Monetary Transmission Through Community and Noncommunity Bank Lending

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Abstract

This paper develops a horizon-by-horizon decomposition of impulse responses to quantify how monetary policy shocks transmit to U.S. real activity through community and noncommunity bank lending. Endogenous responses in lending by both bank types are shown to amplify the output effects of monetary policy, but with distinct timing: noncommunity bank lending contributes more at short horizons, whereas community bank lending contributes with greater delay and persistence. The evidence suggests that this bank-type heterogeneity reflects differences in the responsiveness of output to lending, rather than differences in how strongly lending responds to monetary policy shocks.

JEL Classifications: G21; E51; E52

Keywords: Community banks; FAVAR; lending channel; monetary policy

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1 Introduction

Monetary policy in the United States is transmitted to the real economy through a banking system that has been gradually evolving in recent decades. Consolidation and regulatory change have steadily reallocated intermediation away from small, local, relationship-oriented *community* banks and toward typically larger, geographically diversified, transaction-oriented commercial banks.[1] Consistent with this shift, community banks' collective shares of loans and assets have trended downward as concentration has risen (see Figure 1). This ongoing compositional change is economically consequential because community banks disproportionately supply credit to bank-dependent borrowers, especially small firms. Since small firms employ nearly half of private-sector workers in the U.S., monetary policy–induced movements in community bank lending may be an important driver of real activity. Additionally, community and noncommunity banks may transmit monetary shocks differently, consistent with their contrasting business models. Continued compositional changes in the banking sector could therefore reshape both the aggregate strength and the distributional incidence of monetary policy. Yet the literature remains unsettled on whether lending adjustments by community versus noncommunity banks ultimately amplify or attenuate monetary policy's real effects, and on the extent of heterogeneity in those mediation effects.

Motivated by this uncertainty, this paper tackles two questions. First, to what extent does monetary policy transmit to aggregate output through lending by community versus noncommunity banks? I find that both community and noncommunity bank lending amplify the transmission of monetary policy shocks to aggregate output. However, monetary transmission via noncommunity bank lending is stronger in the short run (peaking within roughly two years), whereas propagation via community bank lending peaks and persists at a longer horizon. Because community banks' transmission contributions emerge more strongly at longer horizons, a continued decline in their

[1] I use the Federal Deposit Insurance Corporation (FDIC) definition of a community bank, which is designed to capture banks' business model characteristics beyond size (FDIC, 2012; Allen et al., 2022; Petropoulou et al., 2025). I designate all other FDIC-insured commercial banks as noncommunity banks. See Appendix A for more details on the FDIC definition.

market share may attenuate the persistence of the real aggregate effects of monetary policy. The results highlight that bank sector composition is a relevant mediator for aggregate monetary policy transmission.

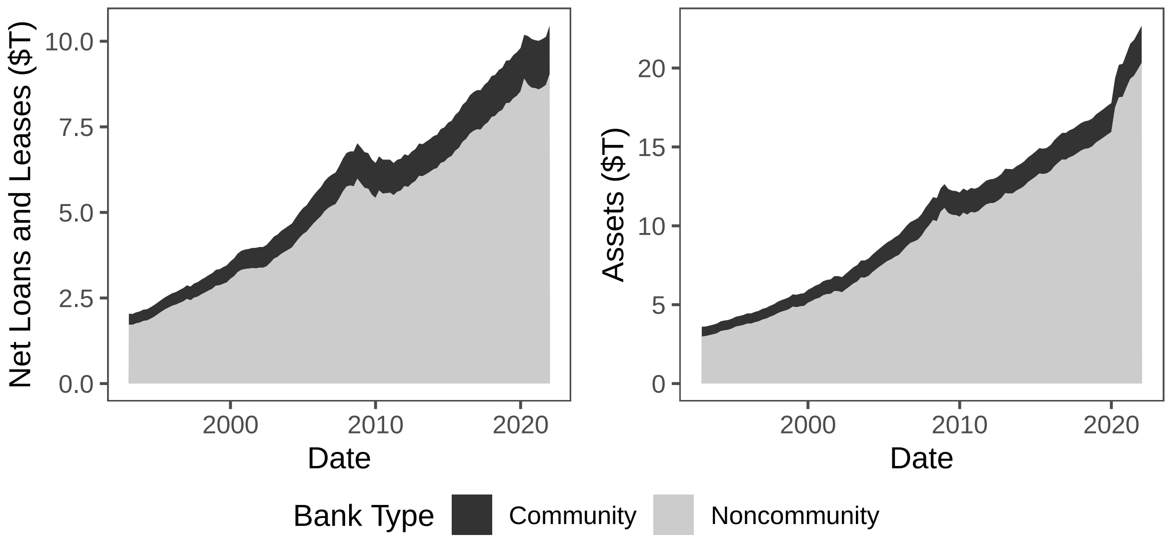


Figure 1: *Left Panel:* Total net loans and leases by bank type. *Right Panel:* Total assets by bank type. *Source:* FDIC Statistics on Depository Institutions.

The second question is whether the observed heterogeneity occurs due to differences in how community and noncommunity banks adjust lending to policy shocks, or because of differences in how their respective lending responses affect aggregate economic activity. The evidence presented in this paper is consistent with the latter narrative: lending responses to policy shocks are broadly similar across the two bank categories, so the more persistent real monetary transmission via community banks appears to reflect differences in the lending-to-output leg of the propagation path. This finding is consistent with a relationship between community bank lending and output that is distinct from that of noncommunity bank lending. This heterogeneous relationship is unlikely to be captured entirely by differences in size, considering the multi-dimensional nature of the FDIC community bank definition (see Appendix A), as well as the significant overlap in the asset size distribution of community and noncommunity banks (as shown in Table 3 in Appendix A). This suggests that the heterogeneity in monetary transmission is likely driven by differences in the business model.

In the baseline empirical analysis, I identify monetary policy shocks externally using the methodology developed by Bu et al. (2021). To quantify and compare the contributions of community and noncommunity bank lending to aggregate monetary transmission, I estimate pass-through impulse response functions (PT-IRFs) in a factor-augmented vector autoregression (FAVAR). A PT-IRF is a propagation accounting method that isolates the portion of a total impulse response that propagates through a designated set of mediating variables. In this study, the mediators of interest are a set of factors that capture lending dynamics common to all, community, and noncommunity banks, respectively. The PT-IRFs empirically quantify the portion of the total response of the aggregate variables in the VAR that can be attributed to endogenous feedback of monetary policy shocks via the lagged effects of these bank lending factors. The result is a sequence of horizon-by-horizon measures of monetary transmission contributions of (i) all bank lending factors, (ii) community bank lending factors, (iii) noncommunity bank lending factors, and (iv) various combinations of these three sets of factors that capture interaction effects. I compare the estimated PT-IRFs to assess which segment transmits more strongly at each horizon.

Contributions. A recurring limitation in the lending channel literature is that many empirical designs speak to only one link in the policy-to-lending-to-output transmission chain, rather than the full process. Some studies estimate how monetary policy shocks affect bank lending, while others study how changes in bank lending affect real activity. The literature does not provide a single measure that summarizes the joint, dynamic importance of the full propagation path — the combined effect of monetary policy on bank lending, and the subsequent endogenous effect of bank lending on output. As a result, even when changes in lending are shown to matter for real outcomes, it remains unclear how this relationship contributes to the propagation of monetary policy shocks via endogenous lending (Peek and Rosengren, 2000; Peek et al., 2003; Driscoll, 2004; Ashcraft, 2006; Lown and Morgan, 2006; Dave et al., 2013). This paper addresses this gap by estimating horizon-by-horizon transmission contribution measures using PT-IRFs. PT-IRFs quantify monetary transmission through bank lending as a combination of two components that are intrinsically non-separable in a dynamic effects setting: (i) the dynamic effect of a monetary policy shock on lending, and (ii) the endogenous feedback from lending to output. I estimate these combined transmission metrics separately for community and noncommunity banks.

Another challenge is that evidence on lending channel mechanisms typically comes from one of two levels of observation that are hard to reconcile. Identification-driven micro designs using bank- or loan-level data deliver sharp evidence on how lending and balance sheet items respond to monetary policy and how those responses vary across banks and borrowers (Kashyap and Stein, 2000; Kishan and Opiela, 2006; Jiménez et al., 2012, 2014; Drechsler et al., 2017), but they often abstract from cross-channel spillovers and general-equilibrium feedback that are central for the aggregate effects of policy. Conversely, work that studies the effect of credit shocks on real outcomes can be informative about aggregate effects. However, studies in that area identify exogenous changes in credit (Peek and Rosengren, 2000; Peek et al., 2003; Driscoll, 2004; Morais et al., 2019). This paper bridges these approaches by using bank-level lending data to construct community and noncommunity lending factors and then embedding those micro-based dynamics in an aggregate FAVAR to quantify each segment's contribution to monetary transmission. This strategy is closely related to factor-augmented VAR approaches that incorporate information from large panels of bank-level balance-sheet data into macro models (Buch et al., 2014). Relative to (Buch et al., 2014), I use bank-level lending factors to quantify the endogenous feedback from lending back to aggregate output following monetary policy shocks, and I do so separately by bank type.

Finally, the literature on heterogeneous bank transmission has largely captured bank heterogeneity using balance-sheet characteristics such as size, liquidity, and capitalization, as well as organizational form (Bernanke and Blinder, 1988; Kashyap and Stein, 1995; Kishan and Opiela, 2000; Bluedorn et al., 2017). While informative, these dimensions do not fully reflect the stable business model features that distinguish relationship lenders from transactional lenders. These features include soft-information production, a local market orientation, and limited geographic reach, all of which are especially salient for community banks (FDIC, 2020; Liberti and Petersen, 2018; Berger and Black, 2011; Mkhaiber and Werner, 2021). Consistent with the view that bank credit markets remain local, reductions in local bank presence due to branch closings generate persistent declines in nearby small-business lending (Nguyen, 2019). More broadly, consolidation and geographic integration can reshape the allocation of bank credit across space (Strahan and Weston, 1998) and enable internal capital markets that reallocate funding across regions in response to shocks (Cortés and Strahan, 2017). This paper therefore assesses heterogeneity through a business-model lens using the FDIC community bank classification, which provides a policy-relevant, multi-dimensional categorization that links the relationship-banking literature to aggregate monetary transmission.

Outline. The remainder of the paper proceeds as follows. Section 2 presents the econometric approach, including the hierarchical factor construction, the FAVAR specification, and the PT-IRF decomposition. Section 3 presents the baseline results and robustness checks. Section 4 concludes.

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 (see Table 4 in Appendix A). 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, 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. I then use the estimated FAVAR to 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. between Q1-1995 and Q4-2019, 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. 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.

Table 1 summarizes the construction of the bank-level panel used to estimate the lending factors. Starting from 14,010 FDIC-insured commercial banks observed with uneven reporting histories, imposing a balanced-panel requirement yields a set of 3,795 banks observed in every quarter of the sample (3,495 community and 300 noncommunity). Transforming lending levels into quarterly growth rates results in a final sample of 3,782 banks and 108 quarterly growth observations per bank. The balanced-panel restriction is substantially more binding for noncommunity banks, reflecting greater entry/exit and consolidation among those institutions over the sample window. The balanced-panel restriction is required for the recursive principal-components procedure used to estimate hierarchical lending factors, ensuring that changes in the factors reflect changes in comovement rather than changes in the cross-sectional composition of banks. Accordingly, the factor estimates (and all subsequent impulse responses) should be interpreted as describing the lending dynamics of banks that operate continuously over the sample period.

The following macroeconomic series used in the VAR are obtained from the Federal Reserve Economic Data (FRED) database: Real Gross Domestic Product (GDPC1; Baseline

Table 1: Sample Construction and Attrition

Step	Type	N Banks	N Obs.	Avg. Obs./Bank
(1) All commercial banks	Community	10,418	696,488	66.9
	Noncommunity	3,592	136,903	38.1
	Total	*14,010*	*833,391*	*59.5*
(2) Balanced panel	Community	3,495	380,955	109.0
	Noncommunity	300	32,700	109.0
	Total	*3,795*	*413,655*	*109.0*
(3) Growth Rates	Community	3,493	377,244	108.0
	Noncommunity	289	31,212	108.0
	Total	*3,782*	*408,456*	*108.0*

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

To identify monetary policy shocks, I use the Bu–Rogers–Wu (BRW) monetary policy shock series (Bu et al., 2021). [2] I aggregate the BRW shocks to the quarterly frequency, as shown in Figure 2. I prefer the BRW series to alternative measures in the literature, including Romer and Romer (2004) and Nakamura and Steinsson (2018) (see also the discussion in Ramey (2016)), because BRW is designed to provide a consistent policy-surprise measure that spans both conventional and unconventional monetary policy. This feature is particularly important for my sample, which includes multiple shifts in the monetary policy operating regime and an extended zero lower bound episode following the 2007–08 financial crisis.

The VAR also includes the excess bond premium (EBP), one of the two components of the corporate credit-spread indicator introduced by Gilchrist and Zakrajšek (2012). [3] As

[2] In Appendix E, I assess robustness by re-estimating the analysis using the Jarociński–Karadi (JK) monetary policy shock series (Jarociński and Karadi, 2020).

[3] The EBP is the portion of the average corporate bond spread that is orthogonal to expected default

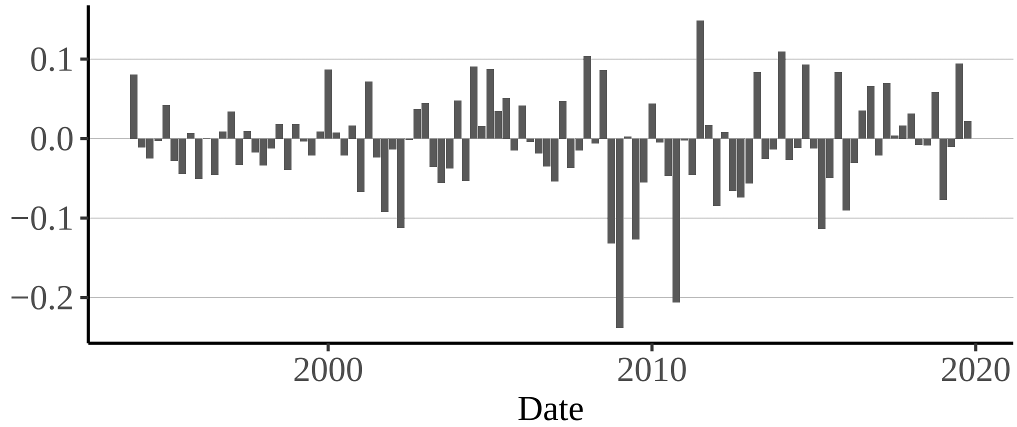


Figure 2: Quarterly BRW monetary policy shock series.

such, the EBP is commonly interpreted as a proxy for aggregate credit supply conditions, reflecting the effective capacity of financial intermediaries to extend credit. Because it embeds high-frequency, forward-looking information from corporate bond markets, including the EBP can improve the informational content and forecasting performance of small-scale VARs (Caldara and Herbst, 2019). Accordingly, modern monetary policy VARs frequently treat the EBP as an endogenous variable to capture time-varying financial conditions and the strength of credit market frictions. Bu et al. (2021) also include the EBP in the monthly VARs they use to validate their monetary policy shock measure. In this paper, I include the EBP for two reasons. First, it aligns the specification with a now-standard convention in the empirical monetary literature. Second, it facilitates comparability by closely mirroring the VAR environment used by Bu et al. (2021) to study the effects of monetary policy.

2.2 Model

The FAVAR has two components. First, it imposes a hierarchical factor structure on a large panel of bank-level loan-growth series. Second, it embeds the resulting lending

losses, and is therefore interpreted as a price-of-risk or intermediary-balance-sheet component rather than default compensation.

factors in a monetary VAR together with a set of aggregate macrofinancial variables. The factor structure extracts the latent drivers of comovement in bank lending growth both across the full cross section of banks and within community and noncommunity bank groups. Equivalently, the model includes economy-wide lending factors that load on all banks, as well as group-specific factors that capture residual comovement unique to each bank type.[4] The VAR then characterizes the joint dynamics among the lending factors, the aggregate macroeconomic variables described in the previous section, and monetary policy.[5]

The hierarchical factor structure for the loan-growth series x_{it} of bank i is

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

where t indexes time and $j_i \in \{\text{community}, \text{noncommunity}\}$ denotes the type of bank i. The vector F_t collects lending-growth factors common to all banks, while $F_t^{j_i}$ collects factors common only to banks of type j_i. The intercept α_i captures bank-specific average growth, Γ_i and Λ_i are the corresponding factor-loading vectors, and u_{it} is an idiosyncratic component. In words, loan growth at bank i is modeled as an affine function of (i) economy-wide lending comovement, (ii) additional comovement specific to the bank's type, and (iii) a residual term capturing bank-level dynamics not explained by the common components. Eq. (1) therefore provides a basis for jointly estimating the latent factors and their heterogeneous bank-level loadings.

The baseline VAR is specified by the following equation:

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

[4]In this sense, the factors can be viewed as time-varying common and group-specific loan-growth components (akin to fixed effects) with heterogeneous bank-level sensitivities given by the factor loadings.

[5]Although the estimated lending factors are latent objects and need not admit a simple structural interpretation, their impulse responses can be combined with the estimated factor loadings to recover bank-specific impulse responses. For example, the FAVAR can be used to trace the implied distribution of bank-level 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, and EBP denote the cumulative BRW shock series (see Figure 3), gross domestic product, GDP deflator, and the 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.[6]

Together, Eqs. (1) and (2) describe the FAVAR in state space form, where the former is the measurement equation and the latter the transition 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.

[6] 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.

2.3 Shock Identification

I identify monetary policy shocks in a recursive structural VAR (SVAR) augmented with an externally constructed policy-shock series. Let z_t denote the cumulative BRW measure. I place z_t first in the VAR and define the monetary policy shock as the Cholesky-orthogonalized innovation to z_t; all remaining variables are allowed to respond contemporaneously to this innovation.[7] This ordering-based identification is the direct analogue of standard recursive SVAR identification used widely in empirical macroeconomics (e.g., Kilian, 2009). Alternative implementations exploit the same type of external information by using the shock series as an instrument in a proxy SVAR (Stock and Watson, 2018; Caldara and Herbst, 2019; Jarociński and Karadi, 2020) or as an exogenous regressor in local projections (e.g., Auerbach and Gorodnichenko, 2012).[8] Under standard regularity conditions, however, VARs and local projections target the same population impulse responses, and proxy (external-instrument) identification can be implemented by ordering the instrument first in a recursive VAR (up to the normalization of the shock) (Plagborg-Møller and Wolf, 2021). I therefore include the policy shock series directly in the VAR because it simplifies inference for PT-IRFs.

Figure 3 plots the cumulative BRW monetary policy series used as the first variable in the recursive SVAR. The underlying BRW innovations are constructed from high-frequency yield-curve movements around FOMC announcements and are best interpreted as surprises to the expected path of policy, which can shift financial conditions persistently. For macrofinancial transmission, the relevant state variable is therefore the level of the policy stance implied by the history of these meeting-day surprises, rather than the (typically sparse) one-period innovations themselves. Accordingly, I cumulate the quarterly BRW innovations and enter the resulting level series z_t in the VAR, so that Δz_t

[7]A common variant treats the external shock series as strictly exogenous by excluding the lags of the endogenous variables from the z_t equation (and, in the extreme, setting all of its lag coefficients to zero), which yields a VAR with exogenous regressors (VARX); see, e.g., Paul (2020). In the baseline model I do not impose such exogeneity restrictions on the slope parameters; Appendix D shows that imposing VARX-style restrictions delivers essentially identical IRFs and PT-IRFs.

[8]For detailed comparisons of these estimators, see Stock and Watson (2018), Plagborg-Møller and Wolf (2021), Caldara and Herbst (2019), and Paul (2020).

corresponds mechanically to the BRW surprise realized in quarter t. This transformation lets the VAR treat monetary policy as a persistent stance variable and avoids the counterfactual implication that policy "resets" after each meeting if the raw BRW shock were entered in levels. This convention follows the narrative and externally identified VAR literature (e.g., Romer and Romer (2004)) and the recommended implementation of the BRW measure in Bu et al. (2021), and it yields impulse responses that can be interpreted as the effects of an unexpected change in the policy stance.

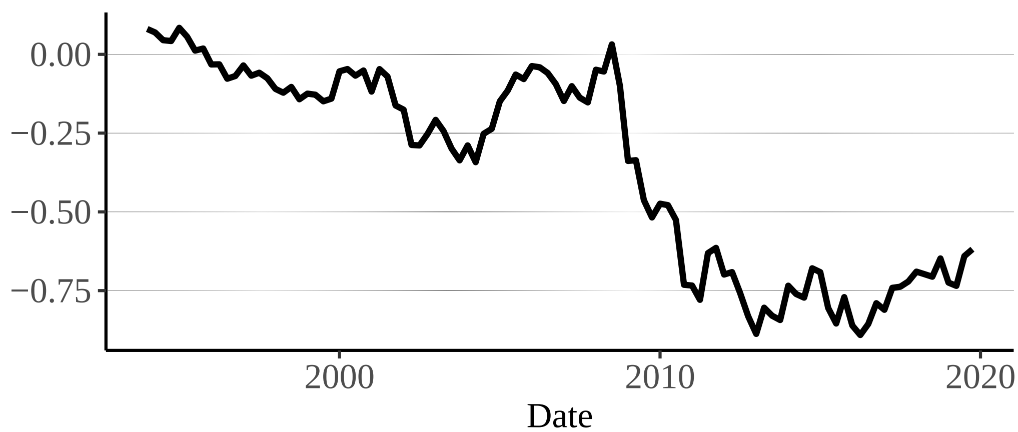


Figure 3: Cumulative quarterly BRW monetary policy shock series.

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).[9]

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

[9]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).

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 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 4 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.[10] A few items of note

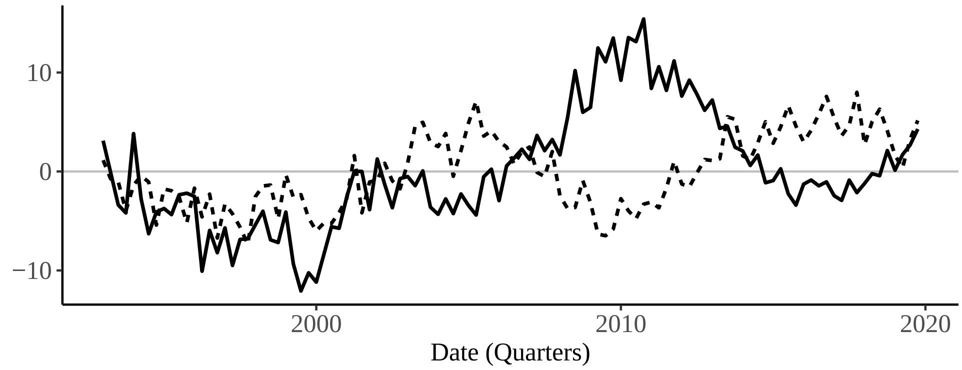
[10]The estimation procedure ensures that the different categories of factors capture orthogonal variation, despite loading on some of the same series. The community and noncommunity bank lending factors are orthogonal to each other, given that all common variation across the set of all banks in the sample is successfully absorbed by the common bank lending factors.

include the following:[11] (1) In Figure 4a, 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 4b with the noncommunity bank factors in Figure 4c 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.

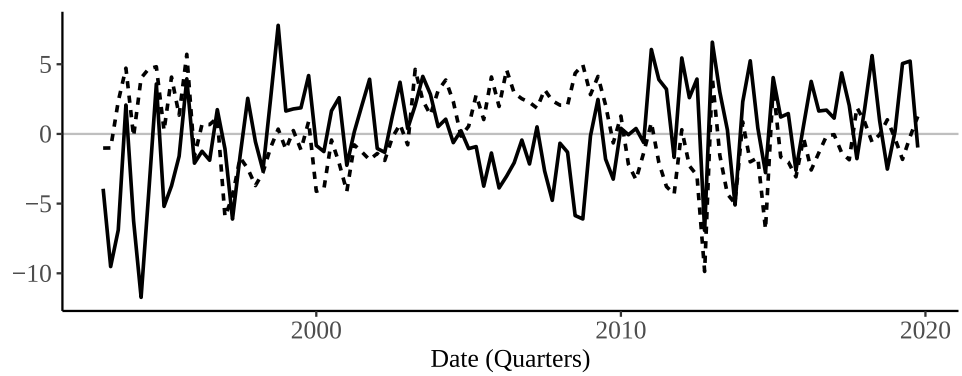
For each category of factors, I extract the first two principal components. Table 2 shows the distribution of R^2 coefficients obtained by regressing each standardized bank loan growth rate series on all of its corresponding bank lending factors, as well as only on the common lending factor. According 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.

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.

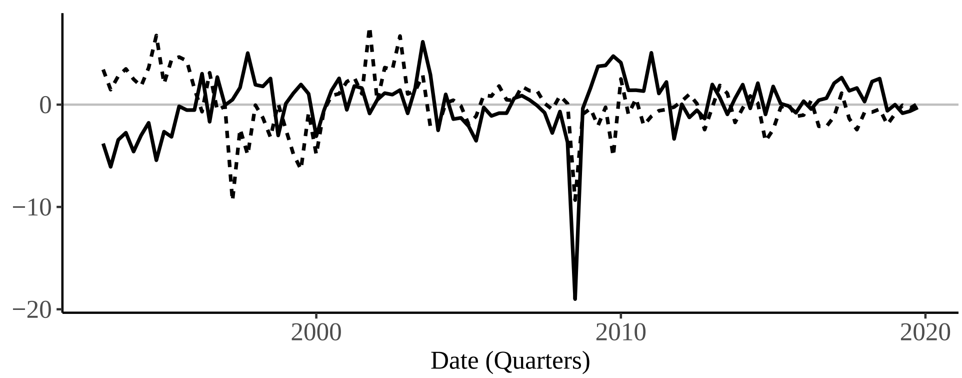
[11] The interpretation of the time variation in the factors is not the focus of the paper – rather, the factors are used for the purposes of dimension reduction.



(a) Common bank loan growth factors.



(b) Community bank loan growth factors.



(c) Noncommunity bank loan growth factors.

Figure 4: 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.

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

Table 2: 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.

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.[12] Consider the following VAR(1) process:

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

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

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

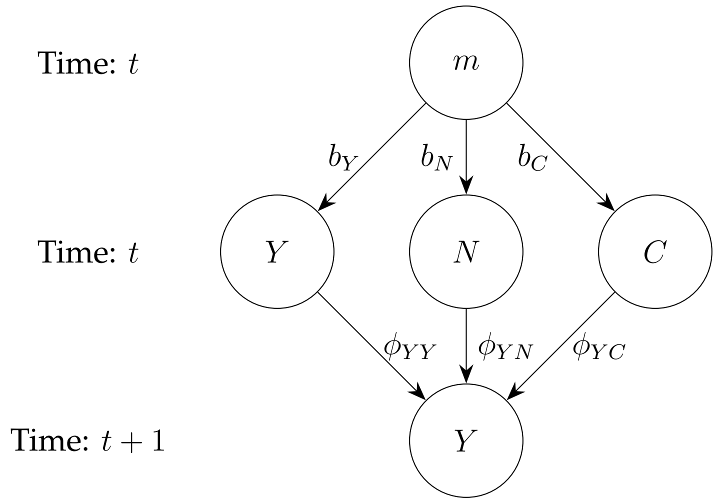


Figure 5: A graph-based illustration of the propagation of an impulse originating at m with destination Y one period ahead in the system determined by Eq. (5).

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 5 – 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 5 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:

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

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 5 – 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 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 $\overline{v}$ 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

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

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

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

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 that are defined over different sets of intermediate variables. Suppose that, for a given dependent variable i, we wish to compare PT-IR$(h, i, J, \overline{\varepsilon})$ and PT-IR$(h, i, J', \overline{\varepsilon})$ in order to assess whether transmission through the set J is stronger than transmission through the set J'. Define the difference

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

This object is itself a nonlinear mapping of the reduced-form parameters of the FAVAR state equation. Confidence intervals for ΔPT-IR$(h, i, J, J', \overline{\varepsilon})$ can be constructed using the same nonparametric bootstrap procedure used for IRFs and PT-IRFs, at the desired significance level. If, for a given horizon range, the confidence interval for ΔPT-IR$(h, i, J, J', \bar{\varepsilon})$ lies strictly above zero, then transmission through J is stronger than transmission through J' for variable i at those horizons. In the application, I use ΔPT-IR to compare the transmission of monetary policy shocks to output through community versus noncommunity bank lending.

3 Results

The baseline FAVAR delivers four main findings. **(i)** When the full set of bank-lending factors is treated as the mediating block in the PT-IRF decomposition, a contractionary monetary policy shock induces a persistent negative contribution of lending to the output response, consistent with the conventional bank-lending view of monetary transmission. **(ii)** Conditioning on the factors that load on *community* bank lending yields a negative lending-mediated output response, indicating that community banks contribute materially to the propagation of monetary policy shocks. **(iii)** Conditioning on the factors that load on *noncommunity* bank lending yields a similarly negative lending-mediated output response, underscoring the role of noncommunity intermediation in monetary transmission. **(iv)** Comparing the community- and noncommunity-conditioned PT-IRFs, the point estimates imply stronger short-horizon amplification through noncommunity bank lending (roughly the first two to three years), while amplification through community bank lending is more delayed and comparatively persistent at medium horizons. The short-run differences are estimated most precisely, whereas the medium-run reversal is less tightly pinned down by the confidence bands.

The qualitative conclusions are robust to a range of modifications to the baseline empirical design, as well as to alternative implementations of the hypothesis tests used to compare PT-IRFs. **(a)** Replacing GDP and the GDP deflator with industrial production and the CPI yields even more pronounced patterns than in the baseline specification (Appendix C). **(b)** Imposing VARX-style exogeneity restrictions in the policy-shock equation (zero restrictions on the relevant slope coefficients) produces IRFs and PT-IRFs that closely match the baseline estimates, with similar statistical significance (Appendix D). **(c)** Using the Jarociński–Karadi shock series in place of BRW yields qualitatively similar point estimates, albeit with less precise inference (Appendix E).

I begin by documenting the aggregate and bank-level impulse responses to an unexpected monetary tightening. I then present the PT-IRFs that quantify lending-based propagation and provide evidence of heterogeneous transmission through community versus noncommunity bank lending.

3.1 IRFs

Figure 6 reports impulse responses of all endogenous variables to a one standard deviation positive innovation to the BRW series (i.e., an unexpected monetary tightening). The cumulative BRW variable increases sharply on impact and then mean-reverts relatively quickly toward its pre-shock level. Real activity and prices adjust more gradually: GDP falls promptly but reaches its trough only after several quarters, and it remains below baseline for roughly five years, while the GDP deflator declines more persistently and remains negative over the full 10-year horizon.[13] The excess bond premium rises on impact and then gradually returns toward baseline, consistent with a tightening of credit conditions as in Bu et al. (2021). The individual lending factor responses are not directly interpretable in isolation; their main role is to recover bank-level responses via the estimated loadings, and their IRFs largely attenuate and become statistically indistinguishable from zero at longer horizons.

Figure 7 summarizes the cross-sectional distribution of banks' cumulative lending responses to a one standard deviation contractionary monetary policy shock, shown separately for community and noncommunity banks. For each bank i, I first recover its implied loan-growth IRF by combining the estimated lending-factor IRFs with the

[13] All references to statistical significance in this discussion are pointwise, based on the 90% bootstrap confidence bands, and do not reflect joint inference across horizons.

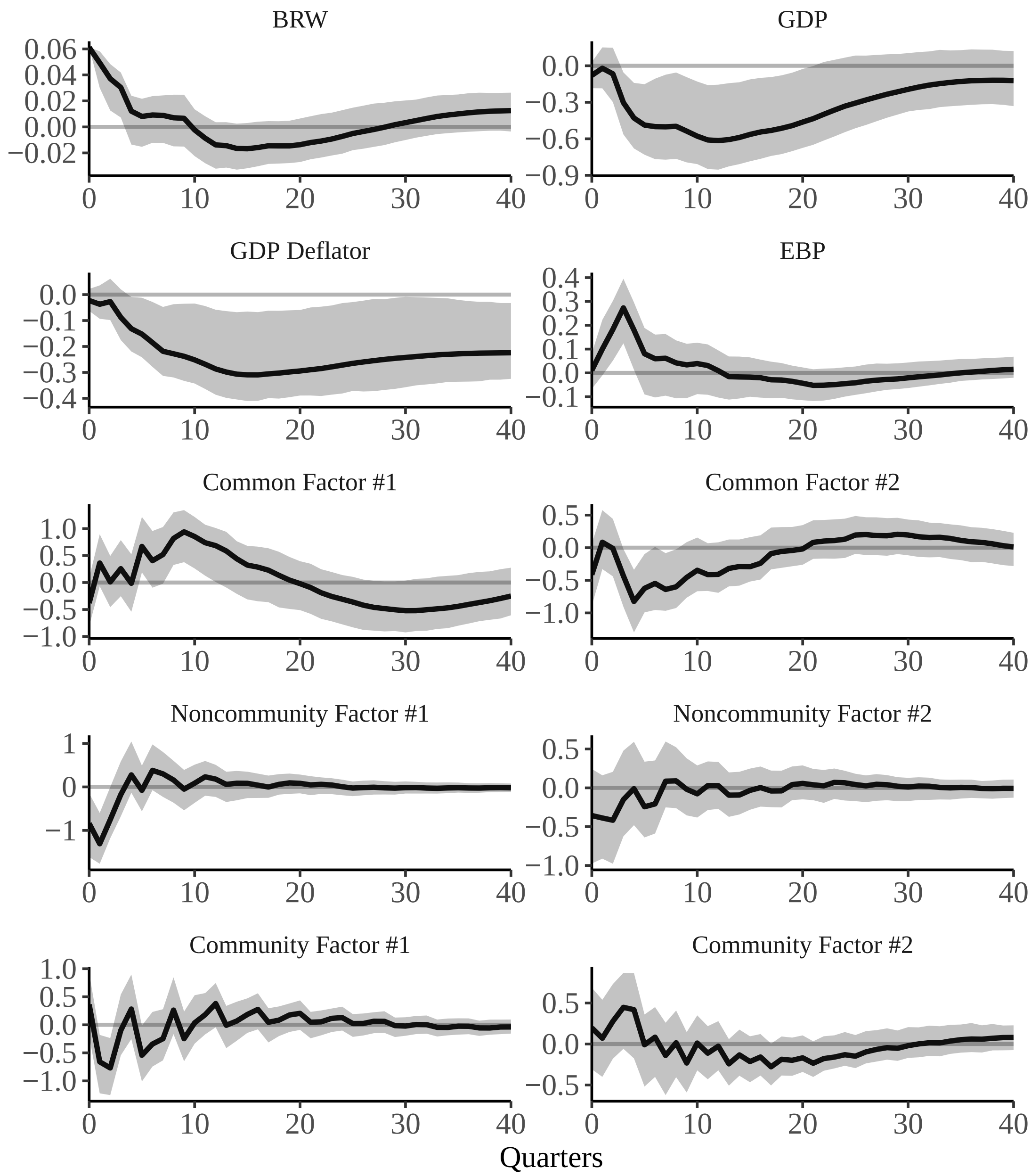
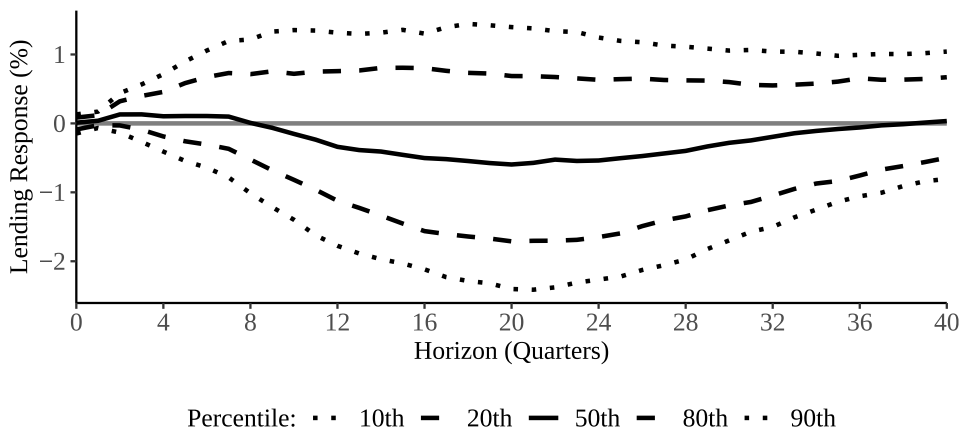


Figure 6: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.

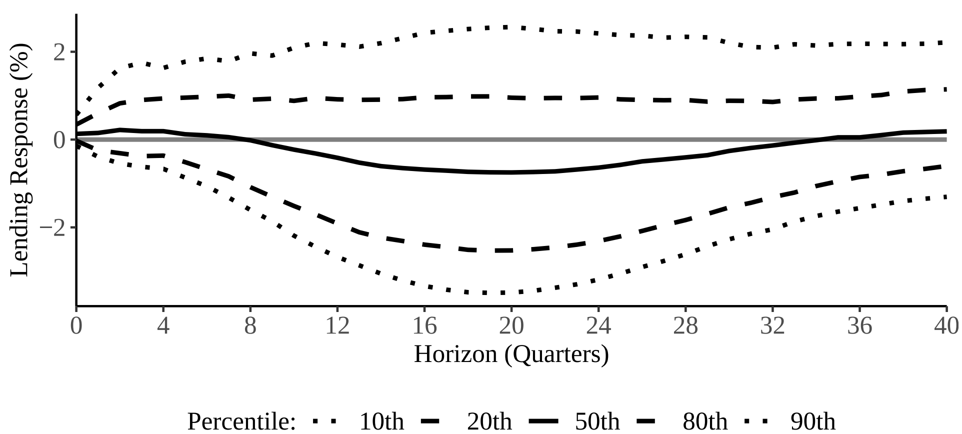
bank's estimated factor loadings from the measurement equation. I then cumulate the resulting loan-growth responses over the horizon to obtain each bank's cumulative lending response path. Finally, at each horizon I compute the 10th, 20th, 50th (median), 80th, and 90th percentiles of these cumulative responses within each bank-type subsample, and plot the resulting percentile paths in each panel. This procedure translates the dynamics of the latent lending factors into a transparent summary of heterogeneity in bank-level lending responses.

The percentile bands in Figure 7 indicate that a contractionary monetary policy shock is associated, on average, with a decline in cumulative lending for both community and noncommunity banks over the 10-year horizon. At the same time, the median response in each group gradually returns toward its pre-shock level by the end of the horizon, suggesting that the contraction in outstanding loan volumes is not permanent in the typical bank. Notably, over roughly the first two years, the cross-sectional distributions for both bank types are centered close to zero and exhibit small positive deviations at upper percentiles. A natural interpretation is that loan stocks may adjust with delay because drawdowns on previously committed credit lines can initially offset (or dominate) slower new loan origination following a tightening. This mechanism is consistent with the evidence in Ivashina and Scharfstein (2010) that commitment utilization can rise even as credit supply conditions tighten, producing a temporary resilience in observed loan volumes.

The baseline responses in Figures 6 and 7 are largely preserved across the three robustness exercises. Figures C.1, D.1, and E.1 report the corresponding aggregate IRFs. With the exception of the specification that imposes shock-exogeneity restrictions — which displays a modest price puzzle — the qualitative behavior of the macro variables and the lending factors is highly stable across models, both in shape and persistence. Figures C.2, D.2, and E.2 present the analogous bank-level lending-response distributions. In the alternative output/inflation specification and in the JK-based identification, the median lending response in both bank groups again exhibits a delayed contraction following a



(a) Distribution of community bank lending responses



(b) Distribution of noncommunity bank lending responses

Figure 7: The distribution of cumulative bank-level loan growth rate responses to a one standard deviation positive (contractionary) monetary policy shock.

tightening shock, with community bank lending reaching its trough at a later horizon.[14] Under the shock-exogeneity restrictions, the median responses in both groups also decline with delay, but the contraction is more persistent and does not fully revert to baseline within the plotted horizon.

3.2 PT-IRFs

Figure 8 plots pass-through impulse response functions (PT-IRFs) for GDP in response to a one standard deviation contractionary monetary policy shock. Panel (a) conditions on the full set of bank-lending factors as the mediating block, while Panels (b) and (c) condition on the factor subsets that load on community and noncommunity bank lending, respectively. Across all three panels, the lending-mediated component of the GDP response is negative, indicating that endogenous lending dynamics *amplify* the contractionary effects of monetary tightening. Comparing Panels (b) and (c), the point estimates suggest that amplification via noncommunity bank lending is larger at short horizons, whereas amplification via community bank lending is more delayed and comparatively persistent at medium horizons.

Figure 8a reports the PT-IRF of GDP to a one standard deviation contractionary monetary policy shock when the full block of bank lending factors is designated as the transmission medium. Because this conditioning set includes the common lending factors as well as both type-specific factor blocks, I interpret this PT-IRF as the lending-mediated component of monetary transmission through the banking sector as a whole. The estimated contribution is negative and economically meaningful for at least six years, although pointwise statistical significance is concentrated in roughly the first four years.

Figure 8b repeats the decomposition while conditioning only on the factors that load on community bank lending (the common factors and the community-specific factors).

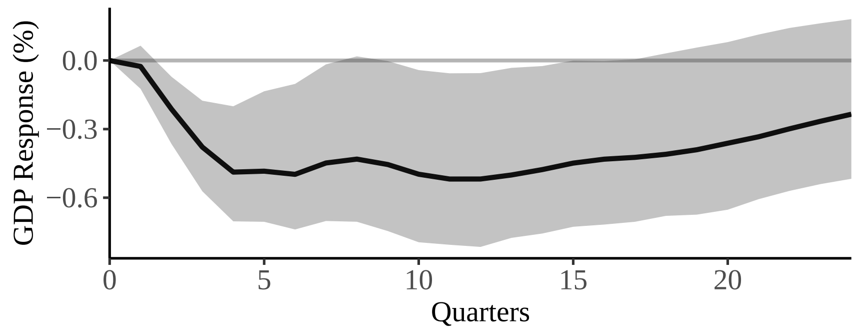
[14] A delayed contraction in bank credit following monetary tightening is a recurring empirical finding under alternative identification strategies; see, e.g., Kashyap and Stein (1994, 1995, 2000); Kashyap et al. (2002).

This PT-IRF therefore isolates the portion of the GDP response attributable to endogenous feedback operating through community-bank lending comovement. The response is more delayed than in the combined specification: it builds gradually, remains strongly negative, and begins to attenuate only around year five, with pointwise significance extending through approximately that horizon.

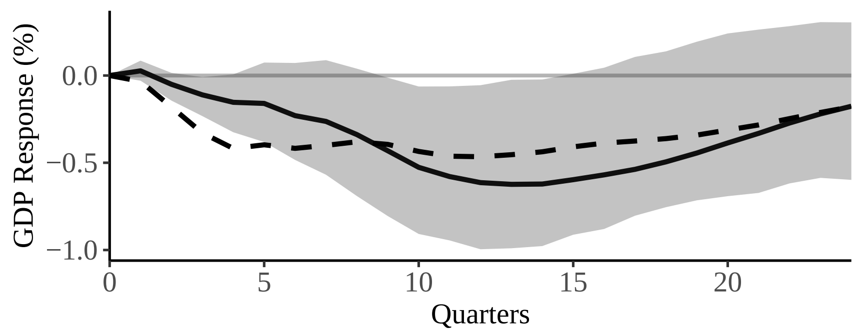
Finally, Figure 8c conditions on the factors that load on noncommunity-bank lending (the common factors and the noncommunity specific factors), and can be interpreted analogously as the noncommunity lending-mediated contribution. Its shape closely tracks the combined-lending PT-IRF but appears less persistent, with the bulk of the contribution concentrated at shorter horizons. When the community and noncommunity PT-IRF point estimates are plotted together in Figure 8b, the noncommunity contribution reaches its peak magnitude roughly two years earlier than the community contribution, consistent with more front-loaded amplification via noncommunity bank lending and more delayed, persistent amplification via community bank lending.

Figure B.1 extends the baseline GDP PT-IRFs by conditioning on alternative mediator blocks built from the hierarchical lending factors. In particular, it reports PT-IRFs that isolate (i) economy-wide lending comovement (conditioning on the common factors only) and (ii) residual comovement within each bank type (conditioning on the community-only or noncommunity-only factors), alongside the baseline specifications that combine the common factors with each type-specific block. This expanded decomposition helps assess whether the community–noncommunity differences documented above are driven primarily by shared lending dynamics or by lending comovement unique to each segment. Qualitatively, the comparison reinforces the baseline interpretation: amplification through noncommunity bank lending is relatively more front-loaded, whereas amplification through community-bank lending is more delayed and persistent. Corresponding PT-IRF decompositions for the robustness specifications are reported in Figures C.3, D.3, and E.3.[15]

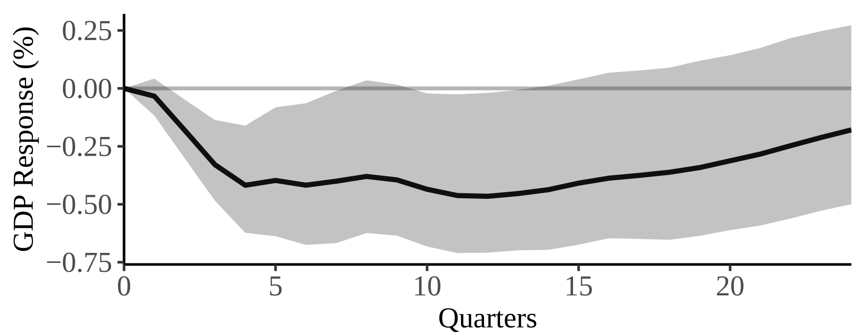
[15]For completeness, Figures B.2, B.3, and B.4 report PT-IRFs for *all* endogenous variables when conditioning on (i) all lending factors, (ii) the common and community-specific factors, and (iii) the common and noncommunity-specific factors, respectively. The analogous full-system PT-IRF figures for



(a) Medium: Combined bank lending



(b) Medium: Community bank lending



(c) Medium: Noncommunity bank lending

Figure 8: 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 heterogeneity in lending-based monetary transmission can be assessed formally by comparing PT-IRFs constructed under different mediator sets. Let $J = \{F, F^C\}$ denote the mediator block consisting of the common lending factors and the community-specific lending factors, and let $J' = \{F, F^{NC}\}$ denote the corresponding block for noncommunity banks. For outcome i (GDP in this subsection) and horizon h, define the difference PT-IRF as $\Delta\text{PT-IR}(h, i, J, J', \bar{\varepsilon}) \equiv \text{PT-IR}(h, i, J, \bar{\varepsilon}) - \text{PT-IR}(h, i, J', \bar{\varepsilon})$. This object is the horizon-by-horizon gap between the community-conditioned and noncommunity-conditioned PT-IRFs reported in Figures 8b and 8c. Because both underlying PT-IRFs are negative over the relevant horizons, positive values of $\Delta\text{PT-IR}(h, i, J, J', \bar{\varepsilon})$ correspond to stronger (larger-magnitude) amplification through noncommunity bank lending, whereas negative values correspond to stronger amplification through community bank lending.

Figure 9 reports point estimates of $\Delta\text{PT-IR}(h, i, J, J', \bar{\varepsilon})$ together with 90% and 68% confidence bands for the baseline specification and for the alternative specification that replaces GDP and the GDP deflator with IP and the CPI. The corresponding difference PT-IRFs for the remaining robustness exercises — the shock exogeneity-restricted model and the JK-based identification — appear in the final row of Figures D.3 and E.3, and they closely mirror the qualitative horizon pattern in Figure 9. In addition, Figures B.1 and C.3 report an alternative comparison that omits the common lending factors, i.e., it contrasts PT-IRFs constructed using only the community-specific versus only the noncommunity-specific factor blocks. Across specifications, this alternative difference generally preserves the shape of the baseline ΔPT-IRF but features wider confidence intervals, with the loss of precision most evident under the JK-shock identification.

The estimated ΔPT-IRFs in Figure 9 exhibit a clear horizon dependence. Over the first 8–12 quarters (roughly 2–3 years), the point estimates are positive, indicating that the noncommunity-conditioned PT-IRF is larger in magnitude (i.e., more negative) than the

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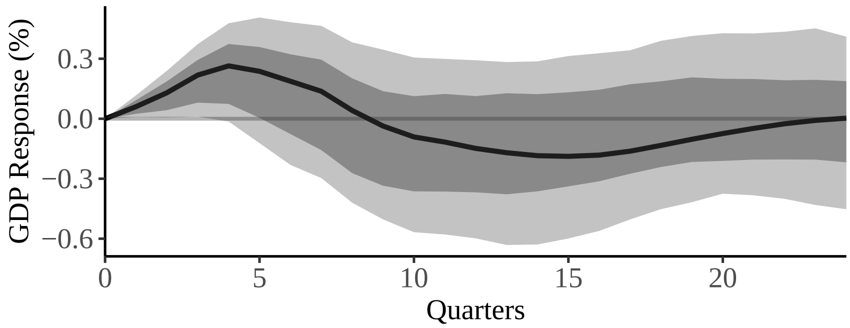
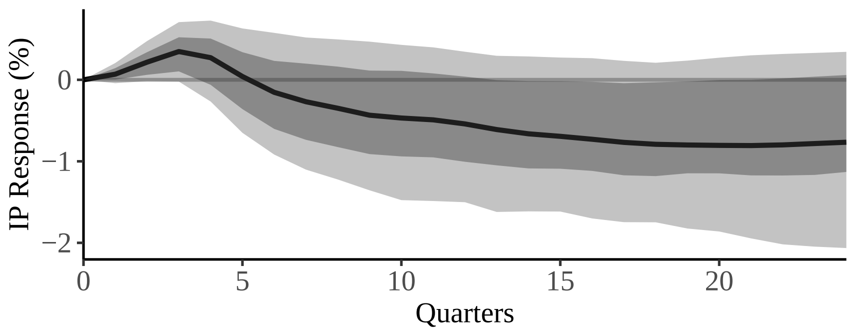
the alternative-variable specification are Figures C.4, C.5, and C.6; for the shock-exogeneity-restriction specification they are Figures D.4, D.5, and D.6; and for the JK-shock specification they are Figures E.4, E.5, and E.6.



(a) Baseline model



(b) Alternative model

Figure 9: 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. Light and dark gray bands are nonparametrically bootstrapped 90% and 68% confidence intervals using 1,000 samples, respectively.

community-conditioned PT-IRF at short horizons. Beyond roughly 8–12 quarters, ΔPT-IRF turns negative, implying that the community bank lending contribution becomes larger in magnitude at medium horizons. Because the underlying type-specific PT-IRFs are negative throughout the plotted horizon (Figure 8), this sign change reflects a shift in relative magnitudes rather than a reversal in the sign of the lending-mediated output response. The short-run differences are also the most precisely estimated: in each specification, at least one early-horizon estimate is statistically significant at the 90% level, and several horizons are significant at the 68% level (based on pointwise confidence bands). At medium horizons, the negative differences are not statistically significant at the 90% level, but their timing and qualitative shape are stable across the baseline and robustness specifications. Overall, the evidence favors a transmission profile in which noncommunity bank lending provides more front-loaded amplification of monetary shocks, whereas community bank lending contributes more gradually and with greater persistence.

4 Conclusion

This paper examines how monetary policy shocks propagate to real activity through bank lending when the banking sector is segmented into community and noncommunity banks. The empirical results support two takeaways. First, bank lending comovement is an economically meaningful propagation margin: conditioning on bank lending factors as mediators yields PT-IRFs indicating that a monetary tightening is associated with a sustained negative contribution to output dynamics. Second, the paper finds that this contribution is heterogeneous across bank types primarily in its horizon profile. Monetary transmission attributed to noncommunity bank lending factors is larger at shorter horizons (roughly within the first two to three years), while transmission attributed to community bank lending factors is more delayed and comparatively persistent. Differences in these responses are most precisely estimated in the short run; the medium-run reversal in relative importance is present in point estimates across specifications but is generally less tightly pinned down by the confidence bands. At the same time, the bank-level lending response distributions indicate broadly similar delayed adjustments in lending across community and noncommunity banks after a tightening shock. Taken together, these findings are consistent with heterogeneity arising more from differences in the mapping from lending comovement to aggregate activity than from stark differences in the direction of lending responses themselves — though the reduced-form empirical design cannot adjudicate the underlying mechanisms.

The paper's main contribution is that it provides a horizon-by-horizon accounting of the lending channel in which the propagation of monetary shocks through lending is quantified *jointly* as the combination of policy-induced movements in lending and the endogenous feedback from lending to output, then decomposed by bank type using a business-model-based (FDIC) classification. This approach complements existing work that focuses on either bank/borrower-level lending responses to policy or the real effects of credit shocks, by delivering a unified dynamic metric of transmission through the banking system and by highlighting that bank heterogeneity is relevant in ways that need not be summarized by size alone. The results also suggest a policy-relevant implication: if the historical relationships documented here remain informative, continued changes in the composition of banking toward noncommunity intermediation could tilt lending-based monetary transmission toward relatively greater short-run and weaker medium-run propagation. Establishing whether and why such a shift would occur requires additional evidence beyond this paper's scope.

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Appendices

A FDIC community bank definition and implementation

This appendix documents the FDIC research definition of a community bank used throughout the paper and describes how the FDIC-provided community bank designation is incorporated into the SDI panel. The FDIC designates community banks at the level of the banking organization (and, when working at the charter level, all charters within a designated organization are treated as community bank charters).

FDIC research definition (summary). The FDIC research definition proceeds in five steps:

1. Aggregate charter-level balance-sheet and office information to the *banking-organization* level using holding-company structure.
2. Exclude organizations that do not engage in traditional intermediation or that operate as specialty institutions, including any organization with (i) no loans or no core deposits, (ii) assets held in foreign offices of at least 10% of total assets, or (iii) more than 50% of total assets in specialty banking charters (e.g., credit card specialists, consumer nonbank banks, industrial loan companies, trust companies, and bankers' banks).
3. For the remaining organizations, require meaningful engagement in basic banking activities, measured by a loans-to-assets ratio greater than 33% and a core-deposits-to-assets ratio greater than 50% (with core deposits defined as non-brokered deposits in domestic offices).
4. Impose limits on geographic scope as a proxy for relationship-based banking. For organizations that meet or exceed the indexed asset-size threshold, the FDIC applies criteria based on (i) a minimum and maximum number of offices (indexed over time), (ii) a maximum level of deposits at any single office (indexed over time), and

(iii) location-based limits on the number of large MSAs (fixed at 2) and states (fixed at 3) in which the organization maintains offices.

5. Apply an indexed asset-size limit below which the geographic-scope and activity tests are waived. In the FDIC 2024 vintage, this indexed asset-size threshold equals \$2.17 billion, the indexed maximum number of offices equals 107, and the indexed maximum branch deposit size equals \$10.87 billion.

Implementation in this paper. I use the FDIC-provided community bank designation from the FDIC Community Banking Reference Data (combined historical and current) and merge it into the quarterly SDI panel. Specifically:

- I merge the community bank flag `CB` (where `CB`=1 designates community bank status and `CB`=0 designates noncommunity status) to SDI bank-quarter observations using `CERT` and the reporting quarter `CALLYM` (expressed as yyyymm).
- I classify a bank-quarter observation as a community bank if `CB`=1, and as a noncommunity bank otherwise.
- Because the FDIC designation is used directly, I do not apply additional screening or reclassification rules for specialty institutions, foreign-office exposure, unusual balance-sheet structures, bank holding company affiliation, or threshold crossing. In the balanced-panel construction, I exclude "switchers" whose FDIC designation changes during the sample period.

Table 3 below cross-tabulates the FDIC community bank designation against broad asset-size bins at five-year intervals. Two patterns are relevant for interpretation. First, although community banks are concentrated in the sub-\$1B range, the FDIC definition is not a pure size cutoff: a nontrivial number of community banks fall in the \$1–10B range throughout the sample, and a small number exceed \$10B. Second, noncommunity banks are not uniformly large, particularly early in the sample, though the number of sub-\$1B noncommunity banks declines sharply over time. The overlap in the \$1–10B segment motivates treating community status as a business-model classification distinct from a simple size partition.

Table 3: Cross-tabulation of FDIC Community Bank Indicator by Fixed Asset Size Bins (Q4 of Every 5th Year)

CB Type	Size Bin	1999	2004	2009	2014	2019
	<$1B	7,069	6,575	5,991	4,942	3,785
Community	$1B-$10B	60	112	208	241	358
	>$10B	0	3	2	2	5
	<$1B	1,308	770	475	209	98
Noncommunity	$1B-$10B	279	265	252	242	199
	>$10B	80	88	88	92	122
Total	*<$1B*	*8,377*	*7,345*	*6,466*	*5,151*	*3,883*
	$1B-$10B	*339*	*377*	*460*	*483*	*557*
	>$10B	*80*	*91*	*90*	*94*	*127*

Table 4 summarizes median asset sizes within each bank type by asset quintile. Two implications are worth noting. First, community banks remain comparatively small throughout the distribution: even in the top quintile, the median community bank remains below $1B in assets by 2019. Second, the noncommunity segment exhibits a highly skewed and increasingly heavy upper tail: the median bank in the top noncommunity quintile rises to roughly $47B by 2019. This widening dispersion underscores why aggregate lending measures for noncommunity banks can be disproportionately influenced by idiosyncratic movements among the largest institutions, motivating the factor-based approach used in the empirical design.

Table 4: Median Asset Size (in Billions of Dollars) by FDIC Community Bank Indicator and Asset Quintiles (Q4 of Every 5th Year)

CB Type	Size Bin (Quintiles)	1999	2004	2009	2014	2019
	1	0.02	0.03	0.04	0.05	0.05
	2	0.04	0.06	0.08	0.10	0.12
Community	3	0.06	0.09	0.13	0.16	0.21
	4	0.11	0.16	0.22	0.27	0.37
	5	0.23	0.37	0.53	0.63	0.93
	1	0.05	0.07	0.09	0.17	0.30
	2	0.12	0.20	0.33	0.71	1.43
Noncommunity	3	0.25	0.43	0.71	1.54	2.77
	4	0.59	1.09	1.85	4.31	9.49
	5	3.53	6.89	10.55	23.25	46.63
Total	*1*	*0.02*	*0.03*	*0.04*	*0.05*	*0.06*
	2	*0.04*	*0.06*	*0.08*	*0.10*	*0.12*
	3	*0.07*	*0.10*	*0.13*	*0.16*	*0.21*
	4	*0.11*	*0.17*	*0.23*	*0.28*	*0.38*
	5	*0.27*	*0.41*	*0.58*	*0.68*	*0.98*

B Baseline Results

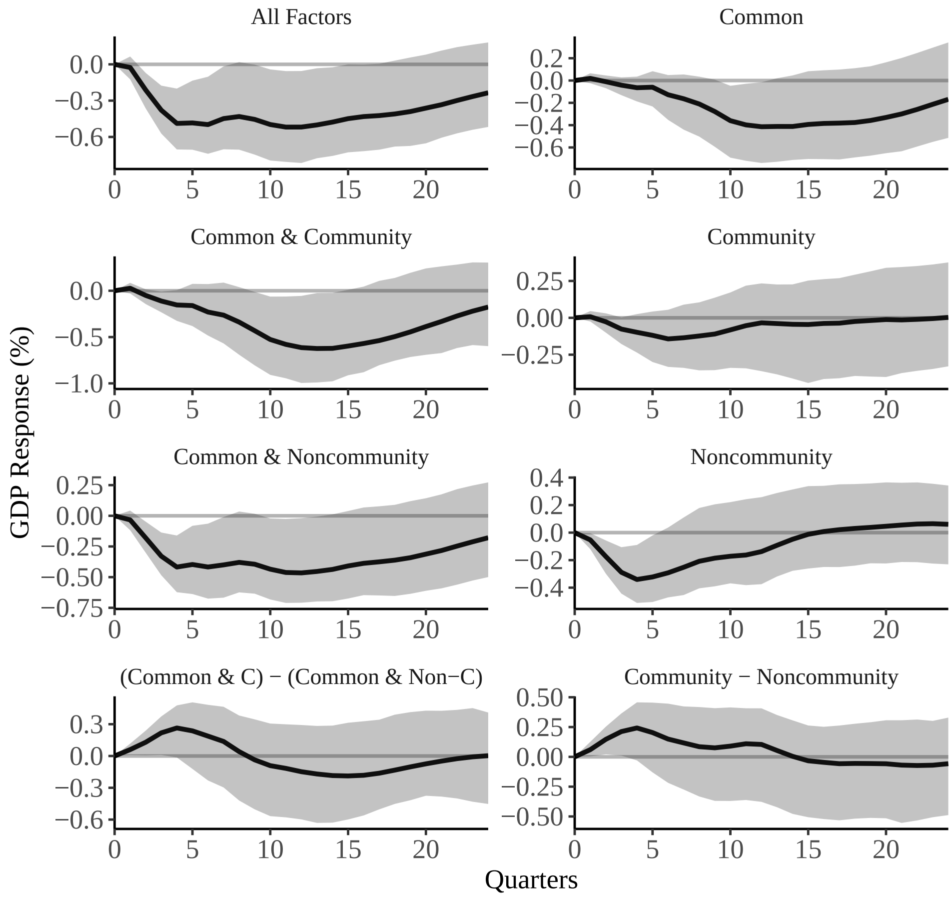


Figure B.1: PT-IRs of GDP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

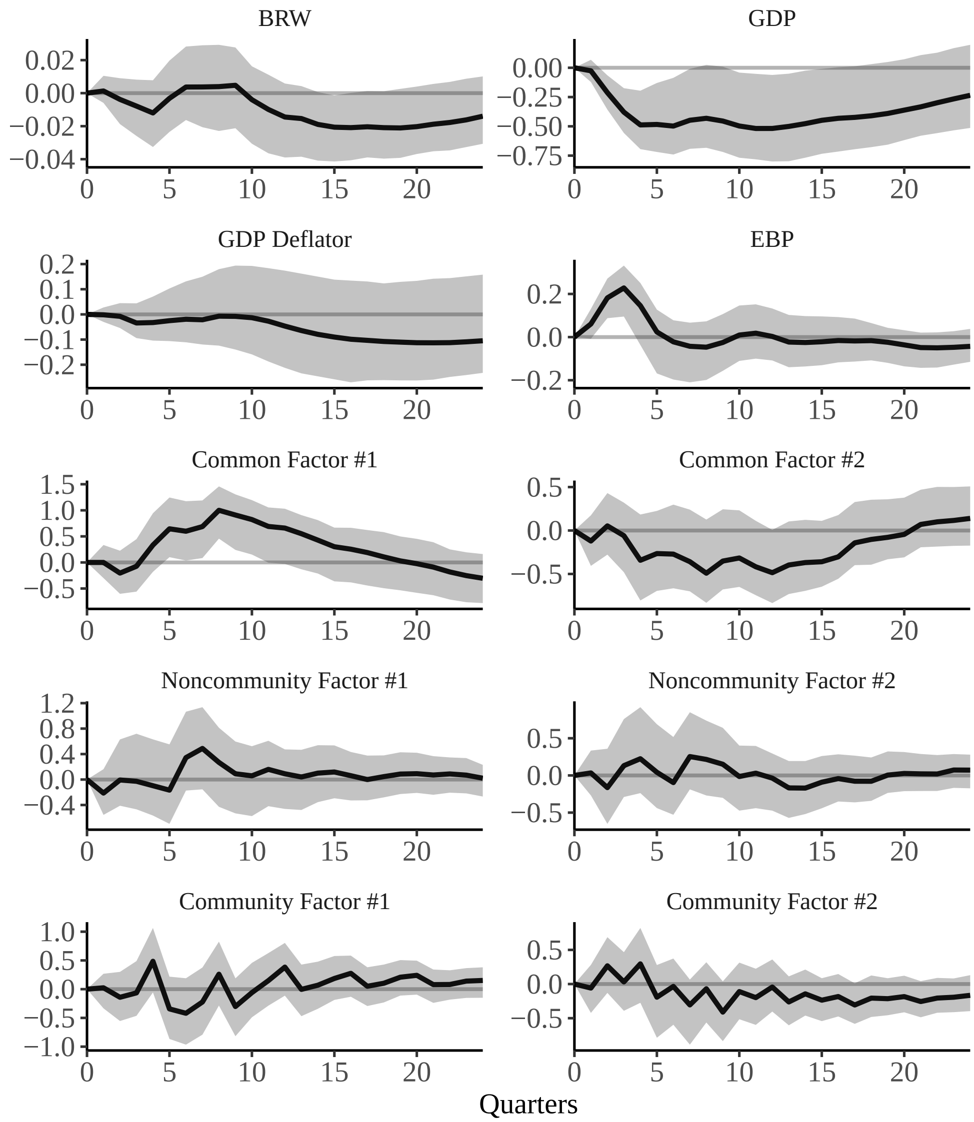


Figure B.2: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

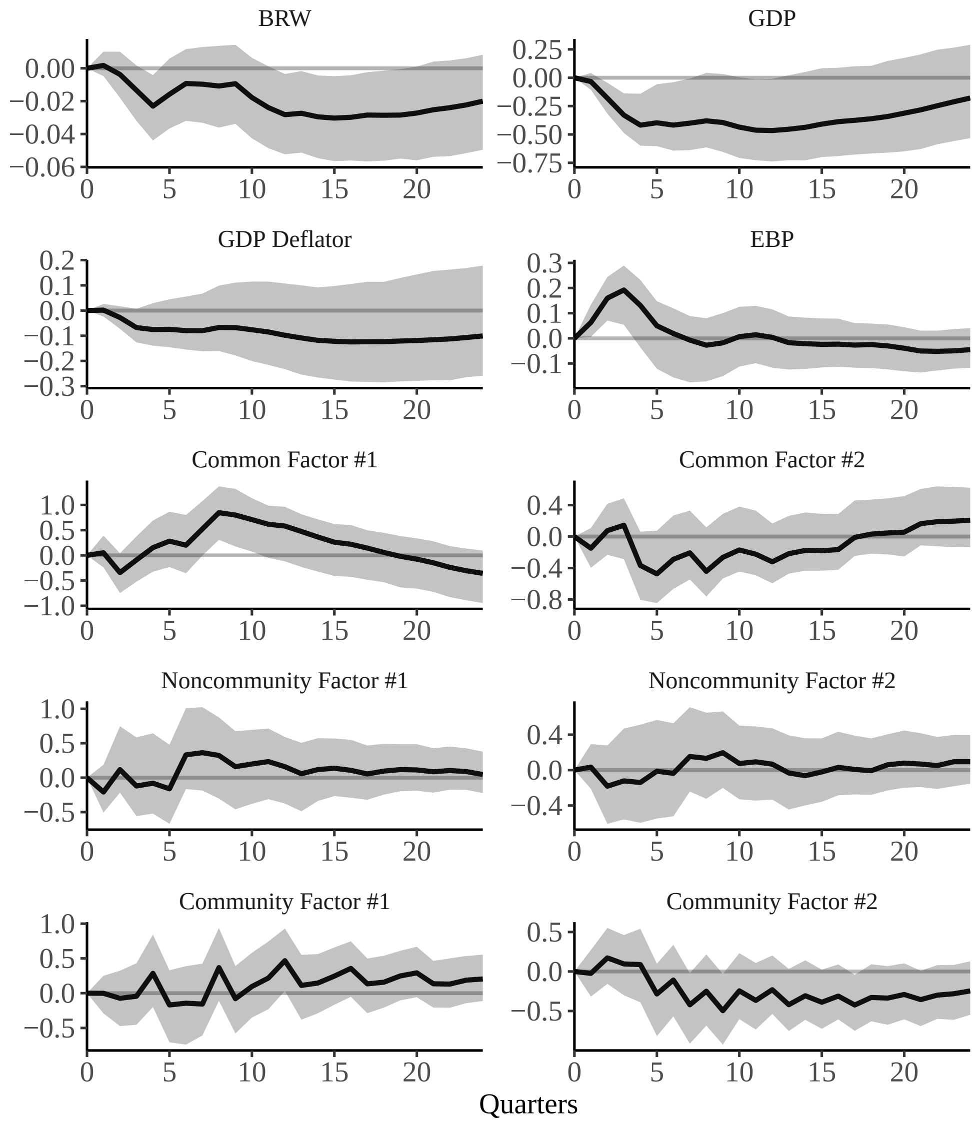


Figure B.3: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000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

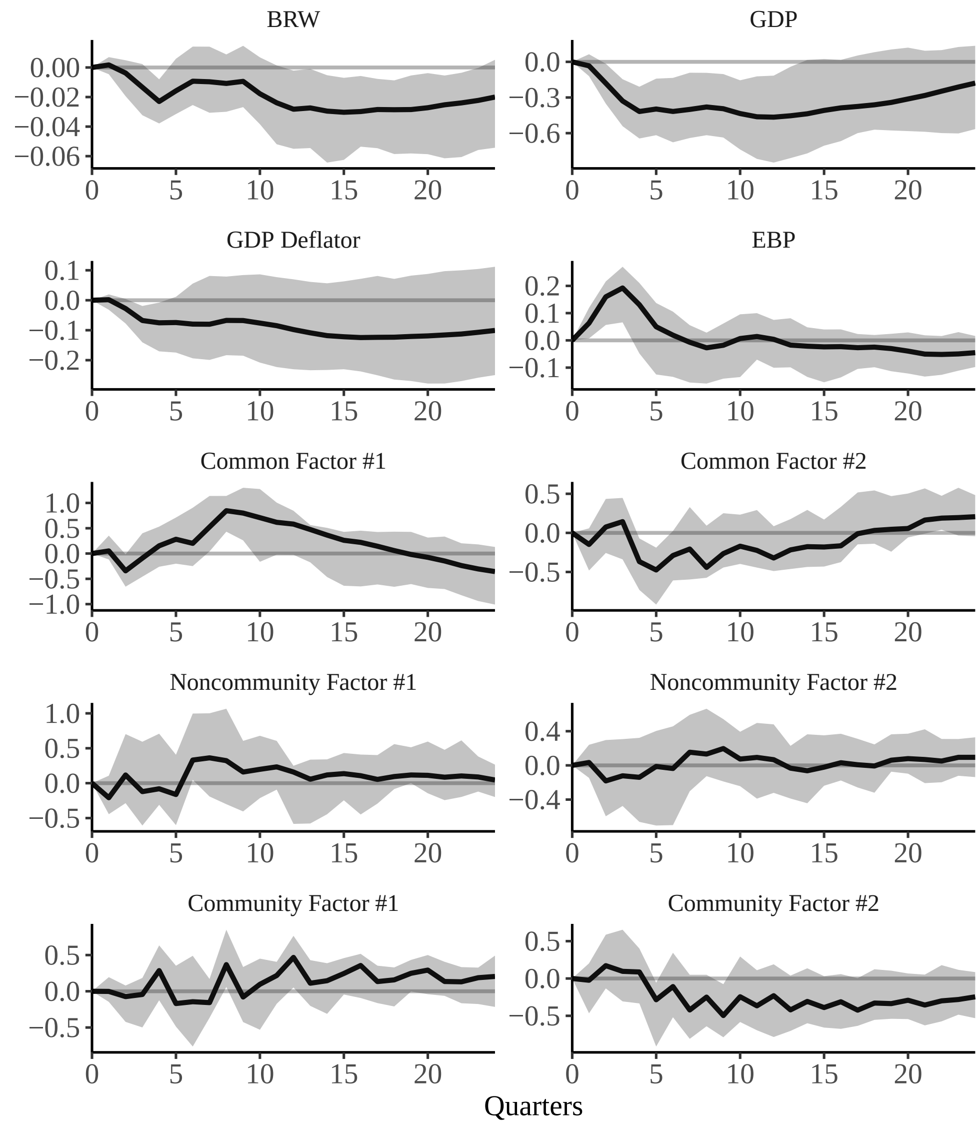


Figure B.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using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

C Robustness: Alternative Output and Inflation Proxies

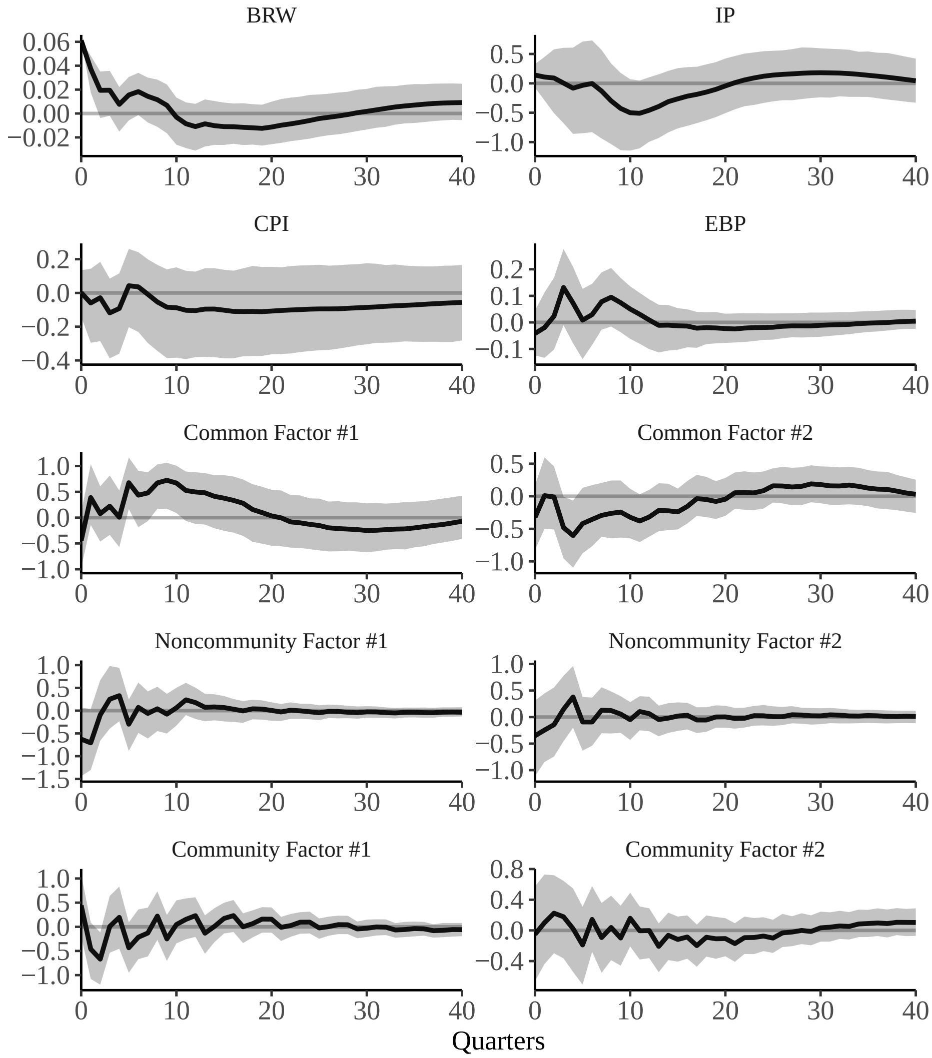
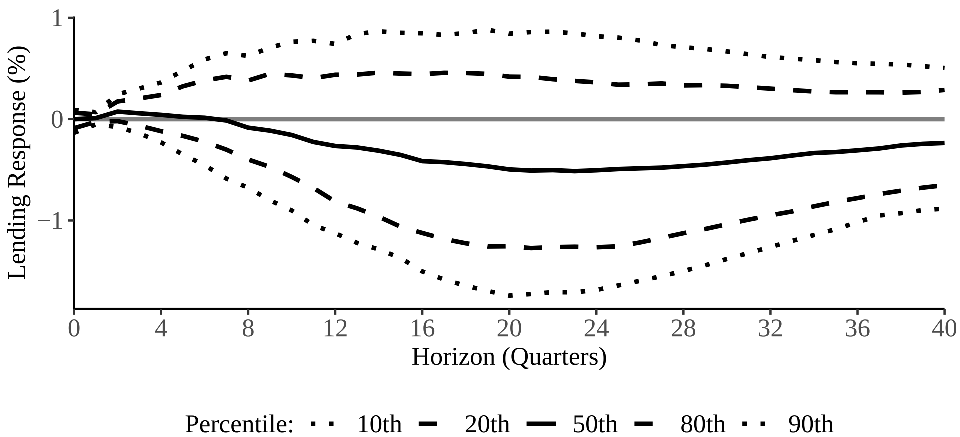
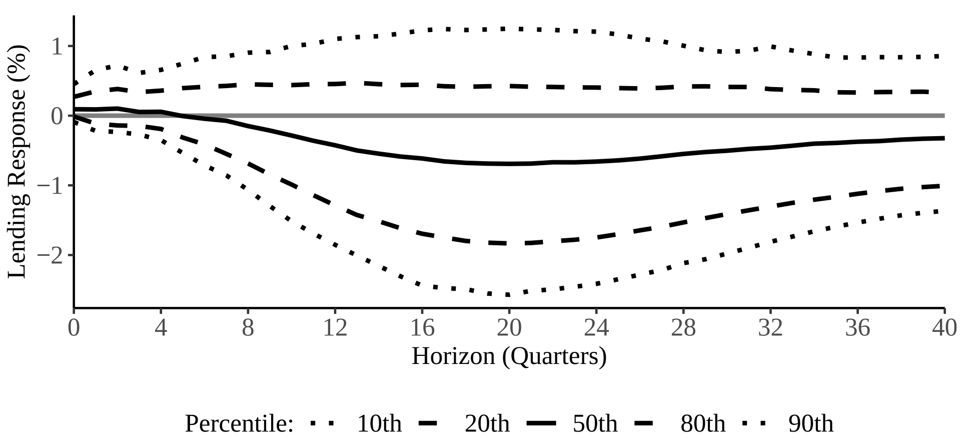


Figure C.1: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

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

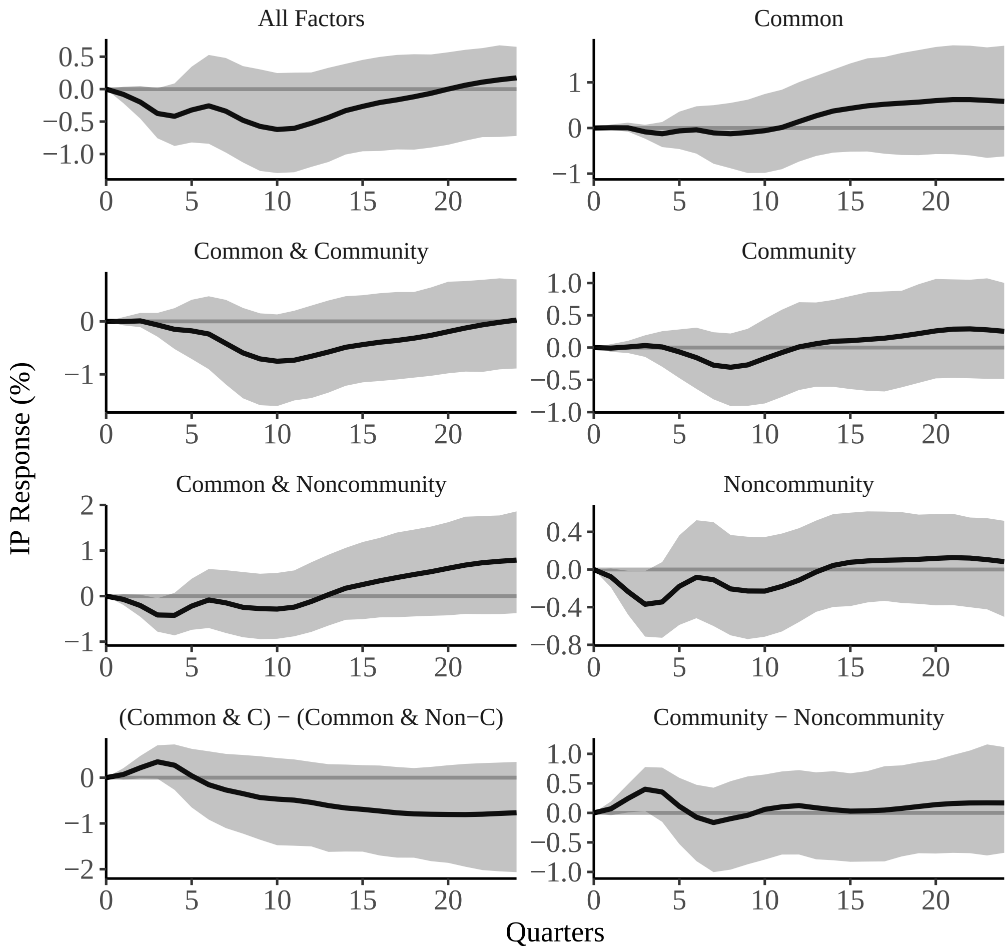


Figure C.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

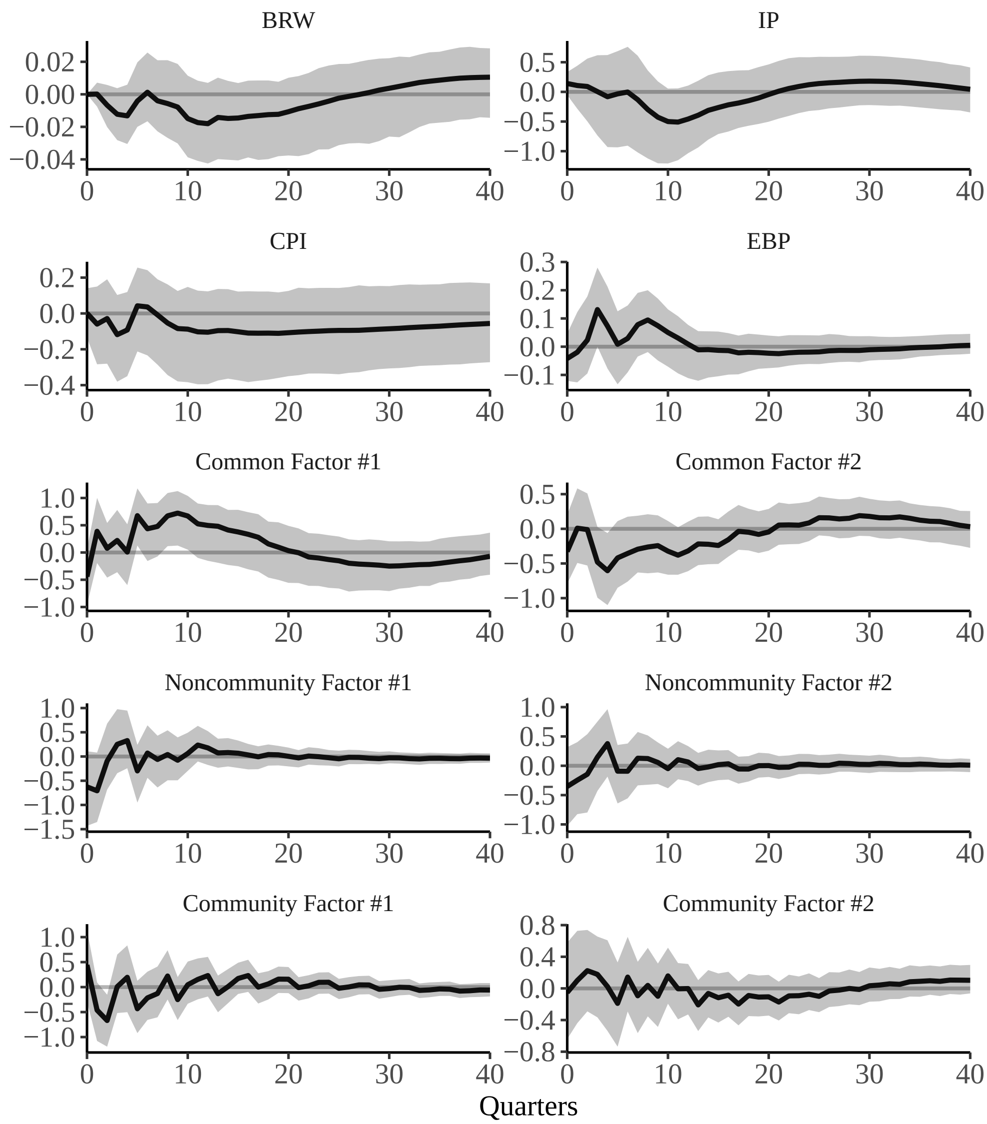


Figure C.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000 samples.

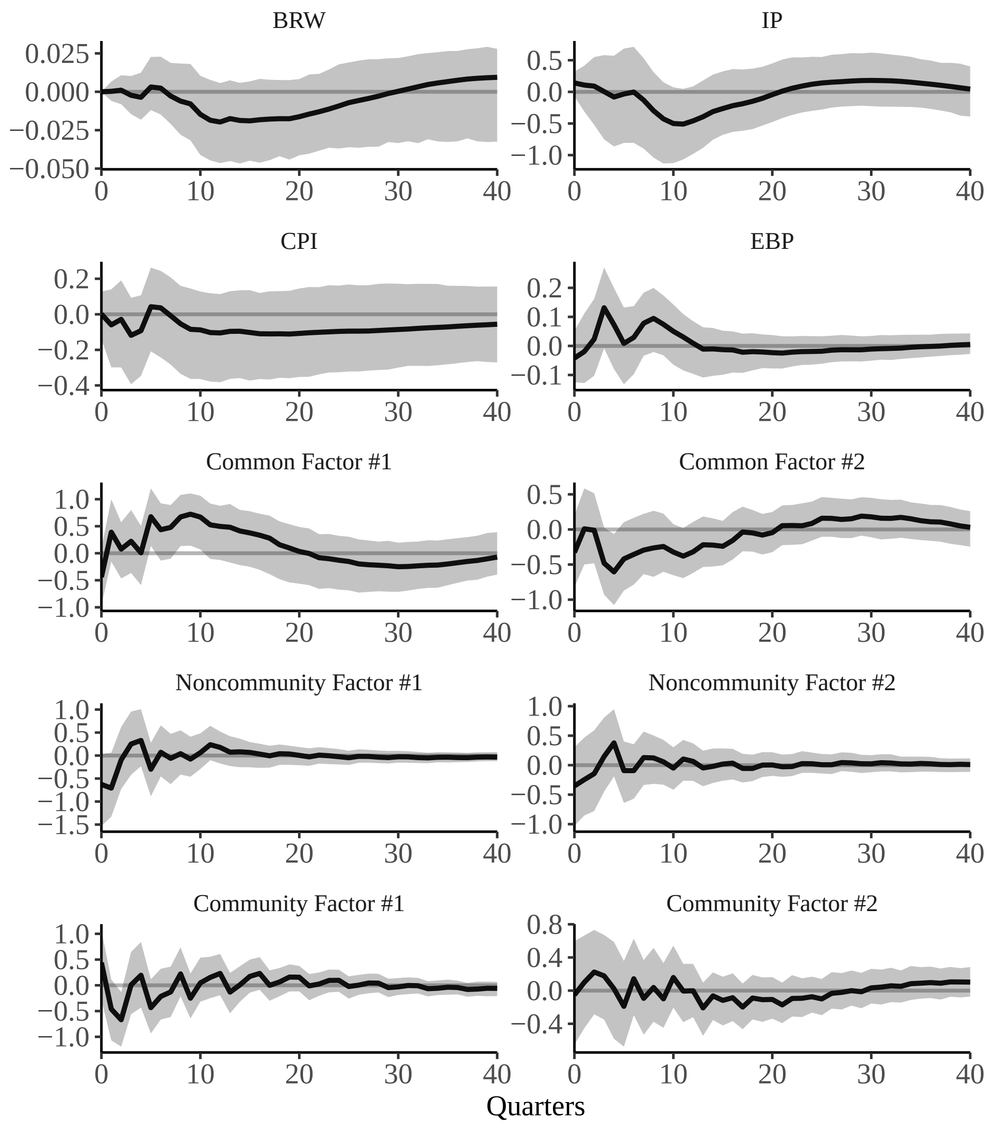


Figure C.5: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using 1,000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

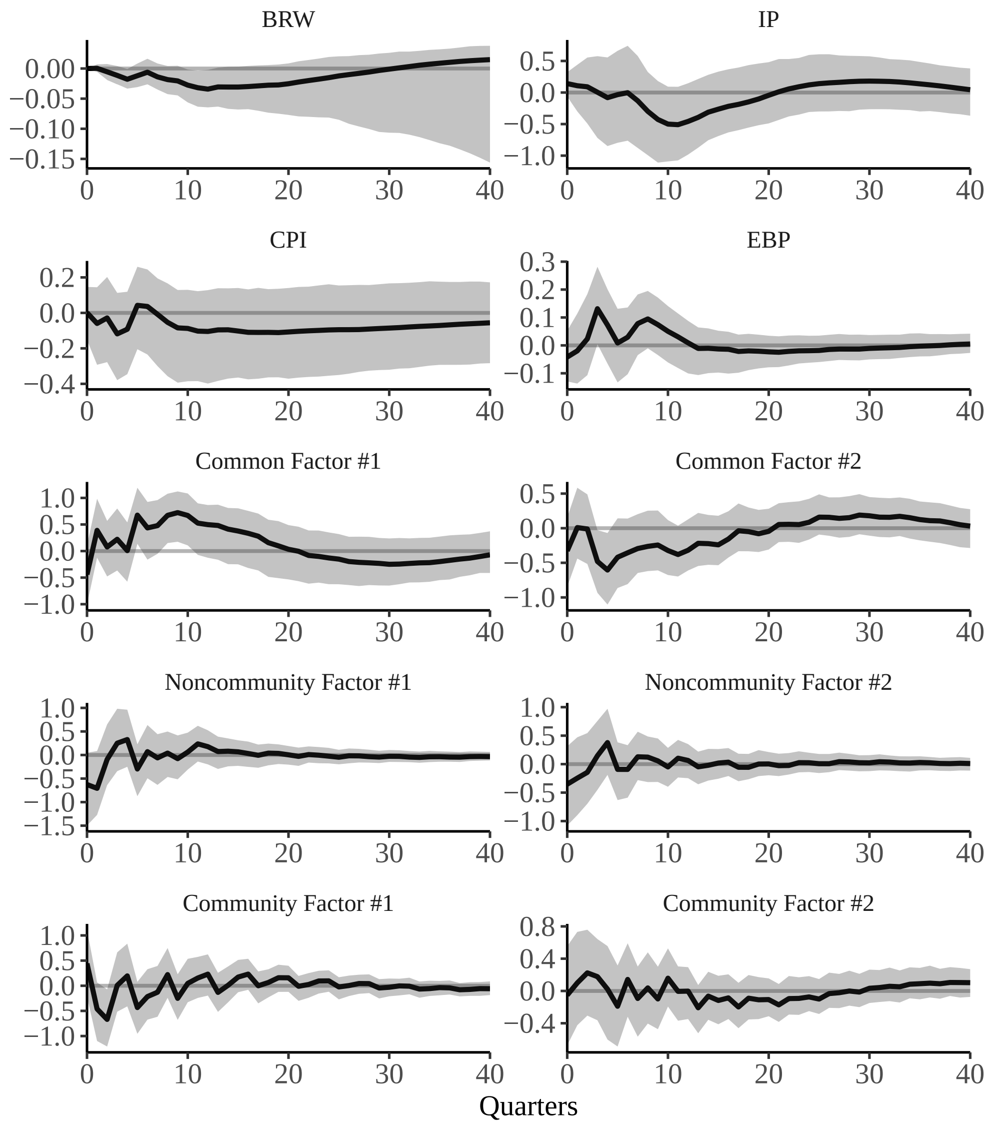


Figure C.6: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are nonparametrically bootstrapped 90% confidence intervals using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

D Robustness: Shock Exogeneity Restrictions

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 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.

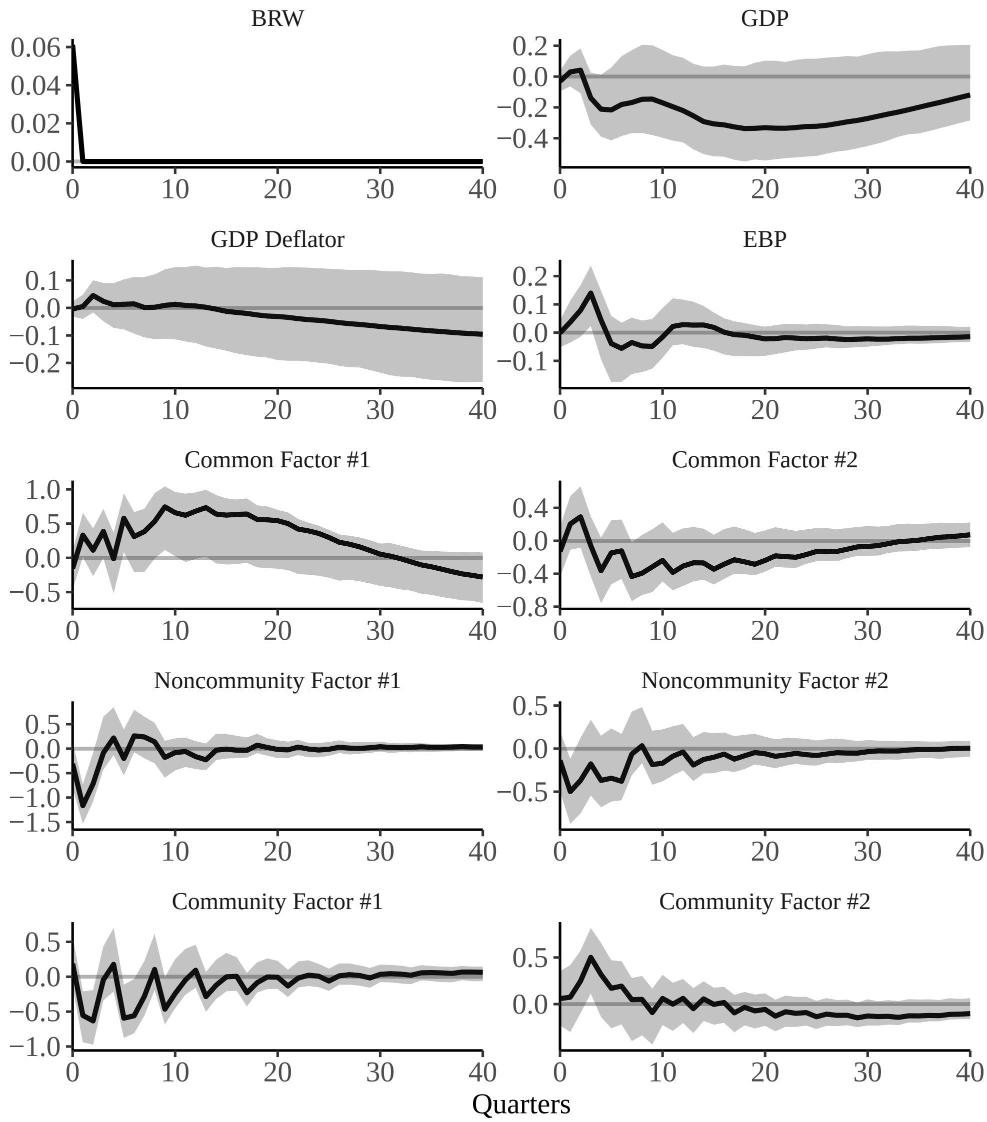
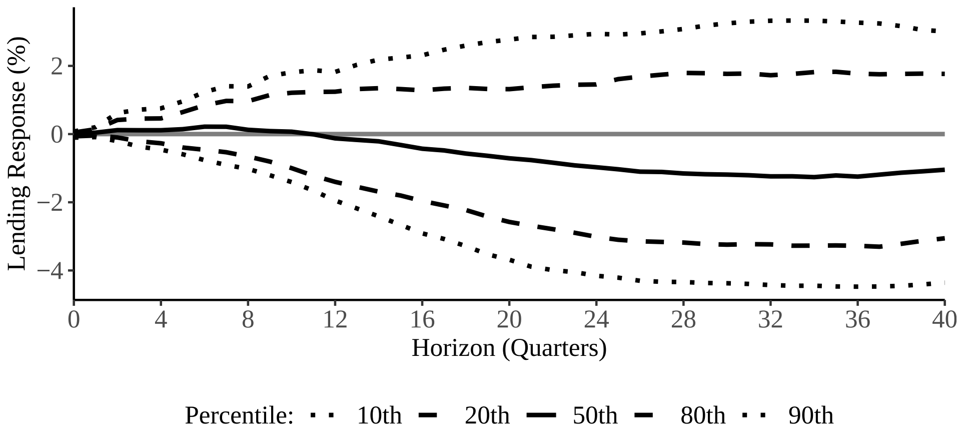
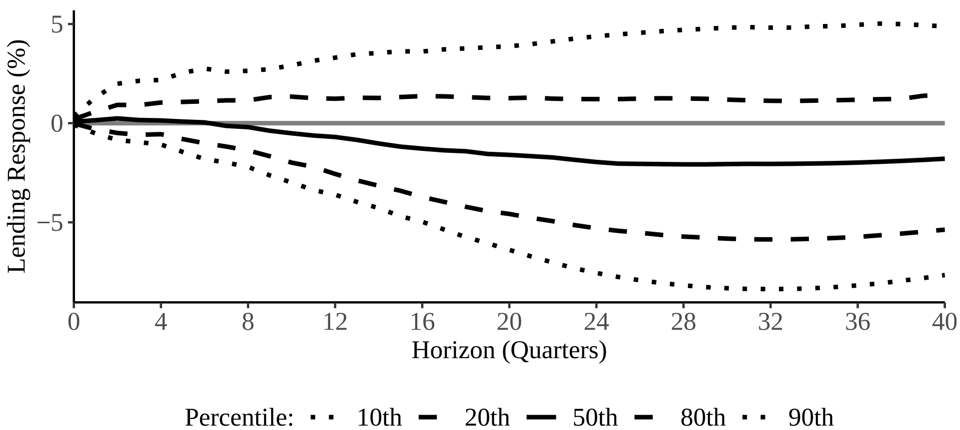


Figure D.1: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

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

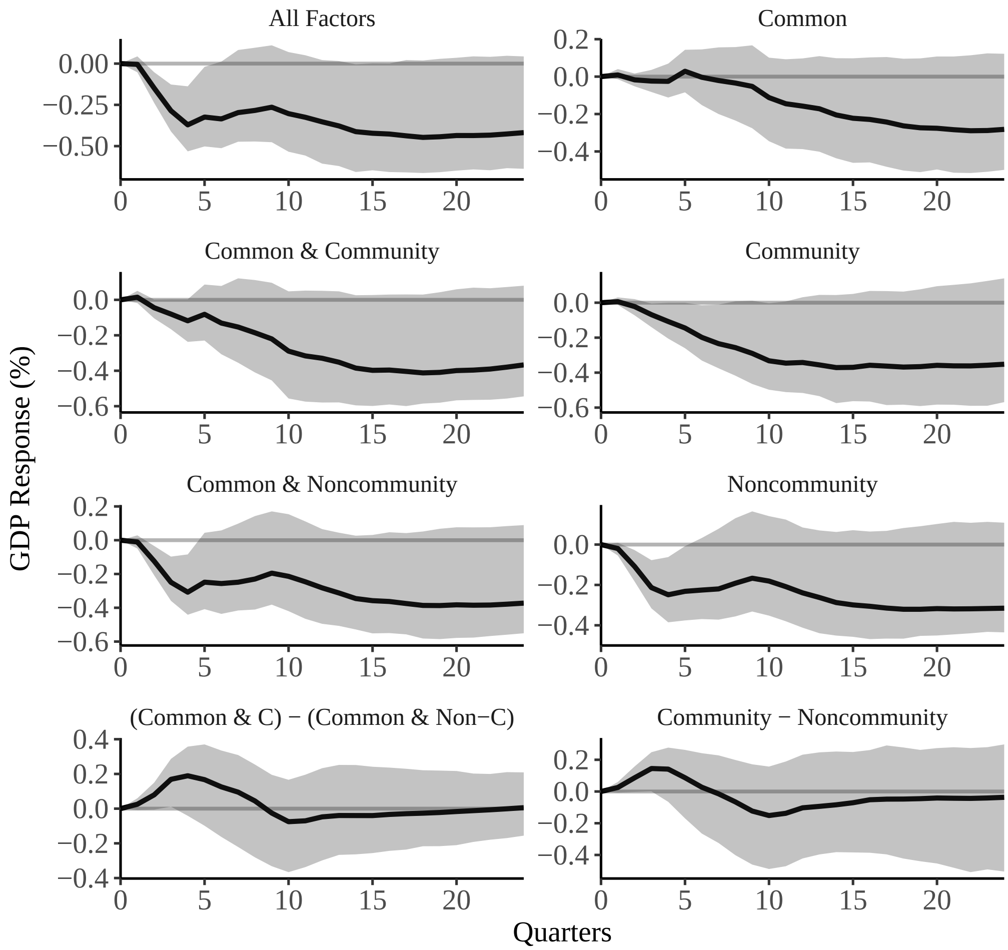


Figure D.3: PT-IRs of IP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.

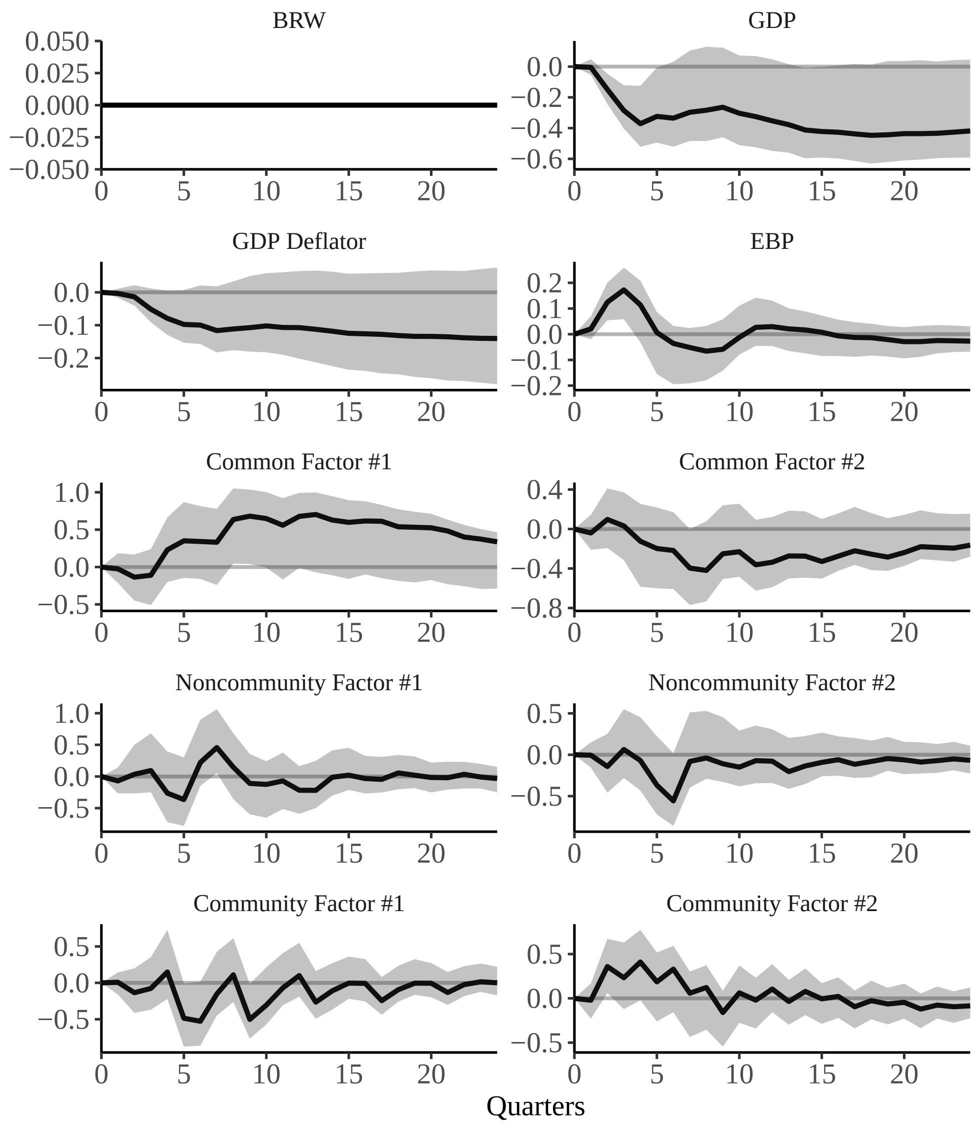


Figure D.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.

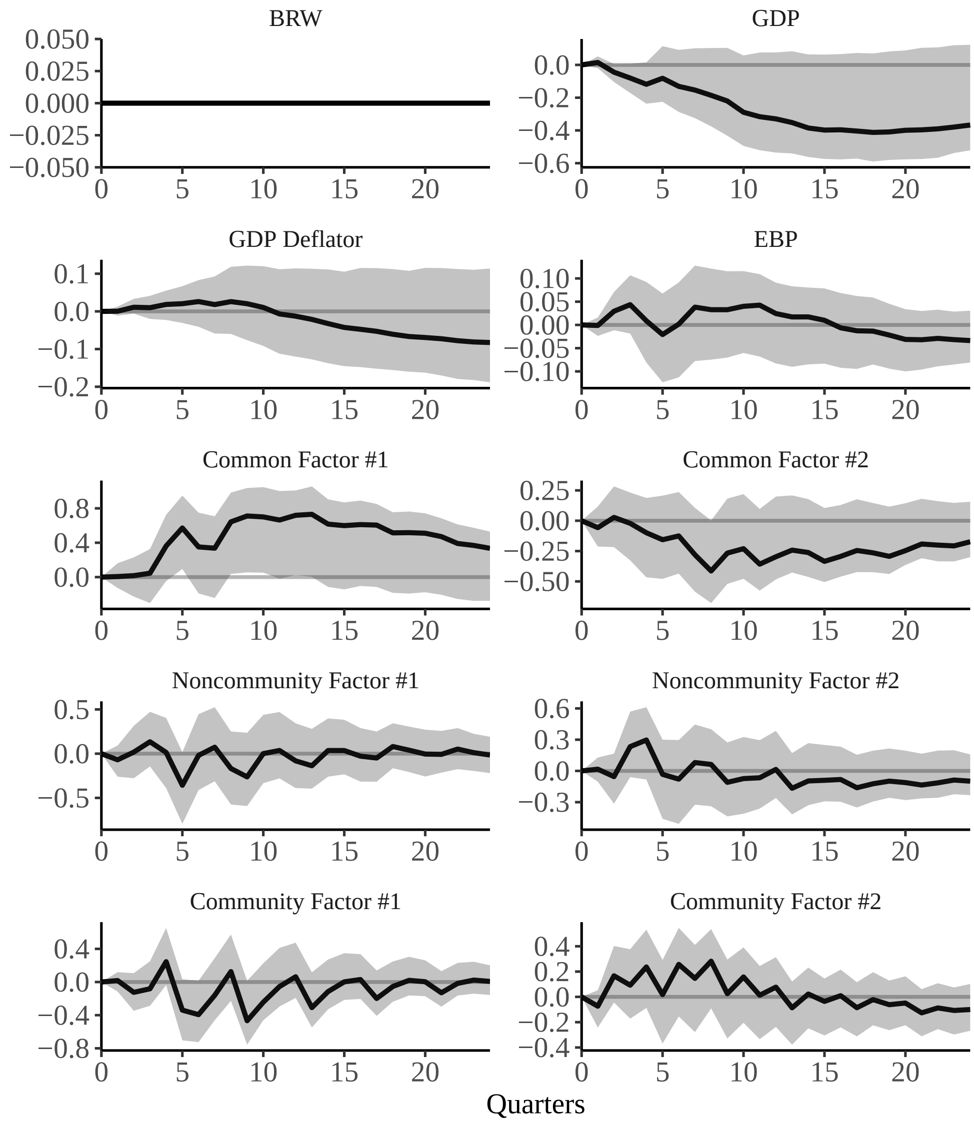


Figure D.5: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000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

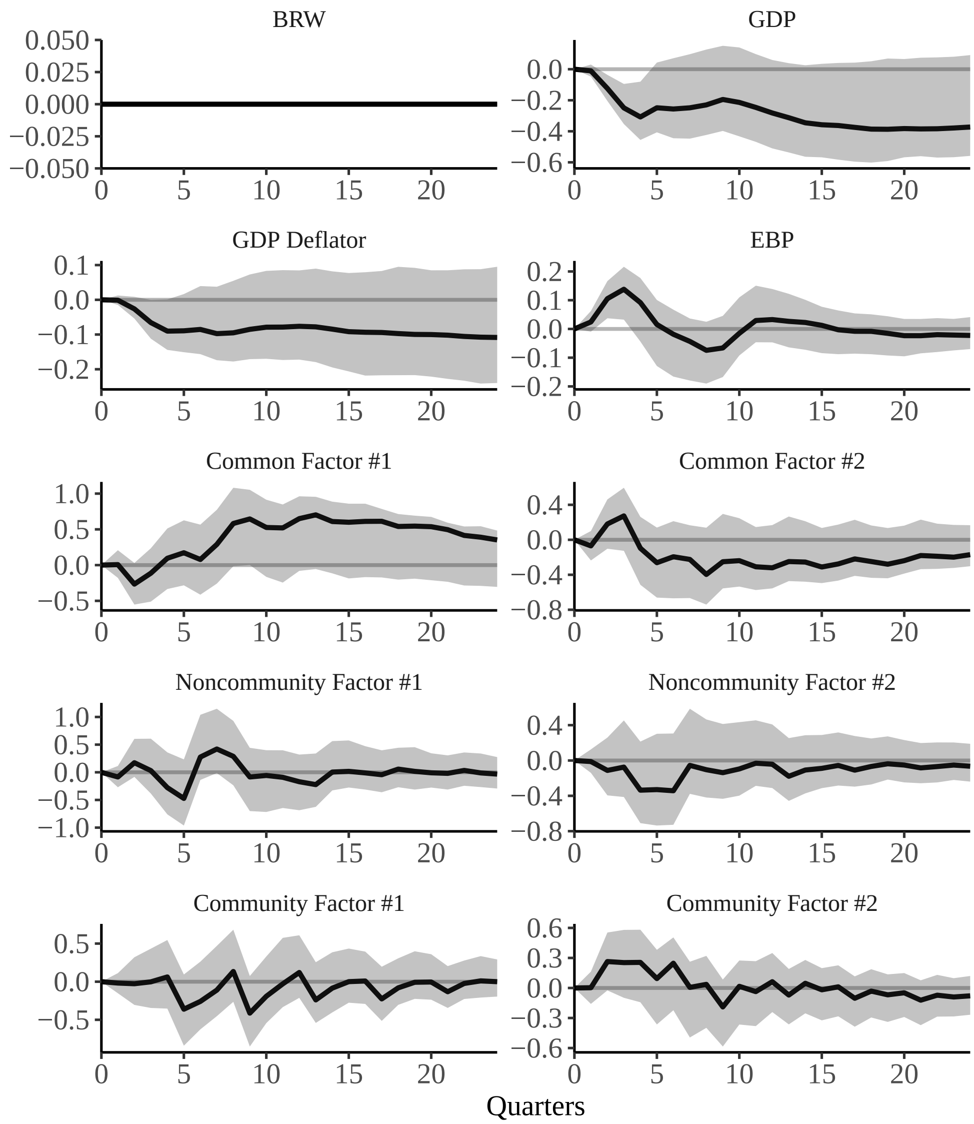


Figure D.6: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using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

E Robustness: JK Monetary Policy Shock

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

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

such that JK, GDP, GDPD, and EBP denote the 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.

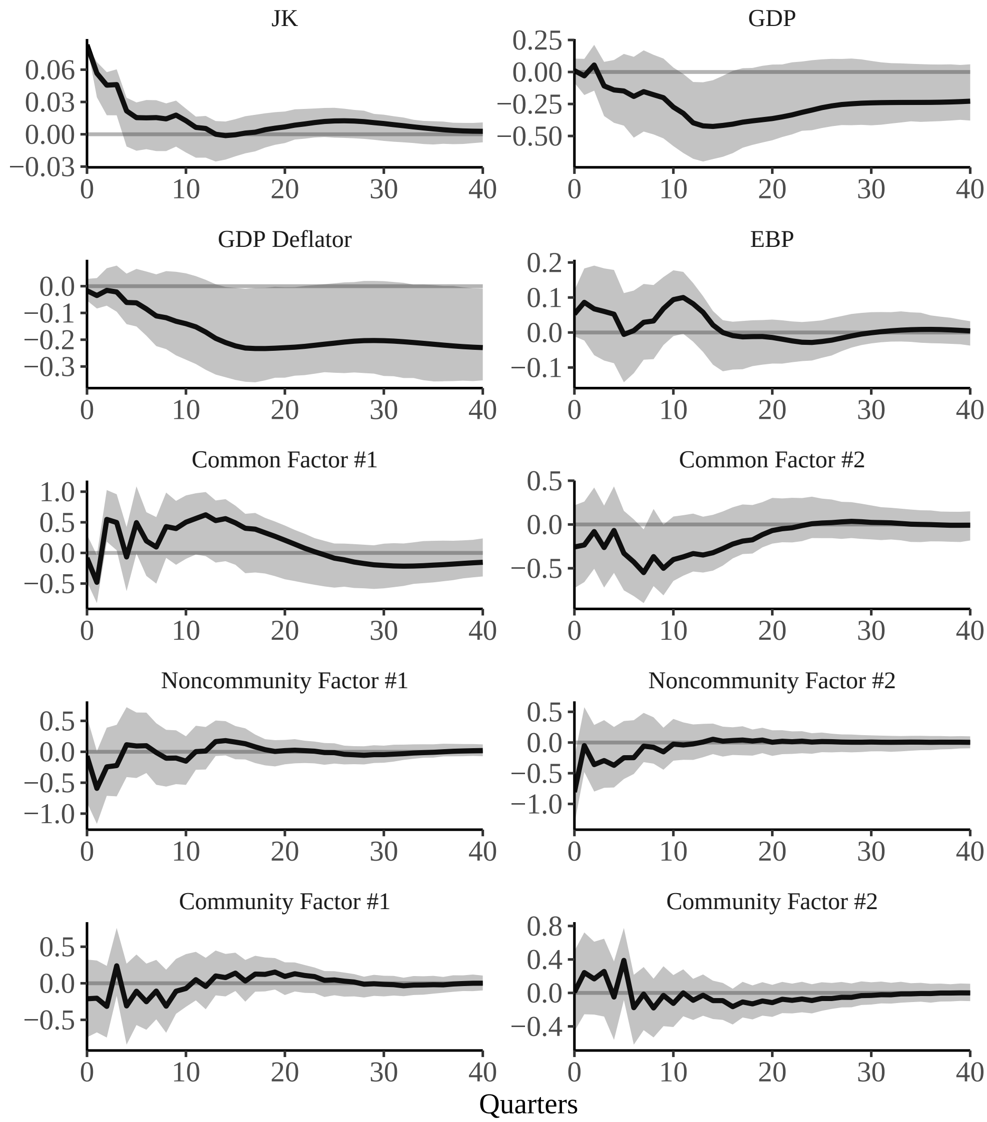
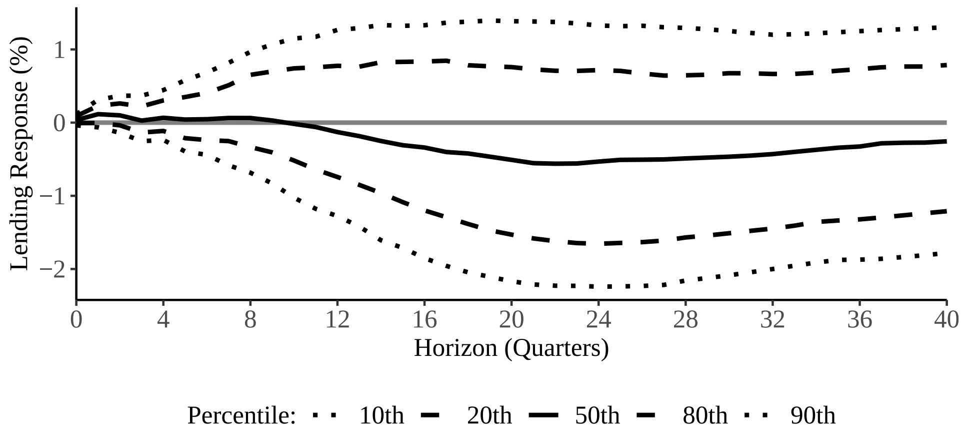
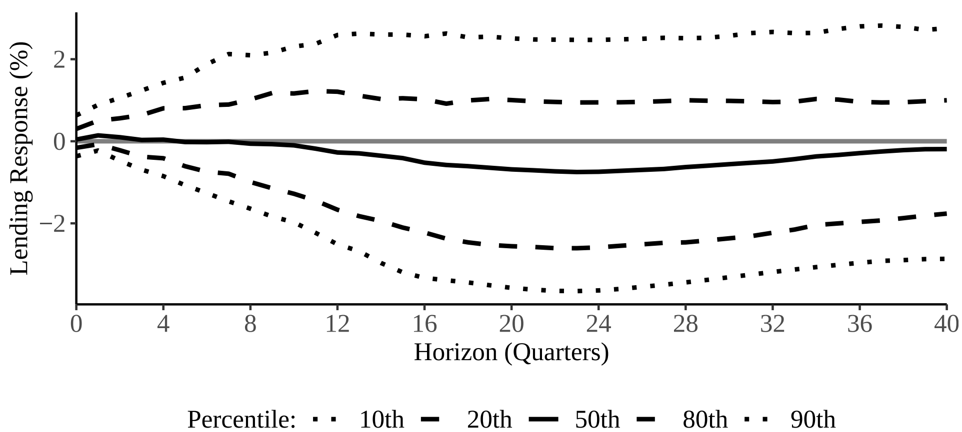


Figure E.1: Impulse responses of all endogenous variables to a one standard deviation positive (contractionary) monetary policy shock. Solid black lines are IRF point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.



(a) Distribution of community bank lending volume responses



(b) Distribution of noncommunity bank lending volume responses

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

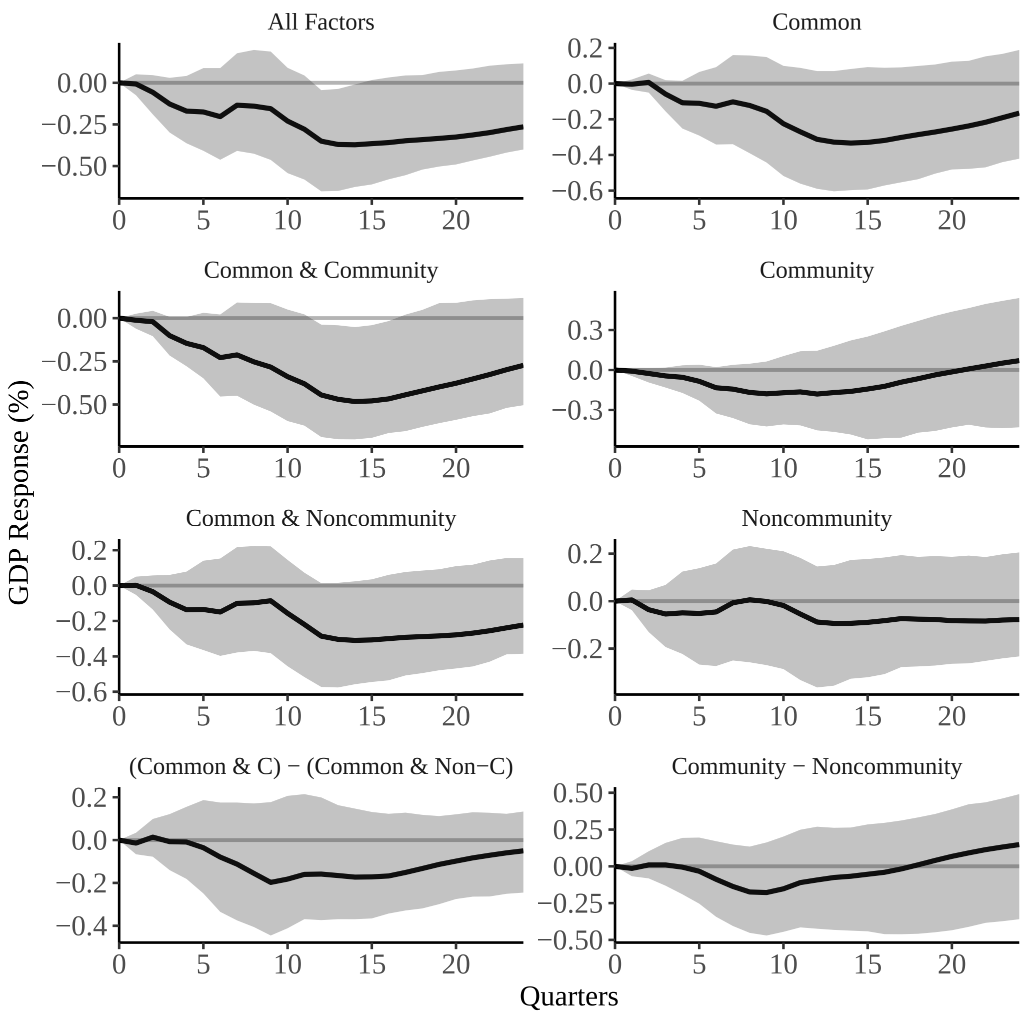


Figure E.3: PT-IRs of GDP in response to a one standard deviation positive (contractionary) monetary policy shock via all relevant combinations of bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.

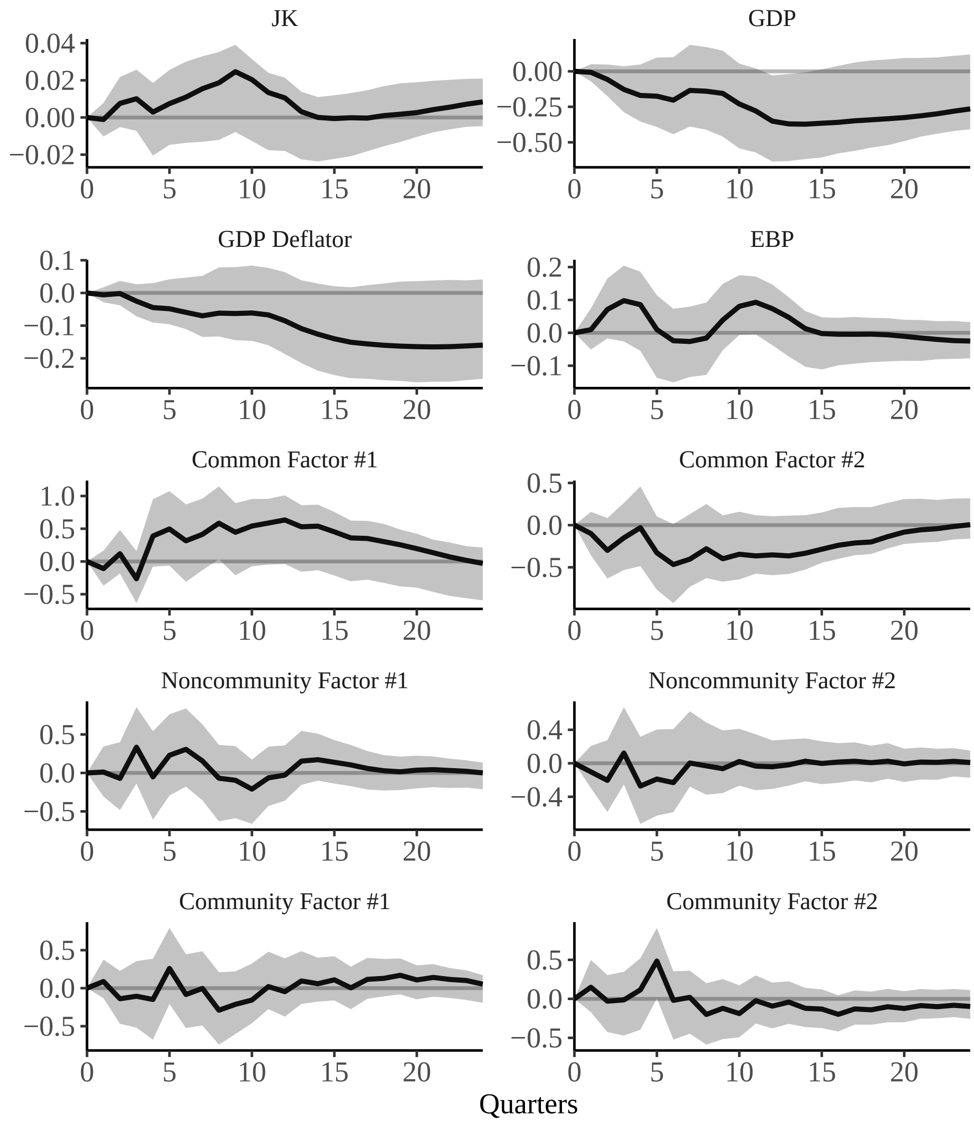


Figure E.4: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via all bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000 samples.

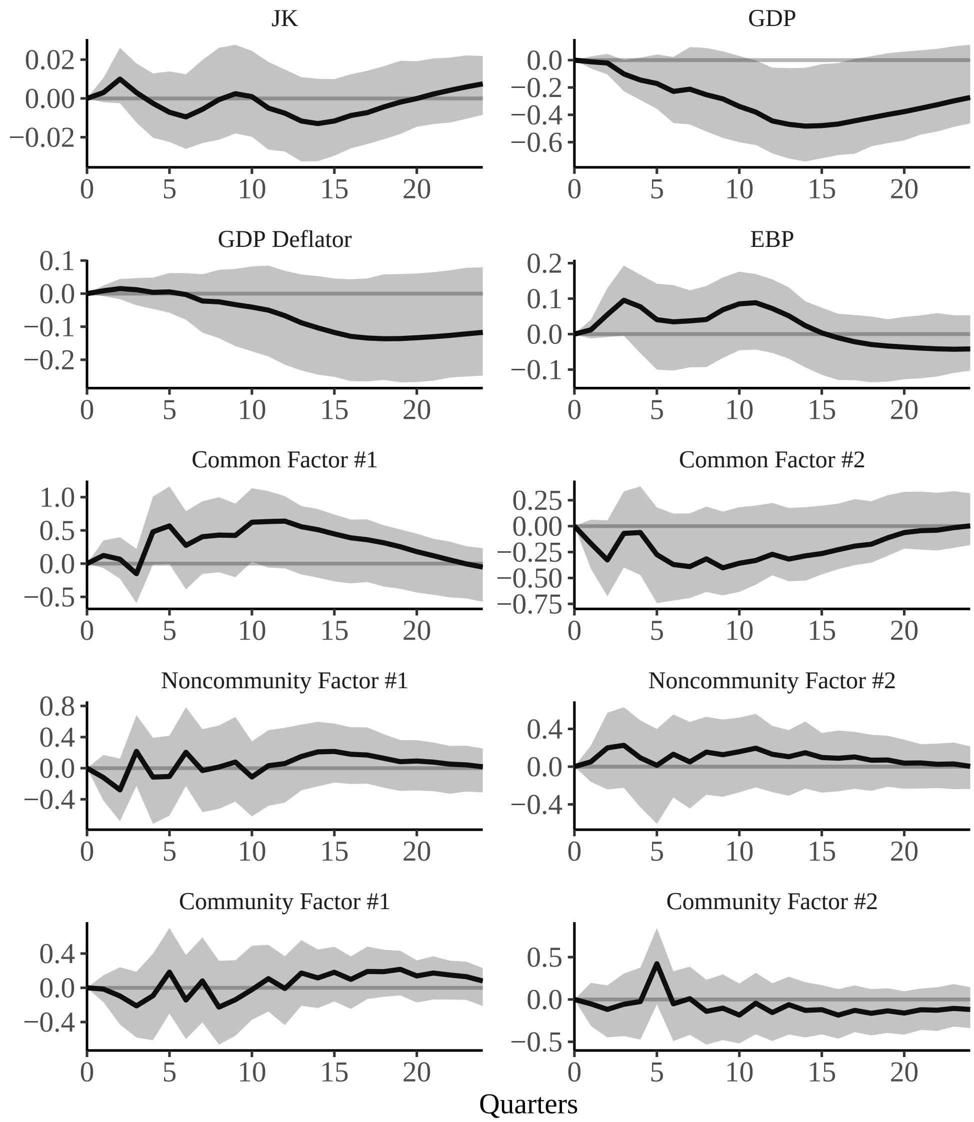


Figure E.5: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and community bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using 1,000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

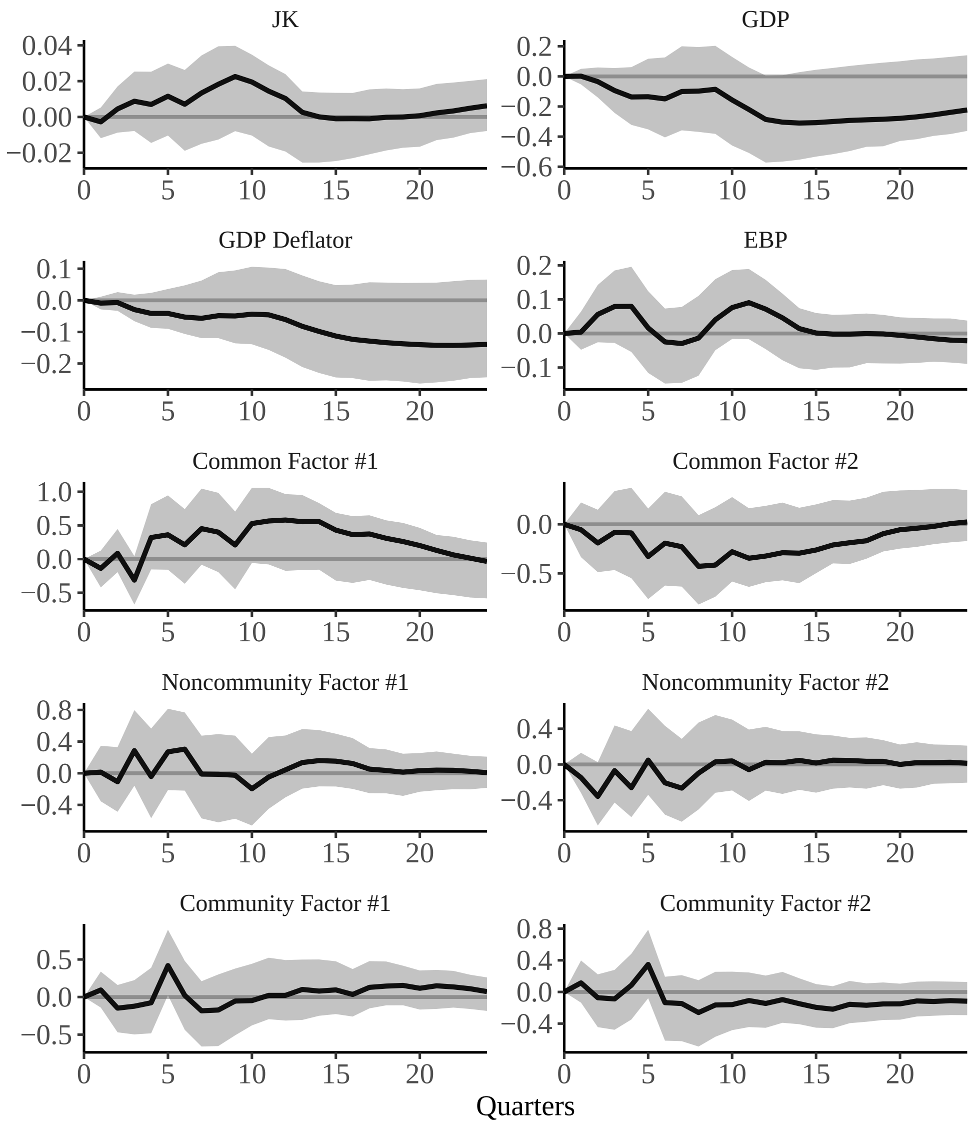


Figure E.6: PT-IRs of all endogenous variables in response to a one standard deviation positive (contractionary) monetary policy shock via common and noncommunity bank lending factors. Solid black lines are point estimates. Gray bands are 90% nonparametrically bootstrapped confidence intervals using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