Monetary Transmission Through Community and Noncommunity Bank Lending

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Abstract

This paper examines the dynamic macroeconomic effects of monetary transmission through community and noncommunity bank lending in the United States. I find that while both types of banks amplify the impact of monetary policy shocks on output, community banks exhibit a more delayed and persistent amplificatory influence than their noncommunity counterparts. These results suggest that continued decline in community banks' market share may dampen the efficacy of monetary policy over longer horizons. Moreover, the adverse real effects of monetary tightening are likely to be longer-lasting for small business borrowers who depend on community banks for funding.

JEL Classifications: G21; E51; E52

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1 Introduction

The commercial banking sector in the United States is currently composed of more than 4,000 banks – the vast majority can be categorized as community banks and the rest as noncommunity banks. Community banks are small standalone financial intermediaries that primarily provide traditional banking services to clients in their respective local markets (Nguyen and Barth, 2020).[1] Noncommunity banks, by contrast, tend to operate at a much larger scale, providing services across at least one region and engaging in a broader array of financial activities. Over the past few decades, the composition of the banking sector has undergone substantial changes, driven largely by consolidation and evolving regulations. As a result, the overall market share of community banks has declined consistently (see Figure 1). These trends have led to a landscape increasingly dominated by noncommunity banks, raising questions about their implications for the broader economy. In this paper, I show that the diminishing relative presence of community banks may hold consequences for the efficacy of monetary policy transmission through the lending channel.

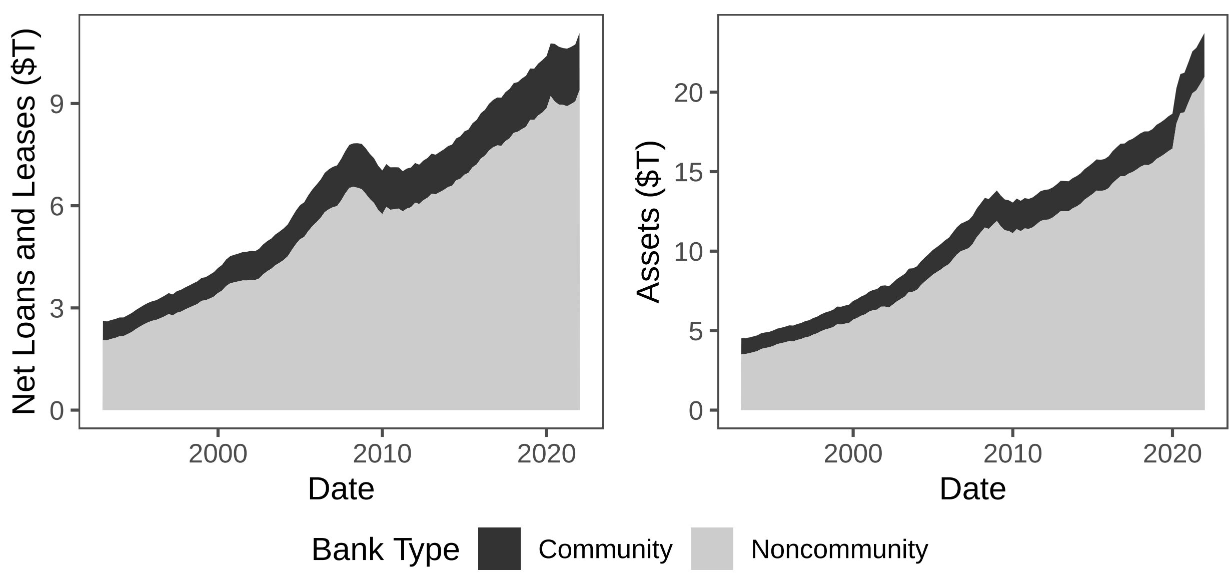


Figure 1: *Left Panel:* Total net loans and leases by bank type. *Right Panel:* Total assets by bank type. *Source:* FDIC Statistics on Depository Institutions.

[1] 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. The FRB simply defines a community bank as an institution with total assets less than $10B. 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 by considering geographical scope.

Beyond differences in directly observable features such as size, asset allocation, and liability structure, community and noncommunity banks differ in their approach to lending. Community banks have a limited geographical scope by definition – most operate within a single state, with many maintaining only one branch (see Figure 2). They are typically locally owned and managed, with a strong emphasis on relationship lending (FDIC, 2020). This approach involves personalized attention, individual analysis, and continuous administration of loans tailored to the needs of borrowers. A hallmark of community banks has been their ability to gather and process soft information about borrowers. This approach is shown to achieve greater loan repayment rates compared to the more transactional approach taken by noncommunity banks (Peirce et al., 2014).[2] Due to these features, community banks play a key role in financing small businesses disproportionate to their total size relative to that of noncommunity banks. In recent times, community banks have held approximately a third of all small business loans despite owning only a tenth of total bank assets (Beiseitov, 2023; FDIC, 2020). Given that small businesses make up the majority of U.S. enterprises and employ nearly half of the country's private sector workforce, this sheds light on the potential of community banks' lending dynamics to influence fluctuations in aggregate real activity. Furthermore, considering monetary policy is shown to affect bank lending, the niche business model shared by community banks may lead to them having a distinct influence on the dynamic aggregate effects of monetary policy as a medium of transmission.

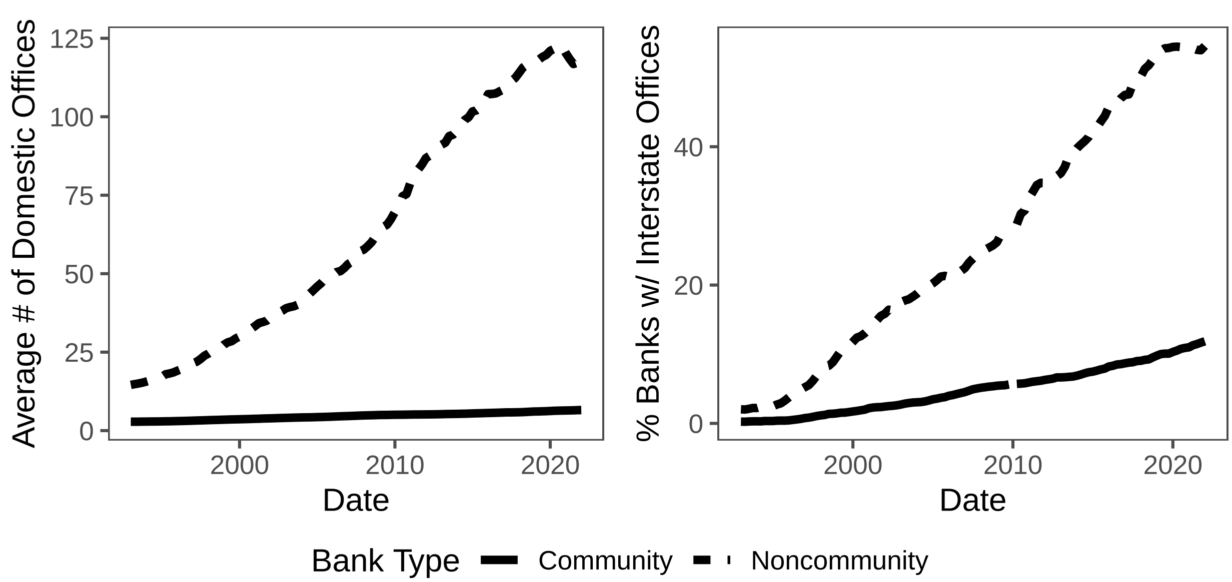


Figure 2: *Left Panel:* Percentage of banks with offices across more than one state by bank type. *Right Panel:* Average number of domestic offices by bank type. *Source:* FDIC Statistics on Depository Institutions.

[2]In essence, transactional lending focuses on individual loan transactions, whereas relationship lending is borrower-centric. Refer to Bolton et al. (2016) for a discussion of transactional and relationship lending.

I employ a novel reduced-form empirical approach to study the extent to which community versus noncommunity bank lending contributes to the dynamic effect of monetary policy on output. I use a combination of aggregate and bank-level data ranging from Q1-1995 to Q4-2019. I create a balanced panel of bank-level lending series for the purpose of extracting latent factors that capture comovements in lending across all U.S. commercial banks, as well as separate factors capturing common dynamics specific only to community and noncommunity banks, respectively. I include these hierarchical bank lending factors in a factor-augmented vector autoregression (FAVAR) containing a standard set of additional aggregate series commonly included in macrofinancial VARs.[3] The FAVAR also includes an externally identified cumulative monetary policy shock series developed by Bu et al. (2021) as an endogenous variable in the VAR, the corresponding innovations to which capture shocks to monetary policy. I use the FAVAR to estimate pass-through impulse response functions (PT-IRFs) in response to a contractionary monetary policy shock, which allow for the direct quantification of the separate contributions of community and noncommunity bank lending to the net effect of the shock on output over a range of horizons (Nikolaishvili, 2025).

My findings reveal that noncommunity bank lending consistently amplifies the contractionary effects of an unexpected monetary tightening over a six-year horizon, whereas the amplificatory contribution of community bank lending peaks approximately 3-4 years after the shock. These results indicate that community banks play a critical role in sustaining the effects of monetary policy over longer horizons. Furthermore, given that community banks specialize in lending to small local borrowers with few outside financing options, the persistence of the contribution of community bank lending to the contractionary effect of a monetary tightening likely stems from a persistent decline in these vulnerable borrowers' spending. In other words, the composition of the commercial banking sector may function into the distributional dynamic impact of contractionary monetary policy on firm activity.

This paper contributes to the empirical literature on the credit channel of monetary transmission. Firstly, it studies the role of differences in banks' business models and approaches to lending as a dimension of bank heterogeneity factoring into the monetary transmission mechanism. Much of the existing research, beginning with the seminal study by Bernanke and Blinder (1988), has focused on dimensions such as bank size, capitalization, and liquidity. For example, Kashyap and Stein (1995, 2000), Kishan and Opiela (2000), and Dave et al. (2013) find that smaller

[3]The specification of the FAVAR is similar to that of Dave et al. (2013), however my model groups banks by business model (community vs. noncommunity) instead of the categorization used by Dave et al.. Additionally, the factor structure in my model is hierarchical – each unit-level series in the panel is assumed to be a linear function of a set of lending factors that load on all banks, as well as a set of group-specific lending factors corresponding to the categorization of each given bank. This ensures that group-specific factors are not contaminated by dynamics common to all banks via smearing once the model is estimated.

banks are more sensitive to monetary policy shocks. Kashyap and Stein (1995, 2000) and Kishan and Opiela (2000) also show a similar relationship across the dimensions of bank liquidity and capitalization, where less liquid and capitalized banks' lending responds more strongly to changes in monetary policy. Bluedorn et al. (2017) argue that belonging to a bank holding company determines banks' sensitivity to monetary shocks. None of the previously explored dimensions of bank heterogeneity fully capture the characteristic differences between community and noncommunity banks, particularly the differences in their reliance on relationship lending and geographical scope. Furthermore, the role of bank heterogeneity in the aggregate transmission of monetary policy remains an under-explored area of research. Community banks, with their focus on local economies, may respond to monetary shocks differently than their larger, geographically diversified noncommunity counterparts. Understanding these differences is critical, particularly in light of the evolving composition of the U.S. banking sector.

The second contribution of the paper is methodological. A challenge with assessing the influence of bank lending on the dynamic effects of monetary policy is that, in a sense, it requires the decomposition of impulse responses according to contributions of different transmission channels. The lending channel may be expressed as a two-step causal chain, whereby changes in monetary policy affect bank lending, and the resulting endogenous responses in bank lending subsequently impact output.[4] Due to methodological constraints, past studies analyze only one of these links in the chain in isolation. For example, Dave et al. (2013) study 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 exogenous shocks to bank loan supply impact output. It is common practice 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 the nature of monetary transmission via bank lending – the changes in bank lending in this setting are endogenous by nature. The PT-IRF offers quasi-decompositions of the total dynamic effects of monetary policy on output via transmission through community and noncommunity bank lending.[5]

[4]Strictly speaking, the bank lending channel refers to changes in output caused by changes in bank loan supply in response to monetary policy shocks, while the balance sheet channel refers to changes caused by bank loan demand responses to monetary shocks. The empirical approach in this paper does not separate these demand- and supply-side channels, and instead refers to them jointly as the lending channel. The identification challenges of separating these two channels is described in Bernanke and Blinder (1992), Bernanke and Gertler (1995), and Kashyap and Stein (2000). Additionally, the paper is agnostic to the different mechanistic interpretations of the bank lending channel offered, e.g. the conventional view offered by Kashyap and Stein (1994), Bernanke and Gertler (1995), Black and Rosen (2007), and den Haan et al. (2007), as well as more recent interpretations by Disyatat (2011) and Drechsler et al. (2017).

[5]An alternative approach is a counterfactual exercise in the style of Sims and Zha (2006), in which community and noncommunity bank lending is held constant in response to a monetary policy shock using a sequence of bank type-specific exogenous lending shocks, and the resulting response of output is compared to the unconditional response.

The remainder of the paper proceeds as follows. Section 2 presents the econometric approach to quantifying and estimating the contributions of community and noncommunity bank lending to the total dynamic effect of monetary policy on output. Section 3 describes the results and their implications. Section 4 concludes the paper.

2 Econometric Approach

The purpose of the empirical approach in this paper is to (1) separately capture lending dynamics specific to community banks and noncommunity banks; and (2) analyze their relationship with the dynamic response of output to monetary policy shocks.

In the case of noncommunity banks, the variation in aggregate bank lending series may be driven by changes idiosyncratic to the largest banks, since they compose a large share of the total. As for community banks, their corresponding aggregate loan series may at times be driven by regional co-movements not inherent to all/most community banks. Furthermore, total community and noncommunity bank lending series may themselves co-move due to commonalities across the entire banking sector. Therefore, in this paper I capture bank lending dynamics using a factor modeling approach, with the goal of isolating sources of dynamic variation unique to community versus noncommunity banks. I construct a FAVAR by augmenting an otherwise standard monetary VAR with factors that capture comovement in the growth of total loans *separately* across all banks, exclusively across community banks, and exclusively across noncommunity banks. The hierarchical nature of these factors, which are estimated using a balanced panel of bank lending series, ensures the isolation of latent forces driving group-specific fluctuations in community and noncommunity bank lending behavior. In other words, explicitly controlling for comovement across all banks guarantees that the model captures bank-type heterogeneity through the group-specific factors. The factors are estimated using a recursive principal components procedure and treated as observables when estimating the augmented VAR.

To achieve the second goal, I include an externally-identified monetary policy shock series in the VAR as an endogenous variable without any restrictions on its lag coefficients in the baseline model, and recursively identify its innovations.[6] I then use the estimated FAVAR to

However, this approach is infeasible due to the challenges associated with identifying exogenous shocks to bank lending. Furthermore, this framework would limit the analysis to using either a single aggregate lending series or factor for each bank type, instead of multiple factors. The potential downsides of this are discussed in Section 2.

[6] This shock identification scheme is common in the empirical macroeconomics literature. For example, Auerbach and Gorodnichenko (2012) use it to identify the effects of news shocks.

generate PT-IRF point estimates as mappings of the slope and contemporaneous impact parameters in response to a monetary policy shock, and nonparametrically bootstrap the corresponding confidence intervals. I use the PT-IRFs to gauge the extent to which monetary transmission through community versus noncommunity bank lending influences the total effect of monetary policy on output at each given horizon.

2.1 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 Q1-1995 until Q4-2019, 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. Banks that have switched types during the sample period are excluded. (4) Each of the series across the two sub-panels are transformed into growth rates and seasonally adjusted by partialling out variation attributable to seasonal dummies in a linear regression. 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 are obtained from the Federal Reserve Economic Data (FRED) database:[7] Real Gross Domestic Product (GDPC1; Baseline proxy for output); GDP Deflator (GDPDEF; Baseline proxy for inflation); Industrial Production (INDPRO; Alternative proxy for output, often used in monetary VARs with monthly data); 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).

To identify monetary policy shocks, I defer to the Bu-Rogers-Wu (BRW) monetary policy

[7]The latter two series are used to estimate an alternative model to test the robustness of baseline results.

shock series (Bu et al., 2021).[8] I aggregate their provided shock series to the quarterly frequency, as shown in Figure 3. 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.

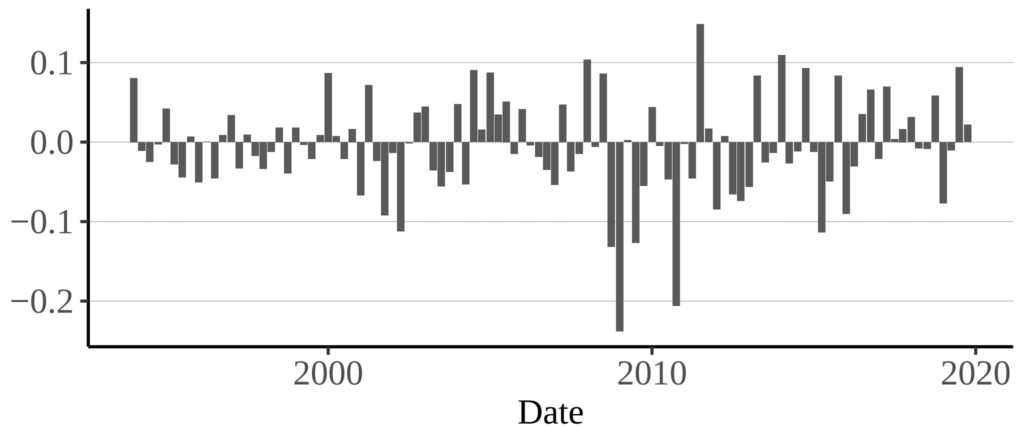


Figure 3: Quarterly BRW monetary policy shock series.

The VAR also includes the excess bond premium (EBP) – one of two components of the credit spread indicator introduced by Gilchrist and Zakrajšek (2012).[9] The EBP is interpreted as an indicator of the capacity of intermediaries to extend loans, or more generally as a proxy of aggregate credit supply conditions. It aggregates high-quality forward-looking information about the economy, which 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. Furthermore, Bu et al. (2021) include the EBP in their monthly VARs with which they test the validity of their monetary policy shock measure. In this paper, I include the EBP in the VAR for two reasons: (1) to follow the convention in the literature, and (2) replicate the VAR model used by Bu et al. (2021) to estimate the effects of monetary policy.

[8] In Supplemental Appendix B, I test the robustness of the BRW-based results using the Jarocinski-Karadi (JK) monetary policy shock series (Jarociński and Karadi, 2020).

[9] The EBP is the average corporate bond spread from which the impact of default compensation has been purged.

2.2 Model

The FAVAR is composed of two distinct parts: (1) hierarchical factor structure applied to a large panel of bank-level lending growth series, and (2) monetary VAR containing the same bank lending factors and a set of macrofinancial aggregate series. The factor structure captures factors driving common variation in the growth of bank loans between and across community and noncommunity banks. In other words, the model simultaneously contains factors representing common sources of variation among all banks, along with a separate set of factors capturing bank type-specific variation.[10] The VAR captures the dynamic relationship between these bank lending factors, aggregate macroeconomic series described in the previous Section, and monetary policy.[11]

The factor structure applied to loan growth rate series x for each bank i is expressed by the following equation:

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

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. In words, the growth rate of lending at bank i at time t is assumed to be an affine function of a set of unobservable 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 j 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 baseline VAR is specified by the following equation:

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

[10] In essence, the factors can be interpreted as common and group-specific time-varying loan growth fixed effects with heterogeneous bank-specific impact magnitudes (loadings).

[11] Although the estimated bank lending factor series do not necessarily have an intuitive interpretation, their impulse responses to various shocks in the VAR can be used in conjunction with their corresponding factor loadings to generate bank-specific impulse responses. For instance, the FAVAR allows to estimate bank-specific lending responses to a contractionary monetary policy shock.

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 (see Figure 4), 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.[12]

Together, Eqs. (1) and (2) describe the FAVAR in state space form, where the former is the transition equation and the latter the measurement equation. For completeness, the full model is expressed as the following set of equations:

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

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

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

2.3 Shock Identification

The cumulative BRW monetary policy shock series is ordered first in the VAR – all variables in the system respond contemporaneously to its corresponding recursively-identified innovation.[13]

[12] Specifying and estimating VARs in levels has become common practice in the literature – recent examples include Bu et al. (2021); Görtz et al. (2022), among many others. VARs expressed in levels produce 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 MSEs than those based on pretested models. For these reasons, I choose to specify my base model in levels.

[13] 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). This is equivalent to specifying a VAR with exogenous variable(s) (VARX), where the policy shock is the exogenous variable. In the baseline model, I do not impose any such exogeneity restrictions on the slope parameters – however, in Supplemental Appendix A, I show that that an alternatively-specified restricted VAR produces largely the same IRFs and PT-IRFs as the baseline VAR.

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, proxy VAR models yield impulse responses that are asymptotically equivalent to the ones obtained using my chosen approach, up to a constant scaling factor.[14] I defer to including the policy shock series in the VAR due to the ease of inference associated with this methodology, particularly in with respect to PT-IRFs.

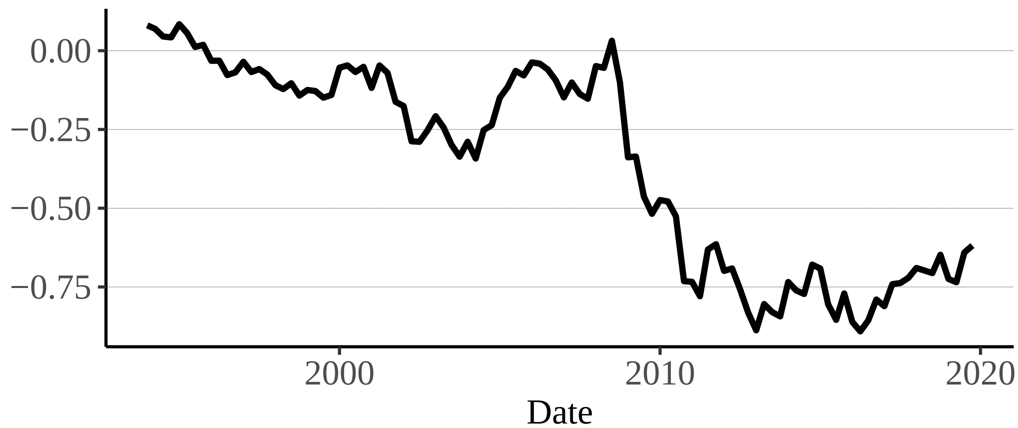


Figure 4: Cumulative quarterly BRW monetary policy shock series.

2.4 Estimation

The bank lending factors in the 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) and used by Dave et al. (2013).[15] The 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 common factor may be capturing group-specific comovement rather than common sources of

[14] 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).

[15] Other approaches include the Bayesian estimators described in Kim and Nelson (1998) and Otrok and Whiteman (1998). Jackson et al. (2015) show that the Bayesian methods are computationally intensive, without offering any obvious advantages in accuracy. For an application of Bayesian HDFMs to community bank data, see Nikolaishvili (2023).

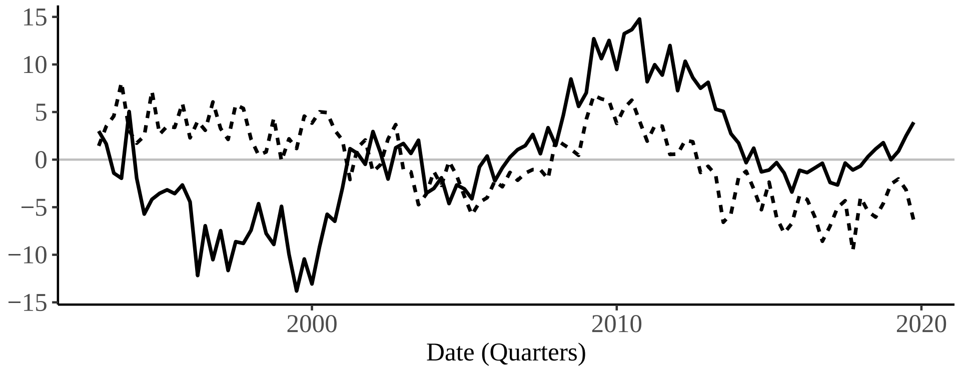
variation across all banks; (2) Normalize all bank-specific data series by de-meaning and dividing each series by its own standard deviation – this ensures that each bank holds equal weight in the computation of the principal component. Group the normalized community and noncommunity bank series into a single data block and use it to estimate common lending factors by computing principal components; (3) Partial out the variation attributable to common factors from each series by subtracting the factor estimate multiplied by the corresponding loadings. Separate the data into community and noncommunity sub-blocks, then use each sub-block to estimate community and noncommunity bank lending factors by computing the corresponding principal components; (4) Normalize all common and 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 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 5 presents the common, community, and noncommunity bank lending factor estimates, respectively. The set of common bank lending factors captures 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.[16] A few items of note include the following:[17] (1) In Figure 5a, 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 5b with the noncommunity bank factors in Figure 5c 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.

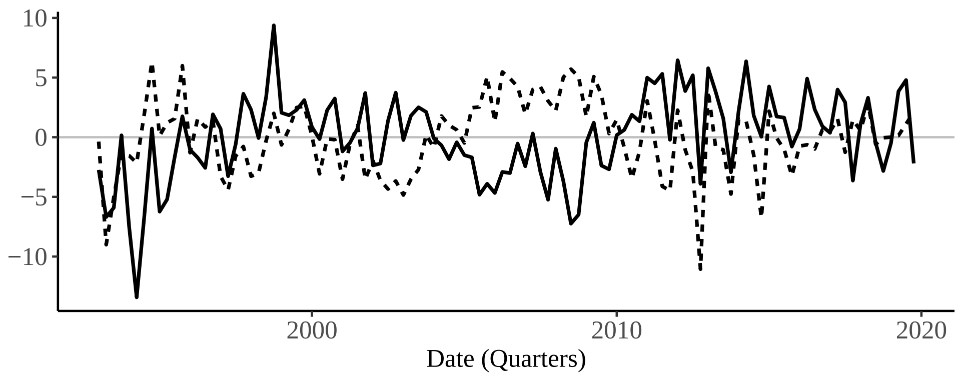
For each category of factors, I extract the first two principal components. Table 1 shows the

[16]The estimation procedure ensures that the different categories of factors capture orthogonal variation, despite loading on some of the same series. 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.

[17]The interpretation of the time variation in the factors is not the focus of the paper – rather, the factors are used for the purposes of dimension reduction.



(a) Common bank loan growth factors.



(b) Community bank loan growth factors.

(c) Noncommunity bank loan growth factors.

Figure 5: 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.

distribution of R^2 coefficients obtained by regressing each standardized bank loan growth rate series on all of its corresponding bank lending factors, as well as only on the common lending factor. 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 goal of this empirical design is not to maximize predictive power – the factors allow for parsimonious identification of common responses in lending behavior among U.S. commercial banks to monetary policy shocks.

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.

The factor estimates are treated as observable series in the transition equation (VAR) of the FAVAR. The VAR parameters are estimated using least squares, then used to construct IRFs and PT-IRFs with nonparametrically bootstrapped confidence intervals.

2.5 PT-IRFs: Illustration and Application

I briefly explain the intuition behind PT-IRFs in a simple setting that emulates the context of this study.[18] Consider the following VAR(1) process:

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

[18]For a thorough exposition of PT-IRFs, refer to Nikolaishvili (2025).

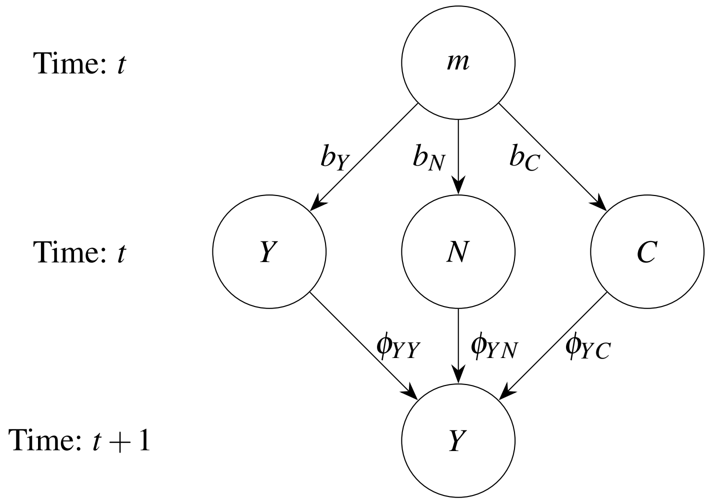


Figure 6: A graph-based illustration of the propagation of an impulse originating at m with destination Y one period ahead in the system determined by Eq. (5).

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 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 6 – 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 6 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.

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 6 – 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.

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 PT-IRF approach to estimate the dynamic response of the GDP to a positive BRW shock, while conditioning on different combinations of the bank lending factors in F_t, F_t^C, and F_t^N as transmission media.

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

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

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 transmission media. In Section 3, I present the PT-IRFs of GDP in response 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 conduct inference on differences between PT-IRFs with different intermediate variables. 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 a set of transmission media J' plays a bigger role in the transmission of the shock $\overline{\varepsilon}$ to i than does J'. We can 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 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 a nonparametric bootstrap for a given level of statistical significance. If for a range of h the confidence intervals of this object are strictly greater than zero, this implies J plays a greater role in the transmission of shock $\overline{\varepsilon}$ to variable i than the influence of J'. I apply ΔPT-IR by comparing the transmission of monetary policy shocks to output via community versus noncommunity bank lending.

3 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 result evidences the significance of noncommunity bank lending in monetary transmission; **(iv)** Finally, conducting inference on the difference between the monetary PT-IRFs conditional on community versus noncommunity bank lending shows evidence of noncommunity bank lending having a greater-magnitude amplificatory effect in the short run and community bank lending playing a more significant role in monetary transmission in the medium run. In other words, I find a more persistent amplificatory effect of monetary transmission via community bank lending on the total effect of monetary policy on output than that of noncommunity bank lending.

The qualitative nature of these results is robust to various modifications to the baseline empirical methodology: **(a)** Using IP and CPI as proxies for output and inflation instead of GDP and GDP Deflator produces even more pronounced/stronger results than the baseline model (see Appendix B); **(b)** Applying exogeneity restrictions (zero restrictions on the slope parameters) produces matching IRF and PT-IRF estimates with similar statistical significance (see Supplemental Appendix A); **(c)** Using the JK shock series instead of the BRW series to identify monetary policy shocks largely confirms the baseline point estimates and their qualitative implications, albeit with less confidence (see Supplemental Appendix B). as well as alternative hypothesis test specifications.

I first discuss the aggregate and bank-level impulse responses to an unexpected monetary tightening, after which I present the relevant PT-IRFs that show evidence of heterogeneous monetary transmission via community versus noncommunity bank lending.

3.1 IRFs

Figure 7 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 effect on the BRW series itself quite rapidly converges back to zero, whereas GDP and GDP Deflator respond with a delay. The former remains significantly below zero for a period of approximately five years post-shock, while the latter persists for the entire 10-year impact horizon.[19] The EBP also behaves in the expected manner, as

[19]These discussions of significance are based on the individual significance of the IRF point estimates, rather than joint significance tests over multiple impact horizons.

documented in Bu et al. (2021). The responses of the individual factors are uninformative, however it is worth noting that all factors converge back to zero by the end of the shown horizon.

Figure 8 shows the dynamic effect of a one standard deviation contractionary monetary policy shock on the distribution of individual banks' lending separately by bank type. More specifically, the IRF distribution shown on each panel is produced by (1) computing the bank-level response to a monetary policy shock for each bank as a function of the lending factor IRF point estimates and corresponding factor loadings for each bank, (2) cumulating lending growth rate responses over the response horizon for each bank, and finally (3) storing the 10th, 20th, median, 80th, and 90th-percentile responses at each horizon.

The two impulse response distribution plots in Figure 8 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 baseline results presented in Figures 7 and 8 are echoed by all three robustness checks. Equivalent aggregate IRFs are presented in Figure B.1 and Supplemental Figures A.1 and B.1. The only notable deviation in these estimates is the presence of the price puzzle in the case of shock exogeneity restrictions. Otherwise, the shapes of the aggregate series and bank lending factor IRFs match consistently across all robustness checks. Alternative bank-level IRF distribution estimates are presented in Figure B.2 and Supplemental Figures A.2 and B.2. The first and last of these exhibit the same kind of delayed median decline in bank lending after a contractionary monetary policy shock, where the decline in community bank lending peaks at a later horizon.[20] The model with shock exogeneity restrictions yields similar delayed median declines in lending across both community and noncommunity banks that persists without converging back to the initial level over the given horizon.

[20]Such delayed lending responses further suggest that the monetary policy shock is correctly identified in the VAR, since a delayed contraction in bank lending is precisely what has been documented in the literature using alternative identification schemes (e.g. Kashyap and Stein (1994, 1995, 2000); Kashyap et al. (2002); Drechsler et al. (2017)).

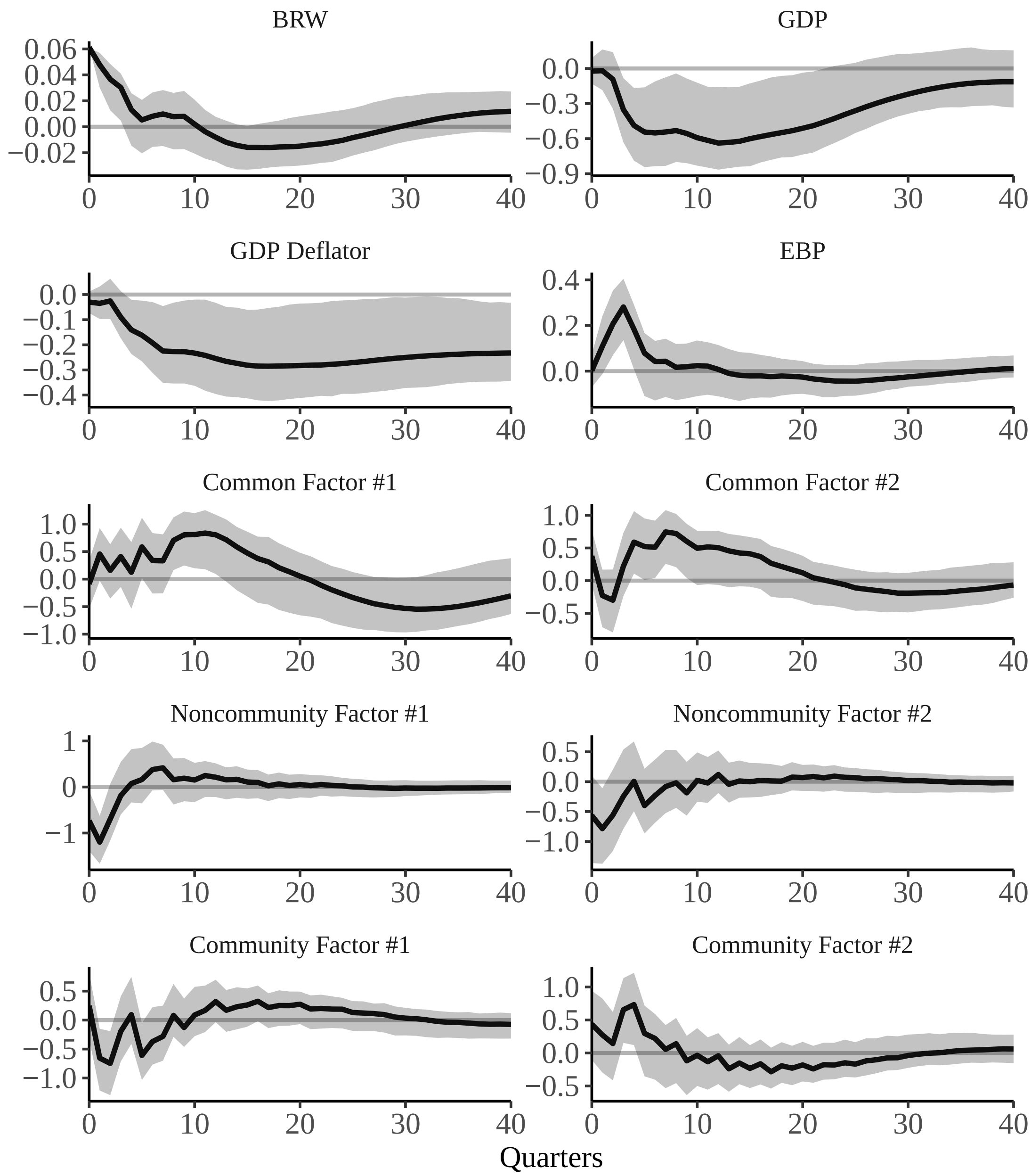
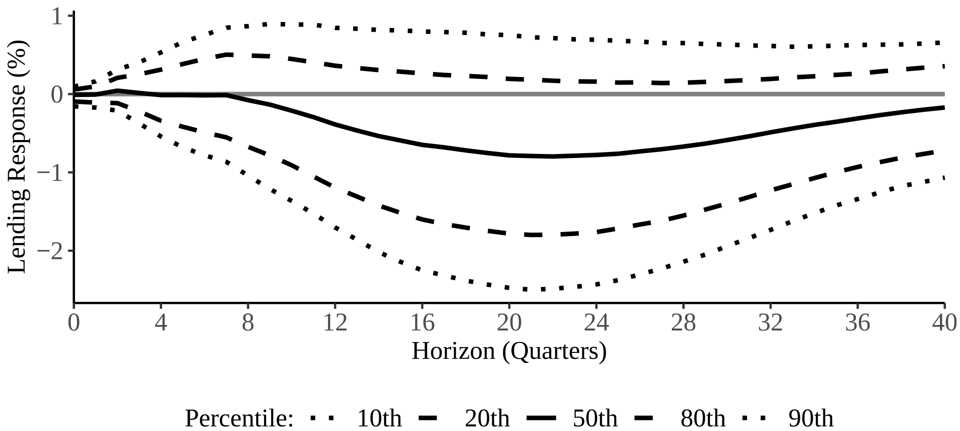
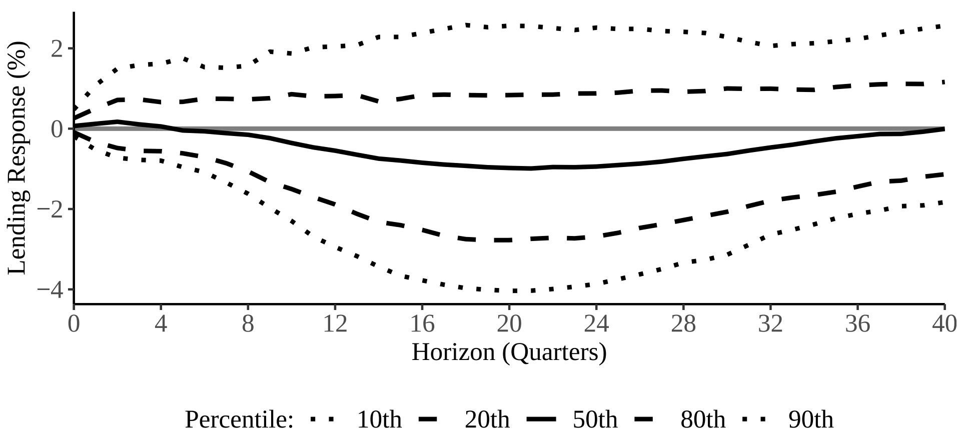


Figure 7: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.



(a) Distribution of community bank lending responses



(b) Distribution of noncommunity bank lending responses

Figure 8: The distribution of cumulative bank-level loan growth rate responses to a one standard deviation positive (contractionary) monetary policy shock.

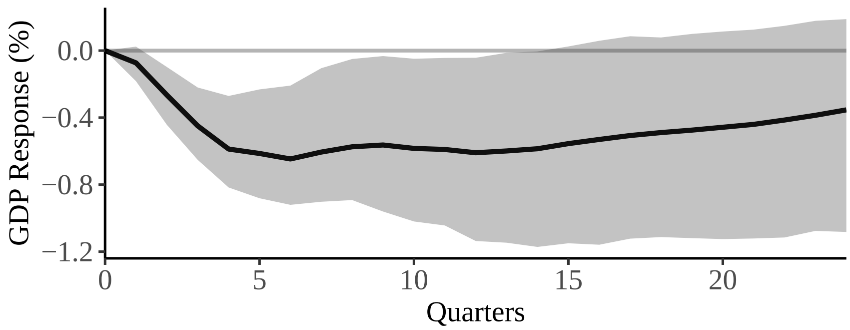
3.2 PT-IRFs

The three panels of Figure 9 present PT-IRF estimates associated with the transmission of a one standard deviation contractionary monetary policy shock to GDP via combined, community, and noncommunity bank lending, respectively. In summary, these results suggest that noncommunity bank lending plays a relatively more significant amplificatory role in the transmission of monetary policy in the short run, whereas community bank lending has a greater amplificatory influence in the medium run.

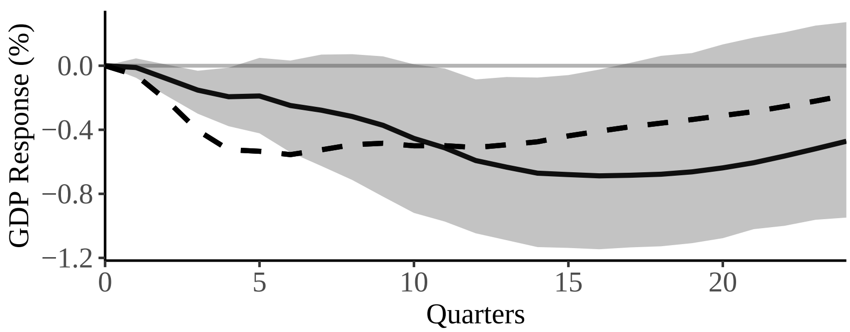
The PT-IRF presented in Figure 9a is conditioned on all bank lending factors in the model as the medium of transmission. I interpret this object as capturing the transmission of monetary policy through lending by all types of banks. It shows that a monetary tightening has a negative expected effect on output that persists for at least six years, although only the effects over the first four years are individually significant. The PT-IRF in Figure 9b is conditioned only on factors that load on the community bank lending series – the common and community bank lending factors – as the medium of transmission for the monetary shock. This object captures the transmission of monetary policy through community bank lending. It shows that a monetary tightening has a negative, delayed 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. Finally, Figure 9c is conditioned on factors that load on the noncommunity bank lending series – the common and noncommunity bank lending factors. This object captures the transmission of monetary policy via noncommunity bank lending. The shape of this PT-IRF matches that of the combined bank lending PT-IRF quite closely, but appears to be less persistent. When simultaneously visualizing and comparing the PT-IRF point estimates of monetary transmission via community versus noncommunity bank lending in Figure 9b, we see that the influence of noncommunity bank lending peaks approximately 2 years prior to the peak of the community bank lending PT-IRF.

Figure A.1 compares these estimates with corresponding PT-IRFs that separately condition only on common, community, and noncommunity bank lending factors to gauge joint, community, and noncommunity bank lending influence on monetary transmission, respectively. The qualitative differences between the role of community versus noncommunity bank lending appear to be the same as with the baseline transmission media. Corresponding robustness checks are presented in Figure B.3 and Supplemental Figures A.3 and B.3.[21]

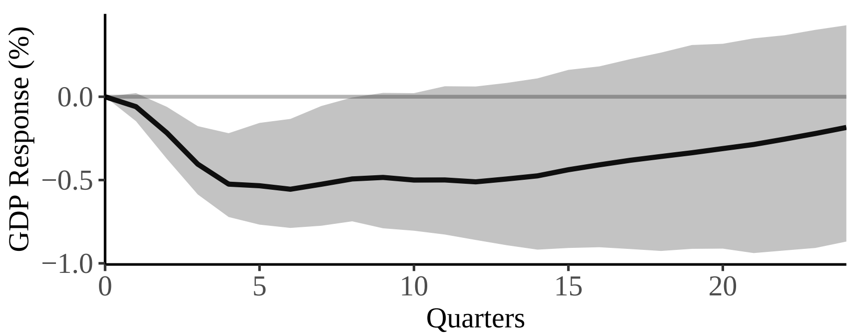
[21]For comprehensiveness, Figures A.2, A.3, and A.4 present the PT-IRFs of all endogenous variables conditioned on combined, community, and noncommunity bank lending as the transmission medium, respectively. Equivalent displays for the three robustness checks are presented in Figures B.4, B.5, and B.6., and Supplemental Figures A.4,



(a) Medium: Combined bank lending



(b) Medium: Community bank lending



(c) Medium: Noncommunity bank lending

Figure 9: PT-IRFs of GDP in response to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples. The dashed line in Panel (b) contains the point estimates of noncommunity bank lending PT-IRFs for comparison.

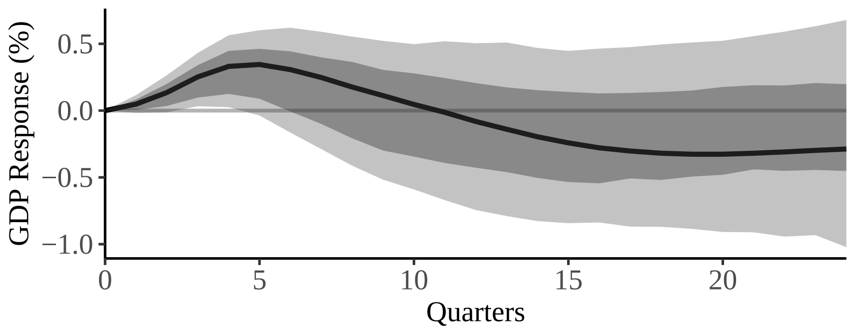
3.3 Heterogeneity in Monetary Transmission

Recall from Section 2 that it is possible to conduct inference on differences between PT-IRFs with differing transmission media. Let $J = \{F, F^C\}$ represent the set of common and community bank lending factors and $J' = \{F, F^{NC}\}$ the set of common and noncommunity bank lending factors. Then ΔPT-IR$(h, i, J, J', \overline{\varepsilon})$ captures the difference between the two type-specific PT-IRFs presented in Figures 9c and 9b.

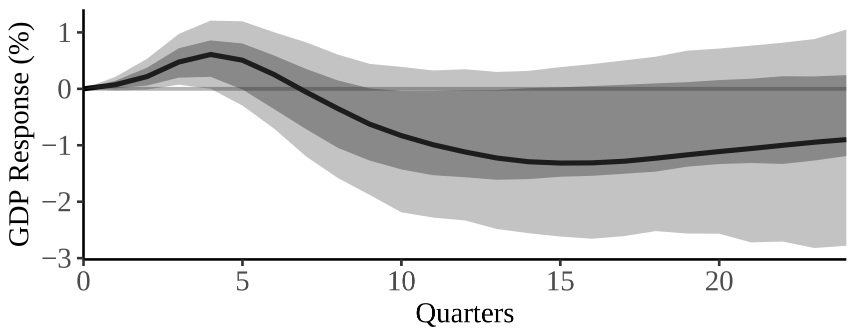
I present point estimates and corresponding 90% and 68% confidence intervals for this ΔPT-IRF in Figure 10 for the baseline model, as well as for its modified version with IP and CPI as proxies of output and inflation. Equivalent results for the remaining robustness checks are presented in the final row of Supplemental Figures A.3 and B.3 – they qualitatively match the results presented in Figure 10. Furthermore, these Supplemental Figures, along with Figures A.1, B.3, also show estimates of a similar ΔPT-IRF comparing monetary transmission via noncommunity versus community bank lending factors – without conditioning on the common factors. In all cases, with the exception of the modified specification using the JK shock to identify monetary policy shocks, this alternative approach to comparing community and noncommunity bank lending to monetary transmission yields similarly-shaped PT-IRFs, but with wider confidence intervals.

The ΔPT-IRFs presented in Figure 10 have point estimates greater than zero in the short run (less than 2-3 years post-impact), and below zero in the medium run (beyond 2-3 years after the initial impact). This result implies the magnitude of monetary transmission via noncommunity bank lending is greater than that of community bank lending in the short run, while the opposite is true in the medium run. We know this to be true since the individual PT-IRF estimates in Figure 9 are all negative over the entire impact horizon, implying any deviations must be due to differences in magnitude rather than sign. At least one of the short run point estimates is statistically significant with 90% confidence across all model specifications, and at least three are significant with 68% confidence. While none of the medium run point estimates are statistically significant with 90% confidence, their signs and relative magnitudes are consistent across all tried variations of the model. Overall, these findings suggest that community bank lending has a more delayed but lasting amplificatory influence on the dynamic effect of monetary policy on output.

A.5, and A.6, and B.4, B.5, and B.6.



(a) Baseline model



(b) Alternative model

Figure 10: Differences between the PT-IRFs of (a) GDP and (b) IP, conditional on community versus noncommunity bank lending factors as the media for transmission, in response to a one standard deviation positive (contractionary) monetary policy shock via bank lending. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

4 Conclusion

This paper investigates the dynamic effects of monetary policy transmission through community and noncommunity bank lending in the U.S. The results highlight the heterogeneity in how these two types of banks allow for the transmission of monetary shocks to the real economy, with noncommunity banks amplifying policy effects more strongly in the short run and community banks exhibiting a delayed but more persistent influence. The empirical findings in this paper suggest the following candidate mechanisms simultaneously causing such heterogeneous influences on monetary transmission: (1) On average, an unexpected monetary tightening causes community banks to contract lending over a longer period of time than noncommunity banks; (2) Due to information frictions associated with their size, small business borrowers that rely on community banks struggle to substitute away to other sources of funding when community banks contract their loan supply. On the other hand, noncommunity banks cater to larger borrowers with better access to financial markets are private funding channels. Given that these mechanisms are indeed the cause of heterogeneous monetary transmission within the lending channel, these results also imply that the sustained decline in output in response to contractionary monetary policy may largely be at the expense of small business activity. Moreover, although the ongoing decline in the presence of community banks may lessen this burden on small borrowers, it may weaken the persistence of monetary policy transmission in the medium run. These results contribute to the literature on the credit channel by documenting how differences in bank business models (relationship vs. transactional lending) may affect the aggregate transmission of monetary policy. They also raise important questions about the broader economic consequences of compositional changes in the banking sector, and highlight the often-underappreciated macroeconomic relevance of community banks.

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Appendices

A Baseline Results

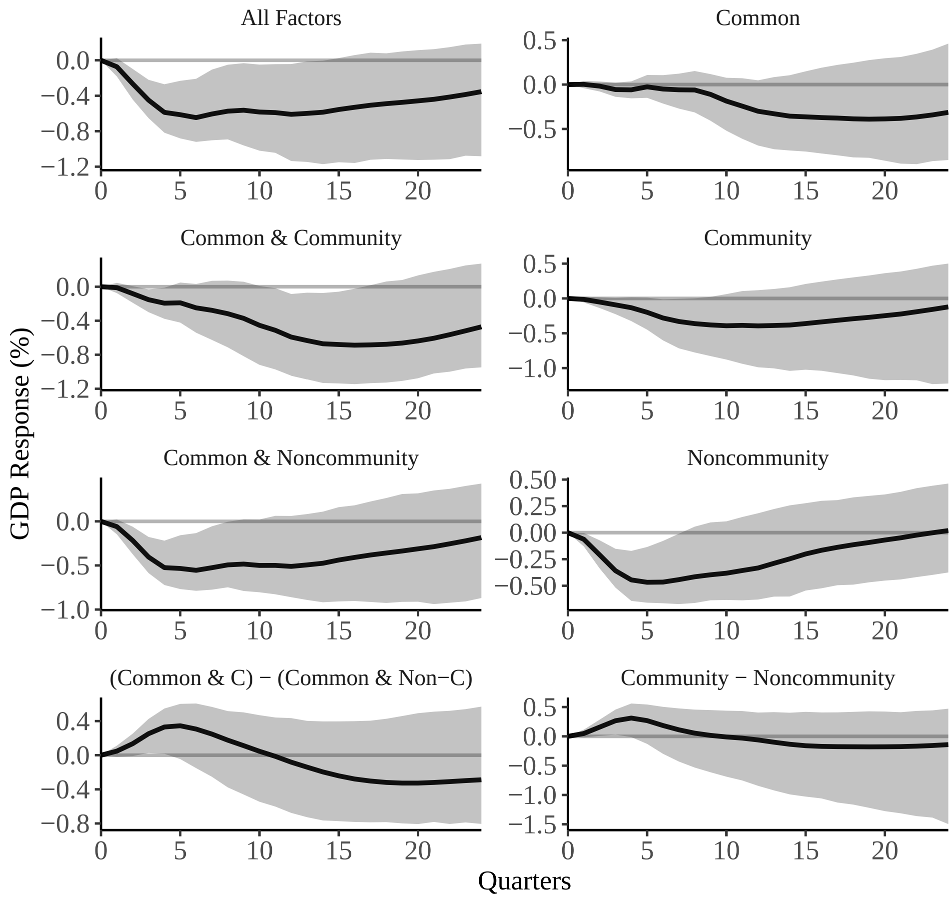


Figure A.1: PT-IRs of GDP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

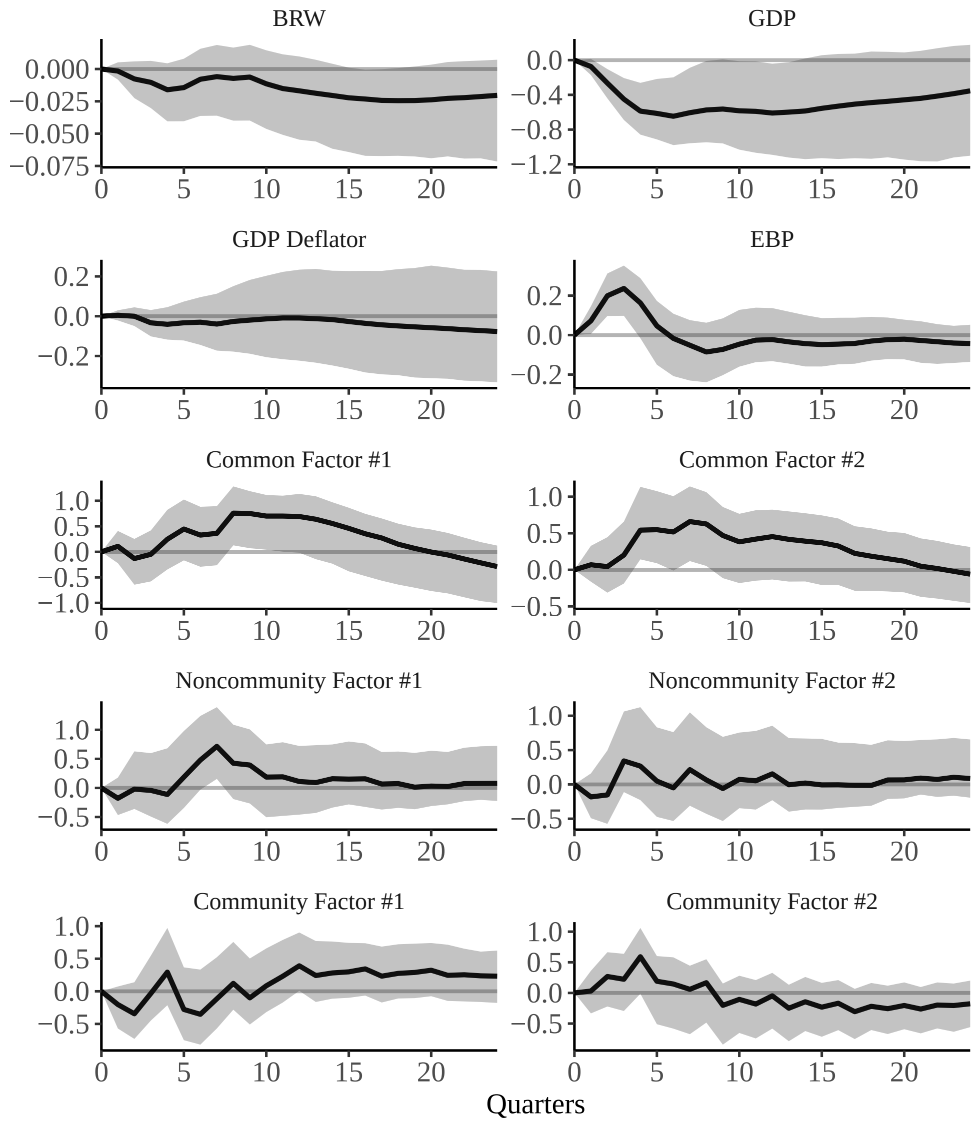


Figure A.2: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

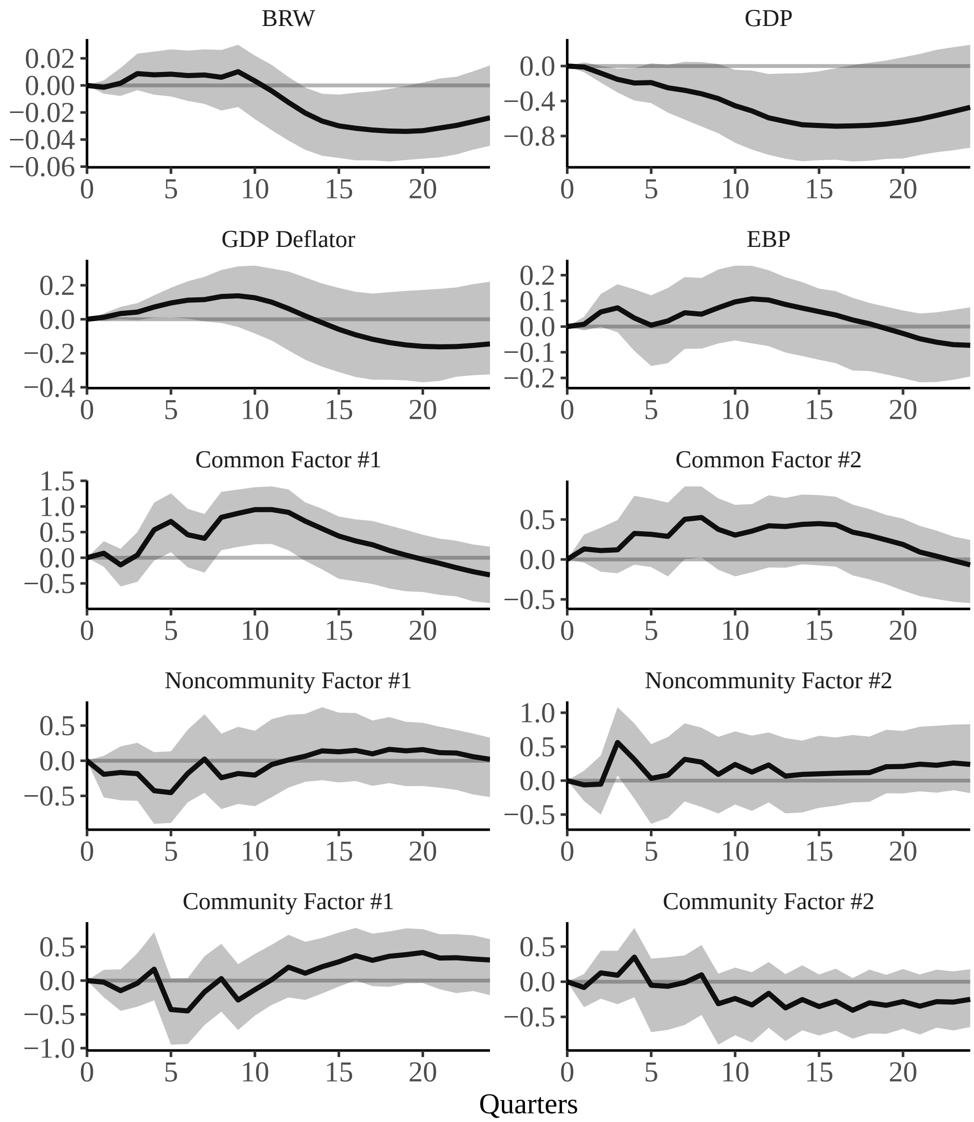


Figure A.3: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

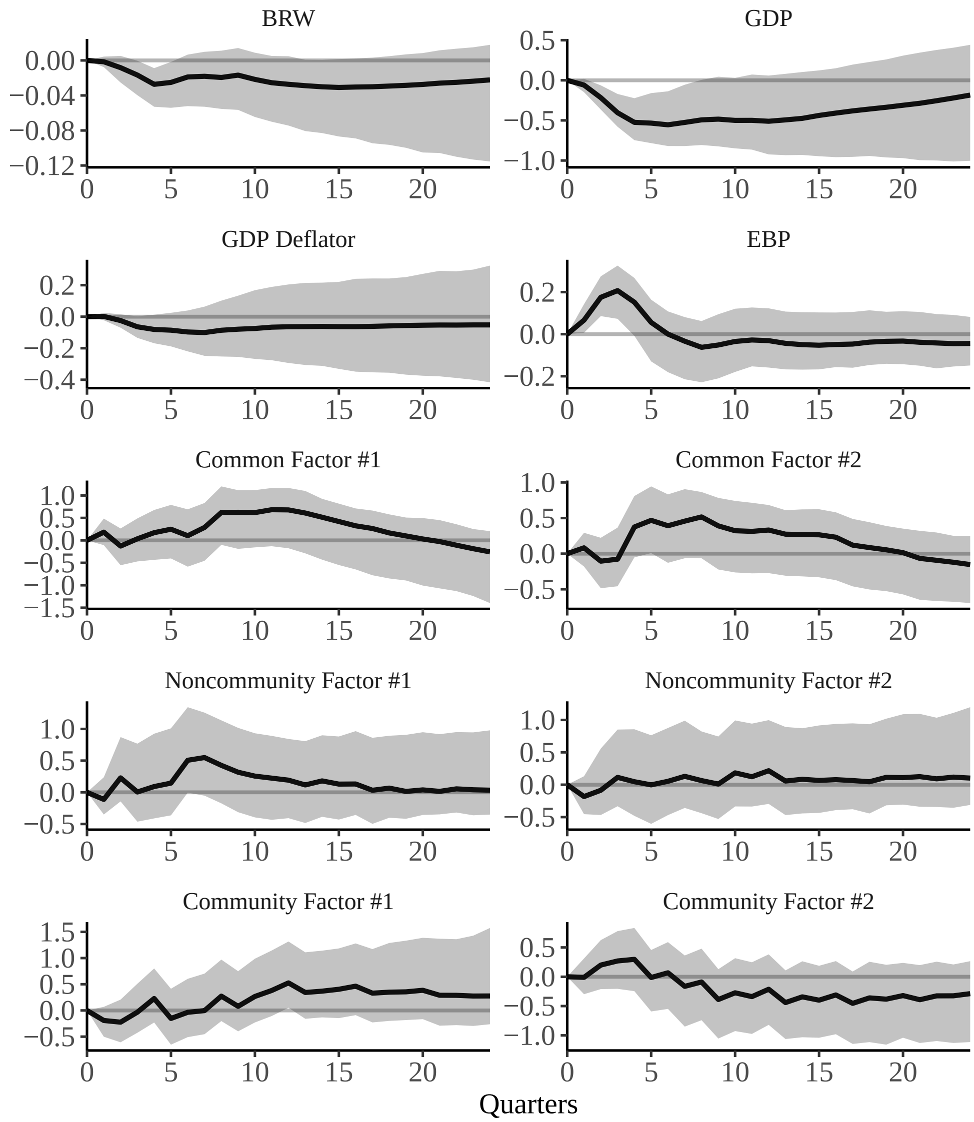


Figure A.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

B Robustness: Alternative Output and Inflation Proxies

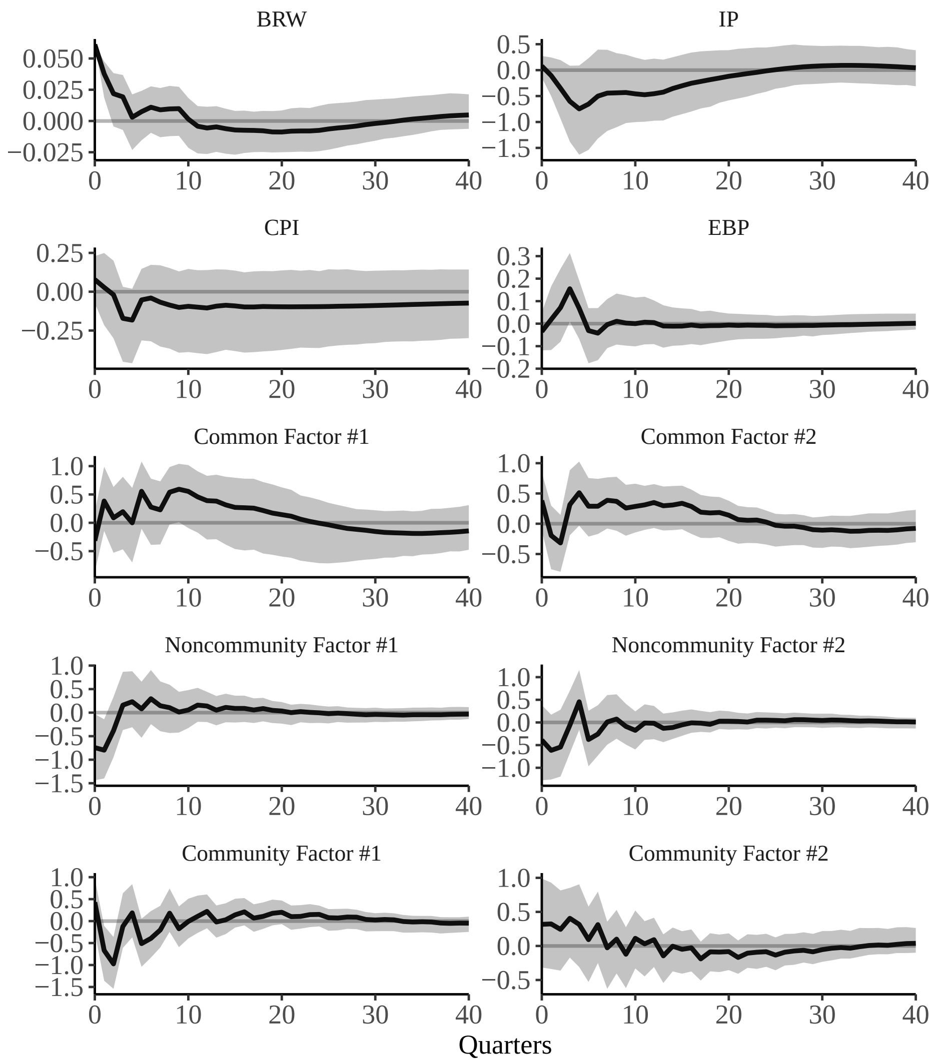
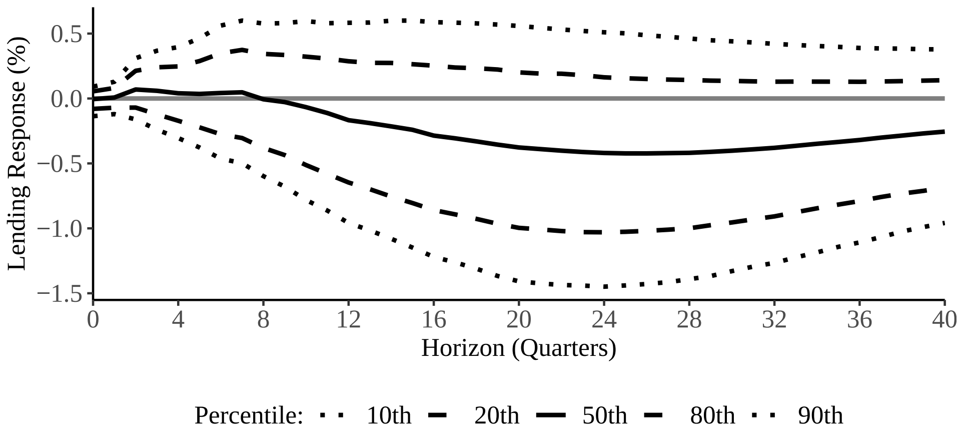
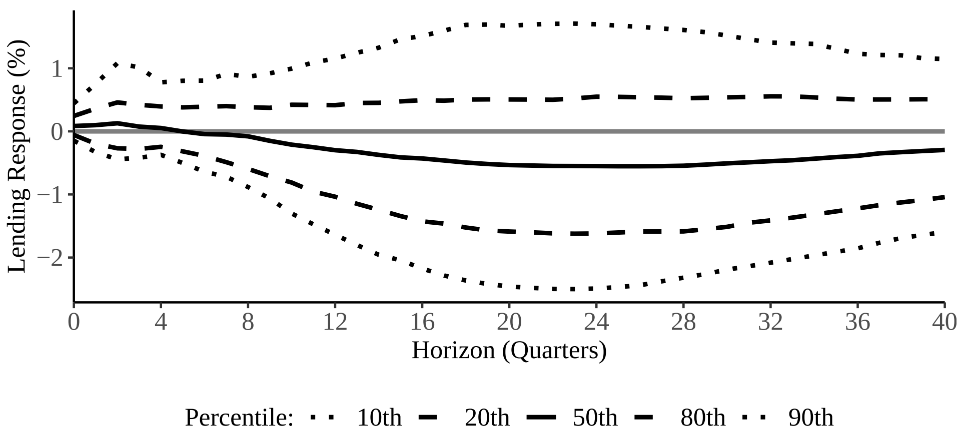


Figure B.1: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

Figure B.2: The distribution of cumulative bank-level loan growth rate responses to a one standard deviation positive (contractionary) monetary policy shock.

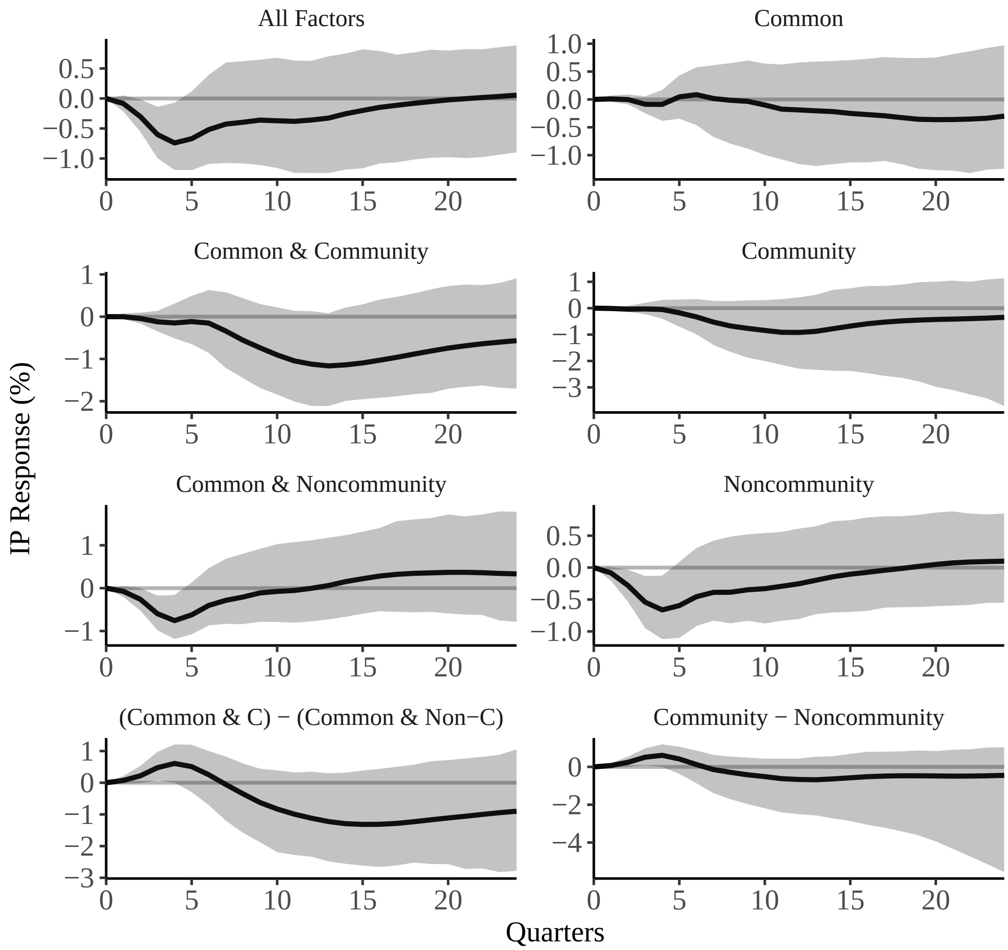


Figure B.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

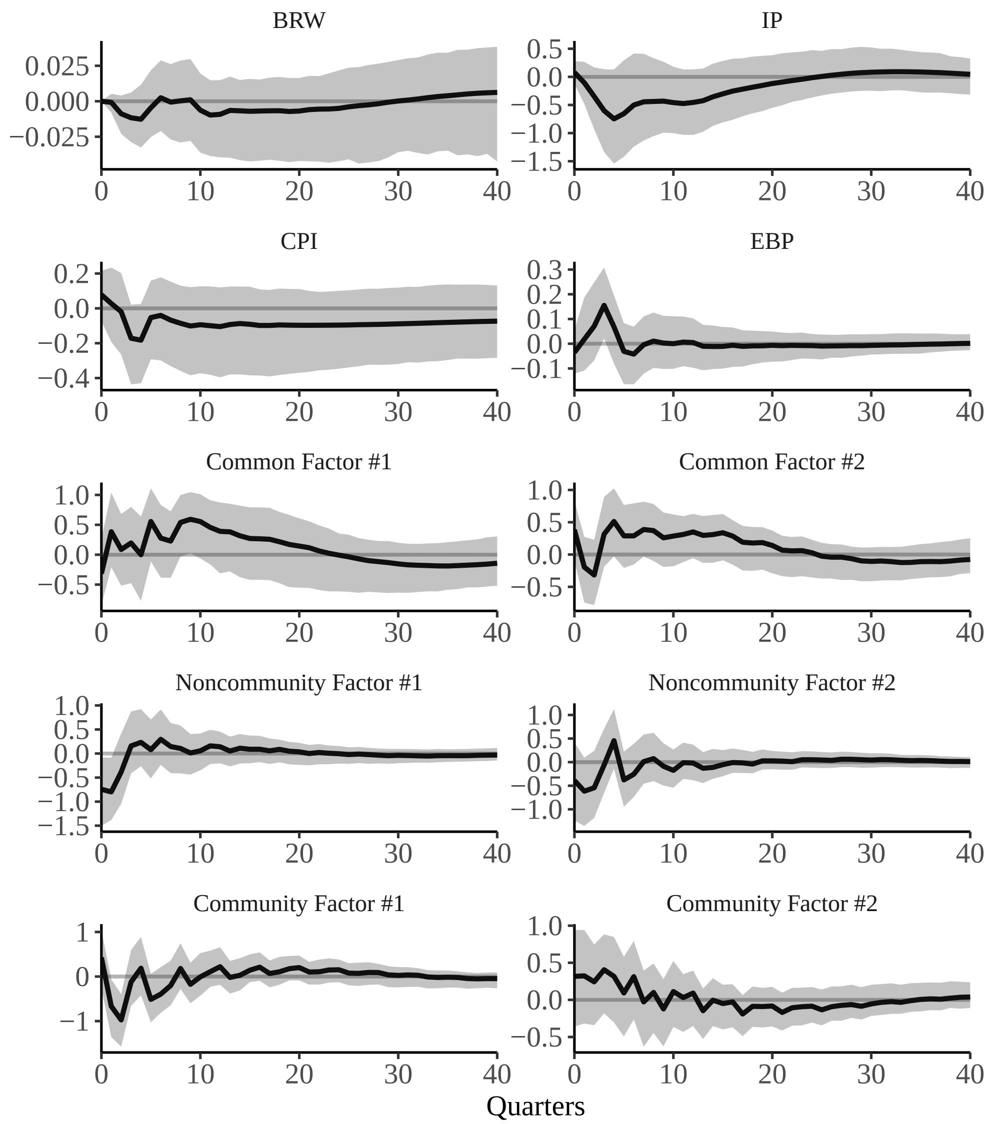


Figure B.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

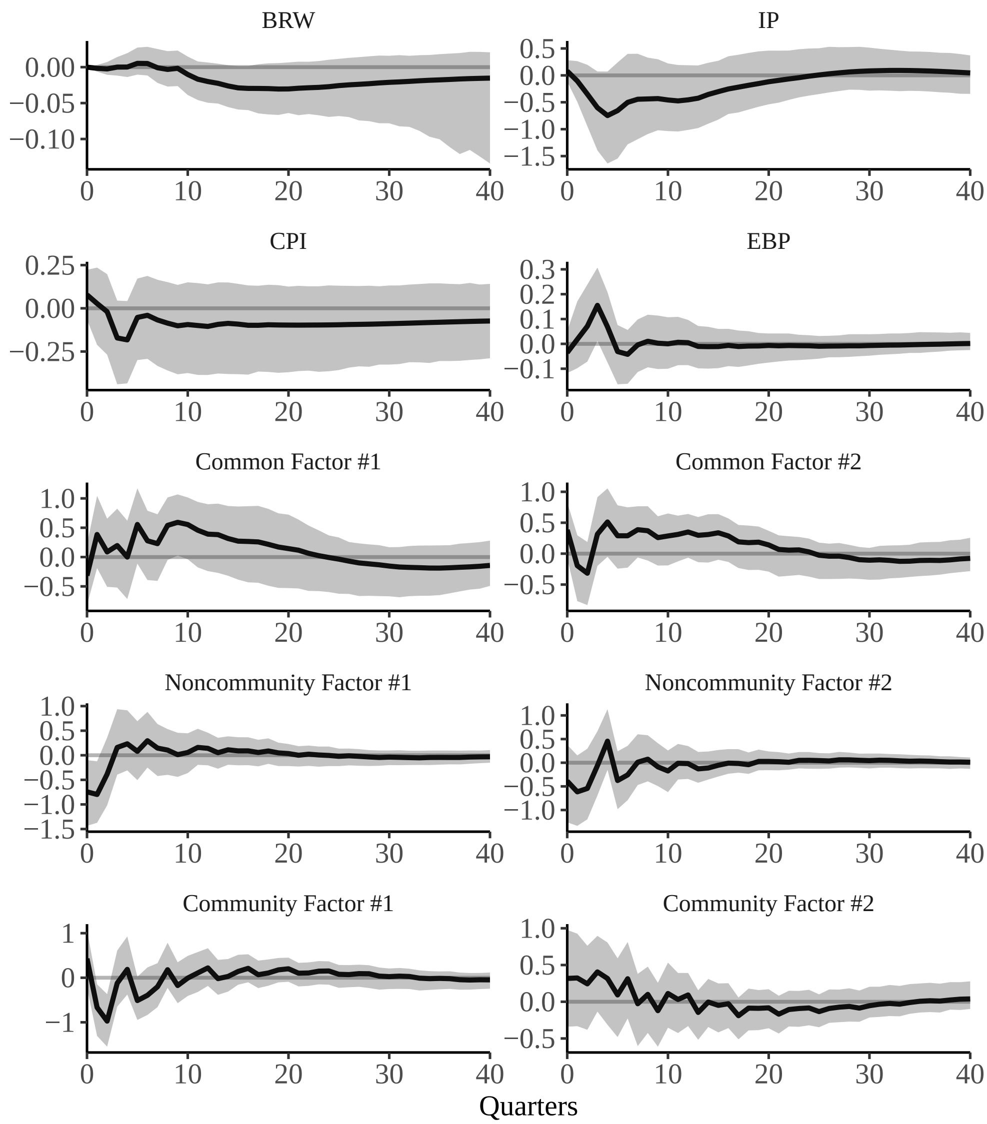


Figure B.5: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

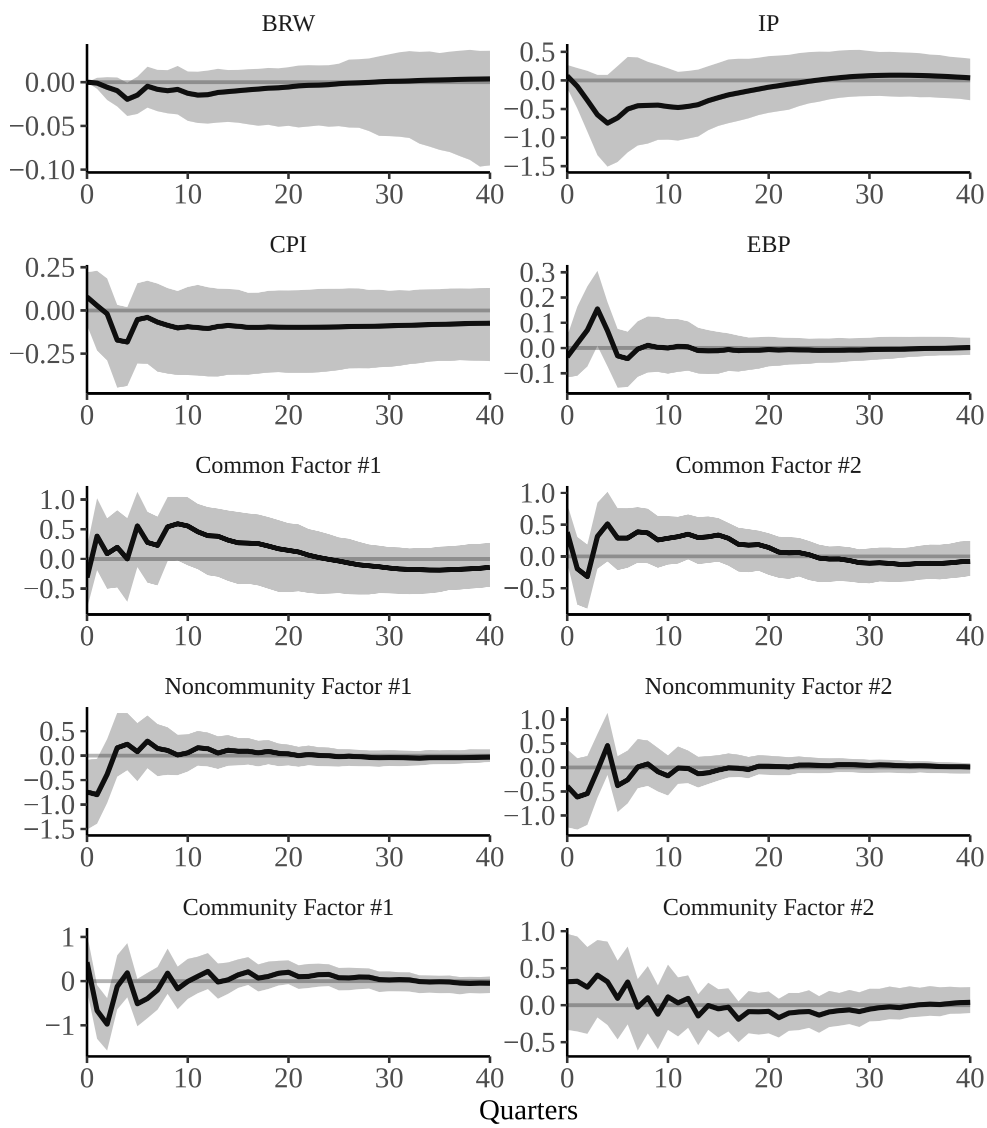


Figure B.6: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.