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## Abstract

The amount of assets managed by non-bank lenders has increased significantly over the last decades. Our research aims to clarify whether such an increase has had any impact on the effectiveness of monetary policy. To this end, we consider several credit aggregates granted from bank and non-bank institutions for different scopes and developments in the US economy. Our analysis is based on the estimation of a large Bayesian VAR. The results suggest that the rise of non-bank lenders has reduced and altered the monetary policy transmission mechanism.

JEL-Codes: E440, E510, G200, G210, C110.

Keywords: bank loans, non-bank loans, monetary interventions, Bayesian VAR.

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# Contents

# 1 Introduction

Western economies have witnessed to the rise of non-bank lenders in the last decades (IMF 2016). The reasons at the basis of this evolution in financial markets are many (Adrian & Ashcraft 2016). Among those, the evolution of bank regulation has played an important role. Accordingly, banks have retreated from some businesses, other businesses have transformed and/or new players have entered into the financial market (Adrian & Shin 2009). Furthermore, the development of new financial practices, firstly securitization, has definitely sustained the growth of non-bank finance (Estrella 2002).

Historically, a large part of the transmission of conventional monetary interventions to the real economy has been through bank credit: the extension of loans and mortgages. In fact, the literature on the transmission mechanism (Bernanke & Gertler 1995, Bernanke 2007) has made clear the different channels through which a monetary tightening (or easing) impacts on bank credit extension and consequently on the real economy (Albertazzi et al. 2020). Nevertheless, the unquestionable evidence about the decreasing size of the bank sector calls for a review of this issue. In fact, it has become of interest to investigate whether such a structural change in the mix of lenders has altered somehow the transmission of monetary impulses to the real economy (Den Haan & Sterk 2011, Nelson et al. 2018, Xiao 2020). Our analysis aims to answer this question.

We study the effectiveness of monetary interventions in terms of their impact on the GDP, and their effect on some credit aggregates by distinguishing between the type of lender (bank versus any other non-bank institution) and the type of credit (mortgages versus loans). We assess how such effects have changed over time in the face of the diminishing size of the bank sector. In our analysis, we construct the non-bank aggregate as a comprehensive heterogeneous entity opposite to depository institutions, as this is functional to reflect the diminishing weight of the bank sector. The analysis is for the United States and covers the period up to the beginning of the Global Financial Crisis. As discussed further on in the text, that is the period when we observe a significant and persistent change of the share of banks' credit vis-à-vis non-banks' (Meeks et al. 2017). Our study is based on the Bayesian estimation of a large vector auto-regression and employs an identification approach consistent with conventional monetary policy before the Global Financial Crisis (Arias et al. 2019). Our strategy consists in comparing results for two subperiods in which the size of the bank sector is significantly different.

We contribute to the current literature by showing a reduced effect of monetary interventions in correspondence of an enlarged non-bank sector; this emerges as a robust result. We find that it is important to distinguish for the type of credit inside the non-bank sector. In fact, after a monetary tightening, loans provided by non-bank institutions tend to behave like bank credit, while mortgages display an opposite dynamics. Furthermore, we succeed to link such a reduced effect to a change into the transmission mechanism. With respect to some previous contributions in this branch of literature, such as Xiao (2020), Nelson (2009), our analysis is developed through a systematic and symmetric study of credit aggregates to account for the smaller size of the bank sector, both in the mortgage and the loan business. At the same time, we apply a shock-identification approach specifically selected to be consistent with conventional monetary policy before the Global Financial Crisis, and we prove the robustness of our conclusions by applying also a different identification approach as well as by means of local projections.

The paper is structured as follows. Section 2 discusses the growth of the non-bank sector and reports on some relevant literature on non-banks and the transmission mechanism. Section 3 details the estimation of the VAR using the Bayesian approach. We report and discuss the results of our analysis in Section 4. Section 5 draws the conclusions.

## 2 The rise of non-bank lenders

The growth of non-bank finance has started in the mid 70s in the USA, much earlier than in any other developed country (Adrian & Shin 2009). More recently, the Euro Area has witnessed to its growth too (Altunbas et al. 2009). The expression *non-bank finance* refers to different instruments and not just to loans and mortgages from non-bank intermediaries, which are the object of our investigation. In fact, it is to point out that one of the main determinants of the increase in non-bank finance has been the issuance of corporate bonds to get funds as a substitute of, or in addition to, bank loans (IMF 2016).

When they grant loans, non-bank institutions compete with banks for possibly the same clients. Furthermore, not only loans and mortgages have crossed the perimeter of banks, but also liquidity is offered by some non-bank entities in a form very much comparable to bank deposit. Drechsler et al. (2018) comment on the birth of money-market funds as an alternative to bank deposits.[1]

In contrast to the homogeneous bank sector, particularly in terms of the regulation in force, the non-bank sector is heterogeneous. It spans from mortgages and loans granted by finance companies, to those by insurance companies, the US government, securities brokers and dealers, money market funds, etc. We use such a large aggregate to account for the diminishing weight of bank credit in the economy. As matter of fact, some uncertainty regarding the exact size and composition of the non-bank sector exists, which is often referred to as *shadow banking system* when it excludes institutional entities.[2] Such uncertainty has undoubtedly consequences for macro-prudential surveillance (Yellen 2014). Relative to this, interest on non-bank institutions has blossomed particularly after the Global Financial Crisis (GFC) since they are considered to have increased remarkably the level of risk into the financial system (Gennaioli et al. 2013). In fact, credit in general, both from banks and non-banks, was one of the mayor causes of the GFC (Cafiso 2021).

Non-bank lenders have grown relatively more than banks for known reasons. A regulation arbitrage has pushed banks to retreat from certain businesses (FSB 2013), but the establishment of a new business model mattered too. Gorton & Metrick (2012) describe the shift of banking from "the traditional *commercial* activities of loan origination and deposit issuing toward a *securitized* banking business model, in which loans were distributed to entities that came to be known as *shadow* banks". Such developments have therefore left room to less regulated players, which have grown substantially more over the same period. Figure 1 shows such a growth by plotting mortgages and loans from banks and non-bank lenders. The distinction between mortgages and other loans is important in this context since the process of securitization has primarily regarded mortgages (Loutskina & Strahan 2009) and because, in relation to our VAR analysis, different instruments might respond differently to the same impulse (Brady 2011).

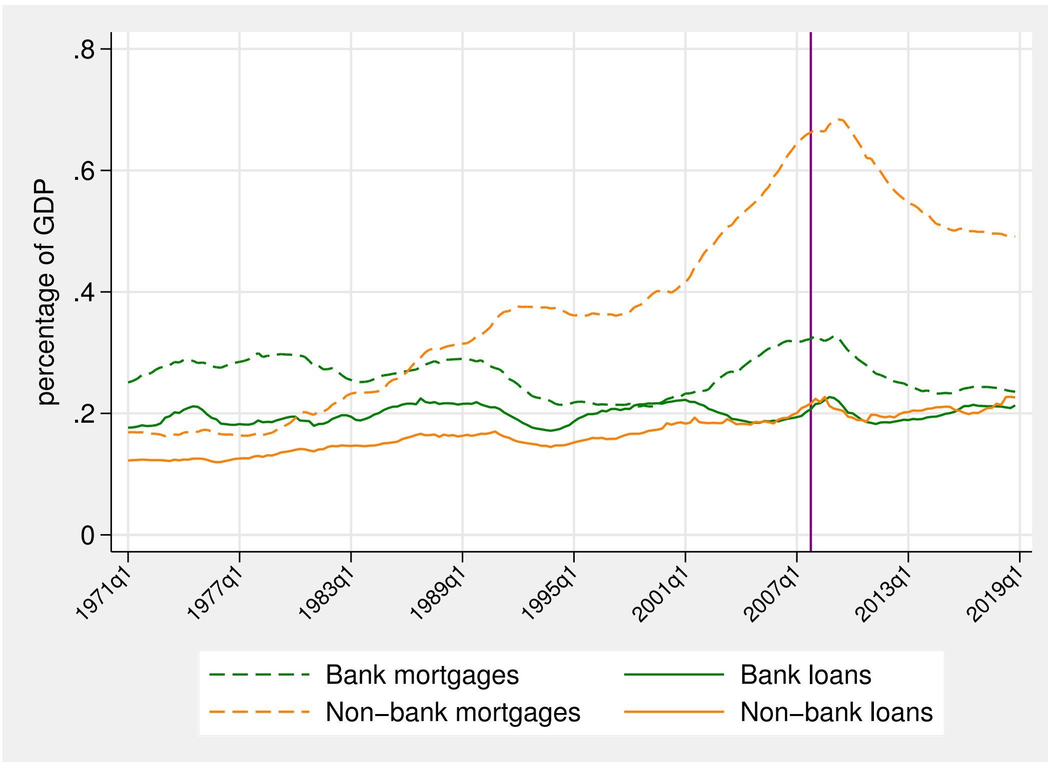
To understand better the evolution in Figure 1, we report weights in Table 1 (panel A includes shares for each category over the total amount of credit extended, panel B keeps mortgages and

[1] For this reason, shares of money market funds are included into the monetary aggregates.

[2] Xiao (2020): "The shadow banking system is a collection of financial intermediaries that conduct maturity, credit, and liquidity transformation outside the traditional commercial banking system. Examples of shadow banks include securitization vehicles, asset-backed commercial paper (ABCP) conduits, MMFs, broker-dealers, and mortgage companies. Like commercial banks, shadow banks transform long-term illiquid assets into short-term money-like claims. Because households and businesses prefer liquidity, issuing money-like claims allows shadow banks to lower their financing costs."

loans separated) and plot them in Figure 2. This data show that non-bank mortgages have definitely outweighed bank mortgages and that their differential has stabilized after the GFC. A similar dynamics emerges also for loans but, in this case, non-bank loans have grown to match bank loans with their difference appearing modest and stable since the GFC. The three vertical lines in Figure 2 make clear that in the first subsample used for our analysis the bank sector is larger than the non-bank, while this reverses afterwards.

Figure 1: Mortgages and Loans




Information on the data used for this Figure is available in the 'Data' subsection.

Table 1: Loan shares

*Panel A*

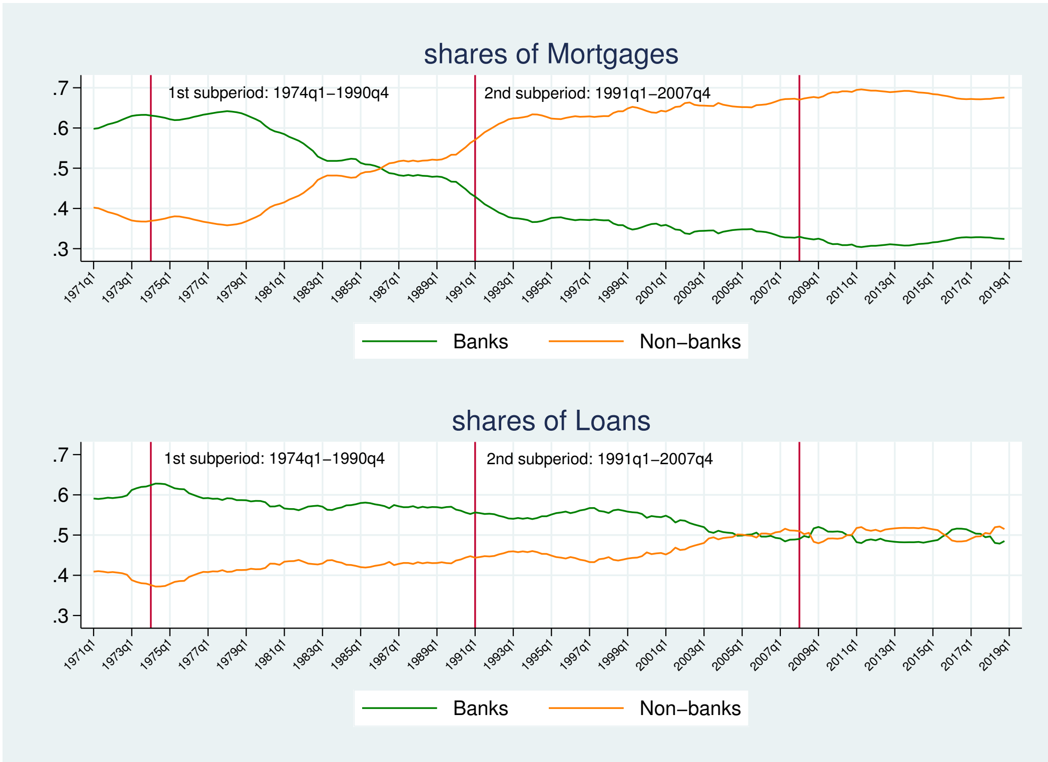
| ten years | BK-TM | NBK-TM | BK-LS | NBK-LS |
|---|---|---|---|---|
| 1970q1-1979q4 | 0.366 | 0.221 | 0.248 | 0.165 |
| 1980q1-1989q4 | 0.310 | 0.287 | 0.230 | 0.173 |
| 1990q1-1999q4 | 0.240 | 0.387 | 0.207 | 0.166 |
| 2000q1-2009q4 | 0.229 | 0.446 | 0.167 | 0.158 |
| 2010q1-2018q4 | 0.209 | 0.452 | 0.167 | 0.172 |
| Total | 0.272 | 0.357 | 0.204 | 0.167 |

*Panel B*

| ten years | BK-TM | NBK-TM | BK-LS | NBK-LS |
|---|---|---|---|---|
| 1970q1-1979q4 | 0.623 | 0.377 | 0.600 | 0.400 |
| 1980q1-1989q4 | 0.520 | 0.480 | 0.571 | 0.429 |
| 1990q1-1999q4 | 0.383 | 0.617 | 0.554 | 0.446 |
| 2000q1-2009q4 | 0.340 | 0.660 | 0.513 | 0.487 |
| 2010q1-2018q4 | 0.316 | 0.684 | 0.493 | 0.507 |
| Total | 0.439 | 0.561 | 0.547 | 0.453 |

Notes: BK is for banks, NBK is for non-banks, LS is for loans, TM is for total morgages.

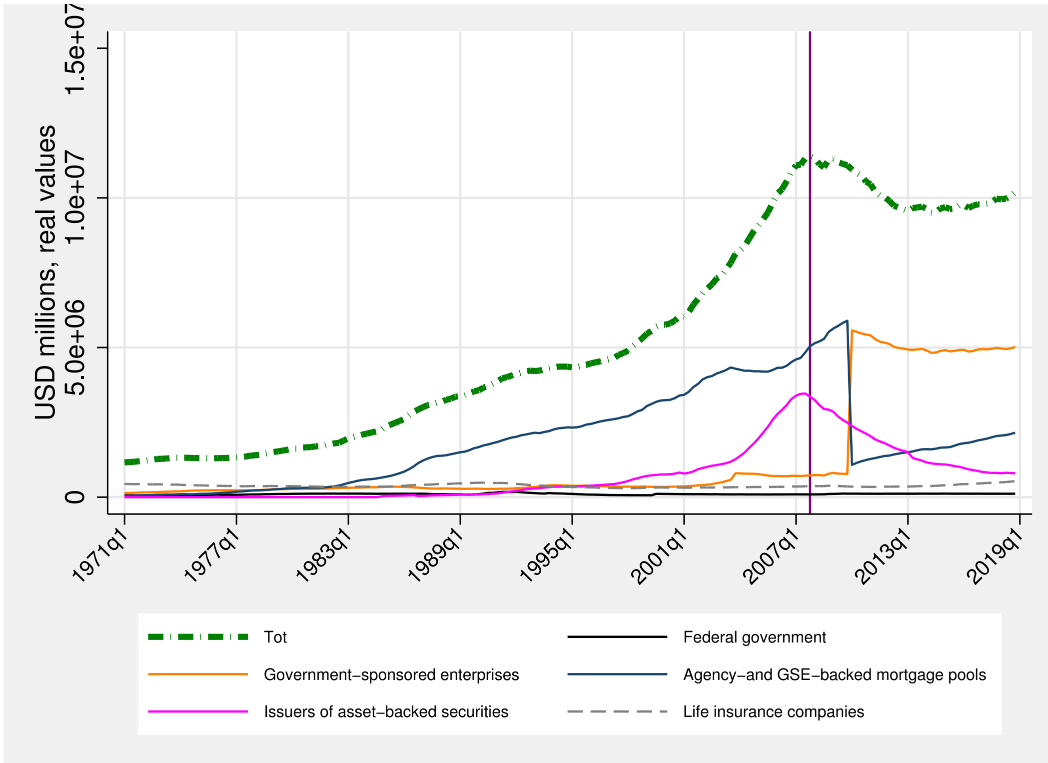
Figure 2: Shares of Mortgages and Loans




The 1st vertical line is for 1974q1, the 2nd is for 1991q1, the third is for 2008q1.

Given the role of mortgages in the GFC and the striking evolution of non-bank mortgages shown in Figure 1, we are interested in the players behind such an evolution. To this end, we disentangle the non-bank mortgages aggregate. *Mortgages pools and trusts* (made of 'Agency and GSE-backed mortgage pools' and 'Issuers of asset-backed securities'), unsurprisingly, are behind the growth observed before the GFC. Because of the GFC and the consolidation measures undertaken, the share of mortgages pools and trusts was absorbed by *government sponsored enterprises* in 2010. The evolution of these components is in Figure 3.

Figure 3: Non-bank mortgages




The figure reports only the largest five components of non-bank mortgages in terms of lenders. Data are from the Federal Reserve Board.

## Potential consequences for the transmission of monetary interventions

Undoubtedly, the rise of non-bank lenders might have had consequences for the transmission of monetary interventions to the real economy. In fact, those have been object of study for some time. Among the others, Xiao (2020) and Nelson et al. (2018) are two recent contributions in this branch of literature. There is no unanimous view about such consequences particularly when more countries are considered. For instance, Schnabel (2021), IMF (2016), Nelson et al. (2018) achieve different conclusions. Trustworthy answers to this question are therefore likely country-specific since the transmission mechanism has its own specific features in each country (Ciccarelli et al. 2015). Furthermore, after the GFC, the so-known shadow banking system has become object of investigation not only in relation to monetary policy, but more and more in relation to systemic risk and macro-prudential policies (Adrian & Shin 2009). Both aspects are related to each other to a certain extent, but we concentrate on the consequences on the transmission mechanism.[3]

Xiao (2020) speaks of a *shadow-banking channel* to refer to how monetary impulses are transferred to the real economy via the non-bank sector. In his framework, this emerges as a further channel to add to the classical ones related to depository institutions (Albertazzi et al. 2020).[4] According to Xiao (2020), a monetary tightening reduces money creation by depository institutions but it expands money creation by shadow banks. This effect can be explained by the widening of the spread between shadow and commercial bank deposit rates after an increase in the Fed-funds rate. This recalls the deposit channel described by Drechsler et al. (2017). The effect is economically significant and this difference explains the expansion of shadow banks in periods of high interest rates. Nevertheless, Xiao (2020) affirms that the overall effect on money creation is still negative, but the magnitude is quite small.

Nelson et al. (2018) find that surprise monetary contractions tend to reduce the assets of commercial banks, while those tend to expand shadow bank assets. This happens because contractions cause a migration of activity beyond the regulatory perimeter to the shadow banking sector.[5] Meeks et al. (2017) write a model that explains why and how commercial banks can offload risky loans to a "shadow" banking sector and financial intermediaries trade in securitized assets.[6] Along the same lines, Borio & Zhu (2012) describe how monetary hikes cause banks to reshuffle their portfolio towards less risky assets in accordance to the risk-taking channel. Chen et al. (2018) have recently contributed on China. They

[3]Before the GFC, the growth of non-bank finance was largely regarded just as a positive development that carried out limited risk. In fact, many argued that the great moderation, alias the period of low volatility starting around the mid-eighties depended on the development of non-bank finance. This thesis is well discussed in Den Haan & Sterk (2011). Accordingly, the development of non-bank finance caused the observed lower correlation between credit aggregates and the business cycle since more smoothing was feasible.

[4]As for the part of the transmission mechanism that involves bank credit, research distinguishes two main channels: A) the Cost of Capital Channel, or cost of credit; B) the so-known Broad Credit Channel, an expression used in Ciccarelli et al. 2015, which can be further disentangled into the balance-sheet channel, the bank-lending channel and the risk-taking channel. Jointly, they describe how credit aggregates respond to a monetary policy change as the result of both demand and supply factors. The cost of capital channel (A) pertains to the demand side, the balance-sheet channel regards both demand (B1i) and supply (B1ii), the bank-lending channel (B2) concerns the supply side as the risk-taking channel (B3). See Cafiso (2022) for a deeper discussion of demand and supply factors.

[5]The mechanism framed in their DSGE model is as follows: "A monetary contraction raises commercial banks' funding costs, while also reducing asset prices, and so the value of their collateral. These two effects both put downward pressure on commercial bank net worth. To maintain their intermediation capacity, commercial banks seek out pledgeable collateral in response. Holding more pledgeable collateral, while switching out of illiquid loans, helps to mitigate the contraction in their balance sheets and maintain profitability. This pledgeable collateral is manufactured in the shadow banking sector, which pools loans and issues ABS against them. As such, monetary contractions result in an increase in the demand for securitized assets relative to loans" (Nelson et al. 2018).

[6]They model the financial system as composed by banks and shadow banks, they assign a specific economic role to each of the two: "Although banks specialize in originating loans, brokers have a comparative advantage in holding them. To fund itself, the shadow banking system produces ABS, which, in turn, find a market among commercial banks eager to expand their balance sheets by acquiring high-quality collateral" (Meeks et al. 2017).

find that contractionary monetary policy during 2009–2015 caused shadow-bank loans to rise rapidly, offsetting the expected decline of traditional bank loans and hampering the effectiveness of monetary policy on total bank credit.[7]

Even though the previously-mentioned contributions suggest a dampening effect of non-bank lenders on the transmission mechanism, as mentioned at the beginning, there is no unanimous view. For instance, IMF (2016) reports on some other alternatives. In theory, non-banks can either dampen or amplify the effects of monetary policy. On one hand, non-banks may be able to step in to lend in lieu of banks when their funding cost is less strongly affected by monetary policy, if they are not subject to the same regulatory constraints, or if their risk-taking incentives are different. For example, a widening of the regulatory gap between banks and non-banks or of the ability of banks to securitize some of their loan portfolio may dampen the transmission mechanism. On the other hand, non-banks may amplify the transmission of monetary policy if their risk appetite is more sensitive to changes in monetary policy. In a recent speech, ECB executive-board member Isabel Schnabel has discussed the potential changes to the transmission mechanism related to the development of non-bank finance (Schnabel 2021). She details how the Euro Area (EA) has changed due to the enlargement of credit from non-bank lenders and to the effect of larger and larger issuance of corporate bonds. She concludes that non-bank finance has expanded the transmission mechanism in the EA. More recently, Holm-Hadulla et al. (2022) clarify that this is not a general result and much depends on the structure of corporate debt (loans versus bonds) as well as on the kind of monetary intervention. In fact, conventional monetary interventions, which act more on short-term rates, have a deeper impact when loans have a larger size relative to corporate bonds. In contrast, asset purchases, which affect long-term interest rates, impact more countries in which corporate bonds have a larger size.

# 3 VAR analysis

The scope of the analysis, whose details are explained in this section and whose results are discussed in the next one, is to study the effect of monetary interventions on the GDP and on four credit aggregates.

[7]Their theory shows that while contractionary monetary policy reduces bank loans as expected, it simultaneously encourages non-state banks to increase investments in risky non-loan assets to circumvent the loan-to-deposit ratio and safe-loan regulations to which bank loans are subject.

We do this both in general and over two properly-defined consecutive subperiods, which are characterized by substantially different magnitudes of the non-bank sector. The research question to which we aim to answer is whether the growth of non-bank lenders has modified the effectiveness and/or the working of monetary interventions.

The empirical analysis is based on a benchmark VAR model estimated through Bayesian techniques to overcome some drawbacks typical of the frequentist approach.[8] This VAR includes the variables 1-14 listed in Table 2. The same benchmark VAR is estimated over the entire period of analysis (1974q1-2007q4, 34 years) and over two consecutive subperiods of the same length (17 years) characterized by a different dimension of the non-bank sector: the 1st subperiod is 1974q1-1990q4, the 2nd is 1991q1-2007q4.

We restrict the analysis to the period before the GFC for different reasons. First and foremost, the period 1974-2007 exhibits an enlarging weight on the non-bank sector, which is what we need to answer our research question, while that weight is more stable after the 2007; see previous section 2. Secondly, we choose to focus on the period of conventional monetary policy because this allows to use consistently a specific identification approach suited for that period. In fact, we follow Arias et al. (2019) and identify the monetary policy rule with sign and zero restrictions on the structural coefficients; see next subsection 3.2. In truth, the larger and larger use of non-conventional policies after 2007 represents a change that undermines the robustness of identification approaches applied before and after the 2007. Shocks over periods including the post-2007 are better caught by high-frequency identification approaches (Gürkaynak et al. 2005, Jarocinski & Karadi 2020) hardly usable for periods of analysis before the mid 90s.[9]

We proceed with caution regarding the estimation over different subperiods, since identification of monetary shocks is in each estimation. As a first step, we estimate the model over the entire period (P) and then over the two subperiods (P1, P2), we save the three series of MP shocks thereby identified (sP, sP1, sP2). Subsequently, we verify the consistency of the shocks identified over the two subperiods (sP1, sP2) with the ones obtained from the estimation over the entire period (sP). When judged by means

[8] First and foremost, Bayesian techniques allow the estimation of large VARs with a standard number of observations, they deal with the over-parametriziation issue (Bańbura et al. 2010) by shrinking the parameter space. Second, the likely non-stationarity of the series under considerations is embedded in the prior distribution by appropriate values of its hyperparameters.

[9] As for this, we have tried the unified measure of MP shock defined by (Bu et al. 2021) but it generates results contrary to economic theory in our sample.

of correlation values, those are consistent with one another at a large extent. To prove the robustness of our results, as a further check, we use also the shock series identified over the entire period (sP) to perform local projections (Jordà 2005) over the two subperiods (P1, P2). Local projections take largely to the same conclusions when we use just one MP shock series (sP) for the analysis.

Details on the estimation of the reduced form as well as on the structural identification of the monetary interventions are in the following subsections 3.2.

## 3.1 Data

The analysis is based on US quarterly credit data extracted from the Financial Accounts of the United States (Board of Governors of the Federal Reserve System).[10] We use two main credit aggregates:

- Mortgages,
- Loans,

granted to US non-financial entities, which are: households and non-profit organizations, corporate business and non-corporate business. Both series are for the following lender groups:

- Banks (alias, depository institutions, BK),
- Non-banks (NBK).

In the case of loans, we use also data for some members of the non-bank group: finance companies, the US government, the Farm Credit System.[11] We decide to develop the analysis by keeping loans and mortgages well distinguished because of the different characteristics, regulation, scope and possible lenders of mortgages with respect to any other loan. Our loan aggregate includes consumer credit to households.

The other variables used in the VAR can be conceptually clustered in the following groups. *Real variables*: the gross domestic product, to account for economic activity and the business cycle. *Prices*: a world index of commodity prices, the house price index, the consumer price index; these are to reflect

[10] The loan series data are made available non-seasonally adjusted, we have seasonally adjusted them by using the X-13ARIMA-SEATS program developed at the U.S. Census Bureau; loan series exhibit a strong seasonality on the 4th quarter.

[11] The latter is a system of borrower-owned lending institutions and specialized service organizations (Monke 2016) serving the US agriculture sector.

price developments of goods and of the real estate sector. *Interest rates*: the federal funds rate, an average interest rate on 3 months business loans (Bank Prime Loan rate), an average interest rate on personal loans with 24 months maturity, an average interest rate on mortgages with 30 years maturity; these are to account for the cost of loans as well as the monetary stance. *Financial market developments and sentiment*: the Standard & Poors 500 index, Gilchrist & Zakrajšek (2012)'s excess bond premium; these are for financial market evolution as well as to reflect investors' sentiment.[12] The list of all variables with the respective source is in Table 2.

Table 2: List of variables

| # | borrower | variable | source | short |
|---|---|---|---|---|
| 1 | | Gross Domestic Product | FRED | GDP |
| 2 | | House Price Index | Datastream | HPI |
| 3 | | World index of commodity prices | Datastream | WCP |
| 4 | | Consumer Price Index | FRED | DEF |
| 5 | | Fed Funds Rate | FRED | FFR |
| 6 | | Interest rate on 3 months business loans | FRED | IR03M |
| 7 | | Interest rate on 24 months personal loans | FRED | IR24M |
| 8 | | Interest rate on 30 years mortgages | FRED | IR30Y |
| 9 | | Excess Bond Premium | GZ2012 | EBP |
| 10 | | Standard & Poors 500 index | Datastream | S&P500 |
| 11 | Bank | Bank mortgages | BGFRS | BK-TM |
| 12 | | Bank loans | BGFRS | BK-LS |
| 13 | Non-bank | Non-bank mortgages | BGFRS | NBK-TM |
| 14* | | Non-bank loans | BGFRS | NBK-LS |
| 15 | | Non-bank loans: Finance Companies* | BGFRS | NBK-FIC-LS |
| 16 | | Non-bank loans: US government* | BGFRS | NBK-USG-LS |
| 17 | | Non-bank loans: Farm Credit System* | BGFRS | NBK-FCS-LS |

Notes: As for the sources, BGFRS is for the Board of Governors of the Federal Reserve System, FRED is the Saint Louis Fed's online application to extract data, GZ2012 stands for Gilchrist-Zakrajšek (2012). The column 'short' reports the acronyms used throughout the paper. *These are just some components of the 'non-bank loan' aggregate, their summation does not sum up to the aggregate.

[12] The excess bond premium is a measure of investor sentiment or risk-aversion in the corporate bond market with a high information content for economic activity. Gilchrist and Zakrajsek (2012) find that an increase in the excess bond premium reflects a reduction in the effective risk-bearing capacity of the financial sector and a contraction in the supply of credit that has recessionary effects on the economy.

## 3.2 Estimation

The empirical analysis is based on the following reduced-form VAR:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + u_t$$

in which $Y_t$ is a 14-variable vector. The variables enter the model in log levels, except for interest rates that are in levels. All monetary variables are deflated using the CPI index. The VAR includes 4 lags for each variable to cover one year as common in this branch of literature. In order to deal with the over-parametrization problem, we apply Bayesian methods and estimate a large-BVAR model (Bańbura et al. 2010).

The informativeness of the prior distributions is crucial to shrink the over-parameterized model. Here, we follow Giannone et al. (2015), i.e., we select the appropriate degree of shrinkage by treating priors' hyperparameters as additional unknown parameters, formulating a prior over them and maximizing the marginal likelihood to derive their posterior values. The prior of the coefficients and of the variance-covariance matrix is a Normal-Inverse-Wishart: $\Sigma \sim IW\left(\Psi, d\right), \; \beta \mid \Sigma \sim N\left(b, \Sigma \otimes \Omega\right)$. Here, $\Psi$, $d$, $b$ and $\Omega$ are functions of a set of hyperparameters $\gamma$. The prior for the VAR coefficients combines three prior densities: the Minnesota, the sum-of-coefficients and dummy-initial-observation priors.[13] The tightness of these priors is determined by the three hyperparameters $\lambda$, $\mu$, and $\delta$, respectively. The innovation in Giannone et al. (2015)'s approach is that they treat these hyperparameters as unknown so that the model has a hierarchical structure.[14]

### Structural Identification

Identification of the MP shocks is crucial to our analysis. We adopt Arias et al. (2019)'s methodology for a specific reason: it can be applied consistently to the period we investigate, which is characterized by conventional monetary policy.[15] Therefore, following Arias et al. (2019), we combine sign and

[13] The Minnesota prior assumes that the limiting form of each VAR equation is a random walk with drift so that it allows to effectively shrink the model. The sum-of-coefficients prior and the dummy-initial-observation prior are necessary to account for unit root and cointegration.

[14] The algorithm draws the hyperparameters with a Metropolis step and then, conditional on the value of $\gamma$, the VAR parameters are drawn from their posterior. This algorithm generates 20.000 draws, of which we discard the first 10.000 as burn-in and use the last 10.000 for inference.

[15] In contrast, high-frequency identification is feasible only for recent periods of time given the use of intensive intra-day data they require. Examples are Jarocinski & Karadi (2020) or Nakamura & Steinsson (2018), which start their

zero restrictions on contemporaneous structural coefficients to specify a plausible policy-rate rule that captures the systematic component of monetary policy. In order to explain this, let us rewrite our VAR model in structural form as follows:

$$A_0 Y_t = c + \sum_{l=1}^{p} A_l Y_{t-l} + \varepsilon_t \ ,$$

$Y_t$ is the $n \times 1$ vector of endogenous variables, $c$ is a vector of intercepts, $A_l$ is an $n \times n$ matrix of structural parameters for $0 \leq l \leq p$ with $A_0$ invertible and $p$ the lag length. The vector of structural shocks $\varepsilon_t$ is Gaussian with mean zero and covariance matrix $I_n$.

The identification strategy of Arias et al. (2019) restricts the elements of the first column of the matrix $A_l$ for $0 \leq l \leq p$ as it represents the monetary policy equation:

$$r_t = \phi_y y_t + \phi_p p_t + \sum_{i=3}^{n} \phi_i z_{i,t} + \sigma \varepsilon_{1,t} \ , \tag{1}$$

in which $\phi_1 = \phi_y$ and $\phi_2 = \phi_p$. This equation abstracts from lag variables and shows that the Fed Funds Rate ($r_t$) depends on real GDP ($y_t$), the GDP deflator ($p_t$), and all the remaining variables in the model ($z_{i,t}$), including commodity prices. The coefficients are restricted to obtain a Taylor-type monetary policy rule: the monetary authority is assumed to react contemporaneously only to output and prices (i.e. $\phi_i = 0$), and its reaction is positive (i.e. $\phi_y > 0$ and $\phi_p > 0$). These restrictions are consistent with Christiano et al. (1996) and discussed in detail in Arias et al. (2019).

Obviously, the central bank does not directly observe the contemporaneous level of output and prices, but other real-time indicators are available that allow to learn about the current state of the economy. If this is plausible when using monthly data as in Arias et al. (2019), then it is even more likely to happen in a quarterly framework. As regards commodity prices, we assume that the central bank does not react to them as this allows us to reduce the probability of models implying a rise in prices, as documented in Arias et al. (2019). Furthermore, we assume that stock prices decline on impact after a contractionary monetary policy shock. This assumption is consistent with the findings of Bernanke & Kuttner (2005) and it has also been used by several authors to identify monetary policy shocks, e.g. Jarocinski & Karadi (2020).

investigation from the mid-nineties or the twenties.

We implement the restrictions considering that the coefficients of the monetary policy rule can be decomposed as $\phi_y = -a_{0,11}^{-1} a_{0,12}$, $\phi_p = -a_{0,11}^{-1} a_{0,13}$, $\phi_i = -a_{0,11}^{-1} a_{0,1i}$ and $\sigma = -a_{0,11}^{-1}$. Therefore, the identifying restrictions imply that $a_{0,11} > 0$, $a_{0,12} < 0$, $a_{0,13} < 0$ and $a_{0,1i} = 0$, which represent the sign and zero restrictions that we impose on the matrix $A_0$. Arias et al. (2019) show that this set of restrictions are sufficient to obtain that output, prices and non-borrowed reserves decline after a contractionary monetary policy and the impulse responses are consistent with those obtained by Smets & Wouters (2007) who estimate a large-scale DSGE model.[16]

# 4 Monetary interventions through mortgages and loans

In this section we first discuss the output of our VAR estimation over the entire period to draw general considerations, then we focus on the comparison between the two consecutive subperiods to unveil whether and how the growth of the non-bank sector has altered the effectiveness or working of monetary policy. The discussion is based on Impulse-Response Functions (IRFs), which quantify the response of the VAR variables to the monetary shocks identified through the procedure described in section V. In addition, we refer also to the decomposition of the forecast error variance (FEVD). The FEVD reports the portion of the prediction error of a variable explained by shocks to another variable.

## 4.1 The transmission of monetary interventions through credit

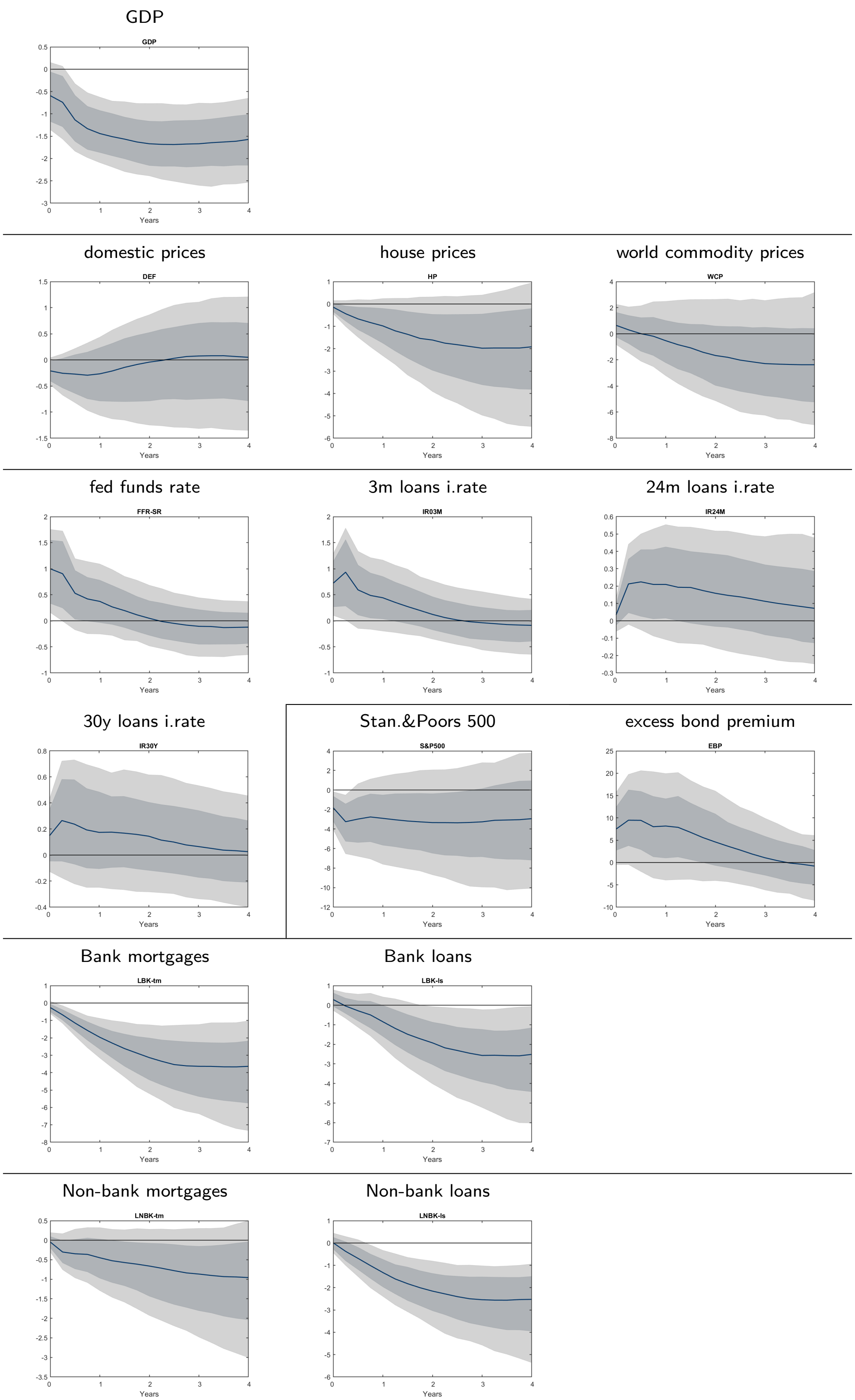
The IRFs obtained from the estimation of our benchmark VAR over the 1974q1-2007q4 period are in Figure 4. When evaluated against the GDP response, MP appears effective. In fact, the GDP is observed to decrease significantly. The response of domestic prices is less strong, but still consistent: they decrease in response to a MP tightening. The question to answer now is: does the observed GDP decrease depend also on the contemporaneous evolution of the credit aggregates in a significant manner?

Apart from non-bank mortgages, which seem responsive at a lower extent, the estimation output

[16] Our algorithm evaluates 10000 draws from the posterior distribution of the model's parameters. In the baseline estimation, 628 draws satisfy the sign and zero restrictions. As recommended by Arias et al. (2018) we computed the effective sample size, i.e. the actual number of independent draws produced by the importance sampler, which is 566. Therefore, the effective sample size represents 0.9 of the draws satisfying the sign and zero restriction; this share is high enough to ensure that our sample is not dominated by only few draws.

does show that credit aggregates decrease significantly, both when extended from banks and non-banks. Consequently, and coherently with the literature on the transmission mechanism, the response of credit aggregates is likely to be responsible for the observed GDP contraction. The response of the other variables is also in line with expectations. For instance, the output confirms that short term rates respond quickly to a monetary interventions, while the others lag behind (den Haan et al. 2007).

Figure 4: Response to a MP shock: benchmark VAR, entire period




The darker grey area in the front and the lighter in the background are respectively for the 16-84 and 5-95 interquantile confidence range.

The FEVD in Table 3 reports the portion of the forecast error variance of each variable explained by MP shocks at specific horizons; we report just the median value for ease of exposition. Such values suggest that MP shocks explain a lot of the GDP forecast error variance, while those portions are lower for the credit categories included. The different magnitude of the FEVD between GDP and credit aggregates somehow recalls the concept of financial accelerator (Bernanke & Gertler 1995). Accordingly, credit transmits and amplifies monetary shocks to the real economy in which they unleash fully their effect.

Table 3: FEVD

| horizon | GDP | DEF | HPI | WCP | FFR-SR | IR03M | IR24M | IR30Y |
|---|---|---|---|---|---|---|---|---|
| 0 | 0.169 | 0.140 | 0.006 | 0.006 | 0.290 | 0.203 | 0.006 | 0.024 |
| 4 | 0.296 | 0.076 | 0.026 | 0.009 | 0.158 | 0.155 | 0.066 | 0.038 |
| 8 | 0.392 | 0.051 | 0.036 | 0.015 | 0.093 | 0.094 | 0.052 | 0.036 |
| 12 | 0.402 | 0.043 | 0.041 | 0.022 | 0.073 | 0.068 | 0.041 | 0.033 |
| 16 | 0.389 | 0.038 | 0.041 | 0.028 | 0.068 | 0.062 | 0.035 | 0.031 |
| **horizon** | **SP5** | **EBP** | **BK-TM** | **NBK-TM** | **BK-LS** | **NBK-LS** | | |
| 0 | 0.016 | 0.020 | 0.014 | 0.003 | 0.013 | 0.004 | | |
| 4 | 0.030 | 0.036 | 0.087 | 0.016 | 0.015 | 0.034 | | |
| 8 | 0.030 | 0.055 | 0.144 | 0.021 | 0.036 | 0.085 | | |
| 12 | 0.030 | 0.056 | 0.157 | 0.025 | 0.055 | 0.112 | | |
| 16 | 0.030 | 0.054 | 0.158 | 0.026 | 0.064 | 0.125 | | |

Check the Table "List of variables" for the full name of the variables.

### The coefficients of the monetary policy rule

Table 4 reports the estimated structural coefficients of the monetary policy equation. In our baseline model, the posterior medians of $\phi_y$ (MP response to GDP) and $\phi_p$ (MP response to Prices) are 1.08 and 2.08, respectively. This means that the federal funds rate responds one-to-one to output and more than one-to-one to prices. All the remaining coefficients are equal to zero by constructions. Therefore, our identification retrieves coefficients that are consistent with those obtained by Arias et al. (2019) and also with the conventional estimates found in the related literature.

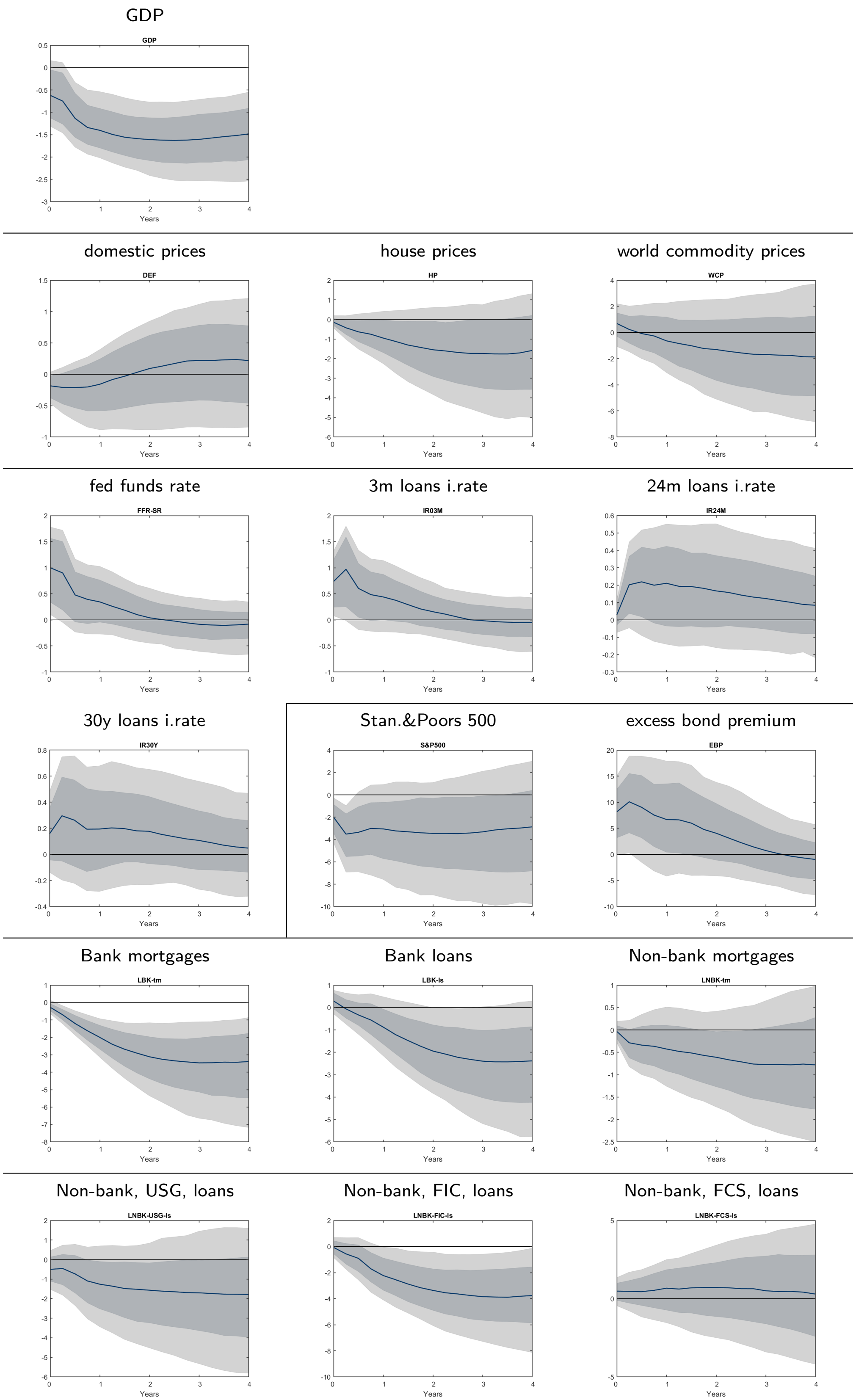
Table 4: Structural coefficients of the MP equation

| | | q16 | **q50** | q84 |
|---|---|---|---|---|
| MP response to GDP | $\phi_y$ | 0.32 | 1.08 | 2.68 |
| MP response to Prices | $\phi_p$ | 0.60 | 2.08 | 4.84 |

#### 4.1.1 Inside non-bank loans

The non-bank sector that we consider is a very heterogeneous aggregate built to include all entities but depository institutions, from insurance companies to brokers and dealers, etc. To have a better insight within this aggregate, we replace loans from non-banks with three of its constituencies: the US government, finance companies and the Farm Credit System. We aim to compare the response of a more dynamic lender, such as finance companies, against less dynamic ones'. The VAR is similar to the one discussed in section 3, but we have replaced non-bank loans with the last three variables listed in Table 2. We therefore estimate a 16 variable VAR in this case. The IRFs obtained from this estimation are in Figure 5.

Figure 5: Response to a MP shock: alternative VAR, entire period




The darker grey area in the front and the lighter in the background are respectively for the 16-84 and 5-95 interquantile confidence range.

Not surprisingly, loans from government agencies (USG) are not responsive to a monetary intervention, as well as loans from the Farm Credit System (FCS). On the contrary, finance companies' loans (FIC) are responsive in a way that is comparable to banks'. This result suggests that more market-oriented entities within the non-bank aggregate behave similar to depository institutions.

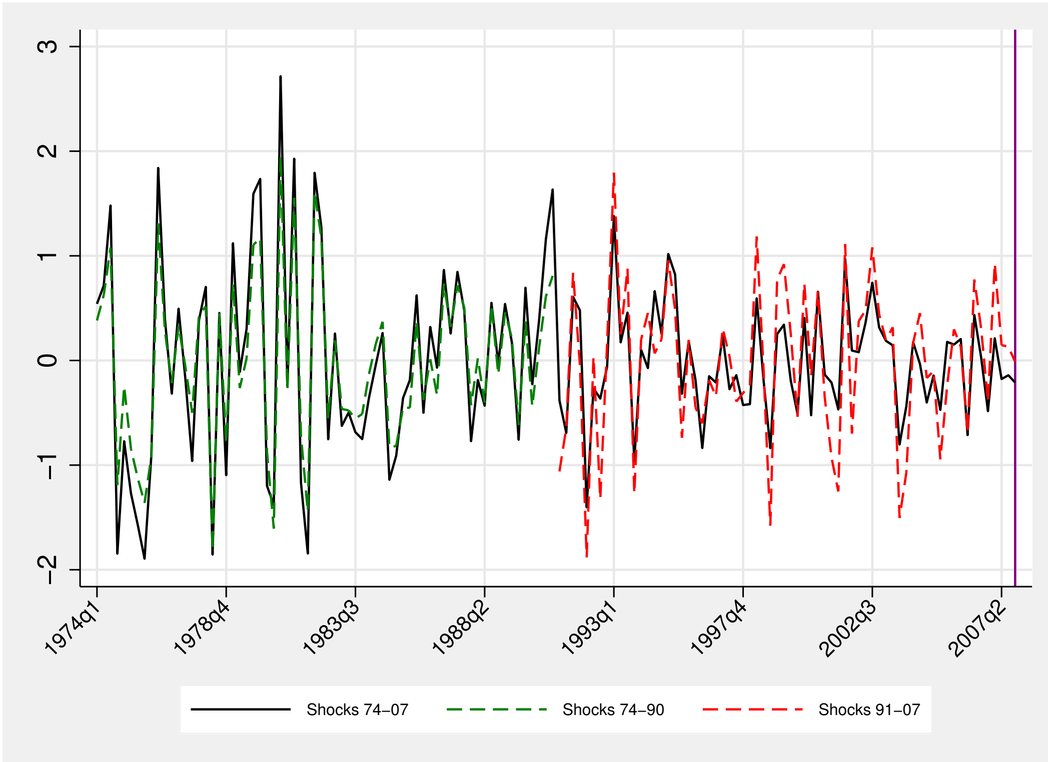
## 4.2 The effect of the rise of non-bank lenders

In section 2 we have shown and discussed the growth of the non-bank sector. In this section we aim to evaluate whether such a growth has altered the effectiveness or the transmission of monetary interventions to the real economy. To this end, as we have detailed in section 3, we split the estimation period over two consecutive subperiods in which the size of the non-bank sector is different: the first period is for the lower size of the non-bank sector, 1974q1-1990q4 (17years); the second period is for the larger size, 1991q1-2007q4 (17 years).

As aforementioned, separate estimations over the two subperiods might imply the identification of different monetary shocks with respect to those at the basis of the results discussed in the previous section 4.1. Our prime concern is therefore to ensure consistency of the identified shocks across the different periods. Figure 6 shows the shock series identified through the estimation over the entire period (black line) against those identified through the estimations over the two subperiods (green dashed line for the period 1974q1-1990q4, red dashed line for the period 1991q1-2007q4). At first look, the series identified are highly comparable. This conclusion is reinforced also by correlation values: it is 0.976 between 1974q1-1990q4 identified shocks and 1974q1-2007q4 identified shocks over the first period, and 0.861 between 1991q1-2007q4 identified shocks and 1974q1-2007q4 identified shocks over the second period. We are therefore confident about the consistency of our analysis over different samples.

The IRFs for the estimations over the two subperiods are in Figure 7, we report only the more relevant IRFs to keep the discussion focused. The respective FEVD is in Table 5. It is to notice that IRFs are in terms of a 1% shock to the FFR, they are therefore comparable across the two different periods. As discussed by Den Haan & Sterk (2011), this is important in order not to draw wrong conclusions when comparing across different periods since the average size of the shocks is different. In

Figure 6: Comparison of identified shocks across different periods




fact, coherently to expectations, shocks are stronger on average in the first period.[17]

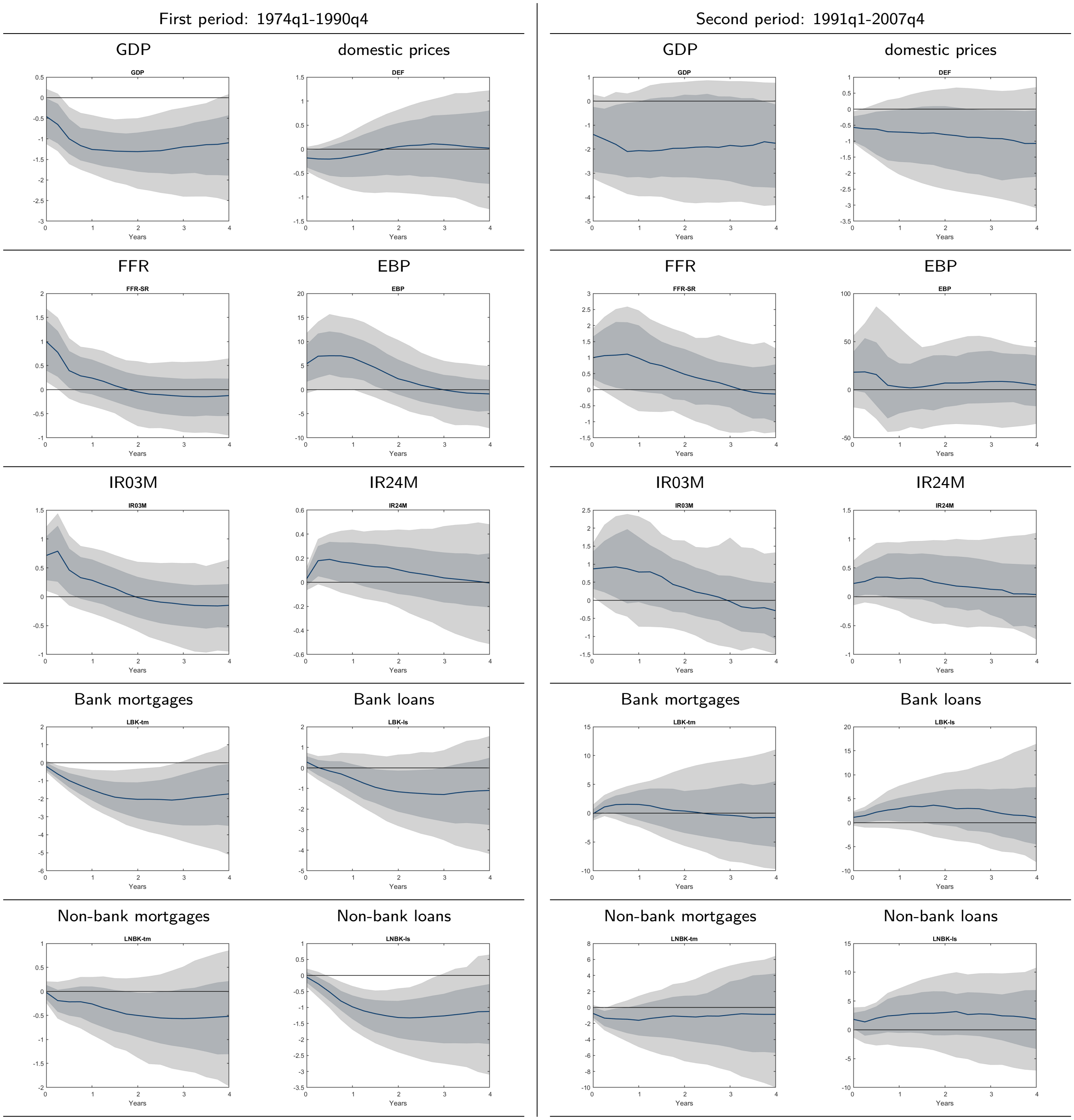
The comparison of Figure 7 against Figure 4 and of the IRFs from the first subperiod against those from the second subperiod in Figure 7 suggest that changes have occurred in the later part of our sample. Moreover, it emerges that the results observed over the entire period depend predominantly on what happens in the first part of the sample, alias 1974q1-1990q4.

First and foremost, monetary interventions have a clearer, more persistent and more significant effect in the first period. Although the median effect appears stronger in the second period, there is much more uncertainty about it. This conclusion is backed also by the FEVD, which signals a by-far larger contribution of monetary shocks to the forecast error variance in the first period than in the second. In contrast, the evolution of domestic prices is not much different across the two periods.

As for the response of the credit aggregates, they are all negatively signed in the first period coherently with what observed over the entire estimation sample and to general economic theory.

[17] The first period comprises the time of high inflation and volatility at the beginning of the eighties that triggered resolute monetary-policy to curb down inflation under the FED chaired by Paul Volcker. In contrast, starting in the mid-eighties, the so-known Great Moderation began. This was a period marked by low volatility and moderate inflation.

Figure 7: Response to a MP shock: benchmark VAR, the two sub-periods




The darker grey area in the front and the lighter in the background are respectively for the 16-84 and 5-95 interquantile confidence range.

Table 5: FEVD, benchmark VAR over the two sub-periods

| | GDP | | DEF | |
|---|---|---|---|---|
| | 1974-1990 | 1991-2007 | 1974-1990 | 1991-2007 |
| h=0 | 0.161 | 0.162 | 0.128 | 0.235 |
| h=4 | 0.338 | 0.170 | 0.065 | 0.152 |
| h=8 | 0.420 | 0.168 | 0.059 | 0.110 |
| h=12 | 0.331 | 0.144 | 0.056 | 0.084 |
| h=16 | 0.260 | 0.126 | 0.049 | 0.074 |
| | BK-TM | | BK-LS | |
| | 1974-1990 | 1991-2007 | 1974-1990 | 1991-2007 |
| h=0 | 0.022 | 0.005 | 0.020 | 0.024 |
| h=4 | 0.152 | 0.026 | 0.023 | 0.041 |
| h=8 | 0.187 | 0.028 | 0.044 | 0.041 |
| h=12 | 0.153 | 0.031 | 0.053 | 0.031 |
| h=16 | 0.111 | 0.028 | 0.052 | 0.025 |
| | NBK-TM | | NBK-LS | |
| | 1974-1990 | 1991-2007 | 1974-1990 | 1991-2007 |
| h=0 | 0.006 | 0.023 | 0.006 | 0.025 |
| h=4 | 0.020 | 0.033 | 0.083 | 0.029 |
| h=8 | 0.032 | 0.025 | 0.154 | 0.039 |
| h=12 | 0.041 | 0.022 | 0.150 | 0.036 |
| h=16 | 0.043 | 0.025 | 0.125 | 0.029 |

Differently, apart from non-bank mortgages, their responses change in the second subperiod. Such a change emerges as a robust result of our analysis as the checks detailed in the next subsection 4.3 prove. In addition to a common loss of significance, bank mortgages and bank loans seem to increase, as well as non-bank loans at the impact. The increase in non-bank loans may be attributed to the deposit channel of monetary policy transmission as discussed by Xiao (2020). More interestingly, we document that the response of non-bank credit is heterogeneous and depends on the type of credit. The related literature does not apply this distinction but only finds a general decrease of non-bank credit after a positive monetary policy shock (Nelson et al. 2018, Xiao 2020).

In the reading of the different response of the credit aggregates across the two subperiods, it is important to notice that the evolution of the interest rates for different maturities remains mostly unchanged. A possible explanation for the altered response of the bank credit aggregates in the second period therefore does not lie in a different evolution of the cost of credit. In truth, an unexpected increase of credit aggregates in the event of a monetary tightening is not an uncommon finding. For instance, the loan puzzle literature discusses a similar result; among others, see den Haan et al. (2007)

and Cafiso (2022). Apparently, drawing from credit lines might explain a large part of the increase (Barraza et al. 2019). As for the constancy of the response of non-bank mortgages, we think it might depend on the fact that they grow regardless of the monetary policy stance. In truth, the understanding of the evolution of such an aggregate is somehow problematic to achieve because it depends also on the extent of securitization realized by the bank sector (Meeks et al. 2017).

## 4.3 Robustness checks

We imagine that two potential criticisms to our results are the following. First, the shocks identified over the second period might not be consistent with those identified using the entire sample. Consequently, the observed differences in the IRFs depend on this point. Second, the differences emerging in the later period might depend upon the specific identification used and not survive to a different approach.

As for the first point, apart from showing the consistency of the identified shocks across the different periods by means of Figure 6 and the correlations reported, we have performed local projections using Jordà (2005)'s method. In details, we have extracted the series of identified shocks through the VAR in section 4.1, and used that series to run local projections over the two subperiods. The plots of the local projections are in Figure 8 in the appendix. These are consistent with the IRFs in Figure 7 since they yield similar differences between the first and the second period. In details, the effect on the GDP is more persistent in the first period and the response of the credit aggregates changes remarkably in the second period.

As for the second point, to prove the robustness of our results, we used also the Cholesky identification approach. We use an order of variables functional to have comparability with the IRFs from our benchmark VAR. The FFR is therefore placed before the credit aggregates so that its shock impacts them contemporaneously. Even though this is a completely different approach, we can draw comparable conclusions from the IRFs obtained. Those are in Figure 9 in the appendix.

## 4.4 Discussion of the results

When considering the estimation output obtained using the entire period under investigation (1974-2007), intuitive and theory-consistent conclusions about the effect of monetary interventions emerge:

GDP decreases, prices decrease, the credit aggregates decrease with the notable exception of non-bank mortgages. The lack of a significant decrease of non-bank mortgages is of interest when read in conjunction with the decrease of bank mortgages. In fact, it is consistent with the literature affirming the off-load of mortgages from banks to non-banks when those become riskier (Nelson et al. 2018), as in the case of a monetary tightening. The study of some specific components of the non-bank group (Figure 5) suggests that more-dynamic entities, such as finance companies, behave as banks in relation to the evolution of loans. Unsurprisingly, the others, alias the less market-oriented, seem instead to diverge from banks in terms of response.

As for the effect of monetary interventions over the two consecutive subperiods under investigation, comparing the IRFs makes possible to draw the following relevant conclusions.

1. Our results suggest that the GDP response is clearer and more persistent in the first period than in the second. The effect obtained over the entire period seems to depend just on the first subperiod, we can therefore explain the first-subperiod dynamics along the lines detailed for the entire sample. On the whole, monetary interventions emerge as more effective in the first subperiod, when the share of non-bank finance is smaller.

2. The response of the credit aggregates is significantly different in the second period with respect to the first. A similar remarkable change has been detected also by Den Haan & Sterk (2011). In fact, while significance is generally lower, some aggregates exhibit a counter-intuitive evolution in the second period.

3. All the other variables respond in a comparable way between the first and the second period. This rules out the possibility that is one of the other variables included in the VAR to contribute to the different GDP response in the second period.

Concentrating on the GDP response, two further questions arise from the reading of our results. The first is whether its more uncertain and short-lived response in the second subperiod depends upon the different effect of monetary interventions on credit aggregates in the same subperiod. The second is whether such an observed different response of the credit aggregates is due to the structural change in the lender mix discussed in section 2, alias to the increase of non-bank finance.

As for the first point, the response of the credit aggregates is consistent with the decreasing effect of monetary interventions on the GDP. So we believe a connection between the two is plausible and likely. To gain more evidence on this point, we have computed Generalized Impulse Response functions (Koop et al. 1996) for impulses to the credit aggregates.[18] These serve to gain insights on the possible GDP variation in response to a change to the credit aggregates without the fatigue of a proper structural identification of the credit shocks. The four GIRFs, one for each credit aggregate, are in Figure 10 in the appendix. Coherently to our hypothesis, their reading suggests that an increase of bank loans and mortgages has indeed a positive effect on the GDP in the first period (this is the expected theory-consistent outcome, see Gambetti & Musso 2017, Cafiso 2021), but that effect is null in the second period.

As for the second question, whether the different response of the credit aggregates depends upon the rise of non-bank finance, a testable causal relationship is hard to establish. As matter of fact, however, we are not aware of any other relevant development over the same period that could explain the different response of the credit aggregates under analysis. Furthermore, our results are in line with Den Haan & Sterk (2011), Nelson et al. (2018), Xiao (2020) that similarly explain the evolution of some credit aggregates through the rise of non-bank finance. We therefore feel confident to conclude that the rise of non-bank finance is behind the change in the response of the credit aggregates observed between 1991 and 2007.

# 5 Conclusions

This research work originates from observing the remarkable increase of non-bank credit before the Global Financial Crisis. We have discussed how such a structural change is explained by some concurrent factors. Among those, bank regulation plays a primarily role when considered against the significantly looser one to which non-bank entities are subject to, as well as the development of securitization.

After having reported on the theoretical reasons why a larger role of non-bank lenders might have

[18] Generalized impulse responses have been introduced by Koop et al. (1996) and are the difference between a conditional and an unconditional forecast of the system: $GIRF_y\left(n, \delta_i, \Omega_{t-1}\right) = E\left(y_{t+n} | \varepsilon_t = \delta_i, \Omega_{t-1}\right) - E\left(y_{t+n} |, \Omega_{t-1}\right)$. Where $\Omega_{t-1}$ represents the history of the economy up to $t-1$ and $\delta_i$ is a specific shock. Therefore, these IRFs do not rely on orthogonalized shocks but on reduced-form ones and integrates out all other contemporaneous and future shocks. This approach is robust to identification problems as the generalized IRFs are unique and account for the historical correlations observed between the other shocks.

consequences on the transmission mechanism. The primary objective of our analysis was to answer to the question whether the rise of non-bank lenders has altered the effectiveness or working of monetary policy in the US over the period before the Global Financial Crisis. To this end we have developed our analysis over two consecutive subperiods characterized by different sizes of the non-bank sector.

On the whole, our results indicate quite clearly that the effectiveness of monetary interventions has diminished in correspondence to the rise of non-bank credit, and that this depends on an altered effect of monetary impulses on credit aggregates over the same period. Furthermore, we also find that non-bank loans behave like bank credit, while non-bank mortgages display an opposite dynamics. This is particularly interesting as it highlights relevant heterogeneity inside the non-bank sector that should be object of further study. Even though our results are country specific, given the peculiarity of the transmission mechanism in each country, we believe that they are instructive also for countries that are likely to see a rise of non-bank credit as the US in the period before the Global Financial Crisis.

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# Appendix

Figure 8: Response to a MP shock (Local Projections)

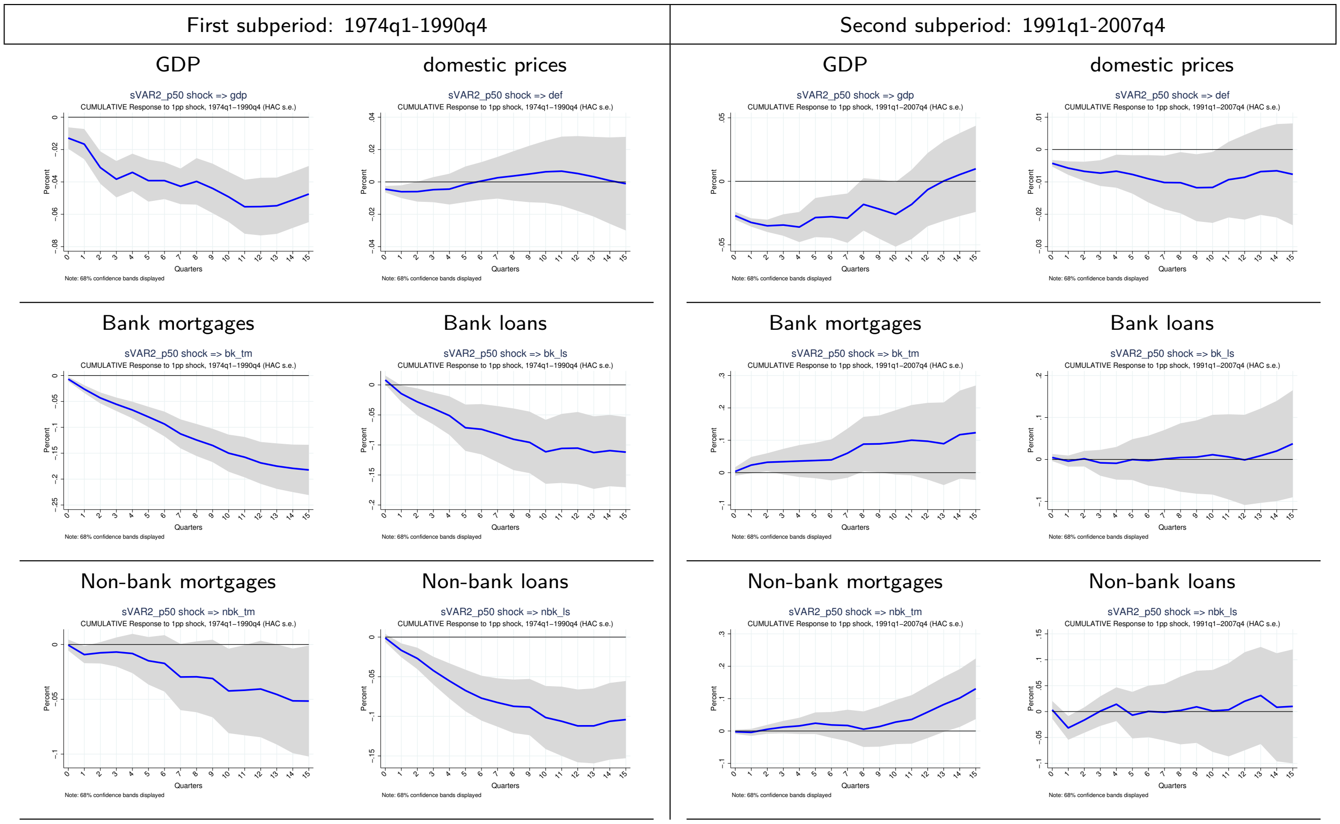


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Figure 9: Response to a MP shock (benchmark VAR, Cholesky)

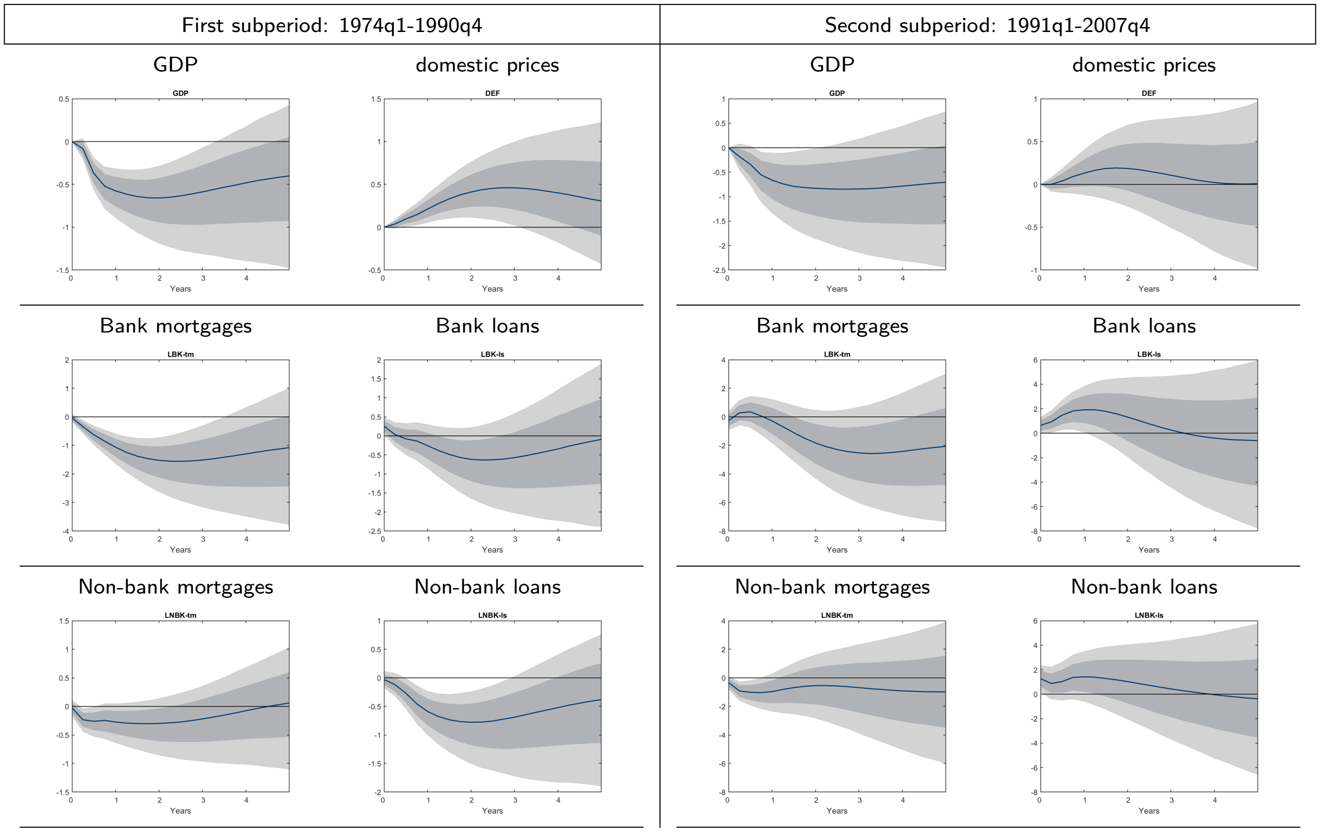


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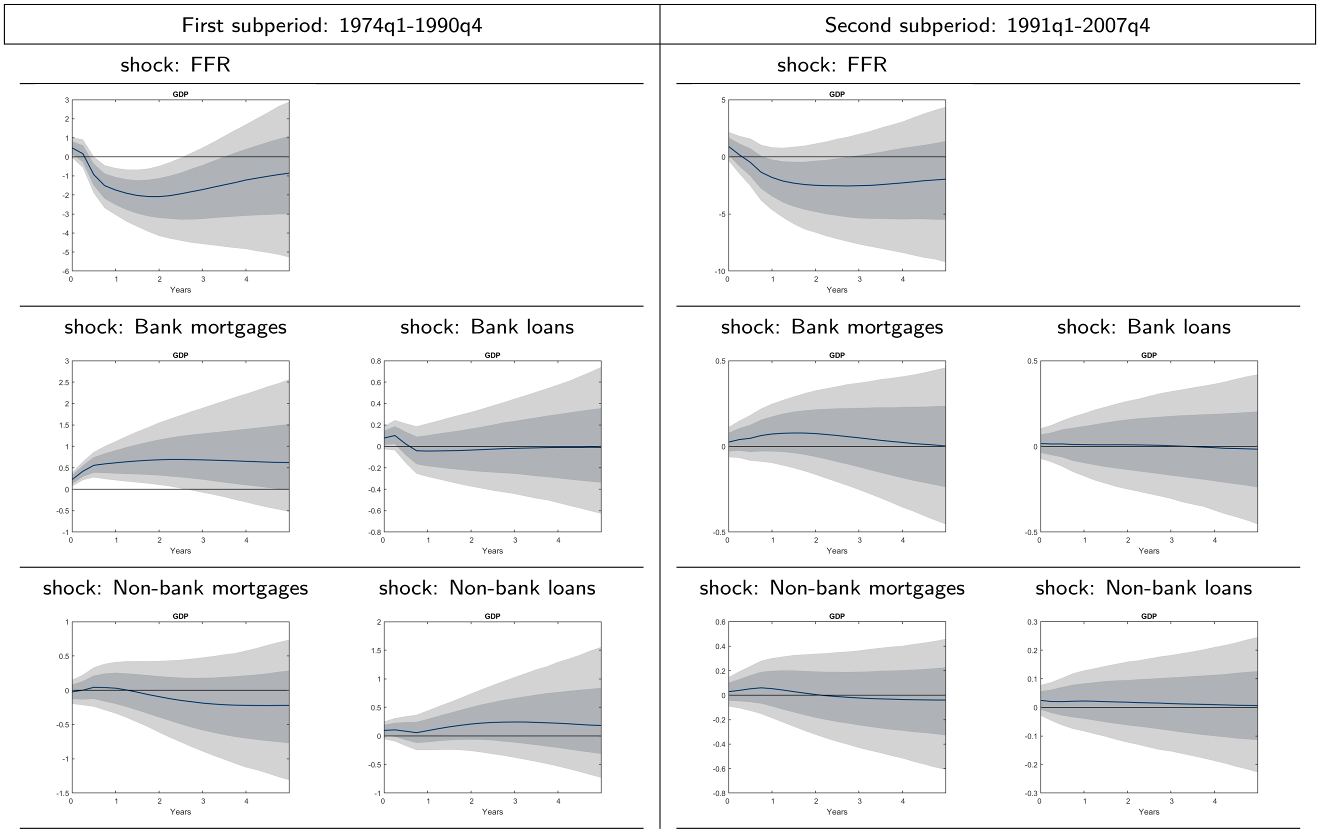
Figure 10: GDP response to specific shocks (Generalized Impulse-Response Functions)

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