FACULTAD DE CIENCIAS ECONÓMICAS Y ADMINISTRATIVAS

EFECTOS DE SHOCKS TECNOLÓGICOS AGREGADOS Y SECTORIALES EN EL ECUADOR: UN ANÁLISIS ESTRUCTURAL

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EFFECTS OF AGGREGATE AND SECTORAL TECHNOLOGICAL SHOCKS IN ECUADOR: A STRUCTURAL ANALYSIS

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Resumen

Este estudio examina el impacto de los shocks tecnológicos en la economía ecuatoriana, con un enfoque a nivel agregado y sectorial. Utilizando el método de vectores autorregresivos estructurales con factores aumentados - FAVAR, la investigación aísla shocks tecnológicos puros, permitiendo un análisis detallado de los efectos de la Productividad Total de los Factores (PTF) en el crecimiento de las ventas en diversas industrias. Los hallazgos indican que, si bien los shocks tecnológicos agregados predominan en la mayoría de los sectores, los shocks sectoriales exhiben una mayor persistencia en las industrias de manufactura y servicios profesionales. Esta predominancia se deba a la capacidad mejorada de estos sectores para integrar innovaciones tecnológicas de manera efectiva, a diferencia de sectores como la agricultura y la construcción, donde los impactos son más transitorios debido a limitaciones estructurales. El estudio subraya la importancia de diferenciar entre shocks agregados y sectoriales para formular políticas económicas más específicas que fomenten la innovación y el crecimiento sostenible. Además, destaca la necesidad de establecer un entorno que respalde los avances tecnológicos, asegurando que todos los sectores puedan aprovechar los beneficios de la innovación. La metodología empleada en esta investigación proporciona un marco integral para comprender las complejas dinámicas de los shocks tecnológicos y ofrece valiosos conocimientos para los formuladores de políticas.

Palabras claves: shocks tecnológicos agregados, shocks tecnológicos sectoriales, ventas

Abstract

This research examines the impact of technological shocks on the Ecuadorian economy, with a focus on both aggregate and sectoral levels. Using the Structural Vector Autoregressions with Factor-Augmented Vectors (FAVAR) method, the research isolates pure technological shocks, allowing for a detailed analysis of the effects of Total Factor Productivity (TFP) on sales growth across various industries. The findings indicate that while aggregate technological shocks dominate in most sectors, sectoral shocks exhibit greater persistence in manufacturing and professional services industries. This predominance is attributed to the enhanced capacity of these sectors to effectively integrate technological innovations, in contrast to sectors such as agriculture and construction, where impacts are more transient due to structural limitations. The study underscores the importance of distinguishing between aggregate and sectoral shocks in order to formulate more targeted economic policies that promote innovation and sustainable growth. Additionally, it highlights the need to establish an environment that supports technological advancements, ensuring that all sectors can capitalize on the benefits of innovation. The methodology employed in this research provides a comprehensive framework for understanding the complex dynamics of technological shocks and offers valuable insights for policymakers.

Keywords: aggregate technology shocks, sectoral technology shocks, sales

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1. INTRODUCTION

In economic policy, understanding aggregate fluctuations is crucial for decision-making and developing effective strategies to address challenges faced by all economic agents, industries and the general welfare conditions. The significance of these fluctuations has been a central focus from the development of theories such as the Real Business Cycle (RBC) theory, which main argument states that nominal shocks only have temporary effects, but real shocks, such as changes in productivity from technological variations, have permanent effects on business cycles (Romer, 2006).

Assessing technological shocks is important for designing public policies that promote a more integral and sustained growth. Technological shocks can have significant distributive effects, impacting different sectors and population groups in a variety of ways. For instance, certain industries may experience productivity boosts and job creation due to technological advancements, others might face obsolescence and job losses (Jorgenson & Stiroh, 2000).

Recent studies emphasize the critical role of technological shocks in driving economic change. For instance, Decker et al. (2017) analyzes how declining business dynamism in the United States might be related to reduced diffusion of technological innovations across firms. This study indicates that understanding technological shocks is also essential for addressing macroeconomic trends like productivity slowdowns. Additionally, Andrews, et. al. (2016) investigate the productivity spillovers from frontier firms towards laggard firms, showing that technological diffusion is critical for broader economic performance and competitiveness.

Technological shocks can affect the entire economy (aggregate shocks) or be confined to specific sectors (sectoral shocks).[1] This criterion laid the groundwork for subsequent research into the role of technological shocks in

[1] Robert Solow's work in the 1950s highlighted that a significant portion of economic growth could not be explained by increases in capital and labor alone, attributing the residual to technological progress (Solow, 1956).

macroeconomic dynamics since these types of shocks can have long-lasting effects on productivity and economic structure (Aghion & Howitt, 1992).

For policymakers, distinguishing between aggregate and sectoral technological shocks is critical. Aggregate shocks necessitate broad-based policy responses, while sectoral shocks may require targeted interventions (Long & Plosser, 1987). Aggregate shocks, due to their widespread impact, may require macroeconomic stabilization policies such as monetary and fiscal interventions. For example, central banks might adjust interest rates to counteract economy-wide productivity changes (Galí, 1999).

In contrast, sectoral shocks might necessitate more targeted policies aimed at specific industries. Governments might provide subsidies or tax incentives to sectors experiencing difficulties in order to amplify the effect of positive technological shocks to foster further innovation. For example, determining productivity in the healthcare sector requires considering the influence of pharmaceutical suppliers, concluding the government role might influence the productive structure of the industry (Newhouse, 1992). On the other hand, sectors negatively affected by technological changes might require support to facilitate structural adjustment and mitigate adverse impacts on employment and income distribution (Rodrik, 1999).

Although sectoral shocks contradict conventional economic theory on business cycles,[2] recent studies emphasize the need to understand fluctuations from a microeconomic perspective due to the presence of interconnections between different sectors, which serve as the primary mechanism for propagating idiosyncratic shocks throughout the economy (Acemoglu, Carvalho, Ozdaglar, & Tahbaz-Salehi, 2012).

At this point, previous arguments explain the importance of understanding aggregate fluctuations from a microeconomic perspective. However, this criterion does not imply that sectoral shocks prevail over aggregate shocks. In fact, determining the predominance of aggregate or sectoral shocks requires rigorous

[2] According to Lucas (1977), microeconomic shocks net out, concluding that only aggregate effects remain.

empirical analysis. Dynamic models are commonly employed to identify and quantify the effects of different types of shocks.

For example, Horvath (1998), using multi-sector models, indicates that the strength of sectoral linkages influences aggregate variability. Gabaix (2011) using network techniques, finds that firm-level shocks translate into aggregate shocks when large firms disproportionately contribute to the production processes. Atalay (2017) concludes that industry-specific shocks are fundamental to aggregate fluctuations by estimating a multi-sector general equilibrium model.

In the same line, Shea (1998) uses the vector autoregression technique and industry-level data to distinguish between aggregate and sectoral shocks, finding that sectoral shocks contribute significantly to employment variability. Applying the same methodology, Basu, et al (2006) investigate the impact of technological change on productivity and the economy, concluding that sectoral technological shocks have significant effects on aggregate economic fluctuations.

Foerster, et al (2011) uses a dynamic factor technique to decompose economic fluctuations into aggregate and sectoral components; the authors find that sectoral shocks account for a significant portion of the variance in aggregate economic activity, highlighting the importance of sector-specific innovations. The same methodology was implemented by Di Giovanni, et al (2014) in the study of the impact of firm-level shocks on aggregate fluctuations, showing that sectoral shocks often have a predominant role in driving macroeconomic variability.

On the other hand, Fernald (2007) explores the effects of technology shocks on productivity, by means of a structural vector autoregression approach. The identification strategy is based on long-run restrictions, and the study assesses the impact on sales and other economic indicators. In the same line, Canova, et al (2020) employ structural model to identify the effects on the labor market and output, concluding that technology shocks have significant and persistent impacts on macroeconomic variables.

In other developing countries the literature is yet scares. In the case of Ecuador, Romero, et al (2018) use network techniques to show the influence of disaggregating economic sectors to understand macroeconomic fluctuations. They use input-output data to determine Ecuador`s productive dynamics and show that there has not been a significant change over time, only a relatively greater presence of the public services in economic activity (Romero, López, & Jiménez, 2018).

Further contributions to understanding productivity and firm dynamics have been made by Camino-Mogro and Bermudez-Barrezueta (2021), who provide a comprehensive analysis of the determinants of total factor productivity (TFP) in the Ecuadorian construction sector from 2007 to 2018. The results indicate that firm age positively correlates with TFP levels but negatively with TFP growth, while being a family firm negatively impacts TFP. Conversely, firm size and access to credit are positively associated with both TFP and its growth (Camino-Mogro & Bermudez-Barrezueta, 2021).

Our research contributes into to the literature in many ways. Firstly, traditional studies in developing countries have used primarily the input-output matrices approach to delineate the productive structure of the economy over time. However, these studies do not analyze the predominance of aggregate and sectoral shocks. This paper aims to fill this gap by focusing specifically on technological shocks, by constructing a new variable to evaluate these shocks through the Total Factor Productivity (TFP). Given the absence of pre-constructed TFP data in Ecuador, this study will calculate both aggregate and sectoral TFP for eight industries[3] on a quarterly basis, providing a nuanced view of productivity dynamics that has previously been inaccessible due to data limitations.

Secondly, previous papers have primarily focused on evaluating aggregate and sectoral shocks within a single industry. This research significantly broadens the scope by analyzing these shocks across additional industries. By incorporating a wider range of sectors, the study provides more tools to understand how technological shocks propagate through the economy. This broader analysis is crucial for improving macroprudential policies.

[3] The study aims to analyze technological shocks in eight industries: agriculture, oil, manufacturing, construction, commerce, transport, financial and professional services.

Thirdly, the methodological approach by employing Factor-Augmented Vector Autoregression (FAVAR) contributes to incorporate a broader set of variables and mitigates the limitations inherent in reduced vector autoregression estimation. In addition, we estimate independent specifications to distinguish the effects of aggregate and sectoral shocks.

The rest of the paper proceeds as follows: in Section 2 we describe the data while Section 3 describes the methodology to construct the quarterly total factor productivity for all the industries and present the methodological framework. In Section 4, we present the empirical results of the paper, in particular, the impulse response functions and the comparison of the shocks persistence. Finally, in Section 5 we present the concluding remarks.

2. DATA DESCRIPTION

The dataset employed in this study spans from the first quarter of 2011 to the second quarter of 2023. This specific timeframe was chosen due to the recent updates of the national accounts by the Central Bank of Ecuador, which introduced a moving base year methodology that is still under review. To maintain consistency and reliability, this study focuses on periods with a fixed base year. This choice ensures a robust and coherent analysis of technological shocks over an extended period, capturing various economic cycles and policy impacts.

Given the advanced econometric methodologies, particularly the Factor-Augmented Vector Autoregression (FAVAR), the study incorporates a broad spectrum of aggregated variables. The FAVAR approach is particularly suited for this analysis as it allows the inclusion of numerous economic indicators, thereby enhancing the comprehensiveness and robustness of the findings. This methodology facilitates a detailed examination of both sector-specific and aggregate impacts of technological shocks, capturing the dynamics of the Ecuadorian economy.

In the context of a fully dollarized economy like Ecuador, by incorporating a wide array of economic indicators related to external flows, the financial sector, expectations, and fiscal policies, the FAVAR model ensures that the impacts of technological shocks are not affected by other macroeconomic variables. The inclusion of variables linked to the balance of payments is particularly important in a dollarized economy (International Monetary Fund, 2003). Since Ecuador cannot use currency depreciation as a tool to correct external imbalances, understanding the effects of external flows becomes critical (Bannister, Turunen, Malin, & Gardberg, 2018).

Furthermore, fiscal policies and expectations significantly influence economic stability in a dollarized economy. Without the ability to set a target for interest rates or engage in independent monetary policy, Ecuador's government must rely on fiscal discipline to maintain economic stability (Baliño, Bennett, & Borensztein, 2003). By controlling aggregate variables into factors as an exogenous variable, the estimation guarantees that the analysis focuses purely on technological shocks.

To ensure the validity of our analysis, all variables in the model should be stationary. Non-stationary data can lead to spurious regressions, rendering the results unreliable. In this paper, we evaluate three different tests to guarantee stationary variables: the Augmented Dickey-Fuller, Dickey-Fuller GLS, and Phillips-Perron for each variable. The data set consists of 49 macroeconomic variables, including national and international indicators linkages to prices and yield curves, monetary and financial variables, real outputs, fiscal and external sector variables.[4]

Finally, the data sources include the Federal Reserve Economic Data (FRED), the Central Bank of Ecuador, the Internal Revenue Service (SRI, for its Spanish name), and the National Institute of Statistics and Censuses (INEC, in Spanish).

3. EMPIRICAL METHODS

In this section, we describe the three techniques to distinguish aggregate and sectoral technology shocks by the impulse response functions. Firstly, we

[4] To see all stationary details, including the inputs for the Total Factor Productivity estimation, see Appendix 1.

estimate the total factor productivity for each industry with its robustness tests. Secondly, we define the factor-augmented model for aggregate shocks. Thirdly, we define the structural vector autoregression model to establish sectoral shocks and its identification scheme.

3.1 Total Factor Productivity Estimation

The TFP is a key concept in development and growth economic theory, a summary statistic that captures the efficiency with which labor and capital inputs are used in the production process (Solow, 1956). It represents the portion of output not directly attributable to the amount of labor and capital used, hence attributable to the effects of technological progress, efficiency improvements, and other factors that enhance productivity.

One of the key advantages of using the Solow residual to estimate the TFP is its simplicity. Additionally, it requires only aggregate data on output, labor, and capital inputs, which are often available at a national or sectoral level. This method allows for a broad analysis of productivity trends across industries and provide valuable insights into the overall efficiency and technological progress within an economy. However, this approach also has notable limitations.[5]

Mathematically, the TFP can be estimated through the Solow residual. From a Cobb-Douglas production function we have:

$$Y_{i,t} = A_{i,t}K_{i,t}^{\alpha}L_{i,t}^{\beta} \tag{1}$$

Where $Y_{i,t}$ is the output of industry i at time t, measured by the gross value added (GVA); $K_{i,t}$ is the capital input, measured by the gross fixed capital formation (GFCF)[6]; $L_{i,t}$ is the labor input, measured by the formal effective hours

[5] The sensitivity to measurement errors in input data can lead to inaccurate TFP estimates (Hulten, 2001). Also, the assumption of constant returns to scale and perfect competition may not hold in all industries, potentially biasing the results (Hall, 1988).

[6] According to Barro (1991), the gross fixed capital formation is used as a proxy variable for capital inputs. In Ecuador, there is no capital information for every industry in a quarterly basis. Recent studies estimate de capital stock by using the gross fixed capital formation, to further details see Égert, et al (2009) and Zhao, et al (2023).

and $A_{i,t}$ represents the TFP. The elasticities of output against each factor, capital and labor, are represented by parameters α and β, respectively. Rearranging this equation, the TFP can be calculated as:

$$\ln(A_{i,t}) = \ln(Y_{i,t}) - \alpha \ln(K_{i,t}) - \beta \ln(L_{i,t}) \tag{2}$$

Importantly, in the TFP estimation we are forced to assume that the gross fixed capital formation is the same across all industries due to the lack of official quarterly data by industry.[7] This assumption is a limitation as it overlooks the potential variations in capital investment's intensity across different sectors, which could impact the accuracy of our TFP estimates. For future research, it is advisable to use firm-level data within each industry to capture these differences more accurately and provide more granular insights into the productivity dynamics across various sectors.[8]

We estimate the TFP by OLS regression. Afterwards, we extract the residuals and exponentiate to obtain the TFP in levels. To control for dynamic and distributive effects, we incorporate lags for the dependent and independent variables to capture the delayed effects of capital and labor on output (Kumbhakar & Lovell, 2000).

To ensure that all the variables are stationary we take the first difference of the logarithm, hence the regression results capture changes in the TFP. The robustness of our estimates depend on the absence of serial correlation in the residuals.[9] We employ the Bartlett and White Noise Tests for consistency of autocovariances, which checks whether the residuals are uncorrelated over time. The Breusch-Godfrey Test is also applied to detect higher-order serial correlation[10].

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[7] The last update of the gross fixed capital formation with an industry subclassification reported by the Central Bank of Ecuador provides annual data and the latest available data is up to 2020.
[8] To further details, see Huo, et al (2023).
[9] If the residuals in the regression model are serially correlated, traditional OLS estimates can be inefficient and biased. To address this, we can use the Newey-West estimator or Prais-Winsten transformation. To further details, see Newey, et al (1987) and Prais, et al (1954).
[10] The null hypothesis of the Barlett and White Noise Test involves that the residuals are white noise. On the other hand, the null hypothesis of the Breusch-Godfrey Test involves there is no serial correlation of any order up to p in the residuals.

Appendix 2 shows the TFP estimations and its robustness test for the aggregate level and the eight industries.

3.2 Factor-augmented vector autoregression (FAVAR)

To accurately evaluate the prevalence aggregated or sectorial technological shocks, it is crucial to control for various factors that might influence the economic environment and could potentially be correlated with the main regressors in the model. Given that TFP captures all productivity changes not explained by capital and labor inputs, it is imperative to control for other factors comprehensively. By doing so, we isolate the impact of technological shocks from other potential dynamic confounders.

Traditional VAR models might omit relevant information, leading to biased and misleading results. FAVAR model overcomes this by including a broader set of indicators, which helps capturing the comprehensive dynamic effects of other variables in the economy, isolating the effects technological shocks on the economy (Park, 2012). This is particularly important for understanding the multifaceted impacts of technology, labor markets, and investment (Stock & Watson, 2002).

Following Bernanke, et al (2005), the FAVAR model explains how a large set of observed variables X_t can be decomposed into a smaller set of common factors f_t, which capture the co-movement of the variables. These factors are then modeled as a VAR process to study their dynamic relationships. This methodology consists of two main components.

First, the factor model, represented by the equation $X_t = \Lambda f_t + e_t$; where X_t is the vector of observed economic indicators, Λ is the matrix of factor loadings, f_t is the vector of unobserved common factors, and e_t is the vector of idiosyncratic errors. Once the factors are extracted by means of traditional principal components analysis, they are combined with observable variables to construct an augmented vector $Z_t = [f_t', y_t']'$ where y_t represents observable macroeconomic variables. The VAR model is then specified for the combined vector. Second, the VAR model represented by the equation $f_t = \Phi(\mathrm{L}) f_{t-1} + \mu_t$

where $\Phi(\mathrm{L})$ represents matrix polynomial in the lag operator and μ_t is the vector of shocks (Bernanke, Boivin, & Eliasz, 2005).

In a dollarized economy, where traditional monetary policy tools are limited, other macroeconomic variables gain relevance, especially when productivity shocks can only be absorbed by the real economy, as opposed to regular nominal variables. By leveraging on the FAVAR methodology, results isolate the specific effects of technological advancements, providing a clearer understanding of their impact on the economy.

To capture the common factors by principal component analysis (PCA) involves several steps. Firstly, the covariance matrix of the standardized data is computed, capturing the variance and covariance among the variables. Secondly, eigenvalue decomposition is performed on this covariance matrix to extract principal components. The eigenvalues indicate the amount of variance explained by each principal component, and factors to be tested and included are selected based on eigenvalue-greater-than-one rule (Stock & Watson, 2002).

The factors extracted are treated as exogenous variables because they summarize many economic indicators, capturing the underlying economic conditions without being influenced by the specific dynamics of the variables in the model. Furthermore, each factor is orthogonal to the next, hence ensuring no potential correlation among them in the estimation process. This exogeneity assumption ensures that the factors reflect broad economic trends, independently of the model’s internal structure (Bernanke, Boivin, & Eliasz, 2005).

Appendix 3 shows the selection criteria for the common factors based on the eigenvalue-greater-than-one criteria.

3.3 Structural vector autoregression model (SVAR)

SVAR models impose theoretical restrictions to uncover the structural shocks, distinguishing the underlying channels based on dynamic restrictions. By incorporating these restrictions, SVAR models can focus on the impact of various shocks in the system providing a clearer interpretation of their effects (Lütkepohl & Kilian, 2017).

To compare the relevance of the source of technological shocks, we separate the aggregate shocks from those based on specific economics sectors. As pointed out by Chang, et al (2006), using TFP as a shock variable is crucial for identifying sector-specific technology shocks because the variation in input combinations is likely to be more unstable at the sectoral level compared to the aggregate level. Additionally, to identify sectoral from aggregate shocks, Francis (2001) suggests including the aggregate TFP in the sectoral vector autoregression model because such measure in the industry-level model substantially influences the sectoral impulse-response functions to each technology shocks.

To control for a diverse set of macroeconomic variables that affect aggregate and sectoral TFP we select and tested ten factors as exogenous regressors to be included in the underlying structural vector autoregression model. The basic econometric model is summarized as follows:

$$\begin{bmatrix} z_t^{agg} \\ z_t^i \\ s_t \end{bmatrix} = \begin{bmatrix} C_i^{11}(L) & C_i^{12}(L) & C_i^{13}(L) \\ C_i^{21}(L) & C_i^{22}(L) & C_i^{23}(L) \\ C_i^{31}(L) & C_i^{32}(L) & C_i^{33}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^{agg} \\ \varepsilon_t^i \\ \theta_t \end{bmatrix} \tag{3}$$

Where z_t^{agg} is the log difference of aggregate TFP, z_t^i is log difference of sectoral TFP and s_t is the global sales growth rate. As pointed out by Park (2012), the objective is to identify a sector-specific technology shock ε_t^i from an aggregate shock ε_t^{agg}. We do not analyze the non-technological shocks θ_t.

To identify aggregate and sectoral structural technological shocks, we impose restrictions on the dynamic structure. Following Park (2012), we impose two main restrictions. The first restriction assumes that only aggregated technological shocks affect the aggregated productivity level in the long run, while sectorial shocks and the growth rate of global sales have no long run effects.

This assumption is rooted in the idea that technological advancements within a single sector are not sufficiently broad or significant to affect the productivity of the entire economy (Chang & Hong, 2006). For the SVAR model represented in (3), the first restriction traduces in setting the long run components $C_i^{12}(L)$ and $C_i^{13}(L)$ are equal to zero.

The second restriction imposed on the SVAR model ensures that only technology shocks—either aggregate or sectoral—can have a permanent, long-run impact on sectoral productivity. This is a crucial aspect of the model, as it ensures that the long-run level of sectoral TFP is driven solely by technological advancements, and not by other types of shocks such as policy changes, which are considered transitory in their effects on productivity (Francis, 2001). This restriction imposes $C_i^{23}(L)$ = 0 in equation 3.

To ensure the robustness of the estimated impulse response functions (IRFs) and variance decompositions, we implement bootstrapped confidence intervals.[11] This approach mitigates the incorrect inference due to non-standard distributions or sampling variability.

4. EMPIRICAL RESULTS

Each model specification controls for macroeconomic variables using estimated factors to isolate the effects of pure technological shocks. Given that changes in total factor productivity (TFP) were estimated as the technological shock variable, the interpretation of each shock is summarized by the effect on the sales growth rate resulting from a one percentage point variation in either aggregate or sectoral technological changes[12].

The comparison of structural shocks is conducted for each industry under the constraints imposed on the dynamic structure, as outlined in the previous section.[13] It is important to note, however, that aggregate technological changes may differ across model specifications, even when the same variable is

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[11] Estimated confidence intervals are develop through 500 replications by using the residual bootstrap method.

[12] Apart from the agricultural technology shock, where the series are stationary in logarithms, the interpretation in this sector centers on how a one percentage point increase in total factor productivity impacts sales.

[13] Each model satisfies the stability condition and overcomes the Lagrange multiplier (LM) for autocorrelation in the residuals.

employed. Lastly, to assess the persistence of the shocks, cumulative effects over twelve quarterly periods are analyzed.[14]

The oil sector is the first industry examined for its technological impacts on aggregate sales. Figure 1 illustrates that a technological shock in the oil industry initially leads to an immediate positive effect on the sales growth rate; however, this effect is not persistent and diminishes over time. Benefits of technological advancements in the oil sector are inherently volatile and highly sensitive to external factors, particularly to fluctuations in global energy demand and available reserves. Furthermore, booms and busts in the oil sector do not necessarily translate into overall welfare enhancements since it is a capital-intensive industry, with a short and specific value chain; hence, its influence in other outcomes, such as labor (Parra-Cely & Zanoni, 2024) are limited to negligible.

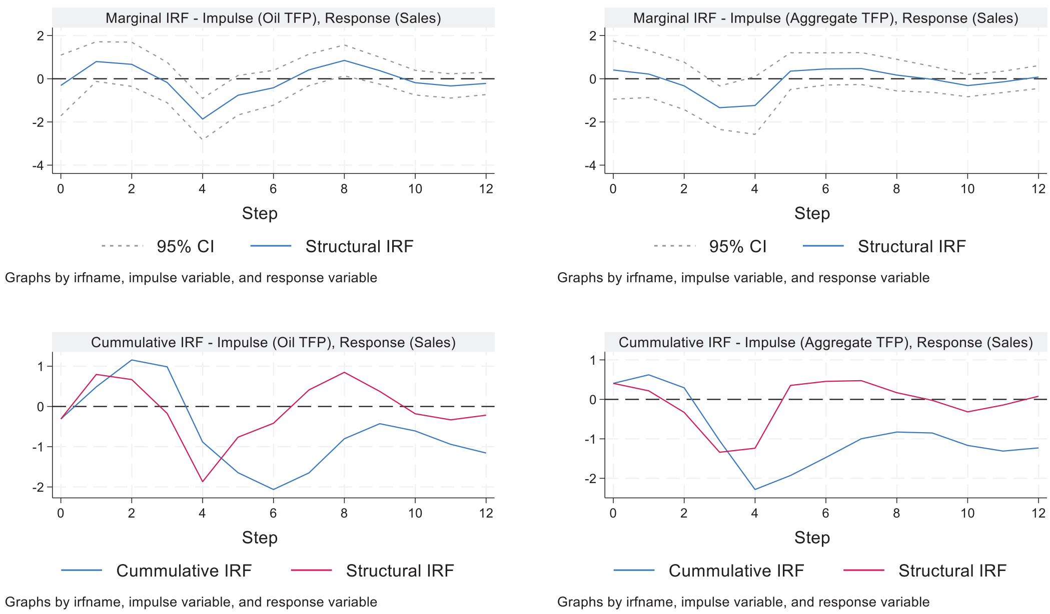

Figure 1: Impulse response function to oil and aggregate technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

[14] Cumulative shocks are the sum of the marginal shocks.

Concerning the persistence of these shocks' effects, an oil technology shock initially exerts a strong cumulative influence on sales, but this effect proves to be short-lived. The initial positive impact of the oil shock fades relatively quickly in the medium term, highlighting a lack of persistence. This pattern emphasizes the risks associated with overreliance on a single sector in an extractive industry. In contrast, the effects of an aggregate technological shock, after the initial adjustment phase, remain sustained over a more extended period. Yet, results deem to be non-significant.

In the manufacturing industry results show that a technological shock significantly influences sales growth, demonstrating the sector's ability to swiftly absorb and leverage technological advancements. This pattern aligns with the critical role of the manufacturing sector in the Ecuadorian economy, serving as a key driver for economic diversification.

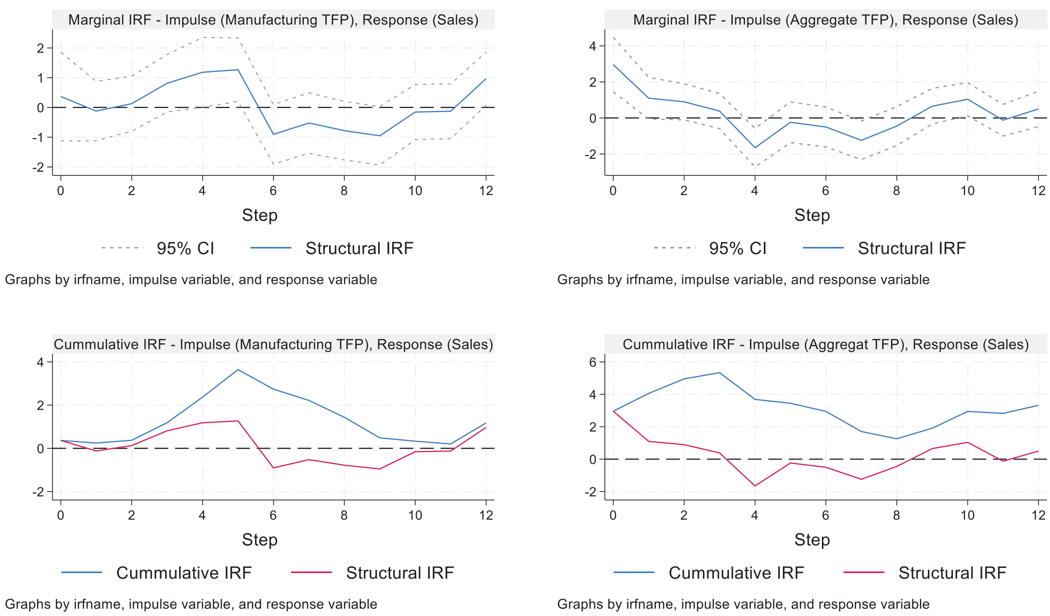

Figure 2: Impulse response function to manufacturing and aggregate technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

The cumulative effect in the manufacturing industry exhibits persistence in sales growth over five consecutive quarters, after which its impact gradually diminishes. The initial surge in productive capacity likely reflects firms' responses to anticipated higher demand, enabling them to stockpile inputs and build up inventory as a precaution against potential supply chain disruptions.

However, as the technological shock extends, manufacturing firms may encounter inventory saturation. Once optimal stock levels are achieved, further production increases may not lead to higher sales, as the market's capacity to absorb additional supply becomes constrained (Khan & Thomas, 2007).

When comparing the persistence of shocks, the cumulative impacts in the manufacturing sector exhibit a stronger and more prolonged effect on sales growth than the aggregate shock. This outcome highlights the manufacturing sector's ability to sustain and amplify the benefits of technological advancements, and stronger spillovers in its longer and more complex value-chain, reinforcing its vital role in the Ecuadorian economy.

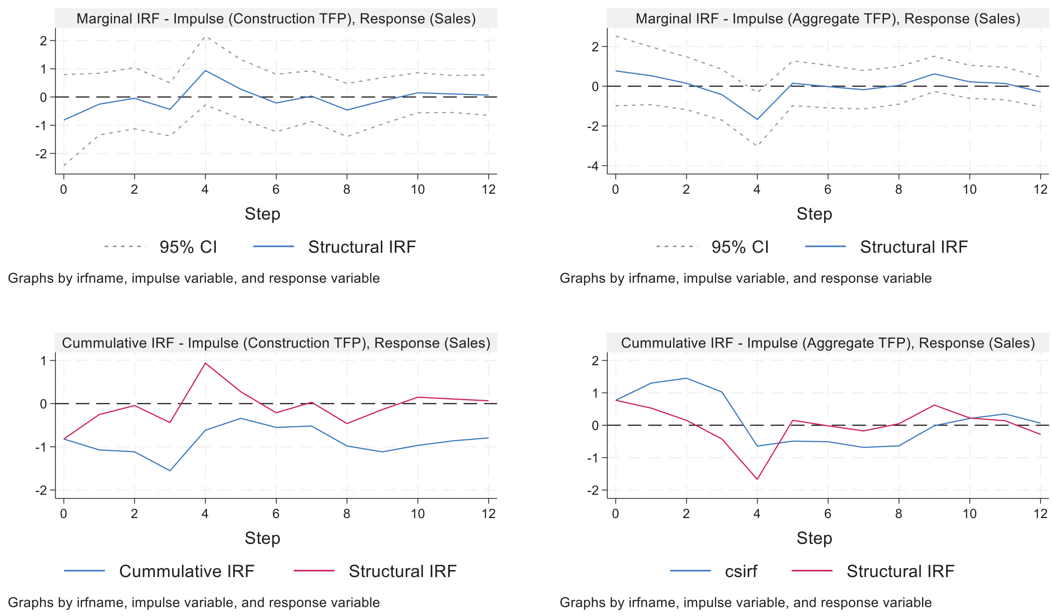

Figure 3: Impulse response function to construction technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

Figure 3 presents the impulse response functions for the construction sector, revealing that a technological shock leads to a modest increase in overall sales. This behavior can be attributed to process rigidity and structural barriers that impede the swift adoption and diffusion of new technologies (Syverson, 2011).

When comparing the persistence of aggregate and construction technological shocks through cumulative effects, it is evident that the sectoral impact is transient. The effect in this industry may take longer to fully materialize, as the sales cycle in construction is extended and often shaped by demand expectations that are influenced by political and socioeconomic changes (Gyourko & Saiz, 2004). In contrast, the cumulative effects of aggregate technological shocks display a more stable and prolonged trend, albeit with a less pronounced initial impact. Overall, estimated effects in this industry are not statistically significant.

Interestingly, in the transport industry, a technological shock initially generates a positive, statistically significant and relatively pronounced impact on sales growth.

Figure 4: Impulse response function to transport technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

The effect is not persistent and diminishes quickly. Technological improvements in the transportation sector are constrained by the existing infrastructure and limited opportunities to improve the capacity, due to structural factors such as limited access to credit, and reduced fleet renovation incentives. If the installed capacity does not accommodate sustained growth following the enhancement of operational efficiencies, sales tend to stabilize relatively quickly (Duranton & Turner, 2012). This observation is consistent with previous studies which suggest that, without complementary investments and considering geographic and demographic factors, the benefits of technological advancements in transportation may be short-lived (Donaldson & Hornbeck, 2016).

When comparing the persistence of shocks, aggregate impacts, despite a slower initial recovery, are sustained.

In the agricultural sector, moderate but fluctuating marginal impacts are observed. This behavior can be attributed to the volatile nature of agriculture, which is particularly vulnerable to external factors such as climatic conditions, harvest cycles and commodity price volatility.

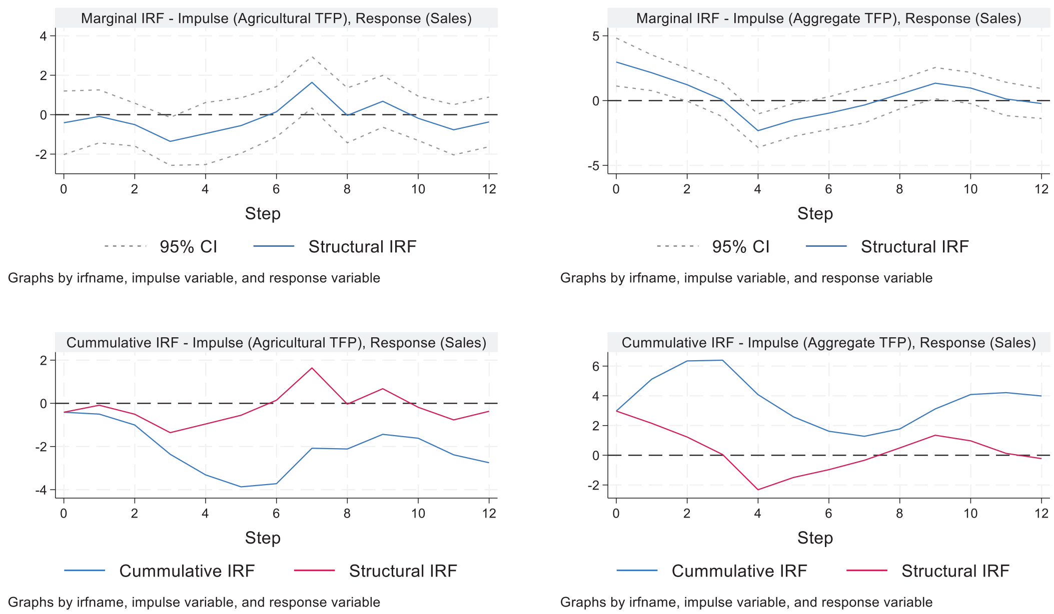

Figure 5: Impulse response function to agricultural technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

When analyzing the cumulative effects, a sectoral technological shock leads to a reduction in sales growth. This outcome highlights the complexity of transmitting technological improvements to sales within this sector, which remains highly dependent on exogenous factors. Consequently, the sector's ability to maintain technological momentum is constrained.

In this context, Pingali (2012) suggests that for technological shocks to have a lasting impact, they must be accompanied by structural reforms, particularly in the development of support networks. Additionally, Restuccia et al. (2008) argue that access to financing and improved resource allocation within the agricultural sector are essential for capitalizing on new innovations.

In contrast, the commercial sector exhibits a different pattern; however, results are not statistically significant. Marginal shocks in this sector initially lead to a decline in sales during the first four quarters, followed by an increase over the subsequent four periods before eventually stabilizing. However, when examining the cumulative effects, it becomes evident that a technological shock in the commercial sector gradually reduces sales, at least in the short term.

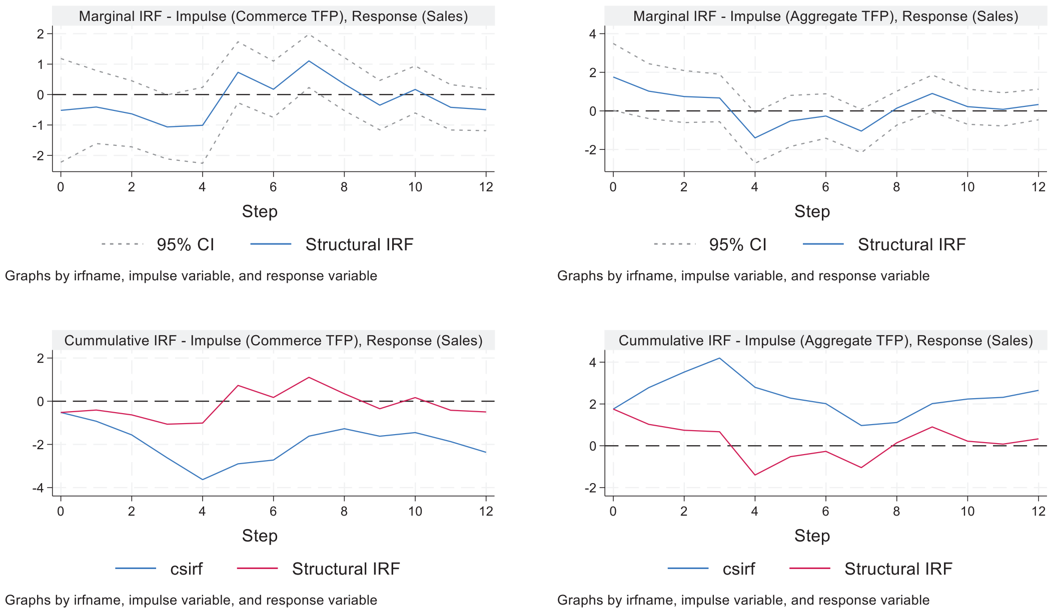

Figure 6: Impulse response function to commerce technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

Observed effects are transitory. This behavior could be explained by the elasticity of demand, market saturation, cyclical demand fluctuations, and consumer preferences (Eichenbaum, Rebelo, & Wong, 2022). For technological benefits to be sustained over time, it is necessary that these demand factors be carefully managed and that policies are directed towards stimulating a broader and more sustained adoption of technologies by both consumers and businesses. However, we abstain from further speculation given the weak statistical support.

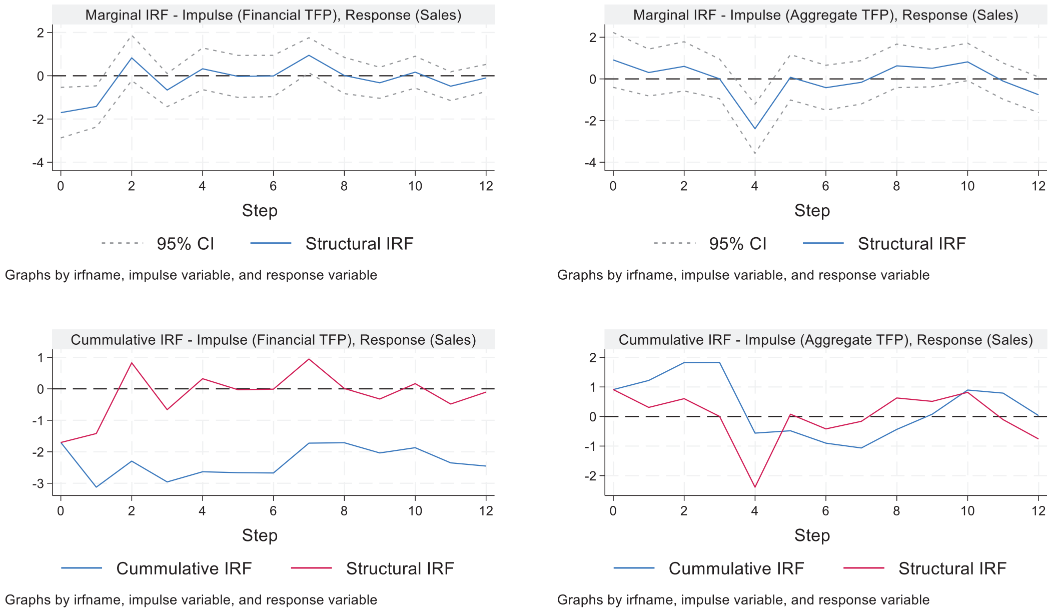

Figure 7: Impulse response function to financial services technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

Figure 7 demonstrates that technological shocks in the financial services industry have a positive and significant short-term effect. The financial sector has experienced considerable transformations in recent decades, including the adoption of digital technologies and the implementation of new regulations. However, the limited impact of these technological advances on sales may be attributed to several inherent challenges, such as market structure incentives, regulatory rigidity, the time required for technological adaptations, and potential market resistance to the rapid adoption of new financial technologies (Philippon, 2016).

When analyzing the persistence of cumulative effects, it is evident that aggregate technological shocks demonstrate a greater capacity for lasting effects. Despite their moderate impact, these aggregate effects tend to prevail over time, indicating that, in this specification, the effects on the broader economy are more persistent. Again, given that effects are not significant under the statistical inference, we abstain from further inspection.

In the professional services sector, it is observed that a marginal technological shock sustains the same marginal sales growth for four quarters. After this period, the effects begin to gradually dilute, suggesting that while technological improvements can initially drive a significant boost in sales, their capacity to maintain this growth over time is limited.

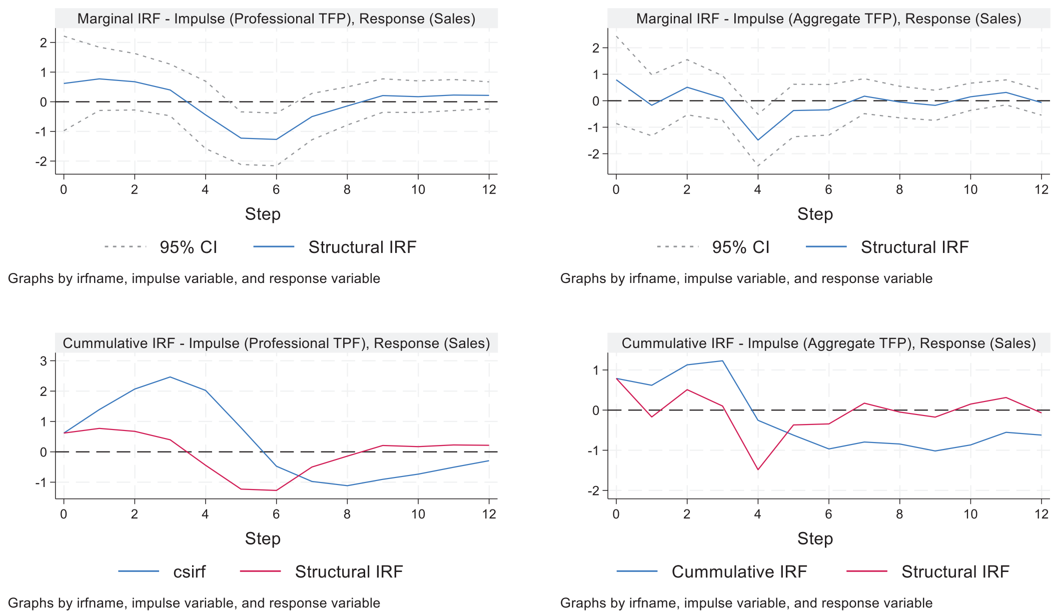

Figure 8: Impulse response function to professional technological shocks

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

This scenario implies that the adoption of new technological processes may remain superficial if these advancements are not fully integrated into deeper organizational changes (Brynjofsson & Hitt, 2000). Similarly, Acemoglu et al.

(2020) argue that technological impacts can be short-lived without the implementation of adequate structural changes. Cumulative effects in the sectorial shock show greater persistence compared to the aggregate technological shock; unfortunately, statistical significance restrict further extensions on the results.

Finally, to ensure the reliability of the results, robustness tests are conducted by modifying the number of latent factors. The aim is to confirm that the dynamics of the impulse-response functions remain consistent regardless of the number of factors included as exogenous variables in the model structure. Appendix 4 presents the robustness of this scenario by comparing the marginal results with 10 and 7 factors, confirming that their patterns are consistent in both cases. If the marginal patterns are consistent, the cumulative patterns will necessarily align as well.

5. CONCLUDING REMARKS

This study provides a valuable contribution to the identification and analysis of technological shocks within the Ecuadorian economy. By focusing on aggregated and sectorial estimations of Total Factor Productivity (TFP) and its interplay with technological shocks, the paper shines some light in understanding of the ways in which innovation affect various sectors and the dynamics of the Ecuadorian economy.

The ability to identify these shocks is critical, as it allows policymakers to design more targeted and effective interventions to foster sustainable economic growth. In a country like Ecuador, where the economy is heavily influenced by external factors and characterized by a heterogeneous productive structure, understanding how and where technological shocks impact productivity is essential for developing policies that bolster the economy's strategic sectors.

The distinction between aggregate and sectoral technological shocks, given the heterogeneous nature of the Ecuadorian economy, allows to identify the source and channel of the shock’s dissemination in the economy. Each sector responds uniquely to technological changes, resulting in varied impacts across the broader economy. Recognizing these heterogeneous effects enhances our understanding of the internal dynamics within each industry, offering valuable insights for the development of targeted, sector-specific policies.

For instance, while a technological shock in the manufacturing industry might result in sustained productivity gains, a similar shock in the agricultural sector could produce more transitory effects due to the structural specificities of the industry. This differentiation allows policy makers to distinguish more effective policies that optimize the positive impact of technological innovations within each sector, and through them, to the economy as a whole, for a more balanced and resilient growth.

By differentiating the impacts of aggregate and sectoral technological shocks, this study offers a roadmap for identifying which sectors are best positioned to capitalize on technological innovations and which require additional support to overcome structural barriers that hinder their adaptive capacity. This insight is vital for developing policies that not only stimulate economic growth but also ensure that such growth is sustainable over the long term.

By means of structural estimation of a VAR system, including orthogonal factors (FAVAR) that summarize the net effects of multiple macroeconomic variables that intervene in the economic growth dynamics, the results of this study reveal that aggregate technological shocks generally dominate sales growth across most industries, with the exceptions of manufacturing and professional activities, where sectoral shocks exhibit greater persistence. In the manufacturing industry, the higher persistence of sectoral shocks can be attributed to the sector's ability to swiftly incorporate technological innovations into its production processes. For professional activities, the persistence of sectoral shocks is largely driven by the knowledge-intensive nature of the sector, where efficiency improvements markedly transform service delivery methods and enhance sales.

On the other hand, the predominance of aggregate shocks across most industries suggests that technological innovations impacting the entire economy tend to have a deeper and more lasting influence than sector-specific innovations. This finding underscores the importance of policies in developing economies that prioritize creating an environment conducive to innovation, ensuring that technological advancements can be leveraged across all sectors for broader economic benefit.

This study lays the groundwork for multiple research that could further deep dive in the dynamics of technological shocks in Ecuador. A particularly valuable path would involve examining the effects of technological shocks on specific subsectors within the industries analyzed. This would provide a more intricate and detailed understanding of each sector's internal dynamics, enabling the identification of subsectors that are particularly susceptible to, vulnerable or resilient against technological changes.

Another promising direction for future research could involve analyzing the long-term effects of technological shocks on productivity and employment. This would entail a more extensive analysis of the shocks identified in this study, incorporating additional variables that capture the impact on social welfare and income distribution. Such research would offer deeper insights into the broader implications of technological change, particularly regarding its influence on economic inequality and overall well-being.

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APPENDIX

Appendix 1: Aggregate Data Set

The stationary codes are: 1 – no transformation, 2 – first difference, 3 – logarithm, 4 – first difference of logarithm, 5 – interannual growth rate and 6 – first difference of interannual growth rate.

Table 1. Macroeconomic Data Set

No.	Classification	Name	Stationary Code	Source
1	National and International Indicators	Consumer Price Index	6	NISC
2		Food Consumer Price Index	6	NISC
3		Non-Food Consumer Price Index	6	NISC
4		Producer Price Index	6	NISC
5		Agricultural Producer Price Index	6	NISC
6		Manufacturing Producer Price Index	6	NISC
7		Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity	6	FRED
8		Market Yield on U.S. Treasury Securities at 5-Year Constant Maturity	6	FRED
9	Monetary and Financial Sector	Financial System Borrowing Rate	5	ECB
10		Financial System Deposit Rate	6	ECB
11		Bank Reserves in million USD	4	ECB
12		Money Supply in million USD	4	ECB
13		Monetary Species in Circulation in million USD	4	ECB
14		Private Bank Demand Deposits in million USD	4	ECB
15		Private Bank Term Deposits in million USD	4	ECB
16		Cooperatives Demand Deposits in million USD	4	ECB
17		Cooperatives Term Deposits in million USD	4	ECB
18		Private Bank Credit in million USD	4	ECB
19		Cooperatives Credit in million USD	4	ECB
20	Real Outputs and Income	Oil Production in million barrels	4	ECB
21		Economic Activity Index	5	ECB
22		Global Economic Expectations Index	5	ECB
23		Commercial Sector Economic Expectations Index	5	ECB
24		Construction Sector Economic Expectations Index	5	ECB
25		Manufacturing Sector Economic Expectations Index	5	ECB
26		Services Sector Economic Expectations Index	5	ECB
27		Oil Revenues in million USD	4	ECB
28		Income Tax Revenue in million USD	4	ECB
29		VAT Revenue in million USD	4	ECB
30		Special Consumption Tax Revenue in million USD	4	ECB
31		Salary Expenditures in million USD	4	ECB
32		Goods Purchase Expenditures in million USD	4	ECB
33		Capital Expenditures in million USD	4	ECB
34		International Reserves in million USD	4	ECB

35	**External Sector**	Oil Exports in million USD	4	ECB
36		Traditional Non-Oil Exports in million USD	3	ECB
37		Non-Traditional Non-Oil Exports in million USD	4	ECB
38		Goods Imports in million USD	4	ECB
39		Raw Material Imports in million USD	4	ECB
40		Capital Goods Imports in million USD	4	ECB
41		Fuel Imports in million USD	4	ECB
42		Services Exports in million USD	4	ECB
43		Services Imports in million USD	4	ECB
44		Income Received in million USD - Primary Income	4	ECB
45		Income Paid in million USD - Primary Income	4	ECB
46		Transfers Received in million USD - Secondary Income	4	ECB
47		Transfers Paid in million USD - Secondary Income	4	ECB
48		Disbursements in million USD	3	ECB
49		Debt and Interest Payments in million USD	4	ECB
50	**Aggregate TFP**	Gross Value Added in million USD	4	ECB
51		Gross Fixed Capital Formation in million USD	4	ECB
52		Effective Hours Worked in million	4	NISC
53	**Agricultural TFP**	Gross Value Added in million USD	3	ECB
54		Gross Fixed Capital Formation in million USD	4	ECB
55		Effective Hours Worked in million	3	NISC
56	**Oil TFP**	Gross Value Added in million USD	4	ECB
57		Gross Fixed Capital Formation in million USD	4	ECB
58		Effective Hours Worked in million	4	NISC
59	**Manufacturing TFP**	Gross Value Added in million USD	4	ECB
60		Gross Fixed Capital Formation in million USD	4	ECB
61		Effective Hours Worked in million	4	NISC
62	**Construction TFP**	Gross Value Added in million USD	4	ECB
63		Gross Fixed Capital Formation in million USD	4	ECB
64		Effective Hours Worked in million, lag	4	NISC
65	**Commerce TFP**	Gross Value Added in million USD	4	ECB
66		Gross Fixed Capital Formation in million USD	4	ECB
67		Effective Hours Worked in million	4	NISC
68	**Transport Services TFP**	Gross Value Added in million USD	4	ECB
69		Gross Fixed Capital Formation in million USD	4	ECB
70		Effective Hours Worked in million	4	NISC
71	**Financial Services TFP**	Gross Value Added in million USD	4	ECB
72		Gross Fixed Capital Formation in million USD	4	ECB
73		Effective Hours Worked in million	4	NISC
74	**Professional Services TFP**	Gross Value Added in million USD	4	ECB
75		Gross Fixed Capital Formation in million USD	4	ECB
76		Effective Hours Worked in million	4	NISC
77	**Public Services TFP**	Gross Value Added in million USD	4	ECB
78		Gross Fixed Capital Formation in million USD	4	ECB
79		Effective Hours Worked in million	4	NISC

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

Appendix 2: Total Factor Productivity

Table 2: Total Factor Productivity Estimations

	Gross Fixed Capital Formation	Employment	Lag - Employment	Lag - Gross Value Added	Adjusted R2	Root MSE
Aggregate TFP	0,193 ***	0,742 ***	-0,003	-0,310 ***	75,70%	0,010
	(0,051)	(0,137)	(0,125)	(0,112)		
Sectoral TFP						
Agriculture	-0,005	0,002	0,223 **	0,970 ***	97,59%	0,015
	(0,079)	(0,144)	(0,098)	(0,031)		
Oil	1,11 ***	0,329 *	-0,375 *	0,403 ***	48,32%	0,074
	(0,296)	(0,205)	(0,197)	(0,112)		
Manufacturing	0,258 ***	0,378 ***	-0,302 ***	-0,159 *	74,95%	0,009
	(0,043)	(0,103)	(0,096)	(0,080)		
Construction	0,440 ***	0,085	0,178 ***	-0,223 *	69,46%	0,019
	(0,094)	(0,080)	(0,074)	(0,141)		
Commerce	0,411 ***	0,247 *	-0,011	-0,126	58,34%	0,017
	(0,079)	(0,138)	(0,117)	(0,117)		
Transport	0,411 ***	1,572 ***	-1,291 ***	-0,419 ***	75,06%	0,026
	(0,141)	(0,455)	(0,287)	(0,101)		
Financial Services	0,336 **	0,796 **	-0,708 **	0,052	43,19%	0,025
	(0,136)	(0,329)	(0,345)	(0,070)		
Professional Services	0,279 ***	0,640 ***	-0,241 *	-0,155	65,35%	0,017
	(0,068)	(0,178)	(0,140)	(0,107)		

Note: Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01 for significance levels. The TFP estimates for the transport, financial, and professional services are calculated using the Newey-West method, which corrects serial correlation.

Table 3. Robustness – Total Factor Productivity Estimations

	Serial Correlation test		Barlett Test		White Noise Test	
	chi2	prob > chi2	B Statistic	prob > B	chi2	prob
Aggregate TFP	8,30	0,08	1,09	0,18	4,76	0,31
Sectoral TFP						
Agriculture	4,79	0,30	0,61	0,85	2,72	0,60
Oil	2,97	0,56	0,58	0,88	2,53	0,63
Manufacturing	5,99	0,20	0,92	0,36	4,52	0,33
Construction	4,89	0,29	0,61	0,85	3,20	0,52
Commerce	7,53	0,11	0,85	0,45	3,46	0,48
Transport	11,83	0,01	1,01	0,25	7,81	0,09
Financial Services	9,37	0,05	0,71	0,69	5,10	0,27
Professional Services	10,85	0,02	1,12	0,16	5,47	0,24

Source: Estimations from Central Bank and NISC Q1. 2011 – Q2.2023.

Appendix 3: Principal Component Analysis and Kaiser Criteria

Table 3. Eigenvalue-greater-than-one rule

Factor	Eigenvalues	Difference	Proportion	Cumulative
Factor1	10,703	5,476	0,218	0,218
Factor2	5,226	1,481	0,107	0,325
Factor3	3,745	0,215	0,076	0,402
Factor4	3,530	0,217	0,072	0,474
Factor5	3,313	0,565	0,068	0,541
Factor6	2,748	0,661	0,056	0,597
Factor7	2,087	0,207	0,043	0,640
Factor8	1,880	0,293	0,038	0,678
Factor9	1,587	0,075	0,032	0,711
Factor10	1,512	0,106	0,031	0,742
Factor11	1,406	0,246	0,029	0,770
Factor12	1,160	0,062	0,024	0,794
Factor13	1,098	0,108	0,022	0,816

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

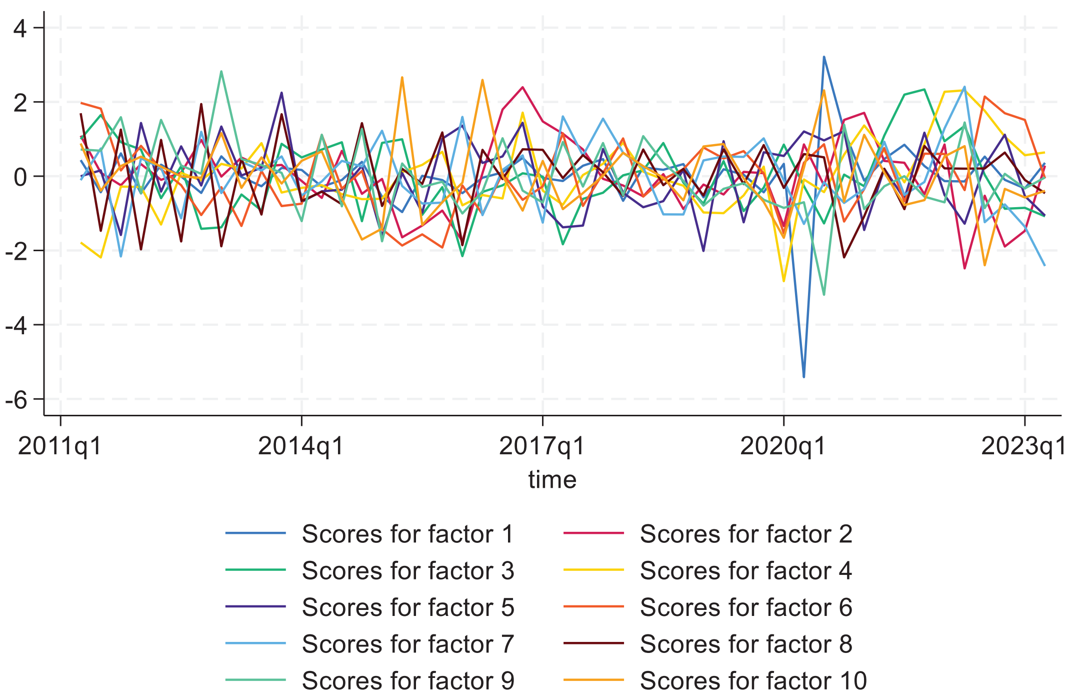

Figure 9. Factors evolution

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

Appendix 4: Robustness Check

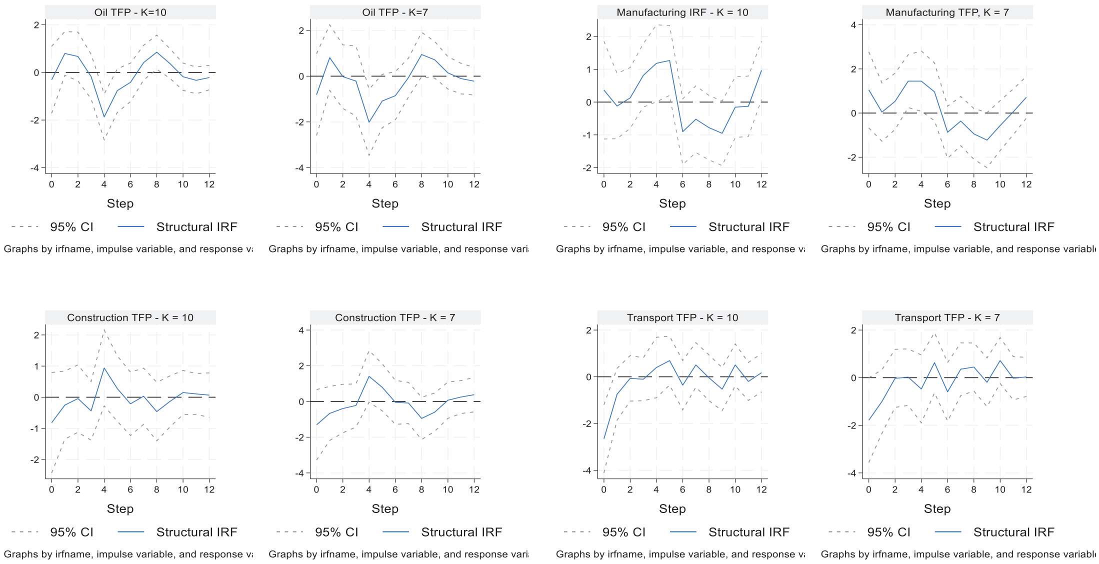

Figure 10. Robustness Check with 7 and 10 factors for oil, manufacturing, construction and transport industries.

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.

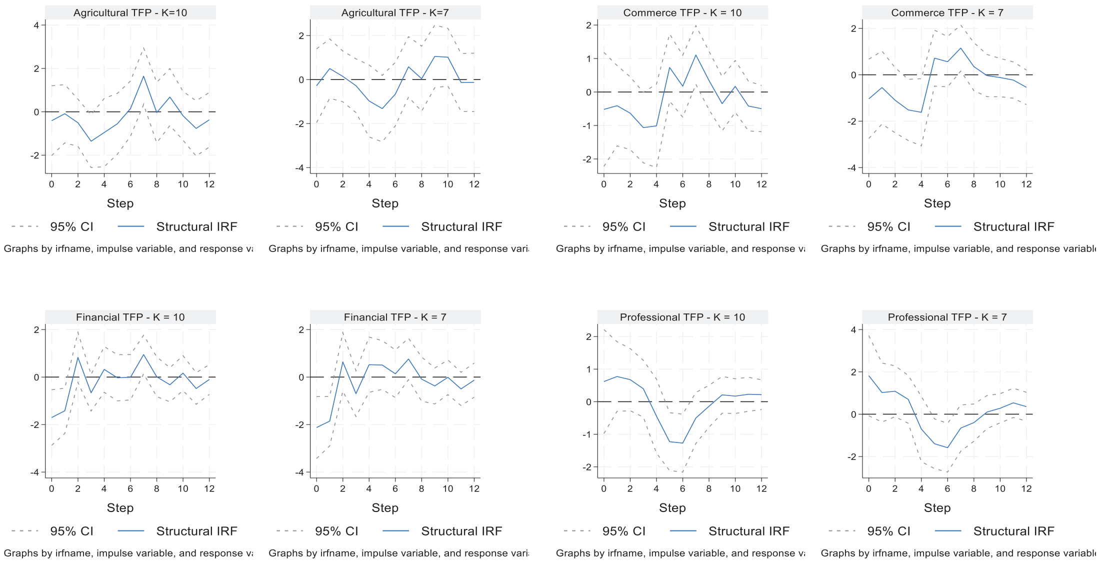

Figure 11. Robustness Check with 7 and 10 factors for agricultural, commerce, financial and professional industries.

Source: Estimations from Central Bank, FRED and NISC Q1. 2011 – Q2.2023.