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Monetary Policy Shocks and Input–Output Characteristics of Production Networks

Petre Caraiani [1,2]

[1] Faculty of Business Administration in Foreign Languages, Bucharest University of Economic Studies, 010374 Bucharest, Romania; petre.caraiani@gmail.com; Tel.: +40-07-2441-5392
[2] Institute for Economic Forecasting, Romanian Academy, 050711 Bucharest, Romania

Abstract: This paper revisits the production network's role in transmitting monetary policy shocks. The study uses macroeconomic data for multiple OECD economies, for which it estimates the time-varying impulse response functions of GDP to monetary shocks. In contrast to recent macroeconomics papers focusing on upstreamness or downstreamness, the paper studies measures from the input–output literature, like average propagation length or fields of influence. When looking at the relationship between the production network measures and the impact of monetary policy shocks on GDP, measures like average propagation length or rows' fields of influence, amplify the negative impact of the monetary policy shocks, while the forward linkage dampens them.

Keywords: production network; input–output; monetary policy; networks

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1. Introduction

With the growth of the importance of networks in the study of economics, see earlier work by Hulten (1978) or Horvath (1998), or recent studies by Acemoglu et al. (2012), Gabaix (2011) or Acemoglu et al. (2016), there is an increased interest in evaluating the importance of networks in the transmission of shocks. Although some studies have been carried out on the role of networks for the transmission of monetary policy shocks, see Weber and Weber (2017) for the case of the stock market or Caraiani et al. (2020) or Ghassibe (2021) at the macroeconomic level, the issue remains relatively open.

This paper aims to answer the question of whether the production network matters for the propagation of monetary policy shocks to the real GDP. In approaching the issue of the impact of monetary policy by focusing on production network, it departs from the previous literature (see the section on the literature review below) in a few ways.

First, it uses a multi-country approach, while most of the previous papers focus on the case of the United States. It also considers a heterogeneous set of countries, using countries from different geographical areas, although the common denominator is that they are all part of the OECD.

Second, it considers a different set of network measures, based on input–output analysis. Most of the research discussed focuses on either upstreamness and downstreamness, which are easier to interpret from an economic point of view, or measures like density and clustering, which are harder to interpret from an economic point of view. The input–output coefficients have been used in economic analysis in the past, although less so in macroeconomics.

Third, it focuses on a specific sample around the last financial crisis from 2007–2009. This is justified by the fact that most countries used monetary policy measures to counteract the negative impact of monetary policy, while, at the same time, the crisis significantly affected the GDP in these countries. While there might be arguments against the use of older data, since this is the last major financial crisis, the results remain relevant for the future.

2. Literature Review

This section focuses on the literature review on this topic: namely, the role of production networks in amplifying the impact of monetary policy shocks.

There are several approaches used in the literature. Weber and Weber (2017) studied the transmission of monetary policy shocks on the stock market by focusing on the importance of production networks. Using spatial regression methods and identifying monetary policy shocks based on event studies, they found a strong network effect that accounted for about 50% to 80% of the overall impact. The paper focused on stock market return and studied only the case of the US, while the present paper considers multiple countries and focuses on GDP response.

An extension of this work was conducted in Di Giovanni and Hales (2022), who studied the impact of monetary policy shocks on the returns at sectoral levels in different countries. They used a spatial structural autoregression model where the global production linkages gave the matrix of weights. Their main finding was that the network linkages explained about 70% of the impact of monetary policy shocks on sector–country returns. However, the present study focuses rather on the role of the production network in the responses of GDP to monetary policy shocks.

Alternatively, Caraiani et al. (2020) studied the impact of monetary policy shocks using production networks. The paper used a two-stage approach, with time-varying impulse response functions derived in the first stage and the impact of network measures on them evaluated in the second. However, the paper focused only on certain measures of a network, i.e. upstreamness and downstreamness. In contrast, the current study uses a much larger set of network measures.

Some studies were carried out with more emphasis on the theoretical framework. For example, Ghassibe (2021) studied the effects of monetary policy shocks on real macroeconomic variables in the US. He found that between 20% and 45% of the effects of monetary policy come through the input–output linkages. Their empirical results are based on a multi-sectoral New Keynesian model with sector-specific price rigidity.

In a more theoretical contribution, La'o and Tahbaz-Salehi (2022) studied optimal monetary policy in a multi-sector economy in which firms buy and sell within a production network. Optimal monetary policy implements a price index for which a greater weight is attached to sectors that are simultaneously larger, stickier, and more upstream.

Another study with a slightly different focus, due to Caraiani (2019), focused on the impact of oil shocks and used a more extensive set of network measures (like density, sector dominance, clustering). In contrast, this paper combines the research on monetary policy shocks with measures derived from input–output analysis, which are easier to interpret from an economic point of view.

The paper is also related to the larger literature strand on monetary policy and the impact on the real economy. While the mandate of central banks refers to price stability, the central banks have also a duty to ensure economic growth (ECB), to reach maximum employment (FED), to support economic growth (Bank of England), to develop the economy (Bank of Japan). As such, one of the topics of high interest in monetary policy is how this affects the output.

As the paper focuses on a sample around the financial crisis from 2007–2009, some mention should be made about the specific actions taken by central banks during this period. Corbo (2010) cites a number of policy actions taken by central banks to stabilize the financial system, including the use of liquidity, the lowering of interest rates, or non-conventional policy measures which became prominent as the nominal interest rates reached the zero lower bank. While the research here does not address the impact of monetary policy shocks during this period on the financial system, the research is, nevertheless, related to this literature as it studies the actual impact on the real economy.

A related paper, Buiter (2008), discusses the performance of the main central banks (FED, ECB and Bank of England) during the financial crisis. The paper finds that the FED performed the worst. Overall, the author finds that central banks were ill prepared for a financial crisis and pretty much did not perform at their best to ensure the stability for the macroeconomy and the financial markets.

3. Modeling Framework

3.1. A Time-Varying BVAR Model

The econometric model used to derive the impulse response functions is a Bayesian VAR model with time-varying coefficients. I used the model proposed by Primiceri (2005). We can formally write it as follows:

$$x_t = a_{0,t} + A_{1,t}x_{t-1} + \ldots + A_{p,t}x_{t-p} + u_t \quad (1)$$

Here x_t is the vector with the endogenous variables, $a_{0,t}$ is the time-varying intercepts vector and $A_{i,t}$ represents the matrices with the time-varying coefficients. It is assumed that u_t is a white noise Gaussian process characterized by a zero-mean and a Σ_t covariance matrix. Furthermore, the reduced form innovations u_t are taken to be linear transformations of the underlying structural shocks, that is $u_t = S_t\epsilon_t$. It is also assumed that $E\{\epsilon_t\epsilon_t'\} = I$, $E\{\epsilon_t\epsilon_{t-k}'\} = 0$ and $S_tS_t' = \Sigma_t$.

Following Gali and Gambetti (2015), the vector of endogenous variables is given by $x_t = [\Delta y_t, \pi_t, \Delta\pi_t^e, r_t]'$. The variable y_t is the GDP, π_t stands for inflation, π_t^e measures inflation expectations[1]. Meanwhile, r_t is the Central Bank's interest rate.

The study follows a recursive approach to identify the monetary policy shocks as in Gali and Gambetti (2015). It assumes that the monetary policy shocks do not impact the GDP or inflation contemporaneously.

3.2. Characterizing Production Networks

This section presents the measures used in the network analysis of the production networks. It looks at several measures that are based on input–output analysis. The presentation follows several reference papers and books; see, for example, Miller and Blair (2009) and Aldasoro and Angeloni (2015).

We can start from an input–output table. This table corresponds to a matrix characterized by dimensions of $N \times N$. Here N gives the number of sectors in the economy. I denote the final product in any sector i by x_i, and the final demand by f_i. The equation below shows the connection between the three variables.

$$x_i = z_{i1} + \ldots + z_in + f_i = \sum_{j=}^{N} z_{ij} + f_i \quad (2)$$

Each $z_{i,j}$ gives the sales between the different industries, namely the sales from an industry i to the sector j. This equation shows how the production from a certain sector i is distributed. However, we can also write this equation in a simpler manner as follows:

$$x = Zi + f \quad (3)$$

x stands for the vector of production for an industry, Z represents a matrix, f is also a vector, and i is a vector consisting of values of one. We can construct a matrix $\hat{x}$, which has the values of the x on the main diagonal. We can write:

$$A = Z\hat{x}^{-1} \quad (4)$$

Since we also have $x\hat{x}^{-1} = I$, we obtain:

$$(I - A)x = f \quad (5)$$

This allows us to write the Leontief matrix as follows $L = (I - A)^{-1}$. This shows the relation between the output given by x and the final demand. While the Leontieff equation shows the demand perspective, we can also have a supply-side approach, see Ghosh (1958), where we start from:

$$x' = i'Z + v' \quad (6)$$

v' stands for total expenditures at sectoral level while $Z = \hat{x}B$. The interpretation is different this time. While A contains the technical coefficients, B consists of the allocation coefficients. At the same time, we also have $i'\hat{x} = x'$, such that we obtain:

$$x' = i'Z + v' = x'B + v' \tag{7}$$

From here, we obtain:

$$x' = v'(I - B)^{-1} \tag{8}$$

We can compute the matrix $G = (I - B)^{-1}$. The value G can be seen as showing the inverse of the output (in contrast to L, the inverse of the input). Each element of the G matrix gives the total value of production in sector j corresponding to a unit of input from sector j. We can construct several measures to characterize the production network using these two matrices.

We can start with the measures of backward linkage and forward linkage, see the early work by Hirschman (1958) and Rasmussen (1956). We can start from a scenario where there is growth in the production of sector j, leading to growth for inputs used in this sector. This growth leads to a backward linkage effect from the demand side. At the same time, we can also consider a similar scenario from the supply side. If there is growth in sector j this leads to an increased supply of goods produced in sector j, which leads to the notion of forward linkage.

Formally, the backward linkage index Rasmussen–Hirschman (RHB, hereafter) can be written as:

$$h_{b_j} = Ni'L/i'Li \tag{9}$$

Here the normalized form is used. From the supply side, a forward linkage Hirschman–Rasmussen index (RHF) can be similarly constructed:

$$h_{b_j} = Ni'G/i'Gi \tag{10}$$

RHB is backward as it reflects shocks from the demand side, while RHF is forward, quantifying the shocks from the supply side.

Another measure that the study uses is the influence field, following Sonis et al. (1995), Sonis and Hewings (2009). To derive it, one can start by measuring a change in L when there is a change in one or several elements of it. This can be written as:

$$F(i,j) = (Li_i)i_j'L = l_i l_j' \tag{11}$$

l_i, and l_j' represent the rows and columns of the Leontieff matrix L. The influence field at the column level can then be formally written as follows:

$$f_{c_j} = N\frac{i'(\sum_{i \neq j} F(i,j))i}{i'\sum_{j=1}^{n}\sum_{i \neq j} F(i,j)i} \tag{12}$$

This expression is in normalized form. One can follow a similar procedure to derive the field influence at row level, resulting in the following normalized formula:

$$f_{r_j} = N\frac{i'\sum_{j \neq i} F(i,j)i}{i'\sum_{i=1}^{n}\sum_{j \neq i} F(i,j)i} \tag{13}$$

Another measure to be used is the total linkage. This measure was first proposed by Cella (1984).

$$t_j = N\frac{i'x - i'x^j}{i'x} \tag{14}$$

Again, x represents the production vector for a given industry. First, we employ the hypothetical extraction method, which implies eliminating a sector. We employ $i'x^j$ to denote the case when a sector j has been eliminated from the economy.

The last measure to be employed is the average propagation length (APL, hereafter). This coefficient has been proposed by Dietzenbacher et al. (2005) or Dietzenbacher and Romero (2007). It quantifies the distance between industries or, more intuitively, how a shock propagates between different industries. First of all, we can define a matrix H, which can be written as:

$$H = L(L - I) \tag{15}$$

Using the above defined matrix, APL is defined as follows:

$$APL = \begin{cases} (h_i j)/(l_i j), i \neq j, \\ (h_i j)/(l_i j - 1), i = j \end{cases} \tag{16}$$

4. Data

The study uses a sample of OECD economies. In total, 24 OECD members were selected. The sample covered the period between 1990 first quarter and 2017 last quarter, see Appendix A.

The analysis uses macroeconomic data to estimate the time-varying Bayesian VAR model. It selected quarterly frequency time series from the OECD database for GDP, the GDP deflator, a commodity-based index for the US, the nominal effective exchange rate for the other countries, and the reference interest rate in each country.

The study takes into account the zero lower bound where possible by using the shadow interest rate, following Wu and Xia (2016)[2]. The data source for the commodity price index and the long-term interest rate used for Mexico was FRED. As an alternative to the shadow interest rate, I used the long-term interest rate (which is not affected by the zero lower bound).

A different database used was the data on input–output matrices for which the source was the OECD STAN. The paper employed the 2018 version and used yearly data for input–output matrices between 2005 and 2011.

5. Results

We look first at the impact of monetary policy shocks on GDP at the country level, after estimating Bayesian VAR models for each country, see Section 5.1, then the estimated impact shocks in panel regression are used to determine their dependence on various network and input–output measures, see Section 5.2.

The estimation was done here at the country-level. Thus, it considers that the central banks in the sample (see Appendix B) might have behaved differently during the financial crisis. The section below discusses the differences in results concerning the impact of monetary policy shocks on GDP.

5.1. Standard VAR Approach

The first part of the analysis estimates and obtains the impulse response functions of GDP to monetary policy shocks. I estimated the time-varying BVAR model in Equation (1) using a Bayesian approach. The estimation uses the Gibbs algorithm to do the Bayesian estimation. The prior choices can be found in Primiceri (2005). The estimation of the BVAR model is done at the country level.

The results are available upon request. They indicate the cumulative IRFs to one standard deviation in the interest rate at 20 periods ahead. There is a negative response by GDP to the monetary policy shocks except for a few periods. We can also see rising volatility around the Great Recession (2008–2009). There is also a short period during which there is a flip in the sign (that is for Australia, Belgium, Denmark, Norway, the UK, and the United States).

5.2. Incorporating Network Measures into Monetary Policy Impact Analysis

5.2.1. Methodology

The second stage of the econometric analysis estimates whether different measures of production network matter for the transmission of monetary policy shocks to the real economy (as measured through the impact of these shocks on real GDP). I considered two measures: a short-term impact, taking into consideration the average impact over the first four quarters (1 year), and a long-term impact, taking into account the average first twenty quarters (5 years). Using these measures makes the endogenous variable less prone to variations if only one period is used (e.g., the fourth quarter).

The following panel specification was employed to quantify the impact of different network measures:

$$irf_{j,t} = \beta_0 + \beta_1 n_{j,t} + \epsilon_{j,t} \tag{17}$$

Here $irf_{j,t}$ stands for the mean impact of a monetary policy shock for a given country j at time t, either at the 1-year horizon or at five years. The coefficient β_0 stands for the intercept. Then, $n_{j,t}$ stands for the network measures discussed in Section 3.2, while their impact on the IRFs is measured through the estimated coefficient β_1 and $\epsilon_{j,t}$ is the residual. I used a fixed effects approach (the random effects approach was rejected for each case). Furthermore, data was at an annual frequency (the IRFs are aggregated at an annual level) for the mean IRFs. At the same time, the network measures were derived based on annual input–output data (a robustness exercise was done for quarterly estimates of input–output data).

The analysis used two different windows around the financial crisis from 2007–2009. First, it used a short window consisting only of three years, from 2007 to 2009. However, it also used a six years window with data from 2005 to 2011 (namely, data for years 2005, 2007, 2008, 2009, and 2011). A further robustness exercise implied the use of 10 years' long-term interest rate, which was associated with government bonds.

In the second step, the analysis aimed to answer the central question in this paper, whether the network measures have a significant role in the propagation of monetary policy shocks. Using a panel regression approach with fixed effects allows one to see whether there is a role for the different network measures used while also allowing for country differences.

5.2.2. Baseline Results

The results are shown in Table 1 for the sample 2005–2011 and Table 2 for the sample 2007–2009. On the one hand, most coefficients were not statistically significant. On the other hand, there were a few key results that can be underlined.

Table 1. Sample 2005–2011.

	VAR Using Shadow Interest Rate		**VAR Using 10 Years Interest Rate**	
Variables	**Short Term Shock**	**Long Term Shock**	**Short Term Shock**	**Long Term Shock**
Constant	−0.228172	−1.768846	0.060942	−3.524160
	(0.601275)	(3.355330)	(0.873214)	(2.397712)
F_c	0.000594	0.000628	−0.002758	−0.003620
	(0.000966)	(0.004916)	(0.004497)	(0.012198)
F_r	−0.001411	−0.012879	−0.002385	−0.036900 **
	(0.008683)	(0.046210)	(0.006677)	(0.018111)
APL	0.016320	0.127267	−0.470731	1.427071
	(0.225778)	(0.766228)	(0.490818)	(1.512345)
T_av	0.001833	−0.006714	−0.002777 *	−0.009350 **
	(0.002390)	(0.012673)	(0.001484)	(0.003613)
RHB	0.001689	0.453119 ***	0.431993 ***	1.073200 ***
	(0.032347)	(0.072053)	(0.140790)	(0.335915)
RHF	0.132360	0.892075	0.359707	4.632593 *
	(0.979907)	(4.872110)	(0.886914)	(2.531392)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	120	120	115	115
R^2	0.98	0.97	0.97	0.95

Note: * denotes statistical significance of the F-test at 0.10 level; ** statistical significance at 0.05 level and *** at 0.01 level.

The smaller sample, 2007–2009, indicated a consistent amplifying role for the average propagation length. For the columns' field of influence F_c, the impact was positive, suggesting a dampening role. In the larger sample, we also identified a clear dampening role of the Rasmussen–Hirschman backward index (RHB), while total linkage T_{av} tended to amplify the negative impact of monetary policy shocks.

We can also see that the results were influenced by the sample choice or the interest rate used in the estimation of the BVAR model.

Table 2. Sample 2007–2009.

	VAR Using Shadow Interest Rate		VAR Using 10 Years Interest Rate	
Variables	**Short Term Shock**	**Long Term Shock**	**Short Term Shock**	**Long Term Shock**
Constant	0.852586	1.240024	2.821854 **	9.995071 **
	(0.971600)	(2.902831)	(1.050945)	(4.13980)
F_c	−0.000159	−0.001219	0.002229 **	0.009494 **
	(0.000926)	(0.002766)	(0.000999)	(0.003935)
F_r	0.003334	0.006449	0.002387	0.011894
	(0.002465)	(0.007364)	(0.002689)	(0.010591)
APL	−0.009709	−0.431226	−1.071616 ***	−3.360880 **
	(0.317436)	(0.9483989)	(0.349563)	(1.376974)
T_av	−0.032746	−0.005676	0.046678	0.038113
	(0.071152)	(0.212580)	(0.076262)	(0.3004051)
RHB	-0.073437	−0.339490	0.042724	0.058545
	(0.084072)	(0.251182)	(0.089877)	(0.354037)
RHF	−0.452264	−0.342382	−0.522790	−2.604085
	(0.559346)	(1.671148)	(0.614379)	(2.420119)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	69	69	69	69
R^2	0.99	0.98	0.98	0.96

Note: ** denotes statistical significance of the F-test at 0.05 level and *** at 0.01 level.

6. Additional Results

6.1. Production Network Properties and the Impact of Monetary Policy Shocks: Quarterly I–O Results

We move here to the first robustness exercise. Given the fact that recent research has shown that quarterly Input–Output matrices can be estimated by combining data from the already available annual Input–Output tables with the quarterly data on GDP by sectors and expenditure, see Avelino (2017), we could first estimate quarterly Input–Output matrices for the countries for which data was available, following the methodology in Avelino (2017). Although it was not possible to find data for all the countries analyzed for the annual case, there were still enough data to consistently estimate quarterly Input–Output tables for a significant number of countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Mexico, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, UK, USA).

The analysis was repeated on the estimated quarterly I–O tables using the data that we already had for the impulse response functions. The results are shown in Table 3 for the 2005–2011 sample and Table 4 for the sample 2007–2009.

First, one can notice that there was a larger number of coefficients that were statistically significant. Second, the results seemed more robust across the samples or the two alternative VAR specifications.

For the smaller sample, there was a dampening role for the columns' field of influence or for the Rasmussen–Hirschman forward index. Furthermore, the average propagation index indicated an amplifying role again, as did the rows' field of influence or RHB. In terms of the total linkage effect, this was found to have a dampening role (taking out a sector smoothed the impact of the shocks). When analyzing the larger dataset between 2005 and 2011, the results remained pretty robust in terms of significance and sign. Average propagation length, or the rows' field of influence, had an amplifying role, while RHF, the columns' field of influence, and total linkage effect, were found to smooth the shocks.

Table 3. Sample 2005–2011.

	VAR Using Shadow Interest Rate		VAR Using 10 Years Interest Rate	
Variables	**Short Term Shock**	**Long Term Shock**	**Short Term Shock**	**Long Term Shock**
Constant	0.778039 **	−1.247803	−5.946580 ***	−7.332207 ***
	(0.331373)	(1.335273)	(1.517736)	(1.483784)
F_c	0.037858	−0.210721	−0.373238	0.070540
	(0.040270)	(0.159519)	(0.301527)	(0.203836)
F_r	0.018068	0.156866	0.054438	−0.333849 *
	(0.026536)	(0.111172)	(0.266850)	(0.178875)
APL	−0.779347 ***	−1.022787 *	−0.793867 *	−2.739725 ***
	(0.188962)	(0.589018)	(0.413587)	(0.625798)
T_av	0.141532 ***	0.072293	0.269326	0.488923 ***
	(0.029305)	(0.075456)	(0.197974)	(0.115973)
RHB	−1.35063	6.484677	9.078438	−3.535077
	(1.396306)	(5.555320)	(10.64256)	(6.970547)
RHF	1.116199	−4.290177	0.319806	14.45134 **
	(1.013516)	(4.166880)	(9.820343)	(6.473956)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	420	420	420	420
R^2	0.93	0.94	0.97	0.96

Note: * denotes statistical significance of the F-test at 0.10 level; ** statistical significance at 0.05 level and *** at 0.01 level.

Table 4. Sample 2007–2009.

	VAR Using Shadow Interest Rate		VAR Using 10 Years Interest Rate	
Variables	**Short Term Shock**	**Long Term Shock**	**Short Term Shock**	**Long Term Shock**
Constant	1.819336 ***	1.875021	−3.798625	−0.881751
	(0.671370)	(3.243204)	(3.619549)	(2.945896)
F_c	0.093713 **	−0.181926	0.296016	0.624964 ***
	(0.047406)	(0.276118)	(0.361172)	(0.221630)
F_r	−0.034912	0.237481	−0.547647 **	−0.663741 ***
	(0.027057)	(0.168202)	(0.282456)	(0.132409)
APL	−0.217645	−0.402678	−0.931216 ***	−2.627528 **
	(0.286841)	(0.948791)	(0.398507)	(1.116856)
T_av	0.187944 ***	0.224569	1.069157 ***	0.871336 ***
	(0.059778)	(0.300661)	(0.344729)	(0.222916)
RHB	−3.441952 **	6.756260	−15.26395	−23.49142 ***
	(1.653273)	(9.598325)	(12.25703)	(7.411267)
RHF	1.353960	−8.928161	21.73512 **	26.34981 ***
	(1.097228)	(6.368217)	(10.03447)	(6.666966)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	252	252	252	252
R^2	0.96	0.97	0.89	0.97

Note: ** statistical significance at 0.05 level and *** at 0.01 level.

6.2. Production Network Properties: Do They Improve the Forecasting of GDP Responses?

In this final robustness section, we look at whether the inclusion of the different network measures considered throughout this paper improved forecasting accuracy. In this forecasting exercise, the analysis adopted a different perspective on the role of the I–O network measures by considering whether models that included network variables led to more accurate forecasting of the main variables of interest in this paper, i.e., the responses of GDP to monetary policy.

We start by considering a baseline AR(1) model for the modeling of the impact of monetary policy shocks on GDP:

$$irf_{j,t} = \beta_0 + \beta_1 irf_{j,t-1} + \epsilon_{j,t} \tag{18}$$

Here, as above, $irf_{j,t}$ is the impulse response function of GDP at time t for country j. I considered an augmented AR(1) model as an alternative model, including measures like average propagation length, fields of influence (for rows or columns), and the forward and backward Rasmussen–Hirschman indices. I used the larger sample between 2005 and 2011 and focused on quarterly data to have enough observations. The results are shown below, in Table 5 for the baseline specification, as well as in Table 6 for the alternative specification.

We can analyze the accuracy of the forecasting accuracy using standard statistics like root mean square error (RMSE), mean absolute error (MAE), and Theil inequality coefficient (Theil), as defined below:

$$rmse_{j,t} = \sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_{j,t} - y_{j,t})^2 / h} \tag{19}$$

$$mae_{j,t} = \sum_{t=T+1}^{T+h} |\hat{y}_{j,t} - y_{j,t}| / h \tag{20}$$

$$Theil_{j,t} = \frac{\sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_{j,t} - y_{j,t})^2 / h}}{\sqrt{\sum_{t=T+1}^{T+h} \hat{y}_{j,t}^2 / h} + \sqrt{\sum_{t=T+1}^{T+h} y_{j,t}^2 / h}} \tag{21}$$

Here, the forecast sample is from $T+1$ to $T+h$, $y_{j,t}$ are the actual values, and $\hat{y}_{j,t}$ are the forecast values. Again, t denotes the time, while j is the country.

When analyzing the results, except for the mean average error metric (and this was only for the alternative specification), the model featuring network measures led to marginally better results in terms of Root Mean Square Error, Average Absolute Error, or Theil Inequality Coefficient.

The implications are not trivial, and they further point to potential developments. First, they indicate again that using input–output measures can improve macroeconomic models based on standard data series. Second, they also suggest the potential of enhancing the current models with measures specific to the input–output analysis. A good step in this direction is the work by Baqaee and Farhi (2018).

Table 5. Sample 2005–2011—VAR using shadow interest rate.

	Short Term Shock		**Long Term Shock**	
Forecast Accuracy	**Without IO**	**With IO**	**Without IO**	**With IO**
Root Mean Square Error	0.0341	0.0315	0.1176	0.1119
Mean Absolute Error	0.0198	0.0194	0.0643	0.0640
Theil Inequality Coefficient	0.0949	0.0870	0.0745	0.0707
Fixed Effects	Yes	Yes	Yes	Yes
Observations	399	399	399	399
R^2	0.99	0.98	0.99	0.98

Table 6. Sample 2005–2011—VAR using 10 years interest rate.

	Short Term Shock		Long Term Shock	
Forecast Accuracy	**Without IO**	**With IO**	**Without IO**	**With IO**
Root Mean Square Error	0.1101	0.1057	0.1162	0.1022
Mean Absolute Error	0.0482	0.0506	0.0570	0.0576
Theil Inequality Coefficient	0.2324	0.2221	0.1066	0.0929
Fixed Effects	Yes	Yes	Yes	Yes
Observations	399	399	399	399
R^2	0.85	0.85	0.99	0.98

7. Discussion of Results

The results here indicate that some of the input–output coefficients had a role in the propagation of monetary policy shocks. The coefficients having a stable sign and being the most robust to the various specifications used were the average propagation length, fields of influence for rows or columns and the Rasmussen–Hirschman forward linkage.

Recent work, see Miller and Temurshoev (2015), established that the upstreamness and downstreamness coefficients are equivalent to total forward and total backward linkage. Thus, the results here underlined again the role of upstreamness, which was also a result found in Caraiani et al. (2020). Miller and Temurshoev (2015) suggested that sectors with higher forward linkage are better targets to stimulate.

Average propagation length can be interpreted as how a shock propagates through industries or how fragmented an economy is. The amplifying role of these coefficients can be understood as indicating that in more fragmented economies, monetary shocks have more negative effects on the GDP.

The third type of coefficient found to be significant was that of fields of influence (at row or at column level). These coefficients can be used to understand the impact of a change in one sector over the economy. Since these coefficients are used to measure the impact of marginal changes in any sector, it is quite clear why the fields of influence were found to have a significant role.

Overall, the research here was pretty much in line with the recent findings in the literature that the structure of production network matters for the transmission of aggregate shocks, see Acemoglu et al. (2016), and of monetary policy shocks on the macroeconomy, see Caraiani et al. (2020) or Ghassibe (2021). Some of the measures can act as amplifiers, like average propagation length, while others help dampen the impact of monetary policy shocks, like forward linkage.

The results here point to the fact that macroeconomics might benefit from the use of additional network measures besides the use of upstreamness and downstreamness. At the same time, the alternative network measures that can be used also need a better theoretical background in order to be integrated within macroeconomics.

8. Conclusions

This study aimed to extend the previous results regarding the role of production networks in transmitting monetary policy shocks. In contrast with previous work, it focused on alternative measures to characterize the production networks. These network measures were derived from input–output analysis, and they were not used in the context of studying the propagation of monetary policy shocks or other types of aggregate shocks.

The analysis showed that there is some evidence that these measures can have a statistically significant role in the propagation of network shocks. The coefficients identified as having a statistically significant role, like the average propagation length or the fields of influence, tended to be robust with respect to the VAR model used, sample, or data frequency. The analysis also identified a positive role of input–output measures in improving forecasting accuracy for the impact of monetary policy on GDP.

The overall assessment is positive concerning the role of input–output-based network measures in the propagation of monetary policy shocks.

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Abbreviations

The following abbreviations are used in this manuscript:

DJIA	Dow Jones Industrial Average
GDP	Gross Domestic Product
OECD	The Organization of Economic Cooperation and Development
STAN	Structural Analysis (Database)
IO	Input–Output
BVAR	Bayesian Vector Autoregression
IRF	Impulse Response Function
AR	Auto-regressive

Appendix A. Data Selection

Table A1. Data sample.

Country	Baseline Sample	Alternative Sample
Australia	1990:1–2017:4	1990:1–2017:4
Austria	1990:1–2017:4	1990:1–2017:4
Belgium	1990:1–2017:4	1990:1–2017:4
Canada	1990:1–2017:4	1990:1–2017:4
Denmark	1990:1–2017:4	1990:1–2017:4
Finland	1990:1–2017:4	1990:1–2017:4
France	1990:1–2017:4	1990:1–2017:4
Germany	1990:1–2017:2	1990:1–2017:4
Iceland	1990:1–2017:4	1992:1–2017:4
Ireland	1990:1–2017:4	1990:1–2017:4
Italy	1990:1–2017:4	1991:2–2017:4
Japan	1990:1–2017:4	1990:1–2017:4
Mexico	1990:1–2017:4	1990:1–2017:4
Netherlands	1990:1–2017:4	1990:1–2017:4
New Zealand	1990:1–2017:4	1990:1–2017:4
Norway	1990:1–2017:4	1990:1–2017:4
Portugal	1990:1–2017:4	1993:3–2017:4
Spain	1990:1–2017:4	1990:1–2017:4
South Africa	1990:1–2017:4	1990:1–2017:4
Sweden	1990:1–2017:4	1990:1–2017:4
Switzerland	1990:1–2017:4	1990:1–2017:4
Turkey	1990:1–2017:4	NA
UK	1990:1–2017:4	1990:1–2017:4
US	1990:1–2017:4	1990:1–2017:4

Appendix B. Data for Central Banks for the Countries in the Sample

Table A2. Regions and Central Banks.

Country	Central Bank	Region
Australia	Reserve Bank of Australia	Oceania
Austria	European Central Bank	Europe
Belgium	European Central Bank	Europe
Canada	Bank of Canada	North America
Denmark	National Bank of Denmark	Europe
Finland	European Central Bank	Europe
France	European Central Bank	Europe
Germany	European Central Bank	Europe
Iceland	Central Bank of Iceland	Europe
Ireland	European Central Bank	Europe
Italy	European Central Bank	Europe
Japan	Bank of Japan	Asia
Mexico	Bank of Mexico	North America
Netherlands	European Central Bank	Europe
New Zealand	Reserve Bank of New Zealand	Oceania
Norway	Norges Bank	Europe
Portugal	European Central Bank	Europe
Spain	European Central Bank	Europe
South Africa	South Africa Reserve Bank	Africa
Sweden	Riskbank	Europe
Switzerland	Swiss National Bank	Europe
UK	Bank of England	Europe
Turkey	Central Bank of Turkey	Europe
US	Federal Reserve	North America

Notes

[1] I used the World Bank commodity index in order to measure inflation expectations for the US while, for the other countries, I employed nominal effective exchange rate.

[2] The shadow interest rate is measured using a term structure model.

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