Commercial Bank Heterogeneity and the Transmission of Monetary Policy: Decomposing the Bank Lending Channel

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Abstract

The literature on the aggregate bank lending channel (BLC) shows evidence of the transmission of monetary policy into the real economy through changes in the supply of bank loans. However, insights on the distributional properties of the BLC are scarce and inconclusive. I study how different dimensions of bank heterogeneity influence their individual roles in the BLC, with a special focus on the distinction between community and non-community banks in the United States. I find that the bank-level responses of lending growth to monetary policy shocks are quite diffuse across both community and non-community banks, but also that the spread of community bank responses to monetary policy shocks is greater than that of non-community banks. My results also suggest that output growth is affected quite differently by shocks to community bank lending than those to non-community bank lending. Lastly, I find that community banks play a key role in influencing the real output growth of certain sectors of the U.S. economy. My findings can be used by monetary and regulatory policymakers in gauging the potential distributional implications of the usage of blunt (monetary policy) or targeted (regulatory policy) policy tools by assessing the heterogeneous impact on the banking sector.

1 Introduction

Monetary policy is a tool through which central banks attempt to maximize employment and stabilize prices. It is often referred to as a “blunt" tool due to the fact that monetary policymaking conventionally involves the manipulation of a single aggregate variable – the money supply. This makes it difficult to conduct monetary policy in a manner that, unlike fiscal policy, targets only a select set of sectors of the economy. Monetary policy shocks are unwieldy in that they ultimately transmit to all parts of the economy to some extent. However, it is not necessarily the case that all parts of the economy respond to monetary policy shocks in a uniform manner – for example, the manufacturing sector may be stimulated much differently by an expansionary shock than the information technology sector. Therefore, although policymakers may have accurate expectations of how policy shocks affect aggregate macroeconomic variables, they may not be privy to the nature of their geographical, sector-specific, or more broadly, distributional effects. To better understand the distributional properties of monetary policy transmission across and within parts of the economy, we must carefully study the heterogeneity within the various channels of monetary policy transmission.

A large literature in macroeconomics studies the identification of the monetary policy transmission mechanism, which is composed of a set of channels through policy shocks ultimately spill over into the real economy. According to the current consensus within this literature, some of the major channels of monetary policy transmission include the following: (1) interest rate channel, (2) exchange rate channel, (3) asset price channel, (4) balance sheet channel, and (5) bank lending channel. In this paper, I analyze the bank lending channel (BLC) of monetary policy transmission. The BLC refers to the notion that changes in interest rates caused by changes in monetary policy affect the amount of reserves and thus the supply of “intermediate” loans issued by banks, the availability of which in turn affects the amount of investment in the economy.[1] A financially constrained bank that is unable to accommodate a negative shock to its deposits through external borrowing is forced to limit the issuance of loans, which may ultimately have a downward pull on output if producers rely on intermediate loans for financing investment.[2] Most studies attempt to identify the bank lending channel by treating the United States commercial banking sector as a single entity – they only observe aggregate lending behavior, thus capturing net effects without accounting for the immense heterogeneity of U.S. banks. Such an approach fails to account for how certain types of banks may respond to policy shocks differently than others.

The U.S. commercial banking sector is outstandingly large, with over 5,000 active banks currently holding just under $25T in combined assets. Furthermore, U.S. commercial banks are remarkably diverse in their characteristics across multiple dimensions, such as capitalization, size, asset allocation, risk, etc. Some studies have attempted to capture the role of heterogeneity in bank behavior by explicitly controlling for some of these dimensions (Kishan and Opiela, 2000; Ashcraft, 2006; Dave et al., 2013; Buch et al., 2014). However, a key confounding factor that the existing literature fails to address is the categorization of banks as community and non-community institutions, which I argue is a key determinant of bank behavior. Community banks tend to be smaller than their non-community counterparts, but more importantly the geographic scope of their service provision is often limited to local economies, and their business model is geared toward relationship-building and provision of traditional banking services to local clients.[3] For

[1]Pg. 222 of Kashyap and Stein (1994) provides a more detailed explanation of the BLC, a key part of which states the following: "…the decrease in reserves can still have important real consequences, if it leads banks to cut back on loan supply: the cost of loans relative to bonds will rise, and those firms that rely on bank lending (say, because they do not have access to public bond markets) will be led to cut back on investment. Put differently, monetary policy can have significant real effects that are not summarized by its consequences for open-market interest rates."

[2]For the BLC to be of significance within the monetary mechanism, it must be the case that some borrowers are unable to perfectly switch over to external funding from non-bank entities in financial markets. Refer to James and Smith (2000) for a literature review on the special role of banks in loan provision.

[3]Refer to Nguyen and Barth (2020) for evidence on the consistency of geographic scope and reliance of community banks on relationship-building.

these reasons, community banks behave and respond to economic shocks differently than others, as further evidenced by their superior performance during the 2007-08 global financial crisis. Much of the existing literature attempts to account for bank heterogeneity by grouping banks by size (total assets),[4] as it appears to be a metric that best captures overall heterogeneity across multiple characteristics. However, such a grouping is uninformative due to the fact that mid-sized banks are equally as likely to be community banks as they are to be non-community banks, so there is crucial heterogeneity within groups that remains unaccounted without further partitioning banks into sub-groups by bank type (community vs. non-community banks).

I estimate a factor-augmented vector autoregression (FAVAR) using a combination of aggregate macroeconomic series obtained through the Federal Reserve Economic Data (FRED) database and bank-level data obtained through the Federal Deposit Insurance Corporation Statistics on Depository Institutions (FDIC-SDI) database. Bank-level data is used to construct factors that capture the co-movement in size and lending across all banks, along with similar factors that separately capture co-movements across community and non-community banks. The factors are then included in a vector autoregression (VAR) along with a set of macroeconomic series necessary to identify the effects of monetary policy shocks on community and non-community bank lending, as well as the spillovers of monetary policy shocks on various sectors of the real economy through the channel of bank lending. All key results are presented as impulse response functions (IRFs) generated using the VAR. Monetary policy shocks are produced according to the existing literature on monetary policy shock measures and included in the VAR explicitly. To identify other structural shocks in the model, I rely on short-run identification restrictions.

Based on my empirical analysis, I propose that what is commonly understood as the bank lending channel in the U.S. is the amalgamation of two dissimilar sub-channels of

[4] As an example, refer to Dave et al. (2013).

bank lending: (1) the *community bank lending channel*, and (2) the *non-community bank lending channel*. I argue that treating these channels as separate is key in accurately identifying the distributional effects of monetary policy on certain sectors of the U.S. economy through bank lending. I find that the bank-level responses of lending growth to monetary policy shocks are quite diffuse across both community and non-community banks, but also that the spread of community bank responses to monetary policy shocks is greater than that of non-community banks. My results also suggest that output growth is affected quite differently by shocks to community bank lending than those to non-community bank lending. Lastly, I find that community banks play a key role in influencing the real output growth of certain sectors of the U.S. economy. My findings can be used by monetary and regulatory policymakers in gauging the potential distributional implications of the usage of blunt (monetary policy) or targeted (regulatory policy) policy tools by assessing the heterogeneous impact on the banking sector.

The remainder of this paper is organized as follows: Section 2 describes the structural heterogeneity of the U.S. commercial banking sector and presents a set of stylized facts that justify the differentiation between community and non-community banks; Section 3 provides an overview of the existing literature on the bank lending channel and discusses the contributions of this study to the existing body of knowledge in this field; Section 4 describes the data, model, and restrictions used to identify the community and non-community bank lending channels of monetary policy transmission; Section 5 presents the results; The final section concludes the paper by discussing the implications of the findings of this study.

2 Background

In this section I describe the heterogeneity of the U.S. banking sector – specifically, I address the distinction between community and non-community commercial banks. I begin the section with a conceptual overview of the peculiarities of the community bank business model relative to non-community banks, as well as a historical overview of the evolution of heterogeneity in the U.S commercial banking sector. I then formulate a set of empirically-backed stylized facts about community and non-community banks that act as the foundation of the analysis carried out in the remainder of the study.

2.1 Community vs. Non-Community Banks

The United States currently has an unusually large number of banks relative to other countries, but the total number of banks has been consistently decreasing since the early 1990s due to consolidation, as can be seen in Fig. 1. Community banks saw the greatest absolute loss in numbers, however they now make up a greater share of the U.S. banking sector due to non-community banks experiencing a greater relative loss. On the other hand, the combined share of non-community bank assets and net loans has grown considerably over the same time period, as can been seen in Figs. 2 and 3, respectively. In summary, the non-community banking sector has consolidated at a greater rate, while also outpacing the community banking sector in terms of growth in size and dominance in credit markets. However, as will become clear in the next part of this section – the loss in size and aggregate presence in credit markets does not imply that community banks are dying out, as in fact they are "specialists" that dominate certain segments of the economy.

In addition to the above aggregate group-specific developments, there have been within-group changes as well. For example, non-community bank size has gradually become more

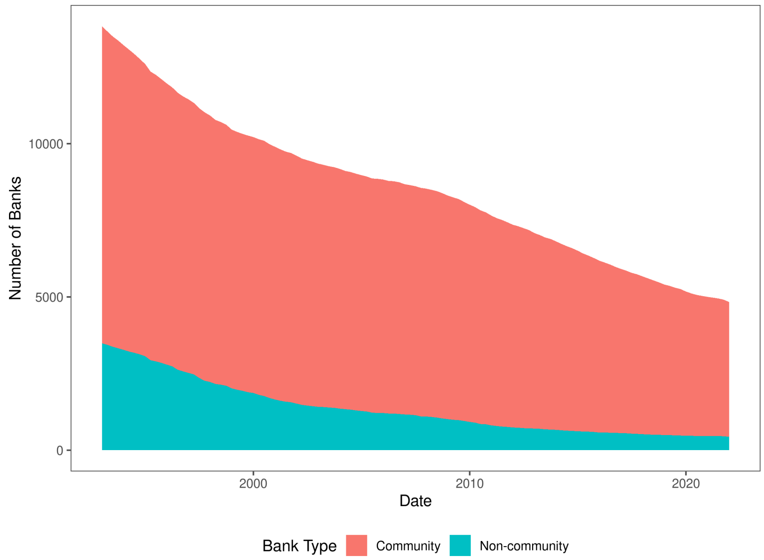


Figure 1: Number of commercial banks in the U.S. over time.
Source: FDIC-SDI.

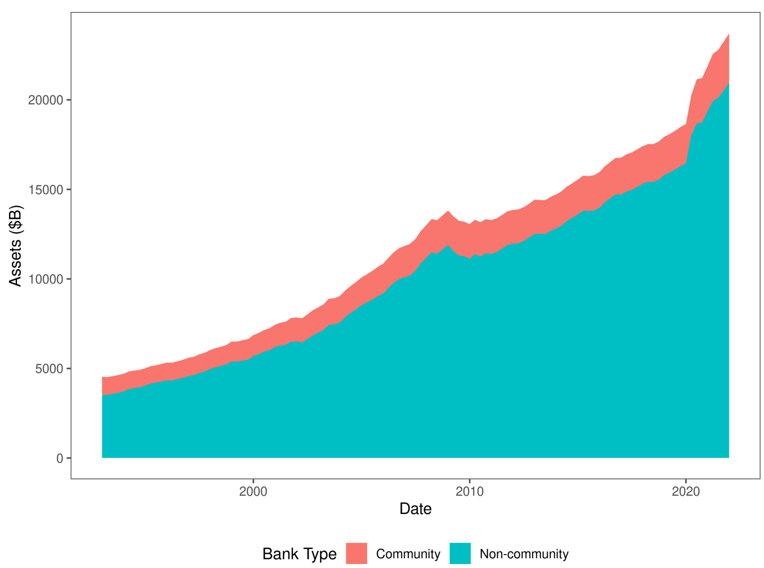


Figure 2: Commercial bank assets in the U.S. over time.
Source: FDIC-SDI.

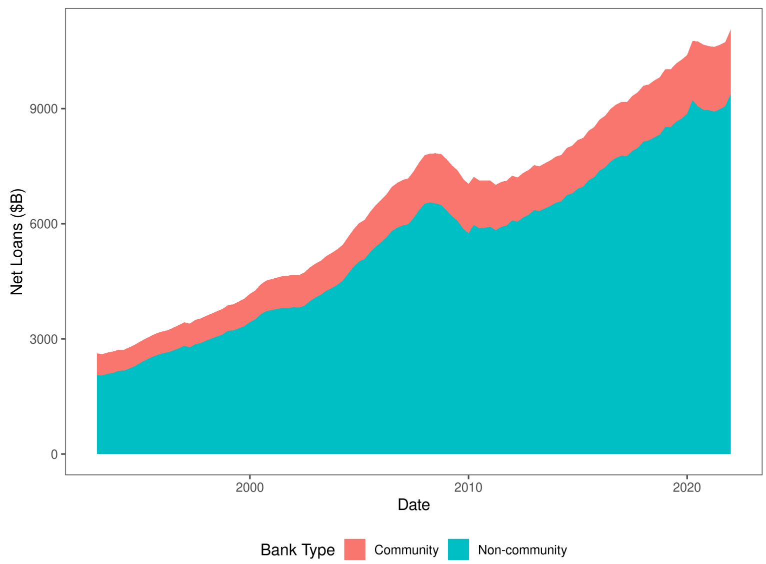


Figure 3: Commercial bank lending in the U.S. over time.
Source: FDIC-SDI.

skewed – large banks have become larger, while holding a greater share of total bank assets. This can be observed in Fig. 4, which presents community and non-community bank size distributions for the years 2000, 2010, and 2020. In a similar vein, it is worth highlighting that currently the majority of small banks in the U.S. are community banks, and the majority of large banks are non-community banks. This phenomenon is illustrated by Fig. 5, which shows the percentage of community and non-community banks across four asset size categories. Note that only a minuscule share of banks with assets above $10B are categorized as community banks, while the opposite is true for banks with assets less than $1B.

An informal definition of a community bank is a small, typically standalone bank that tends to focus on providing traditional banking services to a local community (Lux and Greene, 2015). Community banks are often locally owned and managed, with close ties to their corresponding towns and regions – historically, this defined the "community" aspect of a community bank. Formal definitions of a community bank vary – the FDIC and the Federal Reserve Board, two of the largest federal banking regulators, use different defi-

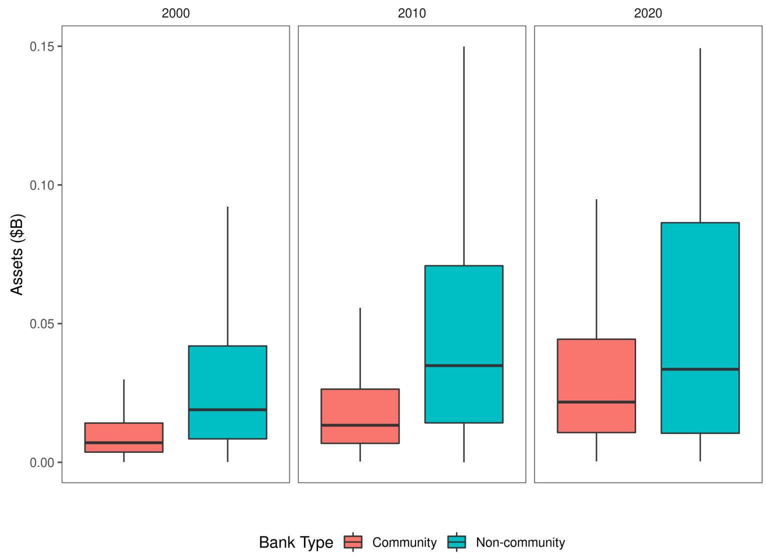


Figure 4: U.S. bank asset distribution over time. All outliers are removed.
Source: FDIC-SDI.

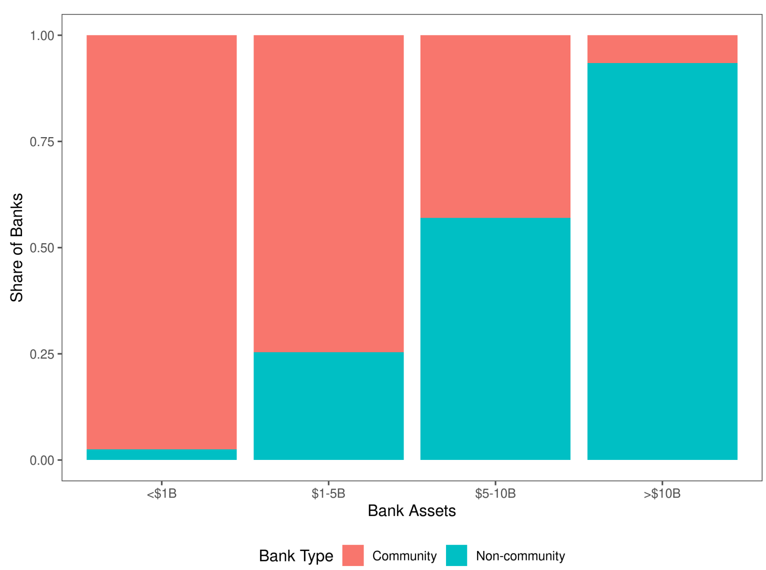


Figure 5: U.S. bank type composition of total asset ranges in 2020.
Source: FDIC-SDI.

nitions. In their definition, the FDIC excludes banks with (1) no loans or core deposits, (2) foreign assets $\geq 10\%$ of total assets, (3) more than 50% of assets in certain specialty banks; it includes remaining banks with (1) total assets <$1B, and (2) total assets >$1B but with loan-to-assets >33%, core deposits to assets >50%, less than 75 offices, number of large metropolitan statistical areas (MSAs) with offices ≤2, and number of states with offices ≤3. The Federal Reserve Board defines a community bank simply as a bank with total assets ≤$10B. In the remainder of this study, I default to the FDIC classification to differentiate between community vs. non-community banks, as it more carefully captures the spirit and historical context of community banking. Particularly, the FDIC specifies the geographical scope of community banks – a community bank must largely operate within a local economy by geographically limiting both its presence and service provision.

So far I have defined community banks, but have not fully discussed what makes them unique from other commercial banks. In my discussion I follow the structure put forth by Lux and Greene (2015) by touching on the following aspects of community banking: (1) lines of business, (2) financials, and (3) areas served. With respect to lines of business, as mentioned earlier, community banks are of special significance to local economies. They distinguish themselves by building and maintaining personal relationships, essentially becoming specialists in monitoring local economic conditions – their ability to gather and process "soft information" enables them to have greater loan repayment success rates than their non-community counterparts (Peirce et al., 2014). In terms of financials, community banks tend to be much less leveraged than their non-community counterparts. Furthermore, their focus on the provision of traditional banking services such lending to households and small businesses causes their margins to be largely dependent on, and sensitive to, the interest rate spread (FDIC, 2020). Finally, it is worth mentioning that community banks disproportionately serve rural American communities, and are approximately four times more likely than non-community banks to have offices in rural areas (FDIC, 2020).

2.2 Facts About the Heterogeneity of U.S. Commercial Banks

The following set of stylized facts informs the empirical analysis carried out later in the study – particularly, it justifies certain areas of interest and decisions in the construction of the FAVAR.

Fact #1: *Non-community banks have portfolios with more diversified asset class and loan allocations than community banks.* First, observing Fig. 6 reveals that community banks are much heavier on loans and leases than non-community banks, while holding essentially no trading account assets. Furthermore, the overall asset allocation of non-community banks seems to be more balanced across all other asset classes. We may also notice by observing 7 that community banks are heavy on real estate loans, and light on loans to individuals and all other types of loans and leases in comparison to non-community banks. Non-community banks have almost a uniform distributions across the four lending categories presented in the graph.

Fact #2: *Community banks are more sensitive to local economic shocks than non-community banks, which tend to be more geographically diversified.* One indicator of this phenomenon is shown in Fig. 8 – in recent years the average non-community U.S. bank has had over 100 domestic offices at any given quarter, while the average community bank has had less than five. Furthermore, as shown in Fig. 9, over 50% of non-community banks have had offices spread across more than one state, while the same holds true for only 15% of community banks. These demonstrations, combined with the fact that community banks tend to base their business model around relationship banking and rely less on technology, imply that community banks are less geographically diversified and more susceptible to local economic shocks.

Fact #3: *Community banks are more sensitive to changes in the interest rate spread than non-community banks.* This fact may partially be inferred from Fig. 6, which shows that

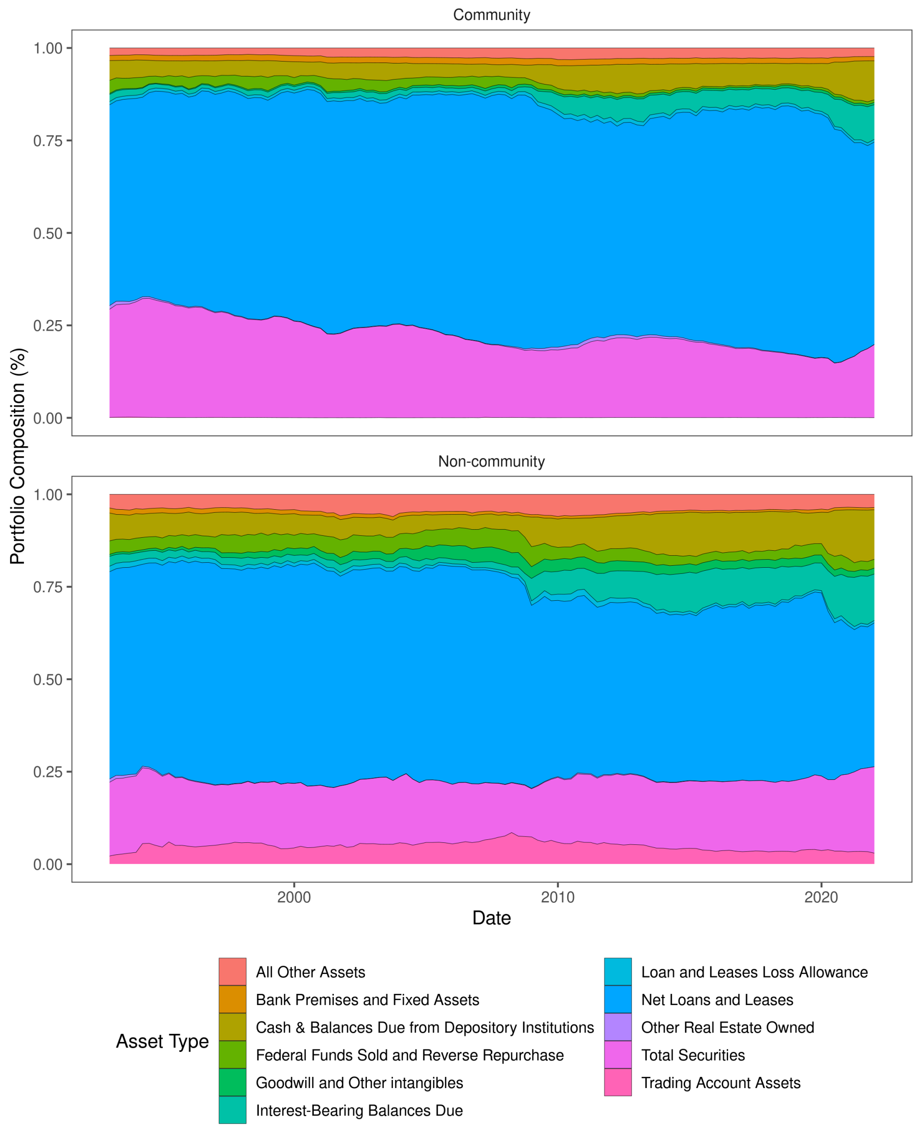


Figure 6: Average asset allocation over time across both bank types. *Source: FDIC-SDI.*

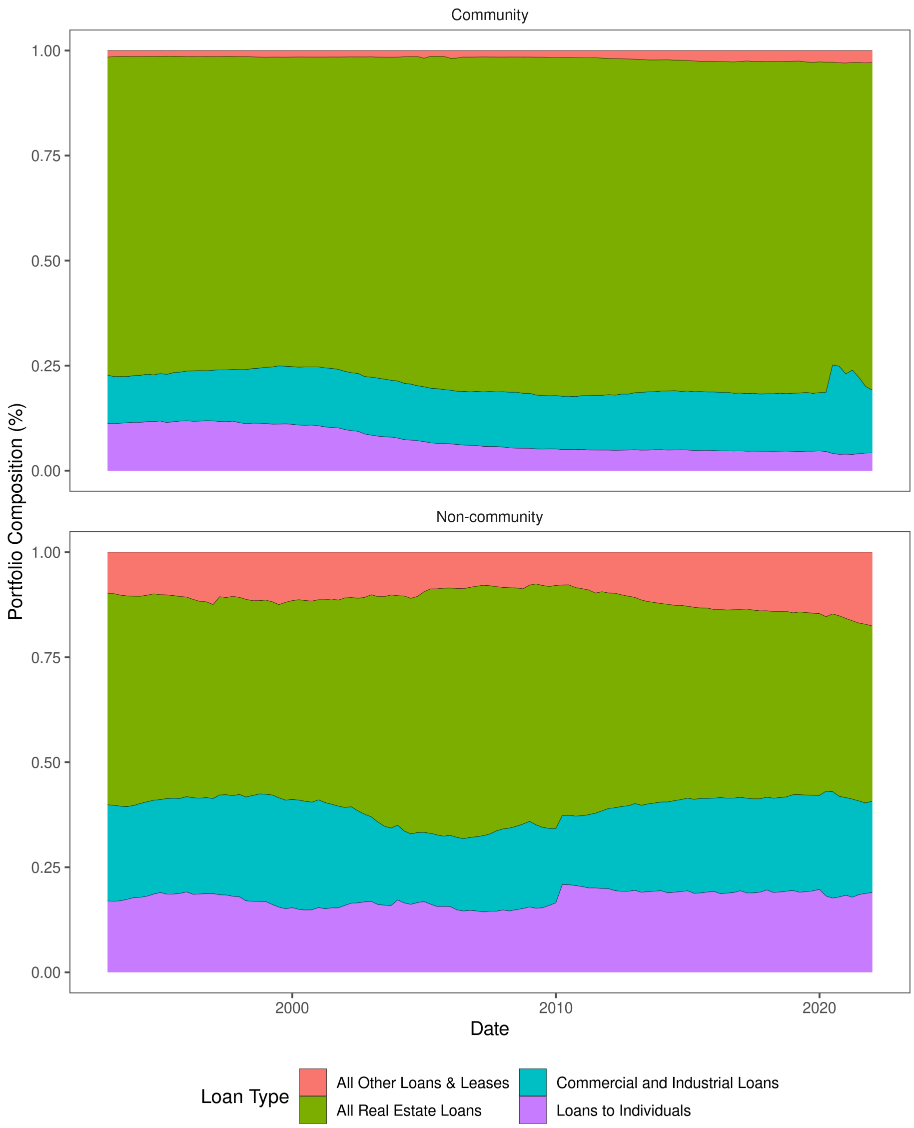


Figure 7: Average loan allocation over time across both bank types. *Source: FDIC-SDI.*

historically loans have dominated community bank asset portfolios more so than those of their non-community counterparts. Since the value of fixed income assets is a direct function of interest rates, then we may infer that changes in interest rates would affect community banks more strongly. We must also consider that the community bank business model is more rigid in terms of allocation shifts – non-community banks are more flexible in their ability to reallocate their assets both geographically and across asset classes. Furthermore, Kashyap and Stein (1995) and Kashyap and Stein (2000) show that small financially constrained banks tend to be more sensitive to interest rate changes – since community bank are more likely to be both small and financially constrained relative to their counterparts, we may conclude that they are also more likely to be sensitive to the interest rate spread.

Fact #4: *Community banks lead non-community banks in total combined agricultural loan provision.* Refer to Fig. 10, which demonstrates that over the last three decades community banks have consistently provided more than half of all agricultural loans in the U.S. It is also notable that since the global financial crisis there has been an upward trend in community bank dominance of the agricultural bank loan market. This highlights the niche role of community banks in the U.S. commercial banking sector, as well as in the greater U.S. economy – agricultural producers are rely on community banks more than non-community banks to finance their activities.

3 Related Literature

The existing literature related to this study may be categorized under the following topics: (1) the bank lending channel; (2) the macrofinancial role of bank heterogeneity; (3) the use of FAVARs in exploring the bank lending channel and bank heterogeneity. In this section I provide a non-exhaustive coverage of studies across all three of these areas in the

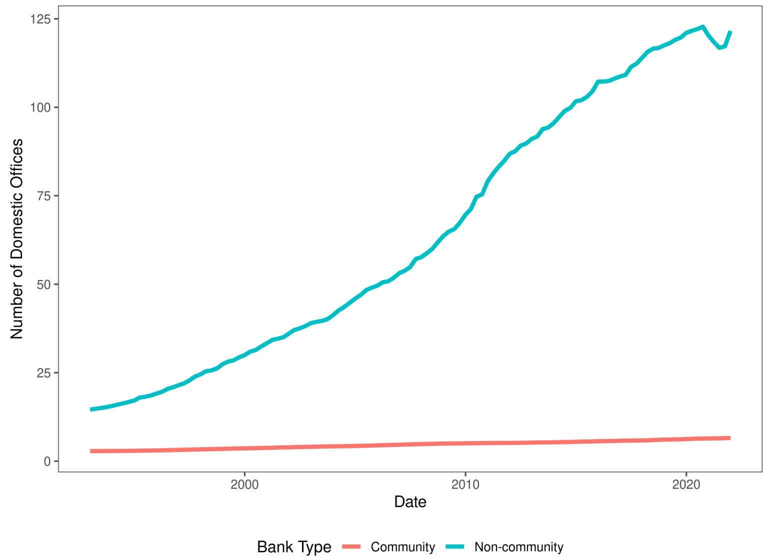


Figure 8: Average number of domestic offices by bank type.
Source: FDIC-SDI.

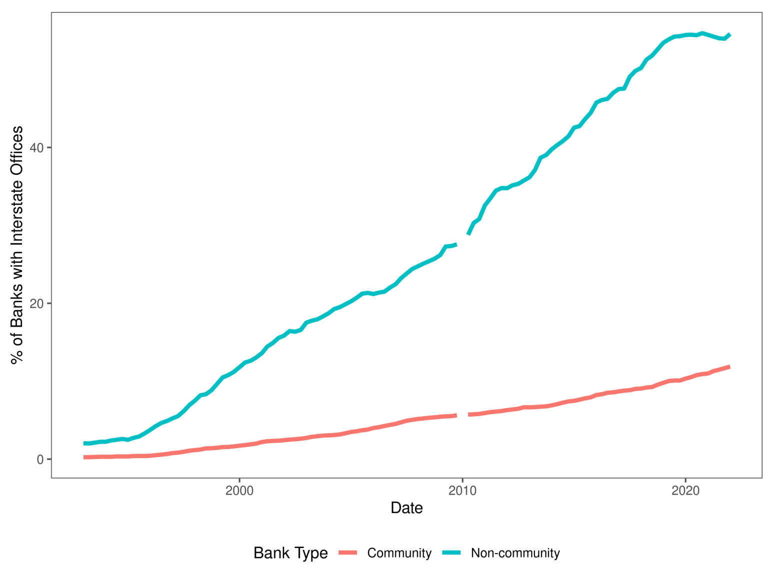


Figure 9: Percentage of banks with offices across more than one state, by type.
Source: FDIC-SDI.

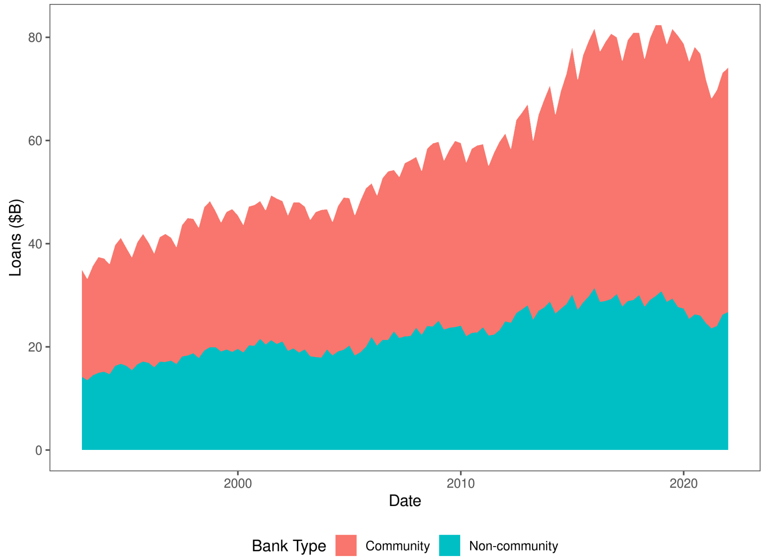


Figure 10: Commercial bank agricultural lending in the U.S. over time.
Source: FDIC-SDI.

given order.

3.1 The Bank Lending Channel

The bank lending channel is part of what is known as the credit channel of monetary transmission, which also includes the balance sheet channel. The literature on the credit channel is quite vast, so it is difficult to pin-point its exact origins and present status. A good contemporary starting point is Bernanke and Gertler (1995), which provides one of the first surveys of the credit channel of monetary policy transmission, and proposes it as a crucial component of the monetary transmission mechanism.

More recently, Black and Rosen (2007) decompose the credit channel into its two sub-channels using loan-level data. They find evidence of both credit sub-channels, with results being stronger for transmission through larger banks. Similarly, Kishan and Opiela (2000) provide evidence of a bank lending channel of monetary policy in the U.S. during the period of 1980-1995. Driscoll (2004) finds that although shocks to money demand have large and statistically significant effects on bank loan supply, changes in the loan supply tend to have negative and statistically insignificant effects on output. Heider et al. (2019) show asymmetries in the effect of monetary policy rates on the supply of bank credit – negative rates are less accommodative and could pose a risk to financial stability if lending is done by high-deposit banks. Ivashina et al. (2022) show that credit growth dynamics and bank lending channels vary across different loan types. Chakraborty et al. (2020) find heterogeneity in the effects of quantitative easing on bank behavior. They show that banks benefiting from mortgage-backed securities (MBS) purchases increase mortgage origination, compared with other banks, while simultaneously reducing commercial lending. Albertazzi et al. (2021) study the transmission of conventional and unconventional monetary policy in the euro area through changes in the credit supply. They find that the transmission conventional policy changes is stronger for weaker banks, with the opposite being true for unconventional policy.

There also exists a recent line of literature exploring the international transmission of monetary policy through the bank lending channel. Santis and Surico (2013) find that the transmission of monetary policy through bank lending across eurozone countries and various bank types is highly heterogeneous. Argimon et al. (2019) study whether the international transmission of monetary policy depends on financial institutions' business models – specifically, they compare banks, insurance companies, and pension funds across the Netherlands, Spain, and the U.S. They find evidence of heterogeneity in the transmission of monetary policy across types of institutions, country-specific banking systems, and banks within each banking system. Albrizio et al. (2020) study how domestic monetary policy in systemically important countries spill over into other countries. They estimate the dynamic effect of monetary policy shocks in systemically important economies (such as the U.S.) on bilateral cross-border bank lending. They find that monetary tightening leads to a statistically and economically significant decline in cross-border bank lending.

3.2 Bank Heterogeneity

Over the last decades, improvements in the availability of bank- and loan-level data seems to have kindled what is now a vast literature on bank heterogeneity. Despite the existence of older studies on bank heterogeneity (see Kashyap and Stein (1995), Kashyap and Stein (2000), and Kishan and Opiela (2000)) I provide a non-comprehensive summary of relatively recent works in this area with the greatest relevance to this study. I begin with an overview of empirical studies, after which I briefly cover theoretical/structural advances.

Empirical studies on bank heterogeneity gather data on bank characteristics over time, and attempt to capture the interactions of those characteristics with bank responses to various types of shocks and/or scenarios. As an example of the estimation of shock responses: Plosser (2014) empirically identifies bank deposit inflow shocks, and uses given estimated shock measures to estimate how banks allocate these deposits over the business cycle. The study finds that in the case of a negative shock, liquid and loan asset allocations increase and decrease, respectively. Furthermore, the results show that banks with fewer funding sources and higher capital ratios reduce loan allocations more. As an example of scenario testing: Gambacorta and Mistrulli (2011) study how bank size, liquidity, capitalization, funding structure and bank-firm relationship characteristics have influenced interest rate setting since the collapse of Lehman Brothers. Using data on a large sample of loans from Italian banks to non-financial firms, they find that interest rate spreads increased by less for well-capitalized, liquid banks, as well as those engaged mainly in traditional lending business.

A subset of the literature on bank heterogeneity focuses specifically on the effects of monetary policy. Brissimis and Delis (2010) study the role of differences in bank liquidity, capitalization, and market power as determinants of banks' lending, risk-taking, and performance responses to monetary policy shocks. Using bank-level U.S. and EU data, they find significant heterogeneity across all of the mentioned impulse responses with respect to bank capitalization, liquidity, and market power. Bluedorn et al. (2017) examine how bank heterogeneity interacts with the effects of monetary policy changes on bank lending. They find greater heterogeneity in bank lending responses to monetary policy changes than previous literature. Their results suggest that studies using realized monetary policy changes confound the monetary policy's effects with those of changes in expected macro fundamentals. Similarly, Rojas (2020) find substantial heterogeneity in the response of banks to monetary policy, but using a structural approach instead of a purely empirical one. In a model with heterogeneous banks, they show that banks with more deposit market power are more sensitive to monetary policy, and experience a larger decline in deposits and lending after an increase in the policy rate, which leads to dampening of monetary policy.

Recent studies have made advances in formulating new approaches to modeling heterogeneous banks and incorporating them into larger macroeconomic models. Goldstein et al. (2020) construct a structural model to study how bank asset heterogeneity affects the fragility of the banking sector during financial crises. They find that some heterogeneity across banks improves the stability of the entire banking sector. Jamilov (2020) builds an empirically-motivated macroeconomic model with uninsurable idiosyncratic rate of return shocks, endogenous markups, costly default, and endogenous entry in the banking sector. Jamilov and Monacelli (2020) combine elements of Jamilov (2020) and Gertler and Kiyotaki (2010) to develop a non-linear, quantitative macroeconomic model with heterogeneous monopolistic financial intermediaries, incomplete markets, default risk, endogenous bank entry, and aggregate uncertainty. The model generates a bank net worth distribution fluctuation problem analogous to the canonical Bewley-Huggett-Aiyagari-Imrohoglu environment. Bellifemine et al. (2022) study how bank heterogeneity and market power shape the transmission of monetary policy by using the structure of the model in Jamilov and Monacelli (2020) to create a Heterogeneous Bank New Keynesian (HBANK) model, featuring permanent and stochastic bank returns heterogeneity, incomplete markets, variable asset and deposit market power, and nominal rigidities. In their model, the aggregate effects of monetary policy shocks depend explicitly on the endogenous distribution of banks' net worth and the competitive structure of asset and deposit markets.

Lastly, in contrast to the previously-mentioned studies – all of which examine the effects of bank heterogeneity – Fernholz and Koch (2016) explore the possible causes of the *emergence* of bank heterogeneity. They use quarterly data on subsidiary commercial banks and thrift institutions and their parent bank-holding companies to show that the increase in the concentration of U.S. bank-holding company assets is a result of lower mean reversion, which they argue is consistent with policy changes such as interstate branching deregulation and the repeal of the Glass-Steagall Act. Furthermore, they find that increased concentration of U.S. commercial bank and thrift assets is caused by increased idiosyncratic volatility, yet, the idiosyncratic volatility of parent bank-holding company assets fell. Their results suggest that diversification through non-banking activities has reduced the idiosyncratic asset volatilities of the largest bank-holding companies. Gambacorta (2008) studies the effects of micro- and macro-level factors on the cross-sectional differences in banks' interest rates, and finds that heterogeneity in responses to monetary policy shocks -— depending on liquidity, capitalization, and relationship lending -— exists only in the short run. For other examples of heterogeneous bank modeling, see Ghossoub and Reed (2015), Corbae and D'Erasmo (2021), and Coimbra and Rey (2021).

3.3 FAVARs

A FAVAR combines dynamic factor modeling with standard VAR methods, which allows for inference using a large number of variables through dimension-reduction. It was first developed by Bernanke et al. (2005) to improve on existing conventional VAR approaches to identifying impulse responses to monetary policy shocks. Since then FAVAR methodology has grown and matured considerably both within and outside of monetary and macroeconomics. The idea is to (1) estimate a set of factors using a large set of variables, such that (2) the factors appear in a VAR along with a set of series without any corresponding factors. The former component of the model captures the comovement of a large set of series using factors, while the latter component allows for a dynamic relationship between the factors and other observable series. A thorough review of the FAVAR literature in macroeconomics is presented in Stock and Watson (2016).

To my knowledge, Dave et al. (2013) are the first to study the bank lending channel of monetary policy transmission using a FAVAR. Their analysis consists of two alternative approaches: (1) estimating the bank lending channel by appending the Bernanke et al. (2005) FAVAR with aggregated lending data, and (2) estimating the bank lending channel by further appending the FAVAR with bank-level lending data. In the latter approach, they create a balanced panel of individual banks grouped by asset size, and then assign factors to each of the groups as part of the FAVAR. They then estimate a FAVAR to decompose bank-level lending into contributions from bank-specific, monetary, and other macroeconomic shocks. Although they find convincing evidence of the bank lending channel using the first approach, their latter analysis yields weak results – individual banks' responses in lending volume to a monetary tightening are diffuse, with only a small percentage of impulse responses being statistically significant. Furthermore, they find that macroeconomic shocks contribute to only 8-22% of variation in bank-level lending across various loan and size categories. Using a similar approach, Buch et al. (2014) estimate a FAVAR using a balanced panel of about 1,500 banks taken from the U.S. Call Reports over the period of 1985-2008 to estimate the effect of supply, demand, monetary policy, and house prices shocks on lending, as well as backward-looking and forward-looking risks, while also estimating the degree of heterogeneity in the responses to these shocks with respect to various bank-specific characteristics. They find substantial heterogeneity in how macroeconomic shocks transmit to banks due to differences in size, capitalization, liquidity, risk, and exposure to real estate and consumer loans.

Both Dave et al. (2013) and Buch et al. (2014) try to control for bank characteristics such as size (total assets), however they do not *explicitly* account for crucial differences in the business models of a large subset of the banks in their sample. This is problematic due to the fact that there is a significant overlap in bank characteristics between many community and non-community banks. For example, as evidenced earlier in Fig. 5, approximately half of all banks with total assets in the $1-10B range are community banks, while the rest are non-community. For this reason, I argue that the discussions of the heterogeneity of responses based on bank-specific factors in Dave et al. (2013) and Buch et al. (2014) are uninformative due to the insufficient separation of community banks from the rest, and that the concept of a "modal" bank described by Buch et al. (2014) is erroneous. There are simply too many complex underlying nonlinearities to achieve proper separation between the two categories of banks to account for heterogeneity.

4 Methodology

The goal of this study is to estimate the heterogeneity in the manner in which monetary policy transmits through community and non-community commercial bank lending into the real economy. I estimate the effects of monetary policy shocks on GDP and agricultural production growth through the bank lending channel, while also accounting for the heterogeneity of monetary policy transmission by way of large non-community commercial banks versus community banks. I exploit the comprehensive bank-level data available through Statistics on Depository Institutions (SDI) provided by the Federal Deposit Insurance Corporation (FDIC) to estimate a structural factor-augmented vector autoregression (FAVAR) as a way of accounting for the dynamic relationship between aggregate economic variables and bank-related factors.

4.1 Data

For the construction of the FAVAR I use a combination of high-dimensional bank-level data and a small set of aggregate macroeconomic series. The raw sample runs from Q4 of 1992 until Q4 of 2021 – a total of 117 observations. The data-gathering and cleaning procedure for bank data is described by the following steps:

1. I begin by downloading the entire SDI database, which consists of a set of subdirectories, with each subdirectory containing bank-level call report data for a given quarter;

2. I pull the following set of quarterly series from the FDIC SDI over the full period of current data availability (1992Q4–2021Q4) for each FDIC-insured bank: (1) total assets, (2) total lending, and (3) agricultural lending;

3. I then discard the data for banks with at least one missing observation across all of the above-mentioned variables – in other words, I create a balanced panel for each variable;

4. For each of the remaining banks, I pull demographic data – of particular interest is the variable classifying each of the banks as being either community or non-community;

5. I partition each of the variable-specific balanced panels by bank type. The final result yields 6 separate sub-panels of bank-specific data – each of these sub-panels will later be used to estimate a bank type- and variable-specific factors;

6. Finally, each of the series across all of the sub-panels are transformed into growth rates and seasonally adjusted simply by partialling out variation attributable to seasonal dummies in a linear regression model.

Additionally, the following macroeconomic series are pulled from the Federal Reserve Economic Data (FRED) database:

1. *Real Gross Domestic Product (seasonally adjusted annual rate)*[5] – The raw series is transformed to growth rates, and interpreted as a measure of output growth in the remainder of this paper;

2. *Median Consumer Price Index (seasonally adjusted percent change at annual rate)*[6] – The raw series is interpreted as a measure of the inflation rate in the remainder of this paper;

3. *Farming Business Gross Value Added to GDP (seasonally adjusted annual rate)*[7] – The raw series is transformed to growth rates, and interpreted as a measure of the growth rate of agricultural production in the remainder of this paper;

The final key data series used in this study is the monetary policy shock measure, which warrants a separate discussion of its own. For the purposes of my analysis, I defer to the Bu-Rogers-Wu (BRW) monetary policy shock measure identified by Bu et al. (2021). I aggregate their provided shock series to the quarterly frequency, which can be observed in Fig. 11. I defer to using 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. Alternatively, I could have estimated a monetary policy shock by directly applying structural restrictions to my FAVAR – however, such an approach yields counter-intuitive results due to the unstable nature of my sample period.

[5]The FRED identifier for the raw series is 'GDPC1'.
[6]The FRED identifier for the raw series is 'MEDCPIM158SFRBCLE'.
[7]The FRED identifier for the raw series is 'B359RX1Q020SBEA'.

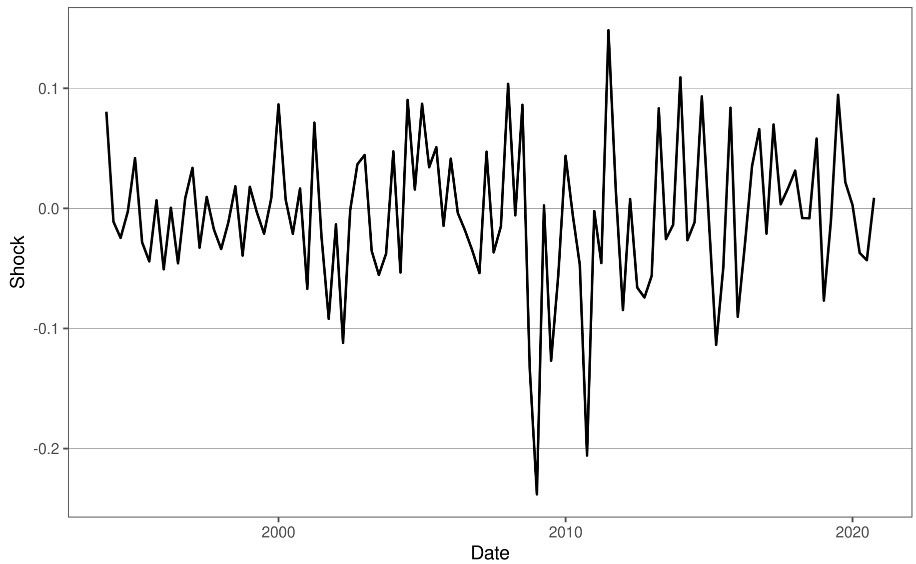


Figure 11: Quarterly aggregated BRW shock.

4.2 The Model

I begin by defining some of the key variables and data that will later be used in the FAVAR. Firstly, the vector of aggregate variables is defined as

$$Y_t \equiv \begin{bmatrix} \%\Delta \text{GDP}_t \\ \%\Delta \text{CPI}_t \\ \text{BRW}_t \\ \%\Delta \text{Agricultural Production}_t \end{bmatrix},$$

where GDP, CPI, and BRW denote gross domestic product, consumer pricing index, and the BRW monetary policy shock, respectively. Next, the vector of non-community bank-level data is defined as

$$X_t^L = \begin{bmatrix} X_{1t}^L \\ X_{2t}^L \\ X_{3t}^L \end{bmatrix} \equiv \begin{bmatrix} \%\Delta\text{Assets}_t \ (N_L \times 1) \\ \%\Delta\text{Loans}_t \ (N_L \times 1) \\ \%\Delta\text{Farm loans}_t \ (N_L \times 1) \end{bmatrix},$$

where N_L is the total number of non-community banks at any given point in time in the sample, so that each of the X_{it}^L are $N_L \times 1$ vectors, and X_t^L is a $(3N_L) \times 1$ vector. Equivalently, the vector of community bank-level data is defined as

$$X_t^C = \begin{bmatrix} X_{1t}^C \\ X_{2t}^C \\ X_{3t}^C \end{bmatrix} \equiv \begin{bmatrix} \%\Delta\text{Assets}_t \ (N_C \times 1) \\ \%\Delta\text{Loans}_t \ (N_C \times 1) \\ \%\Delta\text{Farm loans}_t \ (N_C \times 1) \end{bmatrix},$$

where N_C is the total number of community banks at any given point in time in the sample, so that each of the X_{it}^C are $N_C \times 1$ vectors, and X_t^C is a $(3N_C) \times 1$ vector. There exist a total of $N = N_L + N_C$ individual banks in the sample, and their joint data vector may be expressed as

$$X_t \equiv \begin{bmatrix} X_t^L \\ X_t^C \end{bmatrix}.$$

The given bank-level data vector may be decomposed as the following two-level factor model:

$$X_t = \begin{bmatrix} X_{1t}^L \\ X_{2t}^L \\ X_{3t}^L \\ X_{1t}^C \\ X_{2t}^C \\ X_{3t}^C \end{bmatrix} = \begin{bmatrix} \alpha_1^L \\ \alpha_2^L \\ \alpha_3^L \\ \alpha_1^C \\ \alpha_2^C \\ \alpha_3^C \end{bmatrix} + \left[\begin{array}{ccc} \Gamma_1^{LG} & 0 & 0 \\ 0 & \Gamma_2^{LG} & 0 \\ 0 & 0 & \Gamma_3^{LG} \\ \hline \Gamma_1^{CG} & 0 & 0 \\ 0 & \Gamma_2^{CG} & 0 \\ 0 & 0 & \Gamma_3^{CG} \end{array}\right] \begin{bmatrix} F_{1t}^G \\ F_{2t}^G \\ F_{3t}^G \end{bmatrix}$$
$$+ \left[\begin{array}{ccc|ccc} \Lambda_1^L & 0 & 0 & 0 & 0 & 0 \\ 0 & \Lambda_2^L & 0 & 0 & 0 & 0 \\ 0 & 0 & \Lambda_3^L & 0 & 0 & 0 \\ \hline 0 & 0 & 0 & \Lambda_1^C & 0 & 0 \\ 0 & 0 & 0 & 0 & \Lambda_2^C & 0 \\ 0 & 0 & 0 & 0 & 0 & \Lambda_3^C \end{array}\right] \begin{bmatrix} F_{1t}^L \\ F_{2t}^L \\ F_{3t}^L \\ F_{1t}^C \\ F_{2t}^C \\ F_{3t}^C \end{bmatrix} + \begin{bmatrix} u_{1t}^L \\ u_{2t}^L \\ u_{3t}^L \\ u_{1t}^C \\ u_{2t}^C \\ u_{3t}^C \end{bmatrix},$$

where Γ_k^{LG} and Γ_l^{CG} are $N_L \times 1$ and $N_C \times 1$ loading matrices for level-1 common bank factors, respectively; Λ_i^L and Λ_j^C are $N_L \times 1$ and $N_C \times 1$ loading matrices for level-2 bank type-specific factors, respectively; and u_{it}^L and u_{jt}^C are $N_L \times 1$ and $N_C \times 1$ disturbance vectors, respectively. We may express the above equation more succinctly as

$$X_t = \begin{bmatrix} X_t^L \\ X_t^C \end{bmatrix} = \begin{bmatrix} \alpha^L \\ \alpha^C \end{bmatrix} + \begin{bmatrix} \Gamma^{GL} \\ \Gamma^{CL} \end{bmatrix} F_t^G + \begin{bmatrix} \Lambda^L & \mathbf{0} \\ \mathbf{0} & \Lambda^C \end{bmatrix} \begin{bmatrix} F_t^L \\ F_t^C \end{bmatrix} + \begin{bmatrix} u_t^L \\ u_t^C \end{bmatrix},$$

or even more succinctly as

$$X_t = \alpha + \Gamma F_t^G + \Lambda F_t + u_t\,, \tag{1}$$

where the aggregated matrix and vector objects require no further elaboration. Notice that F_t^G is a 3×1 vector, implying that there are a total of 3 common bank factors, which may be interpreted as

$$F_t^G = \begin{bmatrix} \text{Co-variation in bank size}_t \\ \text{Co-variation in bank lending}_t \\ \text{Co-variation in bank agricultural lending}_t \end{bmatrix} .$$

Furthermore, notice that F_t is a $(3+3) \times 1$ vector, implying that there are a total of 6 bank type-specific factors (3 per bank type), which may be interpreted as

$$F_t = \left[\begin{array}{c} \text{Co-variation in non-community bank size}_t \\ \text{Co-variation in non-community bank lending}_t \\ \text{Co-variation in non-community bank agricultural lending}_t \\ \hline \text{Co-variation in community bank size}_t \\ \text{Co-variation in community bank lending}_t \\ \text{Co-variation in community bank agricultural lending}_t \end{array}\right]$$

To recap: the above implies that bank data may be decomposed into a linear function of three level-1 common bank factors, three level-2 community bank factors, and three level-2 non-community banks factors – this gives us a total of 9 bank factors. In other words, a data series for bank i of type j for variable k at time t may be expressed as

$$x_{ijt}^k = \alpha_j^k + \Gamma_{ij}^k F_t^{Gk} + \Lambda_{ij}^k F_{jt}^k + u_{ijt}^k \, . \tag{2}$$

The F_t^G and F_t vectors are assumed to be interacting with the aggregate variables contained in Y_t in the following vector autoregression (VAR):

$$\begin{bmatrix} F_t^G \\ F_t \\ Y_t \end{bmatrix} = \gamma + \Psi \begin{bmatrix} F_{t-1}^G \\ F_{t-1} \\ Y_{t-1} \end{bmatrix} + e_t \, ,$$

where Ψ is an autoregressive coefficient matrix, and $e_t \sim N(0, \Sigma_e)$. We may think of e_t as being a vector of reduced-form shocks that can be expressed as a mapping of a vector of underlying structural shocks $v_t \sim N(0, I)$:

$$e_t = Bv_t \, ,$$

where B is a transformation matrix. Therefore, the transition equation of the original FAVAR system may be expressed as

$$\begin{bmatrix} F_t^G \\ F_t \\ Y_t \end{bmatrix} = \gamma + \Psi \begin{bmatrix} F_{t-1}^G \\ F_{t-1} \\ Y_{t-1} \end{bmatrix} + Bv_t \, , \tag{3}$$

implying that the dynamics in the observed aggregate variables, Y_t, and the factors F_t^G and F_t are driven by the shocks contained in v_t that pass through the initial linear transformation B. The Eqs. (1) and (3) define the FAVAR model fully. If we define $Z_t \equiv \begin{bmatrix} F_t^{G'} & F_t' & Y_t' \end{bmatrix}'$, then we may succinctly express the SFAVAR in state-space form as

$$X_t = \alpha + \Gamma F_t^G + \Lambda F_t + u_t \, , \; u_t \sim N(0, \Sigma_u) \, , \tag{4}$$

$$Z_t = \gamma + \Psi Z_{t-1} + Bv_t \, , \; v_t \sim N(0, I) \, . \tag{5}$$

4.3 Identification

I impose a simple recursive ordering to identify structural shocks to all of the variables included in the VAR portion of the FAVAR in a manner that follows Christiano et al. (1999) and Christiano et al. (2005).[8] The ordering of variables is as follows (with the i-th variable

[8] All variables "above" the monetary policy variable are those to which the Federal Reserve responds, while the variables "below" the policy variable are those that the Federal Reserve does not necessarily consider.

being contemporaneously affected by all j-th variables for $j < i$, and unaffected by all k-th variables for $k > i$):[9]

1. **GDP growth rate:** It is standard to assume that the monetary policy variable responds instantaneously to the growth rate of aggregate output.

2. **Inflation rate:** Similarly to the GDP growth rate, the inflation rate is assumed to factor into the Federal Reserve's monetary policy decision-making.

3. **Common bank size factor:** Achieving financial stability is a major goal of the Federal Reserve, hence I assume that it monitors the overall state of the banking sector. The common bank size factor may be interpreted as a good proxy for the growth state of the U.S. banking sector as a whole.

4. **Common bank lending factor:** Intermediated credit provision is also important for financial stability, hence I include it as a contemporaneous input into monetary policy. The lending factor belongs below the bank size factor since shocks to the latter (through increase deposits, for instance) determines the former, while loans are simply a components of banks' assets.

5. **BRW shock:** The BRW shock is intended as an estimate of shocks to monetary policy – however, in the given context I decide to include it as an endogenous variable in the VAR instead of an exogenous variable or an instrument. The main reason for doing so is ensuring that all bank-related forces contaminating monetary policy are further partialed out of the shock series to identify an even more accurate monetary shock measure.[10] I believe this approach to be necessary since Bu et al. (2021) does not focus on any such possible contamination.

6. **Non-community bank size factor:** To my knowledge, the Federal Reserve does not

[9] I have not yet performed rigorous tests of the robustness of the given recursive ordering.
[10] I attempted adopting exogenous variable approach and obtained puzzling IRFs.

isolate and track non-community banks separately as a group. Therefore, common factors unique to non-community banks cannot factor into monetary policy, implying that the given variable belongs below the policy variable. It also belongs above the agricultural production growth rate since non-community banks are not reliant on farm output.

7. **Non-community bank lending factor:** The justification for why the common bank lending factor belongs below the common bank size factor also justifies the inclusion of the non-community bank lending factor below the non-community bank size factor.

8. **Agricultural production growth rate:** To my knowledge, the growth state of agricultural production is normally not considered in monetary policymaking – hence, the given variable belongs below the monetary policy variable.

9. **Community bank size factor:** The community bank size factor belongs below the monetary policy variable by the same vein as the non-community bank size factor. On the other hand, I place it below the agricultural production growth rate since farms are common community bank borrowers – hence, the performance of the agricultural sector must be tied closely with the value of loans held as community bank assets.

10. **Community bank lending factor:** Finally, I place the community bank lending factor below the community bank size factor by the same reasoning as with previously-discussed bank size and lending factors.

4.4 Estimation

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

The factor estimation procedure is as follows:

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

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

ing first few principal components;

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

4. 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;

5. Repeat steps 1-4 until some form of convergence is achieved in the factor and coefficient estimates, but modify step 1 by partialing out the most recent estimate of the variation attributable to the type-specific factors from each corresponding series.

The estimated factors are then treated as observable series, and included in the transition equation of the FAVAR, which is essentially a VAR. The parameters of the VAR are estimated using least squares. The VAR estimates are then used to construct orthogonal impulse response functions (IRFs) with 95% bootstrapped confidence intervals. The identification scheme used to obtain the IRFs is a simple recursive ordering of the shocks, with the BRW policy shock ordered last so that it does not affect any of the remaining variables contemporaneously.

5 Results

In this section I present the results of my empirical analysis. **(1)** I begin by discussing the bank factor estimates and their corresponding bank-specific sensitivity coefficients described in the Estimation subsection of Methodology. I find that there exist factors for bank size, profitability, and lending that are common to both community and non-community banks that drive much of the variation in the observed series. On the other hand, the bank type-specific factors that are uncorrelated with the common bank factors show dissimilar behavior across community and non-community banks. Furthermore, there is significant heterogeneity among banks in their sensitivity to common and type-specific factors – notably, a positive change in a factor may have positive effects on some banks and negative effects on others, which introduces difficulties in the interpretation of the estimated factors without the consideration of the full distribution of their respective bank sensitivities.

(2) Next, I present the response functions of key macroeconomic variables to impulses to bank lending factors, as well as the response functions of the factors to monetary policy shocks. I find that on average, community and non-community bank lending factors respond differently to monetary policy shocks – however, there is also evidence of a strong common component in how the two types of banks respond to such shocks. I also find that positive common, community, and non-community bank lending shocks yield varying responses in output growth.

(3) Lastly, I present the heterogeneity in bank responses to monetary policy shock through the common and bank type-specific lending factors. I find that regardless of type, contractionary monetary policy shock is associated with a decrease in the growth rate of lending for most banks. However, the response distribution is much wider for community banks compared to non-community banks, with the latter being concentrated more below zero than the former.

5.1 Factors

Refer to Figs. 21 and 22 in Appendix A for timeplots of the estimated bank size and lending factors, respectively. The common bank factors are uncorrelated with their type-specific counterparts – however, the two bank type-specific factors are considerably correlated across the two variable categories. This indicates that once common variation across the two bank types is partialled out through the common factor, community and non-community bank size and lending still share some common shocks that need to be removed to isolate type-specific variation.[11] The historical behavior of the factors are less interesting than their heterogeneous relationships with individual banks, however. In order to accurately interpret the factors, we must also study their respective bank response sensitivities – an increase in a given bank factor may cause an increase, or perhaps a decrease of varying magnitudes in the associated variable across different banks.

In Fig. 12, I plot the distributions of response sensitivities of individual community and non-community bank asset growth rates to the common bank size factor and their respective bank size type-specific factors. I make the following observations regarding bank-level asset growth responses to common components:

1. **Interpretable Common Factor:** The majority of community and non-community bank asset growth rates are negatively correlated with the common bank size factor. In other words, an increase in the common bank factor is associated with a simultaneous decrease in the growth rate of assets for most U.S. commercial banks. There is still a non-negligible share of banks across both banks types that respond positively to the common size factor that cannot be completely disregarded – however, for the sake of parsimony it is safe to interpret a positive shock to the common bank size factor as a "positive shock to bank assets."

2. **Vague Type-Specific Factors:** Across both community and non-community banks, approximately half respond positively to their respective type-specific size factors, while the remaining half respond negatively. Therefore, it is more difficult to attach

[11] In the next draft, I will include the aggregate macroeconomic variables in the bank-level regressions to partial out their combined common variation across the two bank types.

a clear interpretation to a positive shock to either the community or non-community bank size factor.

3. **Little Inter- but Considerable Intra-Type Heterogeneity:** The distribution of non-community bank sensitivities to the common bank size factor is similar to that of community banks. This implies that, on average, there is not much heterogeneity across community and non-community banks in how they respond to the common factor – all heterogeneity is effectively "soaked up" by the variation in the type-specific factors. However, there is heterogeneity *within* the two bank categories in how they respond to the common size factor.

In Fig. 13, I plot the distributions of response sensitivities of individual community and non-community bank lending growth rates to the common bank lending factor and their respective bank lending type-specific factors. I note the following properties of the given bank response sensitivity distributions:

1. **Interpretable Common Factor:** Most community and non-community bank lending growth rates are positively correlated with the common bank lending factor. In other words, an increase in the common bank factor is associated with an increase in the growth rate of lending for most banks. This allows us to interpret a positive shock to the common bank lending factor as a "positive shock to bank lending." However, the same caveat as with the common bank size factor applies in the given case – a non-negligible share of banks respond negatively to such shock, so the above interpretation is only *mostly* correct.

2. **Vague Type-Specific Factors:** Across both community and non-community banks, approximately half respond positively to their respective type-specific lending factors, while the remaining half respond negatively. The distributions in the given case are slightly more right-skewed than in the bank size case, but almost to a negligible

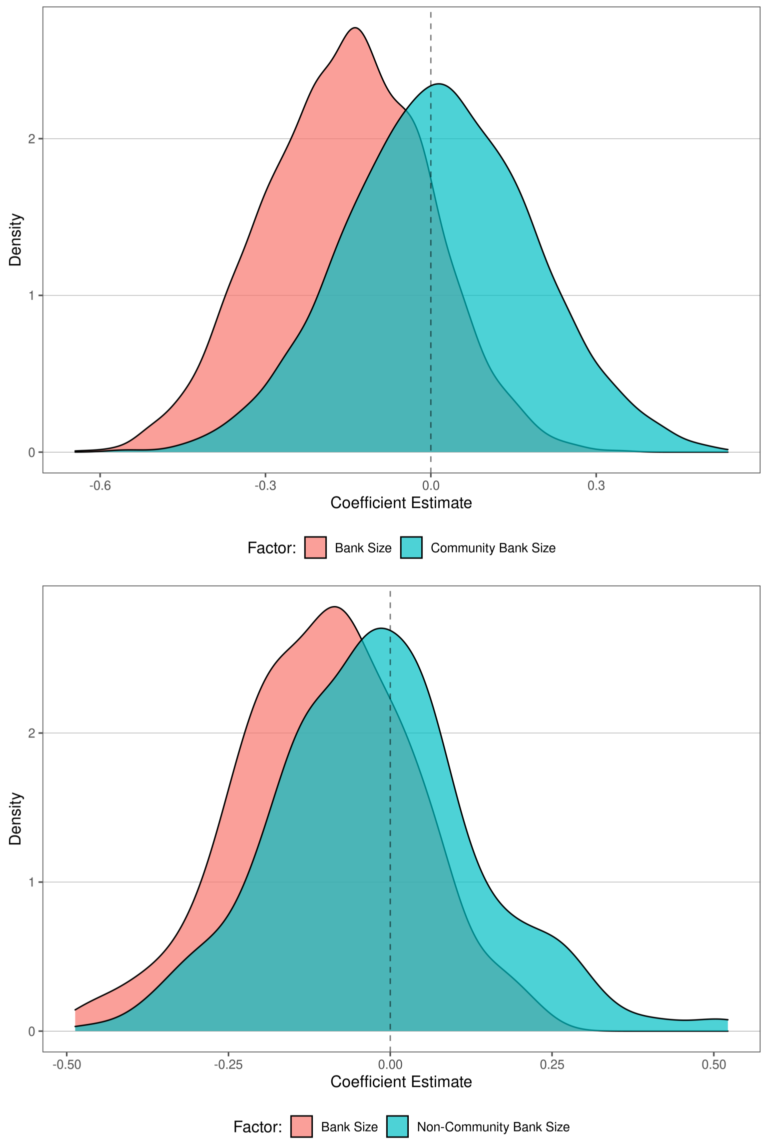


Figure 12: The first graph plots the common and community bank size factor response sensitivity coefficient densities in red and blue, respectively, for community banks. The second graph plots the common and non-community bank size factor response sensitivity coefficient densities in red and blue, respectively, for non-community banks. Recall that, by construction, community banks do not respond to non-community bank factors, and vice versa.

extent. Therefore, it is once again difficult to attach a clear interpretation to a positive shock to either the community or non-community bank lending factor.

3. **Little Inter- but Considerable Intra-Type Heterogeneity:** The distribution of sensitivity coefficients corresponding to the common bank lending factor is similar across the two bank categories. As before, this implies that there is not much heterogeneity across community and non-community banks in their responses to the common factor, but there is heterogeneity *within* the two groups in how they respond to the common lending factor.

So far we have analyzed the distributional properties of the common and type-specific factors across bank size and lending – but exactly how big of a role do these factors play in contributing to the variation in the bank-level series? Fig. 14 presents the distributions of R^2 statistics associated each of the individual regressions in Eq. (4) (measurement equation) for all community and non-community banks across all series. For both blocks of bank-level series (assets and lending), the bank-specific R^2 distributions for community banks closely match those of non-community banks. Each of the given distributions are tightly concentrated on below 0.2, which implies that on average the estimated factors account for only up to 20% of the variation in the bank-level series, with the average being much lower. This means that the factors alone explain only a small portion of the variation in the given bank series, pointing to the possibility that variation in both asset growth and lending at the bank level is highly idiosyncratic.[12] The results presented here are in line with the findings in Dave et al. (2013).

Figs. 15 and 16 present the relationship between bank size and sensitivity coefficients in response to common and type-specific bank lending factors, respectively. We may see

[12] It is also possible that, once again, my model may be improved through the explicit inclusion of aggregate economic and financial variables in the measurement equation to better capture common and type-specific comovement in bank-level variables. However, if the results remain even with the inclusion of aggregate variables in the bank-specific regressions, then my conclusion about the idiosyncrasy of bank variables remains valid.

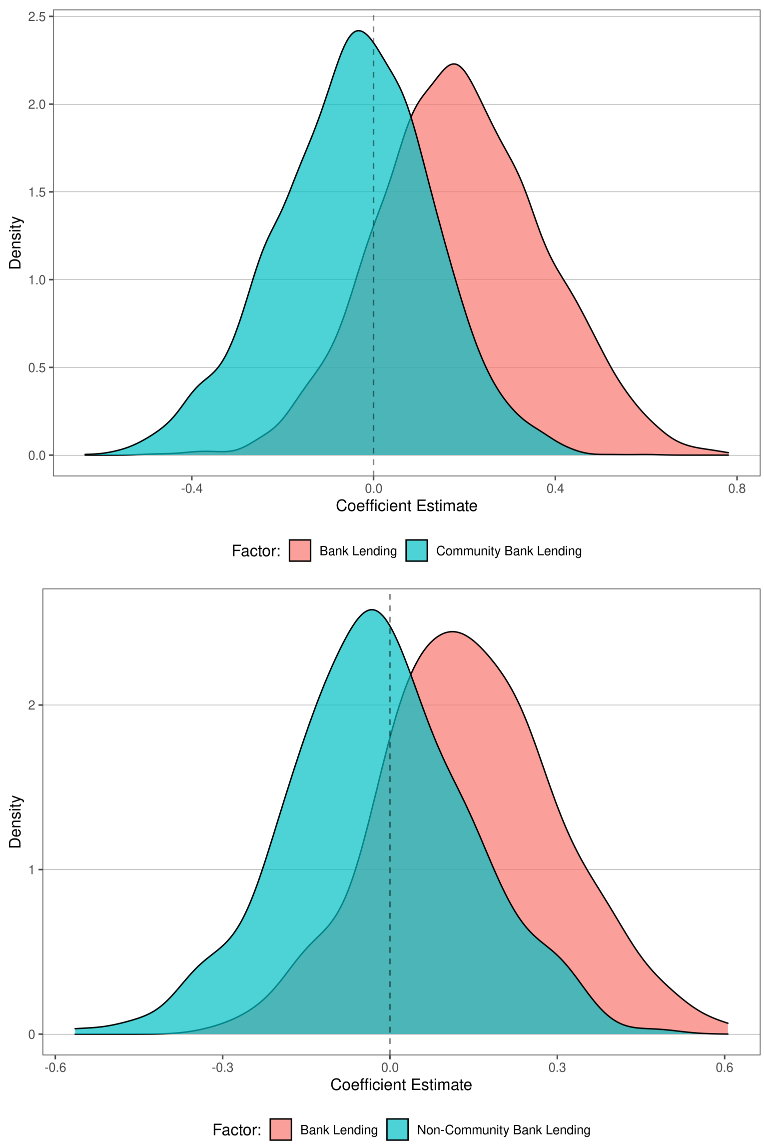
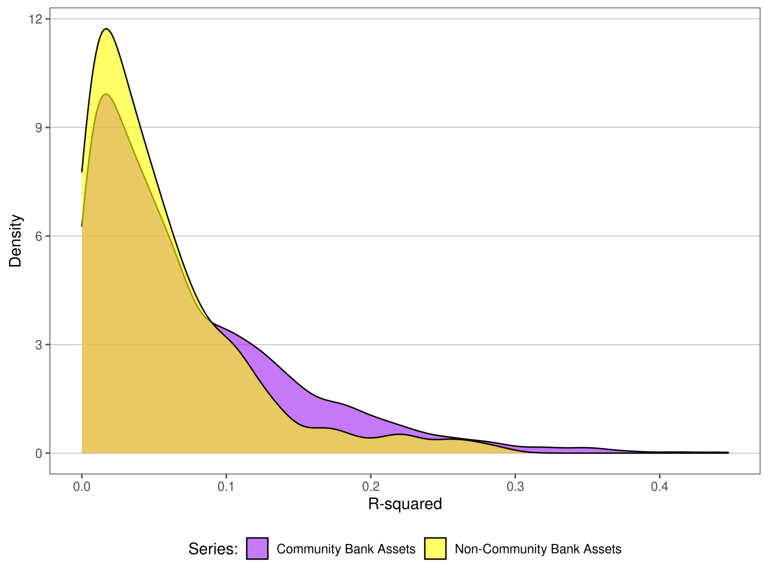


Figure 13: The first graph plots the common and community bank lending factor response sensitivity coefficient densities in red and blue, respectively, for community banks. The second graph plots the common and non-community bank lending factor response sensitivity coefficient densities in red and blue, respectively, for non-community banks. Recall that, by construction, community banks do not respond to non-community bank factors, and vice versa.



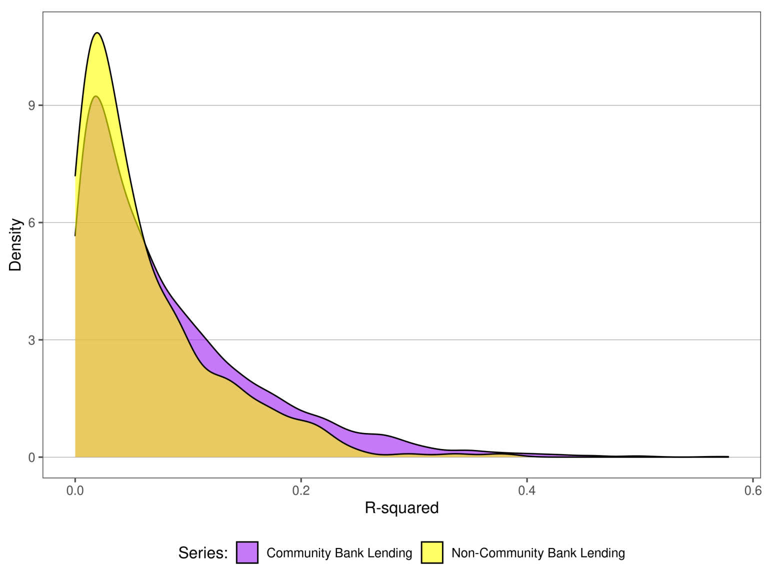


Figure 14: The first graph represents the R^2 distributions for the regressions of community and non-community banks asset growth rates on the common size factor and their respective type-specific size factors.nd their respective type-specific profitability factors. The second graph represents the R^2 distributions for the regressions of community and non-community bank lending growth rates on the common lending factor and their respective type-specific lending factors.

by observing Fig. 15 that there exists a positive relationship between community bank size and sensitivity to the common lending factor among banks with time-average total assets in the <\$1B range, which reverses into a negative relationship in the \$1-10B range. In the <\$1B asset range, the smallest community banks are expected to be only half as sensitive to the common lending growth factor as the those at the upper-end of the size distribution. In the \$1-10B range, the smallest community banks are expected to be twice as sensitive to the common lending growth factor as those at the upper-end of the size range. On the other hand, the correlation between size and sensitivity is negative across both size ranges for non-community banks. The extent of this negative correlation seems economically insignificant in the <\$1B range, but identical to that of community banks in the \$1-10B asset range.

Fig. 16 shows that community banks at the lower end of the <\$1B asset range are more likely to respond negatively to their corresponding type-specific bank lending factor, while those at the upper-end tend to respond positively. The same is true for for non-community banks in the same asset range with respect to the non-community lending factor, but to a lesser degree as the best-fit line is significantly flatter. In the \$1-10B asset range, community banks at the bottom of the range are on average insensitive to the community bank lending factor, while those at the upper-end are significantly more sensitive. In the same range, non-community banks at the lower-end tend to respond negatively to the non-community bank lending factor, while those at the upper-end tend to respond positively. Together, these results demonstrate differences in the heterogeneity of bank lending behavior with respect to size across community and non-community banks. This further highlights the importance of including an explicit categorization of commercial banks by their business model in analyses of bank heterogeneity.

Finally, I address the statistical significance of the above findings. Fig. 23 in Appendix A presents the coefficient p-value distributions corresponding to common and type-specific

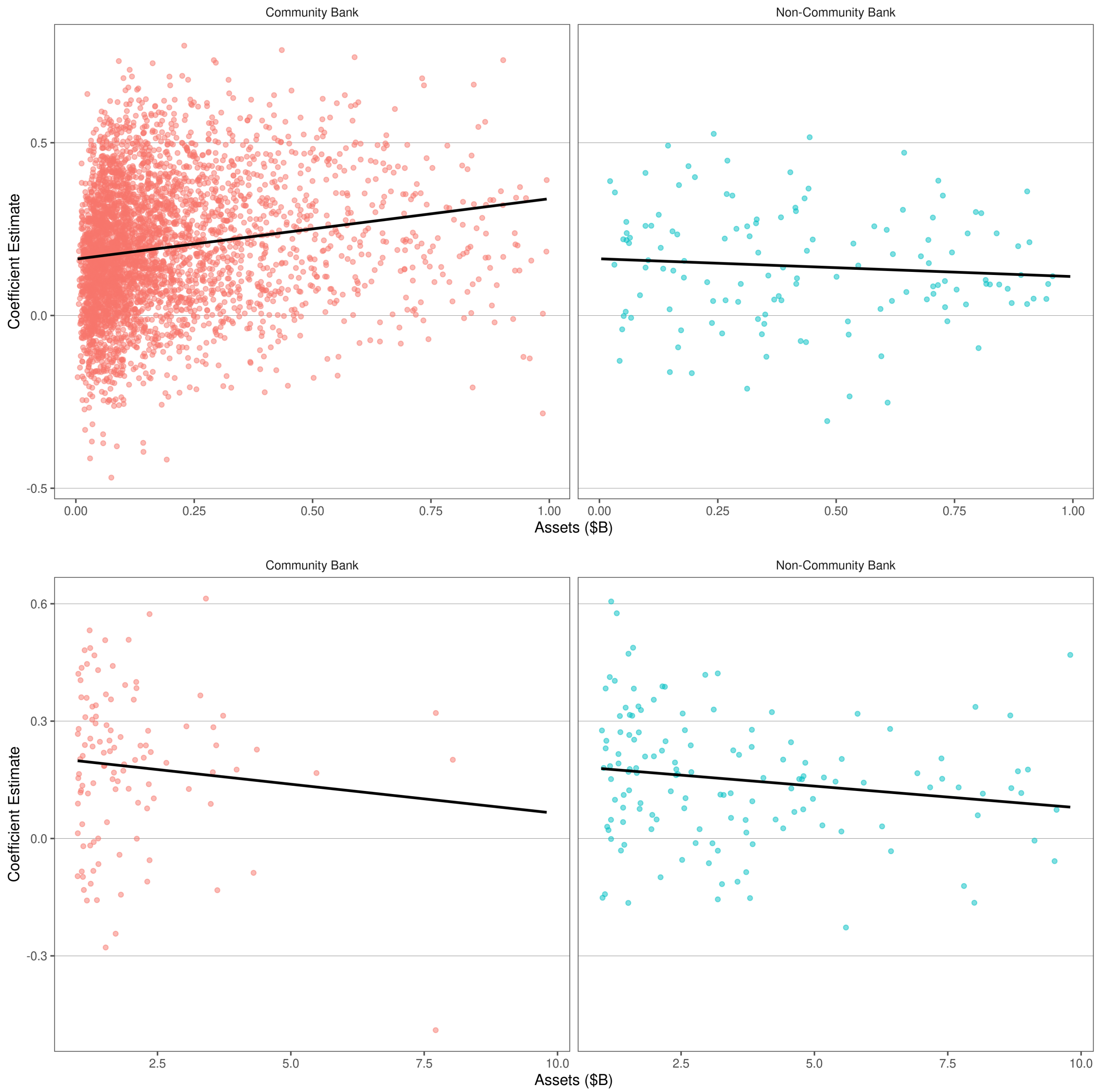


Figure 15: The first row of plots shows the correlation between assets and the sensitivity coefficients to the common bank lending factor among community and non-community banks with assets below $1B. The second row of plots shows the same correlation, but for banks with assets in the $1-10B range.

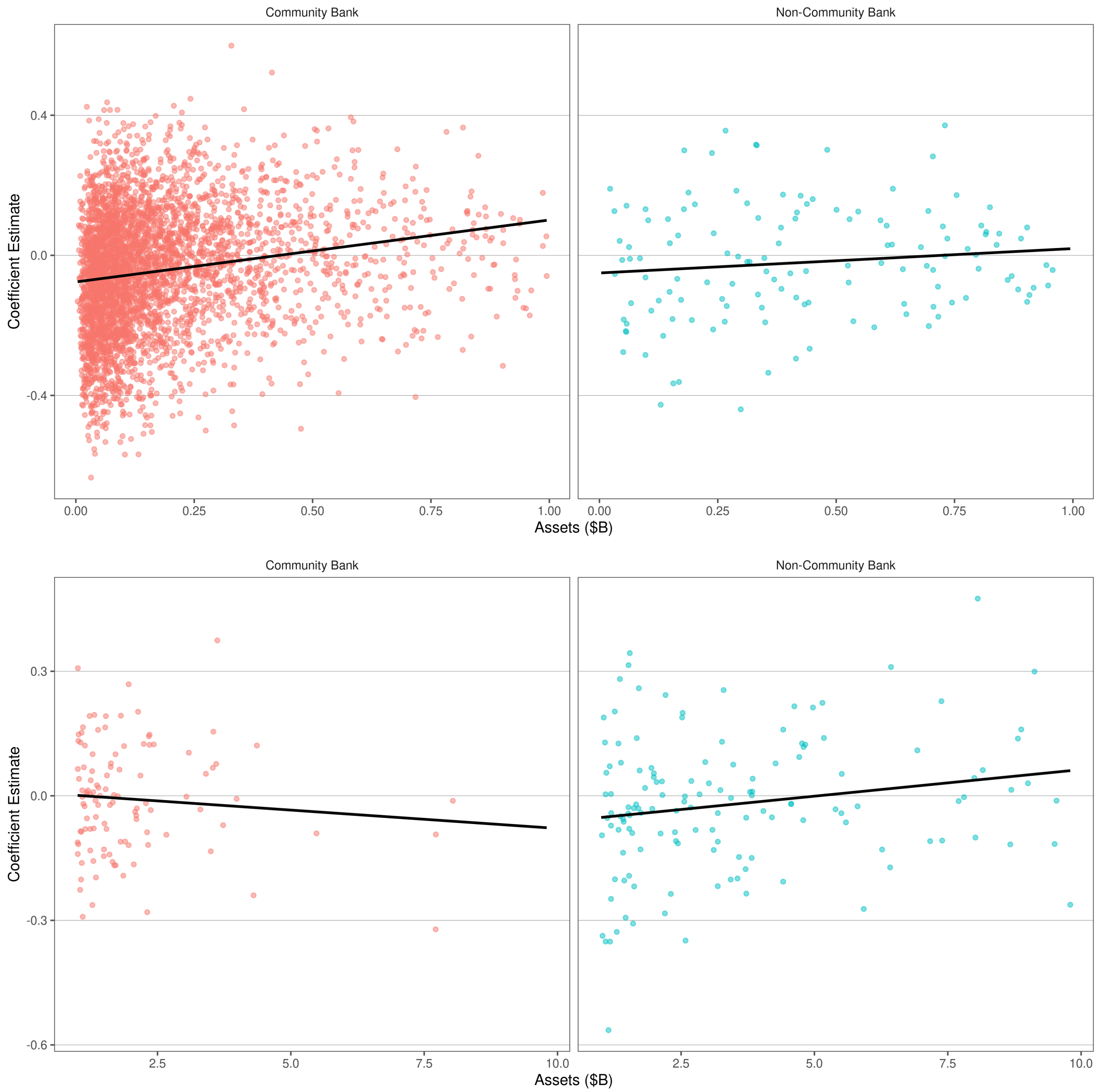


Figure 16: The first row of plots shows the correlation between assets and the sensitivity coefficients to the respective type-specific bank lending factors for community and non-community banks with assets below $1B. The second row of plots shows the same correlation, but for banks with assets in the $1-10B range.

asset, profitability, and lending factors across community and non-community banks. I make the following observations regarding coefficient significance by referring to the plots shown in this Fig. 23:

1. **Low Overall Coefficient Significance:** All of the distributions peak and concentrate below or at approximately 0.1, which implies a tendency toward significance at a 90% level. However, a large portion of the mass of these distributions lies above 0.1, which implies a lack of statistical significance for the factor sensitivity coefficients of a large share of both community and non-community banks. On the one hand, this may just be the result of a small sample size in the time dimension, on the other hand it may be understood as weak evidence of the existence of the bank factors.

2. **Significance Heterogeneity by Bank Type:** The community bank sensitivity coefficient significance distribution is concentrated at the lower end of the p-value spectrum to a greater extent than that of non-community banks – this is apparent by the community bank distributions consistently peaking above the non-community bank distributions near zero. This implies stronger evidence in support of community bank sensitivity to all of the bank factors.

5.2 Impulse Responses

Firstly, I assess how an exogenous monetary policy shock affects bank lending across both community and non-community banks by referring to the IRFs presented in Fig. 17. The figure shows that a positive (contractionary) monetary policy shock causes a negative cumulative response from the common bank lending factor, a largely-negative response from the community bank lending factor, and a consistently-positive response from the non-community bank lending factor. Since we have learned in Fig. 13 that the majority of community and non-community banks respond positively to the common lending factor, and since Fig. 17 shows that the drop in the common lending factor overshadows the variation in the type-specific lending factors, we may conclude that there must be an across-the-board drop in bank lending as a result of the contractionary monetary shock. And since the common lending factor sensitivity coefficient distributions are similar for both community and non-community banks, it must be the case that the heterogeneity in how the two types of banks respond to the shock is therefore driven entirely by the type-specific lending factors. The precise nature of this heterogeneity is examined carefully in the next subsection of the paper, but for now we simply have the insight that there *is* heterogeneity in how community banks respond to monetary policy shocks compared to non-community banks.

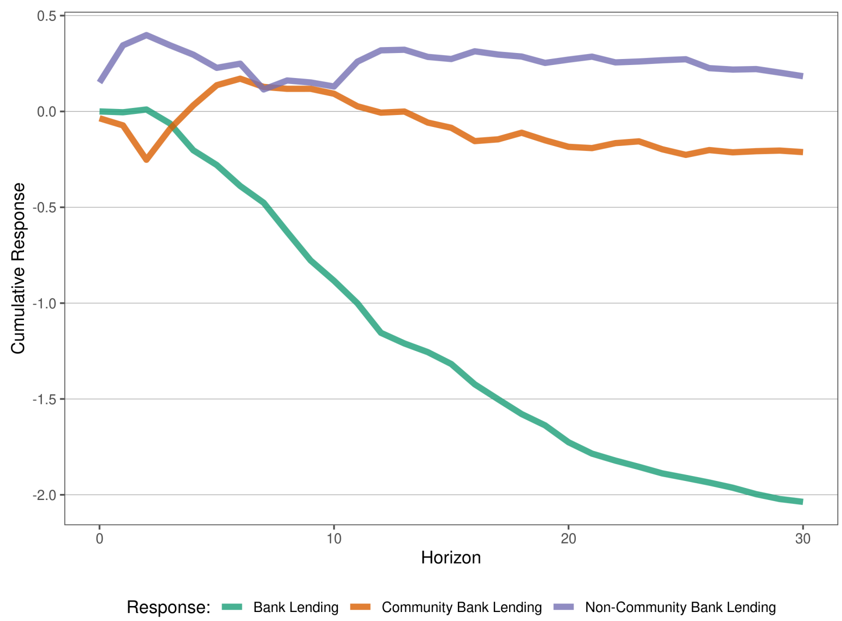


Figure 17: Impulse response functions of common, community, and non-community bank lending factors in response to a one-standard-deviation positive (contractionary) monetary policy shock.

Next, we may check how bank lending affects output growth by referring to Fig. 18, which shows the impulse response functions of GDP growth in response to one-standard-deviation positive community and non-community bank lending shocks. In the case of shocks to the common and community bank-specific lending factors, as one would expect, GDP growth responds positively with a larger response to the common lending shock than the community bank-specific one. On the other hand, GDP growth responds negligibly to the non-community bank lending shock. This implies that output growth is more sensitive to a shock to community bank lending than it is to non-community bank lending shock. One possible explanation for why this may be the case is that borrowers that rely on community banks for financing may be less willing and/or able to switch to external financing in times of tightened community bank lending, and more responsive otherwise, while non-community bank borrowers have other avenues of obtaining financing through financial markets.[13]

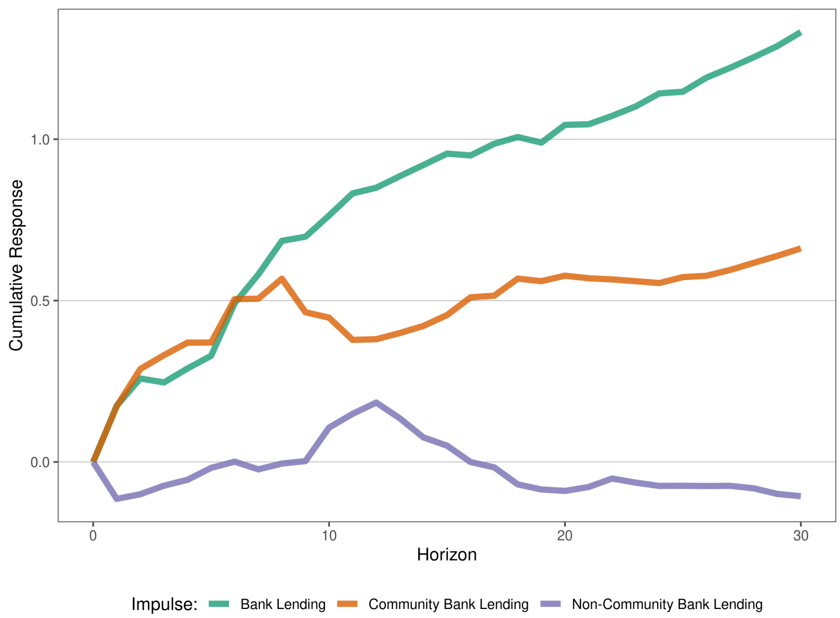


Figure 18: Impulse response functions of GDP growth in response to one-standard-deviation positive common, community, and non-community bank lending shocks.

I also assess the responsiveness of agricultural production growth to exogenous bank lending shocks by referring to Fig. 19, which shows the impulse response functions of agricultural production growth in response to one-standard-deviation positive community and non-community bank lending shocks. In the case of both common and non-community

[13]Testing this hypothesis may be a fruitful pursuit on its own!

bank lending shocks, the growth rate of agricultural production responds negatively – consistently so in the case of the latter, and gradually after the first year in the case of the former.[14] On the other hand, in the case of a positive community bank lending shock, there is a positive cumulative response after the first year. This result highlights the fact that community banks have special influence on the agricultural sector, which should be considered in gauging sector-specific distributional impact of macroeconomic policy that affects community banks.

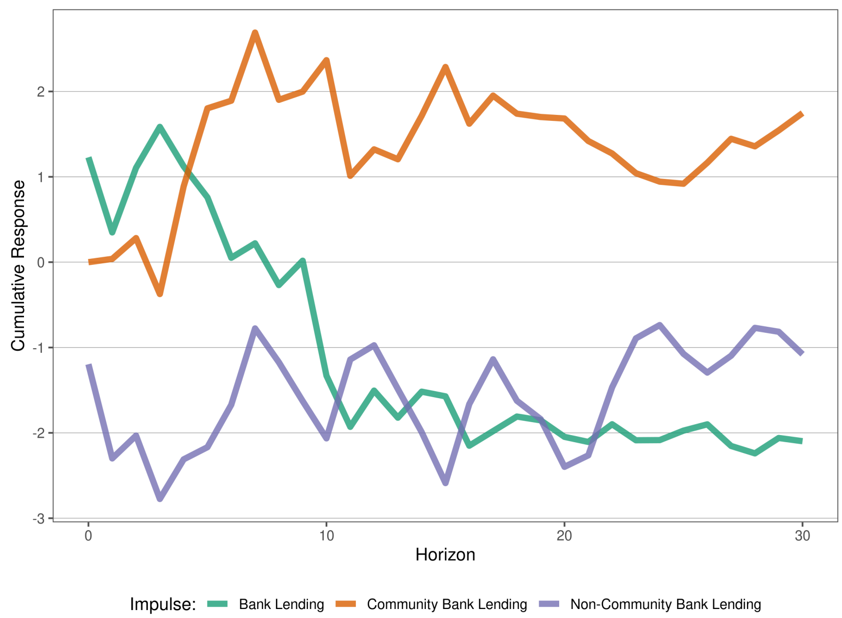


Figure 19: Impulse response functions of agricultural production growth in response to one-standard-deviation positive common, community, and non-community bank lending shocks.

Lastly, in Fig. 24 shown in Appendix A, I present the impulse response functions of the output growth and inflation rates in response to a positive (contractionary) monetary policy shock as a test of the validity of my FAVAR identification approach. The inflation rate impulse response shows that the model largely does not suffer from the price puzzle, as macroeconomic VARs often do, showing some evidence of success in my approach to monetary policy shock identification. In a similar vain, the GDP growth impulse response

[14]These results are puzzling – I expected to see a zero/weakly-positive cumulative effect from both.

function shows that a contractionary monetary policy shock causes a cumulative decline in output growth that seems to converge to some fixed negative level over time, implying that the effect of a monetary policy shock on the real economy is transitory – as standard macroeconomic theory would indicate.

5.3 Impulse Response Heterogeneity

Finally, we may observe the heterogeneity in bank responses to monetary policy shocks. Fig. 20 presents the cumulative IRFs of individual bank lending growth rates to a contractionary monetary policy shock through both of their corresponding bank lending factors (common and type-specific).[15] The takeaways from this figure are as follows:

1. **Banks Respond Negatively:** On average, both community and non-community bank lending growth rates respond negatively to contractionary monetary policy shocks. Furthermore, the average positive response at any given point in time is lower than the average negative response for both types of banks. This confirms that the general mechanism of the bank lending channel works similarly across both bank types in the United States.

2. **Community Banks Are More Sensitive:** On average, community banks respond more negatively to contractionary monetary shocks than non-community banks, given that the average community bank lending growth rate response is below that of non-community banks. This confirms some of the points made in the comparison of community and non-community banks in the Background section, and demonstrates that the community bank business model outweighs the leverage characterizing non-community banks in creating financial constraints for banks.

[15]Responses to a contractionary monetary policy shock through either the common bank lending factor or the type-specific lending factor are shown in Figs. 25 and 26 in Appendix A, respectively. The IRFs plotted in Fig. 20 are simply linear combinations of the corresponding ones in Figs. 25 and 26.

3. **Community Banks Are More Idiosyncratic:** The spread of the impulse response distribution for community banks is noticeably wider for community banks in comparison to non-community banks, implying greater idiosyncrasy/heterogeneity within the former category.[16]

6 Conclusion

In conclusion, I have found heterogeneity across community and non-community banks in how their lending behavior responds to monetary policy shocks, along with heterogeneity in how bank size interacts with sensitivity to monetary policy across community and non-community banks. Also, I have found that both the real aggregate economy and the agricultural sector respond differently to community and non-community bank lending shocks. These results demonstrate that controlling for bank type is important in studying the heterogeneity of the bank lending channel of monetary policy – simply controlling for characteristics such as size is insufficient. Furthermore, the estimated impulse response functions suggest that the form of heterogeneity present in the U.S. banking sector may play a significant role in the distributional outcomes of monetary and regulatory policy decisions, as I have demonstrated in the case of the agricultural sector.

[16]This confirms the argument made by Fayman et al. (2022) that community banks should not be viewed as a homogenous group.

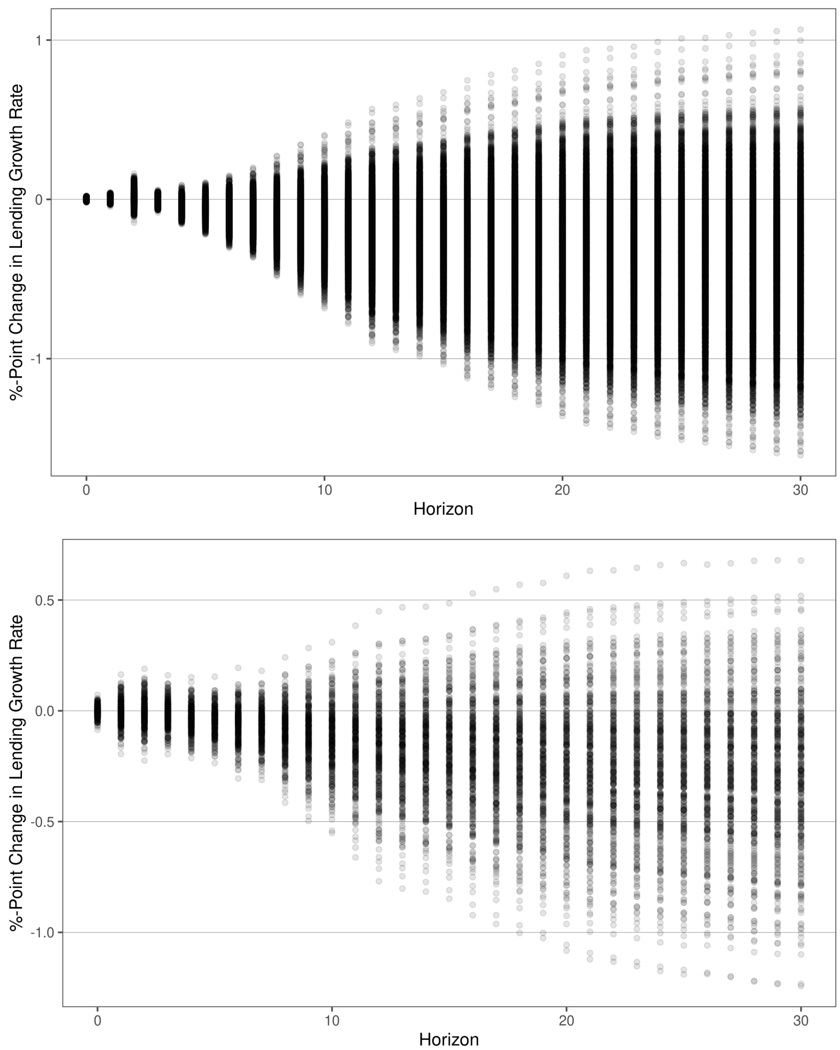


Figure 20: Community (top) and non-community (bottom) bank cumulative impulse responses to contractionary monetary policy shock through all relevant bank factors. **The y-axis does not actually show the ppt change in bank lending growth rates – instead it shows the *standardized* change in bank lending growth rates with respect to each bank. In other words, a value of 1 corresponds to a one-standard-deviation increase in the bank lending growth rate of a given bank.**

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Appendices

A Figures

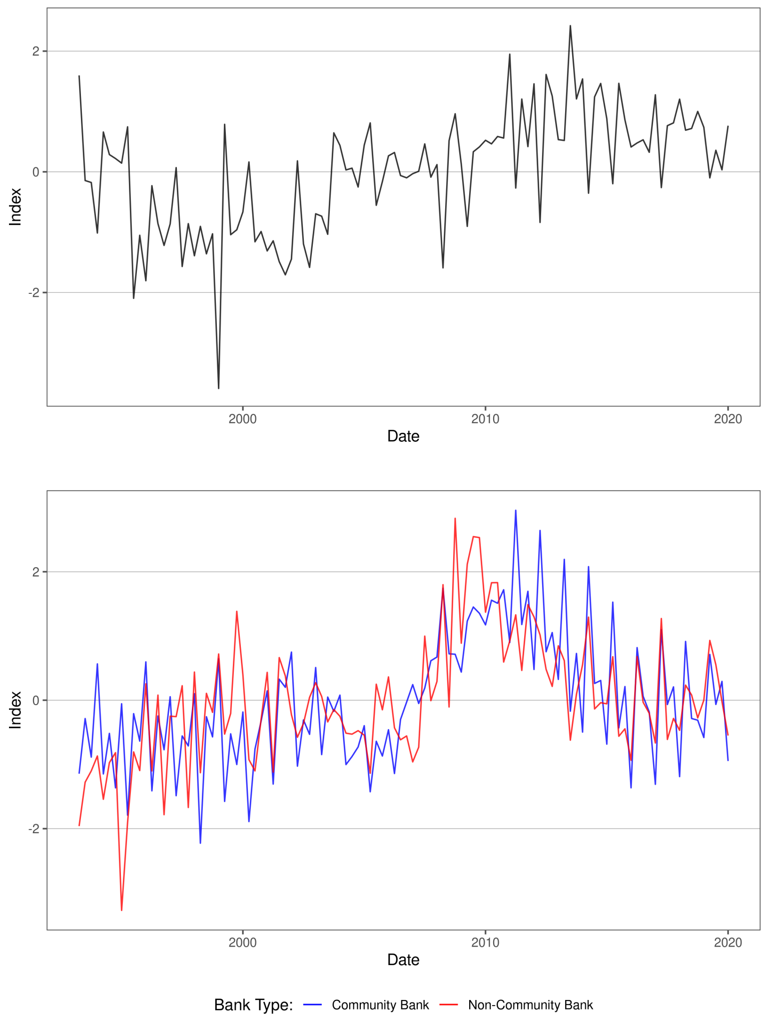

Figure 21: Bank size factor timeplots. The upper graph presents the common bank size factor. The lower graph presents the community and non-community bank size factors.

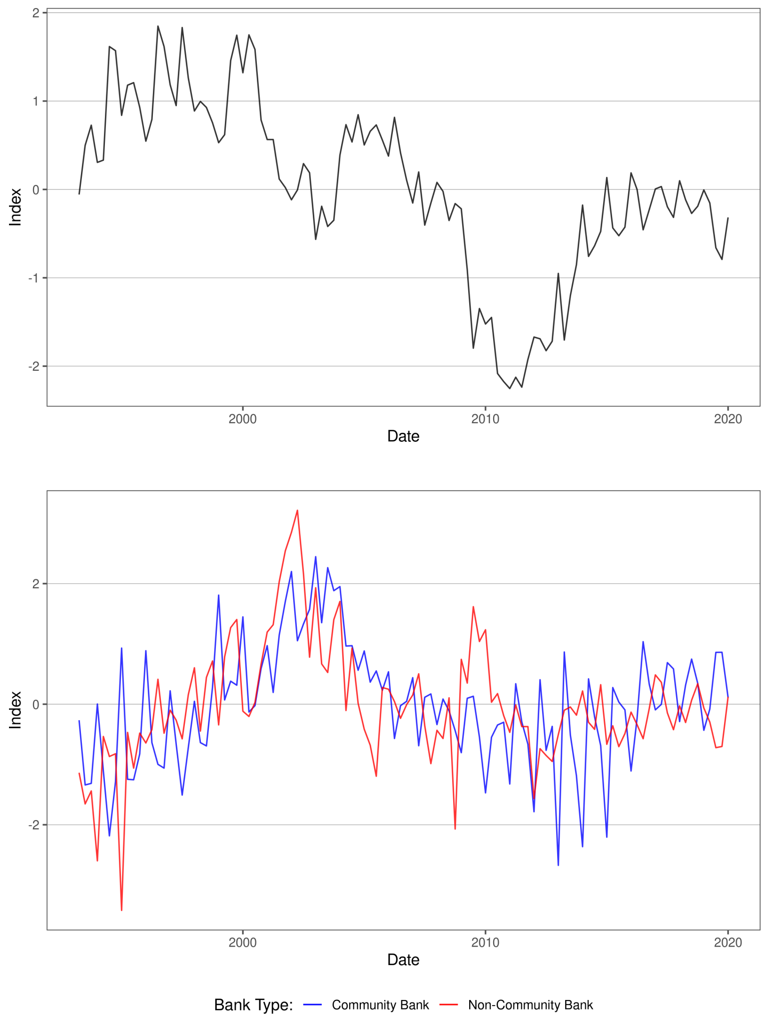

Figure 22: Bank lending factor timeplots. The upper graph presents the common bank lending factor. The lower graph presents the community and non-community bank lending factors.

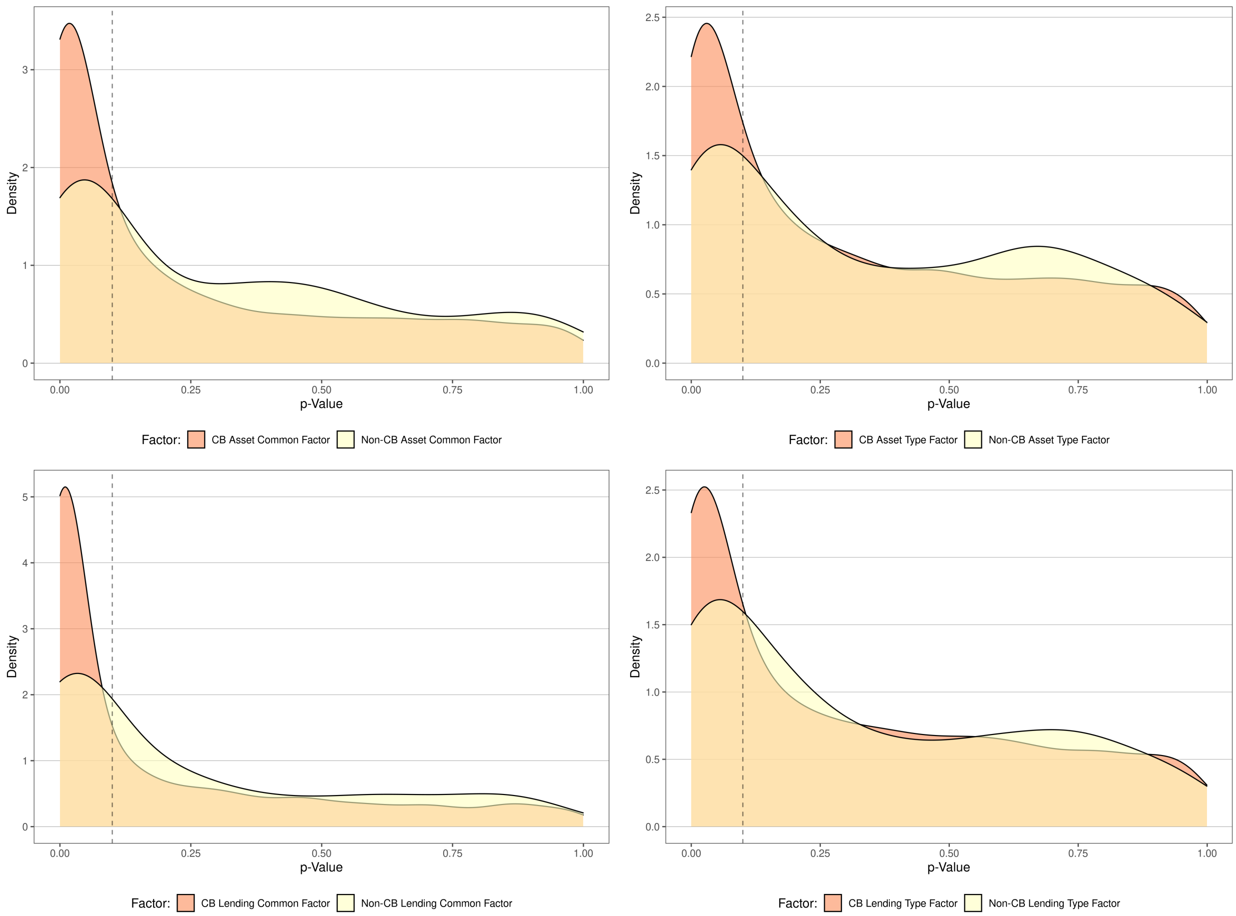

Figure 23: The first row of plots shows the coefficient significance distributions corresponding to the common and type-specific asset growth factors. The second row of plots shows the coefficient significance distributions corresponding to the common and type-specific lending growth factors.

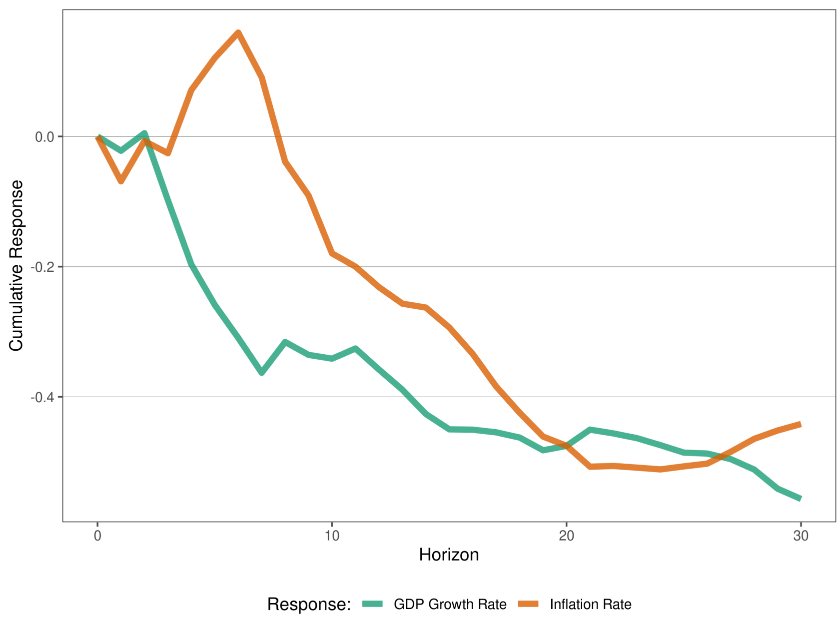

Figure 24: Impulse response functions of GDP growth and inflation rates in response to positive (contractionary) monetary policy shocks.

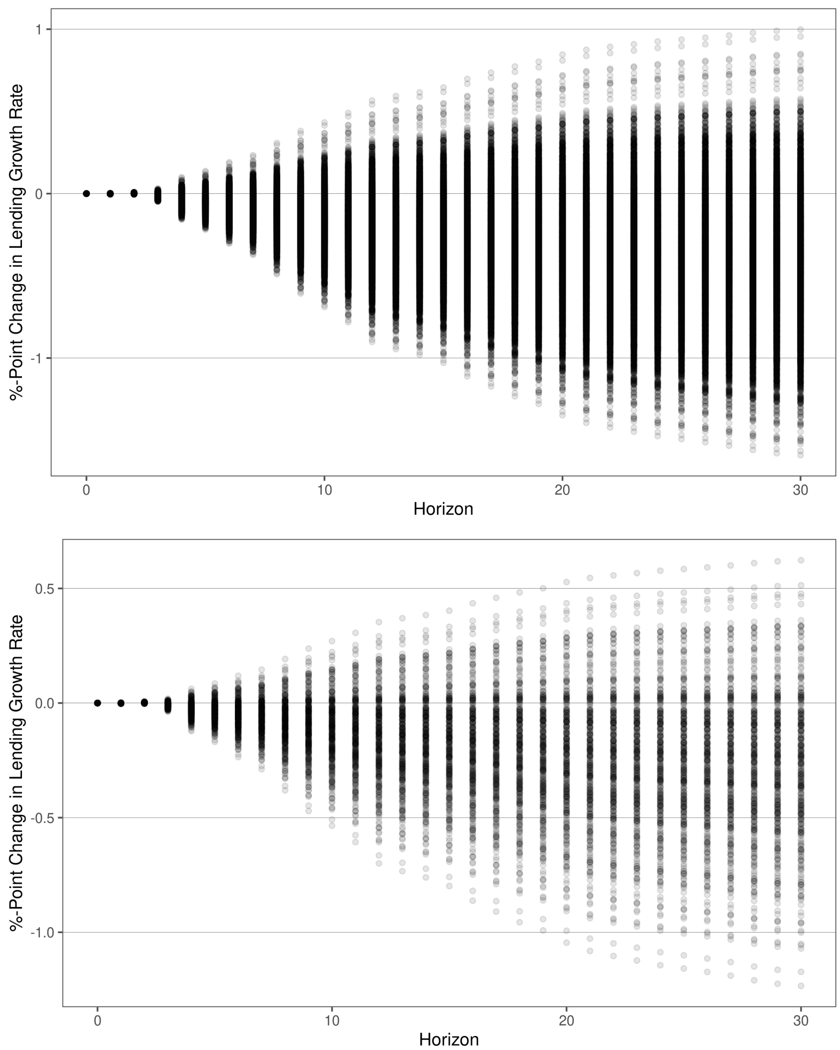

Figure 25: Community (top) and non-community (bottom) bank cumulative impulse responses to contractionary monetary policy shock through the common bank lending factor. **The y-axis does not actually show the ppt change in bank lending growth rates – instead it shows the *standardized* change in bank lending growth rates with respect to each bank. In other words, a value of 1 corresponds to a one-standard-deviation increase in the bank lending growth rate of a given bank.**

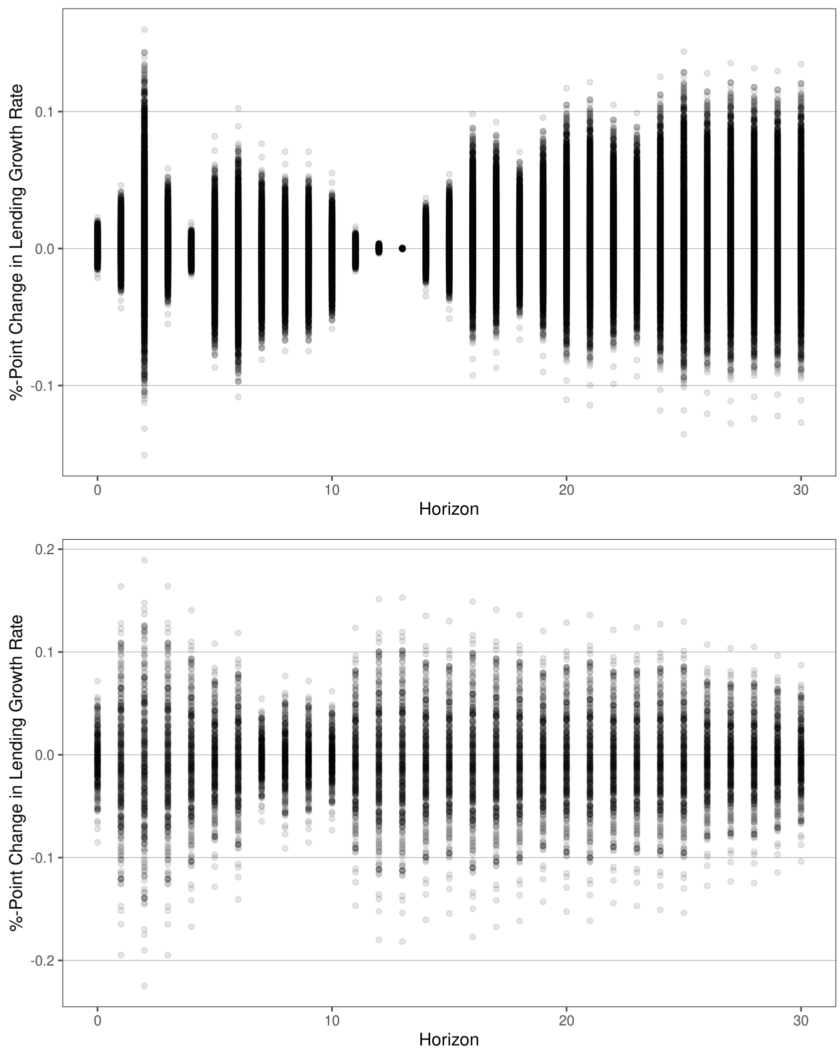

Figure 26: Community (top) and non-community (bottom) bank cumulative impulse responses to contractionary monetary policy shock through their respective bank type factors. **The y-axis does not actually show the ppt change in bank lending growth rates – instead it shows the *standardized* change in bank lending growth rates with respect to each bank. In other words, a value of 1 corresponds to a one-standard-deviation increase in the bank lending growth rate of a given bank.**