I (0)
	Phillips-Perron	I (0)
OPX	ADF	I (1)
	Phillips-Perron	I (1)

Source: Authors' calculations based on databases.

Selecting lags in the VAR panel

The model selection criteria, as shown in Table 4, are calculated using first to third-order panel VAR sets with four lags of the Human Development Index (HDI), number of customers served (NOB), percentage of female borrowers (PFB), portfolio at risk (PAR), operational self-sufficiency (OSS), and operating expenses (OPX) as instruments. The results of the model selection measures, calculated according to Andrews and Lu (2001), are presented in Table 4. Based on these criteria, the panel VAR of order 1 is the preferred model, as it has the lowest MBIC, MAIC, and MQIC.

Table 4: Lag selection criteria in panel VAR

lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	1.000	134.002	0.046	-575.654	-81.998	-272.650
2	1.000	68.486	0.596	-404.617	-75.514	-202.615
3	1.000	17.465	0.996	-219.087	-54.535	-118.086

Source: Authors' calculations based on databases.

Stability of the VAR panel model

Table 5: Stability of the panel VAR model

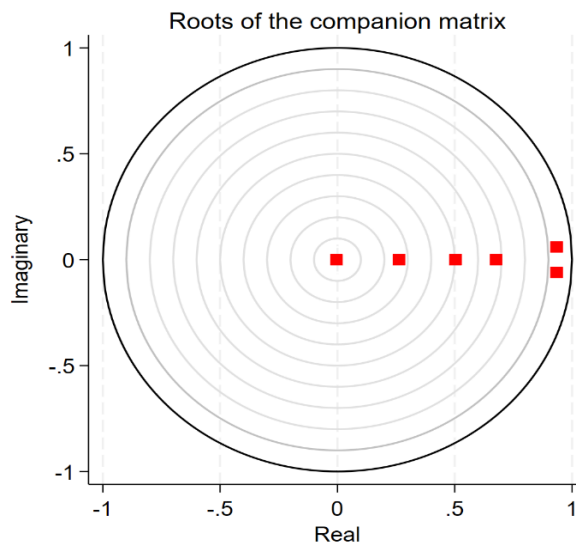
Eigenvalue		
Real	Imaginary	Modulus
0.934	0.060	0.936
0.934	-0.060	0.936
0.676	0	0.676
0.503	0	0.503
0.263	0	0.263
-0.004	0	0.004

Source: Authors' calculations based on databases.

When estimating the panel VAR model, it is essential to check its stability condition. This condition assumes that the panel VAR has a moving average vector of infinite order and is invertible (Abrigo and Love, 2016). The most common method for determining the stability of a panel VAR is to calculate the modulus of each eigenvalue of the estimated model. Hamilton (1994) and Lütkepohl (2005) show that a panel VAR model is stable if the modulus of each eigenvalue of the companion matrix is strictly less than one.

The table of results and the graph of eigenvalues confirm that the estimated panel VAR models satisfy the stability condition. Table 5 shows the eigenvalues of the panel VAR models estimated in Equation 1, with the modulus of each eigenvalue being strictly less than one. In Figure 7, the eigenvalues for the estimated panel VAR models are plotted, with the complex components on the y-axis and the real components on the x-axis. Figure 7 demonstrates that the eigenvalues lie well within the unit circle.

Figure 7: Stability of the panel VAR model.



Source: Authors' calculations based on databases.

Granger causality tests and Panel VAR estimates

To assume that all variables in the system are endogenous, we verify the validity of this condition using a Granger causality test. The null hypothesis of the test assumes that the coefficients of the lags of the dependent variable $Y_{ki,t-p}$ in the Panel VAR equation of $Y_{i,t}$, where $i \neq k$, are all equal to zero. Table 11 in the Appendix presents the results of the Granger

causality test, which shows the existence of bidirectional causality between our variables, suggesting that the variables in our econometric model should be treated as endogenous.

The Granger test confirms the existence of a Granger causal relationship between microfinance and economic development. Specifically, we observe bidirectional causality between the human development index and the number of clients, as well as between the percentage of women entrepreneurs and the human development index. However, we also identify unidirectional Granger causalities, such as from the human development index to portfolio at risk and operational self-sufficiency, as well as from operating expenses to the human development index.

We now present the estimation results of our first-order panel VAR model in a GMM framework. Table 6 shows the estimation results of the panel VAR model in Equation 1. For all specifications, we note that the number of observations per year is significantly smaller than the sample size, as shown in Table 2. According to Abrigo and Love (2016), the panel VAR model excludes by default any observation with missing data from the estimation.

Regarding the effect of economic development (i.e., HDI) on microfinance variables, there is a significant impact. Specifically, we find that the coefficient of the variable is significantly positive for all specifications, except for operational expenses (OPX). In other words, a change in the human development index increases the number of clients served, the percentage of women entrepreneurs, the portfolio at risk, and operational self-sufficiency.

Table 6: Estimation of the panel VAR model.

VARIABLES	-1	-2	-3	-4	-5	-6
	IDH	logNOB	logPFB	logPAR	logOSS	dlogOPX
L.IDH	0.966*** (0.00759)	-3.110*** (0.711)	-0.451** (0.194)	-0.137 (1.019)	-0.139 (0.230)	-4.047*** (0.852)
L.logNOB	0.000926*** (0.000340)	0.870*** (0.0262)	0.00599 (0.00765)	-0.0567 (0.0499)	0.0125 (0.0103)	0.0749*** (0.0287)
L.logPFB	0.00896*** (0.00223)	0.235 (0.218)	0.641*** (0.0588)	-0.948*** (0.294)	-0.127** (0.0620)	0.181 (0.224)
L.logPAR	0.000629* (0.000349)	-0.0376 (0.0357)	-0.0109 (0.00863)	0.457*** (0.0486)	0.0413*** (0.0101)	0.0309 (0.0391)
L.logOSS	0.00376*** (0.00140)	0.528*** (0.158)	0.0312 (0.0350)	-0.453** (0.205)	0.396*** (0.0520)	0.600*** (0.192)
L.dlogOPX	7.27e-05 (0.000273)	0.0455 (0.0413)	-0.00600 (0.00737)	-0.0288 (0.0454)	-0.00582 (0.00907)	-0.0234 (0.0436)

Observations	900	900	900	900	900	900
	Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Source: Authors' calculations based on databases.

Impulse response function (IRF)

To better understand the link between economic development and the performance of microfinance institutions, we complete our analysis by estimating impulse response functions (IRFs). IRFs explain the reaction of an endogenous variable to innovations in another endogenous variable, describing the evolution of a dependent variable over a specific time horizon after a shock at a given point in time. Figures 8 and 9 illustrate the IRF curves corresponding to the specifications in Table 6. The two curves adjacent to the impulse response are the 95% confidence limits, determined using a Monte Carlo simulation based on 1000 simulations.

We begin by examining the relationship between the Human Development Index (HDI) and the social performance of microfinance institutions, specifically the number of clients served (NOB) and the percentage of women entrepreneurs (PFB). The social performance variables positively affect economic development: as the number of clients and the percentage of women entrepreneurs increases, the development index also rises. Counterintuitively, when the HDI increases, both the number of clients and women entrepreneurs decline.

On the one hand, a standard deviation shock to the number of customers has a positive impact on HDI, although this response gradually diminishes. Similarly, the effect of women entrepreneurs on HDI is positive (Figure 8). This can be interpreted as follows: if the population has more access to credit, they can consume more and meet their needs, leading to higher development. This result aligns with the literature, which shows a positive link between financial activity and HDI. For example, Asongu and Odhiambo (2018) argue that increasing the formal financial sector and having a higher number of clients enhances financial access and development. Arora (2014) also states that when access to finance increases, the country becomes more developed.

As the percentage of women entrepreneurs surges, there is a positive impact on the HDI. Similar results were found by Nanda (2017), who argues that the level of financial inclusion reflects a joint evolution with the extension of per capita income and socio-economic development (HDI), as technology can extend financial services to the unbanked population. Furthermore, Ayun and

Mukhlis (2022) argue for a simultaneous positive influence on the contribution of women entrepreneurs and professional workers to women's HDI. Additionally, Sajjad et al. (2020) confirm that women entrepreneurs also contribute to economic development (HDI) when gender inequality is reduced.

On the other hand, a counterintuitive result is that when HDI increases, the number of clients decreases, suggesting that wealthier individuals prefer banks over MFIs. Moreover, higher HDI values are associated with a lower number of women entrepreneurs, although this is statistically insignificant.

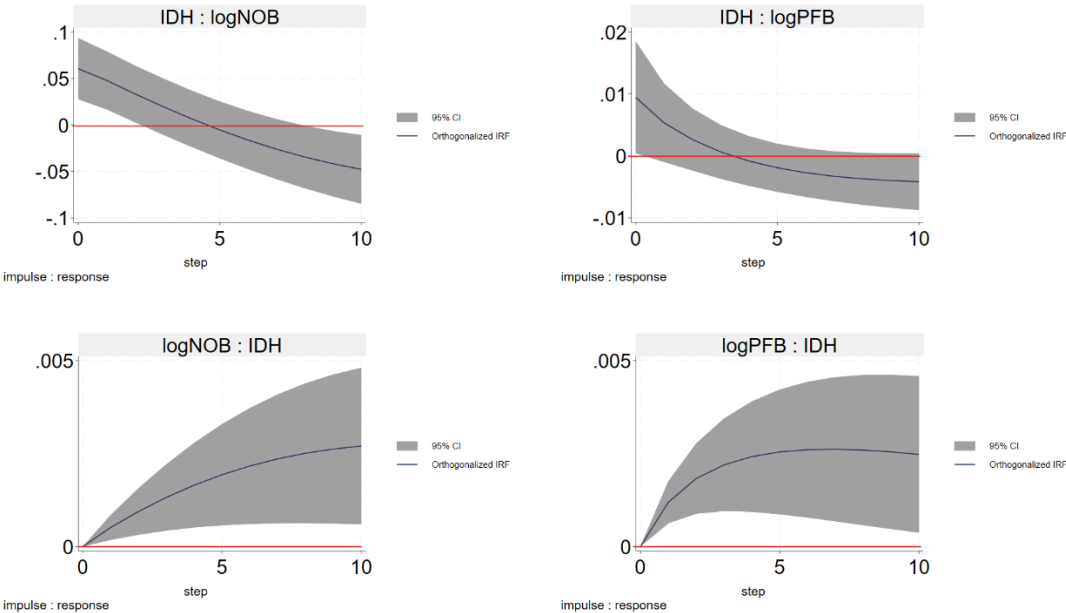
Next, we focus on the relationship between the human development index (HDI) and the financial performance of microfinance institutions, such as portfolio at risk (PAR), operational self-sufficiency (OSS), and operating expenses (OPX). Figure 9 illustrates the IRF plots of this association. We find that shocks to the portfolio at risk, operational self-sufficiency, and operating expenses have a positive and significant impact on the human development index, although this effect diminishes progressively in the long run. For example, a one standard deviation shock to the portfolio at risk increases the value of the human development index in the first year. Portfolio at risk (PAR) is generally associated with credit granted to individuals with a high risk of non-repayment, so a counterintuitive relationship is observed here: as the portfolio at risk increases, the development index accelerates. This result suggests that when the number of loans repaid late increases, economic development also increases. This observation can be explained by the fact that granting loans, even risky ones, leads to higher investments and returns (Cull et al. 2007), which positively impacts individual development.

Moreover, a one standard deviation shock to operational self-sufficiency, which measures an institution's ability to cover its operating costs, positively affects the development index until the tenth year. When microfinance institutions increase their operational self-sufficiency, they can grant more loans to meet the day-to-day needs of the population, thereby improving living standards. Although the literature is limited on the effects of operational self-sufficiency on the HDI, Nawaz and Iqbal (2015) show that the impact of operational self-sufficiency on a corporate governance index is positive, although not statistically significant.

We also present the effects of the Human Development Index (HDI) on the financial performance variables of microfinance institutions. The results indicate that increasing HDI augments the portfolio at risk, as illustrated in Figure (9). This observation can be explained by the fact that an increase in economic development within the population leads to a surge in risky loans as a higher standard of living augments the income, so as the eligibility of loans for the

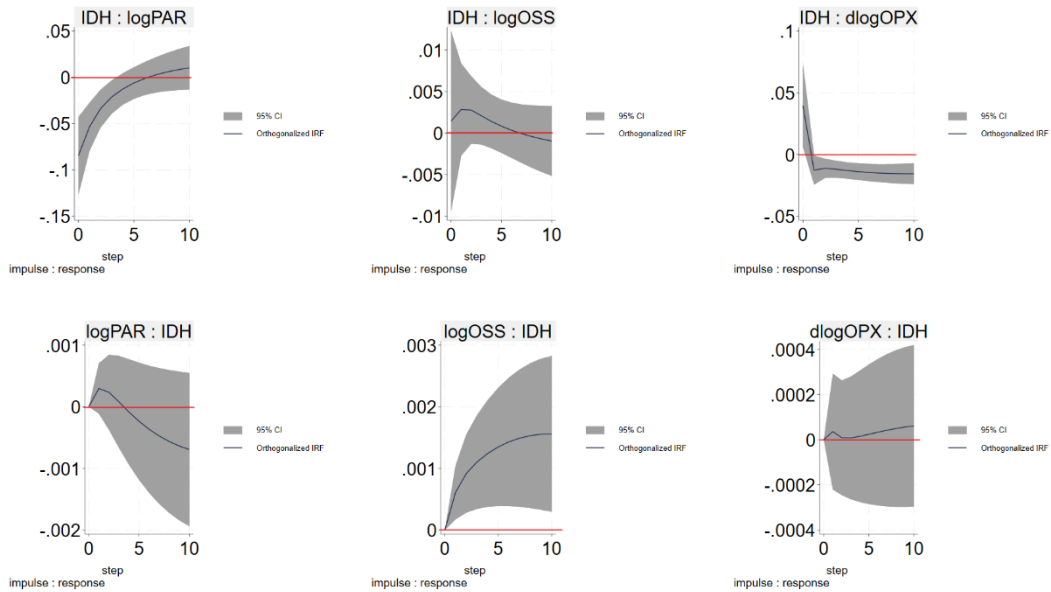
whole population. Indeed, an improvement in the HDI widens the pool of people eligible for loans, introducing new borrowers likely to default, thereby increasing the portfolio at risk. Although the HDI has a positive impact on operational self-sufficiency (OSS), this effect is not statistically significant. Furthermore, the HDI negatively influences operating expenses (OPX) but this effect changes sign from the second year until the end of the analysis. A higher standard of living increases the population's eligibility for higher amounts of loans therefore reducing the operating costs of financial institutions. In an earlier study, Mersland and Strøm (2009) point out that an increase in the HDI translates into greater availability of financial information for the population, thereby encouraging the granting of loans and reducing operating costs.

Figure 8: Impulse response (IRF)(a).



Source: Authors' calculations based on databases.

Figure 9: Impulse response (IRF)(b).



Source: Authors' calculations based on databases.

Forecast error variance decomposition (FEVD)

To complement the impulse response function, we also calculate forecast error variance decompositions (FEVDs) based on the Cholesky decomposition of the residual covariance matrix of the estimated panel VAR models. While the impulse response function examines the responses of a dependent variable to shocks from other variables, the FEVDs describe the contribution of each shock from endogenous variables to the forecast error variance of the other variables.

Table (12) in the Appendix presents the proportions of forecast error variance decompositions (FEVDs) for a 10-year forecast horizon. These results can be summarized as follows: Up to 54% of the variation in the FEVD can be attributed to the number of customers (25%), the percentage of women entrepreneurs (21%), operational self-sufficiency (8%), with negligible contributions from the portfolio at risk and operating expenses after 10 years. Conversely, the number of customers, the percentage of women entrepreneurs, the portfolio at risk, operational self-sufficiency, and operating expenses account for up to 11%, 0.5%, 16%, 0.1%, and 0.5% respectively of the variation in the human development index.

7 Robustness

To ensure the robustness of our conclusions, we conduct a sensitivity analysis to test the stability of our initial results (Table 7). For this analysis, we use a panel VAR modelling approach with alternative indicators of economic development. Specifically, we examine dimensions of human development such as Gross National Income (GNI) per capita, the Education Index (EDI), and Life Expectancy at Birth (LE), which capture both economic and social aspects. By substituting these dimensions for the Human Development Index (HDI), we explore the relationship between microfinance and economic development. We retain the microfinance variables that reflect social and financial performance, highlighting key aspects of the outreach and financial stability of these institutions. Our findings indicate that greater development has led to a larger client base and an increase in the number of women entrepreneurs, while enhanced financial stability has reduced the risk of loan defaults, increased operational autonomy, and improved cost management.

The results of the Granger causality test (Table 13) revealed a two-way Granger relationship between the number of customers (NOB) and life expectancy at birth (LE), as well as between the percentage of women entrepreneurs (PFB) and the education index (EDI). In addition, unidirectional relationships were observed, notably from Gross National Income (GNI) per capita to the Number of Customers (NOB) and the percentage of women entrepreneurs (PFB), from life expectancy at birth (LE) to the percentage of women entrepreneurs (PFB) and from the number of customers (NOB) to the education index (EDI). These findings confirm the significant impact of the social performance of microfinance institutions on economic development.

The financial performance of microfinance institutions and economic development reveals a bidirectional causal relationship, for example between education (EDI) and portfolio at risk (PAR). Moreover, operating expenses (OPX) show a unidirectional relationship with Gross National Income (GNI) per capita, education index (EDI) and life expectancy at birth (LE), which supports the initial results.

The results of the impulse response functions (Figures 10, 11, 12, 13, 14, and 15) using the substituted dimensions of the Human Development Index (HDI) confirm the initial findings, showing that the three alternative variables positively affect social performance indicators (we calculate forecast error variance decompositions (FEVDs) for the three dimensions of human development in Table 14). Figure 10 illustrates the reciprocal relationship between Gross National Income (GNI) per capita and the number of customers (NOB), which aligns with existing literature. Lopatta and Tchikov (2017) noted a positive effect of client numbers on national income, while Vanroose (2008) found that microfinance reaches more clients in

developed countries. Similarly, Waseem (2018) and Maniyalath & Narendran (2016) demonstrated that national income predicts the number of women entrepreneurs. Additionally, Figure 12 shows that education (EDI) positively impacts the number of customers, a result supported by both Vanroose (2008) and Asongu and Odhiambo (2018). Furthermore, Wickstrøm et al. (2022) suggest that life expectancy (LE) is crucial for increasing the number of women entrepreneurs (Figure 14). These results reinforce the significance of HDI dimensions in evaluating the impact of microfinance on social performance.

The results concerning the relationship between development indicators and financial performance (Figures 11, 13, and 15) further validate the initial findings. Specifically, an increase in Gross National Income (GNI) per capita leads to a, on the one hand, rise in the portfolio at risk (PAR), while, on the other hand, a decrease in both operational self-sufficiency (OSS) and operating expenses (OPX) (Figure 11). Moreover, an increase in education levels (EDI) is associated with a lower portfolio at risk (PAR), alongside increases in both operational self-sufficiency (OSS) and operating expenses (OPX) (Figure 13). Additionally, an increase in life expectancy (LE) is linked to higher operating expenses (OSS) (Figure 15).

Although the literature regarding the effects of microfinance on financial performance is limited, Ferdousi (2013) suggests that Gross National Income (GNI) impacts the operational self-sufficiency of microfinance institutions, though the results lack statistical significance. D'espallier et al. (2011) emphasize that other development variables, such as experience, affect the portfolio at risk of microfinance institutions. Wickstrøm et al. (2022) also indicate that life expectancy is related to entrepreneurial activity, suggesting a connection between social welfare and the financial viability of firms.

In conclusion, the robustness analysis reinforces the validity of our initial results and provides a deeper understanding of the effects of microfinance on human development dimensions, highlighting its social and economic significance.

Table 7: Robustness of the panel VAR model estimate.

VARIABLES	1	2	3	4	5	6	7	8
	dlogGNI	dEDI	logLE	logNOB	logPFB	logPAR	logOSS	dlogOPX
L.dlogGNI	0.252*** (0.0515)	0.0197*** (0.00548)	-0.00307 (0.00353)	-0.607 (0.599)	0.0927 (0.143)	-2.841** (1.283)	0.243 (0.152)	1.241** (0.537)
L.dEDI	1.235*** (0.258)	0.361*** (0.0400)	-0.0159 (0.0176)	10.40*** (2.732)	3.228*** (0.908)	- 17.98*** (4.154)	3.249*** (1.074)	12.57*** (3.475)
L.logLE	-0.129** (0.0506)	-0.0180** (0.00856)	0.965*** (0.00593)	- 2.192*** (0.770)	-0.258 (0.200)	-2.285** (1.089)	0.0881 (0.241)	-2.053** (0.803)

L.logNOB	0.00488** (0.00221)	1.93e-05 (0.000365)	0.000523** (0.000262)	0.822*** (0.0332)	-0.00767 (0.00896)	0.0769* (0.0447)	0.00403 (0.0106)	-0.0590* (0.0335)
L.logPFB	0.0230* (0.0137)	0.00627*** (0.00237)	0.00362** (0.00141)	0.164 (0.212)	0.602*** (0.0556)	-0.346 (0.259)	-0.119** (0.0592)	-0.179 (0.198)
L.logPAR	-0.00340 (0.00220)	0.00128*** (0.000355)	-0.000334 (0.000233)	- 0.0714** (0.0305)	- 0.0217*** (0.00840)	0.507*** (0.0576)	- 0.0352*** (0.0103)	-0.00531 (0.0367)
L.logOSS	0.000718 (0.00781)	0.00175 (0.00140)	- 0.00250*** (0.000723)	0.316** (0.126)	-0.0208 (0.0253)	0.0686 (0.156)	0.396*** (0.0429)	0.182 (0.111)
L.dlogOPX	0.00433** (0.00178)	-0.000571 (0.000373)	0.000125 (0.000212)	0.0638* (0.0384)	-0.00232 (0.00815)	-0.00401 (0.0465)	-0.00546 (0.00934)	0.0171 (0.0385)
Observations	898	898	898	898	898	898	898	898

Standard errors in parentheses * p<0.01, ** p<0.05, * p<0.1**

Source: Authors' calculations based on databases.

8 Conclusion and discussion

The relationship between microfinance and economic development has not been thoroughly explored widely in recent years. This paper investigates if there is a relationship between microfinance and economic development in 60 developing countries. For doing so, we use a cross-country dataset from 2000 to 2018 and we employ a Panel VAR model estimated by the generalized method of moments (GMM).

The microfinance institution (MFI) indicators are categorized into social performance variables and financial performance variables. Social performance indicators include the number of clients served (NOB) and the percentage of women borrowers (PFB), while financial performance indicators include the portfolio at risk (PAR), operational self-sufficiency (OSS), and operating expenses (OPX). To measure economic development, we use the Human Development Index (HDI), which integrates economic indicators such as Gross National Income per capita (GNI) with social indicators like life expectancy at birth (LE) and educational attainment (EDI).

Our analysis reveals a causal relationship between the social performance of microfinance institutions (MFIs) and economic development, as measured by the Human Development Index (HDI). Specifically, our results show that increases in both the number of clients and the percentage of women entrepreneurs positively impact the development index. Furthermore, we find that the financial performance of MFIs, as indicated by the portfolio at risk (PAR), operational self-sufficiency (OSS), and operating expenses (OPX), causally interact with economic development and various dimensions of the HDI.

By experimentally distinguishing between the social and financial performance of microfinance institutions (MFIs) and confirming their causal relationship with economic development, our Granger causality studies provide new evidence of the role of microfinance in fostering economic development. Additionally, we expand the scope of this study by examining various measures of economic development affected by microfinance such as GNI per capita, the education index and life expectancy. This supports the causal link between microfinance and the Human Development Index (HDI), a key indicator of economic growth.

Our findings have significant implications for both the theory and study of microfinance. As both the number of clients (NOB) and women entrepreneurs (PFB) impact positively economic development (HDI), MFIs should concentrate their activity on increasing the potential client numbers and to have specific offers for women entrepreneurs to stimulate them to start their own businesses. Better economic development decreases the MFIs costs (i.e., the operating expenses), so MFIs should benefit of this and consider their sustainable development as they have done until now. In the same time, MFIs must watch the clients default risks as portfolio at risk (PAR) urges when economic environmental flourishes.

This approach addresses also the limitations of our study, such as limited data availability, and incorporates additional development indicators to better evaluate the inter-relationships between microfinance and economic development. Further analysis at the country or regional level is recommended to develop targeted measures that can effectively promote economic development.

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Appendix

Table 8: Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) HDI	1.000								
(2) logGNI	0.940	1.000							
(3) EDI	0.933	0.794	1.000						
(4) logLE	0.889	0.818	0.727	1.000					
(5) logNOB	0.103	0.110	0.033	0.184	1.000				
(6) logPFB	-0.113	-0.093	-0.157	-0.037	0.241	1.000			
(7) logPAR	-0.161	-0.119	-0.142	-0.216	0.026	-0.190	1.000		
(8) logOSS	0.260	0.224	0.254	0.265	0.225	-0.029	-0.279	1.000	
(9) logOPX	0.355	0.329	0.318	0.335	0.564	-0.051	-0.029	0.162	1.000

Source: Authors' calculations based on databases.

Table 9: List of countries.

Sub-Saharan Africa	Latin America and the Caribbean	Eastern Europe and Central Asia	East Asia and the Pacific	South Asia	MENA
Benin	Argentina	Albania	Cambodia	Afghanistan	Egypt
Burkina Faso	Bolivia	Armenia	Indonesia	Bangladesh	Jordan
Burundi	Brazil	Azerbaijan	Mongolia	India	Lebanon
Cameroon	Colombia	Bosnia-Herzegovina	Philippines	Nepal	Morocco
Ivory Coast	Costa Rica	Georgia	Vietnam	Pakistan	Tunisia
Ethiopia	Dominique	Kazakhstan		Sri Lanka	
Ghana	Ecuador	Kyrgyzstan			
Kenya	Guatemala	Uzbekistan			
Madagascar	Honduras	Romania			
Malawi	Mexico	Serbia			
Mozambique	Nicaragua	Tajikistan			
Nigeria	Paraguay				
Uganda	Peru				
	Salvador				
Democratic Republic of Congo					
Republic of Congo					
Rwanda					
Senegal					
Tanzania					
Togo					

Source: Authors' calculations based on databases.

Table 10: Unit root test.

	IDH	logGNI	EDI	logLE	logNOB	logPFB	logPAR	logOSS	logOPX
Fisher ADF Test									
	Level								
Inverse chi-squared (120) P	358.138*** (0.000)	113.202 (0.657)	271.762*** (0.000)	477.440*** (0.000)	654.894*** (0.000)	622.303*** (0.000)	490.055*** (0.000)	619.392*** (0.000)	165.943*** (0.004)
Inverse normal Z	-2.193*** (0.014)	4.981 (1.000)	0.528 (0.701)	-5.174*** (0.000)	-15.397*** (0.000)	-13.565*** (0.000)	-12.253*** (0.000)	-16.122*** (0.000)	-0.611 (0.271)
Inverse logit t (299) L*	(-6.288)*** (0.000)	5.071 (1.000)	-1.509** (0.066)	-10.881*** (0.000)	-22.438*** (0.000)	-20.439*** (0.000)	-15.938*** (0.000)	-21.334*** (0.000)	-0.997 (0.160)
Modified inv. chi-squared Pm	15.372*** (0.000)	-0.439 (0.670)	9.796*** (0.000)	23.073*** (0.000)	34.527*** (0.000)	32.423*** (0.000)	23.887*** (0.000)	32.236*** (0.000)	2.966*** (0.002)
	First difference								
Inverse chi-squared (120) P		594.323*** (0.000)	489.155*** (0.000)						977.183*** (0.000)
Inverse normal Z		-17.156*** (0.000)	-13.509*** (0.000)						-23.986*** (0.000)
Inverse logit t (299) L*		-20.790*** (0.000)	-16.504*** (0.000)						-34.422*** (0.000)
Modified inv. chi-squared Pm		30.617*** (0.000)	23.829*** (0.000)						55.331*** (0.000)
Fisher PP Test									
	Level								
Inverse chi-squared(120) P	358.138*** (0.000)	113.202 (0.657)	271.762*** (0.000)	477.440*** (0.000)	654.894*** (0.000)	622.303*** (0.000)	490.055*** (0.000)	619.392*** (0.000)	165.943*** (0.004)
Inverse normal Z	-2.193*** (0.014)	4.981 (1.000)	0.528 (0.701)	-5.174*** (0.000)	-15.397*** (0.000)	-13.565*** (0.000)	-12.253*** (0.000)	-16.122*** (0.000)	-0.611 (0.271)
Inverse logit t (299) L*	(-6.288)*** (0.000)	5.071 (1.000)	-1.509** (0.066)	-10.881*** (0.000)	-22.438*** (0.000)	-20.439*** (0.000)	-15.938*** (0.000)	-21.334*** (0.000)	-0.997 (0.160)
Modified inv. chi-squared Pm	15.372*** (0.000)	-0.439 (0.670)	9.796*** (0.000)	23.073*** (0.000)	34.527*** (0.000)	32.423*** (0.000)	23.887*** (0.000)	32.236*** (0.000)	2.966*** (0.002)
	First difference								
Inverse chi-squared (120) P		594.323*** (0.000)	489.155*** (0.000)						977.183*** (0.000)
Inverse normal Z		-17.156*** (0.000)	-13.509*** (0.000)						-23.986*** (0.000)
Inverse logit t (299) L*		-20.790*** (0.000)	-16.504*** (0.000)						-34.422*** (0.000)
Modified inv. chi-squared Pm		30.617*** (0.000)	23.829*** (0.000)						55.331*** (0.000)
Panels	60	60	60	60	60	60	60	60	60
Parking facilities	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)

Note: (*) and (**)** denote statistical significance at the 1 % and 5 % levels, respectively. P-values are in parentheses.

Source: Authors' calculations based on databases.

Table 11: Granger causality tests.

Equation	Excluded	chi2	df	Prob > chi2
IDH				
	logNOB	7.434	1	0.006
	logPFB	16.177	1	0.000
	logPAR	3.257	1	0.071
	logOSS	7.269	1	0.007
	dlogOPX	0.071	1	0.790
	ALL	24.460	5	0.000
logNOB				
	IDH	19.156	1	0.000
	logPFB	1.156	1	0.282
	logPAR	1.108	1	0.293
	logOSS	11.177	1	0.001
	dlogOPX	1.212	1	0.271
	ALL	41.046	5	0.000
logPFB				
	IDH	5.385	1	0.020
	logNOB	0.614	1	0.433
	logPAR	1.596	1	0.207
	logOSS	0.795	1	0.373
	dlogOPX	0.664	1	0.415
	ALL	12.684	5	0.027
logPAR				
	IDH	0.018	1	0.893
	logNOB	1.288	1	0.256
	logPFB	10.420	1	0.001
	logOSS	4.870	1	0.027
	dlogOPX	0.404	1	0.525
	ALL	11.476	5	0.043
logOSS				
	IDH	0.367	1	0.545
	logNOB	1.463	1	0.226
	logPFB	4.227	1	0.040
	logPAR	16.678	1	0.000
	dlogOPX	0.413	1	0.521
	ALL	23.909	5	0.000
dlogOPX				
	IDH	22.594	1	0.000
	logNOB	6.823	1	0.009
	logPFB	0.653	1	0.419
	logPAR	0.625	1	0.429
	logOSS	9.758	1	0.002
	ALL	45.381	5	0.000

Source: Authors' calculations based on databases.

Table 12: Forecast error variance decomposition (FEVD).

Response variable and Forecast horizon	IDH	logNOB	Impulse logPFB	variable logPAR	logOSS	dlogOPX
<hr/>						
IDH	0	0	0	0	0	0
	1	1	0	0	0	0
	2	0.938	0.008	0.041	0.003	0.011
	3	0.868	0.021	0.086	0.003	0.022
	4	0.806	0.037	0.124	0.002	0.031
	5	0.752	0.055	0.152	0.002	0.039
	6	0.706	0.074	0.173	0.002	0.046
	7	0.666	0.092	0.188	0.002	0.051
	8	0.630	0.110	0.200	0.003	0.056
	9	0.600	0.127	0.208	0.004	0.061
	10	0.573	0.144	0.213	0.006	0.065
<hr/>						
logNOB	0	0	0	0	0	0
	1	0.014	0.986	0	0	0
	2	0.013	0.964	0.003	0.004	0.016
	3	0.011	0.940	0.006	0.010	0.032
	4	0.010	0.920	0.008	0.017	0.044
	5	0.008	0.905	0.010	0.024	0.052
	6	0.008	0.894	0.011	0.029	0.057
	7	0.007	0.885	0.011	0.034	0.061
	8	0.008	0.879	0.011	0.037	0.063
	9	0.008	0.874	0.011	0.040	0.065
	10	0.010	0.870	0.011	0.042	0.065
<hr/>						
logPFB	0	0	0	0	0	0
	1	0.005	0.000	0.995	0	0
	2	0.004	0.000	0.992	0.002	0.001
	3	0.004	0.001	0.988	0.005	0.002
	4	0.004	0.002	0.984	0.007	0.003
	5	0.004	0.003	0.981	0.009	0.003
	6	0.004	0.004	0.979	0.010	0.004
	7	0.004	0.004	0.977	0.011	0.004
	8	0.004	0.005	0.975	0.011	0.004
	9	0.005	0.005	0.974	0.012	0.004
	10	0.005	0.006	0.973	0.012	0.004
<hr/>						
logPAR	0	0	0	0	0	0
	1	0.017	0.001	0.019	0.964	0
	2	0.018	0.002	0.068	0.902	0.010
	3	0.018	0.005	0.103	0.856	0.018
	4	0.018	0.009	0.122	0.828	0.023

5	0.018	0.013	0.133	0.811	0.025	0.000
6	0.017	0.017	0.138	0.801	0.027	0.000
7	0.017	0.020	0.140	0.794	0.028	0.000
8	0.017	0.023	0.141	0.790	0.028	0.000
9	0.017	0.025	0.141	0.787	0.029	0.000
10	0.017	0.027	0.141	0.785	0.029	0.000
<hr/>						
logOSS						
0	0	0	0	0	0	0
1	0.000	0.001	0.000	0.028	0.971	0
2	0.000	0.002	0.007	0.065	0.926	0.000
3	0.001	0.004	0.010	0.082	0.903	0.000
4	0.001	0.006	0.010	0.089	0.894	0.000
5	0.001	0.008	0.010	0.092	0.889	0.000
6	0.001	0.010	0.010	0.093	0.886	0.000
7	0.001	0.012	0.010	0.093	0.884	0.000
8	0.001	0.013	0.010	0.093	0.882	0.000
9	0.001	0.014	0.010	0.094	0.881	0.000
10	0.001	0.015	0.010	0.094	0.880	0.000
<hr/>						
dlogOPX						
0	0	0	0	0	0	0
1	0.006	0.078	0.004	0.010	0.001	0.902
2	0.006	0.079	0.005	0.009	0.035	0.865
3	0.007	0.083	0.005	0.010	0.040	0.855
4	0.007	0.085	0.005	0.012	0.041	0.850
5	0.008	0.087	0.005	0.012	0.041	0.847
6	0.008	0.088	0.005	0.013	0.041	0.844
7	0.009	0.089	0.005	0.013	0.041	0.842
8	0.010	0.089	0.005	0.013	0.041	0.841
9	0.011	0.090	0.006	0.013	0.041	0.840
10	0.011	0.090	0.006	0.013	0.041	0.838

Source: Authors' calculations based on databases.

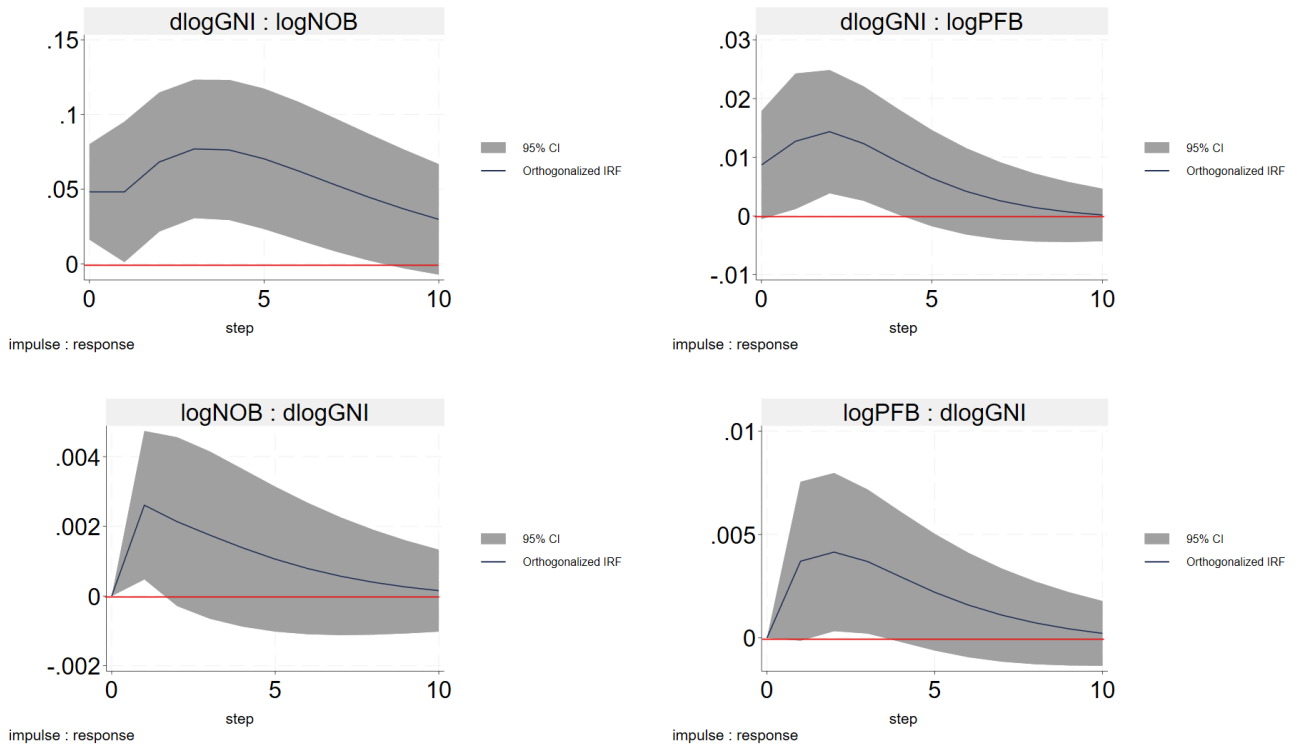
Table 13: Robustness Granger causality tests.

Equation	Excluded	chi2	df	Prob > chi2
<hr/>				
dlogGNI				
	dEDI	22.888	1	0.000
	logLE	6.488	1	0.011
	logNOB	4.891	1	0.027
	logPFB	2.812	1	0.094
	logPAR	2.391	1	0.122
	logOSS	0.008	1	0.927
	dlogOPX	5.926	1	0.015
	ALL	55.157	7	0.000
<hr/>				
dEDI				
	dlogGNI	12.897	1	0.000
	logLE	4.430	1	0.035
	logNOB	0.003	1	0.958
	logPFB	6.988	1	0.008
	logPAR	13.055	1	0.000
	logOSS	1.565	1	0.211
	dlogOPX	2.348	1	0.125
	ALL	51.138	7	0.000
<hr/>				
logLE				
	dlogGNI	0.759	1	0.384
	dEDI	0.815	1	0.367
	logNOB	3.985	1	0.046
	logPFB	6.569	1	0.010
	logPAR	2.051	1	0.152
	logOSS	11.992	1	0.001
	dlogOPX	0.349	1	0.555
	ALL	31.073	7	0.000
<hr/>				
logNOB				
	dlogGNI	1.027	1	0.311
	dEDI	14.493	1	0.000
	logLE	8.109	1	0.004
	logPFB	0.602	1	0.438
	logPAR	5.470	1	0.019
	logOSS	6.329	1	0.012
	dlogOPX	2.767	1	0.096
	ALL	43.005	7	0.000
<hr/>				
logPFB				
	dlogGNI	0.418	1	0.518
	dEDI	12.629	1	0.000
	logLE	1.672	1	0.196
	logNOB	0.732	1	0.392
	logPAR	6.684	1	0.010
	logOSS	0.674	1	0.412
	dlogOPX	0.081	1	0.776
	ALL	34.893	7	0.000
<hr/>				
logPAR				

	dlogGNI	4.902	1	0.027
	dEDI	18.742	1	0.000
	logLE	4.400	1	0.036
	logNOB	2.964	1	0.085
	logPFB	1.781	1	0.182
	logOSS	0.193	1	0.660
	dlogOPX	0.007	1	0.931
	ALL	30.177	7	0.000
<hr/>				
logOSS	dlogGNI	2.574	1	0.109
	dEDI	9.157	1	0.002
	logLE	0.134	1	0.714
	logNOB	0.146	1	0.703
	logPFB	4.032	1	0.045
	logPAR	11.640	1	0.001
	dlogOPX	0.342	1	0.558
	ALL	27.211	7	0.000
<hr/>				
dlogOPX	dlogGNI	5.346	1	0.021
	dEDI	13.083	1	0.000
	logLE	6.532	1	0.011
	logNOB	3.113	1	0.078
	logPFB	0.823	1	0.364
	logPAR	0.021	1	0.885
	logOSS	2.686	1	0.101
	ALL	77.440	7	0.000

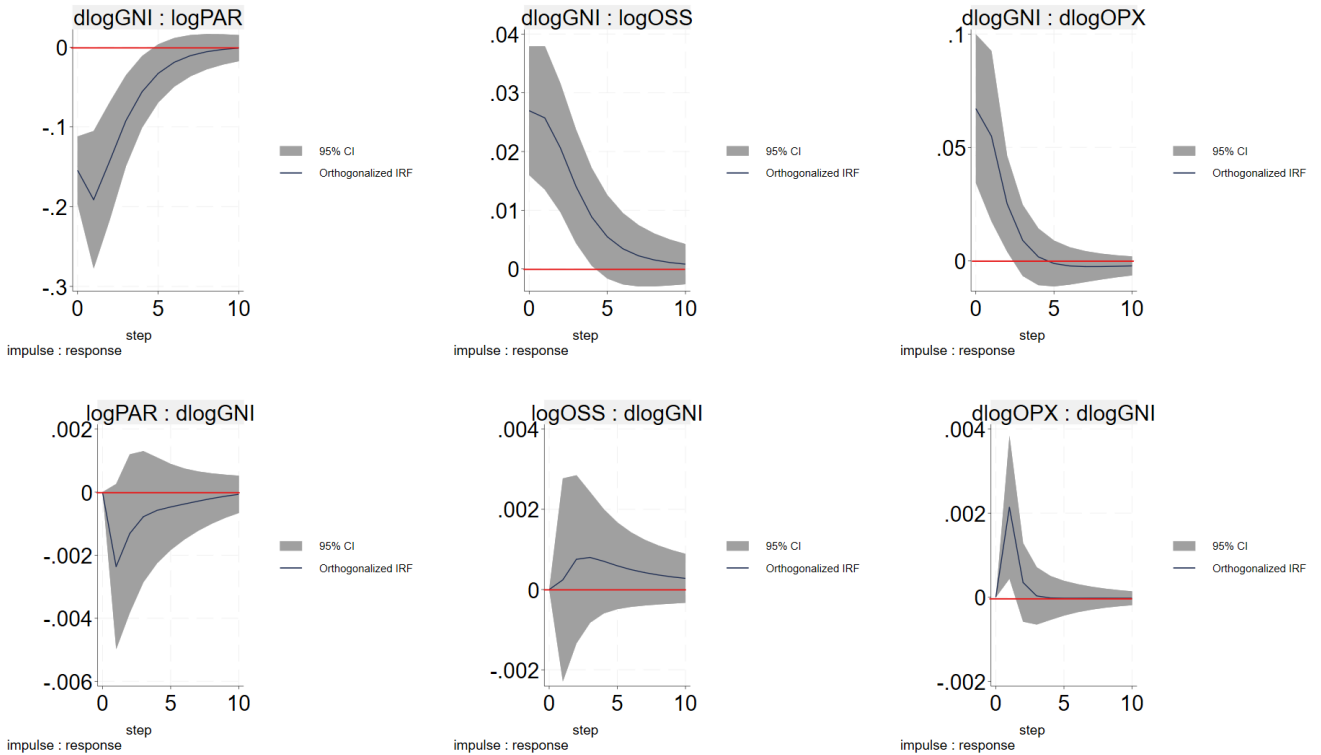
Source: Authors' calculations based on databases.

Figure 10: Impulse response robustness (IRF)(a).



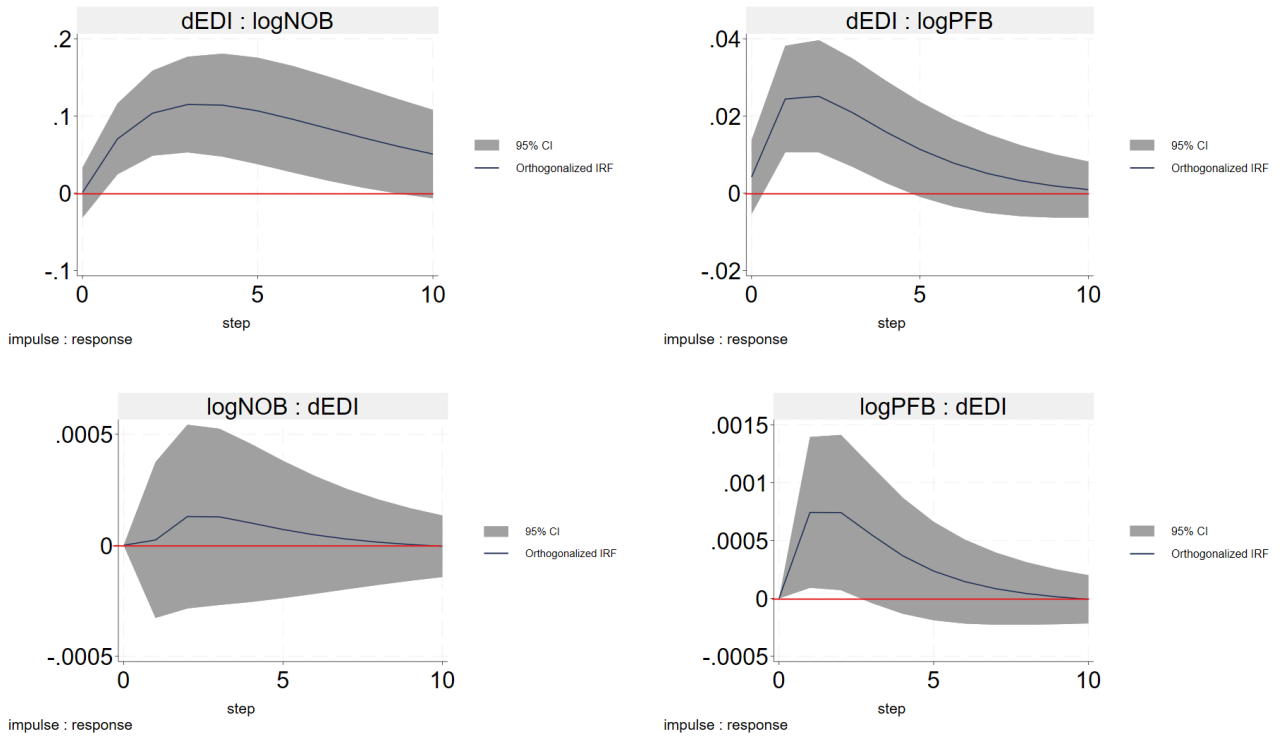
Source: Authors' calculations based on databases.

Figure 11: Impulse response robustness (IRF)(b).



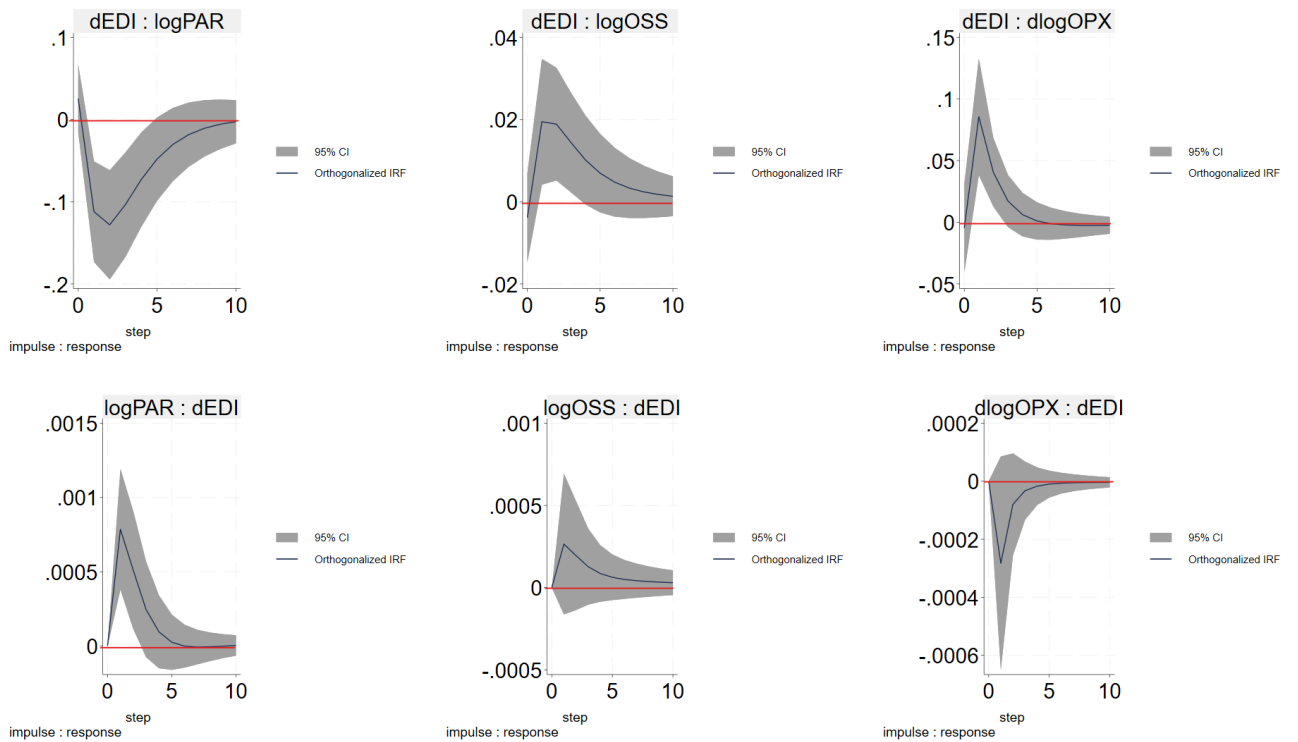
Source: Authors' calculations based on databases.

Figure 12: Impulse response robustness (IRF)(c).



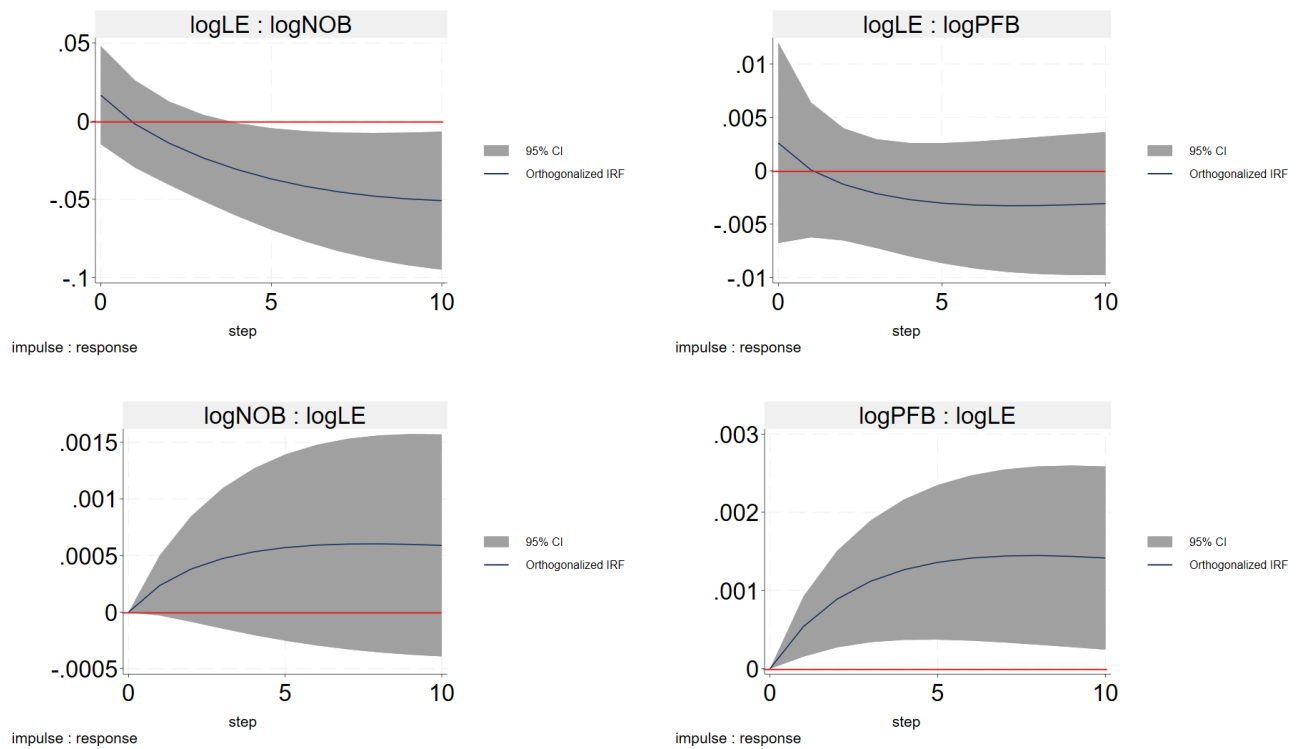
Source: Authors' calculations based on databases.

Figure 13: Impulse response robustness (IRF)(d).



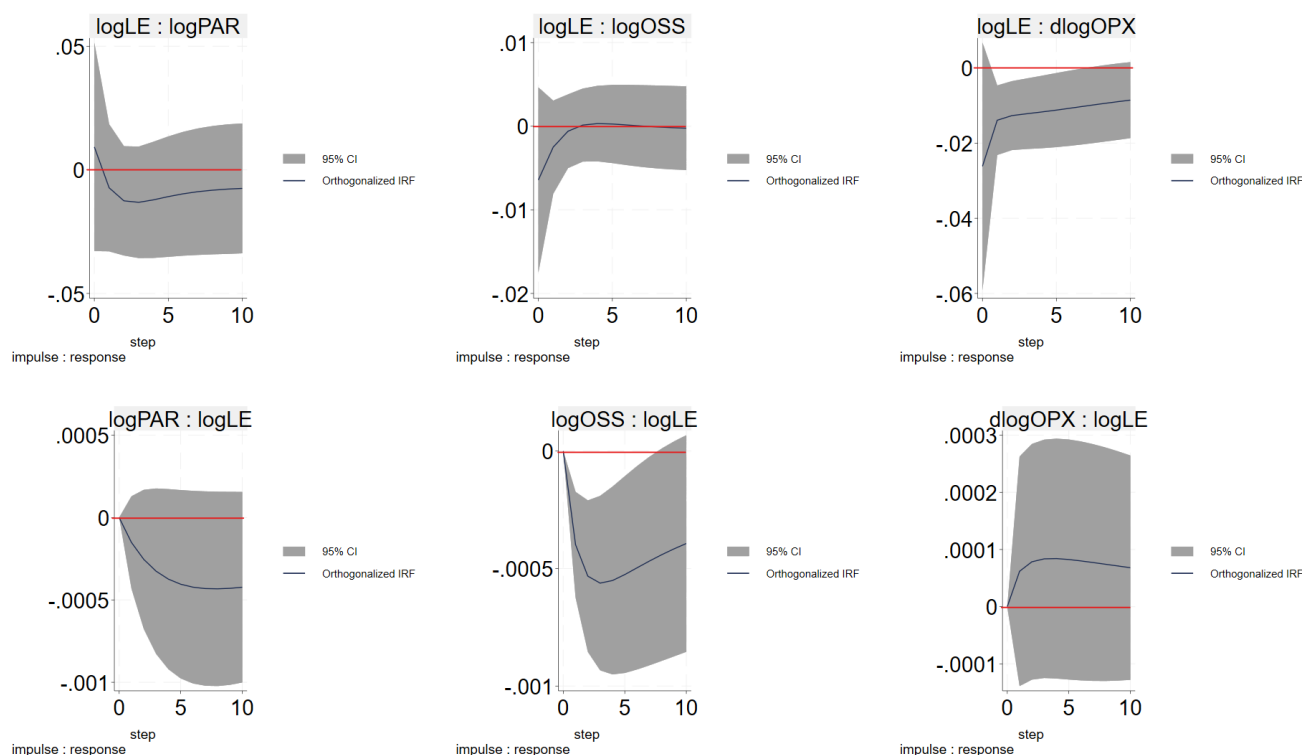
Source: Authors' calculations based on databases.

Figure 14: Impulse response robustness (IRF)(e).



Source: Authors' calculations based on databases.

Figure 15: Impulse response robustness (IRF)(f).



Source: Authors' calculations based on databases.

Table 14: Robustness Forecast Error Variance Decomposition (FEVD).

Response variable and Forecast horizon	Impulse variable								
	dlogGNI	dEDI	logLE	logNOB	logPFB	logPAR	logOSS	dlogOPX	
dlogGNI	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0
2	0.934	0.046	0.000	0.004	0.009	0.004	0.000	0.003	
3	0.894	0.073	0.001	0.007	0.018	0.004	0.000	0.003	
4	0.872	0.084	0.002	0.008	0.026	0.005	0.001	0.003	
5	0.860	0.089	0.002	0.009	0.030	0.005	0.001	0.003	
6	0.853	0.092	0.004	0.010	0.033	0.005	0.001	0.003	
7	0.849	0.093	0.005	0.010	0.034	0.005	0.001	0.003	
8	0.847	0.094	0.006	0.010	0.034	0.005	0.001	0.003	

	9	0.845	0.094	0.007	0.010	0.035	0.005	0.001	0.003
	10	0.843	0.095	0.008	0.010	0.035	0.005	0.002	0.003
dEDI	0	0	0	0	0	0	0	0	0
	1	0.007	0.993	0	0	0	0	0	0
	2	0.017	0.959	0.000	0.000	0.010	0.011	0.001	0.001
	3	0.019	0.943	0.000	0.000	0.019	0.015	0.002	0.001
	4	0.019	0.937	0.001	0.001	0.024	0.016	0.002	0.001
	5	0.019	0.933	0.002	0.001	0.026	0.016	0.002	0.001
	6	0.019	0.932	0.002	0.001	0.027	0.016	0.002	0.001
	7	0.019	0.931	0.003	0.001	0.027	0.016	0.002	0.001
	8	0.019	0.930	0.004	0.001	0.027	0.016	0.002	0.001
	9	0.019	0.929	0.004	0.001	0.027	0.016	0.002	0.001
	10	0.019	0.928	0.005	0.001	0.027	0.016	0.002	0.001
logLE	0	0	0	0	0	0	0	0	0
	1	0.002	0.004	0.995	0	0	0	0	0
	2	0.001	0.005	0.984	0.001	0.005	0.000	0.003	0.000
	3	0.001	0.005	0.972	0.003	0.014	0.001	0.006	0.000
	4	0.001	0.004	0.959	0.004	0.022	0.002	0.007	0.000
	5	0.002	0.003	0.948	0.006	0.031	0.003	0.008	0.000
	6	0.002	0.003	0.937	0.007	0.039	0.003	0.009	0.000
	7	0.003	0.002	0.928	0.008	0.046	0.004	0.009	0.000
	8	0.003	0.002	0.919	0.009	0.052	0.005	0.009	0.000
	9	0.004	0.002	0.912	0.010	0.057	0.005	0.010	0.000
	10	0.004	0.002	0.905	0.011	0.062	0.005	0.010	0.000
logNOB	0	0	0	0	0	0	0	0	0

1	0.010	0.000	0.001	0.989	0	0	0	0
2	0.011	0.012	0.001	0.958	0.002	0.007	0.007	0.002
3	0.017	0.028	0.001	0.918	0.006	0.015	0.013	0.003
4	0.023	0.044	0.002	0.881	0.009	0.020	0.018	0.003
5	0.029	0.058	0.003	0.850	0.013	0.024	0.021	0.002
6	0.033	0.068	0.004	0.827	0.017	0.026	0.023	0.002
7	0.036	0.076	0.006	0.808	0.019	0.027	0.024	0.002
8	0.039	0.082	0.008	0.795	0.021	0.028	0.025	0.002
9	0.040	0.086	0.011	0.784	0.023	0.028	0.025	0.002
10	0.041	0.089	0.013	0.777	0.024	0.028	0.026	0.002

logPFB

0	0	0	0	0	0	0	0	0
1	0.004	0.001	0.000	0.000	0.995	0	0	0
2	0.008	0.022	0.000	0.002	0.962	0.006	0.000	0.000
3	0.014	0.038	0.000	0.003	0.935	0.009	0.001	0.000
4	0.017	0.048	0.000	0.005	0.918	0.010	0.001	0.000
5	0.019	0.054	0.001	0.007	0.909	0.010	0.001	0.000
6	0.020	0.056	0.001	0.008	0.904	0.010	0.001	0.000
7	0.020	0.058	0.001	0.009	0.901	0.010	0.001	0.000
8	0.020	0.058	0.001	0.009	0.900	0.010	0.001	0.000
9	0.020	0.058	0.002	0.010	0.899	0.010	0.001	0.000
10	0.020	0.058	0.002	0.010	0.898	0.010	0.001	0.000

logPAR

0	0	0	0	0	0	0	0	0
1	0.055	0.002	0.000	0.010	0.020	0.913	0	0
2	0.102	0.022	0.000	0.015	0.030	0.830	0.000	0.000
3	0.121	0.044	0.000	0.019	0.042	0.772	0.000	0.000

4	0.127	0.057	0.001	0.022	0.053	0.740	0.000	0.000
5	0.128	0.063	0.001	0.023	0.061	0.723	0.001	0.000
6	0.128	0.066	0.001	0.024	0.066	0.714	0.001	0.000
7	0.128	0.067	0.001	0.025	0.068	0.710	0.001	0.000
8	0.128	0.067	0.001	0.026	0.070	0.708	0.001	0.000
9	0.128	0.067	0.001	0.026	0.070	0.707	0.001	0.000
10	0.128	0.067	0.001	0.026	0.071	0.706	0.001	0.000
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logOSS	0	0	0	0	0	0	0	0
1	0.027	0.001	0.002	0.000	0.000	0.024	0.946	0
2	0.042	0.012	0.001	0.000	0.005	0.050	0.889	0.000
3	0.051	0.021	0.001	0.000	0.007	0.059	0.859	0.000
4	0.056	0.027	0.001	0.000	0.007	0.062	0.847	0.000
5	0.058	0.029	0.001	0.000	0.007	0.062	0.842	0.000
6	0.058	0.030	0.001	0.000	0.007	0.062	0.840	0.000
7	0.058	0.031	0.001	0.001	0.007	0.062	0.839	0.000
8	0.059	0.031	0.001	0.001	0.007	0.062	0.838	0.000
9	0.059	0.031	0.001	0.001	0.007	0.062	0.838	0.000
10	0.059	0.032	0.001	0.001	0.008	0.062	0.838	0.000
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dlogOPX	0	0	0	0	0	0	0	0
1	0.017	0.000	0.003	0.044	0.005	0.009	0.003	0.919
2	0.027	0.026	0.003	0.045	0.007	0.009	0.006	0.877
3	0.029	0.032	0.004	0.046	0.007	0.009	0.007	0.867
4	0.029	0.033	0.004	0.046	0.007	0.009	0.007	0.865
5	0.029	0.033	0.005	0.047	0.007	0.009	0.007	0.864
6	0.029	0.033	0.005	0.047	0.007	0.009	0.007	0.863

7	0.029	0.033	0.006	0.047	0.007	0.009	0.007	0.862
8	0.029	0.033	0.006	0.047	0.007	0.010	0.007	0.862
9	0.029	0.033	0.006	0.047	0.007	0.010	0.007	0.861
10	0.029	0.033	0.006	0.047	0.007	0.010	0.007	0.861

Source: Authors' calculations based on databases.