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# Monetary shocks and production network in the G7 countries

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## Abstract

Understanding the structure and properties of production networks is essential to identify the transmission channels from monetary shocks. While growingly studied, this literature keeps displaying critical caveats from which the investigation of G-7 economies is not spared. To fill this gap, this paper applies a version of Time-Varying Parameters Bayesian Vector-Autoregressions models (TVP-VAR) and investigates the responses of production networks (upstream and downstream dynamics) to endogeneous monetary shocks on key macro-level indicators (GDP, GDP deflator, exchange rate, short-term and long-term interest rates). Two distinct time-lengths are considered: a test (i.e., 2000–2014) and a treated period (i.e., 2007–2009,"the Great Recession"). Prior, key statistical conditions are checked using a stepwise stationary testing framework including the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. in J Economet 112(2):359–379, 2003—KPSS) and panel Breitung (Nonstationary panels, panel cointegration, and dynamic panels. Emerald Group Publishing Limited, London, 2001) unit root tests; followed by the Pesaran (General diagnostic tests for cross section dependence in panels, 2004) Cross-sectional Dependence (CD) test; and the Im–Pesaran–Shin (Im et al. in J Economet 115(1):53–74, 2003—IPS) test for unit root in the presence of heterogenous slope coefficients. Panel Auto-Regressive Distributed Lag Mean Group estimates (PARDL-MG) offer interesting short- and long-run monetary shocks-production networks response functions, stratified by country and sector. Findings clearly indicate that upstreamness forces dominated downstremness dynamics during the period 2000–2014, whereas the financial sector ermeges as the clear transmission channel through which monetary shocks affected the productive economy during the Great Recession. In general, we conclude that the prioduction structure influences the transmission of monetary shocks in the G-7 economies. Adequate policy implications are supplied, along with a methodological note on the forecasting potential of TVP-VAR methodologies when dealing with series exhibiting structural breaks.

## Highlights

- Understanding the structure and properties of production networks is essential to identify the transmission channels of monetary shocks.
- This paper employs a version of Time-Varying Parameters Bayesian Vector-Autoregressions (TVP-VAR) to investigate the responses of production networks (upstream and downstream dynamics) to endogeneous monetary shocks on key

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macro indicators (GDP, GDP deflator, exchange rate, short-term and long-term interest rates), over two distinct time-lengths: a test (i.e., 2000-2014) and a treated period (i.e., 2007-2009, "the Great Recession").

- Findings clearly indicate that upstreamness forces dominated downstremness dynamics over the period 2000-2014, whereas the financial sector ermeges as the clear transmission channel through which monetary shocks affected the productive economy during the Great Recession.
- In general, we conclude that the prioduction structure influences the transmission of monetary shocks in the G-7 economies.
- Adequate policy implications are supplied, along with a discussion on the forecasting potential of TVP-VAR methodologies when dealing with structural breaks and crisis time periods.

**Keywords:** Production network, Monetary policy shocks, Panel ARDL model, Bayesian VAR model

**JEL Classification:** C51, C53

## 1 Introduction

Since the invention of input–output matrices by Wassili Leontief in the 1950s, the question of how productive sectors connect and interact within an economy has attracted an extensive attention from researcher. Over time, many studies in macroeconomics provide evidence for microeconomic shocks that propagate through the production network and influence the global fluctuations. Among the most seminal and relevant contributions to the field, one finds Acemoglu et al. (2012) who developed the theoretical architecture of the original multi-sector framework first introduced in Long and Plosser (1983). They not only showed that some sectors present disproportionate weights in overall economic fluctuations because of the large range and amount of inputs they supply to the global system, but also that sectoral shocks are intrinsically linked to the nature of input–output linkages, which in turn, may trigger business cycle dynamics.

In addition, Barrot and Sauvagnat (2016) provided evidence about the role of networks in aggregate fluctuations and in the propagation of federal spending, technology, trade, and knowledge shocks. Most of the studies analyzed only the propagation of microeconomic supply shocks. Monetary policy may transmit the reaction to supply shocks to the economy, but it cannot create supply shocks, only demand shocks. Ozdagli and Weber (2017) showed that production networks play a significant role in the propagation channel for aggregate demand shocks. The supply shocks present a downstream direction from suppliers to customers, while demand shocks are associated with upstream in the production network.

Pasten et al. (2019) used input–output frameworks, sector size and price stickiness, and offered theoretical and empirical insights regarding the ways through which monetary policy shocks propagate. In particular, they indicated that real effects of nominal shocks become larger when intermediate inputs take higher shares or when major suppliers for other sectors correspond to those named „sticky-price" sectors. Recently, Ghassibe (2021) offered novel econometric evidence on the contribution of production networks to the effect of monetary shocks on real macroeconomic variables. In particular, they constructed a highly disaggregated monthly dataset on US final sectoral consumption to estimate that at least 30% of the effect of monetary shocks on aggregate consumption comes from amplification through input–output linkages, which facilitate downstream propagation of price rigidity. At the sectoral level, they revealed that the network effect rises in the frequency of price non-adjustment and intermediates intensity whereas the network effect turned highly concentrated (i.e., sectors that jointly account for 17% of their sample aggregate consumption accounted for 98% of the total amplification).

If previous empirical applications relied on event study or spatial regression models, this paper follow the approach of Caraiani et al. (2020) for 24 OECD countries and aims at capturing the effect of monetary policy shocks on output using Bayesian vector autoregression with time-varying parameters and stochastic volatility. These authors estimated the time-varying impulse response functions of GDP to monetary shocks and showed that some singular sectors (such as real estate and financial intermediation) sharply strengthen the effective magnitude of monetary shocks on production metrics. Moreover, in Carvalho et al. (2021a, b), the authors moved the literature forward by elaborating a multisector sticky-price DSGE model that can endogenously deliver differential responses of prices to aggregate and sectoral shocks. They showed that input–output production linkages and a (standard) monetary policy rule contribute to a slow response of prices to aggregate shocks, whereas labor market segmentation at the sectoral level induces within-sector strategic substitutability in price-setting decisions. The present paper seeks to offer an empirical application of panel dynamic autoregressive distributed lag models and capture short-run and long-run effects of production network structure on monetary policy shocks, stratifying by country and sector for a G-7 sample. On one hand, there is a point in assessing whether expansionary monetary policy shocks could determine the demand for intermediate products of productive firms, which drive the output production of inputs suppliers, and in turn, positively stimulate the generation of goods of upstream sectors along each stage of the production network. On the other hand, employing a Panel Auto-Regressive Distributed Lag Mean Group model (PARDL-MG) appears more suitable than standard fixed effect models because it reduces the risk of endogeneity bias induced by reverse causality and omitted variable whereas it allows for the estimation of short- and long-run dynamics within a single equation specification.

In sum, understanding the structure and properties of production networks is essential to identify the transmission channels from monetary shocks. While growingly studied, this literature keeps displaying critical caveats from which the investigation of G-7 economies cannot be spared. To fill this gap, this paper applies a version of Time-Varying Parameters Bayesian Vector-Autoregressions models (TVP-VAR) and investigates the responses of production networks (upstream and downstream dynamics) to endogenous monetary shocks on key macro-level indicators (GDP, GDP deflator, exchange rate, short-term and long-term interest rates). Two distinct time-lengths are considered: a test (i.e., 2000–2014) and a treated period (i.e., 2007–2009, "the Great Recession"). Prior, key statistical conditions are checked using a stepwise stationary testing framework including the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. 2003—KPSS) and panel Breitung (2001) unit root tests; followed by the Pesaran (2004) Cross-sectional Dependence (CD) test; and the Im–Pesaran–Shin (Im et al. 2003—IPS) test for unit root in the presence of heterogeneous slope coefficients. Panel Auto-Regressive Distributed Lag Mean Group estimates (PARDL-MG) helped drawing the short- and long-run monetary shocks-production networks response functions, stratified by country and sector, and followed by Impulse Response Functions (IRFs) simulations to model impact of monetary policy shocks on GDP in a time-varying Vector-Autoregressive (VAR) setting. Findings clearly indicate that upstreamness forces dominated downstreamness dynamics during the period 2000–2014, whereas the financial sector emerges as the clear transmission channel through which monetary shocks affected the productive economy during the Great Recession. Adequate policy implications are supplied, along with a methodological note on the forecasting potential of TVP-VAR methodologies when dealing with series exhibiting structural breaks.

Besides the Introduction, this paper is organized as follows. Section 2 provides a theoretical and empirical background on the concept of production networks. Section 3 presents the main econometric features characterizing the TVP-VAR model. In Sect. 4, data collection and empirical results are presented while Sect. 5 provides concluding remarks and policy implications.

## 2 A theoretical and empirical background on production networks

Understanding the structure and properties of production networks is essential to identify the transmission channels of monetary shocks. This Section aims at offering a concise background on production networks, along with an overview of key contributions on this topic.

In the case of industry-level data, the most used source of data are given by the Input–Output Accounts Data provided by the Bureau of Economic Analysis (BEA). This large database presents the sectoral data at the most disaggregated level. The data series are available worldwide. For example, for American economy, data for hundreds of sectors are available. A particular attention was assigned by Acemoglu et al. (2012) and Carvalho (2008) to the data for the US economy. The authors present characteristics of production networks in the case of US industry-level data provided by the Bureau of Economic Analysis. The first property in this case refers to very weak connection of industry-level network. This means that, in average, narrowly-defined specialized sectors supply inputs to around 11 other sectors. The second property reflects the domination of only few hubs. It supposes that industries with a general purpose supply many other industries of that economy. The consequence is that there is a highly skewed distribution of weighted out degrees that could be approximated by a specific distribution like Pareto distribution. The third property is known as "small-world" property and it describes the situation when most of the industry-pairs are not directly connected through an input-supply relationship, but these industries are connected in an indirect way through hub-like sectors. The consequence of the "small-world" property is a network with specific characteristics given by small diameter and short average path length distance (Pereira Marques de Carvalho and Tahbaz-Salehi 2019).

The last property refers to the highly skewed distribution of sectoral centralities of the production network that could also be approximated in a reasonable way by the Patero distribution with diverging second moments. This characteristic shows the existence of relevant heterogeneity in centralities for the breakdown of the diversification argument.

Therefore, micro shocks could determine significant aggregate fluctuations due to this property. In practice, many empirical studies checked this hypothesis.

As mentioned, input–output data at industry-level are available for a lot of other countries, even if the level of disaggregation is not high in all the cases. Cross-country comparative studies of production networks might be done using specific databases like Global Trade Analysis database that is recommended for low-income countries for various levels of aggregation and Structural Analysis (STAN) database that takes into account 37 OECD countries and 47 sectors. For many countries significant heterogeneous distributions of centralities and sectoral outdegrees were obtained in various studies of Blochl et al. (2011), McNerney et al. (2013), and Fadinger et al. (2016). This conclusion is in line with the result for the US economy. Additional analyses were conducted by these researchers. For example, more groups of countries were identified by Blochl et al. (2011) according to central industries. Moreover, Fadinger et al. (2016) showed that high income countries exhibit less productive central industries.

These types of analyses should be completed by researches made at a more granular level based on company-level data. Large databases are available for firms' transactions, one relevant example in this case being given by the database of a Japanese private credit reporting agency. This agency is known as Tokyo Shoko Research (TSR) that started to issue companies' credit scores, with information about of firms' suppliers and customers (Carvalho and Tahbaz-Salehi 2019). In this case, the information on the buyer–supplier relations covers almost one million firms. All the companies in the network refer to Japanese firms with at least 5 employees. Data related to companies' transactions could be taken also from value-added tax (VAT) records that are available in those countries where VAT is levied. In this case, tax authorities in these states impose the reporting of all transactions made between two VAT-liable firms. For this particular source of data, Belgium provided the best designed database.

The data refer to all domestic supplier-customer connections for each firm. Compared to Tokyo Shoko Research, this database for Belgium has as advantage the higher volume of data due to the registration of transaction amounts that are specific to firm-to-firm linkages. Stylized facts based on Belgium data are provided by Bernard and Moxnes (2018) and those based on Japanese database are provided by Carvalho (2008). These studies made for Belgium and Japan provide insights about essential characteristics of production networks at company-level. The conclusion related to heterogeneity at industry level is also observed at firm-level. In these cases, the firm-level production networks present extensive heterogeneity where firms play the role of input-suppliers. Moreover, outdegree distributions follow a distribution that could be approximated by Pareto distribution. However, a difference is identified between industry-level and firm-level approach. In the case of firms, the indegree distributions are very skewed which suggests that these companies have many suppliers. Companies with many employees or high sales have many suppliers and customers. Building firm-to-firm relationships is also explained by geographical distance. Companies in the local proximity are the most connected. Data on firm-level production network in the case of US economy have lower quality compared to data for Japan and Belgium. Compustat database is the most widely source of data on the connection between supplier and customer. This database uses financial accounting regulations that impose the reporting of clients that account for more than 10% of the total sales. A double selection bias is introduced through the small companies that have as suppliers quite large clients and through relations with publicly-traded companies. The data for the US provide relevant data about granular production of the economy. The indegree distribution of the production network associated to publicly-listed US companies is highly skewed as in the case of Belgium and Japan (Atalay et al. 2011).

The current research agenda related to production networks follows more directions of research. First, the shock propagation in production networks is analyzed in key papers for closed-economies by providing theoretical and empirical evidence (Carvalho 2008; Gabaix 2011; Acemoglu et al. 2012; Carvalho et al. 2021a, b; vom Lehn and Winberry 2020). More studies showed how international trade shocks may propagate through production networks. For example, Huneeus (2018), Kikkawa et al. (2017) and Tintelnot et al. (2017) used domestic firm-to-firm transactions to measure the propagation of international trade shocks.

Second, in international macroeconomics, business cycle comovement is analyzed using dynamic international real business cycle models (IRBC models) models based on simple production structures. In these models, fluctuations are determined by productivity shocks and in some cases international comovement is present (Heathcote and Perri 2002).

If sector-specific shocks are considered to assess how production networks augment the impact of economic shocks, the study of Acemoglu et al. (2015) showed that sector specific imports, productivity and fiscal shocks have in most cases a significant effect on value added in the US sectors due to amplification of input–output relationships. Moreover, natural disasters generate firm-level shocks at a more disaggregate level that create significant spillovers from suppliers of inputs to corresponding clients (Barrot and Sauvagnat 2016). Considering the Great East Japan Earthquake in 2011, Carvalho et al. (2021a, b) analyzed the input–output linkages in the context of shocks' propagation and amplification. This natural disaster caused disruption that propagated downstream and upstream among the existent supply chains which negatively influenced suppliers and clients. These propagation effects allow authors to evaluate the total macroeconomic impact of the earthquake based on a general equilibrium model of production networks. Spatial econometric models were used by Ozdagli and Weber (2017) to assess the impact of shocks in the US monetary policy on stock returns caused by amplification through production networks. The authors started from flexible-price framework developed by Long and Plosser (1983), while Ghassibe (2021) brought more empirical contributions in this field. In this context, Ghassibe (2021) indicated precise econometric estimations to highlight the role of production networks in the impact of monetary policy shocks on macroeconomic indicators. Production networks have a contribution of 20 per cent to 45 per cent to the impact of monetary policy shocks on global consumption in the US. Another important empirical finding of the author is related to the time gap of the contribution. Actually, a lag of around 18 months was identified in the transmission of the contribution of production networks.

A multi-sector menu cost model was developed by Nakamura and Steinsson (2010) for 14 economic sectors in the US to show significant increases in short-term money non-neutrality due to intermediate inputs and differential price stickiness across sectors. A multi-sector model with sector-specific probabilities for price adjustment calibrated for 350 sectors in the US was proposed by Pasten et al. (2016). The authors showed that strategic complementarities in price setting determined significant amplifications of monetary policy shocks. Other methodological extensions in this field suppose the use of multi-sector New Keynesian models based on heterogeneous price stickiness and roundabout production. This type of models employs both sectoral and aggregate data sets. In this context, sector-specific probabilities of price adjustment were estimated by Carvalho and Lee (2011) in the case of 15 major sectors in the US economy. A 30-sector menu cost model using a roundabout production was used by Bouakez et al. (2014). The authors showed the match between studies based on a microeconomic approach (Nakamura and Steinsson 2008) and sectoral frequencies associated to price adjustment.

Very recently, Couttenier et al. (2022) proposed a novel approach to estimate the real economic cost of conflict. To do so, they used the production network as a first-order mechanism through which the disruptive effect of localized conflict spreads to firms in peaceful areas. Based on data related to the Maoist insurgency in Eastern India during the period 2000–2009, results showed that the impact of conflict on firms' behavior, which spreads to firms in peaceful areas through input–output connections. Then, the authors applied model of production networks and quantified the overall impact of conflict. They demonstrated that the Maoist insurgency is connected to an average aggregate output loss of 3.8 billion USD per year. Interestingly, 73% of the loss is explained by network propagation.

Using a slightly different approach, Mungo et al. (2022) stressed that, while the importance of micro data is increasingly recognized, data at the firm-to-firm level remain scarcely available. In their paper, they formulated formulate supply chain networks' reconstruction as prediction function and employed Gradient Boosting Algorithms (GDA) derived from Machine Learning (ML). Performed on three distinct supply chains, results suggest that the key drivers laying under their predictions are firms' industry, location, and size.

Using a micro-based lens, Diem et al. (2022) showed how outbreaks like COVID-19 revealed the sensitivity and weaknesses of highly interdependent corporate supply networks and the heavy production processes which rely on them. However, they noticed that quantitative assessment on the impact of individual firms on the networks' overall production lacks in the most recent literature. Based on a unique value added tax dataset, they elaborated a firm-level production network of an entire country and offered a novel approach for computing the economic systemic risk (ESR) index of all firms belonging to the network. They demonstrated that 0.035% of companies have extraordinarily high ESR, impacting about 23% of the national economic production should any of them default. However, the authors reported that firm size cannot explain the ESR of individual companies, whereas, conversely, their position within the production networks does play out a significant role. In general, they concluded that a reliable assessment of ESR remains impossible with aggregated data traditionally used in Input–Output Economics. Thus, alternative methods and frameworks should be employed.

Interestingly, a review of the most recent literature highlights that no previous empirical assessment examining the monetary shocks-production network nexus has explicitly focused on G-7 economies, although they faced (and probably transmitted back) important shocks during the 2008 financial crisis. Thus, while this underlines the presence of a critical lack in the empirical literature, it also calls for further empirical applications of TVP-VAR models, thought more suitable than standard methods to distinguish between short and long run dynamics. For an exhaustive review of the literature on production networks in macroeconomics, we recommend the relevant state-of-the-art offered in Carvalho and Tahbaz-Salehi (2019). The following Section aims at presenting the advantageous statistical features and competitive edges laying under sub-versions of this method. The variables used in the TVP-VAR models are provided by OECD with quarterly frequency (2000–2014) and refer to real GDP rate, GDP deflator, nominal effective exchange rate, short-term interest rate and long-term interest rate (10-years rate). On the other hand, the World Input–Output Tables provides the data necessary to compute downstreamness and upstreamness.

## 3 A Bayesian framework

This section aims at presenting the econoemtric framework.

### 3.1 A monetary shocks-network model set up

Both supply and demand shocks are transmitted at the same time in the monetary policy (Ozdagli and Weber 2017) and the proposed specification reflects both directions. Demand shocks operate upstream, while the supply ones indicate the downstream (Acemoglu et al. 2015).

The output upstreamness (denoted by $U$) indicates the relative localization of a sector inside the production supply chain with respect to governments, households and investors, while the input downstreamness (denoted by $D$) counts for the average distance between suppliers of primary inputs and sectors that act like input purchasers. The gross output ($x_i$) is computed by summing up intermediate output sales to the other sectors $\left(\sum_j z_{ij}\right)$ and the final use $\left(f_i\right)$:

$$x_i = \sum_j z_{ij} + f_i = \sum_j a_{ij} x_j + f_i \tag{1}$$

where the coefficient of interest corresponds to combined ratios of others:

$$a_{ij} = \frac{z_{ij}}{x_j} \tag{2}$$

In the iterative form, we get:

$$x_i = \sum_j a_{ij} f_j + \sum_{j,k} a_{ik} a_{kj} f_j + \cdots + f_i \tag{3}$$

If input-side accounting identity is assumed, the total input of sector $i$ ($x_i$) is the sum of intermediate input purchases from all the other sectors $\left(\sum_j z_{ij}\right)$ and the primary inputs $v_i$. The share of output corresponding to sector $j$ in the total utilisation of the production corresponding to sector $i$ is computed as:

$$b_{ji} = \frac{z_{ji}}{x_j} \tag{4}$$

Given that $x_i = \sum_j b_{ji}x_j + v_i$, we get:

$$x_i = \sum_j b_{ji}v_j + \sum_{j,k} b_{jk}b_{ki}v_j + \cdots + v_i \tag{5}$$

For a certain sector $i$, the output upstreamness $U$ and the input downstreamness $D$ are derived as:

$$U_i = \frac{f_i}{x_i} + 2\frac{\sum_j a_{ij}f_j}{x_i} + 3\frac{\sum_{j,k} a_{ik}a_{kj}f_j}{x_i} + \cdots \tag{6}$$

$$D_i = \frac{v_i}{x_i} + 2\frac{\sum_j b_{ji}v_j}{x_i} + 3\frac{\sum_{j,k} b_{jk}a_{ki}v_j}{x_i} + \cdots \tag{7}$$

If f and $x$ are vectors of final demand and gross output and $A$ is the input matrix with elements $a_{ij}$, then $L = I + A + A^2 + \cdots = (I - A)^{-1}$ is the Leontieff-inverse matrix and $x = Lf$. If $v$ is the vector including primary inputs and $B$ is the output matrix with elements $b_{ij}$, then $G = I + B + B^2 + \cdots = (I - B)^{-1}$ is the Ghosh-inverse matrix and $x' = v'G$. Then, weighted averages are used to compute $U$ and $D$ at country level. The weights are given by th size of sectors. From mathematical point of view, average $D$ and average $U$ are equal (Miller and Temurshoev 2017). This paper used in the panel data models the averages measures for G-7 countries and across states.

### 3.2 Baseline of the time-varying parameters VAR model

The monetary shocks in network economy have been studied in few methodological frameworks: the event analysis and a spatial regression models using weights that are computed based on input–output matrix (Ozdagli and Weber 2017) or a Baysian vector-autoregression (BVAR model) and fixed-effect panel data model (Caraiani et al. 2020). The first approach presents few limits: difficulties in accurate detection of monetary shocks and lack of identification of variation in time starting from input–output tables. The second approach includes the dynamic pattern of variation, but the fixed-effect models do not capture the short-run and long-run relationship between monetary shocks and production network structure which is essential in a network economy. Mandel and Weetil (2021) showed that short-term monetary shocks might have ambiguous effects on network economy. Positive monetary shocks could rise or fall prices in the short-run. A monetary shock generates a temporary variation in prices with propagation through two channels: direct channel that supposes change in demand for inputs and an indirect one referring to companies that respond to those changes in the inputs prices.

Given these limits of the previous methodological approaches, this paper improves the second methodological approach combining a time-varying parameters VAR model (TVP-VAR) based on multivariate stochastic volatility based on Primiceri (2005) with panel autoregressive distributed lag Mean Group estimator (PARDL-MG). In this context, isolating and estimating time-varying coefficients are necessary to extract the impacts of monetary shocks that changes over time. A recursive approach is used to assess the monetary shocks under the hypothesis of no contemporaneous correlation between monetary policy shocks and output and inflation.

Thus, a competitive edge displayed by the TVP-VAR model is the ability to robustly and flexibly capture any time-varying nature in the structure of the economy (Nakajima 2011).

Temporary and permanent changes in the coefficients are considered under the hypothesis that parameters follow the first-order random walk. Stochastic volatility is included in the TVP-VAR model to eliminate any misspecification since data-generating process for many economic variables presents shocks of stochastic volatility. The estimation method is based on Markov chain Monte Carlo (MCMC) in the framework of Bayesian inference. Let's assume a TVP framework where $y_t$ represents the scalar of response and $x_t(k*1)$ and $z_t(p*1)$ are vectors of covariates. We assume constant effects of $x_t$ on $y_t$ and time-varying effects of $z_t$ on $y_t$.

$$\begin{cases} y_t = x_t'\beta + z_t'\alpha_t + \varepsilon_t \\ \text{with} \quad t = 1, 2, \ldots, n; \quad \varepsilon_t\, N\left(0, \sigma_t^2\right) \\ \beta(k*1)\text{-vector of intercepts} \end{cases} \tag{8}$$

The TVPs are given by a vector of time-varying parameters $\alpha_t(k*1)$:

$$\begin{cases} \alpha_{t+1} = \alpha_t + u_t \\ t = 0, 1, 2, \ldots, n-1 \quad \text{and} \quad u_t\, N(0, \Sigma) \\ \alpha_0 = 0; \quad \text{and} \quad u_0\, N(0, \Sigma_0) \end{cases} \tag{9}$$

The drifting coefficient may capture nonlinearity and any spurious movements which require stationarity for time-varying parameters. The stochastic volatility $h_t$ is based on:

$$\begin{cases} \sigma_t^2 = \gamma \exp(h_t) \\ h_{t+1} = \phi h_t + \eta_t \\ t = 0, 1, 2, \ldots, n-1; \quad \text{and} \quad \eta_t\, N\left(0, \sigma_\eta^2\right) \\ h_0 = 0; \quad \gamma > 0 \end{cases} \tag{10}$$

According to Primiceri (2005), the TVP-VAR model is based on a structural VAR model that allows coefficients to change in time:

$$Ay_t = F_1 y_{t-1} + F_2 y_{t-2} + \cdots + F_s y_{t-s} + u_t \tag{11}$$

where $y_t(k*1)$ refers to the vector of variables; $A, F_1, F_2, \ldots, F_s\ (k*k)$ corresponds to the matrices of parameters; $u_t(k*1)$ capture the structural shock; with $u_t\, N(0, \Sigma\Sigma)$. One can derive:

$$\begin{cases} \Sigma = \begin{pmatrix} \sigma_1 & 0 & \ldots & 0 \\ 0 & \ldots & \ldots & \ldots \\ \vdots & \ldots & \ldots & \ldots \\ 0 & \ldots & 0 & \sigma_k \end{pmatrix} \end{cases} \quad \text{and} \quad A = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ a_{21} & \ldots & \ldots & \ldots \\ \vdots & \ldots & \ldots & 0 \\ a_{k1} & \ldots & a_{k,k-1} & 1 \end{pmatrix} \tag{12}$$

The reduced form of the model might be represented as:

$$y_t = B_1 y_{t-1} + B_2 y_{t-2} + \cdots + B_s y_{t-s} + A^{-1} \sum \varepsilon_t = X_t \beta + A^{-1} \sum \varepsilon_t \tag{13}$$

where $\varepsilon_t\, N(0, I_k)$; and $B_i = A^{-1} F_i$, $i = 1, 2, \ldots, s$. The components in the rows of $B_i' s$ are stacked to get the vector $\beta\left(k^2 s * 1\right)$:

$$X_t = I_s \otimes \left(y_{t-1}', \ldots, y_{t-s}'\right) \tag{14}$$

The TVP-VAR model with stochastic volatility can be represented as:

$$y_t = X_t \beta_t + A^{-1} \sum \varepsilon_t \tag{15}$$

where $t = s + 1, \ldots, n$. Here, few assumptions are made: $A$ is a lower-triangular matrix, the coefficients follow a random walk process: $\beta_{t+1} = \beta_t + u_{\beta t}$, $a_{t+1} = a_t + u_{at}$, $h_{t+1} = h_t + u_{ht}$, where $h_t = (h_{1t}, \ldots, h_{kt})', h_{kt} = \log \sigma_{jt}^2, \beta_{s+1}\, N\left(\mu_{\beta_0}, \Sigma_{\beta_0}\right)$, $a_{s+1}\, N\left(\mu_{a_0}, \Sigma_{a_0}\right)$, $h_{s+1}\, N\left(\mu_{h_0}, \Sigma_{h_0}\right)$, $j$=1,..., $k$; $t$=$s$+1,..., $n$. The variance–covariance matrix associated to errors is:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{at} \\ u_{ht} \end{pmatrix} N \left( 0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_a & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix} \right) \tag{16}$$

where $\Sigma_a$, $\Sigma_h$ refer to diagonal matrixes. This set up the baseline of the TVP-VAR model capturing the time-varying responses of GDP to monetary policy shocks based on this model for each country in the sample. The mean impact of a shock in monetary policy for a certain country $j$ at moment $t$ is denoted by $ir_{jt}$ (impulse-responses). In the case of non-stationary data without cointegration, the approach of Acemoglu et al. (2015) can be adapted into a panel ARDL framework, such as:

$$\begin{aligned} ir_{jt} = \delta_j &+ \sum_{l=1}^{p} \vartheta_{0l} ir_{jt-l} + \sum_{l=0}^{q} \vartheta_{1l} \mathrm{down}_{jt-l}^{\mathrm{total}} + \sum_{l=0}^{q} \vartheta_{2l} \mathrm{down}_{jt-l}^{\mathrm{construction}} + \sum_{l=0}^{q} \vartheta_{3l} \mathrm{down}_{jt-l}^{\mathrm{fin}} \\ &+ \sum_{l=0}^{q} \vartheta_{4l} \mathrm{down}_{jt-l}^{\mathrm{ins}} + \sum_{l=0}^{q} \vartheta_{5l} \mathrm{down}_{jt-l}^{\mathrm{estate}} + e_{jt} \end{aligned} \tag{17}$$

$$\begin{aligned} ir_{jt} = \delta_j &+ \sum_{l=1}^{p} \vartheta_{0l} ir_{jt-l} + \sum_{l=0}^{q} \vartheta_{1l} \mathrm{up}_{jt-l}^{\mathrm{total}} + \sum_{l=0}^{q} \vartheta_{2l} \mathrm{up}_{jt-l}^{\mathrm{construction}} + \sum_{l=0}^{q} \vartheta_{3l} \mathrm{up}_{jt-l}^{\mathrm{fin}} \\ &+ \sum_{l=0}^{q} \vartheta_{4l} \mathrm{up}_{jt-l}^{\mathrm{ins}} + \sum_{l=0}^{q} \vartheta_{5l} \mathrm{up}_{jt-l}^{\mathrm{estate}} + e_{jt} \end{aligned} \tag{18}$$

After parameterization, Eqs. (17) and (18) become:

$$\begin{aligned} ir_{jt} = \delta_j &+ \Phi_j \left( ir_{jt-l} - \theta_1 \mathrm{down}_{jt-l}^{\mathrm{total}} - \theta_2 \mathrm{down}_{jt-l}^{\mathrm{construction}} - \theta_3 \mathrm{down}_{jt-l}^{\mathrm{fin}} - \theta_4 \mathrm{down}_{jt-l}^{\mathrm{ins}} - \theta_5 \mathrm{down}_{jt-l}^{\mathrm{estate}} \right) \\ &+ \sum_{l=1}^{p-1} \lambda_{jl} ir_{jt-l} + \sum_{l=0}^{q-1} \lambda_{jl}' \mathrm{down}_{jt-l}^{\mathrm{total}} + \sum_{l=0}^{q-1} \lambda_{jl}'' \mathrm{down}_{jt-l}^{\mathrm{construction}} + \sum_{l=0}^{q-1} \lambda_{jl}''' \mathrm{down}_{jt-l}^{\mathrm{fin}} \\ &+ \sum_{l=0}^{q-1} \lambda_{jl}'''' \mathrm{down}_{jt-l}^{\mathrm{ins}} + \sum_{l=0}^{q-1} \lambda_{jl}''''' \mathrm{down}_{jt-l}^{\mathrm{estate}} + e_{jt} \end{aligned} \tag{19}$$

$$\begin{aligned} ir_{jt} = \delta_j &+ \Phi_j \left( ir_{jt-l} - \theta_1 \mathrm{up}_{jt-l}^{\mathrm{total}} - \theta_2 \mathrm{up}_{jt-l}^{\mathrm{construction}} - \theta_3 \mathrm{up}_{jt-l}^{\mathrm{fin}} - \theta_4 \mathrm{up}_{jt-l}^{\mathrm{ins}} - \theta_5 \mathrm{up}_{jt-l}^{\mathrm{estate}} \right) \\ &+ \sum_{l=1}^{p-1} \lambda_{jl} ir_{jt-l} + \sum_{l=0}^{q-1} \lambda_{jl}' \mathrm{up}_{jt-l}^{\mathrm{total}} + \sum_{l=0}^{q-1} \lambda_{jl}'' \mathrm{up}_{jt-l}^{\mathrm{construction}} + \sum_{l=0}^{q-1} \lambda_{jl}''' \mathrm{up}_{jt-l}^{\mathrm{fin}} \\ &+ \sum_{l=0}^{q-1} \lambda_{jl}'''' \mathrm{up}_{jt-l}^{\mathrm{ins}} + \sum_{l=0}^{q-1} \lambda_{jl}''''' \mathrm{up}_{jt-l}^{\mathrm{estate}} + e_{jt} \end{aligned} \tag{20}$$

where $\text{down}_{jt}^{\text{total}}$, $\text{up}_{jt}^{\text{total}}$ refer to general measure of downstreamness, upstreamness in country $j$ at time $t$, respectively; $\text{down}_{jt}^{\text{construction}}$, $\text{up}_{jt}^{\text{construction}}$ are measure of downstreamness, upstreamness in country $j$ at time $t$ in construction sector, respectively; $\text{down}_{jt}^{\text{fin}}$, $\text{up}_{jt}^{\text{fin}}$ correspond to measure of downstreamness, upstreamness in country $j$ at time $t$ in financial service activities (except insurance and pension funding), respectively; $\text{down}_{jt}^{\text{ins}}$, $\text{up}_{jt}^{\text{ins}}$ indicate measure of downstreamness, upstreamness in country $j$ at time $t$ in insurance, reinsurance and pension funding (except compulsory social security), respectively; $\text{down}_{jt}^{\text{estate}}$, $\text{up}_{jt}^{\text{estate}}$-measure of downstreamness, upstreamness in country $j$ at time $t$ in real estate activities, respectively; $\lambda$, $\lambda^{'}$, $\lambda^{''}$, $\lambda^{'''}$, $\lambda^{''''}$, $\lambda^{'''''}$ are short-run coefficients for lagged endogenous variable, downstream/upstream for entire economy, sectors like construction, financial service activities, except insurance and pension funding, insurance, reinsurance and pension funding, except compulsory social security, real estate activities, respectively. $\theta_1$,..., $\theta_5$ are the long-term coefficients for the same variables whereas the speed of adjustment is captures by the Error Correction Term (ECT): $\Phi_j$.

In this study, we use a particular type of panel ARDL estimator: the Panel Mean Group (PARDL-MG) model. It is based on heterogeneous short-run equilibrium across countries and long-run equilibrium. The PARDL-MG estimator presents the advantegous feature of reducing the endogeneity and allows assessments of short-run and the long-run impacts among endogeneous variables. In the context of our paper, it enables us to exmaine the short- and long-run responses of monetary policy shocks to endogeneous changes in the production network structure. The application of PARDL-MG in this context is a novelty for the literature evaluating the transmission of monetary shocks in the network economy. Only few sectors are considered here, because the purpose of the analysis is to highlight the impact of the production network structure on monetary shocks for those sectors that were deeply affected by the Great Recession. Financial sector, real estate, insurance sector and construction were connected with housing market that was negatively influenced by the previous financial crisis. Other sectors like manufacturing were also affected by the Great Recession, but the consideration of the other sectors will be the subject of a future study. In 2008, around 800,000 manufacturing jobs were lost and 630,000 construction jobs disappeared. However, input–output table includes more sub-sectors of manufacturing and a precise identification of those subsectors affected by economic crisis is required.

### 3.3 Cross-sectional dependence and integration properties

Over the recent decade, the Time-Series Cross-Section (TSCS) econometric literature showed a keen interest for cross-sectional dependence and spatial correlation-related bias. From an empirical standpoint, it is clear that inter-dependencies driven by the economic and financial integration of markets, and taking the form of spatial correlations across countries cannot longer be neglected by estimation models (De Hoyos and Sarafidis 2006). In a globalized context (trade and financial), regional and national linkages operate through common macroeconomic shocks affecting multiple entities; common international policy directions pushed by inter-state organizations [i.e., the Bank for International Settlements (BIS), the Kyoto Protocol and the

Paris Agreement, International Labour Organization (ILO), International Monetary Fund (IMF)]; spillover effects and technology transfers across sectors belonging to different industries and countries (Liddle 2015). From a statistical point of view, a cross-sectionally dependent data structure can emerge in the presence of common shocks, spatial dependence and unobserved components which are captured by the error term (De Hoyos and Sarafidis 2006). However, neither Random and Fixed Effects model (RE and FE), nor the Mean Group (MG) estimator from Pesaran and Shin (1995) are longer robust when cross-sectional dependence arises between panel members (Kapetanios et al. 2011; Eberhardt 2012). When left unturned, those stones introduced inconsistent estimates and spurious inferences (Weinhold 1999; Andrews 2005; Eberhardt and Bond 2009). Here, we stress that appropriate estimation models identifying and accounting for those inferences should be employed. Indeed, the literature commonly uses the Frees' test of cross sectional independence (Frees 1995); the Friedman's test of cross-sectional independence (Friedman 1937); the Breusch Pagan LM test of independence (Breusch and Pagan 1980) or the more recently developed the Pesaran (2004) Cross-section Dependence (CD) test. For a complete discussion on the respective properties of cross-sectional dependence tests, see Eberhardt (2012). Besides addressing this issue, the Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) estimator accounts for time-variant unobservable with heterogeneous effects across panel members and thus can solve mis-identification problems (Eberhardt 2012). Compared to the Pesaran and Shin (1995) Mean Group estimator from the CCEMG model controls for unobservables and potential endogeneity derived from omitted variable bias. This estimator is developed by extending a conventional Pooled Fixed Effects (PFE) regression function using the cross-sectional arithmetic averages of the dependent and $i$ independent factors. Thus, these cross-section averaged regressors are included as additional covariate in each of the $N$ panel specification to capture cross-section dependence dynamics, before calculating the averages of individual-level estimates.

Let's consider a standard panel-data model (Eq. 2), $u_{it}$ is assumed to be Independent and Identically Distributed (IID) over periods and across cross-sectional units. Under the alternative, $u_{it}$ may be correlated but the assumption of no serial correlation remains (Kouassi and Setlhare 2016). Algebraically, we have:

$$\begin{aligned} &H0: \rho_{ij} = \rho_{ji} = \operatorname{corr}(u_{it}, u_{jt}) = 0 \quad \text{for} \quad i \neq j \\ &H1: \rho_{ij} = \rho_{ji} \neq 0 \quad \text{for some} \quad i \neq j \end{aligned} \tag{21}$$

where $\rho_{ij}$ refer to the sample-level estimation of the pair-wise correlation of the residuals computed using $\varepsilon_{it}$; the OLS residuals estimate of $u_{it}$. $\hat{\rho}_{ij}$ are computed as follows:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} \varepsilon_{it}\varepsilon_{jt}}{\left(\sum_{t=1}^{T} \varepsilon_{it}^2\right)^{\frac{1}{2}} \left(\sum_{t=1}^{T} \varepsilon_{jt}^2\right)^{\frac{1}{2}}} \tag{22}$$

Breusch and Pagan (1980) proposed the LM statistics valid for fixed $N$ as $T \rightarrow \infty$. Nonetheless, this is likely to exhibit size distortions when $N$ is large and $T$ is finite. This situation is commonly encountered in empirical panel approaches and does apply to the present case study of G-7 countries. To fill this gap, Pesaran (2004) proposed the alternative test statistic, which presents two competitive features: under the null hypothesis of no cross-sectional dependence, and for large $T$ and $N \to \infty$; CD converge to $N(0, 1)$ (i); unlike the LM statistic, the CD statistic will display a zero mean for fixed $T$ and $N$ values under heterogeneous and non-stationary models (De Hoyos and Sarafidis 2006).

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N=1} \hat{\rho}_{ij} \tag{23}$$

Followingly, Pesaran (2007) developed the Cross-sectionally augmented Im, Pesaran and Shin (CIPS) panel unit root test, which has the advantage to be robust to heterogeneity and cross-sectional dependence of panel units. The CIPS test is based on an extension of the Covariate-Augmented Dickey–Fuller (CADF) test developed by Hansen (1995), where the null hypothesis ($H_0$) refers to homogeneous non-stationary time series; whereas the alternative hypothesis ($H_1$) corresponds to a stationary process for at least one of the individual series tested (Cushman and Michael 2011). Consider a standard Dickey–Fuller (ADF—Dickey and Fuller 1979) framework augmented with lagged levels and first-differences of the cross-section averages of the individual series:

$$\Delta Y_{it} = a_i + b_i Y_{i,t-1} + c_i \overline{y}_{t-1} + \sum_{j=1}^{p} d_{ij} \Delta \overline{y}_{t-1} + \sum_{j=1}^{p} d_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \tag{24}$$

where the Cointegration-Augmented Dickey–Fuller (CADF) statistic for the country $i$ is here the t-statistic when $b_i = 0$. This leads us to formulate the CIPS statistic test of Pesaran (2007), which is computed as the simple arithmetic average of the CADF statistics.

$$CIPS_p = \frac{1}{N} \sum_{i=1}^{N} CADF_{i,p} \tag{25}$$

Besides, the $t$-bar test proposed in Im et al. (2003) assumes that all countries converge towards the equilibrium value at heterogeneous speeds under the alternative hypothesis ($H_1$). However, Maddala and Wu (1999) rose critics towards the Im et al. (2003) test because many real data applications fail to exhibit cross-correlations that are similar to the simple version of those effectively eliminated by Im et al. (2003) while demeaning the data series. Thus, they proposed a panel unit root test based on Fisher (1932) which combines $p$-values of the test statistic in each residual cross-sectional unit. Using the additive property of the chi-squared variable, Maddala and Wu (1999) derived the following test statistic:

$$\lambda = -2 \sum_{i=1}^{N} \log_e \pi_i \tag{26}$$

where the non-parametric test displays a chi-square distribution with $2N$ degrees of freedom, where $N$ is the number of cross-sectional units or countries. Finally, $\pi_i$ refers to the $p$-value of the test statistic for unit $i$. Followingly, Breitung (2001) proposed a panel unit root test using the following extended functional form [later extended in Breitung and Das (2005)]:

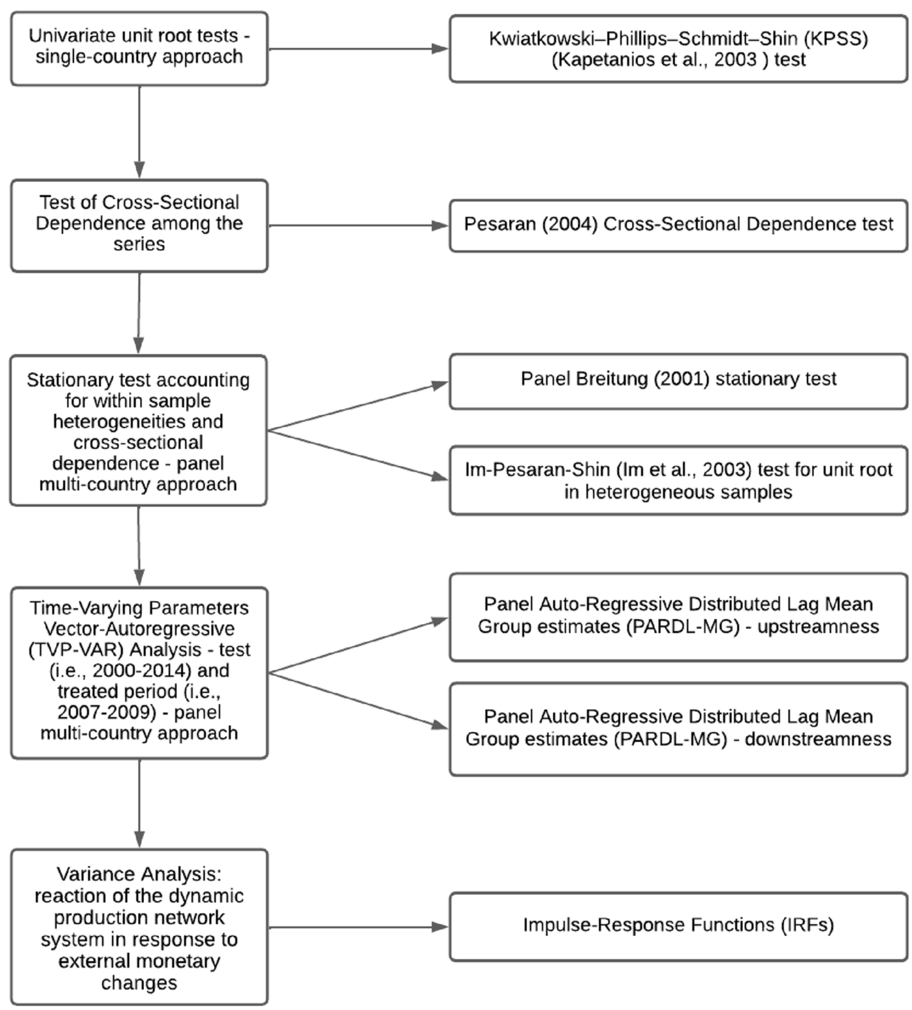


**Fig. 1** Stepwise time-series methodology. *Source*: Our elaboration

$$y_{it} = \alpha_{it} + \sum_{k=1}^{p+1} \beta_{ik} x_{i,t-k} + \varepsilon_t \tag{27}$$

where the null hypothesis laying under Breitung (2001) test statistic is difference stationarity $H_0 : \sum_{k=1}^{p+1} \beta_{ik} - 1 = 0$; against the alternative stationary $H_1 : \sum_{k=1}^{p+1} \beta_{ik} - 1 < 0$ for all $i$. The following transformed vectors are used to construct the test statistic:

$$\left| \begin{array}{l} Y_i^* = AY_i = \left[y_{i1}^*, y_{i2}^*, \ldots, y_{iT}^*\right]' \\ X_i^* = AX_i = \left[x_{i1}^*, x_{i2}^*, \ldots, x_{iT}^*\right]' \end{array} \right. \tag{28}$$

Which leads to the following Maddala and Wu (1999)-augmented test statistic, displaying the advantageous feature of having a standard normal distribution:

$$\lambda_B = \frac{\sum_{i=1}^{N} \sigma_1^{-2} Y_i'^* X_i'^*}{\sqrt{\sum_{i=1}^{N} \sigma_1^{-2} X_i'^* A' A X_i'^*}}. \tag{29}$$

## 4 Summary of the stepwise methodology

In sum, understanding the structure and properties of production networks is essential to identify the transmission channels of monetary shocks. While growingly studied, this literature keeps displaying critical caveats from which G-7 economies cannot be spared. To fill this gap, this paper employs a version of Time-Varying Parameters Bayesian Vector-Autoregressions (TVP-VAR) to investigate the responses of production networks (upstream and downstream dynamics) to endogeneous monetary shocks on key macro indicators (GDP, GDP deflator, exchange rate, short-term and long-term interest rates), over two distinct time-lengths: a test (i.e., 2000–2014) and a treated period (i.e., 2007–2009, "the Great Recession"). Prior, key statistical conditions are checked using a stepwise testing framework including the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. 2003—KPSS) and Breitung (2001) unit root tests; followed by the Pesaran (2004) Cross-sectional Dependence (CD) test; and the Im–Pesaran–Shin (Im et al. 2003) test for unit root in heterogeneous samples. Panel Auto-Regressive Distributed Lag Mean Group estimates (PARDL-MG) helped drawing the response functions of production networks to monetary policy shocks over short- and long-runs, and stratified by country and sector, and followed by Impulse Response Functions (IRFs) simulations to model impact of monetary policy shocks on GDP in a time-varying Vector-Autoregressive (VAR) setting. The stepwise time-series methodology is outlined in Fig. 1.

## 5 Data collection, empirical results and discussion

For the purpose of the analysis, we collected annual series spanning the largest and most relevant period. The average IRs are computed as means of the quarterly IRs. First, the panel data models are performed for the entire period (2000–2014). Second, the models are built for the period 2007–2009 that corresponds to the Great Recession. The data from input–output tables are available only until 2014. Based on such data availability constraint, two distincts models are performed over each time period: short-term and long-term interest rates.

The TVP-VAR models are based on quarterly data related to G-7 economies: France, Italy, Germany, United Kingdom, Japan, Canada and United States. The quarterly time series refer to GDP deflator as a proxy for inflation, real GDP, nominal effective exchange rate, short term interest rate and 10-year long-term interest rate. The quarterly data are provided by OECD for the period 2000–2014. The annual network measures for downstreamness and upstreamness are computed using the World Input–Output Tables.[1] Table 8 summarizes the preliminary statistics of the data and is provided in "Appendix".

Before conducting the estimation strategy, we assess the integration properties of the data using the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. 2003—KPSS) stationarity test. Both growth rates of real GDP and GDP deflator (log-transformed) are considered in the analysis. We remind here that rate of log corresponds to $\frac{\log{[GDP]_{(t)}}}{\log{[GDP]_{(t-1)}}}$.

Associated results are presented in Table 1. In the case of KPSS test, null hypothesis states stationarity (no unit root). If the statistics of the test is lower than critical value, the data series is stationary. Critical value at 1% significance level is 0.739 for KPSS

[1] Those series are available at: <http://www.wiod.org/database/wiots16>.

**Table 1** Results of the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root test. *Source*: Our elaboration

| Country | Variables | LM-stat. | Critical value at 1% significance level |
|---|---|---|---|
| Canada | Rate of log(GDP) | 0.227736 | 0.739 |
| | | 0.089441 | 0.216 |
| | Rate of log(deflator) | 0.280397 | 0.739 |
| | | 0.063875 | 0.216 |
| | Exchange rate | 0.164799 | 0.739 |
| | | 0.094059 | 0.216 |
| | Short-term interest rate | 0.643753 | 0.739 |
| | | 0.101512 | 0.216 |
| | Long-term interest rate | 1.272272 | 1.739 |
| | | 0.135393 | 0.216 |
| | Upstreamness | 0.124288 | 0.739 |
| | | 0.099644 | 0.216 |
| | Downstreamness | 0.335746 | 0.739 |
| | | 0.116678 | 0.216 |
| France | Rate of log(GDP) | 0.246043 | 0.739 |
| | | 0.123371 | 0.216 |
| | Rate of log(deflator) | 0.437472 | 0.739 |
| | | 0.101382 | 0.216 |
| | Exchange rate | 1.113382 | 0.739 |
| | | 0.179687 | 0.216 |
| | Short-term interest rate | 0.062984 | 0.739 |
| | | 0.068089 | 0.216 |
| | Long-term interest rate | 1.101004 | 1.739 |
| | | 0.181645 | 0.216 |
| | Upstreamness | 0.745996 | 0.739 |
| | | 0.183222 | 0.216 |
| | Downstreamness | 0.358485 | 0.739 |
| | | 0.193397 | 0.216 |
| Germany | Rate of log(GDP) | 0.050853 | 0.739 |
| | | 0.045384 | 0.216 |
| | Rate of log(deflator) | 0.345426 | 0.739 |
| | | 0.047690 | 0.216 |
| | Exchange rate | 0.915796 | 0.939 |
| | | 0.309825 | 0.316 |
| | Short-term interest rate | 0.647191 | 0.739 |
| | | 0.068981 | 0.216 |
| | Long-term interest rate | 0.121785 | 0.739 |
| | | 0.147959 | 0.216 |
| | Upstreamness | 0.557484 | 0.739 |
| | | 0.201648 | 0.216 |
| | Downstreamness | 0.489299 | 0.739 |
| | | 0.178668 | 0.216 |

**Table 1** (continued)

| Country | Variables | LM-stat. | Critical value at 1% significance level |
|---|---|---|---|
| Italy | Rate of log(GDP) | 0.189686 | 0.739 |
| | | 0.074762 | 0.216 |
| | Rate of log(deflator) | 0.984406 | 0.739 |
| | | 0.051051 | 0.216 |
| | Exchange rate | 0.390777 | 0.739 |
| | | 0.200546 | 0.216 |
| | Short-term interest rate | 0.062984 | 0.739 |
| | | 0.068089 | 0.216 |
| | Long-term interest rate | 0.662114 | 0.739 |
| | | 0.151603 | 0.216 |
| | Upstreamness | 0.338665 | 0.739 |
| | | 0.088578 | 0.216 |
| | Downstreamness | 0.375655 | 0.739 |
| | | 0.196338 | 0.216 |
| Japan | Rate of log(GDP) | 0.094899 | 0.739 |
| | | 0.056875 | 0.216 |
| | Rate of log(deflator) | 0.713944 | 0.739 |
| | | 0.078380 | 0.216 |
| | Exchange rate | 0.587962 | 0.739 |
| | | 0.175654 | 0.216 |
| | Short-term interest rate | 0.288279 | 0.739 |
| | | 0.187179 | 0.216 |
| | Long-term interest rate | 0.683837 | 0.739 |
| | | 0.227800 | 0.216 |
| | Upstreamness | 0.184647 | 0.739 |
| | | 0.087730 | 0.216 |
| | Downstreamness | 0.447869 | 0.739 |
| | | 0.195547 | 0.216 |
| UK | Rate of log(GDP) | 0.211934 | 0.739 |
| | | 0.087871 | 0.216 |
| | Rate of log(deflator) | 0.103933 | 0.739 |
| | | 0.097026 | 0.216 |
| | Exchange rate | 0.762425 | 0.739 |
| | | 0.205703 | 0.216 |
| | Short-term interest rate | 0.932640 | 0.739 |
| | | 0.109169 | 0.216 |
| | Long-term interest rate | 0.115147 | 0.739 |
| | | 0.159973 | 0.216 |
| | Upstreamness | 0.284644 | 0.739 |
| | | 0.034274 | 0.216 |
| | Downstreamness | 0.363546 | 0.739 |
| | | 0.184738 | 0.216 |

**Table 1** (continued)

| Country | Variables | LM-stat. | Critical value at 1% significance level |
|---|---|---|---|
| US | Rate of log(GDP) | 0.091434 | 0.739 |
| | | 0.060068 | 0.216 |
| | Rate of log(deflator) | 0.436830 | 0.739 |
| | | 0.075610 | 0.216 |
| | Exchange rate | 0.286041 | 0.739 |
| | | 0.176599 | 0.216 |
| | Short-term interest rate | 0.544860 | 0.739 |
| | | 0.099498 | 0.216 |
| | Long-term interest rate | 0.190757 | 0.739 |
| | | 0.088616 | 0.216 |
| | Upstreamness | 0.345375 | 0.739 |
| | | 0.103656 | 0.216 |
| | Downstreamness | 0.448564 | 0.739 |
| | | 0.193664 | 0.216 |

model with constant and it is 0.216 for KPSS model with constant and trend. On the other hand, the same result is obtained if *p*-value is compared with 0.05. If *p*-value is higher than 0.5, the null hypothesis is not rejected and the data series is stationary at 1% significance level.

The null hypothesis of the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. 2003—KPSS) test states stationarity. Two types of models are considered: one including constant and another one including constant and linear trend. The results in Table 1 suggest that all the data series are stationary at 1% significance level. These data series are used to construct TVP-VAR models in Matlab. One TVP-VAR model is constructed for each country.

During the economic crisis, the ECB's monetary policy strategy kept its role as a guidepost for monetary policy decisions. The measures taken in countries like Italy, France and Germany were the response to usual circumstances characterized by instability in financial markets and high degree of uncertainty. The estimation of monetary shocks for these countries with a central bank might be justify by the high uncertainty in periods of crisis and by the implementation of the monetary policy measures with a certain delay.

The vector of variables used in the TVP-VAR model is represented by: nominal effective exchange rate, rate of log GDP rate, rate of log GDP, short-term and long-term interest rate for G-7 countries in the period 2000–2020 (quarterly data). We are interested in the impulse-response functions based on TVP-VAR model for each country. There are two versions of these functions: the impulse-response functions in the model with short-term interest rate (*ir1*) and the impulse-response functions in the model with long-term interest rate (*ir2*). There are persistent and negative responses of output in the case of *ir1* and *ir2*, excepting some periods. Increased volatility based on *ir1* is observed for the UK and Italy during the recession. Moreover, we conducted Impulse Response Functions (IRFs) experiments to simulate the reaction of the dynamic production network

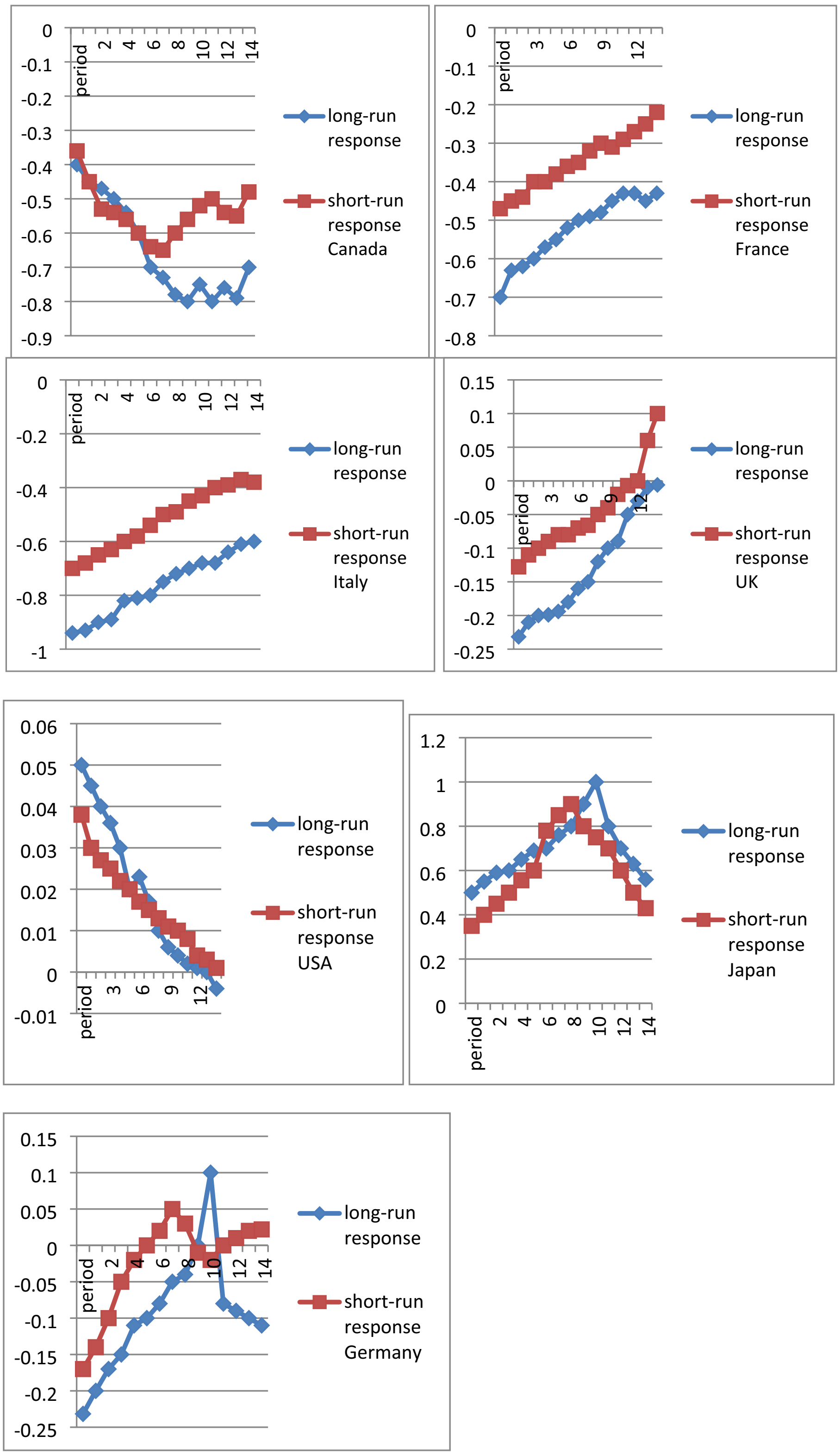


**Fig. 2** Impulse-response function: impact of monetary policy shocks on GDP in the long-run in a time-varying Vector-Autoregressive (VAR) setting. *Source*: Our elaboration

**Table 2** Results of the Pesaran's CD test. *Source*: Our elaboration

| Variables | Computed statistic | *p*-value |
|---|---|---|
| ir1 | 10.86 | < 0.05 |
| ir2 | 17.75 | < 0.05 |
| $up^{total}$ | 14.78 | < 0.05 |
| $up^{construction}$ | 8.08 | < 0.05 |
| $up^{fin}$ | 16.03 | < 0.05 |
| $up^{ins}$ | 13.34 | < 0.05 |
| $up^{estate}$ | 12.52 | < 0.05 |
| $down^{total}$ | 14.33 | < 0.05 |
| $down^{construction}$ | 10.23 | < 0.05 |
| $down^{fin}$ | 12.75 | < 0.05 |
| $down^{ins}$ | 13.95 | < 0.05 |
| $down^{estate}$ | 11.81 | < 0.05 |

**Table 3** Results of panel unit root tests. *Source*: Our elaboration

| Variable | Breitung unit root test | | Im–Pesaran–Shin unit root test |
|---|---|---|---|
| | Statistic (constant and trend) (no lag) data in level | Statistic (constant and trend) (one lag) data in level | Statistic for data in the first difference |
| ir1 | − 0.1703 | − 0.8892 | − 6.2170* |
| ir2 | − 0.1934 | − 0.9458 | − 5.9934* |
| $up^{total}$ | − 0.0226 | − 0.0522 | − 3.5900* |
| $up^{construction}$ | 0.9572 | 1.0230 | − 3.0416* |
| $up^{fin}$ | − 0.5906 | − 0.7778 | − 3.5677* |
| $up^{ins}$ | − 0.0453 | − 0.5564 | − 4.0023* |
| $up^{estate}$ | − 0.0676 | − 0.9084 | − 4.5332* |
| $down^{total}$ | 0.8874 | 1.0768 | − 3.9987* |
| $down^{construction}$ | 0.3324 | 0.6675 | − 4.0336* |
| $down^{fin}$ | 0.2286 | 0.5634 | − 4.1149* |
| $down^{ins}$ | 0.0153 | 0.2946 | − 4.2276* |
| $down^{estate}$ | 0.0785 | 0.3328 | − 3.7865* |

*Denotes *p*-value less than 0.05

system in response to external monetary changes, using a time-varying Vector-Autoregressive (VAR) model as a setting. Associated time-varying IRFs for each of the G-7 members are provided in Fig. 2 below: responses of GDP to shocks in short term interest rate (denoted for simplicity as short-run responses) and responses of GDP to shocks in long-term interest rate (denoted for simplicity as long-run responses). One interesting observation is that impulse-response functions present heterogeneous features across countries. In general, we observe quite similar strong response functions for France, Canada and Italy, whereas the US and UK exhibit weaker responses that quickly become negligible. That is, Japan offers a more non-linear pattern with the emergence of a turning point after which the trend seems to reverse. Notice that we later compute responses

**Table 4** Panel ARDL mean group (PARDL-MG) estimations—upstreamness (2000–2014 and 2007–2009). *Source*: Our elaboration

| **Upstreamness** | **Period: 2000–2014** | | **Period: 2007–2009** | |
|---|---|---|---|---|
| | ***ir1*** | ***ir2*** | ***ir1*** | ***ir2*** |
| *Short-run parameters* | | | | |
| $up^{total}$ | 0.311* | 0.427* | 0.176 | 0.045 |
| $up^{construction}$ | − 0.056 | − 0.045 | 0.276 | − 0.344 |
| $up^{fin}$ | − 0.067 | 0.386 | − 0.202* | − 0.887 |
| $up^{ins}$ | − 0.012 | 0.077 | − 0.106 | − 0.088 |
| $up^{estate}$ | − 0.265 | − 0.678* | 0.192 | 0.065 |
| *ECT* | | | | |
| $\Phi_j$ | − 0.204* | − 0.426* | − 0.588 | − 0.667 |
| *Long-run parameters* | | | | |
| $up^{total}$ | 0.715* | 0.688* | 0.567 | 0.778 |
| $up^{construction}$ | − 0.882 | − 0.905* | − 0.776 | − 0.722 |
| $up^{fin}$ | − 0.083 | 0.227 | − 0.456* | 0.567 |
| $up^{ins}$ | − 0.047 | − 0.225 | − 0.109 | − 0.227 |
| $up^{estate}$ | − 1.582* | − 2.667* | − 0.677 | 1.776 |
| Constant | 0.543* | − 0.873 | 1.027 | 2.339 |

*Denotes significant coefficient at 10% significance level

**Table 5** Panel ARDL mean group (PARDL-MG) estimations—downstreamness (2000–2014 and 2007–2009). *Source*: Our elaboration

| **Downstreamness** | **Period: 2000–2014** | | **Period: 2007–2009** | |
|---|---|---|---|---|
| | ***ir1*** | ***ir2*** | ***ir1*** | ***ir2*** |
| *Short-run parameters* | | | | |
| $down^{total}$ | − 0.009 | − 0.011 | 0.223 | − 0.103 |
| $down^{construction}$ | 0.187 | 0.212 | − 0.278 | 0.188* |
| $down^{fin}$ | − 0.098 | − 0.042 | − 0.045 | 0.008 |
| $down^{ins}$ | − 0.043 | − 0.022 | − 0.021 | 0.062 |
| $down^{estate}$ | − 0.223* | − 0.077 | − 0.199* | 0.155 |
| *ECT* | | | | |
| $\Phi_j$ | − 0.227* | − 0.287 | − 0.445* | − 0.327* |
| *Long-run parameters* | | | | |
| $down^{total}$ | 0.492* | 0.324 | 0.988* | − 0.078 |
| $down^{construction}$ | − 0.302 | − 0.278 | − 1.025* | − 0.167 |
| $down^{fin}$ | 0.007 | 0.188 | − 0.255* | 0.176 |
| $down^{ins}$ | 0.0006 | 0.103 | − 0.988* | 0.148 |
| $down^{estate}$ | − 0.883* | − 0.244 | − 0.805* | 1.229* |
| Constant | 0.055 | − 0.156 | 0.669 | − 0.327 |

*Denotes significant coefficient at 10% significance level

to shocks in both short-term and long-term rates. Below is reported the set of long-run and short-run responses.

**Table 6** Panel ARDL mean group (PARDL-MG) estimations—upstreamness (2000–2014 and 2007–2009) based on median impact of the shock in monetary policy. *Source*: Our elaboration

| Upstreamness | Period: 2000–2014 | | Period: 2007–2009 | |
|---|---|---|---|---|
| | *ir1′* | *ir2′* | *ir1′* | *ir2′* |
| *Short-run parameters* | | | | |
| $up^{total}$ | 0.287* | 0.343* | 0.166 | 0.039 |
| $up^{construction}$ | − 0.035 | − 0.033 | 0.255 | − 0.310 |
| $up^{fin}$ | − 0.055 | 0.366 | − 0.187* | − 0.995 |
| $up^{ins}$ | − 0.009 | 0.061 | − 0.098 | − 0.055 |
| $up^{estate}$ | − 0.230 | − 0.615* | 0.133 | 0.083 |
| *ECT* | | | | |
| $\Phi_j$ | − 0.211* | − 0.403* | − 0.539 | − 0.633 |
| *Long-run parameters* | | | | |
| $up^{total}$ | 0.694* | 0.703* | 0.521 | 0.799 |
| $up^{construction}$ | − 0.807 | − 0.905* | − 0.707 | − 0.455 |
| $up^{fin}$ | − 0.074 | 0.211 | − 0.422* | 0.502 |
| $up^{ins}$ | − 0.03 | − 0.209 | − 0.092 | − 0.207 |
| $up^{estate}$ | − 1.603* | − 2.511* | − 0.544 | 1.998 |
| Constant | 0.765* | − 0.679 | 1.574 | 2.766 |

*Denotes significant coefficient at 10% significance level

However, before performing the panel estimation, few conditions should be checked. Upon them, one should examine the presence of cross-sectional dependence among panel members, using the Pesaran (2004)'s Cross-Sectional Dependence test. Associated results are presented in Table 2.

According to Table 2, the null hypothesis of cross-section independence is rejected for all data series at 5% significance level. Given the balanced panel, the Breitung (2001) test is applied to check for unit root. For the data in first difference Im–Pesaran–Shin (Im et al. 2003) test for unit root in heterogeneous panels is used since the panel is unbalanced (see Table 4).

According to the results displayed in Table 3, the panel data are stationary only the in the first difference. Therefore, a potential cointegration relationship is checked using Westerlund test. Since the computed statistics are [for *ir1* as dependent variable stat. = 0.822 ($p$-value > 0.05) and for *ir2* as dependent variable stat. = 0.922 ($p$-value > 0.05)] when upstreamness is considered and when downstreamness is analyzed [for *ir1* as dependent variable stat. = 0.623 ($p$-value > 0.05) and for *ir2* as dependent variable stat. = 0.756 ($p$-value > 0.05)], the cointegration is rejected in both cases. Therefore, PARDL-MG models are estimated in this study.

According to estimations in Table 4 for upstreamness, the long-run relationship is significant for the entire period, but not during the Great Recession. Few conclusions might be drawn here. First, the short-run and long-run connection between aggregate upstreamness and monetary shocks is significant in the period 2000–2014. The influence of real estate is significant in the long-run, but also in the short-run when long-term interest rate is considered. The Great Recession confirmed the role of financial

**Table 7** Panel ARDL mean group (PARDL-MG) estimations—downstreamness (2000–2014 and 2007–2009) based on median impact of the shock in monetary policy. *Source*: Our elaboration

| **Downstreamness** | **Period: 2000–2014** | | **Period: 2007–2009** | |
|---|---|---|---|---|
| | ***ir1′*** | ***ir2′*** | ***ir1′*** | ***ir2′*** |
| *Short-run parameters* | | | | |
| $down^{total}$ | − 0.003 | − 0.008 | 0.219 | − 0.96 |
| $down^{construction}$ | 0.144 | 0.200 | − 0.207 | 0.177* |
| $down^{fin}$ | − 0.088 | − 0.033 | − 0.039 | 0.005 |
| $down^{ins}$ | − 0.032 | − 0.020 | − 0.028 | 0.054 |
| $down^{estate}$ | − 0.211* | − 0.074 | − 0.178* | 0.167 |
| *ECT* | | | | |
| $\Phi_j$ | − 0.255* | − 0.256 | − 0.436* | − 0.357* |
| *Long-run parameters* | | | | |
| $down^{total}$ | 0.387* | 0.311 | 0.899* | − 0.058 |
| $down^{construction}$ | − 0.387 | − 0.209 | − 1.019* | − 0.198 |
| $down^{fin}$ | 0.004 | 0.167 | − 0.237* | 0.114 |
| $down^{ins}$ | 0.0001 | 0.111 | − 0.977* | 0.167 |
| $down^{estate}$ | − 0.776* | − 0.289 | − 0.826* | 1.334* |
| Constant | 0.112 | − 0.133 | 0.557 | − 0.225 |

*Denotes significant coefficient at 10% significance level

sector in explaining monetary shocks in the long-run and short-run only if short term interest rate is taken into account.

The results in Table 5 for downstreamness indicate a long-run relationship only when short term interest is considered in the TVP-VAR model. In the case of downstreamness, the real estate sector had a significant impact in explaining the monetary shocks in the short and long-run during the Great Recession and in the entire period when short term interest rate is considered. In the long-run, all the sectors explained the monetary shocks during the economic crisis.

The mean impact of a shock in monetary policy for a certain country was used. However, for robustness check, median impact of the shock in monetary policy (ir1′ and ir2′) is considered in Tables 6 and 7.

According to estimations in Table 6 for upstreamness, the long-run relationship is confirmed again for the overall period, but not for the Great Recession. As in the previous case, the recession showed the contribution of financial sector to monetary shocks in the short and long-run when controlling for short term interest rate.

The results in Table 7 for downstreamness are robust with the previous ones based on the annual average of the response in the quarter the shock occurs. The real estate sector explained the monetary shocks in the short and long-run for overall period and during the recession when short-term interest rate is controlled.

Considering the above findings, three key conclusions can be drawn:

- *First*, the total upstreamness has a significant impact in the overall period (2000–2014) with important role in alleviating the monetary policy shocks. In the case of few major intermediate input users, a stronger spillover to upstream sectors is observed from augmented demand from lower interest rates. These major upstream sectors present less importance in final demand. On the other hand, the influence of downstreamness appears relatively weaker stronger and represents a non-negligible information for policy purpose.

- *Second*, the impact of real estate sector significantly grew which is in line with the expectations during the Great Recession. The growth of housing demand caused by expansionary monetary policy will be propagated downstream (Caraiani et al. 2020). On the other hand, more activities in other sectors are explained by the demand from real estate to these sectors which justify the growing importance of upstreamness.
- *Third and finally*, financial intermediation played a major role only during the Great Recession, the influence of financial sector being not relevant in the larger period (2000–2014). Our results corroborate those of Nobi et al. (2014) who stressed and emphasized the transmission role played by the financial sector during the recent global economic crisis and are in line with the *well-established narrative* of the recent financial crisis.

Our findings can be discussed and related to the current literature in networks and monetary shocks propagation. The fact that we empirically observe a significant impact from the total upstreamness in the overall period of study [i.e., with the observation of a stronger spillover to upstream sectors when lower interest rates trigger a positive demand reaction, for a few major intermediate input users, which recalls Miller and Temurshoev (2017)'s results] using real time-series data cannot be disconnected from Barrot and Sauvagnat (2016)'s major and pioneer conclusions derived from their modelling approach. These authors investigated whether and how firm-level idiosyncratic shocks propagate into production networks, and identified idiosyncratic shocks connected to the occurrence of natural disasters. They found that affected suppliers impose substantial output losses on their customers which translates into price adjustment whose costs are rather borne by the demand than the supply, especially when inputs embedding particularly valued characteristics are produced. In turn, output losses translate into significant market value losses, and do spill over to other suppliers, making them sensitive and vulnerable to exogenous shocks. The authors highlighted how the degree of input specificity confound the firm-level shocks-production network relationship and determines the how idiosyncratic shocks propagate to productive sectors, as a whole. Later, Grassi and Sauvagnat (2019) corroborated this theory by offering strong evidence that idiosyncratic shocks hitting one firm or sector in the economy do spread to other sectors through input–output linkages, by setting-up a framework demonstrating the implications of input–output analysis for competition policy (i.e., market shares and market power; imperfect competition with differentiated goods), followed by an empirical example of competition policy in production networks using French data series. Interestingly, they found that the effect of increased competition (i.e., proxied by a decrease of 24 percentage points of the markup in the "Transport Equipment" sector) in the transport equipment industry in France induces a 0.08% rise in the French GDP (about 2 billion euros). Naturally, it is worth noticing that the magnitude of the GDP response is only due to a relatively minor change in the markup charged by firms in one out of the 36 sectors in the French economy, which re-weight our appreciation of the relative importance of this sector in the global economic dynamic of this country. Accordingly, the authors showed that the GDP response to a reduction in the concentration in the Transport Equipment sector is relatively large and affects many sectors through the production network channel. Omitting the presence of a production network in a theoretical set-up which aims at capturing the economic effects of idiosyncratic shocks is likely to underestimate the effective magnitude of associated inferences and costs, equivalent to a downward bias emerging empirically for $\hat{\beta}$, which clearly connects with the main conclusions of the present paper. Finally, our findings corroborate those of Ozdagli and Weber (2017), when stating that production networks do represent a useful leverage through which idiosyncratic, unusual or exogenous shocks propagate within the productive units constituting the economy, but also play the role of active transmission channel along which, monetary policy changes succeed to trigger financial responses. But in general, we conclude that the production structure influences the transmission of monetary shocks in the G-7 economies, in line with Caraiani et al. (2020)'s main take-aways.

Besides, a methodological note can also be opened. While conventional VAR and Bayesian VAR methodologies have shown a strong potential in time-series prediction, they are based on constraining assumptions of linearity which avoid the possibility of time-variation in parameters. Mackowiak and Smets (2008) showed that a New Keynesian model with no additional real rigidities needs to be calibrated with a frequency of price adjustment much lower than that observed in microeconomic studies to match VAR-based estimates of the effect of monetary shocks on real variables. In addition, when integration properties of series do not meet the stationarity condition, associated estimates may be misleading and spurious. Furthermore, VAR models have been criticized for omitting to capture the underlying non-linearities operating in an economy, and especially in crisis and recession times (Lucas 1976). While they relax stationary assumptions, Time-Varying Parameters Vector Autoregressive (TVP-VAR) models emerged as a fruitful alternative to methodological caveats because they enable capturing a possible time-varying nature of the underlying structure in the economy in a flexible and robust manner. As shown by the above illustrative empirical analysis, TVP-VAR models displays the advantageous feature of improving predictability when series suffer from major structural breaks and non-linearities, which cannot be neglected when dealing with crisis and recession periods (Bekiros 2014).

## 6 Concluding remarks and policy implications

Understanding the structure and properties of production networks is essential to identify the transmission channels of monetary shocks. The production network at the level of company is generated by the supplier-customer linkages. However, most of the studies from literature use models that provide good approximations of these interactions, but at the industry level. Moreover, the research made in the network production literature is dominated by between- and within-firm connection assessments, probability of failure in the case of a firm, supplier-customer relationships seen in their endogenous formation, market power. While growingly studied, this literature keeps displaying critical caveats from which G-7 economies cannot be spared. To fill this gap, this paper employs a version of Time-Varying Parameters Bayesian Vector-Autoregressions (TVP-VAR) to investigate the responses of production networks (upstream and downstream dynamics) to endogenous monetary shocks on key macro indicators (GDP, GDP deflator, exchange rate, short-term and long-term interest rates), over two distinct time-lengths: a test (i.e., 2000–2014) and a treated period (i.e., 2007–2009,"the Great Recession"). Prior, key statistical conditions are checked using a stepwise testing framework including the Kwiatkowski–Phillips–Schmidt–Shin (Kapetanios et al. 2003—KPSS) and Breitung (2001) unit root tests; followed by the Pesaran (2004) Cross-sectional Dependence (CD) test; and the Im–Pesaran–Shin (Im et al. 2003) test for unit root in heterogeneous samples. Panel Auto-Regressive Distributed Lag Mean Group estimates (PARDL-MG) helped drawing the response functions of production networks to monetary policy shocks over short- and long-runs, and stratified by country and sector, and followed by Impulse Response Functions (IRFs) simulations to model impact of monetary policy shocks on GDP in a time-varying Vector-Autoregressive (VAR) setting. Findings clearly indicate that upstreamness forces dominated downstremness dynamics over the period 2000–2014, whereas the financial sector ermeges as the clear transmission channel through which monetary shocks affected production networks during the Great Recession. Adequate policy implications are supplied, along with a discussion on the forecasting potential of TVP-VAR methodologies when dealing with structural breaks and crisis time periods. Thus, our findings corroborate those of Ozdagli and Weber (2017)'s modeling approach, when stating that production networks do represent a useful leverage through which idiosyncratic shocks propagate within the economy, but also play the role of active transmission channel following which, monetary policy mechanisms influence the productive economy. But in general, we conclude that the production structure influences the transmission of monetary shocks in the G-7 economies, in line with Caraiani et al. (2020).

In general, this paper provides empirical evidence about the role of production network structure in the mechanism that characterizes the transmission of monetary policy shocks in G-7 countries. Besides aggregate measures of upstreamness and downstreamness, this research includes specific sectors that were deeper affected by recent financial crisis compared to other sectors. Compared to previous studies that were based on global upstreamness for a specific sector with global values starting from weights of countries, this research uses average upstreamness for G-7 countries and this measure is introduced in panel data models. The results supported the strong impact of total upstreamness and the influence of financial sector during the Great Recession. However, the scope of our results is limited by our sample size properties, which exhibit relatively small $T$ and $N$.

While we concur that the present study may exhibit limitations and caveats, we do highlight that it represents an interesting demonstration on how omitting the presence of a production network in an empirical set-up which aims at capturing the economic effects of idiosyncratic monetary shocks is likely to underestimate the effective magnitude of associated inferences and costs, equivalent to a downward bias emerging empirically for $\hat{\beta}$. Conversely, we emphasize that considering this channel in future impact evaluation may help offering estimations whose magnitudes converge to a more precise size effect. While our results are in line with the *well-established narrative* of the recent financial crisis, future studies should consider the co-movements of income trends operating among trade partners to control for eventual unidentified leakages. Such a research

**Table 8** Descriptive statistics. *Source*: Our elaboration

| **Country** | **UK** | | | | |
|---|---|---|---|---|---|
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 2,559,765 | 92.09 | 113.26 | 2.51 | 3.21 |
| Median | 2,546,382 | 92.5 | 109.29 | 0.87 | 3.57 |
| Maximum value | 2,954,951 | 119.2 | 141.47 | 6.36 | 5.60 |
| Minimum value | 2,126,096 | 73.5 | 91.81 | 0.04 | 0.25 |
| Standard deviation | 229,063.1 | 11.7 | 12.58 | 2.23 | 1.59 |
| | **US** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 16,710,911 | 91.91 | 111.72 | 1.91 | 3.31 |
| Median | 16,459,184 | 91.85 | 107.14 | 1.24 | 3.23 |
| Maximum value | 20,144,337 | 109.3 | 147.04 | 6.62 | 6.48 |
| Minimum value | 13,521,843 | 74 | 85.58 | 0.11 | 0.65 |
| Standard deviation | 1,864,814 | 10.36 | 15.24 | 1.91 | 1.32 |
| | **France** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 2,595,399 | 94.07 | 99.85 | 1.58 | 2.78 |
| Median | 2,614,073 | 95.6 | 99.67 | 1.06 | 3.30 |
| Maximum value | 2,926,847 | 108.8 | 102.76 | 5.02 | 5.57 |
| Minimum value | 2,253,220 | 79.6 | 97.84 | − 0.52 | − 0.31 |
| Standard deviation | 176,607.6 | 7.41 | 1.30 | 1.78 | 1.72 |
| | **Germany** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 3,659,890 | 93.47 | 101.30 | 1.61 | 2.49 |
| Median | 3,645,138 | 92.1 | 100.74 | 1.09 | 3.09 |
| Maximum value | 4,170,360 | 108.9 | 107.07 | 5.02 | 5.46 |
| Minimum value | 3,266,829 | 82.4 | 98.67 | − 0.47 | − 0.54 |
| Standard deviation | 286,329 | 7.62 | 1.94 | 1.78 | 1.83 |
| | **Italy** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 2,300,540 | 92.66 | 99.48 | 1.58 | 3.74 |
| Median | 2,298,718 | 94.05 | 99.48 | 1.06 | 4.18 |
| Maximum value | 2,452,427 | 105.7 | 101.93 | 5.02 | 6.61 |
| Minimum value | 1,914,178 | 74.1 | 97.24 | − 0.52 | 0.67 |
| Standard deviation | 74,291.36 | 9.04 | 1.07 | 1.78 | 1.42 |
| | **Canada** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 1,462,292 | 92.36 | 94.25 | 2.17 | 3.19 |
| Median | 1,440,582 | 93.8 | 94.69 | 1.74 | 3.18 |
| Maximum value | 1,741,488 | 109.9 | 108.87 | 5.87 | 6.28 |
| Minimum value | 1,175,337 | 73 | 83.08 | 0.23 | 0.54 |

**Table 8** (continued)

| | Canada | | | | |
|---|---|---|---|---|---|
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Standard deviation | 160,400.5 | 10.53 | 5.78 | 1.49 | 1.50 |
| | **Japan** | | | | |
| **Indicator** | **GDP** | **GDP deflator** | **Exchange rate** | **Short-term interest rate** | **Long-term interest rate** |
| Mean | 5,007,947 | 102.091 | 95.9 | 0.24 | 0.90 |
| Median | 5,004,952 | 101.1 | 90.8 | 0.11 | 1.04 |
| Maximum value | 5,388,769 | 111.5 | 150.34 | 0.88 | 1.91 |
| Minimum value | 4,637,627 | 96.2 | 73.6 | −0.06 | −0.21 |
| Standard deviation | 222,429.8 | 4.05 | 17.18 | 0.25 | 0.63 |

direction could be relevant since input networks may interact across borders. Besides the propagation of disaggregate shocks through interconnected economic sectors, the contribution of production networks in shaping long-run world economic trends should not be overlooked. If data availability allows that, relying on firm-to-firm-level data as suggested in Grassi and Sauvagnat (2019) would enable researchers to better identify the boundaries of studied concentrated markets; as well as open the door towards the analysis of vertical integration's effects between a firm and its outsourcers along each stage of the supply chain on the economy. Overall, wrangling sectoral series over a wider range of industries and countries would also help informing decision makers on which sectors are central for the propagation of monetary shocks; and whether monetary policies can fully smooth occurring breaks.

## Appendix

Table 8 displays the summary statistics of the data. Interestingly, Japan registered the highest GDP in the group, this value being observed in the third quarter of 2019. Canada reached the lowest value for maximum GDP. On the other hand, this country also registered the minimum value for real GDP. Japan reached the highest (last quarter of 2000) and the lowest (the second quarter of 2008) values for nominal effective exchange rate. The maximum inflation was registered by the UK in the second quarter of 2020 in the context of COVID-19 pandemic. Japan reached the highest deflation in the G7 group in the first quarter of 2013.

The amplitude of variation was, in general, high in the case of short term interest rate, while long-term interest rate registered less fluctuation. All the countries registered values less than 1 for minimum of short-term and long-term interest rate, while the maximum values for these two indicators are located in the interval [5;6] excepting Japan. This country registered the lowest values for minimum and maximum of short-term and long-term interest rates. Unlike most of the national banks in the world, Japan's central bank keeps the interest rate at low levels to reduce the inflation.

**Abbreviations**

| | |
|---|---|
| BIS | Bank for International Settlements |
| CD | Cross-sectional dependence |
| FED | Federal Reserve Bank |
| GDA | Gradient boosting algorithms |
| IID | Independent and identically distributed |
| ILO | International Labour Organization |
| IMF | International monetary fund |
| IPS | Im–Pesaran–Shin |
| KPSS | Kwiatkowski–Phillips–Schmidt–Shin |
| MG | Mean group |
| ML | Machine learning |
| PARDL-MG | Panel auto-regressive distributed lag mean group |
| PFE | Pooled fixed effects |
| STAN | Structural analysis |
| TSCS | Time-series cross-section |
| TSR | Tokyo shoko research |
| TVP-VAR | Time-varying parameters Bayesian vector-autoregressions |
| VAT | Value-added tax |

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