Conventional monetary interventions through the credit channel and the rise of non-bank institutions

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Abstract

The amount of credit assets held by non-bank institutions has increased substantially in recent decades, to the point where it exceeded the amount held by depository institutions in the US before the global financial crisis. Our research aims to gain evidence on whether the credit channel of monetary policy, i.e. the transmission of monetary interventions through bank lending, has been altered by the enlargement of the non-bank sector. The analysis is based on the period before the global financial crisis in order to apply a theory-consistent identification of conventional monetary interventions within a large Bayesian VAR. The results indicate an uncertain transmission in the period when the non-bank sector is larger, casting doubt on the grip of monetary interventions in an evolving scenario.

Keywords: banks, shadow banking system, loans, mortgages, monetary interventions, Bayesian VAR.

JEL Codes: E44, E51, G20, G21, C11.

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1 Introduction

Western economies have witnessed to the rise of non-bank institutions in financial markets over the last decades (IMF 2016), the United States in particular have been seat to the strongest growth of the so-called *shadow banking system*. Indeed, in the period leading up to the financial crisis, credit assets held by non-bank institutions in the US exceeded those held by depository institutions. The reasons behind this development in financial markets are many, but changes in the regulation of the financial sector certainly played a role (Adrian & Ashcraft 2016), as did the increase in fees charged for asset management and household loans (Greenwood & Scharfstein 2013). The relationship between banks and non-banks should not be viewed naively, it is complex. Banks and non-banks are likely to compete for the same customers to a limited extent. In fact, these institutions are more likely to interact than compete, as their business activities are largely complementary.[1]

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 (Bernanke & Gertler 1995, Bernanke 2007). The literature on the transmission mechanism has clarified the various channels through which a monetary tightening impacts bank credit and thus the real economy (Albertazzi et al. 2020). However, the unquestionable evidence about the decrease in the relative size of the banking sector over time calls for a reassessment of the transmission of monetary interventions through the credit channel (Den Haan & Sterk 2011, Nelson et al. 2018, Xiao 2020). In this regard, we hypothesise that the transmission of monetary interventions might have been altered by the same factors that underpinned the growth of the non-bank sector. Deregulation, asymmetric regulation, securitisation, and the development of new financial instruments and practices may have allowed banks to respond differently, also thanks to their interaction with non-banks (Meeks et al. 2017). At the same time, the relatively smaller size of the bank sector might have pushed banks to develop strategies aimed at not losing their competitiveness against non-banks, which are known to be less sensitive to a monetary

[1] To wit, the extension of credit granted by banks is then securitized and transferred to others in different ways (Meeks et al. 2017) or, for instance, non-banks are institutions selling financial instruments to cover credit positions extended by banks, etc.

tightening (Borio & Zhu 2012). For example, banks might have started to issue their own liabilities to finance their operations and avoid the increase in their external finance premium (Bernanke 2007).

In this context, our work aims to verify whether or not the transmission of conventional monetary interventions through bank credit, the so-called credit channel, results unchanged in a period when non-banks have gained the largest weight. We also intend to assess the response of the non-bank sector to the same monetary impulses in order to draw conclusions on the impact of monetary interventions on credit in general. The motivations for our study are rooted both in stylised facts about the increase in credit assets held by non-banks, in the literature on the credit channel, which confirms that monetary impulses exert their effect largely through bank credit (Albertazzi et al. 2020), and in some previous contributions about how a larger non-bank sector might alter the transmission of monetary interventions (Den Haan & Sterk 2011). Our research question has important implications for the conduct of monetary policy at a time when conventional monetary interventions are once again the norm, in particular because an altered transmission via the credit channel could imply a lower effectiveness of monetary policy in general.

The analysis is designed to quantify the impact of monetary interventions on credit aggregates. We disaggregate by the type of owner (banks versus all other non-bank institutions) and credit instrument (mortgages versus loans). Our approach is to compare the results for two subperiods in which the size of the banking sector is significantly different. The perspective is to examine the response of banks by controlling for the response of non-bank institutions. Therefore, our non-bank aggregate is a comprehensive heterogeneous block (including finance companies, government agencies, credit cooperatives, etc) to be distinguished from depository institutions, as this is functional to reflect the rise of non-bank players in the most general terms possible. The analysis is for the United States and covers the period up to the Global Financial Crisis, as this is when we observe a significant change in the share of credit holdings held by banks vis-à-vis non-banks (Meeks et al. 2017). We produce results via the Bayesian estimation of a large vector auto-regression and employ an identification approach consistent with conventional monetary policy before the Global Financial Crisis (Arias et al. 2019). We prove the robustness of our results by applying a different identification approach as well as by means of local projections (Jordà 2005).

Our results point to an altered transmission via the credit channel in correspondence with an enlarged non-bank sector, this turns out to be a robust result. Interestingly and coherently, the impact of monetary interventions on economic activity is also less clear, in line with the altered transmission via the credit channel that we detect. Thus, our study contributes by adding evidence on this highly relevant issue in a scenario characterised by the growth of non-bank institutions in financial markets worldwide, which should warn monetary authorities about the effectiveness of their policies and stimulate further research.

The paper is structured as follows. Section 2 presents some relevant contributions to this topic and contextualises our research within this branch of the literature. Section 3 discusses the growth of the non-bank sector in the US. Section 4 details the estimation of the VAR using the Bayesian approach and the various robustness checks we perform. The results of our analysis are reported and discussed in Section 5. Section 6 concludes.

2 Literature review

The potential consequences of the growth of non-bank institutions for the transmission of monetary interventions to the real economy have been object of research for some time. There is no unanimous view on them, especially when more countries are considered; IMF (2016), Nelson et al. (2018), Schnabel (2021) come to different conclusions. Reliable answers to this question are likely to be country-specific, as the transmission mechanism in each country has its own characteristics (Ciccarelli et al. 2015). In this regard, Heryán & Tzeremes (2017) report on how monetary shocks impact differently on old and new euro area countries. There can be many reasons for a different effect across countries: the lender mix, which is the focus of our analysis, but also other factors such as bank competition (Gunji et al. 2009), how monetary policy is conducted and made public (Papadamou et al. 2015), the state of the economy (Aastveit et al. 2017), etc. It is to say that the so-known *shadow banking system* has become the object of investigation not only for monetary policy, but more and more in relation to systemic risk and macro-prudential surveillance (Adrian & Shin 2009, Yellen 2014), particularly after the Global Financial Crisis (GFC). Both aspects are related to some extent, but we focus on the implications for the transmission mechanism.[2]

[2] Before the GFC, the growth of non-bank finance was widely regarded as a positive development that carried out limited risk. Many argued that the great moderation, alias the period of low volatility starting around the mid-eighties

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).[3] According to Xiao (2020), a monetary tightening reduces money creation by depository institutions but it expands money creation by shadow banks and this depends on the amount of funds flowing into the non-bank sector as a consequence of the increase in the Fed-funds rate. In line with the deposit channel described by Drechsler et al. (2017), the spread between shadow and commercial bank deposit rates is described to increase after a monetary tightening and this moves funds from banks to non-bank institutions. This effect is economically significant and it explains the expansion of shadow banks in periods of high interest rates. Nevertheless, Xiao (2020) affirms that the overall effect on money creation (banks plus non-banks) is still negative, but its magnitude is quite small. This therefore points to a lower monetary effectiveness. Our results will differ from Xiao's by showing that the net effect could be non-negative in the period when the non-bank sector is larger. Chen et al. (2018) have recently contributed on China. They 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.[4]

IMF (2016) reports on some alternatives. On the 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, Isabel Schnabel (Schnabel 2021), a member of the Executive Board of the ECB, describes how the transmission mechanism in the euro area has changed as a result

depended on the development of non-bank finance. This thesis is well discussed in Den Haan & Sterk (2011). On the contrary, after the GFC, non-bank institutions started to be considered to have increased excessively the level of risk in the financial system (Gennaioli et al. 2013). Extension of credit in general is regarded as one of the main causes of the GFC (Cafiso 2022).

[3] As for the part of the transmission mechanism that involves bank credit, research distinguishes two main channels: the cost of capital channel, or cost of credit, and the so-known Broad Credit Channel, an expression used in Ciccarelli et al. (2015). See Cafiso (2023) for a deeper discussion of demand and supply factors.

[4] 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.

of the growth of lending by non-bank lenders and the increasingly large issuance of corporate bonds. She concludes that non-bank finance has expanded the transmission mechanism in the EA.[5]

Some other contributions focus on the interaction between banks and non-banks in the case of monetary interventions. Nelson et al. (2018) find that surprise monetary contractions tend to reduce the assets of commercial banks, while they tend to expand the assets of non-banks. This is because the contractions induce a migration of activity across the regulatory boundary to the non-bank sector.[6] 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.[7] These two contributions provide insights into the interplay between banks and non-banks and why their business is more complementary than substitute. Along the same lines, Borio & Zhu (2012) describe how monetary hikes cause banks to reshuffle their portfolio towards less risky assets in accordance with the risk-taking channel, consequentially non-banks might replace banks over those riskier positions. The interaction between banks and non-banks might have itself supported the growth of non-banks because that makes room for business. In addition, given the new regulations and incentives introduced over the years, banks might have found it convenient to develop their activities by working with non-banks as well (Gorton & Metrick 2012), and this might have allowed them to respond differently to a tightening of monetary policy.

Although not unanimous, most of the contributions cited above generally suggest that non-bank institutions dampen the effect of restrictive monetary interventions. It is often suggested that non-banks react differently from banks, while banks are assumed to continue to react in the same way to monetary tightening, regardless of the larger role played by non-bank lenders. In this respect, our

[5] However, 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. 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, have a stronger impact in countries where corporate bonds are larger.

[6] 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).

[7] 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).

research differs from previous contributions since we aim to clarify whether or not banks do indeed continue to respond in the same way, i.e. whether the bank lending channel is altered by the rise of non-bank lenders. Accordingly, our analysis is deigned to show not only the different responses of bank and non-bank credit, but also how these evolve over time for different sizes of the non-bank sector. We therefore update the older literature on the credit channel (Bernanke & Gertler 1995, Bernanke 2007, Albertazzi et al. 2020). Apart from the previous point, we differ from Xiao (2020), Meeks et al. (2017), who define and calibrate their own model, because we estimate a large vector auto-regression (VAR). With respect to Nelson et al. (2018), who use a VAR analysis as we do, we apply a theory-consistent identification method based on the Taylor rule (Arias et al. 2019) suitable for identifying conventional monetary interventions and not only the less likely Cholesky decomposition; Chen et al. (2018) too in their robustness checks acknowledge that this is important.[8] Den Haan & Sterk (2011) remains the article closer to our analysis, we improve on it in a number of important ways. First, by applying the just-mentioned identification, but also by ensuring the consistency of the analysis across subsequent subperiods. Second, we use several disaggregations of the credit aggregates. Our objective is to distinguish between short/medium and long-term credit instruments because of the role of non-bank institutions in the mortgage business (Loutskina & Strahan 2009). To a lesser extent, we will also consider different specific lenders as well as borrowers selected for considerations in terms of risk (Papadamou & Siriopoulos 2012).

3 The rise of non-bank institutions: some stylized facts

The growth of non-bank finance has begun in the mid-70s in the USA (Greenwood & Scharfstein 2013), much earlier than in other developed countries.[9] More recently, the Euro Area has also witnessed its growth (Altunbas et al. 2009). In contrast to the homogeneous bank sector, particularly in terms of the regulation in force, the non-bank sector is heterogeneous. It spans from finance companies to insurance

[8] The study by Chen et al. (2018)'s applies a different methodology using China as a case study over the period after the GFC. They themselves acknowledge that China's specific institutional setting requires an ad hoc identification approach. Interestingly, they test a monetary rule-based approach like ours, even though it is not appropriate for China.

[9] The expression *non-bank finance* refers to different instruments and not just to loans and mortgages from non-bank intermediaries. Non-bank finance has grown particularly with the issuance of corporate bonds used to get funds as a substitute for, or in addition to, bank loans (IMF 2016). Furthermore, also liquidity is offered by some non-bank entities in a form very much comparable to bank deposits. Drechsler et al. (2018) comment on the birth of money-market funds as an alternative to bank deposits.

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 a matter of fact, some uncertainty regarding the exact size and composition of the non-bank sector exists.[10]

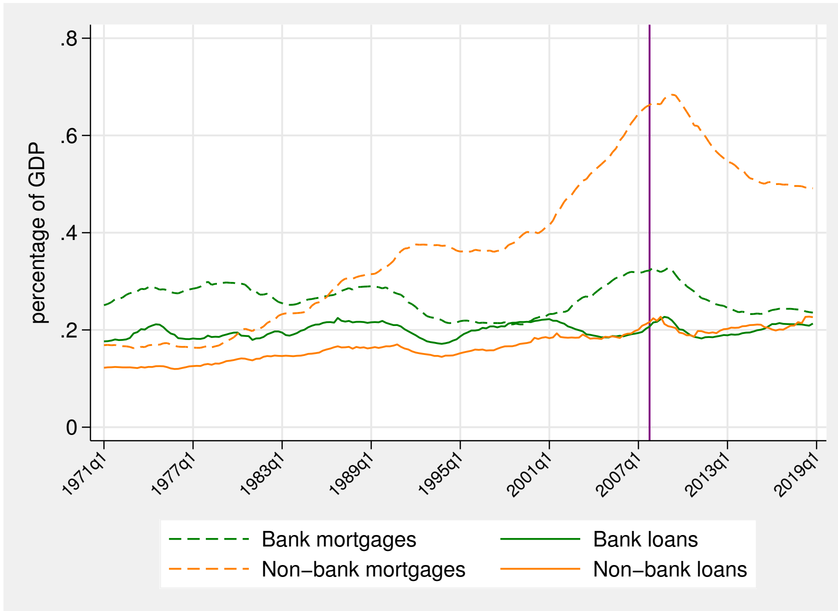
The reasons for its growth are many and a full discussion is beyond the scope of our work, we refer the reader to the extensive work by Jokivuolle (2018) and Adrian & Ashcraft (2016). Here, we only recall one aspect that is relevant for the explanation of our results. Gorton & Metrick (2012) describe 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 made room for less regulated players, which have grown substantially over the same period. Figure 1 shows this growth by plotting mortgages and loans from banks and non-bank lenders. The distinction between mortgages and other loans is important in this context because the process of securitisation has primarily involved mortgages (Loutskina & Strahan 2009, Estrella 2002) and because, in relation to our VAR analysis, different credit instruments might respond differently to the same impulse (Brady 2011).

In order to better understand the developments 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 loans separated) and plot them in Figure 2. These data show that non-bank holdings of mortgages have clearly outstripped those of banks and that the difference has stabilised since the GFC. A similar dynamic emerges for loans, but in this case non-bank loans have grown to match bank loans, and their differential appears modest and stable since the GFC. The three vertical lines in Figure 2 make clear that the bank sector is larger than the non-bank in the first subsample used for our analysis, while this reverses afterwards.

Given the role of mortgages in the GFC and their striking evolution in Figure 1, we have an interest in the players behind such an evolution. To this end, Figure 7 in appendix A disentangles non-bank mortgages. *Mortgage pools and trusts* (made of 'Agency and GSE-backed mortgage pools' and 'Issuers of asset-backed securities'), unsurprisingly, result behind the growth observed before the GFC.

[10] The non-bank sector is often referred to as *shadow banking system* when institutional entities are excluded. 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."

Figure 1: Holdings of Mortgages and Loans



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

Table 1: Shares of Mortgages and Loans

Panel A

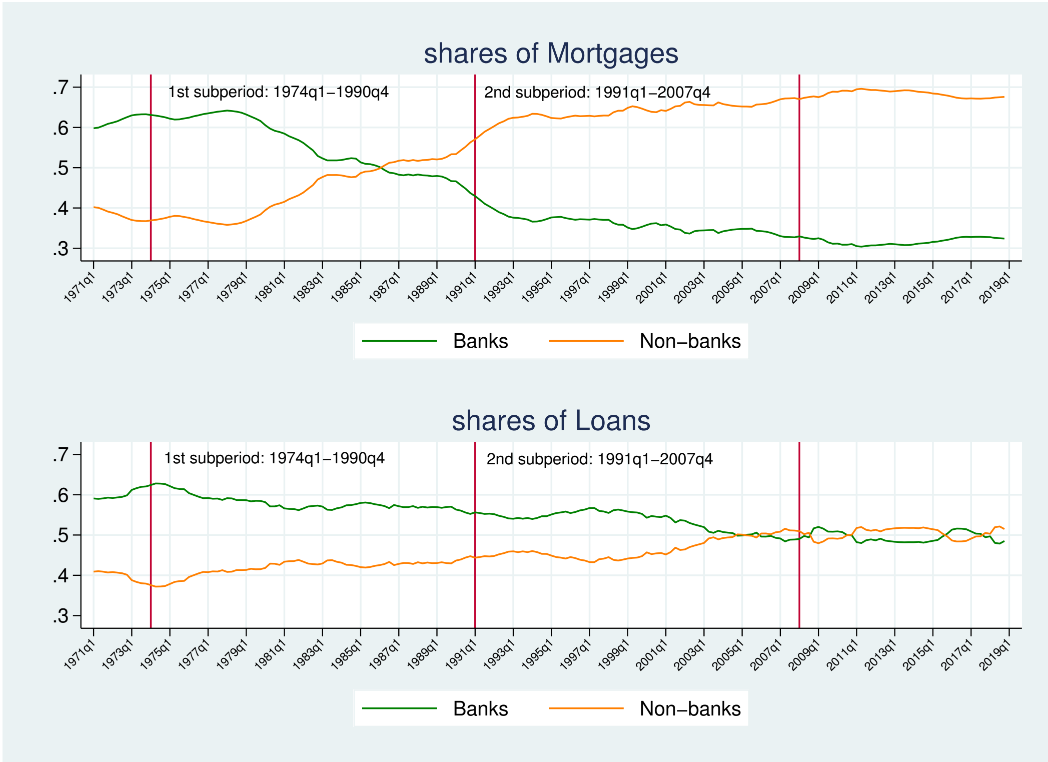
ten years	BK-TM	NBK-TM	BK-LS	NBK-LS
1970q1-1979q4	0.366	0.221	0.248	0.165
1980q1-1989q4	0.310	0.287	0.230	0.173
1990q1-1999q4	0.240	0.387	0.207	0.166
2000q1-2009q4	0.229	0.446	0.167	0.158
2010q1-2018q4	0.209	0.452	0.167	0.172
Total	0.272	0.357	0.204	0.167

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.

4 VAR analysis

For the scope of our analysis, we quantify the effect of monetary interventions (alias, monetary-policy shocks, MP shocks) on four credit aggregates over two consecutive subperiods characterized by substantially different magnitudes of the non-bank sector. We restrict the analysis to the period before the GFC for different reasons. First and foremost, the period 1974-2007 shows an increasing weight of the non-bank sector, which is what we need to answer our research question, while this weight is more stable after 2007 (section 3). Second, we have chosen to focus on the period of conventional monetary policy because it allows us to correctly apply an identification approach that is appropriate for this period. In fact, we follow Arias et al. (2019) and identify shocks by means of a monetary policy rule (see next subsection 4.2).[11]

[11] 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 2007. Shocks over periods including the post-2007 are better caught by high-frequency identification approaches (Gürkaynak et al. 2005, Jarocinski & Karadi 2020), which are hardly usable for periods of analysis before the mid-90s. As for this, we have tried the unified measure of MP shock

We perform three estimations, one over the full period (P0 "1974-2007") and one for each of the two consecutive subperiods (P1 "1974-1990" and P2 "1991-2007"). The estimation over the full period allows us to gain a general overview of the effects of monetary policy and also to extract a series of monetary policy shocks (sP0). This series will be compared with those extracted from the two subperiod estimates (sP1, sP2). As a matter of fact, in principle, each estimation gives rise to a different series of monetary policy shocks, thus it is meaningful to compare them to check their consistency with one another and with the main narratives about the conduct of monetary policy in the US. We do this by looking at the median series of monetary policy shocks. The series of shocks identified in each estimation (sP0, sP1 and sP2) turn out largely consistent with one another. Our conclusions are mainly drawn on impulse-response functions (IRFs), which quantify the effect of a structural shock on the variables in the VAR. As mentioned above, in order to demonstrate the robustness of our results, we also use local projections (Jordà 2005) based on the sP0 series of shocks to compute IRFs over P0, and the P1 and P2 subperiods. Local projections take to the same conclusions as the VAR1 in all cases.

Details on the estimation of the reduced form, the structural identification of the monetary interventions, and the local projections are in the following subsections 4.2.

4.1 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).[12] We use *holdings of mortgages and of loans* extended to US non-financial entities, which are households & non-profit organizations, corporate businesses, and non-corporate businesses. Both series are for banks (alias, depository institutions) and non-banks. Non-banks include all entities having holdings of loans and mortgages either because they originally granted those or because they came into their possession at a later time.

In the case of loans, we use also disaggregated data for some lenders within the non-bank group (finance companies, the US government, the Farm Credit System in VAR2) as well as for specific borrowers (households, corporate business and non-corporate business in VAR3) to add further insights

defined by Bu et al. (2021) but it generates results contrary to economic theory in our sample.

[12] 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.

to our analysis.[13] We decided to develop the analysis by keeping loans and mortgages well distinguished because of the different characteristics, regulations, 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 VARs can be conceptually clustered in the following groups. *Real variables*: the gross domestic product, to account for economic activity and the business cycle. *Prices*: the consumer price index, the house price index, a world index of commodity prices; these are to reflect 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, 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.[14] 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

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.

[13]The Farm Credit System is a cooperative system of borrower-owned lending institutions and specialized service organizations (Monke 2016) serving the US agriculture sector.

[14]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 & Zakrajšek (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.

4.2 Estimation

VAR

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 (VAR1). 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. 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: $\Sigma \sim IW(\Psi, d)$, $\beta \mid \Sigma \sim N(b, \Sigma \otimes \Omega)$. Here, Ψ, d, b and Ω are functions of a set of hyperparameters γ. The prior for the VAR coefficients combines three prior densities: the Minnesota, the sum-of-coefficients and dummy-initial-observation priors.[15] The tightness of these priors is determined by the three hyperparameters λ, μ, and δ, 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.[16]

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

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

[16] The algorithm draws the hyperparameters with a Metropolis step and then, conditional on the value of γ, 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.

by conventional monetary policy.[17] Therefore, following Arias et al. (2019), we combine sign and 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 ε_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).[18]

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

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

[18] The central bank does not directly observe the contemporaneous level of output and prices, but other real-time indicators are available that allow us 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).

the sign and zero restrictions that we impose on the matrix A_0. Arias et al. (2019) show that this set of restrictions is 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.[19]

Local Projections

We use local projections to prove the robustness of our results with respect to the division of the sample in the two subperiods. In fact, these allow to generate IRFs for two subperiods (P1, P2) while performing a single estimation over the entire data sample (P0) by means of interaction terms. The formula we use is for cumulative IRFs:

$$y_{t+h} - y_{t-1} = \alpha + \lambda \cdot \beta_0 \cdot \varepsilon_t + \sum_{m=1}^{M} \beta_m \varepsilon_{t-m} + \sum_{l=1}^{L} \gamma_l y_{t-l} + u_t, \text{ for } h = 1, ..., H. \tag{2}$$

Eq.2 is estimated H times, β_0 quantifies the response of y_t to the ε_t shocks at each step h. The ε_t shocks are those obtained from the estimation of the VAR over the full period 1974q1-2007q4 (sP0). To compute the IRFs specific to the two different subsamples, we specify an indicator variable λ: $\lambda = 0$ for the first subperiod (this serves as the base for the effect), $\lambda = 1$ for the second subperiod. As for the remaining variables in Eq.2: α is the constant in the regression, ε_{t-m} and y_{t-l} serve as controls. We set $L = M = 12$ in our estimations, which is also the autocorrelation order inserted for the computation of the Newey-West standard errors.

To summarize, we restate that for the scope of our analysis, we primarily estimate one benchmark VAR (VAR1) over the two above-mentioned subperiods (P1, P2). However, we estimate also other VARs, as well as local projections, for robustness and to gain further marginal insights useful to explain our results. All the estimations are listed in Table 3. Our main conclusions are therefore based on the estimations coded as in rows 2 and 3 (VAR1-acrr-P1, VAR1-acrr-P2).

[19]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 only by few draws.

Table 3: List of all the estimations

	Model	Identification	Period	Code	Shocks
1	VAR1	ACRR19	P0 (1974q1-2007q4)	VAR1-acrr-P0	identified: sP0
2*	VAR1	ACRR19	P1 (1974q1-1990q4)	VAR1-acrr-P1	identified: sP1
3*	VAR1	ACRR19	P2 (1991q1-2007q4)	VAR1-acrr-P2	identified: sP2
4	VAR1	Cholesky	P1	VAR1-cho-P1	identified
5	VAR1	Cholesky	P2	VAR1-cho-P2	identified
6	LPj1		P0	LPj1-P0	sP0 from est. in line 1
7	LPj2		P1	LPj2-P1	sP0 from est. in line 1
8	LPj2		P2	LPj2-P2	sP0 from est. in line 1
9	VAR1	GIRFs	P1	VAR1-girf-P1	_
10	VAR1	GIRFs	P2	VAR1-girf-P2	_
11	VAR2	ACRR19	P0	VAR2-acrr-P0	identified
12	VAR3	ACRR19	P1	VAR1-acrr-P1	identified
13	VAR3	ACRR19	P2	VAR1-acrr-P1	identified

VAR1 is our benchmark VAR including the 14 variables in Table 2. VAR2 replaces non-bank loans with three of its components: loans held by finance companies, by the US government, and by the Farm Credit System (for further insights, in the appendix). VAR3 replaces banks and non-banks loans with their respective disaggregation by borrower: loans to households, loans to corporate business, loans to non-corporate business (for further insights, in the appendix). ACRR19 stands for Arias et al. (2019) identification approach, the main we apply. Cholesky is for the Cholesky decomposition to identify shocks (for robustness, in the appendix). GIRFs stands for Generalized IRFs (for further insights, in the appendix). LPJ is for the Local Projection model (for robustness, in the text and in the appendix). P0 is for the entire period 1974-2007, P1 is for the first subperiod 1974-1990, P2 is for the second subperiod 1991-2007. To summarize, estimations in lines 1-3 are to produce the main results, in lines 4-8 are for robustness, in lines 9-13 are to gain further information. The column "shocks" indicates whether the shocks are identified in the same estimation, or inserted from another.

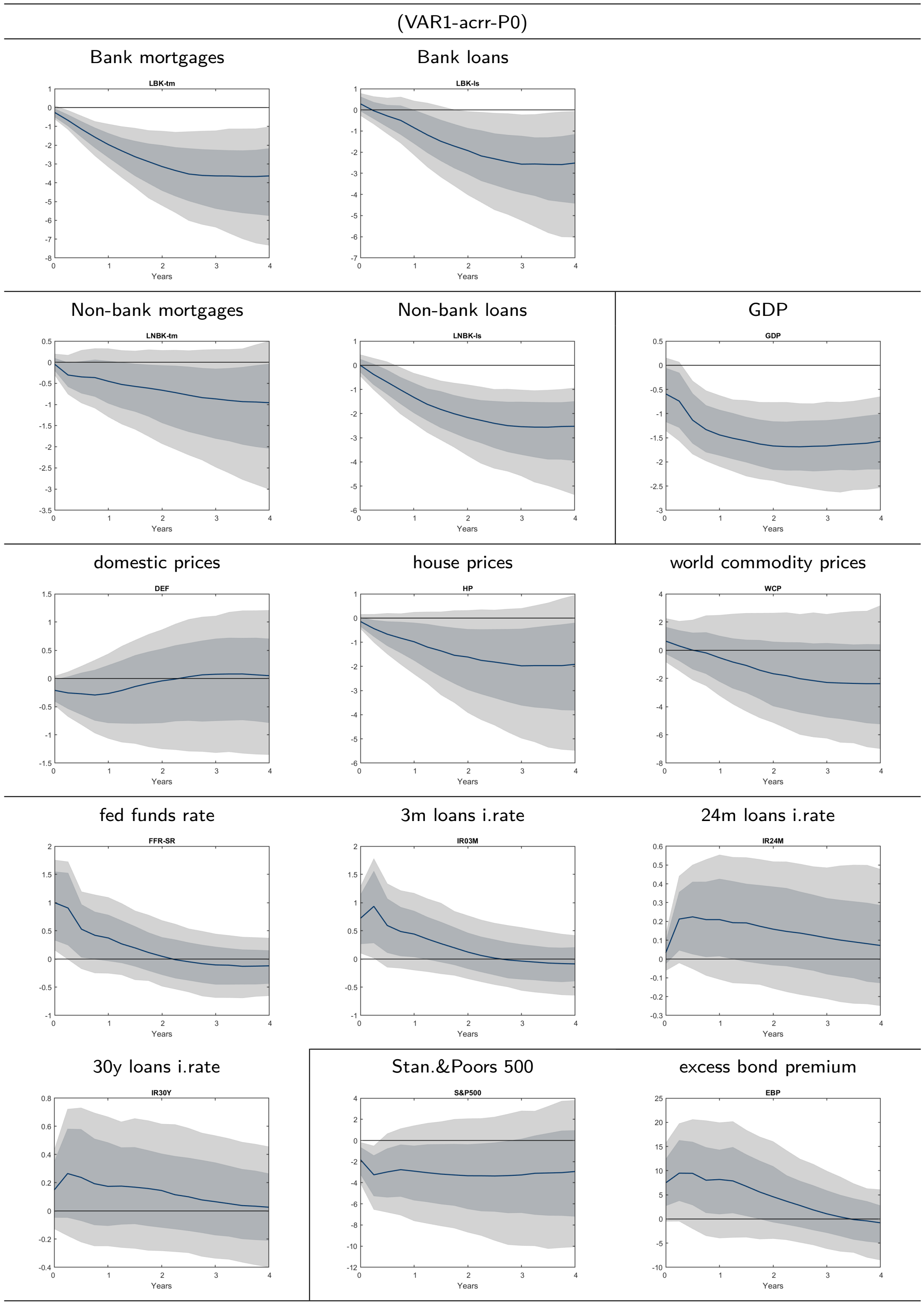
5 Monetary interventions and the credit channel

We begin by reporting the results of the VAR estimation over the whole period. We then focus on the comparison between the two consecutive subperiods. The discussion is based on IRFs, which quantify the response of the VAR variables to the monetary shocks identified through the procedure described in section 4.2. In addition, we briefly discuss also the decomposition of the forecast error variance (FEVD), which reports the portion of the prediction error of a variable explained by shocks to another variable.

5.1 General results for the full period

The IRFs obtained from estimating our benchmark VAR over the period 1974q1-2007q4 are in Figure 3. Apart from non-bank mortgages, which appear to be less responsive, the estimation results show that bank and non-bank credit aggregates decline significantly. A decline in GDP is also observed. The response of domestic prices is less pronounced, but still consistent: they decrease in response to a monetary tightening. Coherently with the literature on the transmission mechanism, the contraction of the credit aggregates is likely to be responsible for the observed GDP decrease. The response of the other variables is in line with expectations as well. For instance, the output confirms that short-term rates react quickly to monetary interventions, while the others lag behind (den Haan et al. 2007).

Figure 3: IRFs, benchmark VAR, full period



Response to the identified MP shocks. 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. At the top, in brackets, the code of the estimation is as defined in Table 3.

The FEVD in Table 4 reports the portion of the forecast error variance of each variable explained by monetary shocks at specific horizons (we report only the median value for ease of presentation). Such values suggest that monetary shocks explain a lot of the GDP forecast error variance, while by far less of the credit aggregates'. The difference in the magnitude of the FEVD between GDP and credit aggregates is somewhat reminiscent of the concept of the financial accelerator (Bernanke & Gertler 1995). Accordingly, credit transmits and amplifies monetary shocks to the real economy in which they unleash fully their effect.

Table 4: FEVD, benchmark VAR, full period

(VAR1-acrr-P0)								
horizon	BK-TM	NBK-TM	BK-LS	NBK-LS	GDP	DEF	HPI	WCP
0	0.014	0.003	0.013	0.004	0.169	0.140	0.006	0.006
4	0.087	0.016	0.015	0.034	0.296	0.076	0.026	0.009
8	0.144	0.021	0.036	0.085	0.392	0.051	0.036	0.015
12	0.157	0.025	0.055	0.112	0.402	0.043	0.041	0.022
16	0.158	0.026	0.064	0.125	0.389	0.038	0.041	0.028
horizon	FFR-SR	IR03M	IR24M	IR30Y	SP5	EBP		
0	0.290	0.203	0.006	0.024	0.016	0.020		
4	0.158	0.155	0.066	0.038	0.030	0.036		
8	0.093	0.094	0.052	0.036	0.030	0.055		
12	0.073	0.068	0.041	0.033	0.030	0.056		
16	0.068	0.062	0.035	0.031	0.030	0.054		

Check the Table "List of variables" for the full name of the variables. The numbers quantify the portion of the forecast error variace of each variable explained by the idenfied MP shocks. At the top, in brackets, the code of the estimation is as defined in Table 3.

The coefficients of the monetary policy rule

To ensure the consistency of our identification approach we check that the estimated coefficients of the monetary-policy (MP) equation are in line with theoretical predictions. Table 5 reports the estimated structural coefficients. In our baseline model, the posterior medians of ϕ_y (MP response to GDP) and ϕ_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 construction. Thus, our identification yields coefficients that are consistent with those obtained by Arias et al. (2019) and also with the conventional estimates found in the related literature.

Table 5: Structural coefficients of the MP equation

		q16	**q50**	q84
MP response to GDP	ϕ_y	0.32	1.08	2.68
MP response to Prices	ϕ_p	0.60	2.08	4.84

q50, q16 and q84 are respectively for the median, the 16th and the 84th percentiles of the distribution. The numbers quantify the response of the monetary-policy rate to a GDP and prices variation.

5.2 The effect of the rise of non-bank lenders

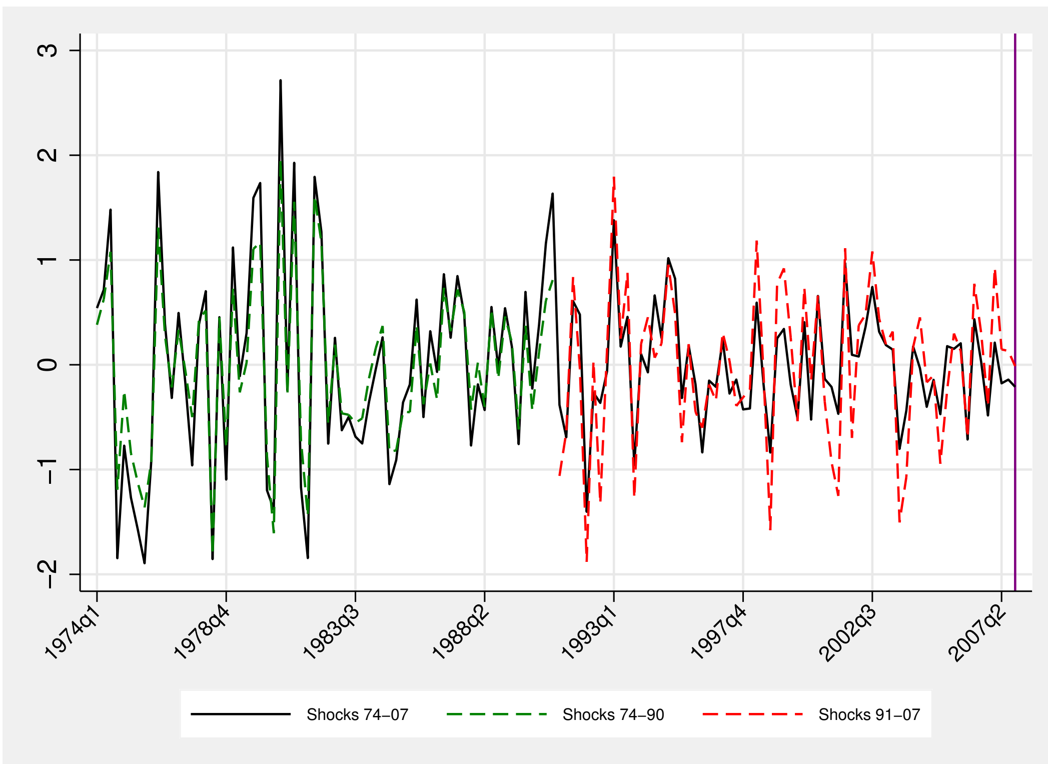
In this section, we present the analysis designed to answer whether the growth of the non-bank sector can be associated with an altered transmission of monetary interventions via the credit channel. To this end, as detailed in section 4, we split the estimation period over two consecutive subperiods 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 mentioned above, identification of the MP shocks is in each VAR estimation. Our main concern is therefore to verify the consistency of the identified shocks across the three different estimations (full period, first and second subperiods). Figure 4 shows the series of median shocks and reports their correlation index. They result highly comparable. We are therefore confident about the consistency of our VAR analysis over different samples, such consistency will be confirmed also further on when using local projections.

The IRFs for the estimations over the two subperiods are in Figure 5, we only report the more relevant IRFs to keep the discussion focused. The corresponding FEVD is in Table 6. 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.[20]

[20] 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 fact, coherently to expectations, shocks are stronger on average in the first period. The first period comprises the time of high inflation and volatility at the beginning of the eighties that triggered resolute monetary policy to curb 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.

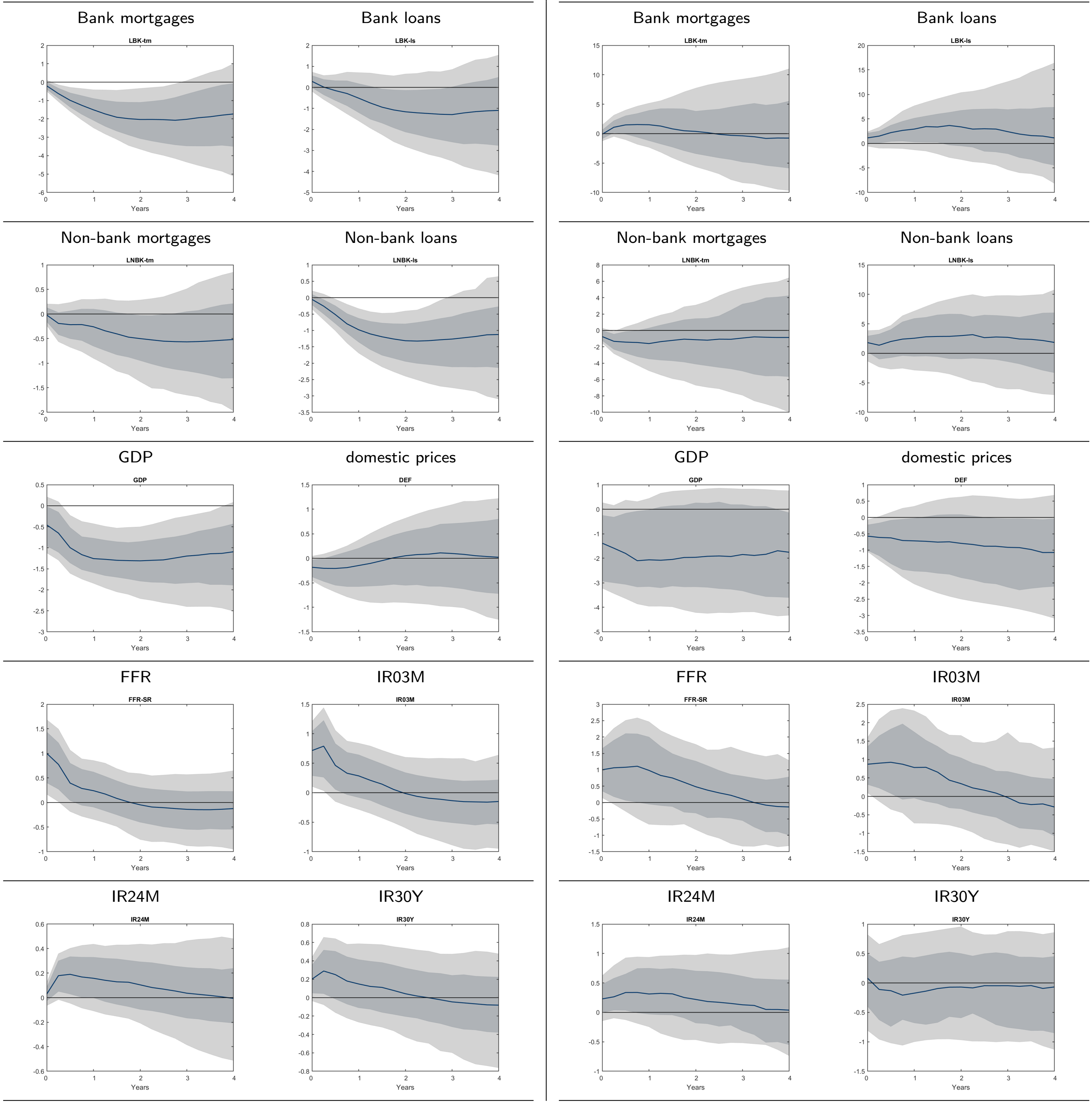
Figure 4: Comparison of identified shocks across different periods



The black line is for the sP0 shocks obtained from VAR1-acrr-P0, the green-dashed line is for the sP1 shocks obtained from VAR1-acrr-P1, the red-dashed line is for the sP2 shocks obtained from VAR1-acrr-P2. The correlation is 0.97 between sP0 and sP1 over the first period, and 0.861 between sP0 and sP2 over the second period. Check Table 3 for more info on each model estimated.

Figure 5: IRFs, benchmark VAR, by subperiod

First period: 1974q1-1990q4	Second period: 1991q1-2007q4
(VAR1-acrr-P1)	(VAR1-acrr-P2)



Reponse to the identified MP shocks. 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. IRFs for house prices and commodities prices are not reported to ease the exposition, they do not add any significant information and are promptely available upon request. At the top, in brackets, the code of the estimation is as defined in Table 3.

Table 6: FEVD, benchmark VAR, by subperiod

	(VAR1-acrr-P1)	(VAR1-acrr-P2)	(VAR1-acrr-P1)	(VAR1-acrr-P2)
	1974-1990	1991-2007	1974-1990	1991-2007
	BK-TM		BK-LS	
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	
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
	GDP		DEF	
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

Check the Table "List of variables" for the full name of the variables. The numbers quantify the portion of the forecast error variace of each variable explained by the idenfied MP shocks. At the top, in brackets, the code of the estimation is as defined in Table 3.

A comparison of Figure 5 against Figure 3, and of the IRFs from the first subperiod against those from the second subperiod in Figure 5 suggest that changes have occurred in the later part of the sample. Moreover, it emerges that the results observed over the full period depend predominantly on what happens in the first part of the sample, alias 1974q1-1990q4. The response of the credit aggregates is negatively signed in the first subperiod coherently with what is observed over the full estimation sample and to general economic theory. In contrast, apart from non-bank mortgages, their response changes in the second subperiod in a direction contrasting economic theory. As the checks detailed in the next subsection 5.3 prove, such a change emerges as a robust result of our analysis. In addition to a general loss of significance, bank mortgages and bank loans seem to increase, as well as non-bank loans at the impact.[21] Interestingly, a heterogeneous response of non-bank credit emerges.

As for the effect of monetary interventions on the GDP, it is clearer and more persistent in the

[21]In truth, an unexpected increase in 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 (2023).

first subperiod. 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. The GDP response is therefore coherent with the credit aggregates'. In contrast, the evolution of domestic prices is not much different across the two periods. It is to notice that the response of the interest rates over different maturities remains mostly unchanged, except for the interest rate on mortgages.

5.3 Robustness checks: local projections and alternative identification

We imagine two potential criticisms of our results. First, the shocks identified over the second subperiod might be said not consistent with those identified using the entire sample. The observed differences in the IRFs could be thought to depend on splitting the sample. Related to this point, critics could also argue that splitting the sample into two subperiods is problematic in terms of the robustness of the estimations. Second, the differences observed over the two subperiods, and consequently our conclusions, might be thought to depend upon the specific identification used and not survive to a different approach.

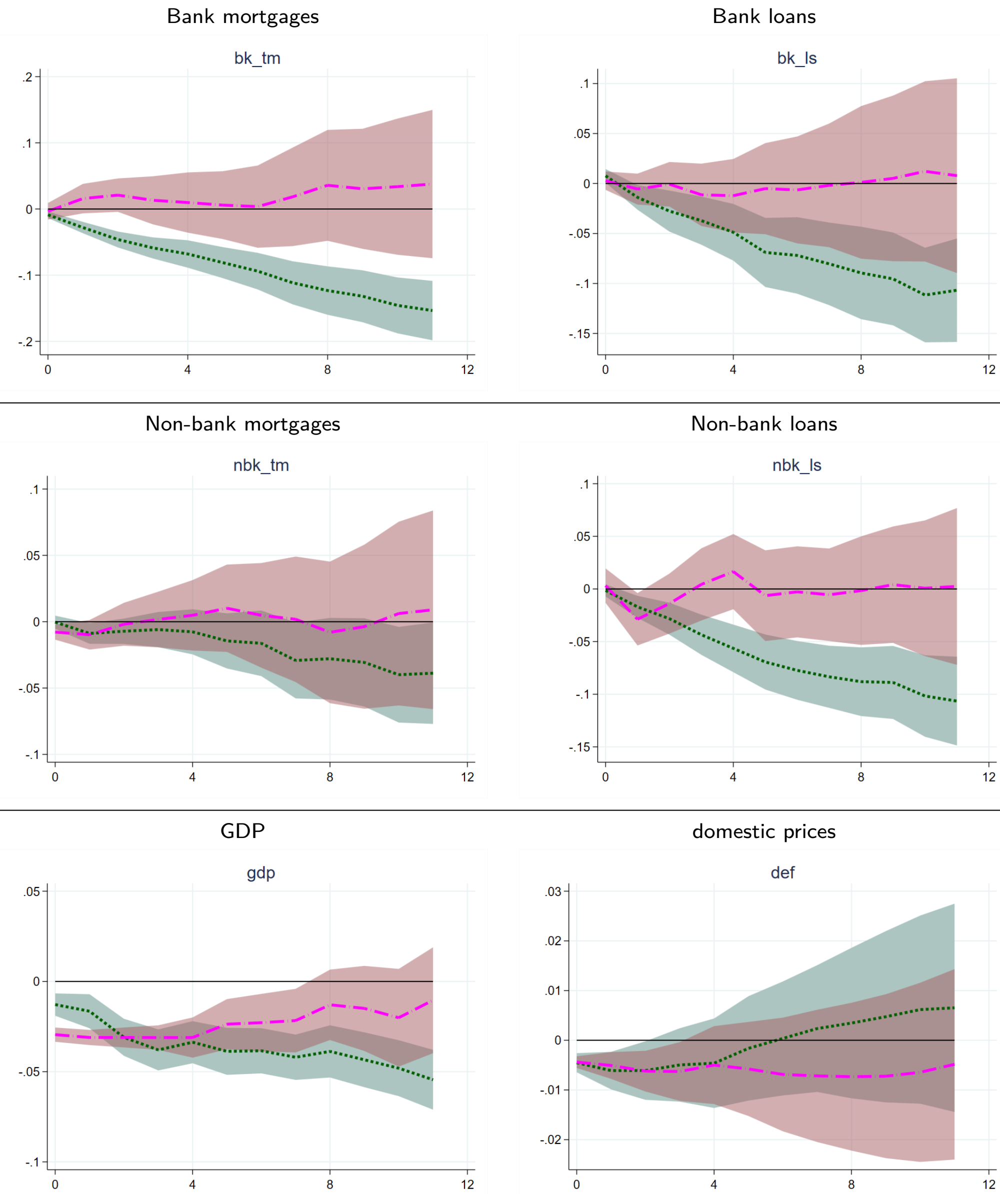
As for the first point, apart from showing the consistency of the identified shocks across the different subperiods (sP0, sP1, sP2) by means of Figure 4 and the correlations reported, we have performed local projections using Jordà (2005)'s method as outlined in section 4.2. In detail, the series of shocks (sP0) identified through VAR1 is used as a regressor to run local projections over the full period. The plots of the IRFs from the local projections are in Figure 6. They are consistent with the IRFs in Figure 5 since they yield similar differences between the first and the second period: the response of the credit aggregates changes remarkably in the second period.[22]

As for the second point, we have tested also the Cholesky identification approach. We instructed an order of variables functional to have comparability with the IRFs from our benchmark VAR, the Fed-funds rate is therefore placed before the credit aggregates so that it impacts them contemporaneously. Even though this is a completely different approach, we can draw comparable conclusions from the IRFs obtained (Figure 9 in appendix A).

[22] As a further check, Figure 8 in appendix A reports also local projections estimated separately in the two subperiods (P1 and P2) just to show the consistency of the IRFs with what was obtained from the VAR also in this case.

Figure 6: IRFs, Local Projections

(LPj1-P0)



Reponse to the sP0 monetary shocks. The green line and area are respectively for the IRF and its confidence interval in the 1st period, the magenta line and area are respectively for the IRF and its confidence interval in the 2nd period. Confidence intervals are for the 16-84 interquantile range. At the top, in brackets, the code of the estimation is as defined in Table 3.

5.4 Discussion of the results

The estimation output obtained using the full period (P0 "1974-2007", Figure 3) delivers intuitive and theory-consistent conclusions about the effect of monetary interventions: credit aggregates decline, GDP declines, prices decline. The weak decline in non-bank mortgages is of interest when read in conjunction with the strong decline in bank mortgages. Indeed, it could be said that these are in line with some literature suggesting that mortgages shift from banks to non-banks when they become riskier (Nelson et al. 2018), as in the case of a monetary tightening. The study of some specific components within the non-bank group (Figure 11 in appendix B) suggests that more-dynamic entities, such as finance companies, behave as banks in terms of the evolution of loans. Unsurprisingly, the least market-oriented seem instead to diverge from banks in terms of response.[23]

As for the transmission of monetary interventions over the two consecutive subperiods under investigation (P1 "1974-1990" versus P2 "1991-2007"), the comparison of the IRFs allows the following relevant conclusions to be drawn. First, the response of the credit aggregates is significantly different in the second period with respect to the first. In fact, while significance is generally lower, some aggregates exhibit a counter-intuitive evolution in the second period. A coherent transmission via the credit channel is only in the first subperiod, when the share of non-bank finance is smaller. A similar remarkable change has been detected also by Den Haan & Sterk (2011). As for the constancy of the response of non-bank mortgages, which contrasts to all the others, its explanation is somehow problematic, as it also depends on the extent of securitisation realised by the banking sector (Meeks et al. 2017). The increase in non-bank loans may be attributed to the deposit channel (Drechsler et al. 2017) of monetary-policy transmission as discussed by Xiao (2020). On the whole, we document that the response of non-bank credit depends on the type of credit. The related literature does not apply this distinction but only finds a general decrease in non-bank credit after a positive MP shock (Nelson et al. 2018, Xiao 2020). The results about the credit aggregates for the second subperiod are coherent with the effect on the GDP. In fact, the GDP response is more uncertain in the second subperiod with respect to what observed in the first.

All the other variables respond comparably between the first and the second period. Even though

[23] These statements are based on the IRFs from VAR2, in which we have replaced loans from non-bank institutions with loans owned by finance companies, the US government and the Farm Credit System; Figure 11 in appendix B.

IRFs are calculated under a ceteris-paribus condition, this strengthens the conclusion that it is not one of the other variables in the VAR to contribute to the different response in the second period, and therefore backs our connection to the role of an enlarged non-bank sector. In particular, except for mortgage rates, the evolution of the cost of credit is similar. Then, a possible explanation for the altered response of banks' credit aggregates in the second period does not lie in a different evolution of the cost of credit. We observe a significant increase in the price of credit, but not a decrease in its quantity. Such an evolution could depend both on supply, demand, and a mix of the two (Gambetti & Musso 2017). There is no easy way to disentangle the effects coming from lenders and borrowers. Banks could be said to have developed ways to avoid the increase of their external finance premium and this allows them to not decrease their supply. Nonetheless, a decrease in demand related to the higher cost on borrowers should be at play anyway. In the spirit of Papadamou & Siriopoulos (2012), we have disaggregated loans for different borrowers. Figure 12 in appendix B reports the IRFs for loans to households, corporate businesses, and non-corporate businesses. Such a decrease does not emerge even when we focus on households, a group likely more sensitive to a cost increase. Then, the explanation of these results remains an open issue for further research on this topic.

The question is whether or not the observed different response of the credit aggregates in the second subperiod depends on the structural change in the lender mix discussed in section 3, alias on the growth of non-bank finance. A testable causal relationship is hard to establish. As a matter of fact, however, after having controlled for all the variables included in the VAR, it is hard to imagine any other relevant development over the same period that could explain the different response of the credit aggregates. Aastveit et al. (2017) explore the interconnection between economic uncertainty and MP effectiveness, they find that US MP shocks affect economic activity less when uncertainty is high. It is acknowledged that the period 1991-2007 was characterized by far less uncertainty than the period 1974-1990 (oil shocks, high inflation, etc). Then, ceteris paribus, transmission should have been stronger in 1991-2007. We find the opposite. Moreover, our results are in line with Den Haan & Sterk (2011), Nelson et al. (2018), Xiao (2020) who similarly explain the evolution of some credit aggregates through the rise of non-bank finance, but differently from Xiao (2020), we find that the net effect on money creation (banks plus non-banks) is not negative. We are therefore 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.

As explained in the introduction, we believe that the activities of banks and non-banks are complementary rather than substitutes, and this is what determines the results. The growth of the non-bank sector has also provided new business opportunities for the banking sector, or allowed new practices (such as the transfer of risky activities), so that bank credit was not bound to decline anymore after a restrictive monetary policy. The behavior of banks is constrained by many factors (the evolution of deposits, risk management, capital adequacy ratios and regulation in general), non-bank finance has probably provided banks with new ways to accommodate their response in the face of such restrictions.

As a final point of discussion, we restate that the response of the credit aggregates is consistent with the less certain impact of monetary interventions on the GDP. We believe a connection between the two is plausible and likely. To gain more evidence on this point, we have computed Generalized IRFs (Koop et al. 1996) for changes in the credit aggregates.[24] 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 appendix A. Coherently to our hypothesis, their reading suggests that an increase in bank loans and mortgages has indeed a positive effect on the GDP in the first period (this is the conventional expectation, see Gambetti & Musso 2017, Cafiso 2022), but that effect is null in the second subperiod.

6 Conclusions

This research has its origins in the observation of the remarkable increase in non-bank credit prior to the global financial crisis. After reporting on theoretical contributions explaining why a larger non-bank sector might have consequences for the transmission of conventional monetary interventions (Xiao 2020, Nelson et al. 2018), the primary objective of our analysis was to gain evidence on this possible evolution in the US. To this end, we have studied the transmission of monetary interventions through bank and non-bank credit over two subsequent properly-defined periods. The first is from 1974 to 1990, a period

[24] 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 Ω_{t-1} represents the history of the economy up to $t-1$ and δ_i is a specific shock. Therefore, these IRFs do not rely on orthogonalized shocks but on reduced-form ones and integrate 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.

partially characterized by turmoils, shocks, high inflation, restrictions to financial markets and a limited size of the non-bank sector. The second goes from 1991 to 2007, a period of *great moderation*, growth, deregulation, almost no significant shocks in the US and characterized by the remarkable growth of non-bank entities.

Our analysis shows that monetary impulses are transmitted correctly both through bank and non-bank credit over the first period, in the sense that a restrictive monetary policy leads to a reduction in loans and mortgages. On the contrary, such a reduction does not occur in the second period. Furthermore, we find that bank loans evolve similarly to non-bank loans both in the first and second periods. Coherently with these results, our analysis nicely reveals a less clear effect of monetary interventions on economic activity in the same period.

We have linked the change in transmission in the later period to the main event that we observe: the growth of the non-bank sector mentioned above. It is likely that the growth of the non-bank sector provided banks with new business opportunities or enabled new practices, so that their credit supply was no longer constrained by a restrictive monetary policy. Indeed, the business of banks and non-banks is largely complementary rather than substitutable (Nelson et al. 2018, Meeks et al. 2017). Regulatory changes have spurred the growth of the non-bank sector, this growth has provided business opportunities for banks, also in terms of changing their practices through interaction with non-bank institutions (Gorton & Metrick 2012), this has also sustained the growth of the non-bank sector and vice versa. Further research is needed to understand the exact mechanisms that allowed banks not to react to monetary tightening in the same way as they used to.

The results of our analysis have important consequences both for monetary as well as supervisory authorities. Monetary authorities have already acknowledged that the growth of non-bank players challenges their traditional conduct of monetary policy (Schnabel 2021). The results of our analysis confirm such concerns since they suggest that conventional monetary interventions do not impact credit aggregates as they should. This implies that the expected effect on prices via the aggregated demand may be softer. At the same time, a stronger monitoring of the shadow banking system has been already put in place. As it is well known, non-bank institutions may expose the financial system to unknown and unforeseeable risks, different from those implied by traditional banking activity (Adrian & Shin 2009). In this regard, a deeper interaction of banks with non-bank institutions may partially lead them to adopt practices that increase their risk exposure. On the contrary, we do not spot relevant consequences for borrowers, if not those related to a higher systemic risk. In fact, the enlargement of the non-bank sector has been suggested to have benefited borrowers and smoothed the business cycle (Den Haan & Sterk 2011).

We conclude by saying that even though our results are country-specific, we believe they are instructive also for countries that are likely to see a rise of non-bank finance as the US. In this sense, a possible extension would be to replicate the analysis for other economies. Furthermore, as our analysis focused on the effects of conventional monetary interventions, it would be interesting to evaluate the effects of unconventional monetary policy. We leave these topics to future research.

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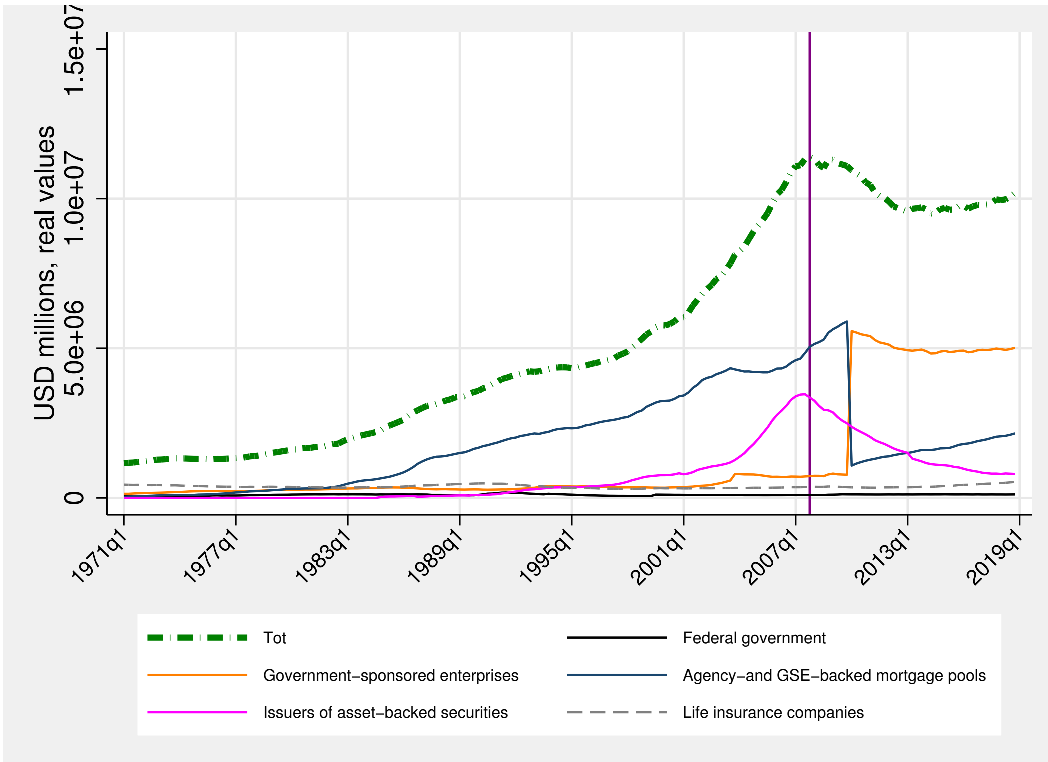
Appendix

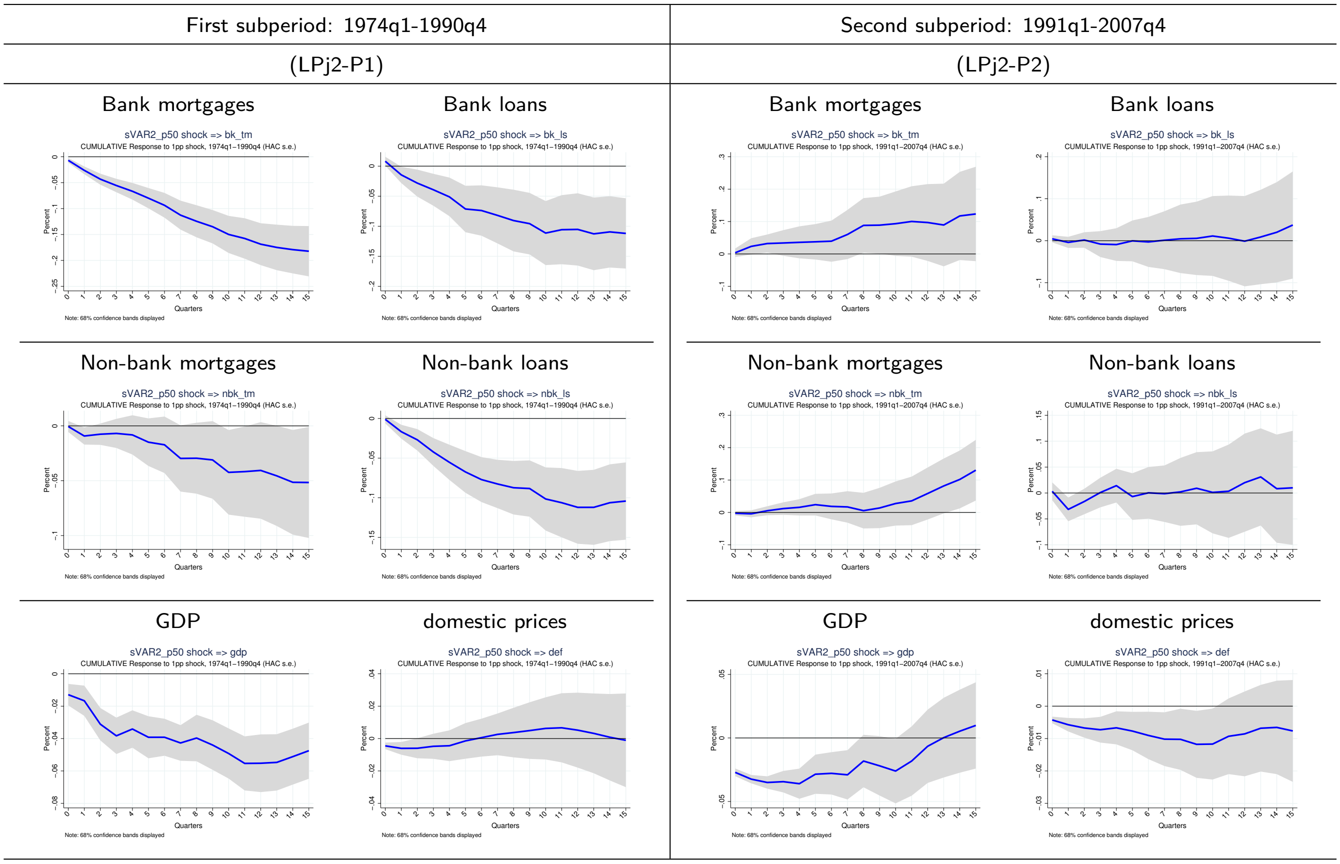
A. Further tables and figures

Figure 7: 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. Because of the financial crisis and the consolidation measures undertaken thereafter, the share of mortgages pools and trusts was absorbed by government sponsored enterprises in 2010.

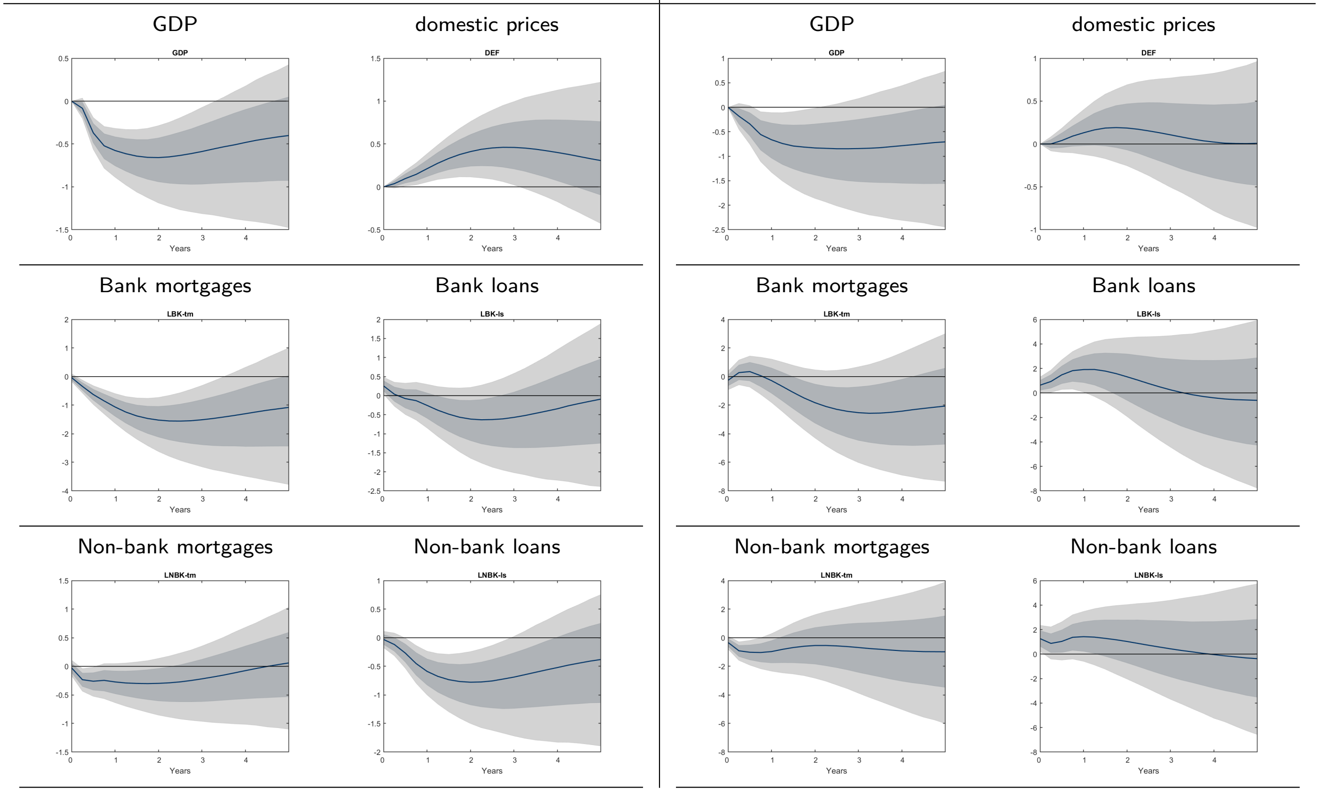
Figure 8: IRFs, Local Projections, by subperiod



Response to the sP0 monetary shocks. The grey area in the background is for the 16-84 interquantile confidence range. At the top, in brackets, the code of the estimation is as defined in Table 3.

Figure 9: IRFs, benchmark VAR, by subperiod, Cholesky id.

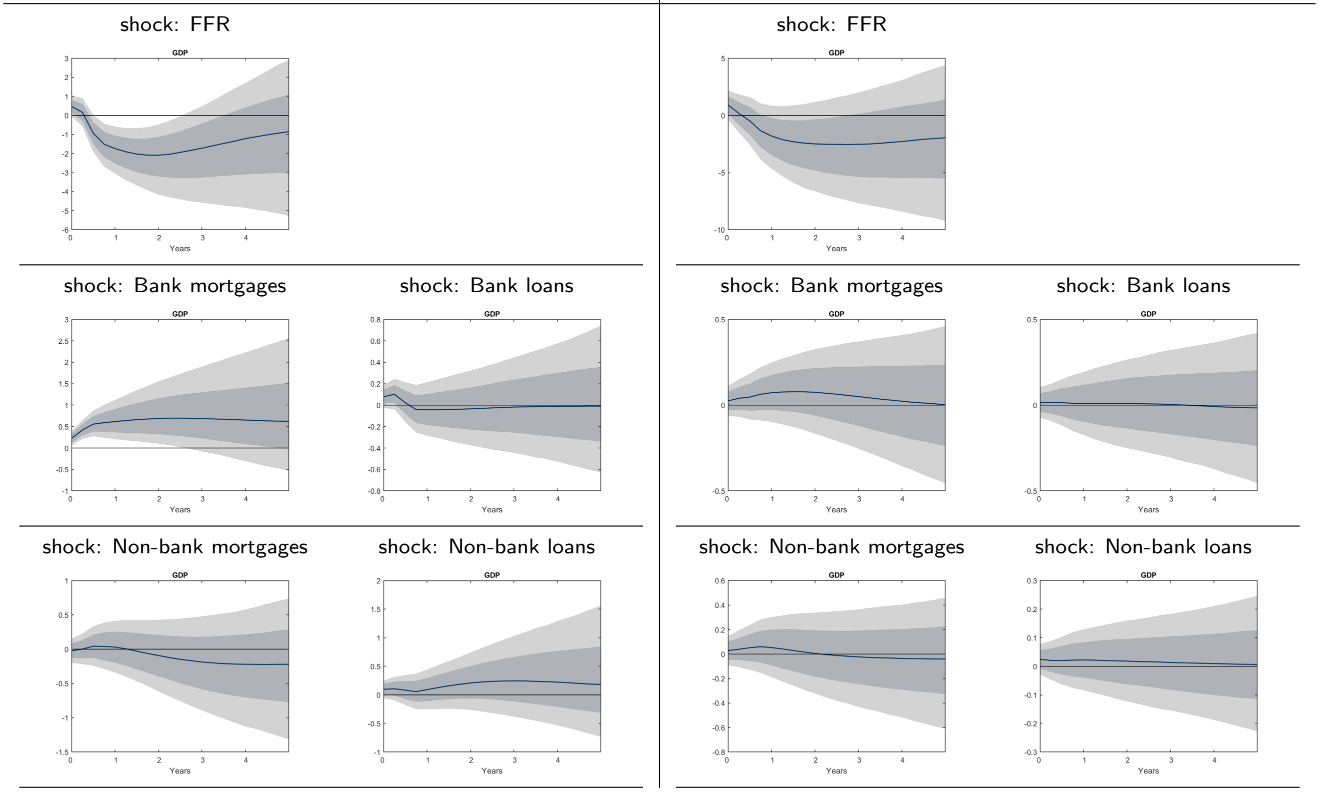
First subperiod: 1974q1-1990q4	Second subperiod: 1991q1-2007q4
(VAR1-cho-P1)	(VAR1-cho-P2)



Reponse to the identified MP shocks. 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 IRFs for the other variables are not reported just to ease the exposition, they do not add any significant information and are promptely available upon request. At the top, in brackets, the code of the estimation is as defined in Table 3.

Figure 10: IRFs, benchmark VAR, by subperiod, Generalized IRFs

First subperiod: 1974q1-1990q4	Second subperiod: 1991q1-2007q4
(VAR1-girf-P1)	(VAR1-girf-P2)



Response of the GDP to different credit shocks.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. At the top, in brackets, the code of the estimation is as defined in Table 3.

B. Disaggregated loans (possibly on-line)

Contributions on the credit channel suggest that the response of loans from specific lenders, as well as to specific borrowers, can be heterogeneous and counter-intuitive (den Haan et al. 2007, Papadamou & Siriopoulos 2012). Among the others, the loan puzzle (Cafiso 2023) is a good example of the heterogeneity that marks the response of loans. In this appendix, we report on the response of disaggregated loans.

As a first step, we investigate how different lenders within the heterogeneous non-bank group respond. As a further step of our analysis, we also report how loans to different borrowers react to the same MP shocks. In both cases, we report IRFs from VARs in which we have replaced the aggregate credit item with its components.

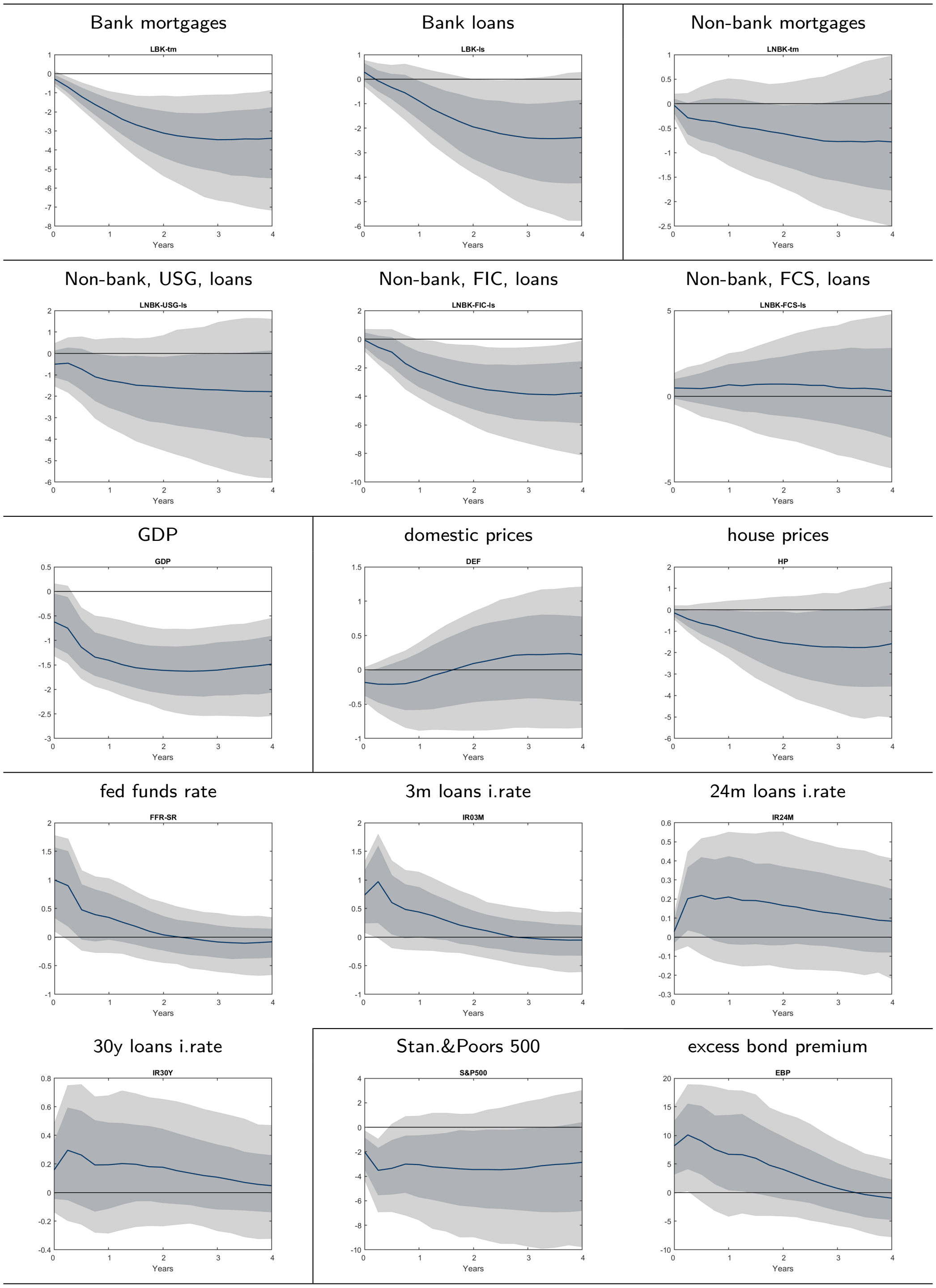
Inside non-bank loans

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 into this aggregate, we replace loans from non-banks with three of its constituencies: loans from the US government (NBK-LS-USG), from finance companies (NBK-LS-FIC) and from the Farm Credit System (NBK-LS-FCS). 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 4, but we have replaced non-bank loans. We therefore estimate a VAR with 16 variables in this case (VAR2). The IRFs obtained from this estimation are in Figure 11.

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.

Figure 11: IRFs, NBK loans by lender VAR, full period

(VAR2-acrr-P0)

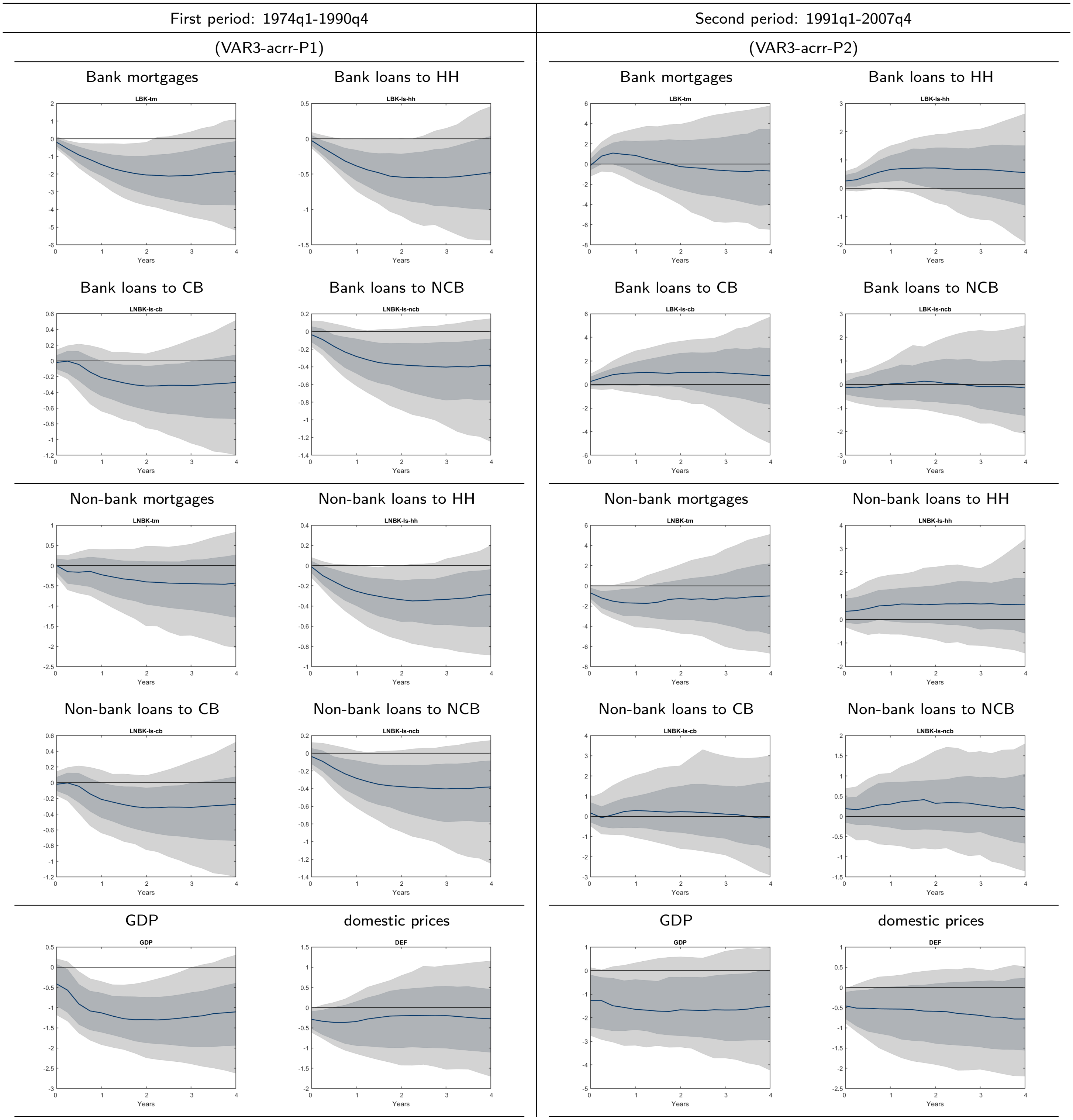


Response to the identified MP shocks. The darker grey area in the front and the lighter in the background are respectively for the 16-84 and 5-95 interquantile confidence range. The IRF for commodity prices is not reported just to ease the exposition, it does not addd any relevant information and it is promtely available upon request. At the top, in brackets, the code of the estimation is as defined in Table 3.

Loans by borrower

We now turn our focus on loans to specific borrowers. We consider bank and non-bank loans to households (BK-LS-HH, NBK-LS-HH), corporate business (BK-LS-CB, NBK-LS-CB) and non-corporate business (BK-LS-NCB, NBK-LS-NCB); mortgages cannot be disaggregated, so we leave the aggregate as in the previous estimations. The IRFs from the estimation of this VAR (VAR3) are in Figure 12. The estimation confirms the main findings of our analysis, alias the change in responses between the first and the second subperiods.

Figure 12: IRFs, Loans by borrower VAR, by subperiod



Response to the identified MP shocks. 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 IRFs for the other variables are not reported just to ease the exposition. They do not add any significant information and are promptely available upon request. At the top, in brackets, the code of the estimation is as defined in Table 3.

C. Data avaialbility

All data used in this research are publicly-available, Table 2 includes the source of each series. Nonetheless, the final dataset tha we use in this study is available from the corresponding author upon reasonable request.