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# FINANCIAL SECTOR INTERCONNECTEDNESS AND MONETARY POLICY TRANSMISSION

**ALESSANDRO BARATTIERI**
*Collegio Carlo Alberto*
*and*
*ESG UQAM*

**MAYA EDEN**
*Brandeis University*

**DALIBOR STEVANOVIC**
*ESG UQAM,*
*CIRPÉE,*
*and*
*CIRANO*

We present a stylized model that illustrates how interbank trading can reduce the sensitivity of lending to entrepreneurs' net worth, thus affecting the transmission mechanism of monetary policy through the credit channel. We build a model-consistent measure of interconnectedness and document that, in the United States, this measure has increased substantially during the period 1952–2016. Finally, interacting the measure of interconnectedness in a structural vector autoregression and a factor-augmented vector autoregression for the US economy, we find that the impulse responses of several real and financial variables to monetary policy shocks are dampened as interconnectedness increases. We confirm the same result using data from 10 Euro area countries for the period 1999–2016.

**Keywords:** Financial Sector Interconnectedness, Monetary Policy Transmission Mechanism

## 1. INTRODUCTION

Two facts constitute the background of this paper. First, in several countries, financial systems underwent radical transformations during the last decades. The

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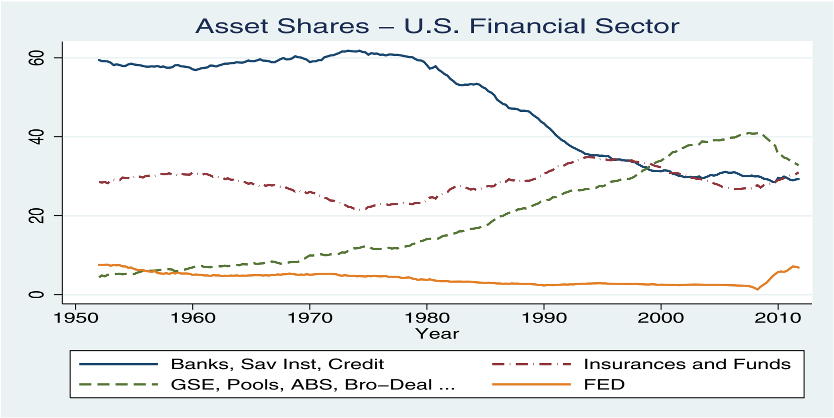


**FIGURE 1.** Asset shares of different actors (source: FED flow of funds.)

complexity and the nature of the process of financial intermediation changed substantially.[1] Figure 1 confirms this well-known phenomenon by reporting the evolution of the share of total assets in the US economy held by three major groups of actors: (i) the traditional actors (commercial banks, savings institutions, and credit unions), (ii) the insurance, pension, and mutual funds, and (iii) the so-called *"shadow banking system"* [government-sponsored enterprises (GSE), assets-backed-securities issuers, GSE mortgage pools, finance companies, brokers, and dealers].[2] While the share of assets held by the traditional actors declined from about 60% to roughly 30% from 1952 to 2010, the share of assets held by the "new" actors increased from almost zero to more than 40% in 2006.

Second, it is well established that in more recent samples, the sensitivity of real variables to monetary policy shocks has declined. A common explanation for this empirical finding is that there has been an increase in the effectiveness of monetary policy, as proposed, for example, by Boivin and Giannoni (2006). Another frequently conjectured (but less studied) hypothesis is that structural changes in the financial sector contributed to the changing nature of the monetary policy transmission mechanism.[3]

This paper presents a model that illustrates how interbank trading can reduce the sensitivity of lending to the entrepreneur's net worth, thereby dampening the credit channel transmission of monetary policy. We focus on the credit transmission channel, which can be summarized as follows. A lower nominal interest rate raises the net worth of borrowers, thereby increasing their "skin in the game" and making them less prone toward excessive risk taking. Banks respond by extending additional credit, which leads to additional investment. Our model's main insight is that this transmission mechanism depends crucially on the presence of a tension between the entrepreneur's preference toward risky projects and the bank's demand for safety (resulting from the need to pay depositors at par). In the presence of an interbank market, banks can pool risk by securitiz-

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ing their loan portfolios and diversifying their assets; the tension between the borrower's preference toward risky projects and the bank's need to pay depositors at par disappears, and with it the credit channel transmission of monetary policy.

We then construct a model-consistent *Measure of Interconnectedness*, defined as the share of the credit market instruments that represent claims whose *direct counterpart* belongs to the financial sector. We compute the measure of interconnectedness for the US financial system using data from the flows of funds. We find that the measure increases by between 13.6 and 18.6 percentage points during the period 1952–2016.

Last, we perform two empirical analyses of the interaction between this measure of interconnectedness and the response of real activity to monetary policy. First, we concentrate on the US time series data. We interact our measure of interconnectedness with a structural vector autoregression (SVAR) for the US economy, and produce impulse responses to a monetary policy shock conditional on different levels of interconnectedness. Then, we employ a factor-augmented VAR (FAVAR) model, where we produce impulse responses for a large set of real and financial variables. Once again, these impulse responses depend on our measure of interconnectedness. For both real variables [like the gross domestic product (GDP), investment, and employment] and financial variables (like credit and loans and leases), we find that the responsiveness to monetary policy shocks is significantly dampened as the financial sector becomes more interconnected, consistent with the theory. Moreover, we show how in the case of the FAVAR the change of the responses of credit-related variables at varying levels of interconnectedness is different from what we obtain by simply interacting our system with a time trend.

Second, we propose an empirical analysis using panel data from 10 countries in the Euro area. The Euro area represents a particularly suitable laboratory to study the question we are interested in, namely the impact of financial interconnectedness on the real effects of monetary policy. While monetary policy is set in Europe solely by the European Central Bank (ECB), it then affects several countries, all characterized by different levels of financial interconnectedness. We find that the sensitivity of loans to the monetary policy rate is significantly dampened as financial interconnectedness increases, even after controlling for a time trend and a measure of economic policy uncertainty (EPU).

This paper is linked to several strands of the literature. First, this paper relates to the theoretical literature on the specific role played by financial intermediaries in the transmission of monetary policy. Beck et al. (2014) provide an excellent and updated survey of the relevant literature. Diamond and Rajan (2006) present a model in which the bank's balance sheet conditions affect the transmission mechanism of monetary policy. Evidence of this is provided by Kayshap and Stein (2000). Freixas and Jorge (2008) propose a model of interbank market and analyze the impact of asymmetric information of the transmission mechanism of monetary policy. Bianchi and Bigio (2014) propose a quantitative model to study the transmission of monetary policy through a banking system.[4] None of these papers, however, analyzes the financial sector interconnectedness as a factor potentially affecting the monetary policy transmission mechanism through the credit channel.

Second, the paper is related to the literature dealing with measurement of financial intermediation and its characteristics. Philippon (2015) provides evidence on the quantitative importance and the cost of financial intermediation in the United States in the last 130 years. Greenwood and Scharfstein (2013) analyze the growth of the share of finance on GDP in the United States, whereas Philippon and Reshef (2013) analyze the growth of the share of finance for several developed countries.[5] A somewhat related and fast-growing literature deals with the analysis of the financial sector using network analysis. This literature, however, is more concerned with the implication of interconnectedness for systemic risk than with the implications for monetary policy.[6] Our paper is instead more concerned with the role played by interconnectedness for the transmission of monetary policy.

Last, the paper is related to the empirical literature on the monetary policy transmission mechanism. Boivin and Giannoni (2006) report evidence that the effects of monetary policy shocks on real variables are muted in the post-1980 period, and show how this finding can be explained by an increase in the effectiveness of monetary policy. Boivin et al. (2011) report FAVAR evidence as well as evidence from dynamics, stochastic, general equilibrium (DSGE) modeling on the change over time of the monetary transmission mechanism. Confirming the results by Boivin and Giannoni (2006), they also find muted responses of real variables to monetary policy innovations in more recent times, and argue that this is mostly accounted for by changes in policy behavior and the effect of these changes on expectations. Adrian and Shin (2011) consider more in general the role of financial intermediaries in monetary economics.[7] Closer to our spirit, Dynan et al. (2006) present evidence of the reduced responsiveness of several economic aggregates to shocks, dividing the sample before and after important regulatory changes. We contribute to this literature by exploring how a measure of financial interconnectedness can account for the change over time of the effects on real variables of monetary shocks. Moreover, in our FAVAR exercise, we extend significantly the set of variables analyzed.[8] Another branch of the empirical literature on the monetary policy transmission mechanism explores microlevel evidence. Jiménez et al. (2012, 2014), for instance, propose evidence on the importance of the credit channel of monetary policy using detailed data from the Spanish credit registry. Ippolito et al. (2017) explore both theoretically and empirically the transmission of monetary policy through bank lending, distinguishing normal times to periods where the zero lower bound on the nominal interest rate is binding.

The paper is organized as follows. In Section 2, we introduce our theoretical model. In Section 3, we present the measure of interconnectedness and document its evolution in the United States. In Section 4, we present our empirical analysis. Section 5 concludes with several suggestions for future research.

## 2. INTERCONNECTEDNESS AND MONETARY POLICY: THEORY

We present a stylized model that captures a possible relationship between the interconnectedness of the financial sector and the sensitivity of real activity to monetary policy. We focus on the credit channel transmission of monetary policy, and show how a more interconnected financial sector generates a lower sensitivity of lending to monetary policy shocks.[9]

There are two periods indexed $t = 0, 1$, and a unit measure of islands. Each island has a unit measure of savers, a unit measure of banks, and a unit measure of borrowers. Each saver is endowed with 1 unit of the final good at $t = 0$. Savers value consumption only at $t = 1$, so they deposit their savings at a bank. Banks cannot write contingent contracts with depositors: rather, they must offer some certain return of $1 + r_d$. Banks are competitive: savers deposit their endowment in the bank that promises the highest return. In equilibrium, all banks post the same deposit rate $r_d$, and we can therefore assume that each bank receives 1 unit of deposits.

Banks have access only to depositors and borrowers from their own island. In addition, banks can store deposits at a rate of return of 1; this store of value will be referred to as "money" ($m$). The interest rate that the borrower (entrepreneur) faces is denoted by $r$.

The entrepreneur can choose to invest in a risky project or in a safe project. The gross return on the safe project is 1. The gross return on the risky project is $R > 2$ with probability 0.5, and 0 otherwise (in other words, the mean of the risky project is higher than the mean of the safe project). The entrepreneur is risk neutral. Importantly, the success of the risky project is perfectly correlated across entrepreneurs within an island, and independent across islands. This reflects some local risk associated with investment, which washes out in the aggregate.

Our stylized environment assumes that shocks are perfectly correlated within islands and completely independent across islands. Of course, in practice, banks can somewhat self-insure by diversifying their loan portfolios, and there might be an aggregate component to project returns. In our context, the important assumption is that returns are not perfectly correlated across banks so that there is a scope for risk sharing.[10]

If the entrepreneur cannot repay his debt, his wealth $A \geq 0$ is taken away from him. We assume that $A$ is an indivisible asset, which is valuable to the entrepreneur but has no resale value; in other words, taking away $A$ is a threat to the entrepreneur, but does not yield any benefits to the lending bank. In addition, $A$ cannot be sold in order to repay the debt. This assumption is useful as it simplifies the analysis, and can be thought of as an extreme form of the more standard assumption that the liquidation value is lower than the continuation value.[11] The expected return to investing $I_r > 0$ units in the risky project is then

$$0.5[R - (1 + r)]I_r - 0.5A. \qquad \textbf{(1)}$$

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We assume the following parametric restriction:

$$0.5(R - A) > 1. \tag{2}$$

This assumption guarantees that, if $r = 0$, there are strictly positive returns for the entrepreneur from choosing $I_r = 1$.[12] The entrepreneur faces a menu of interest rates $r(I)$, which depend on the size of his loan. We assume that loans from other banks are observable, so that the interest rate may depend on the entrepreneur's total level of debt.[13] The entrepreneur allocates $I_s$ units of investment to the safe project, and $I_r$ units of investment toward the risky project. The entrepreneur maximizes

$$\max_{I_s, I_r}\{0.5[R - (1 + r)]I_r\} - 0.5A\chi(I_r > 0) + I_s(-r), \tag{3}$$

such that

$$I_s + I_r = I, \tag{4}$$

$$r = r(I), \tag{5}$$

where $\chi\{I_r > 0\}$ is an indicator function that takes the value 1 if $I_r > 0$ and 0 otherwise.[14] The bank maximizes expected profits at $t = 1$, subject to the constraint that it must have enough profits to repay depositors. It allocates its unit of deposits between loans ($I$) and money ($m$). Importantly, the bank can only choose the size of loans $I$; it cannot choose $I_s$ and $I_r$ directly. It solves

$$\max_{I,m} E_s[(1 + r(I, s))I] + m - 1 - r_d \tag{6}$$

such that

$$I + m = 1, \tag{7}$$

$$(1 + r(I, s))I + m \geq 1 + r_d, \tag{8}$$

where $r(I, s)$ is the state-dependent return to loans, given a loan size of $I$. In other words, if the entrepreneur is unable to repay the loan, $r(I, s) = -1$; otherwise $r(I, s) = r(I)$.

The timing of the events is summarized in the following table:

| | $t = 0$ | $t = 1$ |
|---|---|---|
| Savers | Deposit endowment of 1 | Consume $1 + r_d$ |
| Banks | Portfolio choice: $I$, $m$ | Collect debt, repay deposits |
| Entrepreneurs | Project choice: $I_r$, $I_s$ | Repay debt, $A$ seized if default |

*Benchmark: no interbank markets.* In the absence of an interbank market, an equilibrium is defined as a set $(I, I_s, I_r, m, r(I), r_d)$, such that (a) no bank can make strictly positive profits from deviating from $r_d$ and $r(I)$, (b) $I$ and $m$ solve the bank's optimization problem given $r_d$ and $r(I)$, and (c) $I$, $I_s$, and $I_r$ solve the entrepreneur's maximization problem given $r(I)$.

To solve for the equilibrium, note that, as banks must repay depositors, they cannot take on the risk of failed projects.[15] The bank therefore chooses the size of the loan so that the entrepreneur does not choose to invest in the risky project.[16] In this case, $r_d = 0$ as a rate of return of 1 is the maximum that any bank can guarantee. When $R > 1 + r$, it is easy to see that this can be achieved only when $A > 0$ and

$$0.5[R - (1 + r(I))]I_r - 0.5A \leq 0 \Rightarrow I_r \leq \frac{A}{R - (1 + r(I))}. \quad \textbf{(9)}$$

It follows that $r(I) = 0$ for $I \leq \frac{A}{R-1}$ and $r(I) = \infty$ otherwise. In other words, the bank rations credit to induce entrepreneurs to select the safe project.[17]

In this environment, the quantity of lending is sensitive to $A$. In equilibrium, the entrepreneur chooses $I = I_s = \frac{A}{R-1}$. Note that given the parametric restriction we made, this is an interior solution, with $I_s < 1$. Hence, changes in his net worth ($A$) translate into changes in the quantity of investment:

$$\frac{\partial I}{\partial A} = \frac{1}{R-1}. \quad \textbf{(10)}$$

For simplicity, we assume in the background an interaction between monetary policy and $A$. We would agree that there are indeed other transmission channels for monetary policy, but we choose to focus on this one just to illustrate a potential channel of how interconnectedness can dampen transmission. $A$ represents the entrepreneur's equity in an indivisible investment good (such as a house or a factory), which is partially financed by nominal debt contracts. An increase in the nominal interest rate raises the value of these debt contracts and effectively reduces the entrepreneur's equity and the size of the loan offered to him by the bank. The fact that investment depends on $A$ corresponds, in this environment, to the transmission of monetary policy. In other words, equation (10) is equivalent to a situation where the real activity ($I$) is sensitive to monetary policy, in the absence of an interbank market.

*Interbank trading.* Consider an alternative environment in which banks can pool risk across islands. A bank issuing a loan can then sell its returns and purchase other bank's returns. Let $I^{\text{sec}}$ denote the securitized loans sold by the bank, and let $I^d$ denote the bank's demand for securitized loans. $p$ is the price of securitized loans (in terms of $t = 1$ goods). The bank's problem is modified to

$$\max_{I,m,I^{\text{sec}},I^d} E_s[(1+r(I,s))(I - I^{\text{sec}})] + m + pI^{\text{sec}} - pI^d + \int_0^1 (1+r(s))I^d ds - 1 - r_d \quad \textbf{(11)}$$

such that

$$I + m = 1 \quad \textbf{(12)}$$

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and, for every state $s$

$$(1+r(I,s))(I-I^{\text{sec}})+m+pI^{\text{sec}}-pI^{d}+\int_0^1(1+r(s))I^{d}ds\geq 1+r_d, \quad \mathbf{(13)}$$

where $r(s)$ is now defined as the equilibrium return on securitized loans in state $s$. The definition of equilibrium is now modified to include $I^{\text{sec}}$ and $I^{d}$ that must be optimal for the bank given $p$. The market-clearing condition for $p$ is $I^{\text{sec}}=I^{d}$ (otherwise, $p$ implies either excess supply or excess demand of securities).

We conjecture an equilibrium in which banks sell their entire loan portfolio ($I^{\text{sec}}=I$) at the price $p$, and buy a diversified portfolio of loans ($I^{d}=I$). Entrepreneurs implement the risky project, and the interest rate is such that entrepreneurs make no profits from investing $I_r=1$:

$$0.5[R-(1+r)]=0.5A\Rightarrow 1+r=R-A. \quad \mathbf{(14)}$$

The interest schedule $r(I)$ is given by $r(I)=R-A-1$ for $I\leq 1$ and $r(I)=\infty$ otherwise. The price $p$ is the expected return to securities, $p=0.5(1+r)=0.5(R-A)$. Since $I=I_r$, $m=0$, and $I^{\text{sec}}=I^{d}$, the bank's (deterministic) profits are given by the expected value of securitized loans minus the gross return on deposits:

$$0.5(1+r)-1-r_d=0.5(R-A)-1-r_d. \quad \mathbf{(15)}$$

The deposit rate $r_d$ is then determined by the zero-profit condition, that sets $r_d=0.5(R-A)-1$, which is positive given our parametric restriction.

Note that this is an equilibrium, as banks competing for deposits would like to offer the highest possible deposit rate; any deviation from this strategy would result either in losses (for a higher deposit rate) or in no deposits (for a lower deposit rate). Furthermore, it is easy to see that given $r(I)$ and $p$, neither banks nor entrepreneurs can make strictly positive profits from deviating from the proposed equilibrium strategies.[18] In this environment, banks have no incentive to ration credit in order to induce entrepreneurs to stay away from the risky project; thus, in this equilibrium, $I=1$ and the entire deposits are invested in the risky project. This corner solution implies that banks' lending decisions are insensitive to small changes in the borrower's net worth:

$$I=1\Rightarrow\frac{\partial I}{\partial A}=0. \quad \mathbf{(16)}$$

In other words, equation (16) is equivalent to a situation where interbank trading makes banks insensitive to the net worth of their borrowers, and, in this environment, insensitive to monetary policy.[19]

*Interconnectedness and aggregate sensitivity to monetary policy.* While up to now we described two alternative environments, suppose that only a measure $\lambda\leq 1$ of islands are able to share risk, while a measure $1-\lambda$ of islands do not participate in interbank markets. Then, we can characterize the aggregate sensitivity of the real activity to changes in $A$ (and hence to monetary policy) as

$$\frac{\partial I}{\partial A} = (1-\lambda)\frac{1}{R-1} + \lambda \cdot 0. \qquad \textbf{(17)}$$

Quite clearly, we see from equation (17) that the sensitivity of real activity to monetary policy is decreasing in $\lambda$:

$$\frac{\partial^2 I}{\partial \lambda \partial A} = -\frac{1}{R-1} < 0. \qquad \textbf{(18)}$$

In this model, $\lambda$ is a proxy for the interconnectedness of the financial sector. In the next section, we propose an empirical counterpart to this proxy.

Before proceeding, it is worth emphasizing that the purpose of this model is to illustrate a mechanism relating financial interconnectedness to monetary policy transmission, rather than to comment whether or not interconnectedness is stabilizing or destabilizing. The mechanism that we highlight relies only on the assumption that interconnectedness increases risk sharing. In general, allowing for risk sharing across banks may be either stabilizing or destabilizing [see Acemoglu et al. (2015)].

## 3. A MEASURE OF INTERCONNECTEDNESS

Starting from the model presented in the preceding section, we propose a measure of interconnectedness of the financial system based on the composition of assets of the aggregate financial sector.

Note that the $\lambda$ banks that participate in interbank markets on the asset side hold securities from other banks amounting to the value of deposits. Thus, all of their assets have counterparts that are in the financial system. In contrast, the banks who do not participate in the interbank market hold only assets whose direct counterpart is not in the financial sector (and some cash).

It is possible to measure an empirical counterpart for $\lambda$ as the share of the total credit market instruments held by the financial sector (CREDIT) that represent claims whose *direct counterparts* belong to the financial sector (CREDIT_FINANCE). We call this measure a "measure of interconnectedness" (INTER):

$$\text{INTER} = \frac{\text{CREDIT\_FINANCE}}{\text{CREDIT}}. \qquad \textbf{(19)}$$

The flow of funds database provides a quarterly snapshot of the US financial system balance sheet.[20] For our baseline measure, we focus on credit market instruments, which include mortgages, loans, consumer credit, treasuries, municipal bonds, corporate and foreign bonds, open market papers, and agency and GSE-backed securities.

Unfortunately, the level of aggregation of the data in the flow of funds prevents us from perfectly measuring the expression in equation (19). Therefore, we compute

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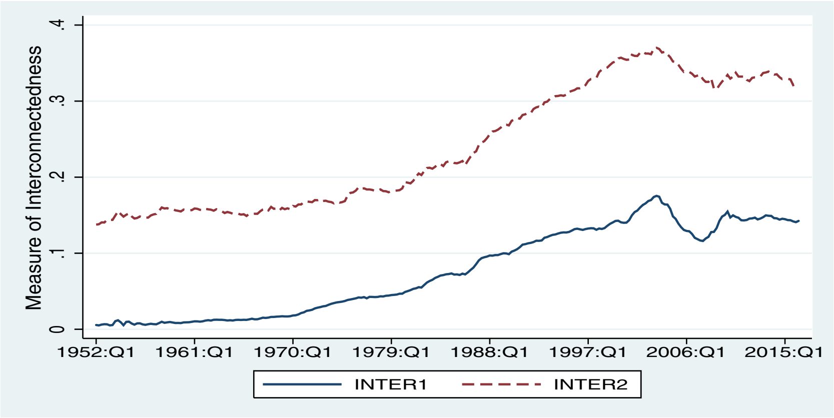


**FIGURE 2.** The *measure of interconnectedness*: US 1952–2016, assets.

two different measures, which we interpret as a lower-bound and an upper-bound for the concept we want to capture.

We label the first as $\text{INTER}_1$, and compute it simply as the ratio between total agency and GSE-backed securities and total credit market instruments. Especially in more recent times, these securities represented an essential element of the growth of the interconnectedness of the financial network, fostered by the process of securitization. Mortgages originated by banks and mortgage brokers were sold to special investment vehicles (SIV). These SIVs were then issuing different "tranches" of securities, which were backed by those mortgages, and characterized by a stratified risk profile. The safest of these emissions (the "Senior Tranches") were often given triple-A ratings, and hence could be bought by some players in the financial system (such as pension funds) that can only invest in safe securities.

The second measure we compute, $\text{INTER}_2$, is defined as the share of total credit market instruments consisting of agency and GSE-backed securities, corporate and foreign bonds, and open market papers. Within these last two categories, the flow of funds data unfortunately does not distinguish by the sector of the counterpart. By adding their entire value to the numerator of $\text{INTER}_2$, we are obviously overestimating the share of credit market instruments whose counterpart is in the financial sector.[21]

Figure 2 reports the evolution of our measures $\text{INTER}_1$ and $\text{INTER}_2$ in the period 1952:1–2016:2. Three features stand out. First, both measures are increasing over time. $\text{INTER}_1$ increases by 13.6 percentage points, whereas $\text{INTER}_2$ increases by 18.6 percentage points. Second, the two measures are highly correlated.[22] The difference between the two seems to be purely a level effect. At a more disaggregated level, this result is driven by the evolution of the shares of corporate and foreign bonds and open market papers, which we report in the online appendix.[23] These two variables had opposite dynamics in the period considered. The share of open market papers share in total market instruments increased until the two thousands

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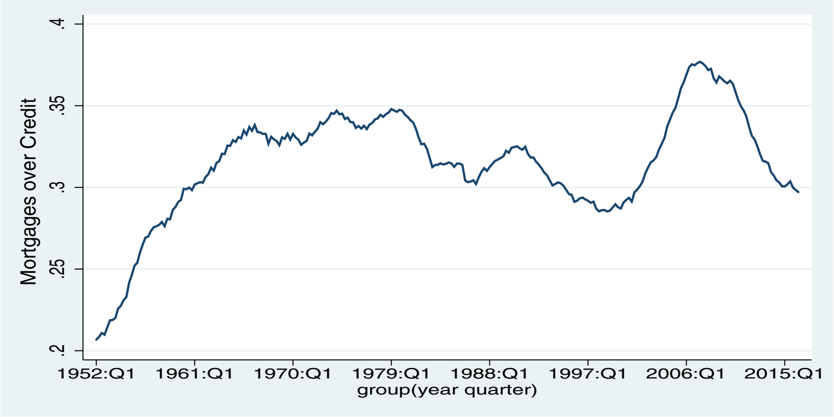


**FIGURE 3.** Mortgages over total credit, US 1952–2016.

and then started declining. The weight of corporate and foreign bonds, instead, declined from the fifties to the eighties, and then started rising.

A third notable feature of Figure 2 is the decline in the measures of financial interconnectedness during the housing bubble of 2003–2007. While the reader might be perhaps puzzled at this point, there is a simple explanation for these dynamics. Figure 3 reports the share of mortgages over total credit market instruments. After the big rise in the fifties, sixties, and seventies, during the eighties and the nineties, the share of mortgages in total credit declines steadily. Then, we see a huge increase in the mortgage share during the early two-thousands. The securities backed by those mortgages were partly sold outside of the United States and bought by foreign investors.[24] So, while US mortgages were growing, the securities backed by those mortgages recorded as assets by US financial institutions, and thus included in the flow of funds asset data, were growing *by less*, thus explaining our declining measure of interconnectedness during the US housing bubble.

We also construct alternative measures of interconnectedness that, rather than focusing on the asset side of the balance sheet, focus on the liability side. Consistent with our explanation, we show that the liability-based measure does not decline during the housing bubble. In particular, we compute a measure $\text{INTER}_3$, which is the ratio of credit market instruments and repurchasing agreements over total liabilities, and a restricted measure $\text{INTER}_4$, which is the ratio of credit market instruments and repurchasing agreements over a smaller set of liabilities.[25] In Figure 4, we report the results obtained for these alternative measures. These measures peak at end of 2008. Unsurprisingly, the two measures are highly correlated, and they both grow significantly during our sample period: $\text{INTER}_3$ grows by 19.3 percentage points and $\text{INTER}_4$ grows by 22.3 percentage points. The drawback of these measures is that they are not tightly linked to our model, which strictly speaking does not feature noncore liabilities. Importantly, however, the empirical

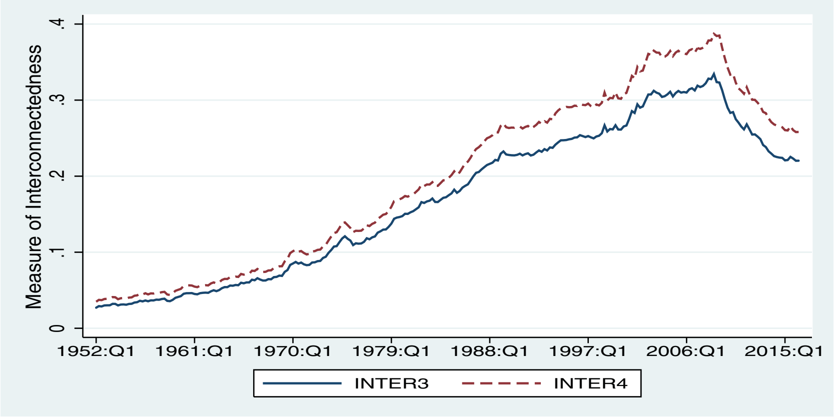


**FIGURE 4.** Measure of interconnectedness: US 1952–2016, liabilities.

results we present in the next section are fully robust to the use of $\text{INTER}_3$ and $\text{INTER}_4$.[26]

Naturally, Figures 2 and 4 point toward an important limitation of our data: We are using a source of information for a single country (flow of funds data) to assess a phenomenon of global scope, which is financial interconnectedness. That said, the advantages of our measures are that they are simple, readily available, and potentially extendible to other countries as well as to single financial institutions.[27] We therefore suggest that, despite their limits, our measures can be useful for investigating the interplay between financial sector interconnectedness and the monetary policy transmission mechanism, as we do in the next section.

Before proceeding in our investigation, we make three remarks regarding: (i) the relation between interconnectedness and liquidity, (ii) the relation between our measure and financial deregulation, and (iii) the relation between our measure and the share of finance in GDP.

*Measure of interconnectedness and liquidity.* Kayshap and Stein (2000) present evidence using microlevel data for US commercial banks on the interplay between the balance sheet liquidity and the effect of monetary policy on lending decisions. While the concept of liquidity is linked to the one of interconnectedness, they are not identical. To make this point, we computed an indicator of liquidity similar to what done by Kayshap and Stein (2000), who measured liquidity as the share of credit market instruments represented by securities, thus including agency and GSE-backed securities, corporate and foreign bonds, and open market papers, but also treasuries and municipal bonds. In the online appendix, we show how the correlation between the two series is pretty low over the period (about 0.27). The liquidity measure first declines from the fifties to the eighties, and then increases. The decline since the 1950s was driven by a decline in the holding of treasuries,

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which represented nearly 40% of credit market instruments in 1952 (and about 10% in 1980).

*Measure of interconnectedness and financial deregulation.* It is also interesting to note how our measure of interconnectedness shows some relation with key moments in the history of the deregulation of the US financial system, as reported in the online appendix. The measure has a change in trend in the 1980s, when several deregulation acts were promoted in the United States.[28] Moreover, in 1986, the Fed reinterpreted the Glass-Steagall act of 1933, which had separated commercial banks from investment banks. This reinterpretation allowed for a maximum of 5% of commercial bank revenues to come from investment banking activities, thus opening the way for banks to handle mortgage-backed securities, commercial papers, municipal bonds [see Sherman (2009)], with clear potential effects on the system overall interconnectedness.[29] Finally, in 1999, The Financial Modernization Act, also known as the Gramm-Leach-Bliley Act, repealed the Glass-Steagall of 1933 and removed the separation between the activities of commercial banking and investment banking, thus spurring a wave of mergers and acquisitions in the US financial sector and leading to a transformation of the business model in several US financial institutions.

*Measure of interconnectedness and the share of finance in GDP.* It is instructive to relate our measures of interconnectedness and the share of finance in GDP, constructed by Philippon (2015). In the online appendix, we report a plot of our measures together with the share of finance in nondefense value added.[30] While the two series are conceptually different, they are interestingly highly correlated (with a correlation index of 0.98). Our measure of interconnectedness is a way of representing the structural transformation that affected the US financial system in the last 50 years. Philippon (2015) measures the share of finance in US GDP. One could conjecture that the structural transformation of the US financial sector captured by our measure might have contributed to a reallocation of resources toward finance, thus implying a greater share of finance in GDP. However, other factors, such as capital-biased technological change or the increasing trend toward financial globalization, might also help explaining Philippon's findings.

Since this paper focuses mainly on the implications for monetary policy of the structural transformation that affected the US financial system, we focus in what follows on our measure of interconnectedness, without taking a strong stance on its contribution to the increase in the share of finance in GDP.

## 4. INTERCONNECTEDNESS AND MONETARY POLICY: EMPIRICS

This section presents two empirical investigations of how financial interconnectedness affects the responses of economic variables to monetary policy. We first use US time series data, interacting our measure of interconnectedness within SVAR approach and FAVAR. Second, we use panel data from 10 Euro area countries.

### 4.1. Time Series Data: United States

*SVAR.* In order to explore the responses of the real variables to a monetary policy shock, and how these change with financial sector interconnectedness, we adapt the approach of Boivin and Giannoni (2006) by including our measure of interconnectedness INTER as an exogenous variable. The result obtained in Figure 2 indicates that the movements in the interconnectedness are more long-run smooth movements, and thus we believe it can be considered as exogenous when using business cycle frequency data.[31] In addition, the interconnectedness is included with one lag. The model can be written as follows:

$$Y_t = \Phi(L)Y_{t-1} + \beta \mathrm{INTER}_{t-1} Y_{t-1} + e_t, \tag{20}$$

where $Y_t$ is a $K \times 1$ vector of endogenous variables, $\Phi(L)$ is a matrix polynomial of order $p$, and $\mathrm{INTER}_{t-1}$ is exogenous. The reduced form errors, $e_t$, are assumed to be linear combinations of structural shocks, $\varepsilon_t$:

$$e_t = H\varepsilon_t$$

with $E(\varepsilon_t \varepsilon_t') = \Sigma$, a diagonal matrix.[32]

It is easy to see that the impulse responses to any shock in $\varepsilon_t$ will depend on $\mathrm{INTER}_{t-1}$. For simplicity, we assume $p = 2$. Developing $\Phi(L)$, we get

$$\begin{aligned} Y_t &= \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \beta \mathrm{INTER}_{t-1} Y_{t-1} + e_t \\ &= (\Phi_1 + \beta \mathrm{INTER}_{t-1})\, Y_{t-1} + \Phi_2 Y_{t-2} + e_t \\ &= \Phi_{1,t-1} Y_{t-1} + \Phi_2 Y_{t-2} + e_t, \end{aligned}$$

where $\Phi_{1,t-1} = (\Phi_1 + \beta \mathrm{INTER}_{t-1})$. Hence, the impulse response functions (IRFs) are obtained for any level of $\mathrm{INTER}_{t-1}$ by inverting the previous expression:

$$Y_t = \left[\mathbf{I} - \Phi_{1,t-1} L - \Phi_2 L^2\right]^{-1} H\varepsilon_t. \tag{21}$$

In practice, the coefficient matrices $\Phi(L)$ and $\beta$ are estimated by ordinary least squares (OLS) regression on (20), and $H$ is deduced by imposing enough identification restrictions. The IRFs are then easily computed using (21). The confidence bands can be constructed using a parametric bootstrap.[33] Following Boivin and Giannoni (2006), $Y_t$ contains the deviation of the natural logarithm of quarterly real GDP (GDPQ) from a linear deterministic trend, the annualized rate of change in the quarterly GDP deflator (GDPD), the natural logarithm of the quarterly average of the monthly spot market commodity price index (PSCCOM), and the quarterly average of the federal funds rate (FFR). The exogenous variable $\mathrm{INTER}_{t-1}$ contains our aggregate measure of interconnectedness. We present here the results obtained using $\mathrm{INTER}_1$.[34] The data ranges from 1959Q1 to 2009Q1.[35] Four lags are included in the VAR.[36] The identification of structural shocks is achieved by the following recursive ordering: [PSCCOM, GDPQ, GDPD, FFR].

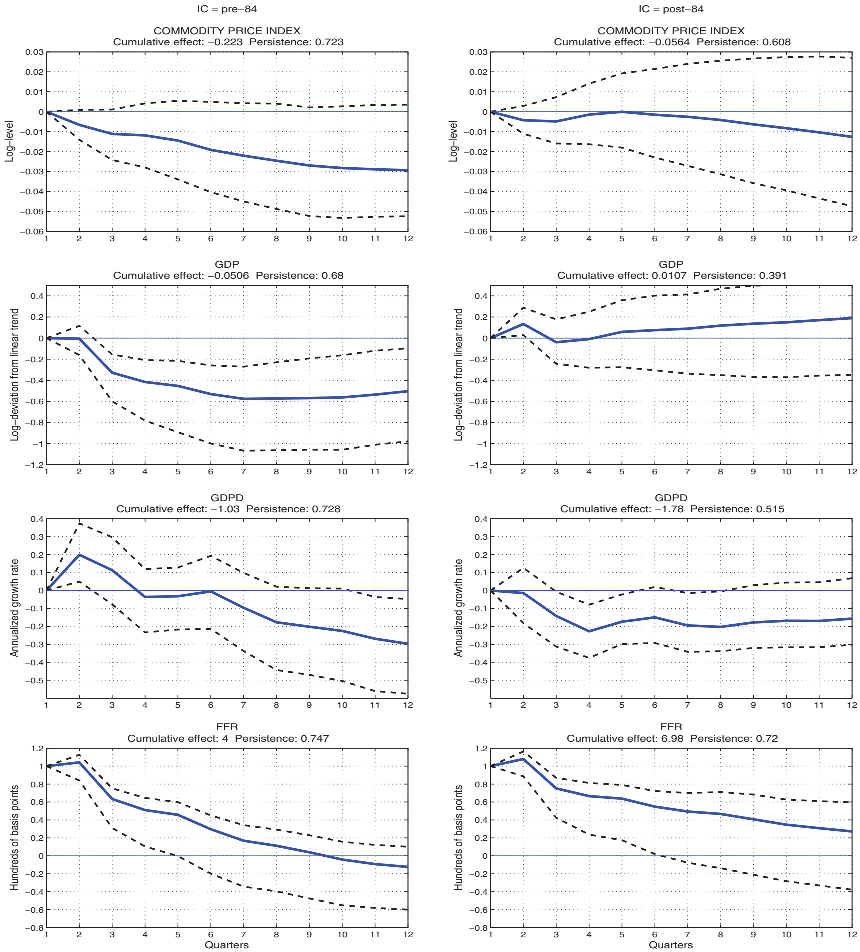


**FIGURE 5.** Comparison of IRFs to a monetary policy shock conditional on different degrees of interconnectedness in SVAR.

Hence, the unexpected monetary policy shock is ordered last in $\varepsilon_t$. The rotation matrix $H$ is obtained using Choleski decomposition of the covariance matrix of $\hat{e}_t$. The 90% confidence intervals are computed using 1,000 bootstrap replications.

In Figure 5, we compare the impulse responses of elements in $Y_t$ to an adverse monetary policy shock when the measure of interconnectedness is low and high, respectively, $\text{INTER}_1 = 0.028$ and $\text{INTER}_1 = 0.11$. These are the average values of our interconnectedness measure $\text{INTER}_1$ for the periods 1959Q1–1983Q4 and 1984Q1–2009Q1. As we can see from the figure, at the level of interconnectedness of 0.028, the adverse monetary shock generates a decrease in output, which exhibits a hump-shaped response. The price level decreases too, but only after a few

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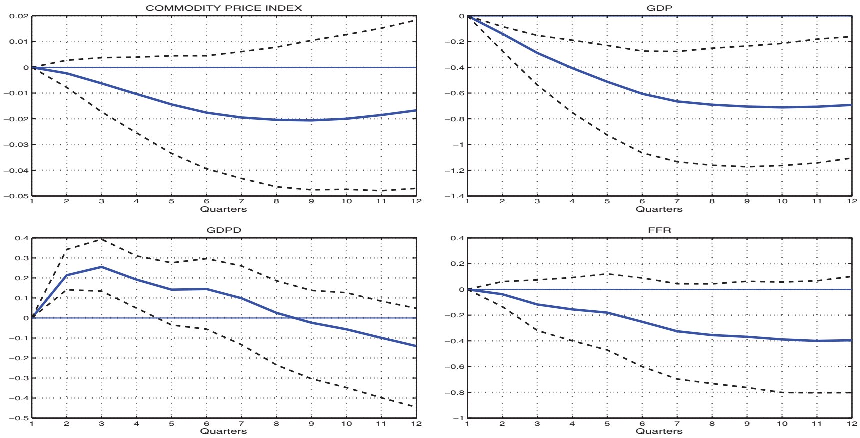


**FIGURE 6.** Difference between IRFs to a monetary policy shock with different levels of connectedness.

quarters (the well-known price puzzle phenomenon). When we consider a higher level of interconnectedness of 0.11, instead, we see that the response of the GDP to the same monetary policy shock is now not statistically different from zero. The responses of the quarterly GDPD and the spot market commodity price index are muted at the higher level of interconnectedness. Interestingly, there is no evidence of a price puzzle in that case.[37]

In order to assess whether the *difference* in the impulse responses we obtained under different levels of interconnectedness is statistically significant, we plot the difference in Figure 6, and we include confidence intervals at 90% significance level. As the figure shows, the impulse responses of GDP and GDPD are statistically different under the two scenarios, while the impulse responses of the commodity price index and the FFR are not statistically significantly different.

The results reported in Figure 6 are robust to the inclusion of a time trend in the model, as well as to a different specification of the lag structure. However, the results are not statistically different from those that one would obtain by simply interacting a time trend in place of our measure of interconnectedness, and then considering the impulse responses for the pre-1984 versus post-1984 period.[38] This is not terribly surprising, given the presence of a time trend (albeit a nonlinear one) in our measure. In the next subsection, we show how this is not the case when moving to the FAVAR analysis.

*FAVAR.* We conduct a more refined exercise, inspired by the model from Bernanke et al. (2005). In contrast to standard SVAR models, factor models have a number of advantages: (i) they allow for the consideration of large amounts of information potentially observed by agents, and thus minimize the risk of omitted variable bias; (ii) they are not sensitive to the choice of a specific data series, which may be arbitrary; (iii) they are less likely to be subject to nonfundamentalness issues raised by Forni et al. (2009)[39]; and (iv) they allow us to compute the response of a larger set of variables of interest to identified shocks.

As in the case of SVAR, we introduce our measure of interconnectedness through interaction terms, in order to obtain IRFs that are conditional on a certain level of interconnectedness.

Formally, we consider the following static factor model with latent and observed factors:

$$X_t = \Lambda^F F_t + \Lambda^R R_t + u_t \tag{22}$$

$$\begin{bmatrix} F_t \\ R_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ R_{t-1} \end{bmatrix} + \beta \text{INTER}_{t-1} \begin{bmatrix} F_{t-1} \\ R_{t-1} \end{bmatrix} + e_t, \tag{23}$$

where $F_t$ is vector of $K$ latent factors and $R_t$ is the observed factor. In our case, $R_t$ is the FFR, since the objective here is to identify the monetary policy shock. $X_t$ contains $N$ macroeconomic and financial indicators organized into a block of "slow-moving" variables that are largely predetermined to monetary policy, and another consisting of "fast-moving" variables that are sensitive to the Fed's rule.[40] The idiosyncratic errors are assumed such that (21) is an approximate factor model [see Bai and Ng (2006) for details].

In our application, $X_t$ contains $N = 108$ quarterly time series from Stevanovic (2012), that run from 1959Q1 to 2009Q1. Data include both macroeconomic variables, such as GDP, employment, investment, hours worked, inflation rate as well as financial variables such as credit spreads, loans, etc. This represents another contribution of our paper, which extends significantly the set of variables analyzed relative to previous studies. The data have been transformed to induce stationarity and are standardized prior to estimation.[41] The $IC_{p2}$ information criterion from Bai and Ng (2002) and Onatski (2010) suggests $K = 3$ latent factors. The lag order of $\Phi(L)$ is set to 4.[42] The estimation and identification of structural shocks consist of several steps. First, following Bernanke et al. (2005), we impose $R_t$ as an observed factor when estimating $F_t$. Second, using $\hat{F}_t$, we estimate (23) as in the case of the SVAR model. Since $\hat{F}_t$ can be correlated with $R_t$, we identify the monetary policy by ordering $R_t$ last.[43] Finally, we invert (23) to obtain factors' impulse responses, and multiply them by factor loadings to get the IRFs of all the elements in $X_t$. While all the impulse responses are available upon request, we present here only a subset of them.

As before, we compare the impulse responses to an adverse monetary policy shock when the interconnectedness is low and high, respectively, $\text{INTER}_1 = 0.028$ and $\text{INTER}_1 = 0.11$.[44] In Figure 7, we report the responses of several variables of interest to an identified monetary policy shock.[45] The responses of real variables (such as GDP, consumption, investment, employment) to a monetary innovation are generally muted at higher level of interconnectedness.[46] Moreover, several financial variables display a similar pattern. Of particular interest is to notice how the response of credit-related variables are dampened as the interconnectedness within the financial sector increases. This is true both for quantities (bank credit,

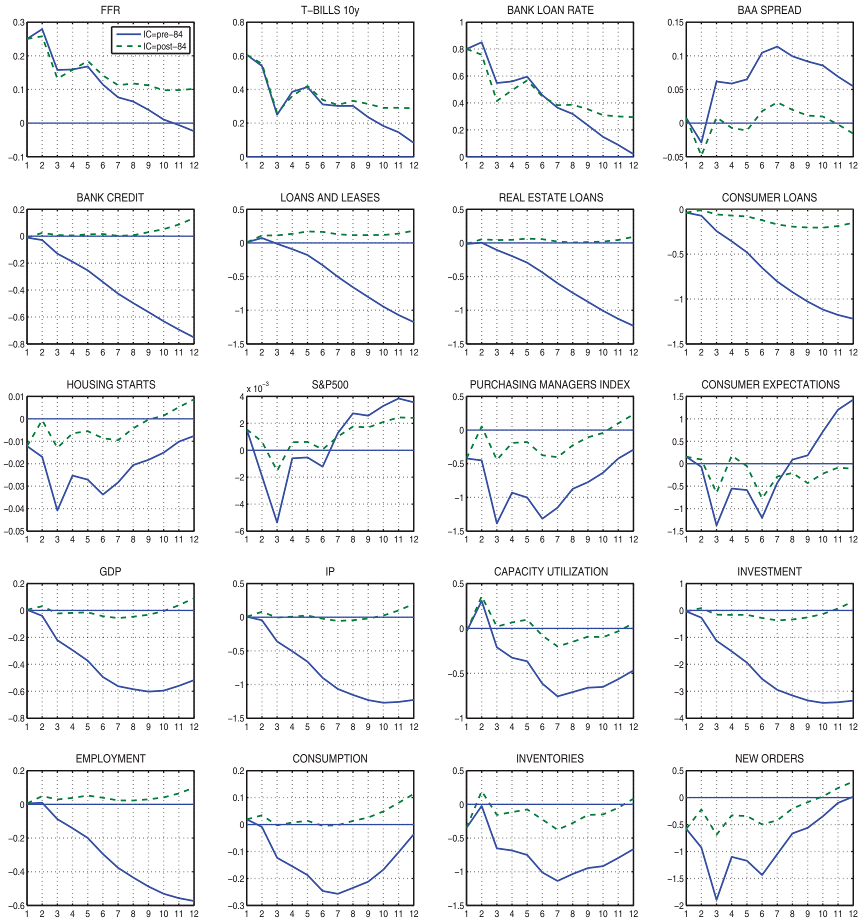


**FIGURE 7.** Comparison of IRFs to a monetary policy shock with different levels of interconnectedness, FAVAR-selected variables.

loans and leases, and real estate loans) and, to a lesser extent, for prices (in particular, the BBA spread). These responses are consistent with the mechanism that we proposed in our theoretical model, based on the sensitivity of lenders to the financial soundness of the borrowers.

In order to test whether these differences are statistically significant, we compute the difference between the impulse responses and we compute via bootstrap a 90% confidence internal. In Figure 8, we report the results. The impulse responses of most variables analyzed are indeed statistically different, at least in the first few quarters.

Finally, we repeat the exercise but including a simple time trend instead of our measure of interconnectedness. In the online appendix, we report the results

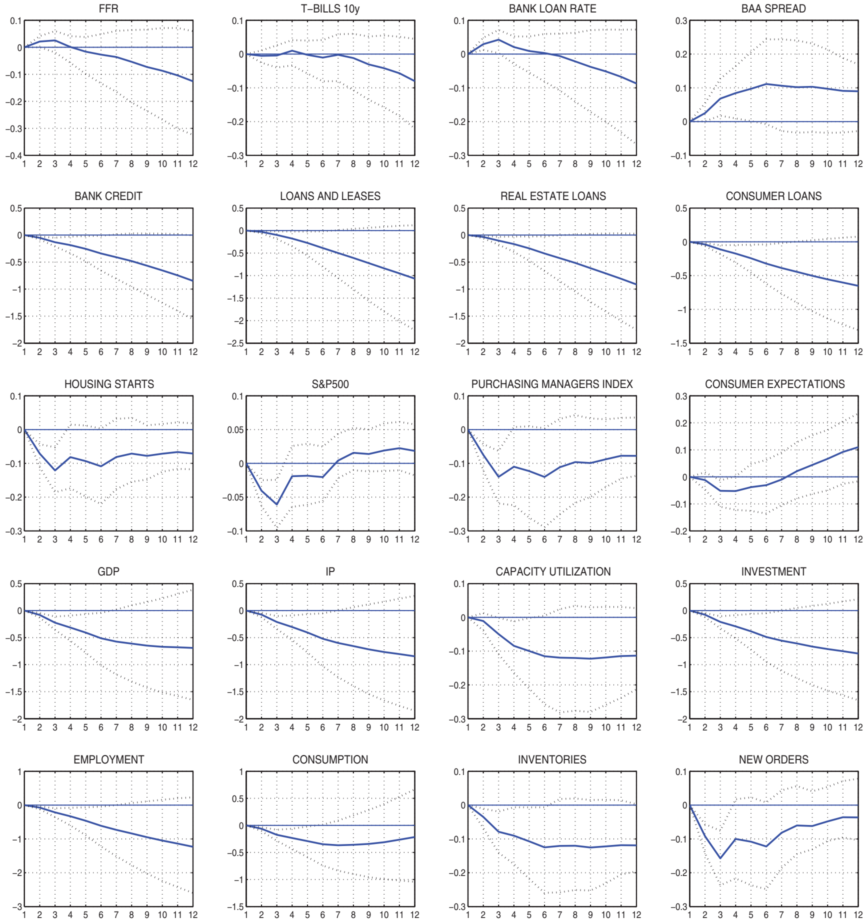


**FIGURE 8.** Difference between IRFs to a monetary policy shock with different levels of interconnectedness, FAVAR-selected variables.

obtained just dividing the sample into pre-1984 and post-1984. We still find a certain attenuation in the responses of several variables to a monetary policy innovation, but the attenuation displayed is significantly lower than the one obtained using our measure of interconnectedness. In fact, by computing via bootstrap a 90% confidence interval, we can see how for most of the variables, the two impulse responses are not statistically different (with the exception of some real variables, like GDP, investment, and employment, where the difference if significant for the first few quarters). It is interesting to notice how the responses of the financial variables such as credit, loans ad lease, and the real estate loans are not statistically different under the two time periods considered.[47]

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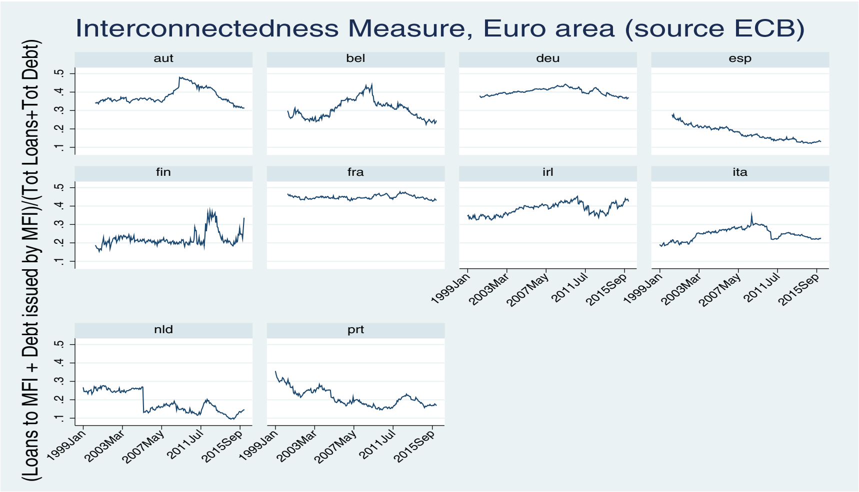


**FIGURE 9.** Interconnectedness measures for selected Euro area members, 1997:1–2016:2.

We conclude that the inclusion of our measure of interconnectedness into a SVAR or a FAVAR for the US economy generates statistically different responses to monetary policy innovations, as predicted by the theoretical model. Moreover, while in the case of the SVAR these results are not substantially different from those that one would obtain by interacting the system with a time trend, including the measure of interconnectedness in the FAVAR generates results, especially for the credit-related variables, which are different from those obtained simply including a time trend.

### 4.2. Panel Data: The Euro Area

In order to corroborate the evidence presented for the United States, we present here an empirical analysis using the Euro area countries. The Euro area represents a particularly suitable laboratory to study the question we are interested in, namely the impact of financial interconnectedness on the real effects of monetary policy. While monetary policy is set in Europe solely by the ECB, it then affects several countries, all characterized by different levels of financial interconnectedness. The main drawback is that this situation is in place only since 1999, and so we do not have long time series.

We collected data from the ECB data warehouse for the original members of the Euro area.[48] Similarly to the preceding section, we computed the measure of interconnectedness as the share of credit market instruments whose direct counterpart is in the financial sector.[49] Figure 9 reports the evolution of these measures over the period 1999:1–2016:2 (at monthly frequency). As the figure illustrates, there is some important heterogeneity in the dynamics of this proxy for financial interconnectedness. In some countries, such as Germany, Ireland, or

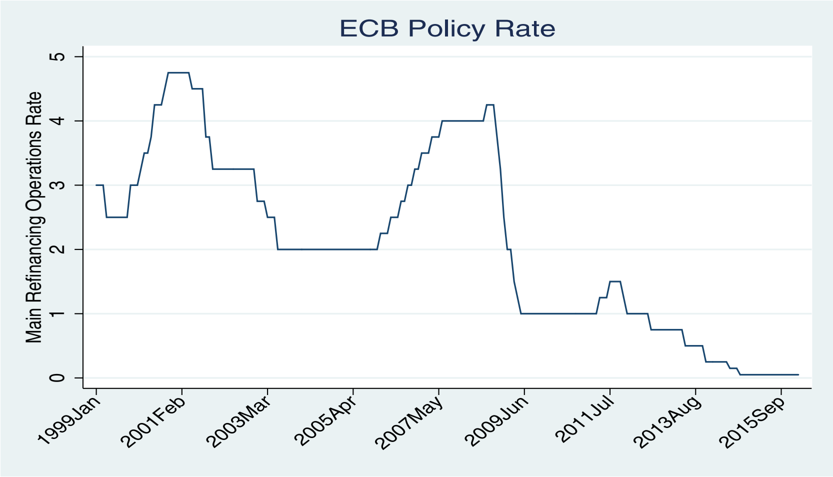


**FIGURE 10.** ECB policy rate.

Belgium, we notice an "cycle" around the crisis of 2008, while in other countries (like France or Italy) the dynamics seems to be much more stable.

Moreover, we report in Figure 10 the evolution of the ECB main policy rate: the rate for main refinancing operation, reported at monthly frequencies (at the end of the month). We can see a fair amount of variation within the sample period.

We check whether lending's sensitivity to the policy rate is affected by financial interconnectedness using a simple model (in its most complete form):

$$\begin{aligned} \text{Ln}(\text{loans}_{it}) &= \alpha_0 + \alpha_1 \text{ECB\_}R_{t-1} + \alpha_2 \text{INTER}_{it-1} + \alpha_3 \text{ECB\_}R_{t-1} * \text{INTER}_{it-1} \\ &+ \alpha_4 \text{Trend} + \alpha_5 \text{ECB\_}R_{t-1} * \text{Trend} + \alpha_5 \text{EPU}_{t-1} + \alpha_6 \text{ECB\_}R_{t-1} * \text{EPU}_{t-1} \\ &+ \delta_i + \eta_y + \eta_m + \epsilon_{it}. \end{aligned} \tag{24}$$

The log loans are regressed on the lagged interest rate, the lagged measure of interconnectivity, and an interaction term between the measure of interconnectivity and the policy rate. $\alpha_3$ is our main coefficient of interest. A positive value would indicate that more interconnected financial system the monetary policy effects on lending are *attenuated*. We then control if our results are robust to the inclusion of fixed effects for countries, years, and months, as well as a time trend and a measure of EPU (and their interactions with the policy rate).

Table 1 reports the results we obtain. In the first column, we can see how the semielasticity of the log loans with respect to the policy rate is negative and highly statistically significant. In the second column, we add our measure of interconnectedness, as well as the interaction term with the policy rate. As expected, the interaction term is positive and highly statistically significant, while the direct effect of interconnectedness seems to be positive, but not statistically significant. In column (3), we check how our results are robust to the inclusion

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**TABLE 1.** Dependent variable: Log loans

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ECB_$R_{t-1}$ | −0.1148*** | −0.3621*** | −0.0510 | −0.0936** | −0.0958** |
| | (0.0167) | (0.0494) | (0.0373) | (0.0427) | (0.0424) |
| INTER$_{t-1}$ | | 0.4934 | −0.8887* | −0.8978** | −0.8967** |
| | | (0.3640) | (0.4563) | (0.4566) | (0.4572) |
| ECB_$R_{t-1}$*INTER$_{t-1}$ | | 0.8129*** | 0.2492** | 0.2489** | 0.2489** |
| | | (0.1601) | (0.1208) | (0.1206) | (0.1207) |
| Trend | | | | 0.0014 | 0.0015 |
| | | | | (0.0027) | (0.0027) |
| ECB_$R_{t-1}$*Trend | | | | 0.0005** | 0.0005** |
| | | | | (0.0002) | (0.0002) |
| EPU$_{t-1}$ | | | | | −0.0001 |
| | | | | | (0.0001) |
| ECB_$R_{t-1}$*EPU$_{t-1}$ | | | | | 0.0000 |
| | | | | | (0.0000) |
| Country FE | No | No | Yes | Yes | Yes |
| Year FE | No | No | Yes | Yes | Yes |
| Month FE | No | No | Yes | Yes | Yes |
| *R*-squared | 0.022 | 0.071 | 0.981 | 0.981 | 0.981 |
| *N* | 2,050 | 2,050 | 2,050 | 2,050 | 2,050 |

Robust standard errors in parentheses.
***, **, and * correspond to a significance level of respectively 1%, 5%, and 10%.

of country, year, and month fixed effects, and we find consistently positive and significant interaction terms coefficients.[50] Moreover, in column (4), we also add a trend and an interaction term of the trend with the policy rate. We find that not only the interaction term of the measure of connectedness remains positive and highly significant, but it is also quantitatively larger that the interaction term of the policy rate with the simple time trend. Finally, we explore what is the role played by EPU, which was found by Bordo et al. (2016) to have negative effects on loan growth for a sample of US banks. We downloaded the indicator of EPU proposed by Backer et al. (2016) for the European countries.[51] In column (5), we add to our regression both the level of EPU and its interaction with the interest rate. We do find a negative coefficient on EPU, which is, however, very small and not statistically significant. We do not find a significant coefficient for the interaction term.

The size of the coefficients reported in Table 1 allows concluding that the attenuation effect implied by interconnectedness is economically sizeable. Taking as a reference point column (4), an interaction term of 0.2489 implies that moving from a level of interconnectedness of 0.2, at the 25th percentile of the distribution (for instance, the case Spain in 2005) to an interconnectedness level of about 0.38

(the 75th percentile, as Ireland in 2005), the semielasticity of loans with respect to the policy rate would move from about 4% to almost zero.

We conclude that effectively a higher interconnectedness within the financial system seems to dampen the sensitivity of lending to monetary policy, as our model would predict.

## 5. CONCLUSIONS

This paper proposes a model in which the credit channel of monetary policy is affected by the extent of the interconnectedness in the financial sector. We present a model-consistent measure of interconnectedness, and document its increase in the period 1952–2016. Finally, we establish that the responses of several US real and financial variables to monetary policy shocks are dampened as financial interconnectedness increases, and document how an increase in interconnectedness dampens the effects of the ECB policy rate on loans in a sample of 10 Euro area countries. The changing nature of the interconnectedness within the financial sector, therefore, might have been one of the factors leading to a reduced responsiveness of real variables to monetary policy shocks in recent times.

Of course, the implications of this structural change in the financial system may go far beyond the transmission of monetary policy shocks. We outline here several potential avenues for future research that make use of the measure of interconnectedness. First, it would be interesting to develop a quantitative macroeconomic model embedding the concept of interconnectedness explored in this paper. This could also be used to evaluate the relative importance of the policy behavior and the interconnectedness in explaining the muted responses of monetary policy innovations on economic variables found using more recent samples. Second, in our stylized model, the interbank market only serves the purpose of providing a risk diversification mechanism. However, one might argue that a greater interconnectedness might also imply a greater risk of contagion (which we shut off by assuming that risks are uncorrelated across islands). Enriching the model in that direction would allow us to consider some intriguing research questions, such as the existence of a potential trade-off offered by interconnectedness in terms of enhanced possibilities of risk diversification coupled with a greater exposure to shocks and contagion, potentially affecting financial stability.[52] Finally, and especially for policy purposes, it would be important to go beyond the aggregate perspective we take in this paper and use balance sheet data on individual financial institutions to analyze the impact of their interconnection with other financial firms on a range of performance measures. This could also help improve the regulation and monitoring of financial institutions.

## SUPPLEMENTARY MATERIAL

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S1365100517000177.

*NOTES*

1. See Gorton and Metrik (2012).
2. See Adrian and Shin (2010), Poznar et al. (2012), and references therein for a comprehensive explanation of the concept of shadow banking.
3. A notable exception is Dynan et al. (2006), who analyze the impact of monetary policy on real activity before and after relevant regulatory changes.
4. See also Mesonnier and Stevanovic (2016) for empirical evidence on the impact of shocks to large banks' leverage on the macroeconomy.
5. See also the survey on Financial Intermediation by Gordon and Winton (2003).
6. See, for instance, Acemoglu et al. (2015), Farboodi (2015), and the many references therein.
7. A recently proposed complementary channel through which changes in the financial conditions can affect the transmission mechanism of monetary policy is the "risk taking channels," proposed by Borio and Zhu (2012). See also Bruno and Shin (2013).
8. See Balabanova and Bruggemann (2017) for a recent study of monetary policy transmission in the new EU member states using a FAVAR.
9. See Ciccarelli et al. (2015) for a recent empirical exploration of the importance of the credit channel for the transmission of monetary policy.
10. Adding a partial self-insurance possibility through loan portfolio diversifications, an aggregate element to the projects return or bank heterogeneity would complicate the analysis, without affecting the key qualitative insight of the model.
11. However, making this more standard assumption would not affect the main qualitative results of our model, at the cost of complicating the analysis.
12. For this to be true, it would be sufficient, from (7), the weaker condition $R - A \geq 1$. The reason why we make a stronger parametric restriction is going to be clearer later.
13. Otherwise, if $r(\cdot)$ is increasing, the entrepreneur would borrow small amounts from many banks.
14. Notice that if the entrepreneur chooses the safe project, whose return is 1, the profits for him are equal to $1 - 1 - r$.
15. We abstract here from the possibility that a bank might rely on government interventions, for instance, because it is too-big-to-fail. While this could be an interesting feature to consider, it would not affect the main message of the model. We thank an anonymous referee for having pointed this out.
16. It is assumed that the bank can observe the entrepreneur's credit with other banks, and takes the market interest rate schedule $r(I)$ as given.
17. In this simplified setting, there is also a less-interesting equilibrium with no lending ($I = 0$ and $m = 1$). We concentrate our attention to the equilibrium with lending. While additional assumptions, at the cost of complicating the analysis, could rule out the no lending equilibrium, this would not add much to the qualitative insights on which we want to focus here.
18. To see this, note that the entrepreneur's profits are 0. If the entrepreneur invests $I_r < 1$, his expected profits are negative because

$$0.5[R - (1 + r)]I_r - 0.5A = 0.5[R - (R - A)]I_r - 0.5A = 0.5A(I_r - 1) \geq 0 \Leftrightarrow I_r \geq 1.$$

Furthermore, since $r(I) = \infty$ for $I > 1$, the entrepreneur cannot make strictly positive profits from choosing $I > 1$. Obviously, since the return to the safe project is 1 there are no profits to be made from choosing $I_s > 0$. To see that the bank cannot increase its profit by deviating from the schedule $r(I)$, note that if a bank offers $r(I) < R - A - 1$ for $I \leq 1$ it will be unable to sell its securities at the price $p$, as the expected return is lower than $p$. The bank will then be unable to diversify and will not be able to repay depositors in all states. If a bank offers $r(I) > R - A - 1$ for $I \leq 1$, it will be unable to lend as entrepreneurs will prefer to borrow from another bank. The bank obviously cannot lend more than $I = 1$ so it cannot increase its profits by changing $r(I) = \infty$ for $I > 1$.
19. See Hobjin and Ravenna (2010) for a more quantitative model of bank securitization and monetary policy transmission. See Moran and Meh (2013) for a quantitative model of the shadow banking system.
20. Table L.108 of the Z1 release of September 2016.

21. Another important drawback of using flow of funds data is that we are not able to say much about nonbalance sheet items, such as derivatives. Since derivatives are typically used as a common example of the interconnectedness of the financial sector, we are aware that we are missing an important piece of information, which would make of $\text{INTER}_2$ an inaccurate estimate of an upper bound for the concept of financial sector interconnectedness. However, we can confidently say that $\text{INTER}_1$ represent a lower bound estimates of the interconnectedness of the financial sector, and this is the reason why in our empirical section we will use it as our benchmark.

22. In fact, the correlation between the two is 0.99.

23. These two asset classes represent the difference between the numerators of $\text{INTER}_1$ and $\text{INTER}_2$.

24. Such as European Commercial Banks, Asian Pension Funds, etc.

25. We include in this "adjusted" liabilities series time and savings deposits, the money market mutual funds deposits, the credit market instruments, the repurchasing agreements, the mutual funds shares, and the pension funds shares.

26. We report these results in an online appendix.

27. Obviously, this would require single institutions' balance sheet data.

28. For instance, the Depository Institutions Deregulation and Monetary Control Act in 1980, which removed the interest rate ceilings that commercial banks were facing on their offer of deposits, thus allowing them to better compete for customers with money market mutual funds.

29. A second reinterpretation would follow in 1996, when the ceiling on the maximum revenues obtainable from investment banking activities was lifted to 25%, though this does not seem to have any significant impact on the trend of our measures.

30. While Philippon's data are at annual frequency, we interpolated them to transform them into a quarterly series.

31. We have also studied the cyclical behavior of INTER. Results suggest that the cyclical component of our measure of interconnectedness does not Granger cause any of endogenous series in the VAR.

32. We thus implicitly assume here a time-invariant distribution of the shocks.

33. We use the following procedure:

1. Shuffle the time dimension of OLS residuals $\hat{e}_t$ and get bootstrap innovations $e_t^*$.
2. Using $\left[Y_1, \ldots, Y_p\right]$ as initial values and $\text{INTER}_{t-1}$, get the bootstrap endogenous variables from
$$Y_t^* = \hat{\Phi}(L)Y_{t-1}^* + \hat{\beta}\text{INTER}_{t-1}Y_{t-1}^* + e_t^*.$$
3. Impose the identification restrictions to get $H$ and calculate impulse responses.

34. The results obtained using $\text{INTER}_3$ (the measure built using liabilities data) are broadly similar, and included in an online appendix.

35. We stop our analysis in 2009 because after that time the nominal interest rate in the United States reached the zero lower bound.

36. Bayesian, HQ, and Akaike information criteria suggest between two and six lags. We have tried several lag structures and the results are quite robust. We have decided to use the same number of lags as in Boivin and Giannoni (2006).

37. In the online appendix, we report also the results obtained without inserting the interaction term with our measure of interconnectedness, and dividing the sample into the two subperiods analyzed in Boivin and Giannoni (2006). We find results broadly consistent with theirs. Moreover, we checked that the model is stationary: Under each regime, the maximum eigenvalue is less than unity. Some seemingly nonreverting trajectories are just due to the fact that we plot only the first 12 periods after the shock in order to make the figures more readable.

38. We omitted the results here, they are available upon request.

39. If the shocks in the VAR model are fundamental, then the dynamic effects implied by the moving average representation can have a meaningful interpretation, i.e., the structural shocks can be recovered from current and past values of observable series. Forni et al. (2009) argue that while nonfundamentalness is generic of small-scale models, it is highly unlikely to arise in large dimensional dynamic factor models.

40. See the online appendix for details.

41. The complete description of the data and their transformation is presented in the online appendix.

42. Standard information criteria suggested two to six lags. We selected four as in the VAR, but results are robust to other orders of $\Phi(L)$.

43. Bernanke et al. (2005) divide the series in $X_t$ into "fast" and "slow" moving variables in order to estimate the space spanned by latent factors only. The slow-moving variables (for instance, GDP, consumption, inflation) are supposed *not* to react on impact to a monetary policy shock. Ordering $R_t$ last is natural as long as we believe that the latent factors are not affected contemporaneously by an orthogonalized shock on short interest rate. Bernanke et al. (2005) found that including factors from fast-moving series (such as stock price indexes and exchange rates) and ordering them after $R_t$ does not change the impulse responses of series in $X_t$ to monetary policy shock (see the online appendix for the complete list of slow- and fast-moving variables). Finally, as discussed in footnote 26, the cyclical component of our measures of interconnectedness does not comove strongly with macroeconomic series, hence we do not consider the interconnectedness as an observed factor.

44. Also for the case of the FAVAR, we repeated our procedure using all the measures proposed in Section 3, and we obtained very similar results.

45. We report here only the point estimates, while we report in the online appendix two separate figures, including also confidence bands at 90%.

46. Note that the data in the FAVAR analysis must be demeaned and standardized before estimation. Therefore, the impulse responses in Figure 7 have been multiplied by the standard deviation of the stationary series. Hence, the impulse responses for the real variables can be interpreted as the quarterly percentage deviation from the trend.

47. See the online appendix for details.

48. We excluded Luxembourg for its peculiar role of financial hub. We thus included Austria, Belgium, Germany, France, Finland, Ireland, Italy, Spain, Portugal, and the Netherlands.

49. In the terminology of the (ESCB), we take the sum of loans to other monetary and financial institutions (MFIs) with the exception of the European System of Central Banks (ESCB), and holding of debt securities issued by other MFIs as a fraction of total loans and total debt securities.

50. In columns (3), (4), and (5), we correct the standard errors for heteroskedasticity and autocorrelation using a Newey–West correction.

51. The aggregate European indicator is an average for the indicators of Germany, France, Italy, and the United Kingdom.

52. See Cabrales et al. (2016) for a model featuring this trade-off.

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