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RESEARCH ARTICLE



A Bayesian vector-autoregressive application with time-varying parameters on the monetary shocks–production network nexus

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ABSTRACT

Transmission channels from monetary shocks might be identified by studying the features of the production network. The main aim of this paper is to provide insights about the role of production network into the propagation of monetary policy shocks in G7 economies. Time-varying Bayesian vector-autoregressions were built to compute impulse response functions of output to monetary policy shocks in these countries. Panel Auto-Regressive Distributed Lag Bound Approach based on Mean-Group estimator was used to assess the long and short-run connections between production network structure and various shocks associated to monetary policy in the period 2000–2018 and during the Great Recession (2007–2009). The results show that upstreamness is more significant than downstreamness in the period 2000–2018, while the financial sector significantly contributed to the spread of various monetary shocks during the Great Recession.

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1. Introduction

The study of inter-industry linkages and the interconnectedness of economic sectors has been a central theme in economic analysis since the pioneering work of Wassily Leontief in the mid-20th century. His development of input–output matrices provided a powerful tool for understanding the complex interactions between different industries, revealing how each sector relies on the outputs of others and how changes in one sector can ripple through the entire economy.

The study designed by Acemoglu et al. (2012) marked a significant advance in our understanding of how microeconomic shocks can circulate in the production network and influence macroeconomic fluctuations. Their study built upon the earlier paper of Long and Plosser (1983), who introduced a multi-sector framework for analyzing the

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effects of sectoral shocks. Acemoglu et al. (2012) demonstrated that some branches have a more prominent role in transmitting shocks than others due to their position within the production network. Sectors offering many inputs to other sectors, or those that use inputs from a wide range of sectors, are more likely to amplify shocks and have a broader effect on the entire economy.

Other studies have further expanded our analysis regarding the contribution of production networks in transmitting economic shocks (see Barrot & Sauvagnat, 2016; Ozdagli & Weber, 2017). In particular, Barrot and Sauvagnat (2016) examined the propagation of various types of shocks, including federal spending shocks, technology shocks, trade shocks, and knowledge shocks. They found that the impact of these shocks on aggregate fluctuations is significantly amplified by production networks. Their study highlights the importance of considering network effects when evaluating the impacts of economic policies. Ozdagli and Weber (2017) specifically analyzed the spread of aggregate demand shocks through production networks. They showed that demand shocks can also propagate through the network, but in a different direction compared to supply shocks. While supply shocks move downstream from providers to clients, demand shocks move upstream from customers to suppliers. This finding implies that production networks contribute to the transmission of both supply and demand shocks, and that the direction in which shock circulates is important for understanding its impact on the economy.

Some recent studies like those of Pasten et al. (2019) and Ghassibe (2021) have further explored the role of production networks in the transmission of monetary policy shocks. Pasten et al. (2019) highlighted the importance of sector size and price stickiness in determining the effects of these specific shocks. They found that shocks have a larger impact on real economic activity when intermediate inputs account for a larger share of production costs or when major suppliers are price-sticky sectors. These findings suggest that production networks can increase these consequences of monetary policy by creating rigidities in input prices. Ghassibe (2021) provided empirical evidence on the contribution of production networks to the amplification of monetary policy shocks. Utilizing a highly disaggregated dataset focused on U.S. sectoral consumption patterns, a study revealed that network effects explain at least 30% of the impact monetary shocks have on aggregate consumption. This evidence emphasizes the substantial role production networks play in transferring the consequences of monetary policy to the real economy.

The previous studies are based on spatial regressions and event study, but this paper employs the direction of research proposed by Caraianni et al. (2020) for 24 OECD states. The objective of this article is to measure the impact of the monetary policy shocks on production using TVP-VAR models and macroeconomic variables like exchange rate, GDP deflator, GDP, short-run, and long-run interest rates. This approach was further extended by C. Carvalho et al. (2021) that proposed a multisector sticky-price DSGE model to identify differential responses of prices to global and sectoral shocks. By using a PARDL-MG in our paper to study the connection between production network structure and monetary policy shocks over 2000–2018, we alleviate the endogeneity generated by reverse causality and omitted variable and provide an evaluation for short- and long-run relationships.

Impulse Response Functions (IRFs) simulations were made to assess the effect of monetary policy shocks on output in the TVP-VAR framework. The findings show the domination of upstreamness on downstreamness in the period 2000–2018. The financial sector played an important role as a transmission channel for monetary shocks affected to impact the overall economy in the Great Recession. By implementing this methodology, this paper covers the gap in literature for this type of analysis conducted for G7 countries. The research on network-based propagation of shocks has important implications for macroeconomic policy. By understanding how shocks move through the production network, policymakers can design more effective policies to mitigate the impacts of shocks and promote economic stability. Additionally, incorporating network effects into macroeconomic models can improve the accuracy of policy simulations.

After this section, this paper introduces the background related to production networks. The next section develops the methodological framework based on TVP-VAR model. In the fourth section, data description and results are reported, while the last part of the paper provides relevant conclusions and policy proposals.

2. Production networks in literature

Grasping the features and structure of production networks is crucial for identifying the pathways through which monetary shocks propagate. This section provides a concise introduction to production networks along with a summary of key contributions in this area.

Using data sets from industries, the Input–Output Accounts Data supplied by the Bureau of Economic Analysis (BEA) serves as the most widely used source. This extensive database offers sectoral data at the most granular level. The data sets can be found globally. For instance, data sets belonging to many sectors (hundreds) can be found for the American economy. Acemoglu (2012) and Carvalho (2008) paid particular attention to the data for the U.S. economy. The authors examine the features of production networks using U.S. data for industry published by the Bureau of Economic Analysis.

The first characteristic of these networks is the very weak connectivity at the industry level. This implies that, on average, narrowly defined specialized sectors provide inputs to 11 sectors. The second characteristic is the dominance of a small number of hubs. This indicates that sectors producing widely applicable inputs serve a multitude of other sectors within the economy. Consequently, the distribution of output connections across industries is highly uneven, resembling a pattern often modeled by the Pareto distribution. Additionally, the network exhibits a “small-world” structure, where most industry pairs are indirectly linked through intermediary core sectors rather than direct input–output relationships. This network topology is characterized by a limited number of steps between any two industries and a relatively short average distance (Carvalho & Tahbaz-Salehi, 2019).

Another key feature is the highly uneven distribution of industry influence within the production network, which closely resembles a Pareto distribution with increasing variance. This pattern signifies substantial differences in industry importance, contradicting the notion of diversification. Consequently, localized shocks can have far-

reaching effects on overall economic activity. Extensive research has explored this phenomenon.

Industry-level input–output data is accessible for various economies, although data granularity differs. Cross-country comparisons of production networks can be facilitated by databases such as the Global Trade Analysis database, suitable for lower-income nations due to its flexibility, and the Structural Analysis (STAN) database, encompassing 37 OECD countries and 47 sectors. Research by Blöchl et al. (2011), McNerney et al. (2013), and Fadinger et al. (2016) has uncovered similar patterns of uneven industrial influence and output connections in multiple countries, aligning with U.S. findings. These studies have delved deeper, with Blöchl et al. (2011) categorizing countries based on core industries, and Fadinger et al. (2016) demonstrating a correlation between higher income and less productive central sectors.

To gain a deeper understanding of these dynamics, research at the company level is essential. Comprehensive datasets tracking firm transactions exist, such as the Tokyo Shoko Research (TSR) database in Japan, which includes supplier and customer information for nearly a million companies (Carvalho & Tahbaz-Salehi, 2019). Value-added tax (VAT) for states like Belgium offer another rich source of company transaction data. The dataset captures all domestic provider-clients links for each company. Compared to Tokyo Shoko Research, the Belgian database offers a more extensive dataset, including detailed transaction values between firms. Bernard and Moxnes (2018) analyze stylized facts from Belgian data, while Carvalho (2008) explores similar patterns using Japanese data. These studies illuminate key characteristics of company-level production networks. Similar to industry-level findings, firm-level production networks demonstrate significant heterogeneity, with firms acting as diverse input suppliers. The distribution of a firm's suppliers (indegree) follows a Pareto-like pattern, indicating a concentration of suppliers among larger firms. Geographic proximity also influences business connections, with nearby companies forming stronger ties. While U.S. data is less comprehensive, Compustat offers insights into supplier–customer relationships for publicly traded companies. However, financial reporting regulations, requiring disclosure of clients representing more than 10% of sales, introduce biases. Despite these limitations, the indegree distribution of U.S. publicly traded companies exhibits a similar skewed pattern observed in Belgium and Japan (Atalay et al., 2011).

Recent research on production networks has focused on several key areas. First, studies have examined how economic shocks propagate within domestic production networks, employing both theoretical and empirical approaches (Carvalho, 2008; Gabaix, 2011; Acemoglu et al., 2012; Carvalho et al., 2021; Vom Lehn & Winberry, 2020). Second, researchers have explored how international trade shocks transmit through these networks. For instance, Tintelnot et al. (2017) and Huneus (2018), and Kikkawa et al. (2017) utilized domestic firm-level data to quantify the impact of global trade fluctuations on domestic production networks.

Second, within the realm of international macroeconomics, researchers have explored business cycle synchronization using dynamic international real business cycle (IRBC) models built on simplified production structures. These models attribute economic fluctuations primarily to productivity shocks, and in certain instances, demonstrate international business cycle comovement (Heathcote & Perri, 2002).

Acemoglu et al. (2015) demonstrated that industry-specific shocks, such as import fluctuations, productivity changes, and fiscal policy shifts, can significantly impact overall economic output due to the amplifying effect of inter-industry relationships. Barrot and Sauvagnat (2016) highlighted the substantial ripple effects of natural disasters on businesses interconnected through supply chains. Carvalho et al. (2021) investigated how the Great East Japan Earthquake disrupted supply chains, both upstream and downstream. By analyzing these interconnections, they quantified the overall economic consequences of the disaster using a comprehensive economic model.

Weber and Ozdagli (2016) employed spatial econometric methods to examine how monetary policy shocks in the U.S. can amplify stock returns through production networks. Building upon the flexible-price framework established by Long and Plosser (1983), Ghassibe (2021) expanded on this research. Through precise econometric analysis, Ghassibe demonstrated the significant role of production networks in transmitting monetary policy shocks to the broader economy. His findings indicate that production networks contribute between 20 and 45 percent to the overall impact of monetary policy shocks on U.S. consumption. Importantly, Ghassibe also revealed a delay of approximately 18 months in the transmission of these effects through production networks.

Authors like Nakamura and Steinsson (2010) introduced a multi-sector model incorporating menu costs to demonstrate how intermediate inputs and varying price adjustment speeds across different sectors can significantly amplify the short-term impact of monetary policy changes. Pasten et al. (2016) expanded on this by developing a model with sector-specific price adjustment probabilities for 350 U.S. sectors, revealing that strategic interactions between firms can further magnify the effects of monetary shocks. Subsequent research has employed multi-sector New Keynesian models with diverse price stickiness and complex production processes to explore these issues. Carvalho and Lee (2011) estimated price adjustment frequencies for 15 major U.S. sectors, while Bouakez et al. (2014) utilized a 30-sector model with a more intricate production structure. Both studies found results consistent with previous microeconomic research and observed price patterns. Couttenier et al. (2022) proposed a new way to estimate the real economic cost of conflict. They used production networks to show how the disruptive effects of conflict can spread to firms in peaceful areas. Using data from the Maoist insurgency in Eastern India during 2000–2009, they found that the conflict reduced aggregate output by an average of 3.8 billion USD per year, with 73% of the loss due to network propagation. Mungo et al. (2022) recognized the importance of micro data in understanding the impact of conflict on production networks, but noted that firm-to-firm data is scarce. They used machine learning to reconstruct supply chain networks based on firm industry, location, and size. Both studies provide important insights into the impact of conflict on production networks. Couttenier et al. showed that the network propagation effects of conflict can be significant, while Mungo et al. showed how machine learning can be used to reconstruct supply chain networks even with limited data.

Diem et al. (2022) employed a micro-level analysis to demonstrate how the recent medical crisis exposed the vulnerabilities of interconnected corporate supply chains. Recognizing a gap in quantifying individual firm impact on overall network production, they leveraged a comprehensive value-added tax dataset to construct a nationwide firm-

level production network. The authors introduced a novel metric, the Economic Systemic Risk (ESR) index, to assess the potential impact of firm failures on the economy. Their findings revealed that a minuscule fraction of firms (0.035%) carried an exceptionally high ESR, capable of disrupting nearly a quarter of national economic output if they were to default.

There are also recent studies tackling this research topic. For example, Baqaee et al. (2024) proposed a novel supply-side channel through which monetary policy impacts the economy. By introducing heterogeneous firms with varying markups, the authors demonstrate that monetary easing can reallocate resources towards more efficient firms, boosting productivity and output. This supply-side response amplifies and prolongs the effects of monetary policy, mitigating inflation, and flattening the Phillips curve. The paper of Baqaee et al. (2024) develops a theoretical model to support these claims and provides empirical evidence for both macro- and micro-level predictions. The study of Huo et al. (2024) investigates how global production networks influence economic fluctuations across countries. The authors develop a model to separate the impact of shock transmission through these networks from the impact of correlated shocks. Their analysis of G7 countries from 1978 to 2007 reveals that while network effects are significant, they primarily contribute to short-term economic fluctuations. Long-term co-movements are more strongly driven by correlated shocks affecting multiple countries simultaneously. The paper further explores the role of various economic factors, such as multiple shocks and financial integration, without altering the core finding.

There is a significant gap in the existing research on the relationship between monetary shocks and production networks, particularly within G7 economies. Despite the severe economic shocks experienced by these countries during the 2008 financial crisis, there is a notable absence of empirical studies exploring this connection. This paper employs Time-Varying Parameter Vector Autoregression (TVP-VAR) models as a suitable methodological approach to investigate the short- and long-term dynamics between monetary shocks and production networks. The necessary data for this analysis can be obtained from the OECD for macroeconomic variables and the World Input–Output Tables for production network metrics.

3. Model set-up and Bayesian framework

This section aims at presenting a quick model set up on output upstreamness input and downstreamness concepts, and their relationship with global production (3.1), followed by an econometric framework (3.2).

3.1. Output upstreamness and input downstreamness: a background

It is worth re-offering a brief conceptual discussion on how different degrees of upstreamness and downstreamness should affect the transmission of monetary policy shocks. However, for an exhaustive review of the various possible functional forms of the model set-up, we recommend the seminal contribution from Acemoglu et al. (2015). In a nutshell, monetary policy shocks are assessed through unexpected modifications in the interest rate set by federal funds (Caraianni & Lazarec, 2021). Hence, both supply and demand shocks should be modelled as simultaneously throughout the monetary policy

and the proposed specification should thus reflect both directions (i.e., both demand and supply shocks affecting the economy through production networks) (Ozdagli & Weber, 2017). Demand shocks operate upstream, whereas supply shocks impact the economy downstream the production network.

Output upstreamness (u) looks at a sector's position in relation to the final consumer, while input downstreamness (d) focuses on its position in relation to raw material suppliers. Output upstreamness (U) measures a sector's relative position in the production supply chain relative to governments, households, and various investors. Moreover, input downstreamness (D) measures the mean of the distance between a sector and its suppliers of primary inputs. The gross output (x_i) is calculated by aggregating intermediate output sales to the other sectors ($\sum_j z_{ij}$) plus the final use (f_i):

$$x_i = \sum_j z_{ij} + f_i = \sum_j a_{ij}x_j + f_i \quad (1)$$

The coefficient of interest is related to combined ratios of others:

$$a_{ij} = \frac{z_{ij}}{x_j} \quad (2)$$

Consequently, the relationship becomes:

$$x_i = \sum_j a_{ij}f_j + \sum_{j,k} a_{ik}a_{kj}f_j + \dots + f_i \quad (3)$$

Under the hypothesis of input-side accounting identity, the total input of sector i (x_i) is computed by summing up intermediate input purchases coming from the other sectors ($\sum_j z_{ij}$) and the primary inputs known as v_i . The share of output for sector j in the total use of production related to sector i is:

$$b_{ji} = \frac{z_{ji}}{x_j} \quad (4)$$

Knowing that $x_i = \sum_j b_{ji}x_j + v_i$, equation (3) becomes:

$$x_i = \sum_j b_{ji}v_j + \sum_{j,k} b_{jk}b_{ki}v_j + \dots + v_i \quad (5)$$

Considering the sector i , the output upstreamness U and the input downstreamness D are computed as:

$$U_i = \frac{f_i}{x_i} + 2 \frac{\sum_j a_{ij}f_j}{x_i} + 3 \frac{\sum_{j,k} a_{ik}a_{kj}f_j}{x_i} + \dots \quad (6)$$

$$D_i = \frac{v_i}{x_i} + 2 \frac{\sum_j b_{ji}v_j}{x_i} + 3 \frac{\sum_{j,k} b_{jk}b_{ki}v_j}{x_i} + \dots \quad (7)$$

Knowing that the vectors f and x refer to final demand and gross output, while input matrix A has the elements a_{ij} , then $L = I + A + A^2 + \dots = (I - A)^{-1}$ represents the Leontief-inverse matrix and $x = Lf$. The vector v includes primary inputs and the output matrix B is composed by the elements b_{ij} , then $G = I + B + B^2 + \dots = (I - B)^{-1}$ is the Ghosh-inverse matrix and $x' = v'G$.

Consequently, the U and D at country level are computed using weighted averages. The weights represent the dimension of the sectors. Considering the mathematical approach, averages for D and U are equal (Miller & Temurshoev, 2017). The panel data models are employed in this study based on the means for the entire G7 group and across countries.

3.2. Time-varying parameters VAR model: framework

Researchers have employed several methodologies to examine the influence of monetary shocks on network economies. Event analysis and spatial regression models leveraging input-output matrices have been utilized, as have Bayesian vector autoregression (BVAR) and fixed-effect panel data models (Ozdagli & Weber, 2017). While the latter approaches incorporate dynamic patterns, they often fall short in capturing the intricate short-term and long-term relationships between monetary shocks and production network structures, which are essential for understanding these complex systems. Moreover, the ambiguous nature of short-term monetary shock effects on prices, as demonstrated by Mandel and Veetil (2021), underscores the challenges in modeling these phenomena.

Building upon existing methodological approaches, this paper presents an enhanced framework that combines a time-varying parameter vector autoregressive (TVP-VAR) model with panel autoregressive distributed lag Mean Group estimator (PARDL-MG). This novel approach enables the isolation and estimation of time-varying coefficients, which are crucial for capturing the dynamic effects of monetary shocks that change over time. A recursive identification strategy is employed to measure monetary shocks under the assumption of no actual correlation between all the economic elements like inflation, GDP, and monetary policy shocks.

A key advantage of the TVP-VAR model lies in its ability to robustly and flexibly capture any time-varying characteristics within the economic structure (Nakajima, 2011). The hypothesis of parameters following a first-order random walk allows for the consideration of both temporary and permanent changes in coefficients. To account for the potential presence of stochastic volatility shocks in the data-generating process of many economic variables, the TVP-VAR model incorporates stochastic volatility. The estimation procedure utilizes Markov chain Monte Carlo (MCMC) within a Bayesian inference framework, as detailed in the Appendix. While the fundamental principles of the applied methods have been extensively discussed in the literature, specific details may not be familiar to all readers. Therefore, the Appendix provides a comprehensive overview of the econometric structure underlying the TVP-VAR model. Following the estimation of time-varying responses of selected variables to monetary policy shocks using the TVP-VAR model under a recursive identification assumption, an ARDL model is specified and applied to the data.

Let us establish a foundation for a TVP-VAR model, enabling the analysis of time-varying GDP responses to monetary policy shocks for each state. The average impact of a monetary policy shock on a specific country j at time t is represented by ir_{jt} (coming from impulse

responses). To accommodate non-stationary data without cointegration, the methodology of Acemoglu et al. (2015) can be extended to a panel ARDL framework, similar to:

$$ir_{jt} = \delta_j + \sum_{l=1}^p \vartheta_{0l} ir_{jt-l} + \sum_{l=0}^q \vartheta_{1l} down_{jt-l}^{total} + \sum_{l=0}^q \vartheta_{2l} down_{jt-l}^{construction} + \sum_{l=0}^q \vartheta_{3l} down_{jt-l}^{fin} + \sum_{l=0}^q \vartheta_{4l} down_{jt-l}^{ins} + \sum_{l=0}^q \vartheta_{5l} down_{jt-l}^{estate} + e_{jt} \quad (8)$$

$$ir_{jt} = \delta_j + \sum_{l=1}^p \vartheta_{0l} ir_{jt-l} + \sum_{l=0}^q \vartheta_{1l} up_{jt-l}^{total} + \sum_{l=0}^q \vartheta_{2l} up_{jt-l}^{construction} + \sum_{l=0}^q \vartheta_{3l} up_{jt-l}^{fin} + \sum_{l=0}^q \vartheta_{4l} up_{jt-l}^{ins} + \sum_{l=0}^q \vartheta_{5l} up_{jt-l}^{estate} + e_{jt} \quad (9)$$

After parameterization, Equation (8) and (9) become:

$$ir_{jt} = \delta_j + \Phi_j \left(ir_{jt-l} - \theta_1 down_{jt-l}^{total} - \theta_2 down_{jt-l}^{construction} - \theta_3 down_{jt-l}^{fin} - \theta_4 down_{jt-l}^{ins} - \theta_5 down_{jt-l}^{estate} \right) + \sum_{l=1}^{p-1} \lambda_{jl} ir_{jt-l} + \sum_{l=0}^{q-1} \lambda'_{jl} down_{jt-l}^{total} + \sum_{l=0}^{q-1} \lambda''_{jl} down_{jt-l}^{construction} + \sum_{l=0}^{q-1} \lambda'''_{jl} down_{jt-l}^{fin} + \sum_{l=0}^{q-1} \lambda''''_{jl} down_{jt-l}^{ins} + \sum_{l=0}^{q-1} \lambda'''''_{jl} down_{jt-l}^{estate} + e_{jt} \quad (10)$$

$$ir_{jt} = \delta_j + \Phi_j \left(ir_{jt-l} - \theta_1 up_{jt-l}^{total} - \theta_2 up_{jt-l}^{construction} - \theta_3 up_{jt-l}^{fin} - \theta_4 up_{jt-l}^{ins} - \theta_5 up_{jt-l}^{estate} \right) + \sum_{l=1}^{p-1} \lambda_{jl} ir_{jt-l} + \sum_{l=0}^{q-1} \lambda'_{jl} up_{jt-l}^{total} + \sum_{l=0}^{q-1} \lambda''_{jl} up_{jt-l}^{construction} + \sum_{l=0}^{q-1} \lambda'''_{jl} up_{jt-l}^{fin} + \sum_{l=0}^{q-1} \lambda''''_{jl} up_{jt-l}^{ins} + \sum_{l=0}^{q-1} \lambda'''''_{jl} up_{jt-l}^{estate} + e_{jt} \quad (11)$$

In this case, $down_{jt}^{total}$ and up_{jt}^{total} represent measures for downstreamness and upstreamness for state j at time t ; $down_{jt}^{construction}$, $up_{jt}^{construction}$ represent measures for downstreamness and upstreamness for state j at moment t in construction sector; $down_{jt}^{fin}$, up_{jt}^{fin} represent measures for downstreamness and upstreamness for state j at moment t in financial sector (without pension funding and without insurance), respectively; $down_{jt}^{ins}$, up_{jt}^{ins} represent measures for downstreamness and upstreamness for state j at moment t in insurance, reinsurance sector, and pension funding (without compulsory social security); $down_{jt}^{estate}$, up_{jt}^{estate} represent measures for downstreamness and upstreamness for state j at time t in real estate; We consider that λ , λ' , λ'' , λ''' , λ'''' , λ''''' represent short-term parameters associated to lagged dependent variable, downstream or upstream for overall economy, and for the specific sectors like construction, financial sector, without insurance and pension funding, insurance, reinsurance, and pension funding

minus compulsory social security, real estate activities. $\theta_1, \dots, \theta_5$ represent the long-run parameters for the indicators. Error Correction Term known simply as ECT represents speed of adjustment being reflected by Φ_j .

This study employs the Panel Mean Group (PARDL-MG) estimator, a panel ARDL model accommodating heterogeneous short-run and long-run dynamics across countries. PARDL-MG mitigates endogeneity concerns and enables the analysis of both short-term and long-term relationships between endogenous variables. In this context, it allows for an examination of how monetary policy shocks impact the evolving structure of production networks. The application of PARDL-MG to this problem offers a novel approach to understanding monetary shock transmission within a network economy.

To focus the analysis on sectors most severely affected by the Great Recession, this study concentrates on finance, real estate, insurance, and construction – industries closely linked to the crisis-impacted housing market. While manufacturing was also significantly impacted (with approximately 800,000 job losses in 2008), the input–output table’s granular detail necessitates a more targeted analysis of specific sub-sectors in the future research.

3.3. Description of the methodology

Comprehending the organization and features of production networks is crucial for unraveling how monetary policy shocks spread through the economy. Despite growing interest in this area, research limitations persist, even among G7 economies. This paper advances TVP-VAR model to examine how production networks (upstream and downstream linkages) respond to endogenous monetary policy shocks affecting key macro-economic variables (GDP, GDP deflator, exchange rate, short-term, and long-term interest rates) across two distinct periods: a baseline period (2000–2018) and a crisis period (2007–2009, the Great Recession). Preliminary analysis involved more diagnostic tests, including the KPSS and Breitung unit root tests (Breitung, 2001; Kapetanios et al., 2003), Pesaran’s Cross-Sectional Dependence test (Pesaran, 2004), and the Im–Pesaran–Shin panel unit root test for heterogeneous panels (Im et al., 2003). Subsequently, PARDL-MG estimates were generated to assess the short- and long-run responses of production networks to monetary policy shocks, disaggregated by country and sector. To further explore these dynamics, Impulse Response Functions (IRFs) were derived from a time-varying VAR model to evaluate the impact of monetary policy shocks on GDP. The methodology is illustrated in Figure 1.

4. Data, results, and discussion

To conduct this analysis, we gathered annual data spanning the longest relevant period. Quarterly impulse responses (IRs) were averaged to obtain annual values. Panel data models were initially estimated for the entire 2000–2018 period, followed by a specific focus on the 2007–2009 Great Recession. Due to limitations in input–output table data, separate models were developed for short-term and long-term interest rates in both time periods.

The analysis leverages quarterly data for G7 economies (France, Italy, Germany, U.K., Japan, Canada, and the U.S.) obtained from the OECD, spanning the period 2000–2018.

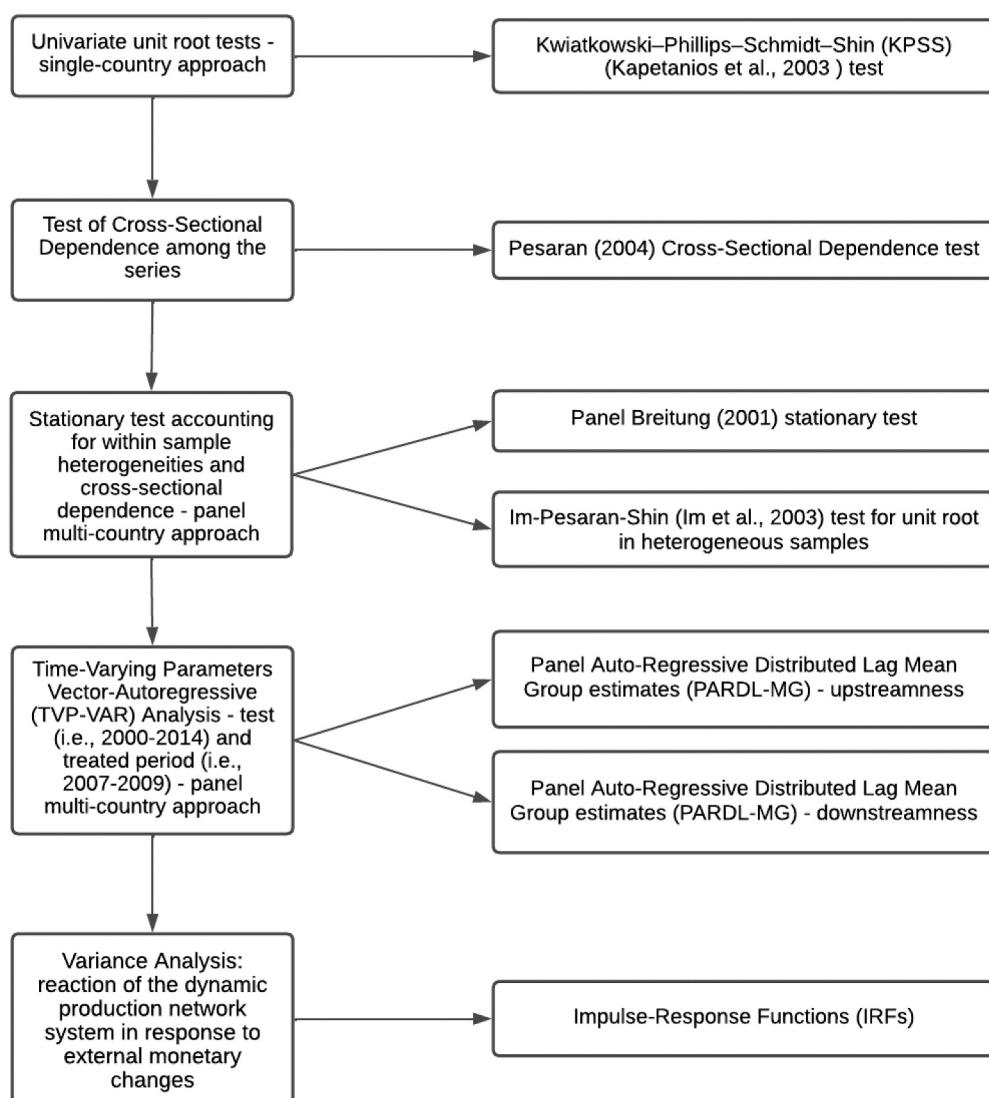


Figure 1. Methodological approach. Source: Authors' elaboration

These quarterly time series include real output (GDP), nominal effective exchange rate, short-term interest rate, GDP deflator (inflation proxy), and 10-year long-term interest rate. Annual network measures for downstreamness and upstreamness were calculated using World Input–Output Tables.¹ Table A1 in Appendix A4 summarizes the preliminary data statistics.

Before any estimation, we examined the data's integration properties using the KPSS stationarity test (Kapetanios et al., 2003). The analysis included the log growth rates of both real GDP and the GDP deflator, computed using the formula that involves the use of natural logarithms: $\frac{\log[GDP]_{(t)}}{\log[GDP]_{(t-1)}}$.

¹Source of data: <<http://www.wiod.org/database/wiots16>>.

Table 1. The main results based on the KPSS test.

State	Variables	Statistics
<i>Canada</i>	GDP rate	0.245
	GDP deflator	0.265
	ER	0.173
	SRIR	0.653
	LRIR	1.302
	Upstreamness	0.158
	Downstreamness	0.391
<i>France</i>	GDP rate	0.257
	GDP deflator	0.454
	ER	1.127
	SRIR	0.073
	LRIR	1.106
	Upstreamness	0.765
	Downstreamness	0.375
<i>Germany</i>	GDP rate	0.064
	GDP deflator	0.386
	ER	0.964
	SRIR	0.674
	LRIR	0.131
	Upstreamness	0.562
	Downstreamness	0.501
<i>Italy</i>	GDP rate	0.192
	GDP deflator	0.998
	ER	0.403
	SRIR	0.074
	LRIR	0.674
	Upstreamness	0.345
	Downstreamness	0.397
<i>Japan</i>	GDP rate	0.097
	GDP deflator	0.721
	ER	0.594
	SRIR	0.292
	LRIR	0.693
	Upstreamness	0.193
	Downstreamness	0.466
<i>U.K.</i>	GDP rate	0.225
	GDP deflator	0.115
	ER	0.773
	SRIR	0.945
	LRIR	0.121
	Upstreamness	0.295
	Downstreamness	0.372
<i>U.S.</i>	GDP rate	0.096
	GDP deflator	0.502
	ER	0.303
	SRIR	0.623
	LRIR	0.204
	Upstreamness	0.367
	Downstreamness	0.489

Source: Authors' elaboration.

ER – exchange rate, SRIR – short-run interest rate, LRIR – long-run interest rate.

Table 1 presents the KPSS test results. The null assumption for KPSS test involves stationary around a deterministic trend or mean. If the statistic is below the critical value, null hypothesis of stationarity is not rejected. For the KPSS model with a constant, the 1% critical value is 0.739, while for the model with an intercept and trend, it is 0.216.

The KPSS test results in Table 1 indicate that all data series are stationary at the 1% significance level, under both constant-only and constant-trend model specifications. The 2008 financial crisis prompted exceptional monetary policy measures from central banks, including the ECB. Countries like Italy, France, and Germany implemented policies to address heightened financial market volatility and uncertainty. Consequently, estimating monetary shocks for these countries during this period is justified by the extraordinary circumstances and the lagged implementation of monetary policy actions.

The TVP-VAR model employed quarterly data for G7 countries spanning 2000–2020, encompassing the nominal effective exchange rate, log GDP growth, log GDP level, and short-term and long-term interest rates. Impulse response functions (IRFs) were derived for each country, considering both short-term (ir1) and long-term (ir2) interest rate shocks. Generally, IRFs revealed persistent negative output responses to both ir1 and ir2, with some country-specific variations. The U.K. and Italy exhibited increased volatility based on ir1 during the crisis.

Figure 2 presents time-varying IRFs for G7 countries, illustrating GDP responses to short-term and long-term interest rate shocks. While France, Canada, and Italy displayed pronounced responses, the U.S. and the U.K. exhibited weaker and more transient effects. Japan's response was notably non-linear, with a reversal in trend.

Before undertaking panel data estimation, it is essential to verify underlying assumptions. One critical assumption is the absence of cross-sectional dependency among panel units. To examine this, the Pesaran (2004) test for cross-sectional dependence was applied. The results, summarized in Table 2, indicate a significant cross-sectional dependence across all data series at the 1% level.

Table 2 confirms the cross-sectional dependence among the data series at the 5% significance level. Having a balanced panel in this case, the Breitung test (2001) was employed to examine the presence of unit roots. For the first-differenced data, the unbalanced panel necessitated the use of the Im–Pesaran–Shin (Im et al., 2003) panel unit root test (Table 3).

The panel data exhibited stationarity only after first differencing, as evidenced by the results in Table 3. To assess the presence of a long-run relationship, the Westerlund cointegration test was applied. However, with p-values consistently exceeding 0.05 for both upstreamness and downstreamness, regardless of whether short-term or long-term interest rates served as the dependent variable, the hypothesis of cointegration was rejected. Consequently, PARDL-MG models were employed for the analysis.

Table 4's findings for upstreamness reveal a significant long-term relationship across the entire sample period but not during the deep crisis. This indicates a robust link between aggregate upstreamness and shocks during 2000–2018, encompassing both short- and long-run changes. While the real estate sector exerted a substantial long-term influence, its short-term impact was pronounced only when considering long-term interest rates. The financial sector's role in transmitting monetary shocks during the Great Recession became evident solely when short-run interest rates were included in the model.

Table 5 indicates a long-run relationship between downstreamness and monetary policy shocks only when the TVP-VAR model includes short-term interest rates. The real estate sector was a key driver of monetary shock transmission for both the entire sample

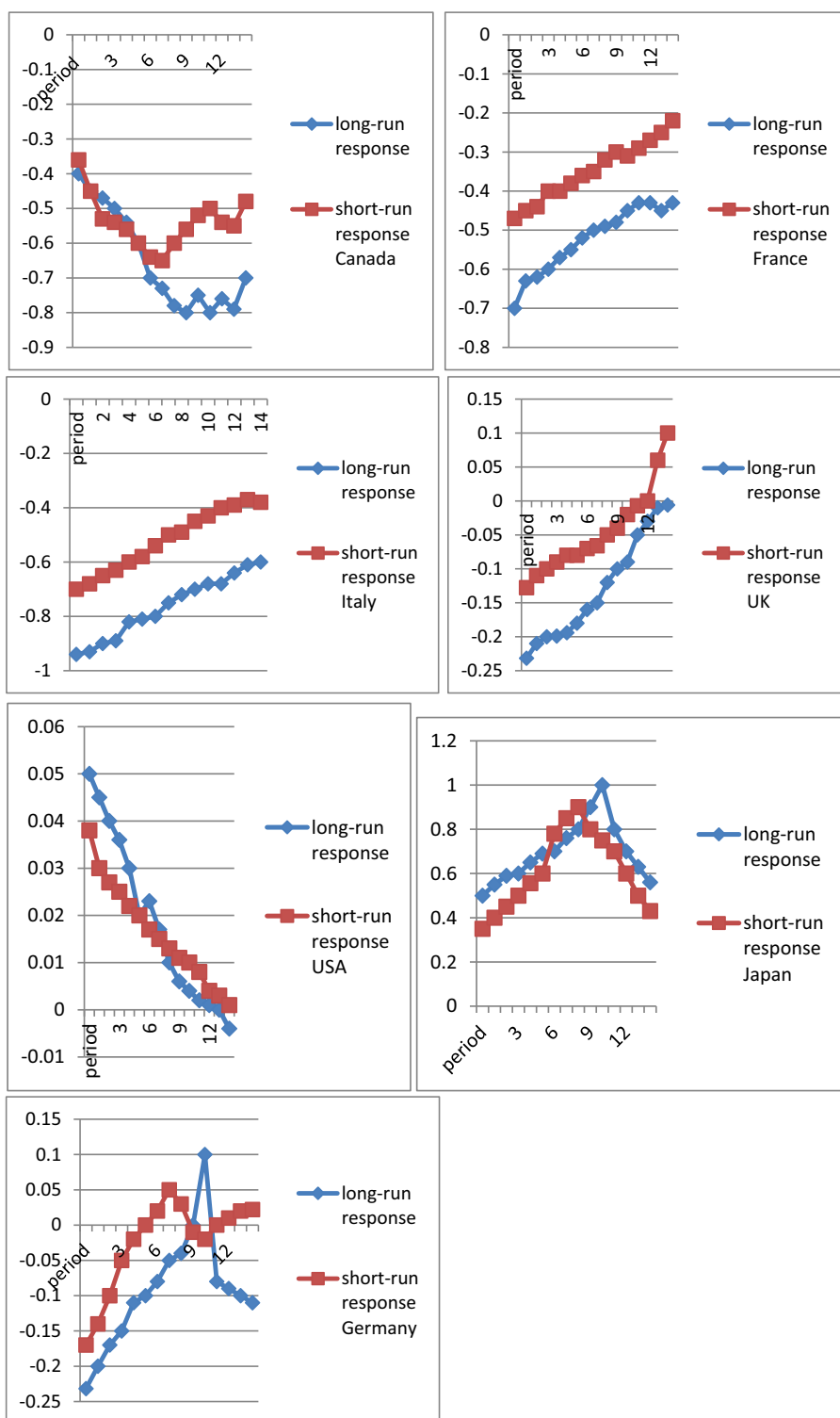


Figure 2. IRF to assess the long-run effect of monetary policy shocks on GDP based on TVP-VAR model. Source: Authors' elaboration. Period represented on OX and output on OY

Table 2. Evidence from Pesaran's CD test.

Variables	Computed statistic (p-value in brackets)
impulse-response functions based on short-run interest rate	10.55 (0.000)
impulse-response functions based on long-run interest rate	15.86 (0.000)
upstreamness ^{total}	14.11 (0.000)
upstreamness ^{construction}	8.11 (0.000)
upstreamness ^{financial sector}	16.23 (0.000)
upstreamness ^{insurance}	13.55 (0.000)
upstreamness ^{estate}	12.75 (0.000)
downstreamness ^{total}	14.86 (0.000)
downstreamness ^{construction}	10.29 (0.000)
downstreamness ^{financial sector}	12.87 (0.000)
downstreamness ^{insurance}	12.75 (0.000)
downstreamness ^{real estate}	12.39 (0.000)

Source: Authors' elaboration.

Table 3. Evidence from panel unit root tests.

Variable	Breitung unit root test for data in level (constant & trend)		Im–Pesaran–Shin test for data in the first difference
	Stat. (no lag)	Stat. (one lag)	Stat.
impulse-response functions based on short-run interest rate	–0.186	–0.902	–6.455**
impulse-response functions based on long-term interest rate	–0.203	–0.956	–5.986**
upstreamness ^{total}	–0.065	–0.089	–3.603**
upstreamness ^{construction}	0.875	0.965	–3.106**
upstreamness ^{financial sector}	–0.606	–0.786	–3.559**
upstreamness ^{insurance}	–0.544	–0.754	–3.887**
upstreamness ^{real estate}	–0.044	–0.598	–4.056**
downstreamness ^{total}	0.965	1.034	–3.057**
downstreamness ^{construction}	0.605	0.798	–4.122**
downstreamness ^{financial sector}	0.255	0.522	–4.007**
downstreamness ^{insurance}	0.065	0.576	–4.332**
downstreamness ^{real estate}	0.074	0.933	–4.003**

Source: Authors' elaboration.

**denotes p-value less than 5%.

period and the Great Recession, particularly in the long and short-run when short-term interest rates were considered. During the crisis, all sectors contributed to explaining the long-run monetary shock transmission.

To assess the average influence of a monetary policy shock on a particular country, mean values were initially employed. However, to enhance the robustness of the findings, the median impacts of monetary policy shocks (ir1'and ir2') are presented in [Tables 6](#) and [7](#).

[Table 6](#) estimates for upstreamness reiterate the long-term relationship observed for the entire sample period but not during the Great Recession. Consistent with previous results, the recession period highlights the significant contribution of the financial sector to monetary policy shocks in both the short and long runs, even after controlling for short-term interest rates.

The findings presented in [Table 7](#) for downstreamness align with the earlier conclusions, which were based on the quarterly average reaction in that quarter of occurrence for that shock. The real estate sector significantly influenced the transmission of

Table 4. PARDL-MG approach corresponding to upstreamness (periods: 2000–2018 and 2007–2009).

Upstreamness		2000–2018		2007–2009	
		IRFs for short-run interest rate	IRFs for long-run interest rate	IRFs for short-run interest rate	IRFs for long-run interest rate
Short-run parameters	upstreamness ^{total}	0.357*	0.407*	0.111	0.033
	upstreamness ^{construction}	–0.022	–0.013	0.223	–0.296
	upstreamness ^{financial sector}	–0.056	0.328	–0.228*	–0.955
<i>ECT</i>	upstreamness ^{insurance}	–0.089	0.065	–0.158	–0.095
	upstreamness ^{real estate}	–0.206	–0.699*	0.153	0.083
	Φ_j	–0.266*	–0.476*	–0.549	–0.699
Long-run parameters	upstreamness ^{total}	0.699*	0.664*	0.593	0.594
	upstreamness ^{construction}	–0.882	–0.905*	–0.776	–0.722
	upstreamness ^{financial sector}	–0.077	0.254	–0.485*	0.538
	upstreamness ^{insurance}	–0.050	–0.235	–0.176	–0.255
	upstreamness ^{real estate}	–1.492*	–2.597*	–0.684	1.855
	<i>Constant</i>	0.446*	–0.275	1.275	2.674

Source: Authors' elaboration.

*shows significant parameter only at 10% significance level.

Table 5. PARDL-MG approach corresponding to downstreamness (periods: 2000–2018 and 2007–2009).

Downstreamness		2000–2018		2007–2009	
		IRFs for short-run interest rate	IRFs for long-run interest rate	IRFs for short-run interest rate	IRFs for long-run interest rate
Short-run parameters	downstreamness ^{total}	–0.005	–0.008	0.219	–0.098
	downstreamness ^{construction}	0.174	0.197	–0.256	0.179*
	downstreamness ^{financial sector}	–0.087	–0.064	–0.056	0.009
	downstreamness ^{insurance}	–0.049	–0.029	–0.027	0.074
	downstreamness ^{real estate}	–0.230*	–0.054	0.149	0.157
	Φ_j	–0.244*	–0.273	–0.553*	–0.329*
	downstreamness ^{total}	0.434*	0.310	0.887*	–0.056
	downstreamness ^{construction}	–0.285	–0.224	–1.033*	–0.145
	downstreamness ^{financial sector}	0.008	0.202	–0.275*	0.166
	downstreamness ^{insurance}	0.0007	0.099	–0.856*	0.122
	downstreamness ^{real estate}	–0.904*	–0.304	–0.939*	1.334*
	<i>Constant</i>	0.065	–0.176	0.683	–0.395

Source: Authors' elaboration.

*shows significant parameter only at 10% significance level.

monetary policy shocks both in the short and long terms, particularly during the deep crisis when short-run interest rates were actively managed.

4.1. Key conclusions are

- First, Total upstreamness significantly influenced the economy throughout the 2000–2018 period, acting as a buffer against monetary policy shocks. Key intermediate input consumers amplified this impact by stimulating demand for upstream sectors following interest rate reductions. While less pronounced, downstreamness also played a significant role and offers valuable insights for policymakers.

- Second, the real estate sector's influence expanded significantly in the recession, as anticipated. The surge in housing demand, fueled by a monetary policy of expansion, spreads downstream (Caraiani et al., 2020). Conversely, the sector's increased demand for other sectors underscores the growing importance of upstreamness.

Table 6. PARDL-MG approach for upstreamness (periods: 2000–2018, 2007–2009) using median effect of monetary policy shock.

Upstreamness		Period: 2000–2018		Period: 2007–2009	
		IRFs considering median of short-run interest rate	IRFs considering median of long-term interest rate	IRFs considering median of short-term interest rate	IRFs considering median of long-term interest rate
Short-run parameters	upstreamness ^{total}	0.294*	0.318*	0.112	0.056
	upstreamness ^{construction}	−0.057	−0.017	0.305	−0.438
	upstreamness ^{financial sector}	−0.006	0.333	−0.195*	−0.986
ECT	upstreamness ^{insurance}	−0.007	0.056	−0.076	−0.038
	upstreamness ^{real estate}	−0.34	−0.567*	0.186	0.091
	Φ_i	−0.267*	−0.495*	−0.528	−0.623
Long-run parameters	upstreamness ^{total}	0.676*	0.698*	0.506	0.678
	upstreamness ^{construction}	−0.886	−0.954*	−0.754	−0.499
	upstreamness ^{financial sector}	−0.096	0.232	−0.409*	0.365
	upstreamness ^{insurance}	−0.06	−0.216	−0.086	−0.185
	upstreamness ^{real estate}	−1.576*	−2.605*	−0.538	1.877
	Constant	0.748*	−0.648	1.476	2.856

Source: Authors elaboration.

*denotes significant coefficient at 10% significance level.

Table 7. PARDL-MG approach for downstreamness (periods: 2000–2018, 2007–2009) using median effect of monetary policy shock.

Downstreamness		Period: 2000–2018		Period: 2007–2009	
		IRFs considering median of short-run interest rate	IRFs considering median of long-term interest rate	IRFs considering median of short-term interest rate	IRFs considering median of long-term interest rate
Short-run parameters	downstreamness ^{total}	−0.009	−0.007	0.211	−0.865
	downstreamness ^{construction}	0.129	0.118	−0.296	0.204*
	downstreamness ^{financial sector}	−0.075	−0.028	−0.045	0.009
ECT	downstreamness ^{insurance}	−0.045	−0.032	−0.011	0.065
	downstreamness ^{real estate}	−0.305*	−0.097	−0.184*	0.189
	Φ_i	−0.287*	−0.217	−0.456*	−0.388*
Long-run parameters	downstreamness ^{total}	0.317*	0.364	0.905*	−0.066
	downstreamness ^{construction}	−0.396	−0.322	−1.034*	−0.233
	downstreamness ^{financial sector}	0.006	0.175	−0.296*	0.127
	downstreamness ^{insurance}	0.0002	0.304	−0.986*	0.128
	downstreamness ^{real estate}	−0.556*	−0.185	−0.819*	1.225*
	Constant	0.122	−0.156	0.585	−0.189

Source: Authors' elaboration.

*denotes significant coefficient at 10% significance level.

- In the end, financial intermediation proved critical only in the recession, with the financial sector's impact minimal during the broader 2000–2018 period. Our findings align with Nobi et al. (2014), who highlighted the financial sector's transmission role during the recent global financial crisis, consistent with prevailing narratives.

These results align with other findings on the propagation of monetary shocks through output networks. The significant effect of total upstreamness observed in our study is similar to the results presented by Miller and Temurshoev (2017), who found that lower interest rates can lead to a more powerful spillover to upstream sectors, particularly for major intermediate input users. This suggests that production networks have a crucial influence in moving monetary shocks throughout the global economy.

Furthermore, our findings corroborate with the conclusions of Barrot and Sauvagnat (2016), who demonstrated that companies' shocks can move into production networks, causing substantial decreases in production. Their findings highlight the importance of input specificity in determining how idiosyncratic shocks spread to those sectors of production. This notion is reinforced by Grassi and Sauvagnat (2019) by providing results that idiosyncratic shocks can affect other activities because of input–output interconnections. They found that increased competition in one sector can lead to positive GDP growth across the economy, emphasizing the interconnectedness of production networks.

Our study also aligns with the conclusions of Ozdagli and Weber (2017), who argued that production networks serve as a conduit for the propagation of both idiosyncratic and monetary policy shocks. They found that these networks can amplify the effects of shocks, making them an important factor to consider in economic policymaking.

Overall, our findings show that the production structure affects the spread of monetary shocks in G7 region. This is consistent with the main takeaways of Caraianni et al. (2020), who emphasized the utility of considering production networks when assessing the impact of monetary policy.

Conventional and Bayesian VAR models, while effective in time-series prediction, are constrained by linearity assumptions, limiting their ability to capture time-varying parameters. As demonstrated by Maćkowiak and Smets (2008), this rigidity can lead to misaligned estimates of monetary shock impacts on real variables when compared to microeconomic evidence. Moreover, non-stationary data and the inherent non-linearity of economic systems, particularly during crises, pose challenges for VAR models (Lucas, 1976). TVP-VAR models emerged as a promising alternative to address these methodological limitations. By incorporating parameters that change in time, TVP-VAR models can capture the dynamic nature of the underlying economic structure in a simple and robust manner. As illustrated in the empirical analysis above, TVP-VAR models exhibit the advantageous feature of enhanced predictability when dealing with series characterized by major structural breaks and non-linearities, which are prevalent during crisis and recession periods (Bekiros, 2014).

5. Conclusions and policy proposals

Identifying the transmission channels of monetary shocks necessitates an understanding of the organization and features specific to production networks. While supplier-

customer linkages generate production networks at the company level, many studies in the literature employ approaches to measure interdependences in economic sectors.

Furthermore, research in the field of network production has been dominated by assessments of between- and within-firm connections, the likelihood of firm failure, supplier-customer connections in the endogenous construction, and market strength. While this body of work is expanding, it continues to exhibit critical shortcomings that G7 states could not escape. To bridge this scientific gap, this study employs a TVP-VAR model to analyze how the networks (upstream and downstream linkages) respond to endogenous monetary shocks on macroeconomic variables across two distinct periods: a benchmark period (2000–2018) and a crisis period (2007–2009, the Great Recession). Preliminary analysis involves diagnostic tests, including the KPSS and Breitung unit root tests (Breitung, 2001; Kapetanios et al., 2003), Pesaran's Cross-Sectional Dependence test (Pesaran, 2004), and the Im–Pesaran–Shin panel unit root test for heterogeneous panels (Im et al., 2003). Subsequently, PARDL-MG estimates are generated to examine the short- and long-run responses of production networks to monetary policy shocks, disaggregated by country and sector. To further explore these dynamics, IRFs are derived from a TVP-VAR model to assess the impact of monetary policy shocks on GDP.

The results indicate that upstream production stages exerted a stronger influence than downstream stages during the 2000–2018 period. Conversely, the financial sector emerged as the primary transmission channel for monetary policy shocks during the Great Recession. Policy recommendations are offered, and the forecasting capabilities of TVP-VAR models in the context of structural breaks and crises are discussed. Our findings align with Ozdagli and Weber (2017) in highlighting the role of production networks in shock propagation and monetary policy transmission. However, we extend these insights by demonstrating the broader influence of production organization on monetary policy transmission across G7 states, as suggested by Caraiani et al. (2020).

This study empirically demonstrates that the structure of production networks significantly influences the transmission of monetary policy shocks across G7 states. Beyond examining aggregate upstreamness and downstreamness, the research delves into specific sectors disproportionately affected by the recent financial crisis. Unlike prior studies relying on globally derived sector-specific upstreamness weights, this analysis employs average upstreamness within the G7 and integrates it into panel data models. Findings corroborate the substantial impact of overall upstreamness and the financial sector's role during the Great Recession. Nevertheless, the study's scope is constrained by the relatively small sample size.

This study acknowledges inherent limitations and offers a valuable demonstration of the consequences of omitting production networks in empirical analyses of monetary shock impacts. Such oversights can underestimate the true magnitude and costs of these shocks, leading to downwardly biased estimates of the coefficient β . Incorporating production networks into future impact assessments is likely to yield more precise estimates.

While the findings align with existing narratives of the financial crisis, future research should consider income co-movements among trading partners to account for potential spillover effects, especially given the cross-border nature of input networks. Beyond the

propagation of disaggregate shocks, the role of production networks in shaping long-term global economic trends warrants further investigation. Leveraging firm-level data, as suggested by Grassi and Sauvagnat (2019), could refine market boundary identification and enable analysis of vertical integration impacts. Expanding sectoral and geographical coverage will provide deeper insights into shock propagation and the efficacy of monetary policy responses.

Highlights

- Transmission channels from monetary shocks might be identified by studying the properties of the production network.
- The results indicate that upstreamness is more significant than downstreamness in the period 2000–2018.
- The financial sector significantly contributed to the transmission of various monetary shocks during the Great Recession.

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Disclosure statement

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Ethical approval

This article does not include any studies with human participants or animals that would have been conducted by or on behalf of the authors.

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Appendix

A.1. TVP-VAR model set-up

Let us consider a TVP model with y_t being a scalar of response and $x_t(kx1)$ and $z_t(px1)$ as vectors of covariates. We make the hypothesis of time unchanged effects of x_t on y_t and time-changing effects of z_t on y_t .

$$\begin{cases} y_t = x_t' \beta + z_t' \alpha_t + \varepsilon_t \\ \text{with } t = 1, 2, \dots, n; \varepsilon_t \sim N(0, \sigma_t^2) \\ \beta(kx1) - \text{vector of constants} \end{cases} \quad (A1)$$

The TVP models are represented by a vector including coefficients that change in time $\alpha_t(kx1)$:

$$\begin{cases} \alpha_{t+1} = \alpha_t + u_t \\ t = 0, 1, 2, \dots, n-1 \text{ and } \alpha_t \sim N(0, \Sigma) \\ \alpha_0 = 0; \text{ and } \alpha_0 \sim N(0, \Sigma_0) \end{cases} \quad (A2)$$

The drifting parameter can consider spurious changes and nonlinearity that suppose stationarity in the case of coefficients that change in time. It is important to describe the stochastic volatility h_t as:

$$\begin{cases} \sigma_t^2 = \gamma \exp(h_t) \\ h_{t+1} = \phi h_t + \eta_t \\ t = 0, 1, 2, \dots, n-1; \text{ and } \eta_t \sim N(0, \sigma_\eta^2) \\ h_0 = 0; \gamma > 0 \end{cases} \quad (A3)$$

The TVP-VAR approach starts from a structural VAR process with coefficients changing in time as in Primiceri (2005):

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \dots + F_s y_{t-s} + u_t \quad (A4)$$

$y_t(kx1)$ is the vector of indicators; A, F_1, F_2, \dots, F_s (kxk) are matrices of parameters; $u_t(kx1)$ considering the structural shock; with $u_t \sim N(0, \Sigma)$. Next, we have:

$$\begin{cases} \Sigma = \begin{pmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \dots & \dots & \dots \\ \vdots & \dots & \dots & \dots \\ 0 & \dots & 0 & \sigma_k \end{pmatrix} \text{ and } A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & \dots & \dots & \dots \\ \vdots & \dots & \dots & 0 \\ a_{k1} & \dots & a_{k,k-1} & 1 \end{pmatrix} \end{cases} \quad (A5)$$

The reduced approach is described below:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \dots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t = X_t \beta + A^{-1} \sum \varepsilon_t \quad (A6)$$

$\varepsilon_t \sim N(0, I_k)$; and $B_i = A^{-1} F_i$ $i = 1, 2, \dots, s$. The elements in the rows of B_i' are stacked to result a vector β (k^2sx1):

$$X_t = I_s (y_{t-1}', \dots, y_{t-s}') \quad (A7)$$

The version based on stochastic volatility transforms the TVP-VAR model as:

$$y_t = X_t \beta_t + A^{-1} \sum \varepsilon_t \quad (A8)$$

$t = s + 1, \dots, n$. Hypotheses: A represents lower-triangular matrix, with parameters following random walk: $\beta_{t+1} = \beta_t + u_{\beta t}$, $a_{t+1} = a_t + u_{at} h_{t+1} = h_t + u_{ht}$,

$h_t = (h_{1t}, \dots, h_{kt})'$, $h_{kt} = \log \sigma_{jt}^2$, $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$, $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$,
 $j = 1, \dots, k$; $t = s + 1, \dots, n$. For the errors, we might define variance-covariance matrix:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \Sigma_{\beta} & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right) \quad (A9)$$

Σ_a, Σ_h are diagonal matrices.

A.2. Data cross-sectional dependence and integration

Over the past decade, we observed a growing preference in managing the issue of cross-sectional dependence and spatial correlation-related bias in the TSCS econometric literature. According to De Hoyos and Sarafidis (2006), the empirical evidence shows that interdependencies stemming from markets integration, and manifesting as spatial correlations between units, can no longer be ignored by regressions. In a globalized economy, economic interconnections between regions and nations are influenced by shared macro-economic fluctuations, unified international policy frameworks guided by intergovernmental organizations (such as the BIS, Kyoto Protocol, Paris Agreement, ILO, and IMF), and the cross-border dissemination of technological advancements and spillover effects across diverse industries and countries (Liddle, 2015). From a statistical standpoint, these interdependencies can manifest as cross-sectional dependence in data, arising from common shocks, spatial correlations, and unobserved factors captured within the error term (De Hoyos & Sarafidis, 2006). Traditional estimation methods like Random and Fixed Effects, as well as the Mean Group estimator, are susceptible to bias when cross-sectional dependence is present (Eberhardt, 2012; Kapetanios et al., 2011). Ignoring this issue can result in misleading parameter estimates and erroneous conclusions (Andrews, 2005; Eberhardt & Bond, 2009; Weinhold, 1999). Therefore, it is crucial to employ appropriate estimation models that can identify and account for these dependencies.

The literature commonly uses various tests to assess cross-sectional independence, such as Frees' test (Frees, 1995), Friedman's (1937) test, Breusch and Pagan (1980) LM or Pesaran (2004) Cross-section Dependence (CD) test. Eberhardt (2012) provides more details on these tests.

To address the cross-sectional dependence, Pesaran (2006) introduced the Common Correlated Effects Mean Group (CCEMG) estimator. This estimator takes into account the time-variant unobservables with non-homogenous effects across units, effectively addressing mis-identification (Eberhardt, 2012). Unlike the Mean Group estimator of Pesaran and Shin (1995), the CCEMG model has the benefit to manage the unobservable features and endogeneity arising from the biasness introduced by the lack of some relevant variables. The CCEMG estimator extends the traditional Pooled Fixed Effects (PFE) function by including the cross-sectional means computed for predictors and endogenous variable as supplementary for all specifications. This approach captures the change in cross-section dependence prior to the computation of means corresponding to initial estimates.

Let us start from a traditional regression (Equation 2), u_{it} are i.i.d. over time and across units. Considering the alternative hypothesis, Kouassi and Setlhare (2016) showed that u_{it} might be linked, but the hypothesis of lack of any correlation is still valid.

$$H0 : \rho_{ij} = \rho_{ji} = \text{corr}(u_{it}, u_{jt}) = 0 \text{ for } i \neq j \quad (A10)$$

$$H1 : \rho_{ij} = \rho_{ji} \neq 0 \text{ for some } i \neq j$$

ρ_{ij} is estimation on initial data of the pair-wise correlation corresponding to regression's residuals based on ε_{it} ; $\hat{\rho}_{ij}$ is:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^T \varepsilon_{it} \varepsilon_{jt}}{\left(\sum_{t=1}^T \varepsilon_{it}^2\right)^{\frac{1}{2}} \left(\sum_{t=1}^T \varepsilon_{jt}^2\right)^{\frac{1}{2}}} \quad (A11)$$

While the LM test is valid when N has a fix value as T approaches infinity, it can present dimension distortions for large cross-sections N and the number of time periods T is a finite number (Breusch & Pagan, 1980). This scenario is common in various panel data studies, including the G7 states. To address the limitation, an alternative statistic was developed by Pesaran (2004) due to key advantages: as De Hoyos and Sarafidis (2006) suggested, under the null assumption of cross-sectional independence, CD converges to $N(0,1)$ as T and N approach infinity; CD exhibits a null average for certain T and N values even in case of non-stationarity and heterogeneity.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \quad (A12)$$

Subsequently, the Cross-sectionally augmented Im, Pesaran, and Shin (CIPS) unit root test, which offers the benefit of being robust to lack of cross-sectional independence and homogeneity among units (Pesaran, 2007). This test is built upon an improvement of the Covariate-Augmented Dickey – Fuller (CADF) test of Hansen (1995). Under the null assumption (H_0), the time data sets are assumed as homogeneously non-stationary. In contrast, the alternative assumption (H_1) implies that the minimum of one individual series tested exhibits stationarity as Cushman and Michael (2011) suggested. The CIPS test incorporates lagged initial values and data in the first difference for cross-section means of data sets into a standard Dickey–Fuller (ADF) framework.

$$\Delta Y_{it} = a_i + b_i Y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^p d_{ij} \Delta \bar{y}_{t-1} + \sum_{j=1}^p d_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (A13)$$

The statistic corresponding to Cointegration-Augmented Dickey – Fuller (CADF) for the state i is t-stat. when $b_i = 0$. The CIPS stat., developed by calculating the simple mean of the individual CADF statistics as by Pesaran (2007) suggested.

$$CIPS_p = \frac{1}{N} \sum_{i=1}^N CADF_{i,p} \quad (A14)$$

In contrast to the CIPS test, which assumes a common speed of convergence towards the equilibrium value with an alternative assumption (H_1), the t-bar test allows for heterogeneous convergence speeds across countries (Im et al., 2003). However, authors like Maddala and Wu (1999) raised concerns about this t-bar test, arguing that real-world data often exhibits cross-correlations that are not adequately captured by the simple demeaning procedure employed by Im et al. (2003). To address this issue, Maddala and Wu proposed a panel unit root test using Fisher's (1932) method that merges the p-values associated to each residual cross-sectional element. By utilizing the additivity specific to the chi-squared distribution, Maddala and Wu (1999) came up with the following statistic:

$$\lambda = -2 \sum_{i=1}^N \log_e \pi_i \quad (A15)$$

This nonparametric test follows chi-square repartition of $2N$ degrees of freedom, with N cross-sectional units. π_i is the p-value corresponding to unit i . Subsequently, the panel unit root test of

Breitung (2001) using a more complex functional form was later elaborated by Breitung and Das (2005):

$$y_{it} = \alpha_{it} + \sum_{k=1}^{p+1} \beta_{ik} x_{i,t-k} + \varepsilon_t \quad (\text{A16})$$

The null hypothesis for Breitung (2001) test states non-stationarity $H0 : \sum_{k=1}^{p+1} \beta_{ik} - 1 = 0$; while the alternative stationary $H1 : \sum_{k=1}^{p+1} \beta_{ik} - 1 < 0$ for any i . The test statistic uses transformed vectors:

$$\begin{cases} Y_i^* = AY_i = [y_{i1}^*, y_{i2}^*, \dots, y_{iT}^*]' \\ X_i^* = AX_i = [x_{i1}^*, x_{i2}^*, \dots, x_{iT}^*]' \end{cases} \quad (\text{A17})$$

The Maddala and Wu (1999)-augmented test statistic:

$$\lambda_B = \frac{\sum_{i=1}^N \sigma_i^{-2} Y_i'^* X_i'^*}{\sqrt{\sum_{i=1}^N \sigma_i^{-2} X_i'^* A' A X_i'^*}} \quad (\text{A18})$$

A.3. A description of the priors used in the TVP-VAR

In this case, let us consider Σ_β the diagonal matrix. The priors mentioned by Nakajima (2011) are adapted in this study. The priors assumed for the i -th diagonals corresponding to the covariance matrices are:

$$(\Sigma_\beta)_i^{-2} \sim \text{Gamma}(50, 0.01)$$

$$(\Sigma_a)_i^{-2} \sim \text{Gamma}(5, 0.01)$$

$$(\Sigma_h)_i^{-2} \sim \text{Gamma}(5, 0.01)$$

Flat priors are considered for the initial state belonging to the time-varying coefficient.

$$\mu_{\beta_0} = \mu_{a_0} = \mu_{h_0} = 0$$

$$\Sigma_{\beta_0} = \Sigma_{a_0} = \Sigma_{h_0} = 10 \times I$$

Ten thousand samples (M) are drawn after discarding the first 1,000 samples and posterior estimates are computed. Then, the variable set is estimated and the MCMC algorithm produces posterior draws efficiently for each country.

A.4. Summary statistics

Table A.1 presents a summary of the data. Notably, Japan holds the record for the maximum GDP in the sample of states, achieved in the Q3:2019. Canada, on the other hand, recorded the lowest maximum GDP. Conversely, Canada also exhibits the lowest real GDP value. Japan's nominal effective exchange rate reached its highest point in the Q4:2000 and its lowest point in the Q2:2008. The U.K. experienced the highest inflation rate in the Q2:2020, coinciding with the recent epidemic. Japan also holds the distinction of experiencing the most significant deflation within the G7 sample, observed in the Q1:2013.

Table A1. Descriptive statistics.

State Indicator	U.K.				
	GDP	GDP deflator	ER	SRIR	LRIR
Average	2559765	92.09	113.26	2.51	3.21
Median	2546382	92.5	109.29	0.87	3.57
Max.	2954951	119.2	141.47	6.36	5.60
Min.	2126096	73.5	91.81	0.04	0.25
Std. deviation	229063.1	11.7	12.58	2.23	1.59
<i>U.S.</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Average	16710911	91.91	111.72	1.91	3.31
Median	16459184	91.85	107.14	1.24	3.23
Max.	20144337	109.3	147.04	6.62	6.48
Min.	13521843	74	85.58	0.11	0.65
Std. deviation	1864814	10.36	15.24	1.91	1.32
<i>France</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Average	2595399	94.07	99.85	1.58	2.78
Median	2614073	95.6	99.67	1.06	3.30
Max.	2926847	108.8	102.76	5.02	5.57
Min.	2253220	79.6	97.84	-0.52	-0.31
Std. deviation	176607.6	7.41	1.30	1.78	1.72
<i>Germany</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Average	3659890	93.47	101.30	1.61	2.49
Median	3645138	92.1	100.74	1.09	3.09
Max.	4170360	108.9	107.07	5.02	5.46
Min.	3266829	82.4	98.67	-0.47	-0.54
Std. deviation	286329	7.62	1.94	1.78	1.83
<i>Italy</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Average	2300540	92.66	99.48	1.58	3.74
Median	2298718	94.05	99.48	1.06	4.18
Max.	2452427	105.7	101.93	5.02	6.61
Min.	1914178	74.1	97.24	-0.52	0.67
Std. deviation	74291.36	9.04	1.07	1.78	1.42
<i>Canada</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Average	1462292	92.36	94.25	2.17	3.19
Median	1440582	93.8	94.69	1.74	3.18
Max.	1741488	109.9	108.87	5.87	6.28
Min.	1175337	73	83.08	0.23	0.54
Std. deviation	160400.5	10.53	5.78	1.49	1.50
<i>Japan</i>					
Indicator	GDP	GDP deflator	ER	SRIR	LRIR
Mean	5007947	102.091	95.9	0.24	0.90
Median	5004952	101.1	90.8	0.11	1.04
Max.	5388769	111.5	150.34	0.88	1.91
Min.	4637627	96.2	73.6	-0.06	-0.21
Std. deviation	222429.8	4.05	17.18	0.25	0.63

Source: Authors' elaboration.

ER- exchange rate, SRIR-Short-run interest rate, LRIR- Long-run interest rate.