Commercial Bank Heterogeneity and the Transmission of Monetary Policy Through Bank Lending

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Abstract

I study the role of bank heterogeneity in the transmission of monetary policy to the real economy via bank lending. Using the novel pass-through impulse response function (PT-IRF) – introduced in Nikolaishvili (2023) – I quantify the respective contributions of community and noncommunity bank lending in the United States to the dynamic effect of a monetary policy shock on output. I estimate PT-IRFs using a factor-augmented vector autoregression with externally-identified monetary policy shocks and hierarchical bank lending factors based on a large panel of bank-level data. My results show that: (1) An unanticipated monetary tightening contributes negatively to output through changes in bank lending, both in the short and medium run; (2) Community and noncommunity banks differ in the extent to which their lending behavior allows for the pass-through of monetary policy shocks to output. These findings highlight the importance of the composition of the commercial banking sector in assessing the potency and timing of monetary transmission.

JEL Classifications: G21; E51; E52
Keywords: Monetary transmission; bank lending; community banks; FAVAR; PT-IRF

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1 Introduction

Does bank lending facilitate the transmission of monetary policy? If so, to what extent does it contribute to the impact of monetary policy shocks on output? Since the seminal work by Bernanke and Blinder (1988), there has been much debate regarding these fundamental questions in the monetary policy literature. For instance, Dave et al. (2013) and Drechsler et al. (2017) show evidence in favor of an active channel of monetary transmission through bank lending in the United States, while Romer and Romer (1990) and Ashcraft (2006) cast doubt upon its current existence at the aggregate level. These studies yield alternative conclusions, but cannot refute each other directly. A primary reason for this discord stems from an absence of consistent methodological frameworks for the measurement of channels of monetary transmission. Moreover, the aggregate role of bank heterogeneity in monetary transmission through bank lending is ambiguous. Considering the ever-evolving composition of the U.S. commercial banking sector, this presents limitations to policy optimization.

In this paper, I employ a flexible reduced-form empirical approach with minimal identification assumptions, leveraging granular panel data to quantify and estimate the nature of aggregate monetary transmission through bank lending. To estimate the effect of bank lending on the transmission of monetary policy shocks, I combine bank-level loan data with a standard set of aggregate macroeconomic series. I use the data to estimate a factor-augmented vector autoregression (FAVAR) with externally identified monetary policy shocks introduced in Bu et al. (2021). I then estimate and conduct inference on pass-through impulse response functions (PT-IRFs) – a novel class of IRFs developed in Nikolaishvili (2023) – which characterize the dynamic response of output to monetary policy shocks via bank lending. I categorize the U.S. commercial banking sector into community and noncommunity banks, and examine how variation in their respective lending volumes facilitates the dynamic influence of monetary policy shocks on output. My findings reveal that the transmission of unanticipated monetary policy shocks through bank lending occurs through changes in both community and noncommunity bank lending, such that the latter has a greater effect in the short run, whereas the former drives the persistence of monetary transmission into the medium run.

A key methodological contribution of this paper is the use of PT-IRFs to estimate and quantify monetary policy transmission through bank lending directly. This lending channel of monetary transmission can be described as the effect of monetary policy on output growth via changes in the supply of bank loans, expressed as a two-step causal chain: (1) a change in monetary policy affects the quantity of bank loans, and (2) the change in the quantity of bank loans affects output growth. Previous literature has studied each of these components individually.[1] For example, Dave et al. (2013) analyzes the effect of monetary policy shocks on the quantity of bank loans, while Peek and Rosengren (2000), Peek et al. (2003), Driscoll (2004), and Ashcraft (2006) test whether shocks to bank loan supply impact output. The common practice is to conclude that if either of these relationships is insignificant, then bank lending plays no role in the transmission of monetary policy to the real economy. However, separately estimating these relationships cannot directly quantify or test the nature of monetary transmission via bank lending – the shocks to bank lending in this setting are *endogenous* by definition. Therefore, an understanding of the effect of exogenous shocks to lending on output provides limited insight regarding the transmission of monetary shocks to output via lending. I demonstrate that the PT-IRF can estimate impulse responses that *simultaneously* capture both components of the above-mentioned two-step causal chain, allowing for the direct quantification and inference on the dynamic nature of monetary transmission through bank lending.

Another benefit of my empirical approach is that it is effectively agnostic to the different mechanistic views of monetary transmission through bank lending. The last few decades have seen the emergence of a variety of views on the true mechanism underlying the bank lending channel (BLC), which is the elusive supply-side subchannel of the more general lending channel. The conventional formulation argues that the BLC operates through reserve requirements, which create binding liquidity constraints for commercial banks, forcing responses in bank loan supply in the face of monetary policy shocks (Kashyap and Stein, 1994; Bernanke and Gertler, 1995; Black and Rosen, 2007; den Haan et al., 2007). An alternative perspective is that the BLC operates through the effect of monetary policy on banks' external finance premia, which either limits or enhances the ability of banks to issue new loans (Disyatat, 2011). A more recent formulation offered by Drechsler et al.

[1] My analysis does not separate the contributions of the bank lending and balance sheet channels in the transmission of monetary policy via bank lending. In other words, similar to Dave et al. (2013), I do not distinguish between changes in bank loan supply and demand caused by monetary policy shocks. The identification challenges of separating these two channels is described in Bernanke and Blinder (1992), Bernanke and Gertler (1995), and Kashyap and Stein (2000).

(2017) argues that monetary policy affects the supply of bank loans through changes in the quantity of deposits available to commercial banks as a source of funding.

This work contributes to the literature by analyzing the role of bank business model heterogeneity in the monetary transmission mechanism. The U.S. commercial banking sector is remarkably large and diverse, with over 5,000 active banks holding just under $25T in combined assets. Furthermore, banks are heterogeneous across multiple dimensions, such as capitalization, size, asset allocation, and exposure to systemic risk. The BLC literature has attempted to capture the role of heterogeneity in bank behavior by explicitly controlling for some of these dimensions. Kashyap and Stein (1995), Kashyap and Stein (2000), and Kishan and Opiela (2000) find that smaller, less liquid, and less capitalized banks are more sensitive to monetary policy shocks, respectively. Dave et al. (2013) confirms that smaller banks tend to be more sensitive to monetary policy. Bluedorn et al. (2017) find that belonging to a bank holding company, and not bank size, is what determines the insensitivity of banks to monetary shocks. Altavilla et al. (2020) studies banks in the European Union to find that the capital ratio, exposure to domestic sovereign debt, the share of non-performing loans and the stability of the funding structure of a bank contribute to the heterogeneity in monetary pass-through to bank loan supply.

I argue that a key determinant of bank behavior neglected by the above literature is the business model, driven largely by the geographical scope of service provision. The vast majority of banks in the U.S. are community banks, as evidenced by Figure 1. Community bank activity is often limited to local economies, with their business model geared towards relationship-building and the provision of traditional banking services to local firms and households (Nguyen and Barth, 2020) – unlike their geographically-diversified noncommunity counterparts. The most common approach to controlling for bank heterogeneity in the existing literature is to group them by size. However, such grouping may be problematic due to the equal split between community banks and noncommunity banks in the mid-range of the bank size distribution. There is crucial heterogeneity within this group that remains unaccounted for without partitioning banks according to their business model. Furthermore, as evidenced by Figure 1, the composition of the U.S. banking sector has changed drastically since the early 1990s as a result of consistent consolidation. The evolving composition of the commercial banking sector may have implications for the magnitude and delays in the effects of monetary policy changes. Understanding the role of bank heterogeneity across the business model dimension can be crucial in anticipating changes in the behavior of monetary transmission.

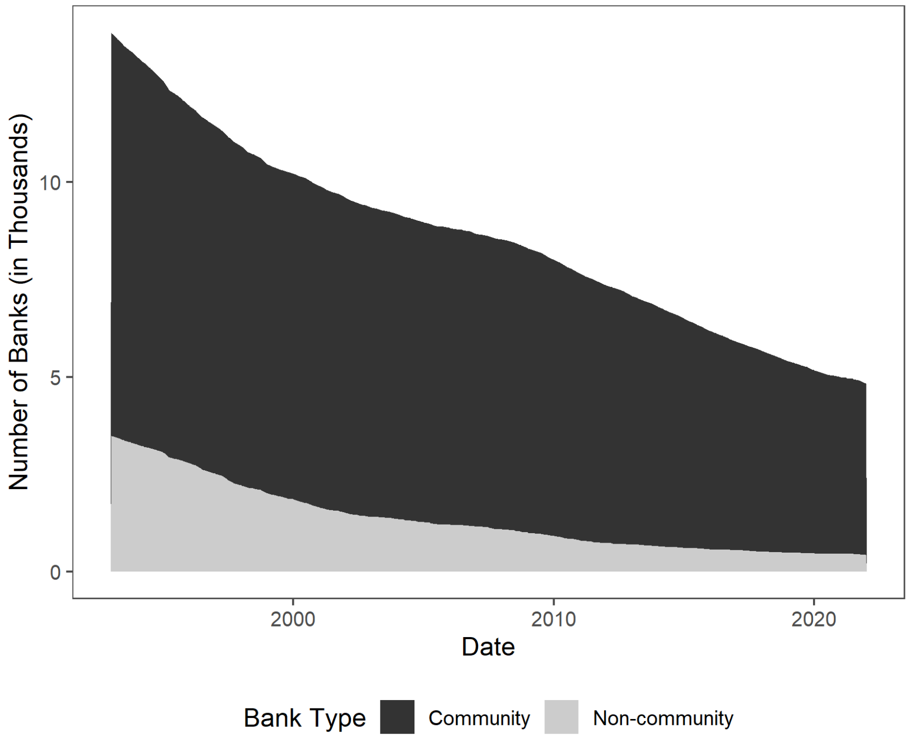


Figure 1: The size and composition of the commercial banking sector in the U.S. by business model. *Source: FDIC Statistics on Depository Institutions.*

Over the sample period from 1994 to 2019, I find that community bank lending enables contractionary monetary policy shocks to negatively impact output growth. In other words, the pass-through of monetary policy to the real economy through bank lending occurs partially through community bank lending. This finding suggests that bank relationship lending still matters, perhaps even to a greater extent than argued by Fields et al. (2006). Moreover, given that community banks lend to small local borrowers (FDIC, 2020), this result may also have distributional implications. Specifically, an unanticipated monetary tightening may have a contractionary effect on output in the medium run via a persistent decline in small business activity caused by limited funding opportunities for such borrowers.

The remainder of this paper is organized as follows. Section 2 discusses differences between community and noncommunity banks in the U.S. Section 3 presents the empirical approach to estimating the nature of monetary transmission through bank lending. Section 4 describes the results and their implications. The final section concludes the paper.

2 Composition of the U.S. Commercial Banking Sector

A community bank can be informally defined as a standalone financial intermediary that primarily provides traditional banking services to local communities. These banks are typically locally owned and managed, with strong ties to their corresponding credit markets -– a defining feature of the "community" aspect of community banks. Formal definitions of a community bank vary, with the Federal Deposit Insurance Corporation (FDIC) and the Federal Reserve Board (FRB) using different criteria. The FDIC's definition excludes banks that have no loans or core deposits, have foreign assets accounting for $\geq$10% of total assets, and have more than 50% of assets in certain specialty banks. The FDIC includes remaining banks that have total assets of less than \$1B, and have total assets over \$1B but meet specific criteria such as loan-to-assets $>$33%, core deposits to assets $>$50%, fewer than 75 offices, and restricted geographical presence. On the other hand, the FRB simply defines a community bank as an institution with total assets less than \$10B. In this study, I adhere to the FDIC's classification to distinguish between community and noncommunity banks, as it better encapsulates the essence and historical context of community banking. Notably, the FDIC emphasizes the geographical scope of community banks, which must predominantly operate within a local economy by restricting both their presence and service offerings.

The U.S. boasts an exceptionally high number of banks compared to other countries. As depicted in Figure 1, however, the total number of banks has been consistently decreasing since the early 1990s due to consolidation. Community banks have experienced the largest absolute reduction in numbers, while noncommunity banks have undergone a more substantial relative decline. Conversely, the combined share of noncommunity bank assets and net loans has increased notably during the same time frame, as illustrated in Figures A.1 and A.2, respectively. The noncommunity banking sector has experienced more rapid consolidation while simultaneously surpassing the community banking sector in terms of growth, size, and prominence in credit markets. The diminished size and collective presence of community banks in credit markets does not necessarily indicate their decline.

In fact, community banks continue to thrive as "specialists" within specific segments of the economy. For example, despite issuing only 15% of the industry's total loans, community banks are responsible for 30% of commercial real estate, 36% of small business, and 70% of agricultural loans. In 2019, community banks based in rural areas and small metropolitan regions held 67% of all CRE loans in those areas (FDIC, 2020).

With respect to lines of business, as previously mentioned, community banks are of special significance to local economies. Community banks prioritize relationship-based lending, offering loans that require personalized attention, individual analysis, and ongoing administration. They distinguish themselves by building and maintaining personal relationships, and specializing in monitoring local economic conditions. Their ability to gather and process "soft information" enables them to achieve greater loan repayment success rates than their noncommunity counterparts (Peirce et al., 2014). Unlike noncommunity banks, the vast majority of community banks operate within a single state, and most have only one branch, as evidenced by Figures 3 and 2, respectively. They tend to focus on non-formulaic loans, requiring local knowledge and a personal touch.

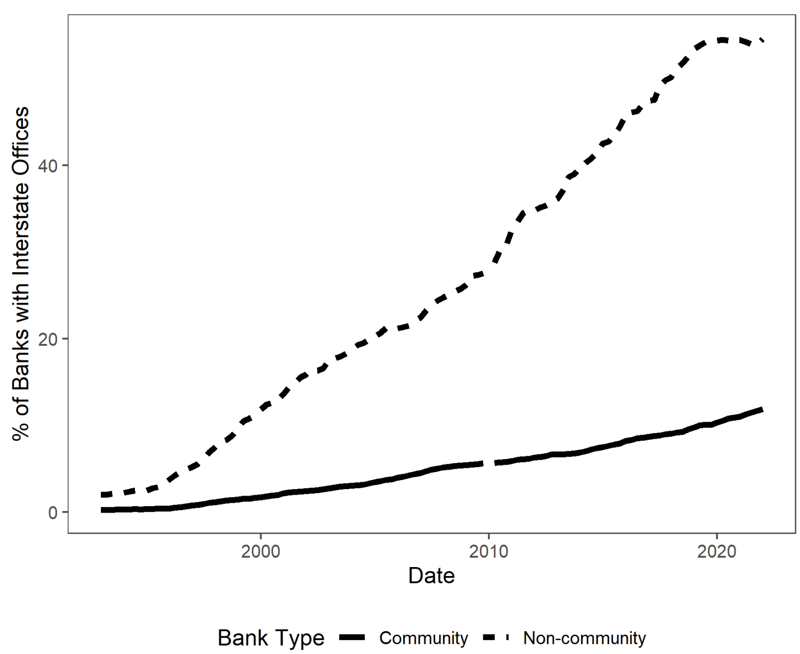


Figure 2: Percentage of banks with offices across more than one state, by type. *Source:* FDIC Statistics on Depository Institutions.

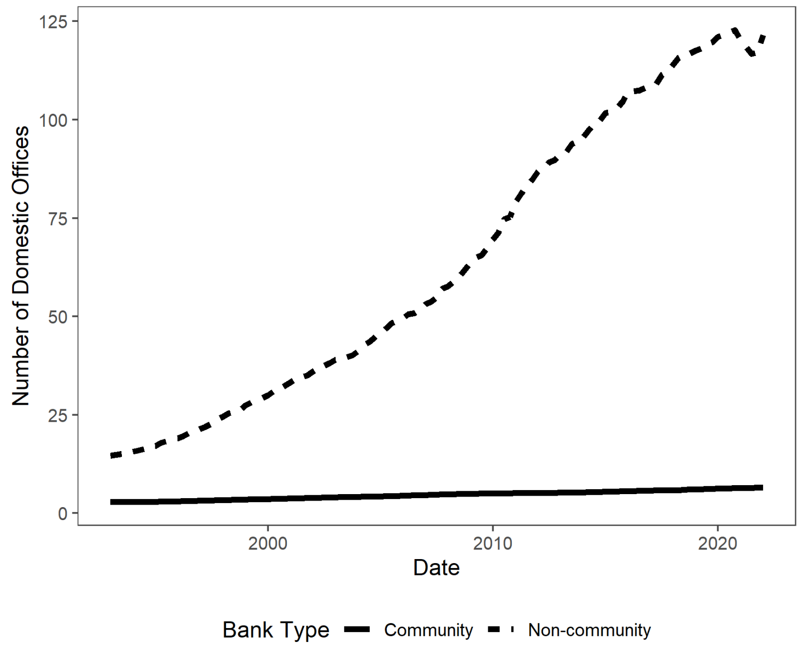


Figure 3: Average number of domestic offices by bank type. *Source:* FDIC Statistics on Depository Institutions.

Community banks' focus on the provision of traditional banking services, such as lending to households and small businesses, causes their margins to be sensitive to the interest rate spread (FDIC, 2020; Lux and Greene, 2015). Noncommunity banks provide a larger portion of small business loans in terms of the total dollar amount, but community banks specialize in lending to small businesses. Small businesses play a vital role in the economy, employing nearly half of the private sector workforce and making up the vast majority of all businesses. These businesses frequently turn to banks for credit, with banks providing approximately 44% of small business financing, compared to 22% from online lenders and 6% from credit unions. Community banks hold 36% of the industry's total small business loans, which is double their share of the industry's total loans (FDIC, 2020).

Furthermore, the size of loans issued to small businesses differs significantly across community and noncommunity banks. Noncommunity banks tend to originate and hold more loans under $100,000 than loans between $100,000 and $1M. In contrast, community banks hold a more significant share of loans between $250,000 and $1M, focusing on larger loans that require greater interaction and analysis to build a relationship between the bank and the borrower. Data also shows that community banks do not limit their small business loans to \$1M; in fact, the majority of loans originated by community banks are for amounts greater than \$1M (FDIC, 2020). It follows that community bank borrowers are more dependent on community bank loans than noncommunity bank borrowers are to theirs.

3 Econometric Approach

In this section, I describe the construction of the FAVAR using bank-level loan data, aggregate economic series, and an externally-identified proxy for monetary policy shocks. I also explain how I estimate the model, and use it to generate PT-IRFs in order to gauge the contribution of community, noncommunity, and joint bank lending to the transmission of monetary policy shocks to output growth.

In short, the FAVAR is constructed around a standard monetary VAR with variables capturing quarterly variation in monetary policy, output, inflation, and credit conditions in financial markets. In addition to these aggregate variables, the VAR is augmented with bank lending factors that separately capture comovement in the growth of lending volume of all banks, community banks, and noncommunity banks, respectively. The hierarchical nature of these factors, which are estimated using a large panel of bank lending series, ensures that I isolate latent forces driving group-specific fluctuations in community and noncommunity bank lending behavior. In other words, controlling for comovement across all banks guarantees that the model captures bank type heterogeneity through the group-specific factors. The hierarchical lending factors are estimated using a recursive principal components estimator, beyond which the estimated factors are treated as observables during the estimation of the VAR using least squares. The externally-identified monetary policy shock series is included in the VAR as an endogenous variable without any restrictions on its lag coefficients (similar to the approach taken in Auerbach and Gorodnichenko (2012) to identify news shocks), and its corresponding innovation is further recursively internally-identified. Finally, PT-IRFs point estimates are generated directly as mappings of the lag coefficient and contemporaneous impact matrix estimates from the previous step. Confidence intervals on the PT-IRFs are obtained using a wild bootstrap (Gonçalves and Kilian, 2004, 2007), such that at each iteration of the bootstrap, the newly-estimated lag coefficients and contemporaneous impact loadings produce a new draw of a PT-IRF of interest. I elaborate on each step in this process in the remainder of this section.

3.1 Data

I use a combination of quarterly bank-level loan data, a small set of aggregate macroeconomic series, and externally-identified monetary policy shock series developed by Bu et al. (2021). The sample runs from Q1 of 1995 until Q4 of 2019, constrained by the start of the monetary policy shock series and the beginning of COVID-19. The cleaning procedure for bank loan series, obtained from the FDIC Statistics on Depository Institutions (SDI) database, is described by the following steps:

1. For each FDIC-insured commercial bank that has existed in the U.S. throughout the duration of my sample, I obtain a quarterly series of net loans and leases at the bank level. Net loans and leases equals to loans and lease financing receivables, net of unearned income and the allowance for loan and lease losses. For the remainder of this text, I refer to net loans and leases as "total lending" or simply "lending" interchangeably;

2. I create a balanced panel of bank lending series by discarding data associated with banks with at least one missing observation – in other words, I maintain data only for those banks that have been operational throughout the full sample period;

3. I partition the panel by bank type, yielding two separate sub-panels of bank-level data – one for community bank lending, and another for noncommunity bank lending.

4. Each of the series across the two sub-panels are transformed into growth rates and seasonally adjusted simply by partialling out variation attributable to seasonal dummies in a linear regression model.

The cleaned bank-level data is used to estimate bank lending factors and their loadings in the factor structure of the FAVAR.

The following macroeconomic series, used in the VAR portion of the FAVAR, are obtained from the Federal Reserve Economic Data (FRED) database:

1. **Real Gross Domestic Product** (GDPC1): Baseline proxy for output.

2. **GDP Deflator** (GDPDEF): Baseline proxy for inflation.

3. **Industrial Production** (INDPRO): Alternative proxy for output, often used in monetary VARs with monthly data.

4. **Consumer Price Index** (CPIAUCSL – Consumer Price Index for All Urban Consumers: All Items in U.S. City Average): Alternative proxy for inflation, also frequently used in monthly monetary VARs.

An additional aggregate indicator included in the VAR is the excess bond premium (EBP). The EBP is the average corporate bond spread that is purged from the impact of default compensation. It is one of two components of the credit spread indicator introduced by Gilchrist and Zakrajšek (2012), often referred to as the GZ spread. The EBP is interpreted as an indicator of the capacity of intermediaries to extend loans, or more generally the overall credit supply conditions in the economy. It aggregates high-quality forward-looking information about the economy – therefore, it improves the reliability and forecasting performance of small-scale VARs (Caldara and Herbst, 2019). Modern monetary VARs often contain the EBP as an endogenous variable to reflect credit market conditions. I follow this convention in the literature due to the desirable properties of the EBP described above. Furthermore, Bu et al. (2021) include the EBP in their monthly VARs with which they test the validity of their monetary policy shock measure – by including the EBP in my model, I am able to more closely replicate their setting.

The final key data series used in this study is the monetary policy shock measure. For the purposes of my analysis, I defer to the Bu-Rogers-Wu (BRW) monetary policy shock measure identified by Bu et al. (2021). I aggregate their provided shock series to the quarterly frequency, as shown in Figure 4. I use the BRW shock instead of others in the literature, such as Romer and Romer (2004), Nakamura and Steinsson (2018), and others mentioned in Ramey (2016), since it is specifically tailored to account for both conventional and unconventional monetary policy over the course of my sample period, which is plagued with a variety of monetary policy regime changes and a long zero lower bound (ZLB) period following the 2007-08 financial crisis.

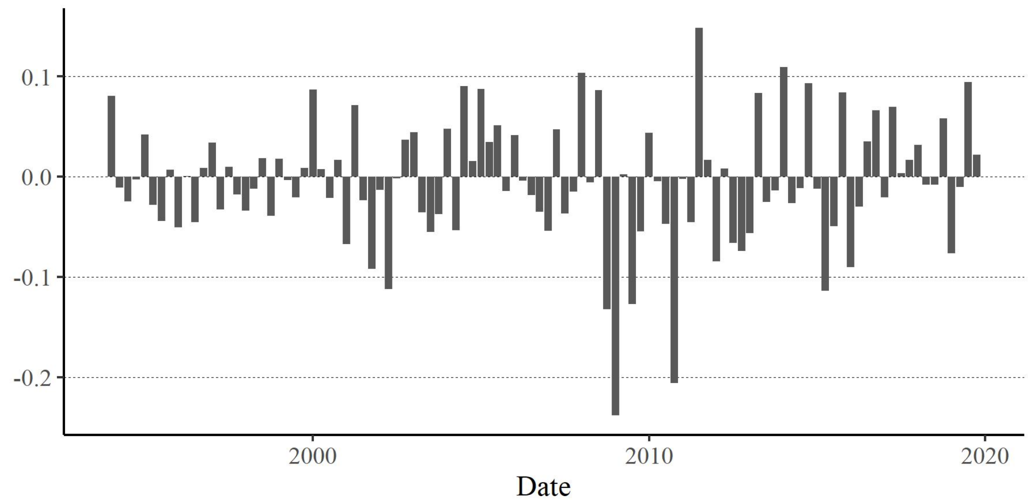


Figure 4: Quarterly BRW shock.

3.2 Model

I estimate a FAVAR that applies a hierarchical factor structure to the bank loan growth rates series in my sample and a shared VAR structure to the corresponding bank lending factors, macroeconomic series, and the monetary policy shock series. The hierarchical factor structure captures factors driving common variation among the growth of bank loans between and across community and noncommunity banks – in other words, it simultaneously contains factors representing common sources of variation among all banks, along with a separate set of factors capturing bank type-specific variation. The VAR yields the dynamic relationship between these bank lending factors, macroeconomic series, and monetary policy. Although the bank lending factors themselves do not have an intuitive interpretation, their impulse responses to various shocks to the observed series in the VAR can be used in conjunction with their corresponding factor loadings to generate bank-specific impulse responses. For example, the FAVAR allows us to estimate bank-specific lending responses to a contractionary monetary policy shock.

The factor structure applied to the loan growth rate series x of each bank i is as follows:

$$x_{it} = \alpha_i + \Gamma_i F_t + \Lambda_i F_t^j + u_{it}\,, \tag{1}$$

where t indexes time, $j \in \{\text{community bank}, \text{noncommunity bank}\}$ indexes bank type, F is a vector of lending growth factors common to all banks, F^j is a vector of lending growth factors common only to banks of type j, u is an idiosyncratic disturbance term, α is an intercept coefficient, and Γ and Λ are vectors containing factor loadings. Note that the factors are unobservable. In words, the growth rate of lending at bank i at time t is assumed to be an affine function of a set of factors representing the comovement in lending across all banks, F_t, a set of factors capturing the comovement in lending across all community or noncommunity banks (depending on the category to which bank i belongs), F_t^j, and an idiosyncratic term capturing dynamics specific to the given bank, u_{it}. Eq. (1) can be used to estimate the factor loadings, along with the factors themselves. The hierarchical or multi-level structure of the factors allows me to directly separate common variation across all banks from community and noncommunity bank-specific variation.

The VAR may be expressed as follows:

$$Z_t = \gamma + \Psi(L)Z_{t-1} + Bv_t\,, \tag{2}$$

where

$$Z_t \equiv \begin{bmatrix} \mathrm{BRW}_t \\ \log(\mathrm{GDP}_t) \\ \log(\mathrm{GDPD}_t) \\ \mathrm{EBP}_t \\ F_t \\ F_t^{\mathrm{N}} \\ F_t^{\mathrm{C}} \end{bmatrix},$$

such that BRW, GDP, GDPD, CP, and EBP denote the cumulative BRW shock series, gross domestic product, GDP deflator, commodity price index, and excess bond premium, respectively; F^N represents the vector of noncommunity bank lending factors; F^C represents the vector of community bank lending factors; $\Psi(L)$ is a lag matrix polynomial; $v \sim N(0,I)$ is a vector of structural shocks; and B is a recursively identified contemporanous impact matrix. Refer to Figure 5 for a plot of the cumulative BRW shock.

Together, Eqs. (1) and (2) describe the FAVAR in state space form – Eq. (1) acts as the transition equation, and Eq. (2) as the measurement equation. For completeness, the full

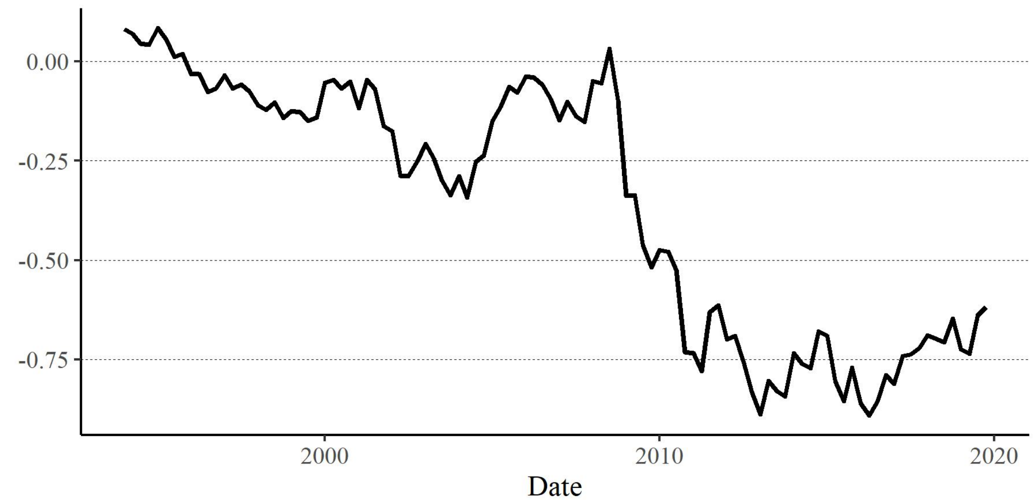


Figure 5: Quarterly cumulative BRW shock.

model is expressed below:

$$X_t = \alpha + \Gamma F_t + \Lambda^N F_t^N + \Lambda^C F_t^C + u_t\,,\, u_t \sim N(0, \Sigma_u)\,, \tag{3}$$

$$Z_t = \gamma + \Psi(L) Z_{t-1} + B v_t\,,\, v_t \sim N(0, I)\,, \tag{4}$$

where X_t is the data matrix containing all bank loan growth rate series.

3.3 Monetary Policy Surprise Identification

The VAR in Eq. (2) includes the monetary policy shock as an endogenous variable. The cumulative BRW shock series is ordered first in the VAR, so that all variables in the system respond contemporaneously to its innovation identified recursively – this is a standard in the VARX literature (Kilian, 2009; Auerbach and Gorodnichenko, 2012). This specification often has zero restrictions imposed on all of the lag coefficients in the equation for the externally identified shock (Kilian, 2009; Jarociński and Karadi, 2020). In the baseline model, I do not impose these restrictions – however, in Appendix C, I show that that an alternatively-specified restricted VAR produces largely the same IRFs and PT-IRFs as the baseline VAR. As an additional robustness test, I also estimate the baseline model using industrial production (IP) and the consumer price index (CPI) as proxies for aggregate output and prices, respectively, instead of GDP and the GDP Deflator. Once again, the nature of the results, presented in Appendix D, qualitatively matches that of the IRFs and PT-IRFs produced using the baseline model.

Alternative approaches in the literature use externally-identified shocks as instruments in VARs or in local projections – this approach is sometimes called a proxy VAR model. Plagborg-Møller and Wolf (2021) show that, under regularity conditions, VARX and proxy VAR modeling approaches yield asymptotically equivalent impulse responses up to a constant scaling factor. For more comparisons of these two methodologies, refer to Stock and Watson (2018), Plagborg-Møller and Wolf (2021), Caldara and Herbst (2019), and Paul (2020). I defer to the VARX approach in this paper due to the ease of inference associated with this methodology, particularly in extending it to PT-IRFs.

3.4 Factor Estimation

The factors of the described FAVAR are estimated using a principal components approach that combines the hierarchical structure of the Bayesian procedure outlined in Jackson et al. (2015) with the frequentist two-step procedure described in Boivin et al. (2009) (also used by Dave et al. (2013)). Other common approaches to estimating factors in hierarchical models include the Bayesian estimator described in Kim and Nelson (1998), which relies on the posterior distribution of the factors developed by Carter and Kohn (1994), and an alternative Bayesian estimator described in Otrok and Whiteman (1998) (and applied in Kose et al. (2003) and Kose et al. (2008)) which constructs a different method of sampling from the posterior of the factors. The pros and cons of all three of the above estimators are discussed in Jackson et al. (2015). For an application of Bayesian HDFMs to community bank data, see Nikolaishvili (2022). The main reason for choosing the principal components approach in this study is due to the size of the bank-level dataset – a key disadvantage of the above-mentioned Bayesian methods preventing me from using them is that they are significantly slower, despite being useful for conducting inference on the factor distributions.

The factor estimation procedure is as follows:

1. Randomly select the same number of community banks as there are noncommunity banks in the sample, and discard the rest. This reduction in the data matrix serves

the purpose of estimating the common bank lending factor on an equal number of community and noncommunity banks – otherwise, if the sample is unbalanced, the estimated factor may be capturing group-specific comovement rather than common sources of variation across all banks.

2. Normalize all bank-specific data series by de-meaning and dividing each series by its own standard deviation – this ensures that each series (bank) holds equal weight in the computation of the principal component. For each of the three variable blocks (asset growth rate, change in ROA, and lending growth rate), group the normalized community and noncommunity bank series into a single data block and use it to estimate common bank size, profitability, and lending factors by computing the corresponding first few principal components;

3. For each of the three normalized bank data blocks, partial out the variation attributable to their corresponding common factors from each series by subtracting the factor estimate multiplied by the corresponding coefficient estimates from the series. Once again, separate each normalized data block into community and noncommunity sub-blocks, then use each sub-block to estimate community and noncommunity bank size, profitability, and lending factors by computing the corresponding first few principal components;

4. Normalize all common bank and bank type-specific factors with respect to their corresponding means and standard deviations – this is done to improve the ease of interpretability of bank responses to factor variation;

5. Regress each series in the normalized bank type-specific data blocks associated with each of the three bank variables on their corresponding set of two factors. This final step yields coefficient estimates that represent bank-specific sensitivities to the variation in the relevant bank factors across all series and factors;

6. Repeat steps 2-5 until some form of convergence is achieved in the factor and coefficient estimates, but modify step 1 by partialing out the most recent estimate of the variation attributable to the type-specific factors from each corresponding series.

Figure 6 presents the estimated (1) common, (2) community, and (3) noncommunity bank lending factors. Recall that the first category refers to principal components that load on all standardized bank loan growth series in the sample, while the second and third load only on their respective community and noncommunity bank sub-groups. The set of common bank lending factors capture common variation in bank loan growth across the set of all banks in the sample, while the community and noncommunity bank lending factors capture the remaining comovement specific to community and noncommunity banks, respectively. Note that the estimation procedure makes sure that the different categories of factors capture orthogonal variation, despite loading on some of the same series. In words – the community and noncommunity bank lending factors are independent of each other, given that all common variation across the set of all banks in the sample is successfully absorbed by the common bank lending factors.

For each of these three categories of bank lending factors – common, community, and noncommunity – I estimate two factors, corresponding to the first two principal components. Table 1 shows the distribution of the joint explanatory power associated only with the common bank lending factors across all community and noncommunity bank loan growth series in my sample. In other words, the table shows the distribution of R^2 coefficients obtained by regressing the individual standardized bank loan growth rate series on the two common bank lending factors. Table 1 also shows the distribution of the joint explanatory power associated with the common and corresponding group-specific bank lending factors across all community and noncommunity banks. In this table, I shows the distribution of R^2 coefficients obtained by regressing each of the standardized (non)community bank loan series on the common and (non)community bank lending factors. According to the results presented in these tables, the group-specific lending factors approximately double the explanatory power of the factor structure of the FAVAR, as captured by the R^2 coefficient – therefore, their inclusion is warranted. Despite the inclusion of all of the lending factors in the factor structure, it seems that bank lending is largely idiosyncratic at the bank-level – this matches the results in Dave et al. (2013). Regardless, the factors can help identify common responses in lending behavior among U.S. commercial banks to monetary policy shocks.

The interpretation of the time variation in the factor estimates is not the focus of the paper – rather, the factors are used for the purposes of dimension reduction. However, a few items of note include the following: (1) In Figure 6a, the first principle component captures a gradual decline in bank loan growth after the 2008 recession, followed by a slow recovery. The second principle component captures a similar post-crisis dip that recovers much quicker. (2) A comparison between the community bank factors in Figure 6b with the noncommunity bank factors in Figure 6c shows a much sharper response to the crisis by noncommunity banks, as evidenced by outlying drop in the second principle component in 2008, and the temporary decline in the first principle component post-2008. The comovement among community banks is more difficult to interpret once the common bank lending factors are partialed out, however, as evidenced by the community bank lending factors.

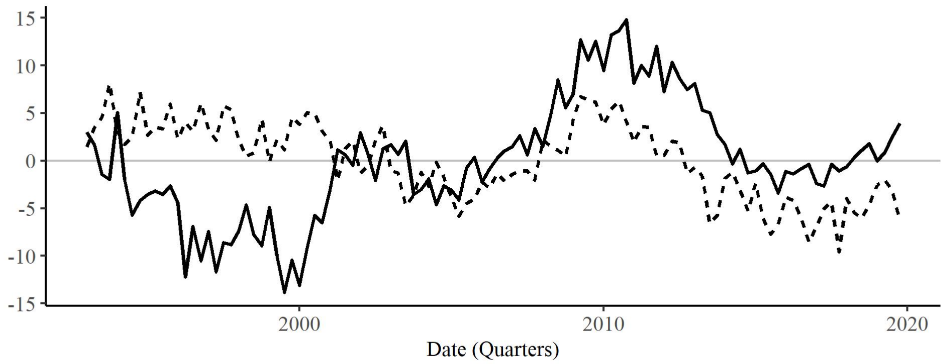
Bank Type	**10%**	**25%**	**50%**	**75%**	**90%**
Community	0.04	0.07	0.12	0.22	0.31
	(0.007)	(0.021)	(0.064)	(0.125)	(0.228)
Noncommunity	0.02	0.05	0.09	0.16	0.27
	(0.005)	(0.017)	(0.047)	(0.098)	(0.171)

Table 1: R^2 percentiles obtained by regressing individual bank loan growth series on the common bank lending factors, along with their corresponding type-specific factors. In parentheses, I show the R^2 percentiles associated with regressing only on the common factors.

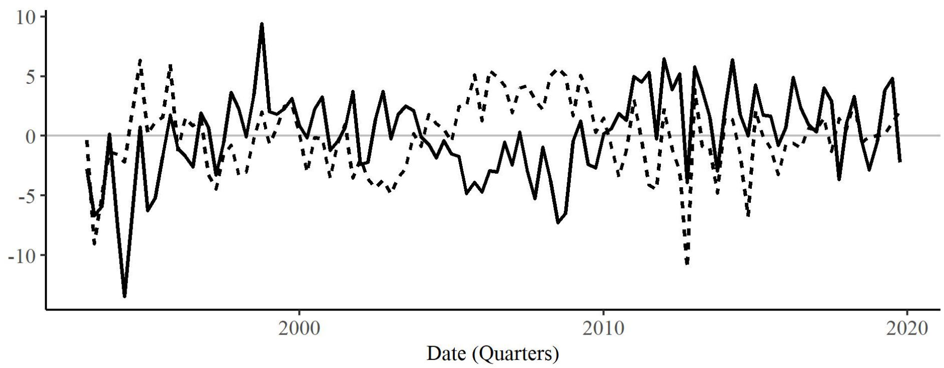
3.5 VAR Estimation

The estimated factors are treated as observable series, and included in the transition equation of the FAVAR, which is essentially a VAR. The parameters of the VAR are estimated using least squares. The VAR estimates are then used to construct IRFs and PT-IRFs with bootstrapped confidence intervals. The recursive identification scheme used to obtain the IRFs and PT-IRFs is a simple recursive ordering of the shocks, with the BRW policy shock ordered first so that it can potentially affect all variables in the system contemporaneously. Practically, in my application, this scheme is exploited only for the identification of monetary policy innovations – my analysis does not rely on the clean identification of the remaining "structural" shocks in v_t.

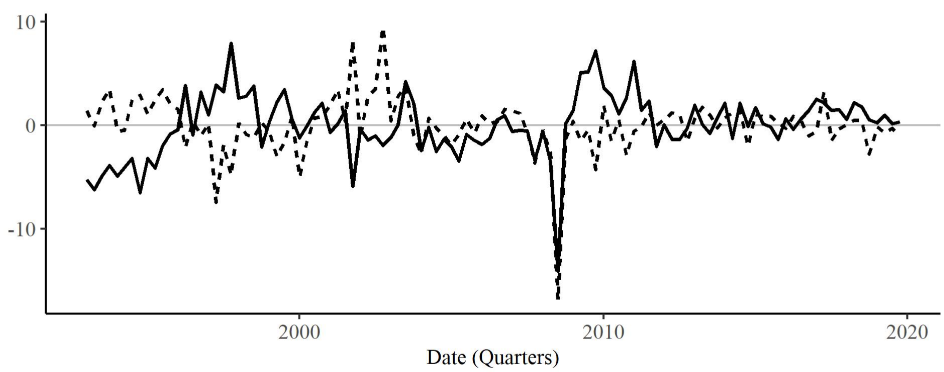
Specifying and estimating VARs in levels has become common practice in the literature



(a) Common bank loan growth factors.



(b) Community bank loan growth factors.



(c) Noncommunity bank loan growth factors.

Figure 6: Bank lending factor timeplots. The solid and dashed lines represented the first and second principal components of their corresponding panels of bank loan growth rate series, respectively.

– recent examples include Bu et al. (2021); Görtz et al. (2022), among many others. This deviates from the past common practice of differencing and/or otherwise transforming seemingly integrated variables to achieve stationarity before estimating the VAR. However, VARs expressed in levels produced unbiased estimates of smooth functions of the model parameters. More importantly, Gospodinov et al. (2013) show that structural IR estimators based on the levels specification have consistently and significantly lower MSE than those based on pretested models. For these reasons, I choose to specify my base model in levels. However, it is worth noting that the the results obtained using this specification are robust to transformations of the macroeconomic indicators to growth rates, with the latter specification having wider confidence intervals and more persistent impulse responses. The growth rate specification results are available upon request.

3.6 PT-IRF Illustration

In this section, I briefly explain the intuition behind PT-IRFs in a simple setting that emulates the context of this study.[2] Consider the following VAR(1) process:

$$\begin{bmatrix} Y_{t+1} \\ N_{t+1} \\ C_{t+1} \end{bmatrix} = \begin{bmatrix} \phi_{YY} & \phi_{YN} & \phi_{YC} \\ \phi_{NY} & \phi_{NN} & \phi_{NC} \\ \phi_{CY} & \phi_{CN} & \phi_{CC} \end{bmatrix} \begin{bmatrix} Y_t \\ N_t \\ C_t \end{bmatrix} + \begin{bmatrix} b_Y \\ b_N \\ b_C \end{bmatrix} m_{t+1} \tag{5}$$

where Y, N, and C denote output, noncommunity bank lending, and community bank lending as the endogenous variables of the system, respectively, and m denotes a monetary policy shock. We may represent the dynamics of the system dictated by the above VAR(1) as a directed weighted graph – this representation can be used to motivate IRFs, and naturally extend them to PT-IRFs.

Notice that ϕ_{ij} represents the one-period-ahead impact of a change in the j-th variable on the i-th variable. In the context of a directed weighted graph, we may think of each endogenous variable at a given point in time as a vertex, and ϕ_{ij} as the intensity of the travel path of a signal from variable j at time t to variable i at time $t+1$. Also notice that b_i represents the contemporaneous impact of a change in m on variable i. Therefore, we may think of the set of all b_i as composing an adjacency matrix in the context of a directed

[2]For a thorough exposition of PT-IRFs in higher-order nonlinear settings, refer to Nikolaishvili (2023).

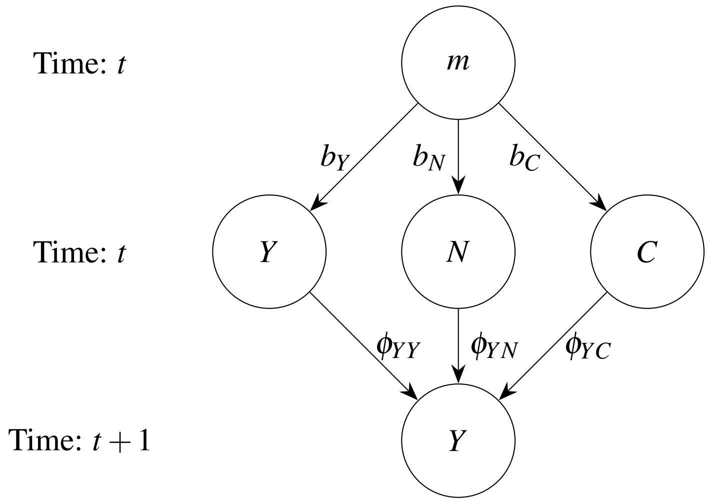


Figure 7: A graph-based illustration of the propagation of an impulse originating at m with destination Y one period ahead in the system determined by Eq. (5).

weighted graph that determines the intensity of arrival of a signal through the monetary policy shock for all endogenous variables in the system. A visual representation of this mapping of the given VAR(1) to a graph is presented in Figure 7 – a monetary shock that arrives at time t must first pass through all of the variables in the system before reaching a given destination at time $t+1$.

Suppose we are interested in gauging the one-period-ahead effect of a monetary policy shock on output. Figure 7 shows us that there are three distinct paths through which m ultimately affects Y – (i) a path through Y; (ii) a path through noncommunity bank lending, N; (iii) a path through community bank lending, C. The contribution of each path to the overall effect of m_t on Y_{t+1} is the product of the weights of its corresponding edges: (i) $\phi_{YY}b_Y$; (ii) $\phi_{YN}b_N$; and (iii) $\phi_{YC}b_C$, respectively. Summing these contributions, or path weights, yields the one-period-ahead response of Y with respect to an impulse from m:

$$\frac{\delta Y_{t+1}}{\delta m_t} = \frac{\delta Y_{t+1}}{\delta Y_t}\frac{\delta Y_t}{m_t} + \frac{\delta Y_{t+1}}{\delta N_t}\frac{\delta N_t}{m_t} + \frac{\delta Y_{t+1}}{\delta N_t}\frac{\delta N_t}{m_t} = \phi_{YY}b_Y + \phi_{YN}b_N + \phi_{YC}b_C\,. \tag{6}$$

Extending this framework for gauging the effects of an impulse in a VAR(1) to longer horizons gives us an IRF.

Now, suppose instead that we are interested in gauging the one-period-ahead contribution of community bank lending to the transmission of a monetary policy shock to output. Clearly, two of the three paths shown in Figure 7 – the ones passing through Y and N – are irrelevant to community bank lending, and do not reflect its influence on the transmission of m. Therefore, we may subtract the contributions/weights of these paths from the overall impulse response expressed in Eq. (6) to obtain the contribution of C to the one-period-ahead effect of m on Y: $\phi_{YC}b_C$ – the weight of the only path passing through C. Extending this framework to longer horizons is precisely a PT-IRF that conditions on community bank lending as a medium of transmission for monetary policy shocks to output.

3.7 PT-IRF Application

The FAVAR can be used to generate PT-IRFs that allow for the assessment of the effect of a contractionary monetary policy shock on output growth via its transmission through bank lending. Specifically, once the VAR specified in Eq. (4) is estimated, I use the approach developed in Nikolaishvili (2023) to estimate the dynamic response of the GDP growth rate to a positive shock to the BRW series, while conditioning on different combinations of the bank lending factors in F_t, F_t^C, and F_t^N as media for the transmission of the shock.

Let us represent the linear VAR(p) expressed in Eq. (4) as a VAR(1) with companion matrix Φ and augmented contemporaneous impact matrix $\Gamma = \begin{bmatrix} B' & \mathbf{0} \end{bmatrix}'$:

$$Z_t = \theta + \Phi Z_{t-1} + \Gamma v_t \,. \tag{7}$$

Then for $h \geq 0$ the corresponding PT-IR to a monetary policy shock $\bar{v}$ with pass-through medium variable z_j (the j-th component of vector Z – let us suppose this is one of the bank lending factors) may be expressed as

$$\text{PT-IR}(h, j, \bar{\varepsilon}) \equiv \left(\Phi^h - \widetilde{\Phi}^h \right) \Gamma \bar{v} \,, \tag{8}$$

where $\widetilde{\Phi}$ is the companion matrix of a modified version of the process described in Eq. (4) with the i-th lag coefficient matrix restricted to equaling

$$\widetilde{\Psi}_i \equiv \begin{bmatrix} \vec{a}_1 & \dots & \vec{a}_{j-1} & \vec{0} & \vec{a}_{j+1} & \dots & \vec{a}_N \end{bmatrix} , \tag{9}$$

where $\vec{a}_m$ denotes the m-th column of Ψ_i. Notice that $\widetilde{\Phi}^h \Gamma \overline{\varepsilon}$ captures the impulse response to the shock for a restricted version of the given linear VAR(p) in which the Granger causality of the j-th endogenous variable is completely removed (Kilian and Lütkepohl, 2017) – all paths passing through the j-th variable are assigned a weight of zero. Therefore, PT-IR$(\cdot)$ sums the weights of only those paths that pass through the j-th variable, which can be interpreted as the impulse response of the system attributable to the Granger-causality of the j-th endogenous variable.

The above framework can be extended to allow for multiple pass-through media. In the next section, I present the pass-through impulse responses of the GDP to a contractionary monetary policy shock separately via (1) all bank lending factors, (2) only common and community bank lending factors, as well as (3) only common and noncommunity bank lending factors. We may interpret the first PT-IRF described above as measuring the combined transmission of monetary policy to output via (all) bank lending. The second and third PT-IRFs may be interpreted as measuring the transmission of monetary policy to output separately via community and noncommunity bank lending, respectively.

It is also possible to easily conduct inference on differences between PT-IRFs with different media. Suppose that for some dependent variable i, we would like to compare PT-IR$(h,i,j,\overline{\varepsilon})$ to PT-IR$(h,i,j',\overline{\varepsilon})$ to assess whether j plays a bigger role in the transmission of the shock $\overline{\varepsilon}$ to i than does j'. We can define a new object ΔPT-IR$(h,i,j,j',\overline{\varepsilon}) \equiv$ PT-IR$(h,i,j,\overline{\varepsilon}) -$ PT-IR$(h,i,j',\overline{\varepsilon})$, which is also a nonlinear mapping of the reduced form parameters of the state equation of the FAVAR. We can then estimate confidence intervals for the ΔPT-IR object the same way as we do for IRFs and PT-IRFs, using the wild bootstrap, for a given level of statistical significance. If for a range of h the confidence intervals of this object is above 0, that implies j plays a greater role in the transmission of shock $\overline{\varepsilon}$ to variable i than does j'. I apply ΔPT-IR by comparing the transmission of monetary policy shocks to output via community versus noncommunity bank lending.

4 Results

The baseline FAVAR produces the following key results: **(i)** Output responds negatively to a contractionary monetary policy shock through the set of all bank lending factors as the medium of transmission – this confirms the traditional understanding of the role of bank lending in the monetary transmission mechanism; **(ii)** Output responds negatively to a contractionary monetary policy shock through the set of factors that load on *community* bank lending series – this demonstrates that community banks contribute to the overall transmission of monetary policy through bank lending; **(iii)** Output responds negatively to a contractionary monetary policy shock through the set factors that load on *noncommunity* bank lending – less surprisingly, this evidences the significance of noncommunity bank lending in monetary transmission; **(iv)** Finally, conducting inference on the difference between the monetary PT-IRs conditional on community versus noncommunity bank lending shows evidence of community bank lending having a greater (in magnitude) effect in the short run, whereas noncommunity bank lending plays a more significant role in monetary transmission in the medium run.

These results are echoed by the alternative model, which uses IP and CPI as proxies for output and inflation instead of GDP and the GDP Deflator. Furthermore, both models confirm that unexpected monetary policy shocks are identified correctly – macroeconomic indicators respond as expected (mimicking the monthly VAR results in Bu et al. (2021)), and the distribution of individual bank loan responses lies mostly below zero for the entire 10-year post-shock period. I begin by discussing the aggregate and bank-level impulse responses in the following two subsections, after which I return to the discussion of PT-IRFs and evidence of heterogeneous pass-through via community versus noncommunity bank lending.

4.1 Aggregate IRFs

Figure 8 shows the dynamic responses of all variables in the VAR as a result of a one standard deviation shock to the cumulative BRW series. The BRW series itself quite rapidly converges back to zero, whereas the GDP and the deflator respond with a delay – the former remains significantly below zero for a period of approximately five years post-shock, whereas the latter persists for the entire 10-year period of examination. The EBP also behaves in the expected manner, as documented in Bu et al. (2021). The responses of the individual factors are uninformative – however, it is worth noting that they all converge back to zero with time. The shapes and directions of these impulse responses are closely matched by those of the model with zero restrictions, presented in Figure C.1, as well as the model with alternative measures of output and inflation, presented in Figure D.1. Furthermore, these impulse responses are statistically significant at comparable horizons.

4.2 Bank-Level Loan IRFs

Figure 9 shows the effects of a one standard deviation contractionary monetary policy shock on individual bank lending separately for community and noncommunity banks. The two impulse response distribution plots imply that, on average, both community and noncommunity banks tighten lending over the course of a 10-year horizon as a result of a contractionary shock, although the median of both groups converges back to its original level by the end of the period. In the first two years after the shock however, the distribution of responses for both groups centers at approximately zero, with minor positive deviations. This type of delay in loan volume contraction may potentially be caused by the rate of loan commitment draw-downs outpacing the slowdown in loan issuance in some of the banks, as described in Ivashina and Scharfstein (2010).

The same behavior can be seen in the bank-level loan impulse responses generated using the model with alternative measures of output and inflation, presented in Figure D.2 – perhaps even more starkly. The VAR with zero restrictions yields similar delayed declines in loan volume across both community and noncommunity banks, but without convergence back to a zero-centered distribution for the former group, as shown in Figure C.2. Overall, the distributions of these responses across all three models further confirm that the monetary policy shock is correctly identified, since a delayed contraction in bank lending is precisely what has been documented in a wide range of existing studies in the literature (Kashyap and Stein, 1994, 1995, 2000; Kashyap et al., 2002; Drechsler et al., 2017).

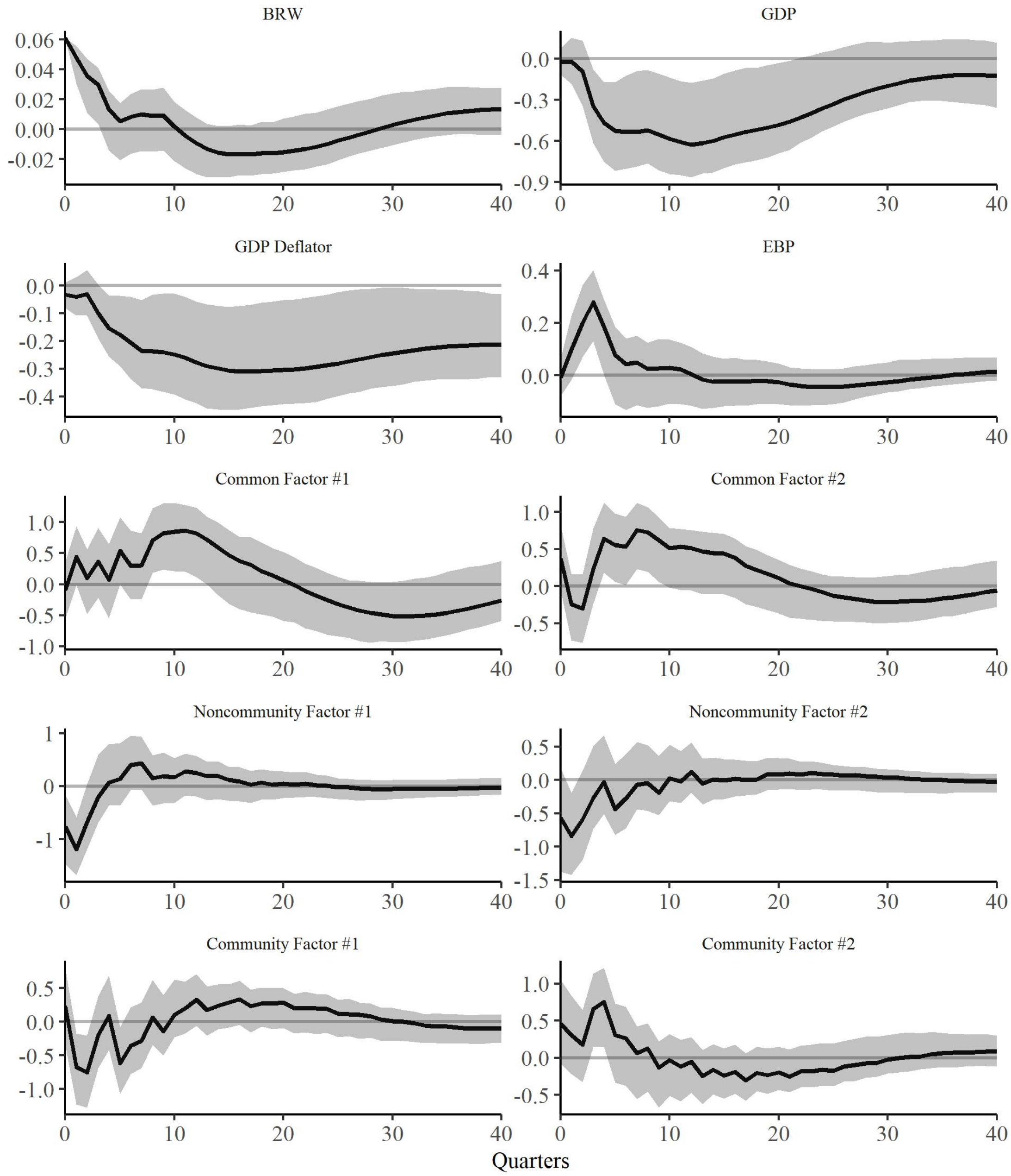
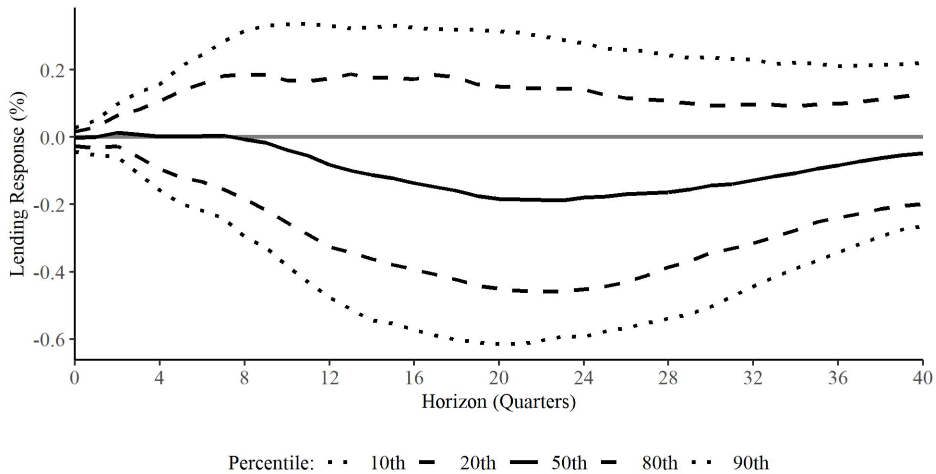
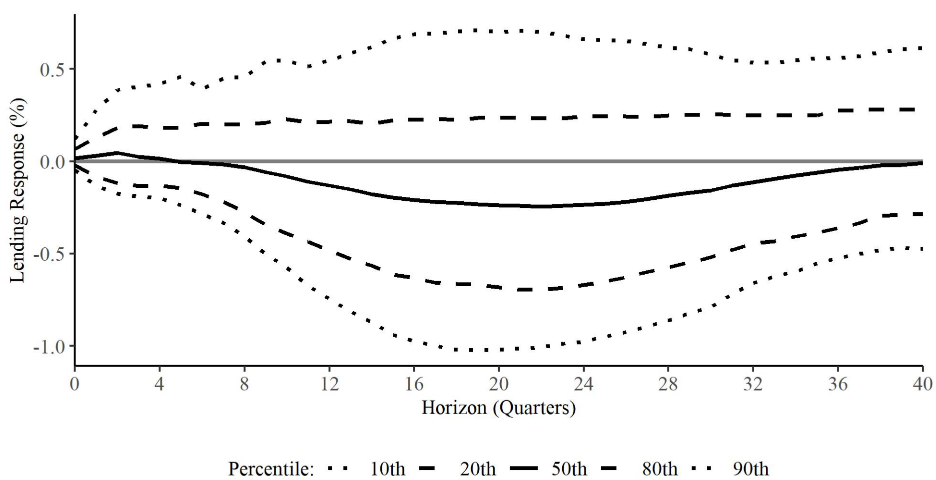


Figure 8: Impulse responses of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

Figure 9: Bank-specific responses in loan quantity (cumulative loan growth rate) to a one standard deviation positive (contractionary) monetary policy shock.

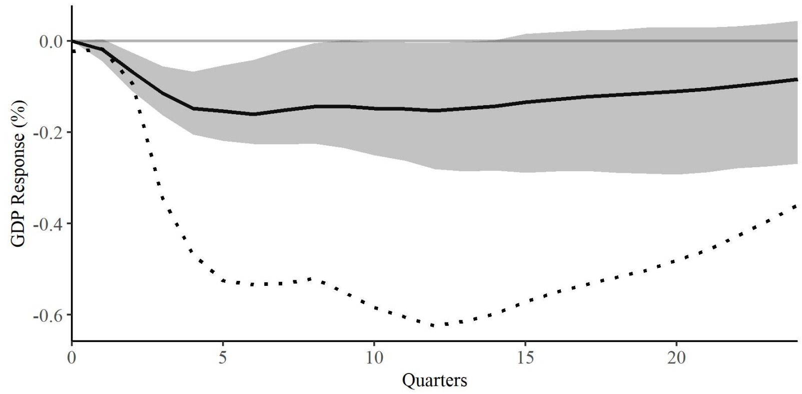
4.3 PT-IRFs

Figure 10 shows plots of the PT-IRFs associated with the pass-through of a one standard deviation contractionary monetary policy shocks to GDP via combined, community, and noncommunity bank lending. Figures B.2, B.3, and B.4 in Appendix B each present PT-IRFs conditioned on combined, community, and noncommunity bank lending, respectively, for all endogenous variables in the model. The same figure for the zero-restricted VAR is presented in Figures C.4, C.5, and C.6. Equivalent displays for the model with alternative measures of output and inflation are presented in Figures D.4, D.5, and D.6, respectively, in Appendix D.

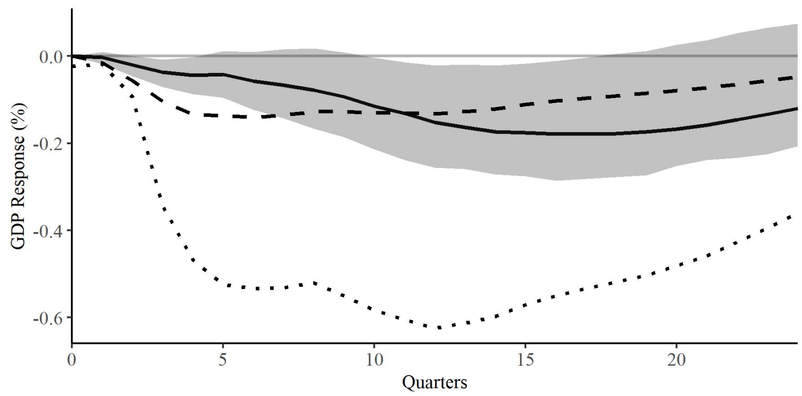
The PT-IRF presented in Figure 10a is conditioned on all bank lending factors in the model as media of transmission. I interpret this object as capturing the transmission of monetary policy through bank lending of all types. It shows that a monetary tightening has a negative expected effect on output that persists for at least six years, although only approximately the first four years are significant with 90% confidence. The same kind of behavior is displayed by the equivalent PT-IRF generated using the alternative model specification, presented in Figure D.4.

Figure 10b is conditioned only on factors that load on the community bank lending series – the common and community bank lending factors – as media of transmission for the contractionary monetary shock. I interpret this object as capturing the overall transmission of monetary policy through community bank lending. It shows that a monetary tightening has a negative, delayed expected effect on output that persists quite strongly before beginning to converge back to zero at around the fifth year. For this PT-IRF, the effect is statistically significant as far as the fifth year after the shock. The same kind of behavior is displayed by the equivalent PT-IRF generated using the alternative model specification, presented in Figure D.5.

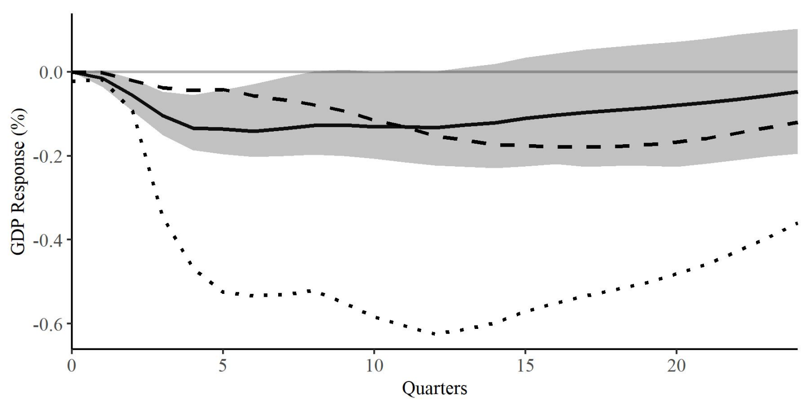
Finally, Figure 10c is conditioned on factors that load on the noncommunity bank lending series – the common and noncommunity bank lending factors – as media of transmission for the contractionary monetary shock. This object captures the transmission of monetary policy via noncommunity bank lending. The shape and magnitude of this PT-IRF match that of the combined bank lending PT-IRF quite closely. However, its confidence interval crosses zero at a faster rate, and covers a larger portion above zero by the end of



(a) Medium: Combined bank lending



(b) Medium: Community bank lending



(c) Medium: Noncommunity bank lending

Figure 10: PT-IRs of GDP to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs. The dash-dotted gray lines represent the point estimates of the “other” bank type-specific PT-IRs, included for easy reference.

the six-year horizon – implying less persistence in the response compared to the combined PT-IRF. As with the previous PT-IRFs, this behavior is matched by the equivalent PT-IRF generated using the alternative model, presented in Figure D.6.

These PT-IRFs suggest that community bank lending plays a larger role in the transmission of monetary policy in the medium run, and noncommunity bank lending operates more strongly in the short run. As discussed in the methodology section on PT-IRFs, this hypothesis can be tested more directly using inference on ΔPT-IR objects. I present the results of that analysis in the next subsection.

4.4 Heterogeneity in Monetary Transmission

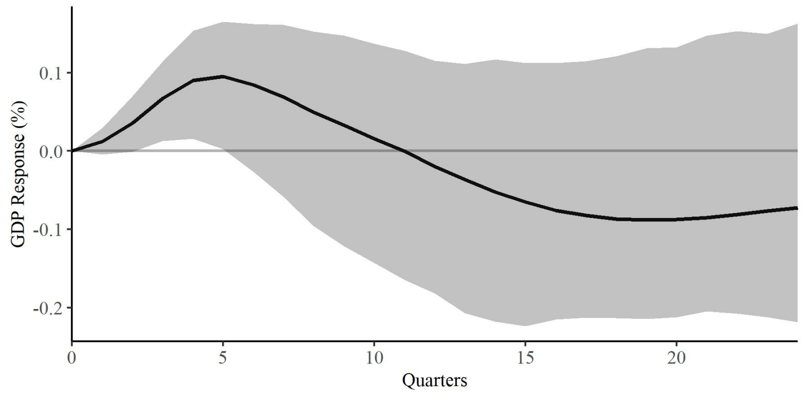
Recall that it is possible to conduct inference on differences between PT-IRFs with different media. Let $J = \{F, F^C\}$ represent the set of common and community bank lending factors, which I use to estimate PT-IR$(h, GDP, J, \overline{\varepsilon})$ – the transmission of monetary policy to output via *community* bank lending. On the other hand, let $J' = \{F, F^{NC}\}$ represent the set of common and noncommunity bank lending factors, which I use to estimate PT-IR$(h, GDP, J', \overline{\varepsilon})$ – the transmission of monetary policy to output via *noncommunity* bank lending. I define a new object

$$\Delta\text{PT-IR}(h, i, J, J', \overline{\varepsilon}) \equiv \text{PT-IR}(h, i, J, \overline{\varepsilon}) - \text{PT-IR}(h, i, J', \overline{\varepsilon}), \tag{10}$$

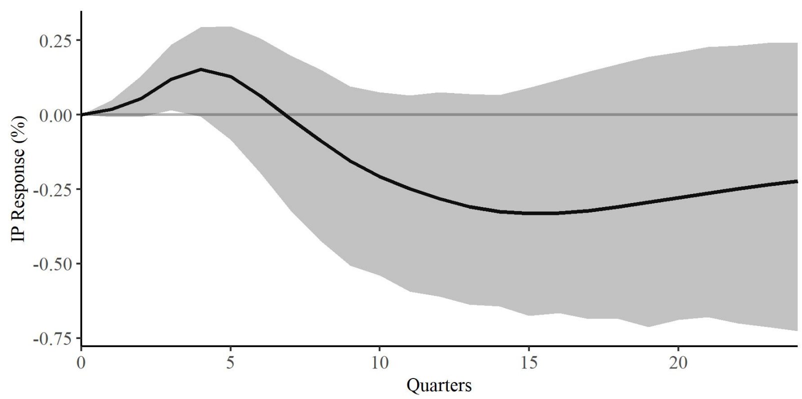
which captures the difference between the two PT-IRFs. I obtain point estimates and confidence intervals for ΔPT-IR using the wild bootstrap, for a 90% level of statistical significance. The resulting ΔPT-IRs are presented in Figure 11 for both the baseline and alternative model specifications.

Across both models, I find that the estimated ΔPT-IR is above zero in the short run, and below zero in the medium run. Considering that both PT-IRFs being compared are shown to be negative in the specified time frame, this implies that the magnitude of monetary transmission via noncommunity bank lending is greater than through community bank lending in the short run, while the opposite is true in the medium run. The short run results are statistically significant with 90% confidence across all model specifications. Refer to the final rows of Figures B.1, D.3, and C.3 for an alternative formulation of this test, where

PT-IRFs that condition on only the group-specific lending factors are compared – the results match the ones presented in this section.



(a) Baseline model



(b) Alternative model

Figure 11: Differences between the PT-IRs of (a) GDP and (b) IP, conditional on community versus noncommunity bank lending factors as the media for transmission, with respect to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

5 Conclusion

I use a factor-augmented vector autoregression (FAVAR) with bank lending factors and externally identified monetary policy shocks to estimate pass-through impulse response functions (PT-IRFs), which characterize the dynamic response of output growth to monetary policy shocks via changes in community, noncommunity, and combined bank lending. For robustness, I carry out the analysis using three alternative model specifications – a baseline model, a model with exclusion restrictions enforce the exogeneity of the monetary policy shock series, and an additional model which uses alternative proxies for output and inflation. I find that across all of these model specifications, there is evidence of the following outcomes as a response to a contractionary monetary policy shock: (i) negative short and medium run monetary transmission via joint bank lending; (ii) negative short run transmission via noncommunity bank lending; (iii) negative medium run transmission via community bank lending. Direct inference on the difference between monetary transmission via community versus noncommunity bank lending also shows evidence of heterogeneity in the short run, with some evidence of heterogeneity in the medium run.

These results suggest that monetary transmission via bank lending occurs mainly through resulting changes in noncommunity bank lending in the short run, while changes in community bank lending drive the persistence of the response of output to monetary shocks into the medium run. Therefore, the evolving composition of the U.S. commercial banking sector may have implications for the magnitude and delays in the effects of monetary policy changes. Understanding the role of bank heterogeneity across the business model dimension can be crucial in anticipating changes in the behavior of monetary transmission. This study provides a step in that direction.

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Appendices

A Additional Figures

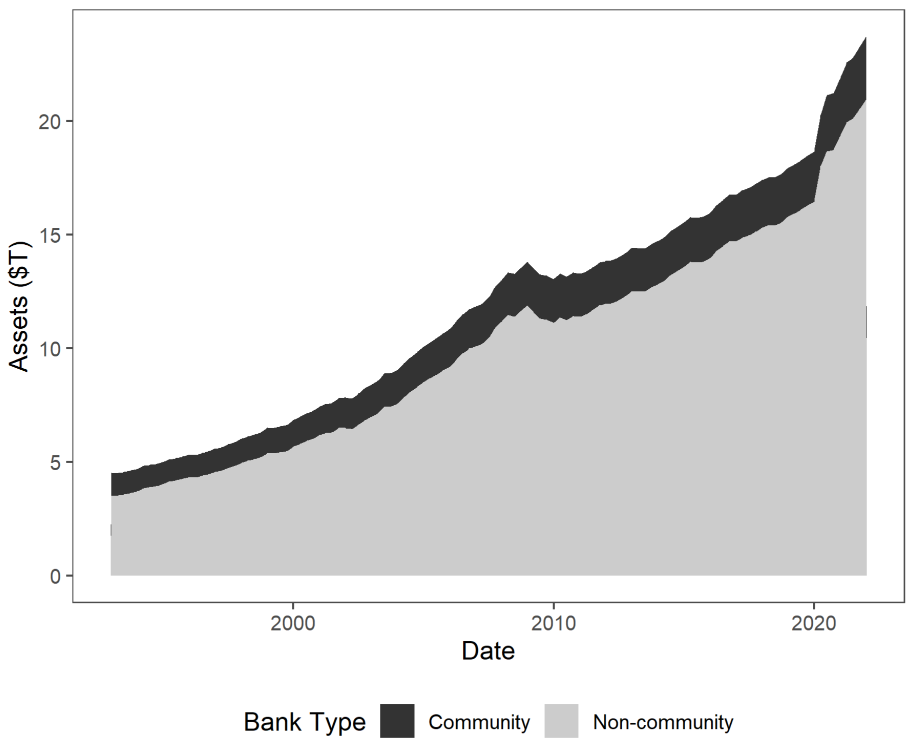


Figure A.1: Commercial bank assets in the U.S. over time. *Source: FDIC-SDI.*

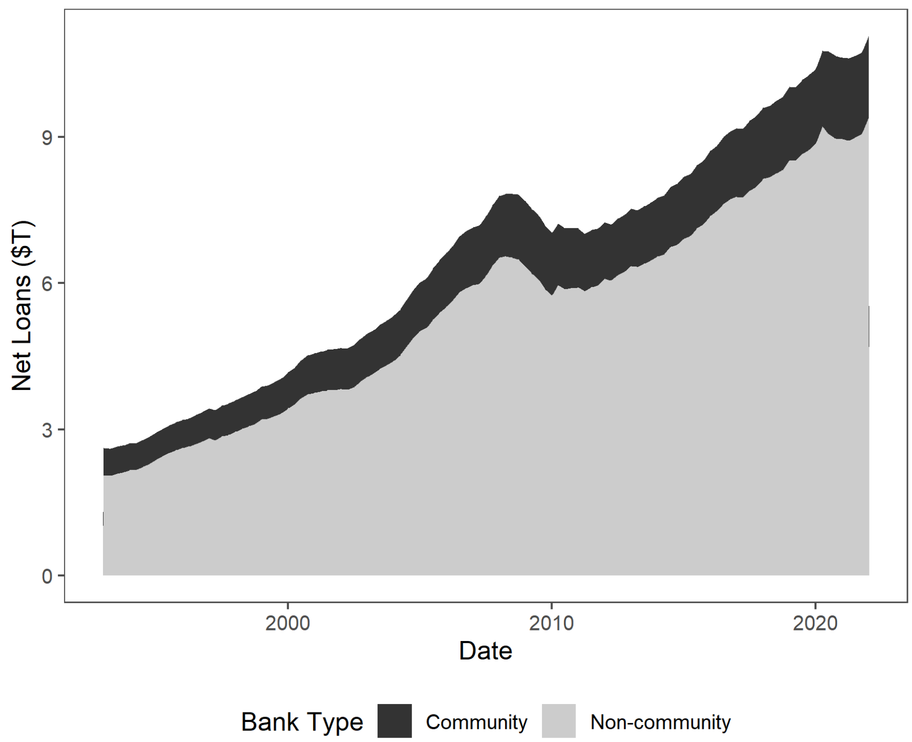


Figure A.2: Commercial bank lending in the U.S. over time. *Source: FDIC-SDI.*

B Baseline Model IRFs & PT-IRFs

The baseline model is expressed as

$$X_t = \alpha + \Gamma F_t + \Lambda^N F_t^N + \Lambda^C F_t^C + u_t \, , \, u_t \sim N(0, \Sigma_u) \, ,$$
$$Z_t = \gamma + \Psi(L) Z_{t-1} + B v_t \, , \, v_t \sim N(0, I) \, ,$$

where X_t is the data matrix containing all bank loan growth rate series and

$$Z_t \equiv \begin{bmatrix} \mathrm{BRW}_t \\ \log(\mathrm{GDP}_t) \\ \log(\mathrm{GDPD}_t) \\ \mathrm{EBP}_t \\ F_t \\ F_t^{\mathrm{N}} \\ F_t^{\mathrm{C}} \end{bmatrix} ,$$

such that BRW, GDP, GDPD, and EBP denote the *cumulative* BRW shock series, gross domestic product, GDP deflator, and excess bond premium, respectively; F^N represents the vector of noncommunity bank lending factors; F^C represents the vector of community bank lending factors; $\Psi(L)$ is a lag matrix polynomial; $v \sim N(0, I)$ is a vector of structural shocks; and B is a recursively identified contemporanous impact matrix.

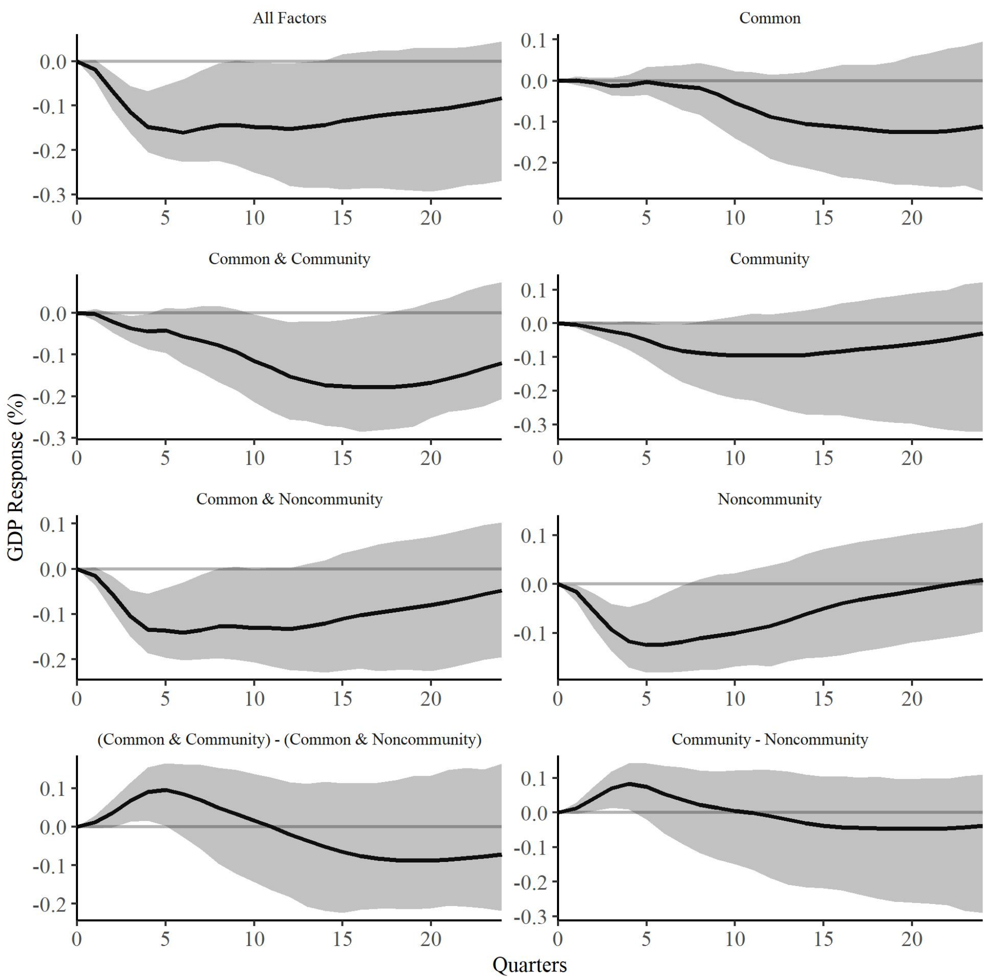


Figure B.1: PT-IRs of GDP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

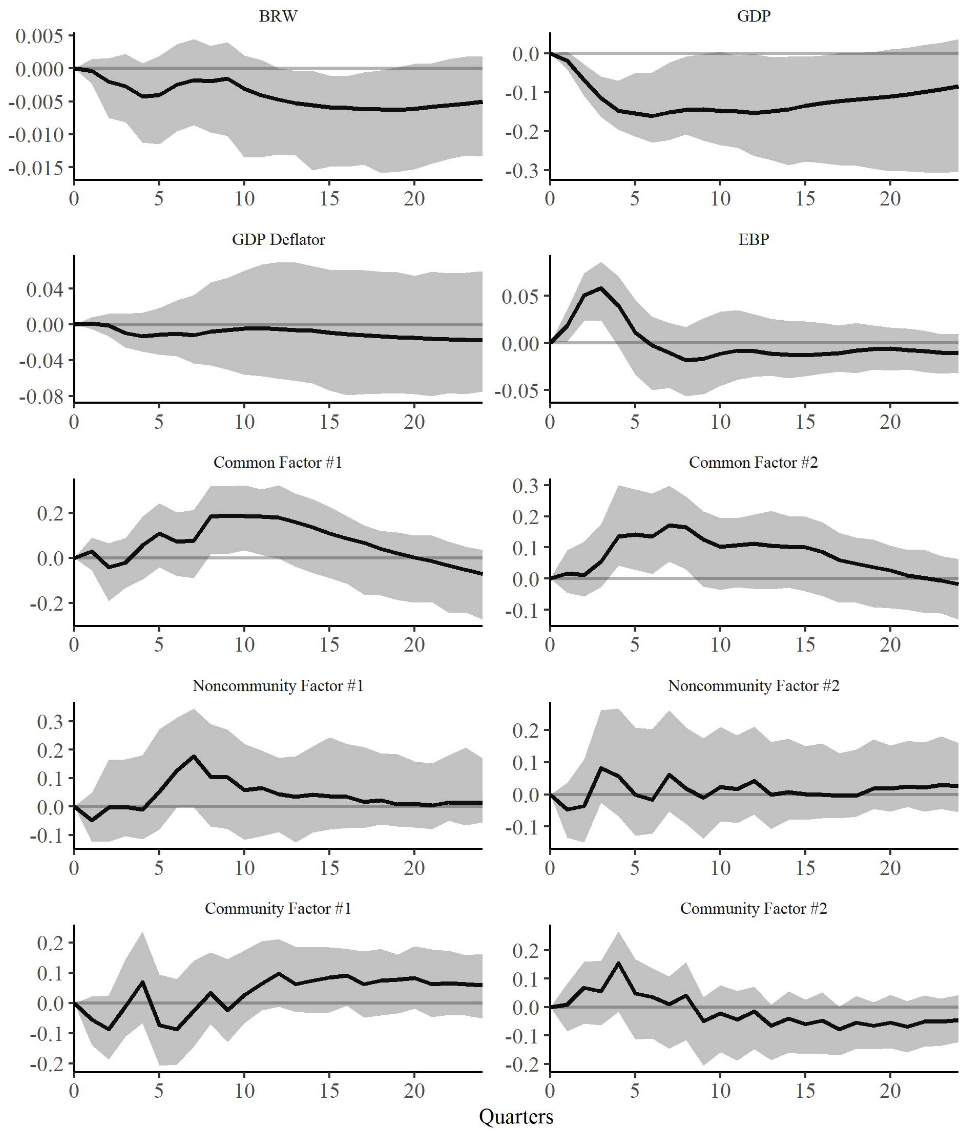


Figure B.2: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

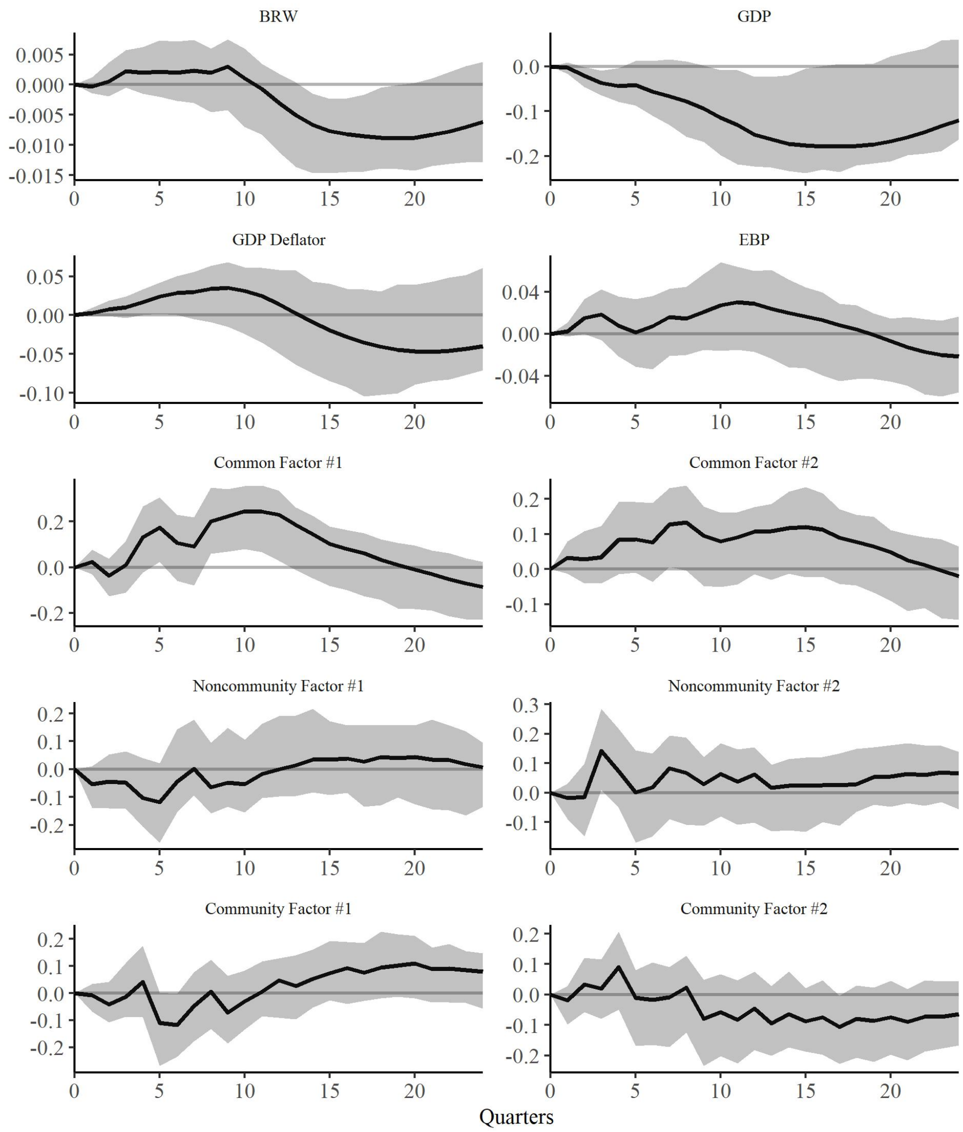


Figure B.3: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

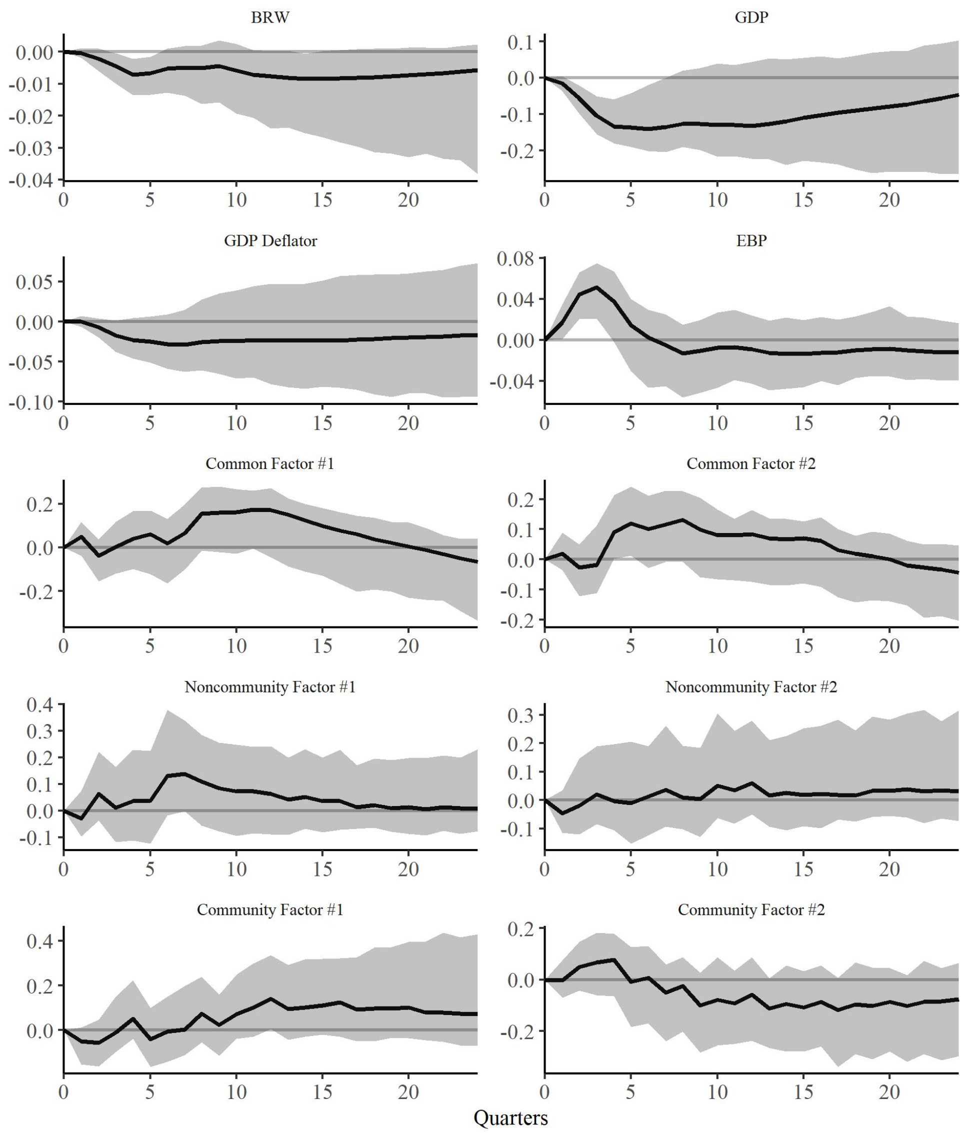


Figure B.4: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

C Robustness: Policy Shock Exogeneity Restriction

The alternative model is expressed as

$$X_t = \alpha + \Gamma F_t + \Lambda^N F_t^N + \Lambda^C F_t^C + u_t \, , \, u_t \sim N(0, \Sigma_u) \, ,$$
$$Z_t = \gamma + \Psi(L) Z_{t-1} + B v_t \, , \, v_t \sim N(0, I) \, ,$$

where X_t is the data matrix containing all bank loan growth rate series and

$$Z_t \equiv \begin{bmatrix} \mathrm{BRW}_t \\ \log(\mathrm{GDP}_t) \\ \log(\mathrm{GDPD}_t) \\ \mathrm{EBP}_t \\ F_t \\ F_t^{\mathrm{N}} \\ F_t^{\mathrm{C}} \end{bmatrix} ,$$

such that BRW, GDP, GDPD, and EBP denote the *raw* (non-cumulative) BRW shock series, gross domestic product, GDP deflator, and excess bond premium, respectively; F^N represents the vector of noncommunity bank lending factors; F^C represents the vector of community bank lending factors; $\Psi(L)$ is a lag matrix polynomial; $v \sim N(0, I)$ is a vector of structural shocks; and B is a recursively identified contemporanous impact matrix.

This alternative specification deviates from the baseline model in that the lag coefficients of all variables in the equation for the monetary policy shock series are restricted to zero.

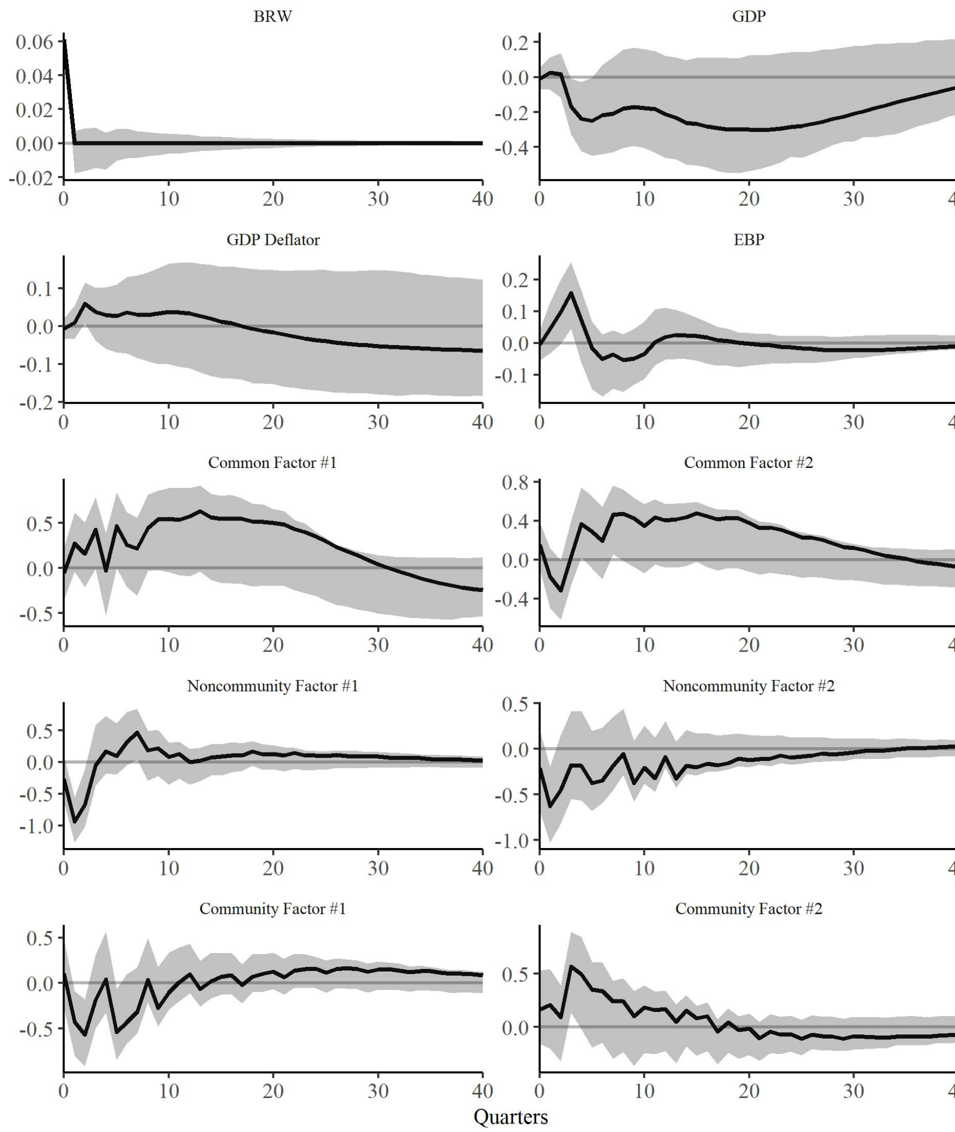
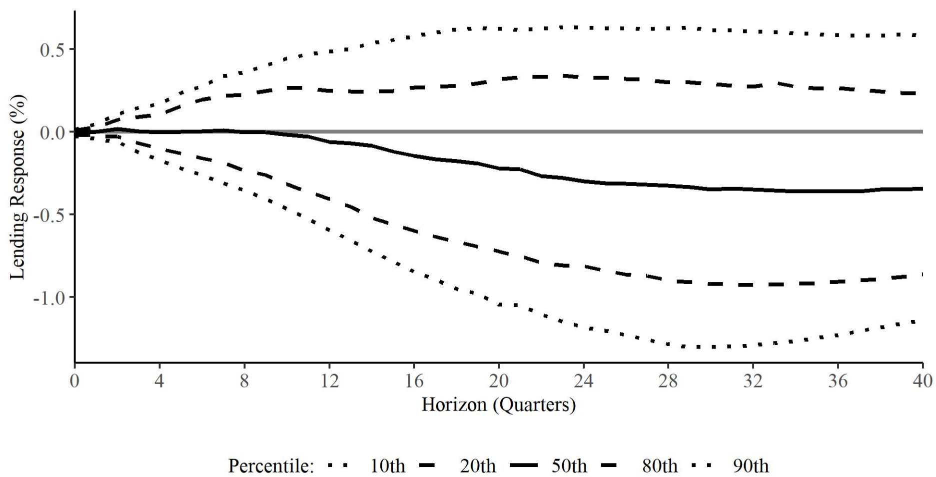
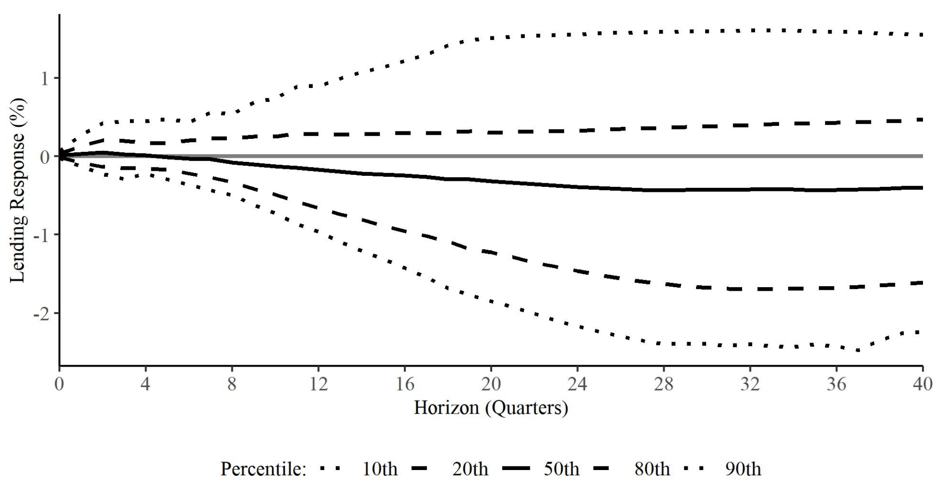


Figure C.1: Impulse responses of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

Figure C.2: Bank-specific responses in loan quantity to a one standard deviation positive (contractionary) monetary policy shock.

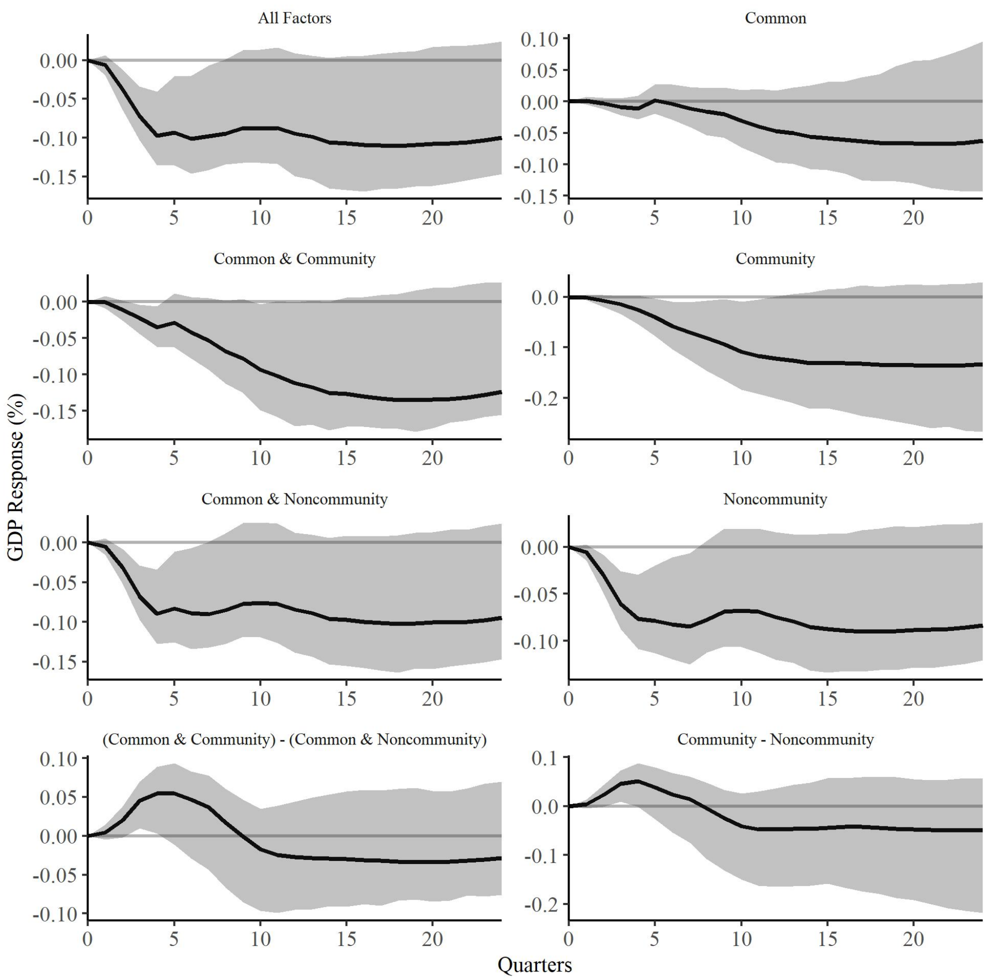


Figure C.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

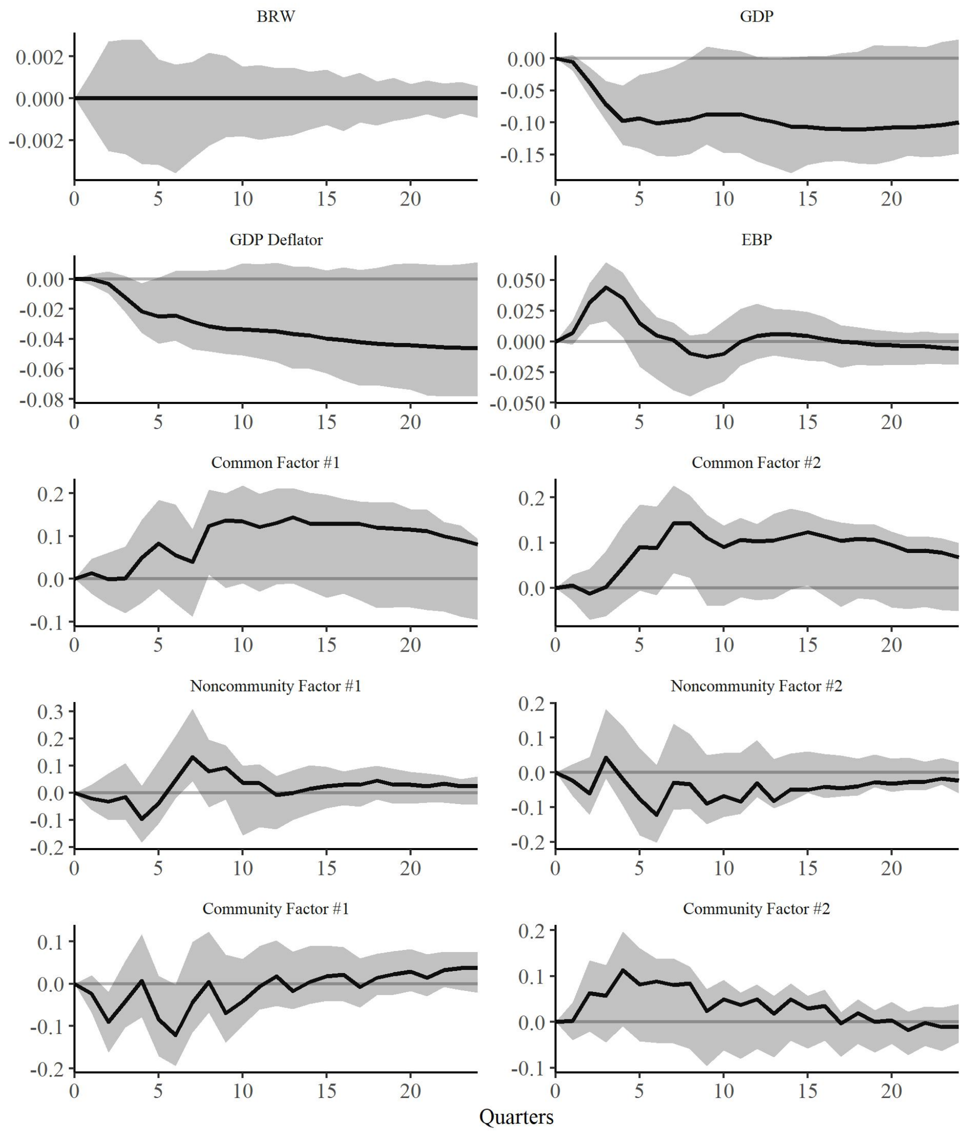


Figure C.4: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

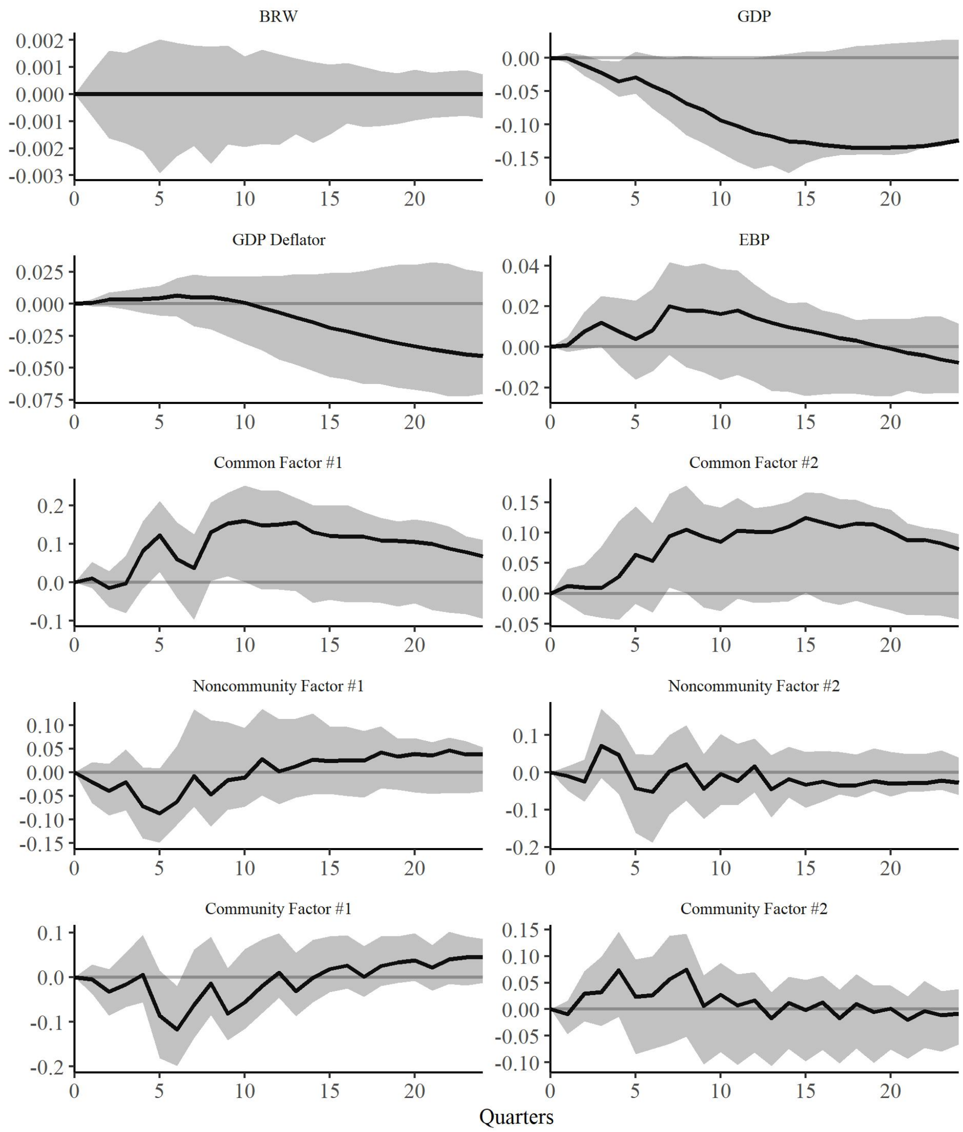


Figure C.5: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

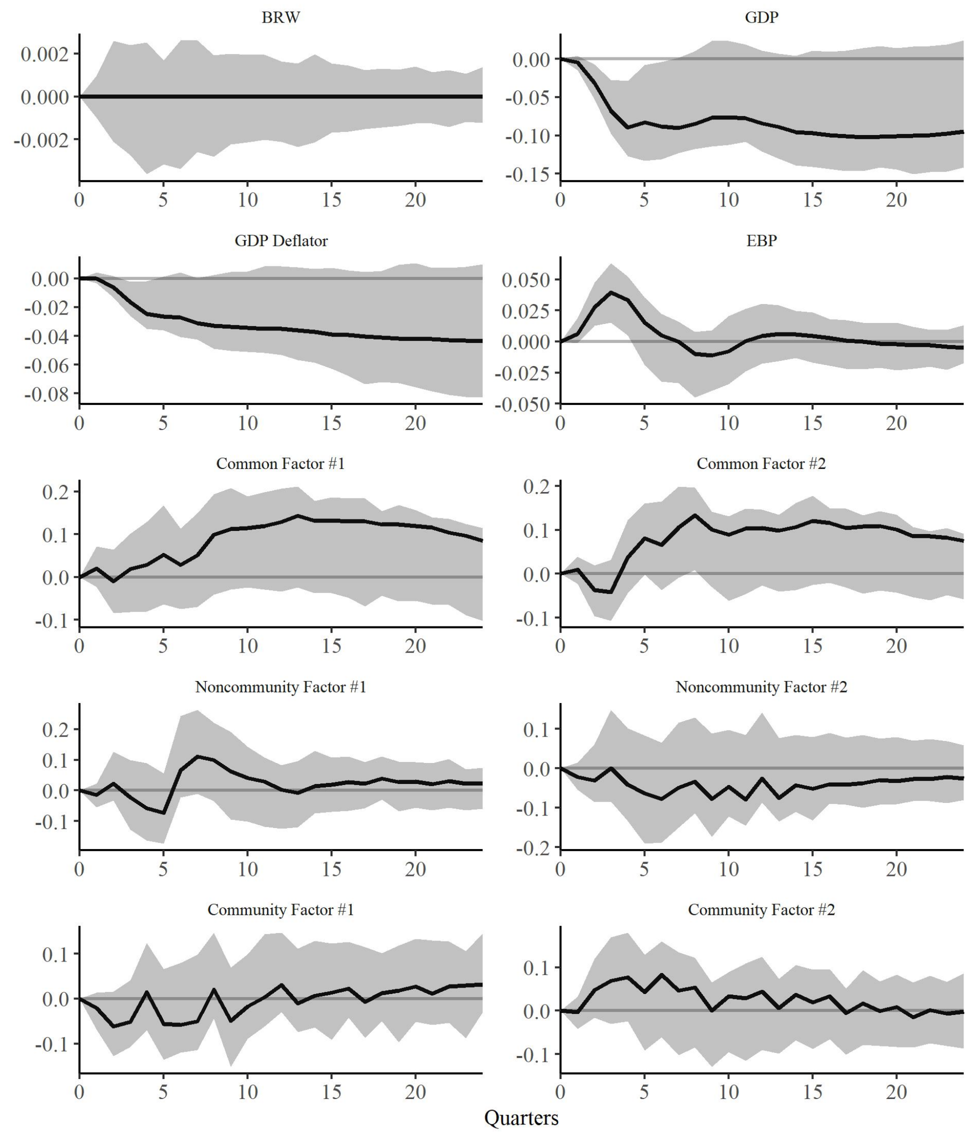


Figure C.6: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

D Robustness: Alternative Variables

The alternative model is expressed as

$$X_t = \alpha + \Gamma F_t + \Lambda^N F_t^N + \Lambda^C F_t^C + u_t\,,\; u_t \sim N(0, \Sigma_u)\,,$$
$$Z_t = \gamma + \Psi(L) Z_{t-1} + B v_t\,,\; v_t \sim N(0, I)\,,$$

where X_t is the data matrix containing all bank loan growth rate series and

$$Z_t \equiv \begin{bmatrix} \mathrm{BRW}_t \\ \log(\mathrm{IP}_t) \\ \log(\mathrm{CPI}_t) \\ \mathrm{EBP}_t \\ F_t \\ F_t^{\mathrm{N}} \\ F_t^{\mathrm{C}} \end{bmatrix},$$

such that BRW, IP, CPI, and EBP denote the *cumulative* BRW shock series, industrial production, consumer price index, and excess bond premium, respectively; F^N represents the vector of noncommunity bank lending factors; F^C represents the vector of community bank lending factors; $\Psi(L)$ is a lag matrix polynomial; $v \sim N(0, I)$ is a vector of structural shocks; and B is a recursively identified contemporanous impact matrix.

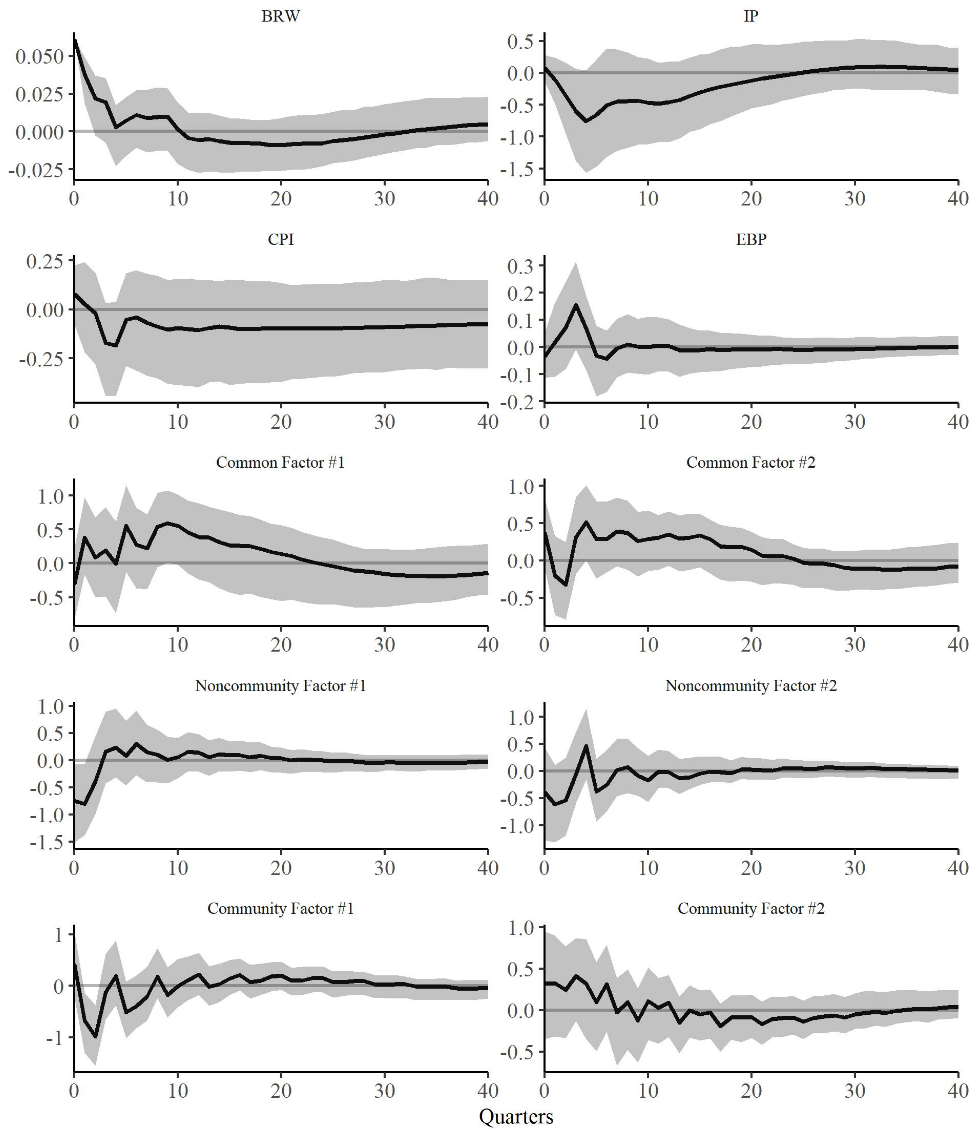
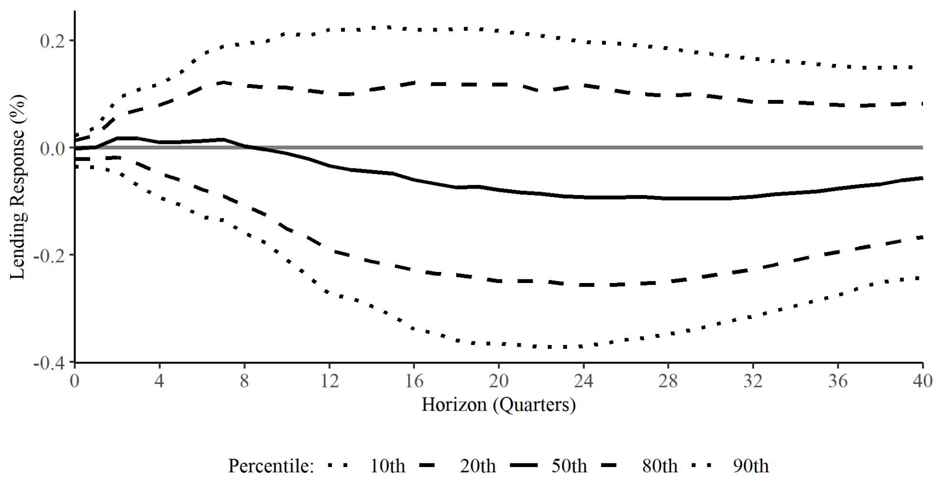
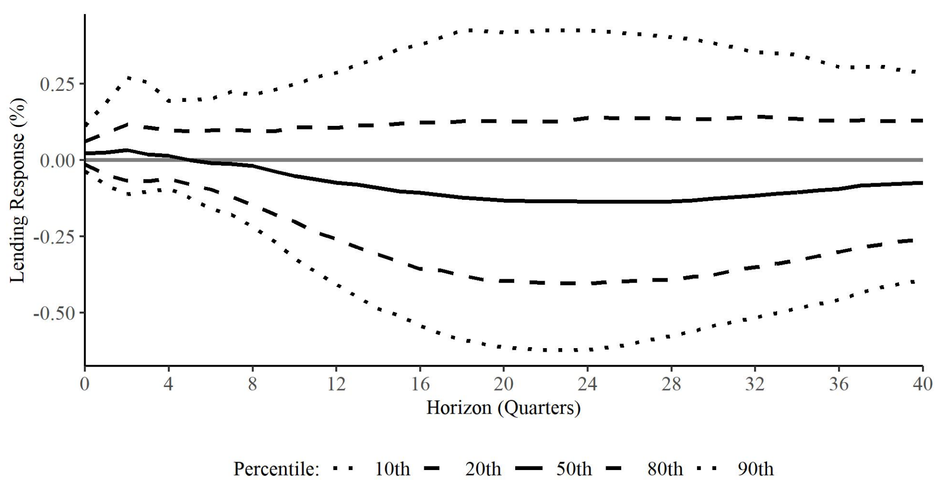


Figure D.1: Impulse responses of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

Figure D.2: Bank-specific responses in loan quantity to a one standard deviation positive (contractionary) monetary policy shock.

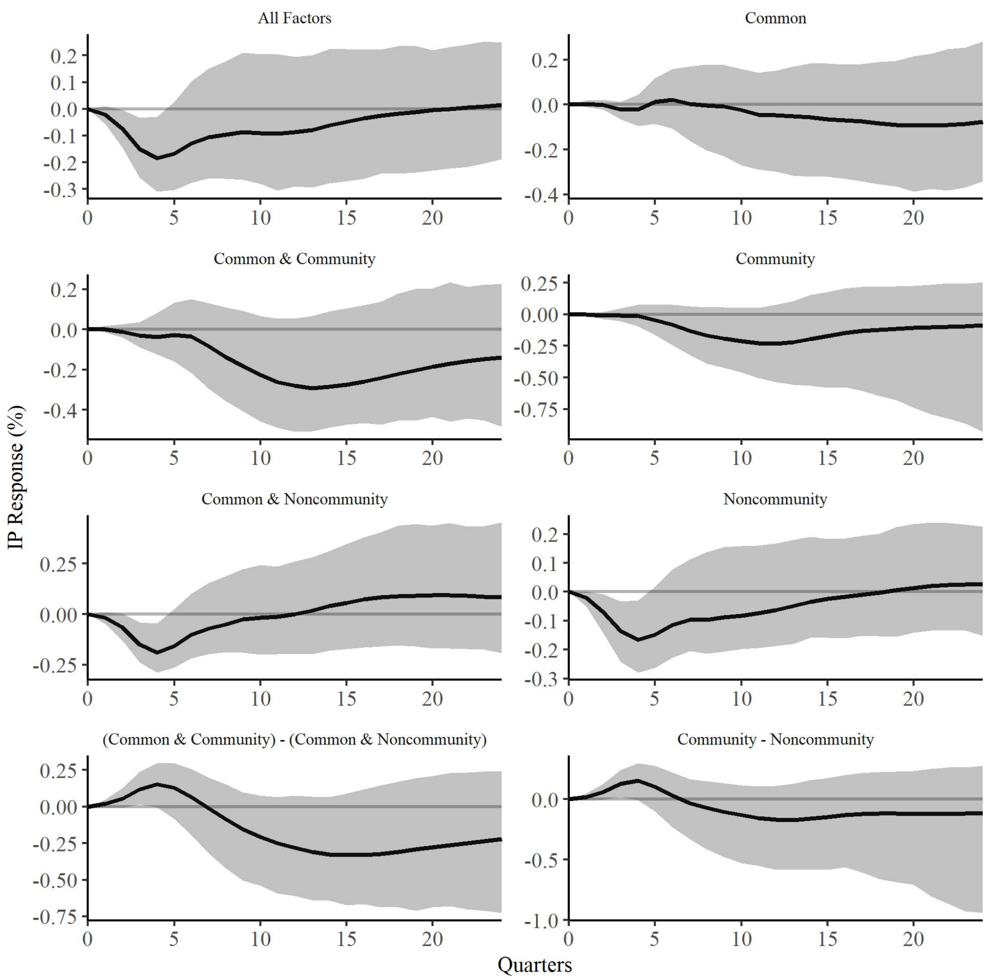


Figure D.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

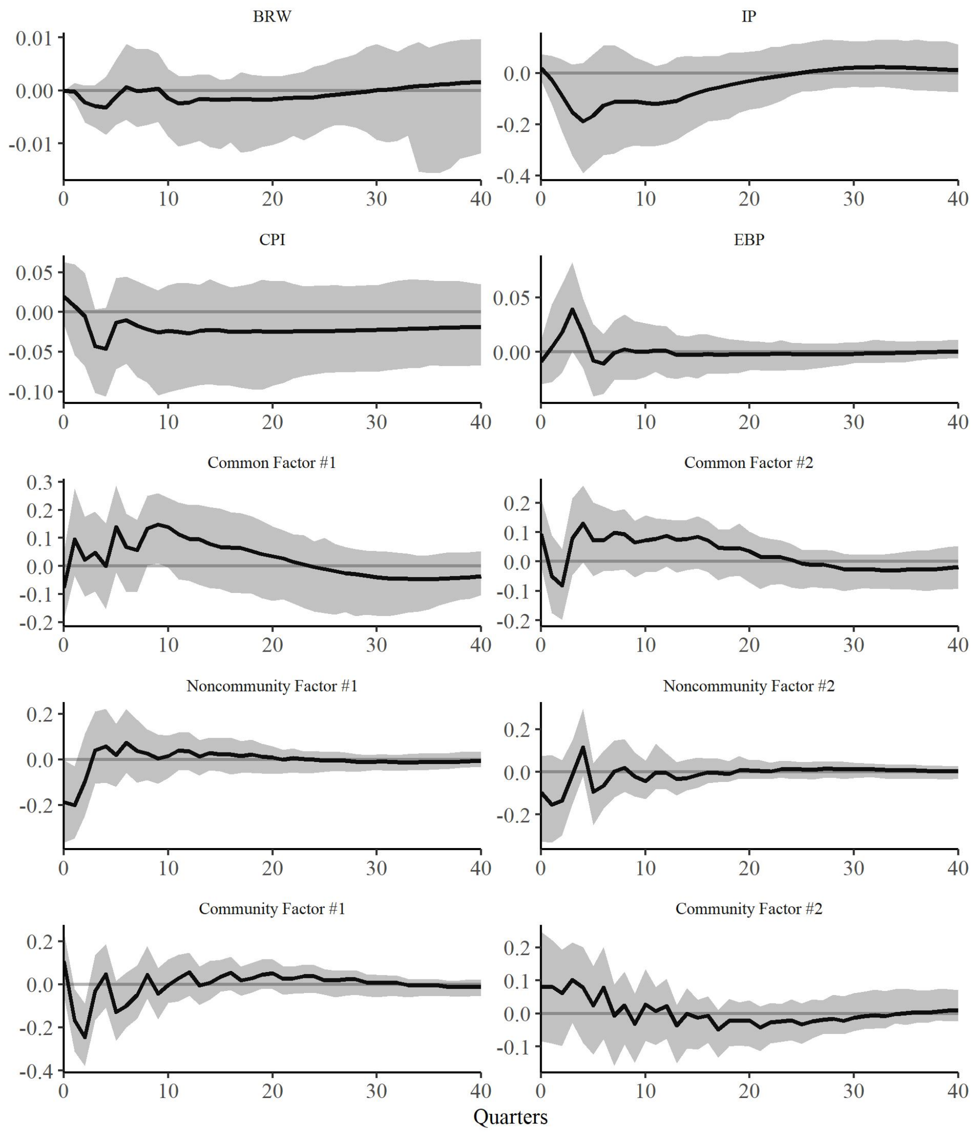


Figure D.4: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

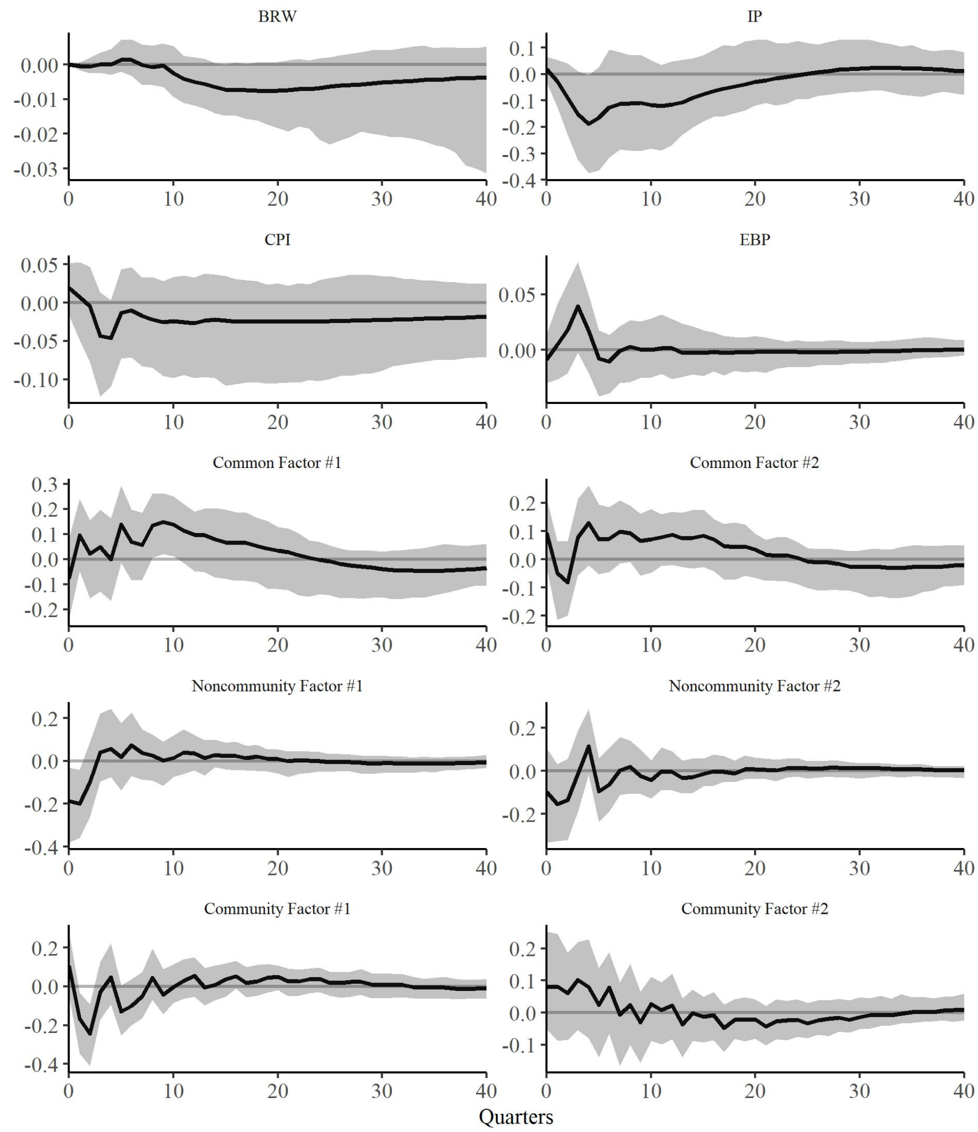


Figure D.5: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

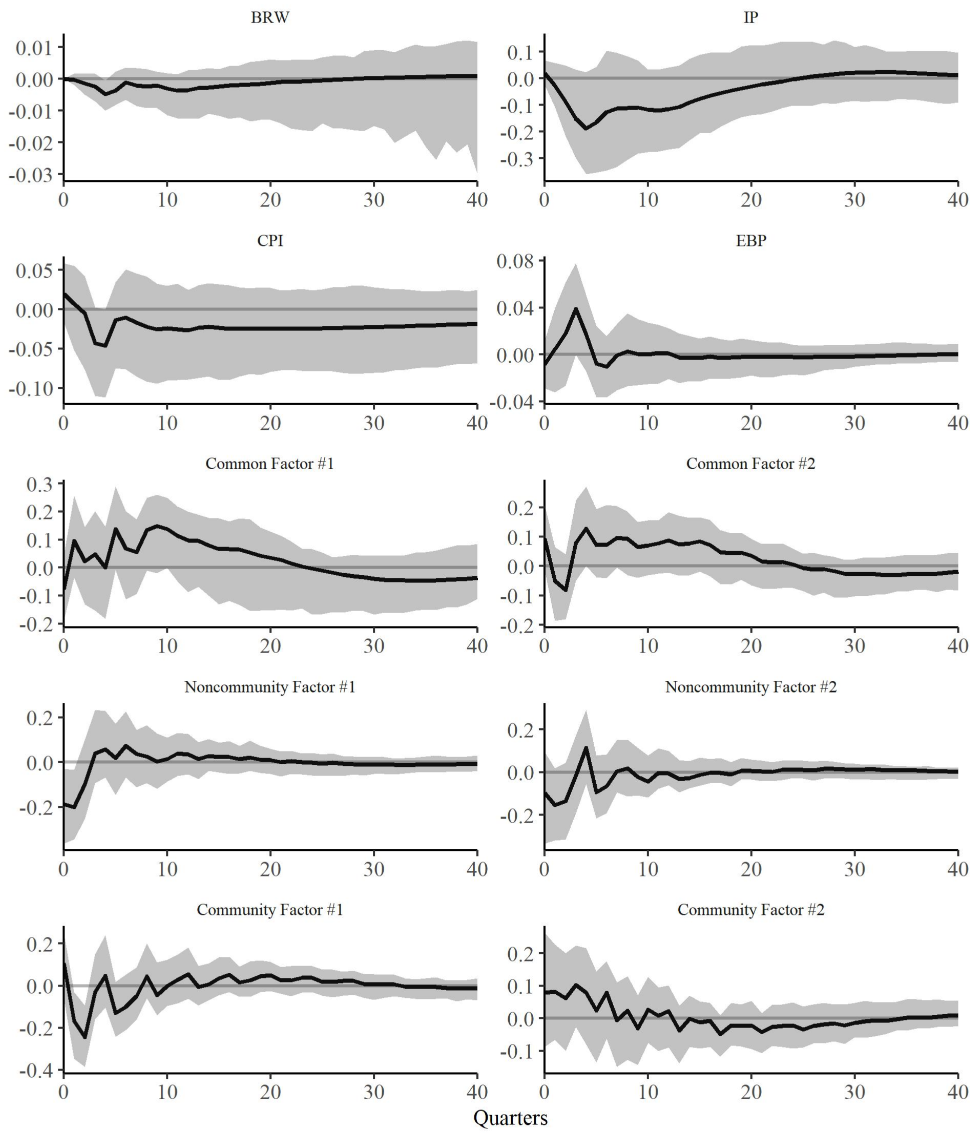


Figure D.6: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

E Robustness: Alternative Monetary Policy Shock

The alternative model is expressed as

$$
\begin{aligned}
X_t &= \alpha + \Gamma F_t + \Lambda^N F_t^N + \Lambda^C F_t^C + u_t \,,\, u_t \sim N(0, \Sigma_u)\,, \\
Z_t &= \gamma + \Psi(L) Z_{t-1} + B v_t \,,\, v_t \sim N(0, I)\,,
\end{aligned}
$$

where X_t is the data matrix containing all bank loan growth rate series and

$$
Z_t \equiv \begin{bmatrix} \mathrm{JK}_t \\ \log(\mathrm{GDP}_t) \\ \log(\mathrm{GDPD}_t) \\ \mathrm{EBP}_t \\ F_t \\ F_t^{\mathrm{N}} \\ F_t^{\mathrm{C}} \end{bmatrix},
$$

such that JK, GDP, GDPD, and EBP denote the *raw* cumulative JK shock series, gross domestic product, GDP deflator, and excess bond premium, respectively; F^N represents the vector of noncommunity bank lending factors; F^C represents the vector of community bank lending factors; $\Psi(L)$ is a lag matrix polynomial; $v \sim N(0, I)$ is a vector of structural shocks; and B is a recursively identified contemporanous impact matrix.

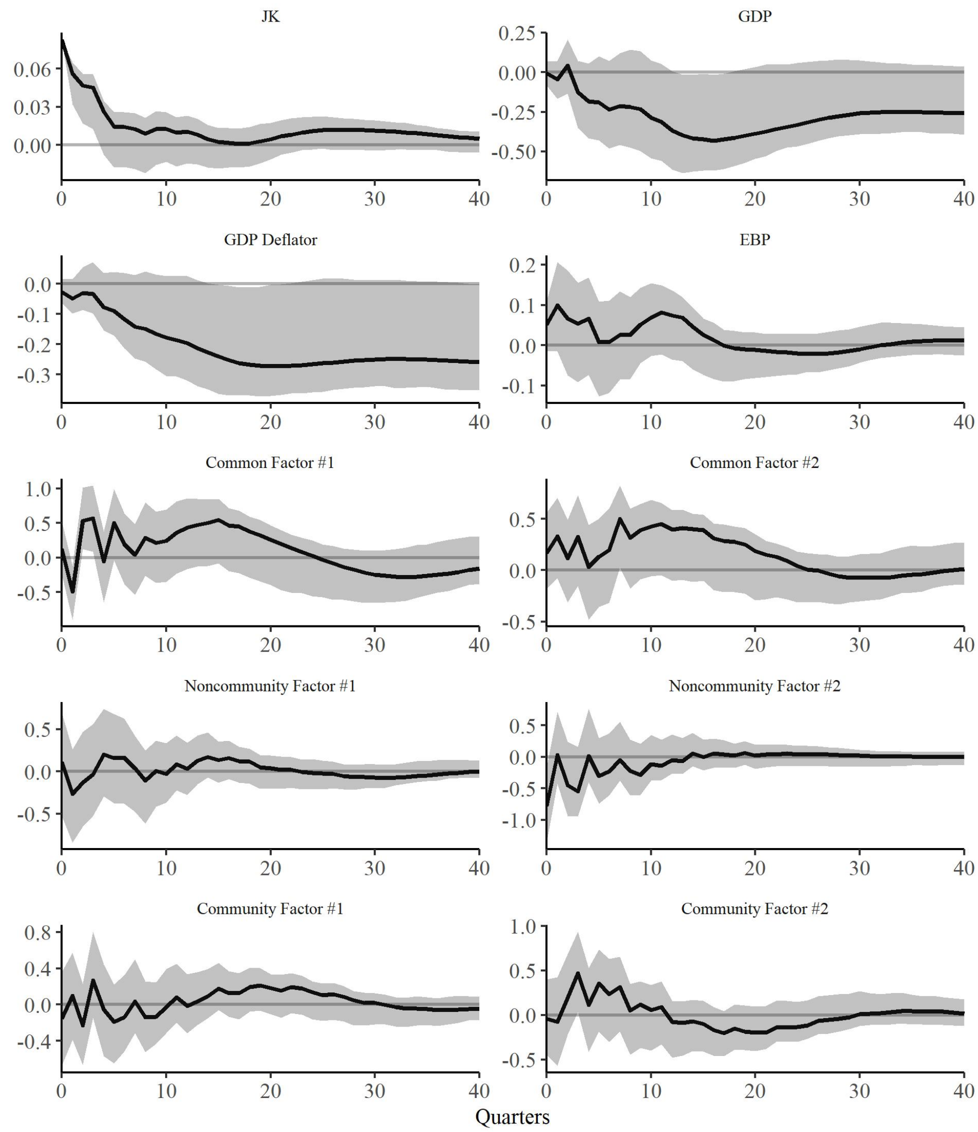
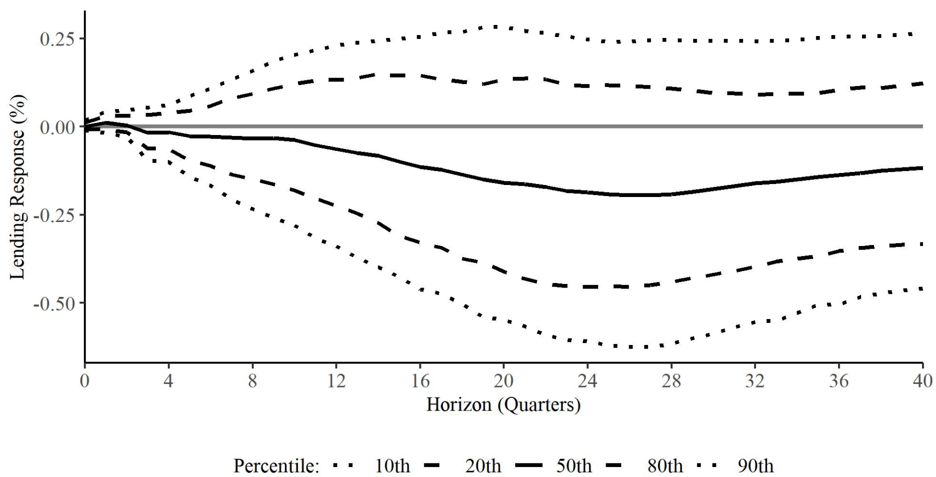
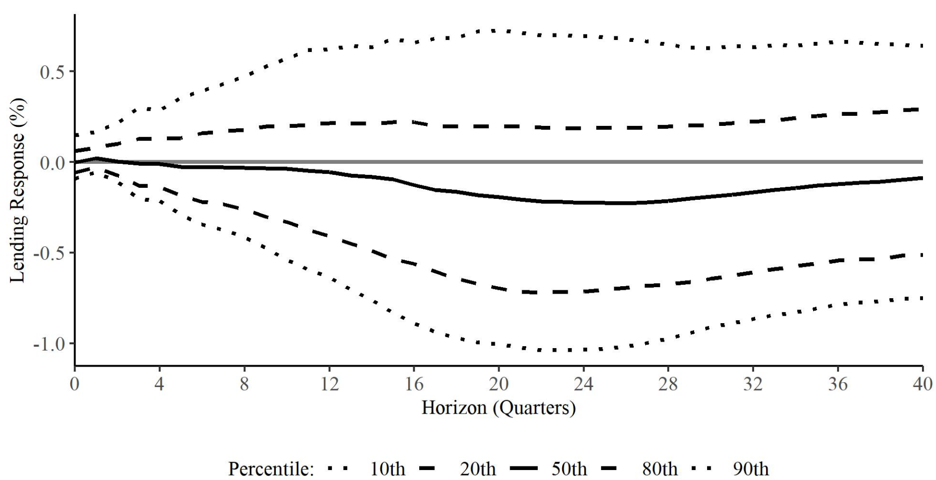


Figure E.1: Impulse responses of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

Figure E.2: Bank-specific responses in loan quantity to a one standard deviation positive (contractionary) monetary policy shock.

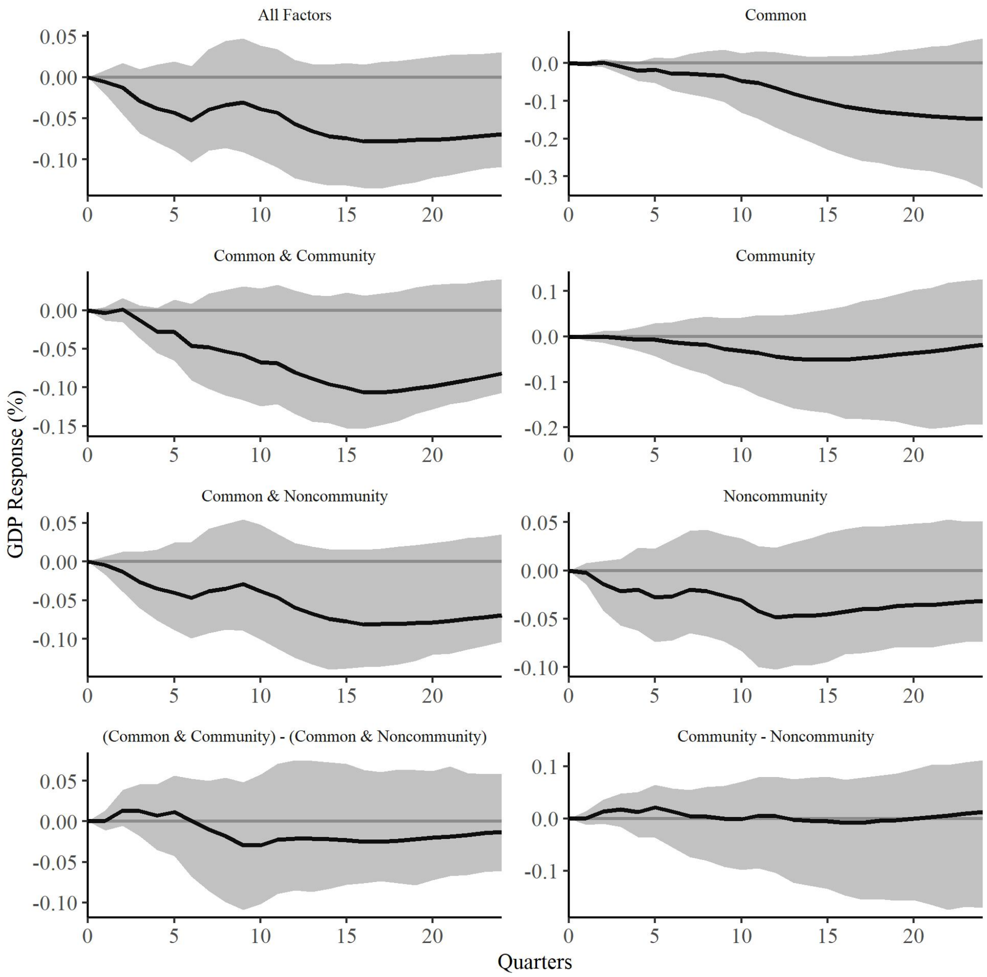


Figure E.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

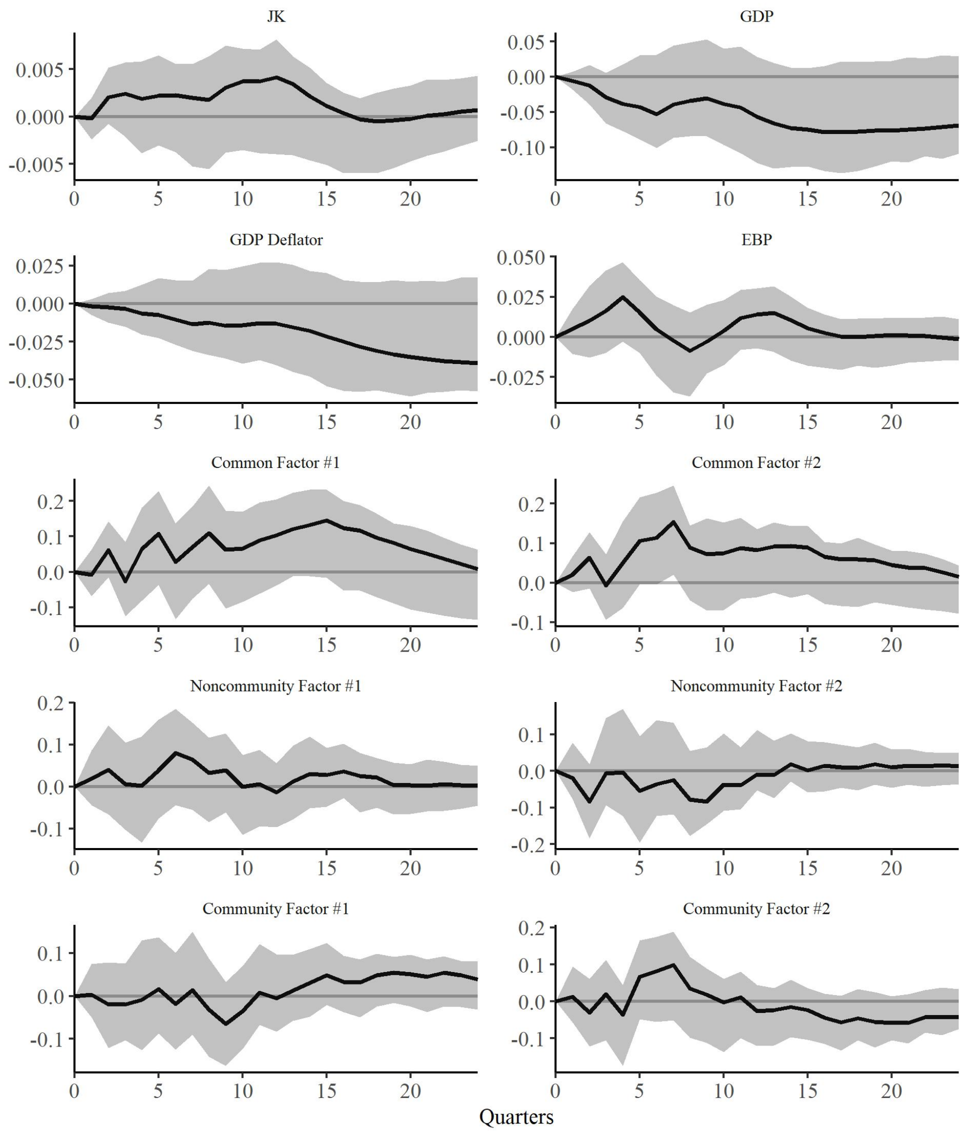


Figure E.4: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

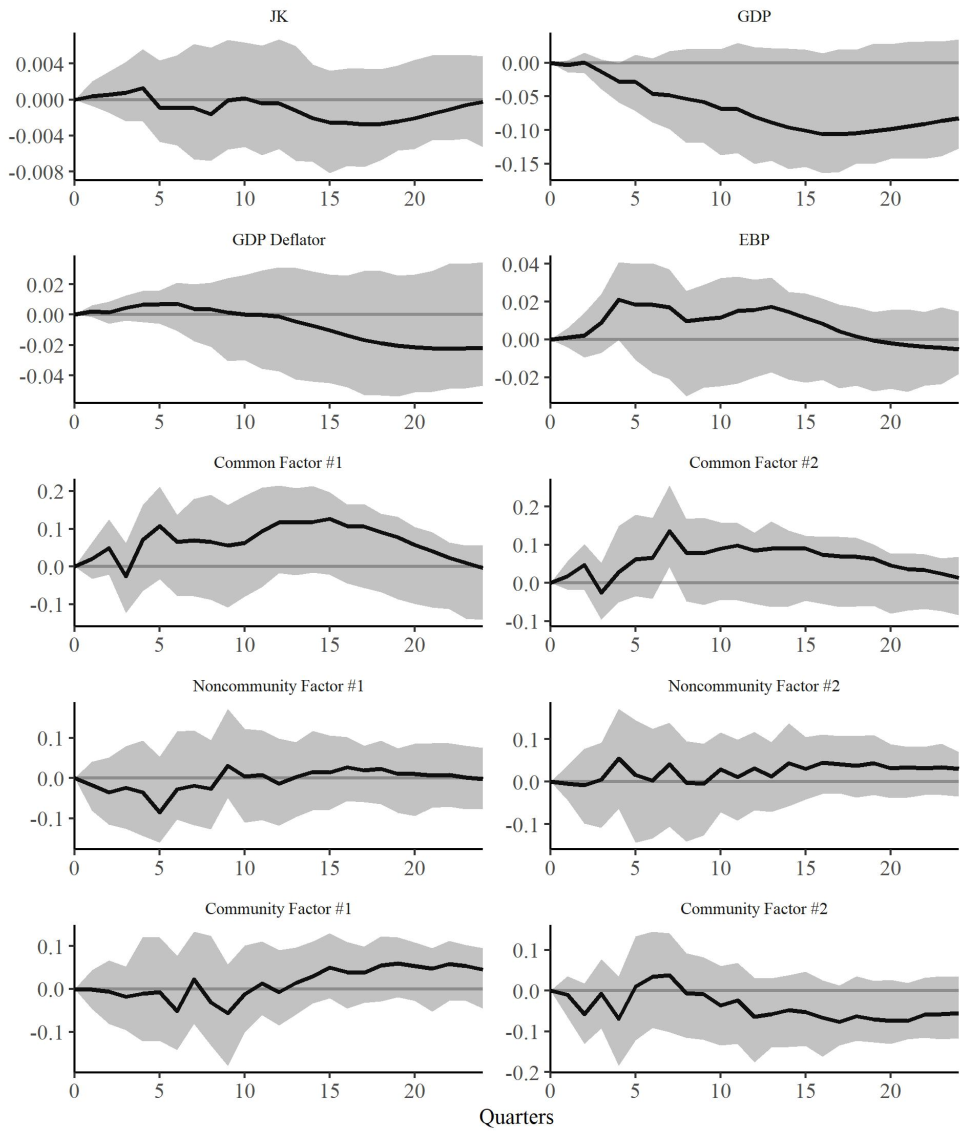


Figure E.5: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.

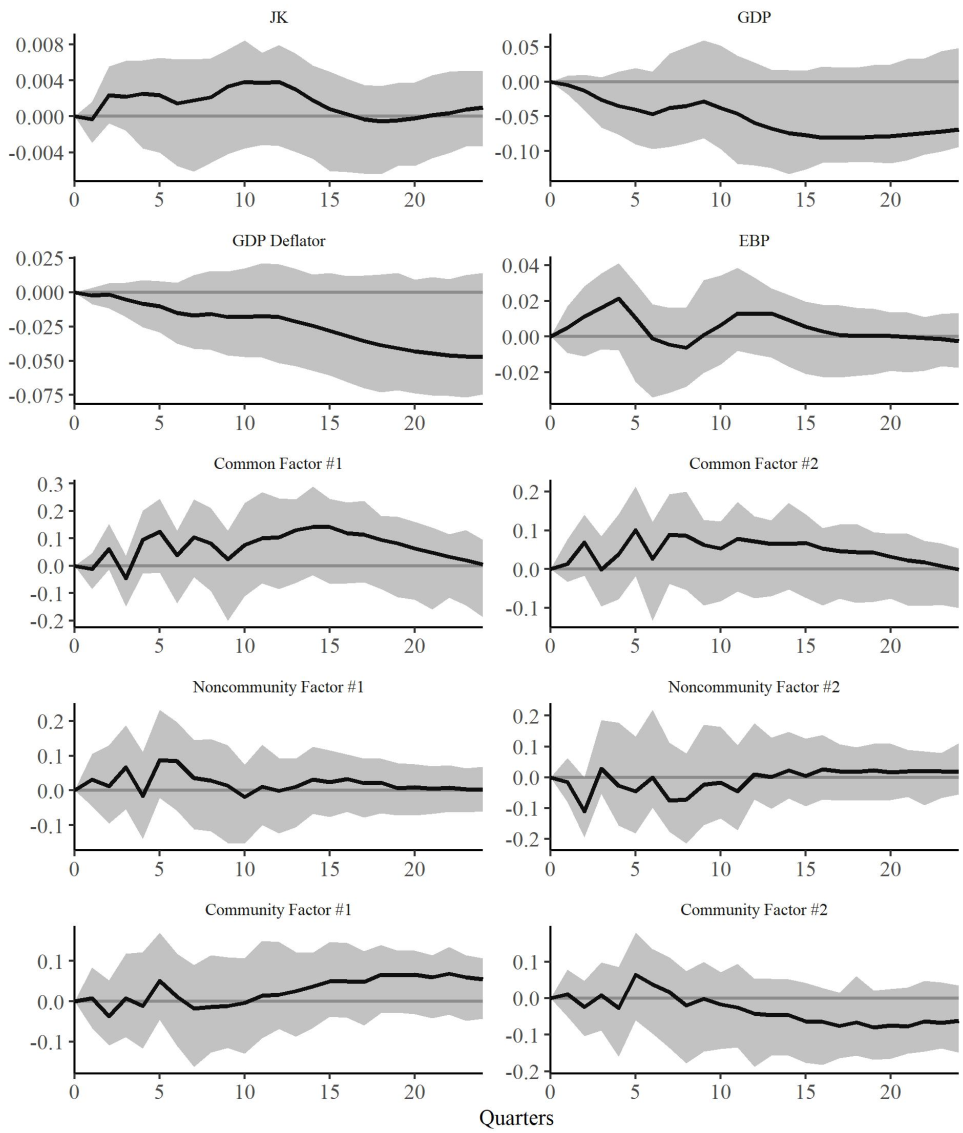


Figure E.6: PT-IRs of all variables in the VAR to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines represent point estimates, and the gray bands represent 90% confidence intervals estimated using the wild bootstrap with 1,000 runs.