BANK CAPITALIZATION HETEROGENEITY AND MONETARY POLICY

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Abstract

This paper shows that heterogeneity in bank capitalization ratios plays a crucial role in the transmission of monetary policy to bank lending. First, I offer new empirical evidence on how banks' lending responses to monetary policy shocks depend on their capitalization ratios. Highly capitalized banks reduce their lending more after a monetary tightening, even after controlling for bank liquidity, size and market power in the deposit market. I also document how highly capitalized banks have a riskier portfolio, as measured by loan charge-off rates, and default rates on their loans increase relatively more after a tightening in monetary policy. I then construct a dynamic macroeconomic model that rationalizes the empirical evidence through the interaction of the heterogeneous recovery technologies of banks facing a risk-weighted capital constraint. In particular, after an increase in the policy rate, the model predicts that loan rates and default probabilities increase in both sectors. Highly capitalized banks with a riskier portfolio are more sensitive because the risk-weighted capital constraint affects them more, so they contract lending more. In a counterfactual analysis, I find higher capital requirements amplify the effects of monetary policy.

Keywords: monetary policy, banks, heterogeneity.

JEL classification: E43, E52, E58, E60, G21.

Resumen

Este trabajo muestra que la heterogeneidad de las ratios de capitalización bancaria desempeña un papel importante en la transmisión de la política monetaria a los préstamos bancarios. Primero, muestro nueva evidencia empírica sobre la dependencia de las respuestas de los préstamos bancarios a los choques de política monetaria en sus ratios de capitalización. Los bancos altamente capitalizados reducen más sus préstamos tras un endurecimiento monetario, incluso después de controlar la liquidez bancaria, el tamaño y el poder de mercado en el mercado de depósitos. También documento que los bancos altamente capitalizados tienen una cartera de mayor riesgo, medida por las tasas de cancelación de préstamos; y, finalmente, que las tasas de incumplimiento de sus préstamos aumentan relativamente más después de un endurecimiento de la política monetaria. Por otra parte, construyo un modelo macroeconómico dinámico que racionaliza la evidencia empírica a través de la interacción de tecnologías de recuperación heterogéneas de bancos que enfrentan una restricción de capital ponderada por riesgo. En particular, después de un aumento en la tasa de política, el modelo predice que las tasas de préstamo y las probabilidades de incumplimiento aumentan en ambos sectores. Los bancos más capitalizados con una cartera de mayor riesgo son más sensibles porque la restricción de capital ponderado por riesgo les afecta más, por lo que reducen más sus préstamos. En un análisis contrafáctico, encuentro que los requisitos de capital más altos amplifican los efectos de la política monetaria.

Palabras clave: política monetaria, bancos, heterogeneidad.

Códigos JEL: E43, E52, E58, E60, G21.

I. Introduction

The Global Financial Crisis (GFC) reinvigorated the literature that stresses the central role of financial intermediaries in macroeconomic fluctuations. This paper contributes to this literature by studying the role of the bank capitalization rate in shaping the pass-through of monetary policy shocks to bank lending.

Specifically, I first provide three new empirical facts related to the response of bank lending to monetary policy shocks across banks with different capitalization rates, the response of default rates on loans with different riskiness to monetary policy shocks, and the portfolio composition of banks with different capitalization rates. I then rationalize these cross-sectional facts in a dynamic macroeconomic model with heterogeneous banks that face a risk-weighted asset (RWA) constraint. The model emphasizes the role the RWA constraint plays in shaping banks' portfolios and capitalization rates, and their response to the monetary policy shock.

In the empirical part of the paper, I combine data on monetary shocks, measured using high-frequency event-study approach, as proposed by Gurkaynak (2005) and Gorodnichenko and Weber (2016), with cross-sectional U.S. banking data sets known as "call reports." I also test other factors that previous empirical papers determined to be important for the propagation of monetary policy through the banking sector.

First, I document that banks with higher capitalization rates reduce their lending more than less capitalized banks in response to monetary policy tightening. In particular, a bank with a capitalization rate one standard deviation above the mean of the capitalization-rate distribution reduces lending by 0.75 percentage points more than a bank that lies at the mean of the capitalization-rate distribution. These results are robust to controlling for size, liquidity, and market power on deposits, and are consistent across all types of loans (Commercial and Industrial (C&I), Real Estate, and Personal loans). The contraction in credit is not substituted with investment in other assets—I show that in response to a monetary tightening, better-capitalized banks reduce their overall balance sheets more than their less-capitalized counterparts.

Second, I document that loan default rates, proxied with delinquency rates and charge-off rates, increase after a monetary policy shock. This result is also consistent across all types of loans. Third, I also document the heterogeneity in the composition of bank loan portfolios. Portfolios of highly capitalized banks are more oriented toward C&I and personal loans, which are riskier than real estate loans, as measured by charge-off rates.

In the second part of the paper, I propose a theoretical mechanism consistent with the empirical evidence described above. Consider banks that differ in their ability to recover debtors' assets after a loan default and face a RWA constraint whereby the risk weights reflect the default risk but not the bank-specific recovery rates. Banks with better recovery technologies have a comparative advantage in lending to riskier borrowers, and hence hold riskier loan portfolios. The RWA constraint then forces them to hold more capital against this loan risk.

A tightening monetary policy translates into increases in loan rates across different sectors. Because of this effect on rates, as well as due to other general equilibrium effects, the default rate of each type of loan increases. This effect is stronger for riskier loans, which in the data correspond to C&I lending and personal loans, as opposed to less-riskier real estate loans. Banks will then seek to reduce their exposure to riskier assets. Banks with better recovery technology, which are better capitalized in equilibrium, have their portfolios more heavily tilted toward riskier loans, and the RWA constraint forces them to contract lending more than their counterparts with worse recovery technology.

In the model, I treat the heterogeneity in banks' ability to recover assets from defaulting debtors as a bank-specific technological primitive. The RWA constraint is a policy primitive. In the main text, I present a stripped-down version of the model that highlights the theoretical mechanism, while preserving relevant quantitative aspects. The central bank directly controls the real rate at which deposits are supplied to the banking sector. Two types of banks exist that differ in their recovery technologies, and these banks lend to two types of firms that differ in their riskiness.[1] Banks with the better recovery technology tilt their portfolios toward lending to riskier firms, and endogenously choose a higher capitalization rate due to the presence of the RWA constraint.

The model generates all three empirical relationships that I documented in the first part of the paper. Note that the second and third fact play a crucial role in supporting the economic mechanism underlying the above result. The RWA constraint in the presence of differences in recovery technologies generates the positive association between bank capitalization and riskiness of banks' portfolios. After monetary policy tightening, loan default rates increase, the better-capitalized banks holding riskier portfolios contract lending more in response.

To assess the quantitative performance of the calibrated model, I study the model-implied bank-specific lending responses to a monetary policy shock as a function of a bank's capitalization rate. In my baseline calibration, I find the model generates sensitivity in the lending response to the capitalization rate that is very close to the data, but not enough cross-sectional differences in capitalization rates. This finding suggests not all the heterogeneity in the capitalization rate can be explained by differences in recovery technologies. I only focus on one dimension, but I explore other factors that might contribute to the capitalization-rate heterogeneity in ongoing work.

The key to understanding this mechanism is that there is another factor at play: heterogeneity across banks in their ability to collect defaulting loans. This heterogeneity in loan-recovery technology generally impacts the mix of loans each bank chooses to hold, its overall portfolio risk, and hence the regulatory requirements that the bank is subject to. Specifically, banks with riskier portfolios are subject to stricter minimum capitalization requirements. The capitalization rate per se is therefore not essential for understanding why banks with higher capitalization rates react most strongly. Rather, the banks with the riskiest portfolios react most strongly to monetary policy tightening because they have more loans that risk becoming non-performing. These banks, having riskier loan portfolios, are also subject to greater capitalization rate requirements. But their greater capitalization rates are symptom, not the cause, of the stronger reaction.

In addition, I use the model to conduct a policy experiment that analyzes the implications of bank regulation for the bank lending channel of monetary policy. The question is: What is the effect of higher capital requirements on the effectiveness of monetary policy? I find that in an economy with higher capital requirements, the monetary policy shock has more adverse effects. Therefore, a monetary policy shock generates a higher reaction of the main economic variables.

Literature. This paper is not the first to study the cross-sectional implications of changes in interest rates for banking sector lending. For example, Anil K Kashyap and Jeremy C Stein (1994) stress the importance of bank liquidity, whereas Itamar Drechsler, Alexi Savov and Philipp Schnabl (2017) emphasize the role of bank market power in the deposit market. Closest to this

[1]A full general equilibrium model that features a riskier corporate sector and a less riskier mortgage sector, as well as a New-Keynesian structure linking a nominal policy rate to the real economy, is in the appendix.

paper in its aim is the work of Skander J Van den Heuvel (2012), who also links bank capitalization to the sensitivity of bank lending. These papers study the relationship between the level of interest rates and the cross-sectional implications of bank lending; instead, I revisit these views with better data and careful identification of monetary policy shocks.

This paper adds to three strands of literature. First, I contribute to the literature on how the effect of monetary policy varies across banks, by showing banks with higher capitalization rates contract their lending more than lower-capitalized banks after a monetary policy tightening. Studies such as Kashyap and Stein (1994), Bernanke and Gertler (1995), and Kashyap and Stein (2000), argue that banks with low liquidity in their balance sheets are more responsive to monetary policy, a mechanism that I denote the "liquidity view." Van den Heuvel (2012) advocates a "bank capital view" of the transmission of monetary policy. He uses state-level data and argues the effect of monetary policy is stronger in states where banks have a low capital-asset ratio. He finds bank liquidity measures are not associated with variation in the impact of monetary policy on output at the state-level monetary policy.[2] However, I finds the opposite association between capitalization rates and the sensitivity of bank lending.

Recent empirical studies focus on how the transmission of monetary policy to households and the real economy depends on banks' market power. A number of papers, including Drechsler, Savov and Schnabl (2017), find empirical evidence of market power in the deposit market and show monetary policy has a powerful impact on the price and quantity of deposits supplied by the banking system. Additionally, Scharfstein and Sunderam (2016) find evidence of market power in the loan market, where higher market power leads to lower pass-through of secondary market rates to households and lower refinancing activity in response to declining interest rates.

In this paper, I find a key role for heterogeneity in capitalization rates. After monetary tightening, better-capitalized banks reduce lending more, in contrast to the results of Van den Heuvel (2012). When I simultaneously allow for different channels. I do not find the market-power view to be statistically significant. Here, I use the Herfindahl index of geographical concentration to measure bank market power in deposits, as explained by Drechsler, Savov and Schnabl (2017). Also, the liquidity channel is substantially weakened, whereas the capitalization rate continues to play an important role. Additionally, Indarte (2021) estimate the causal effect of asset losses (which impact capitalization) - while this is informative about the causal effect of changes in capitalization, my work tells us about how banks that tend to be well-capitalized behave differently on average.

Second, on the theoretical front, I contribute to the literature on how micro-level heterogeneity affects the understanding of monetary policy relative to traditional representative-agent models in a real model and a New Keynesian model. A growing strand of literature focuses on how household-level heterogeneity affects the consumption channel of monetary policy; see, for example, Auclert (2019), Wong et al. (2019), Greg Kaplan, Benjamin Moll and Giovanni L Violante (2018), and Alisdair McKay, Emi Nakamura and Jón Steinsson (2016). Another strand of the literature analyzes the role of firm-level heterogeneity in determining the investment channel of monetary policy; see, for example, Ottonello and Winberry (2020), and Jeenas (2019). By contrast, my paper analyzes the role of bank-level heterogeneity in determining the lending channel

[2]This result implies the bank lending channel is not operational; and uses a panel of state-level data to assess the bank capital channel.

of monetary policy and explores bank heterogeneity in recovery rates on defaulting loans as a theoretical mechanism that affects the lending channel.

Finally, I contribute to the literature that embeds the banking sector in a general equilibrium macroeconomic model. To date, papers such as Gertler and Kiyotaki (2010), Gertler and Karadi (2011), Wang (2018), and Oscar Arce, Galo Nuno, Dominik Thaler and Carlos Thomas (2020) assume a representative bank in a standard New Keynesian DSGE to assess unconventional monetary policy. Other papers, such as Balloch and Koby (2019) or Coimbra and Rey (2020), develop a heterogeneous banking sector. Coimbra and Rey (2020) present a flexible-price model that introduces heterogeneity in the value at risk of financial intermediaries and assess monetary and financial stability jointly. Balloch and Koby (2019) focus on how low-nominal-rate environments affect bank credit supply. Their model assumes banks have market power on deposits and that a leverage constraint limits lending. My heterogeneous-bank model is based on the work by Vadim Elenev, Tim Landvoigt and Stijn Van Nieuwerburgh (2021), who study the effect of tighter bank capital requirements in response to the GFC. I contribute to this literature in three ways. First, I incorporate heterogeneity in the banking sector, specifically for commercial banks. Second, I incorporate borrower heterogeneity across sectors, with a high-risk and a low-risk sector that differ in their equilibrium default rates due to differences in the volatility of their productivity shocks. Third, I use my framework to study how bank heterogeneity affects the transmission of monetary policy shocks.

Outline. The remainder of the paper is structured as follows. Section 1 presents data and empirical analysis. Section 2 builds the baseline dynamics equilibrium model. Section 3 lays out the qualitative analysis of the model and counterfactual. The last section concludes and explains ongoing work. Additional details can be found in the Appendix.

II. Empirical work: Data, methodology, and empirical results

In this section, I summarize the main data sources, focusing on the U.S. economy. Detailed descriptions can be found in appendix subsection A.A1 First, I use bank-level variables from the Consolidated Reports of Condition and Income (known as "Call Reports") filed quarterly by all banks. I use quarterly income and balance-sheet data for all U.S. public commercial banks (only commercial banks are indicated by the SIC Codes 60, 61, and 6712 and charter type equal to 200). The bank-level data is a panel sample for 1990-2007. I end the sample before the GFC, because the latter was followed by a period of unconventional monetary policy and an effective lower bound on interest rates. For example, after 2008, monetary policy is not based on the interest rate, but on unconventional monetary policy such as quantitative easing (QE) and forward guidance. Therefore, using the interaction with Fed-Funds-rate changes could yield misleading or biased results, because it has not been the main monetary policy tool after 2008. Table 1 shows the cross-sectional average for the top 10th percentile of bank size of banks and the bottom 90th percentile of bank size in the sample about the components of the balance sheet. Bank size is measure as logarithm of the total assets. The table shows deposits and loans are the most important elements of the balance sheet and the high-capitalized bank have are the small banks. In addition, I follow Drechsler, Savov and Schnabl (2017) to get a measure of bank market power in the deposit market, measured as the weighted-average HHI across all of a bank's branches, using branch deposits as weights.

Second, I use a measure of monetary policy shocks based on high-frequency identification. These monetary policy shocks must be understood as surprises

TABLE 1—BANK BALANCE-SHEET STATISTICS

Fraction total assets (\%)	All sample: 1990-2007	
	top 10 %	bottom 90%
Cash / Fed funds repo	9	11
Securities	23	28
Loans	63	57.5
Deposits	79	86
Other borrowing, Fed funds repo	12.2	3
Equity	8.8	11

(Top 10 % and botton 90% refers to percentile of bank size in the sample)

Note: Summary statistics of the commercial banking sector. The data are from U.S. Call Reports covering the years 1990 to 2007.

or unanticipated economic forces uncorrelated with other structural shocks implied by the Fed funds rate. The strategy for measuring monetary policy shocks based on high-frequency identification builds on the series used by Gurkaynak, Sack and Swanson (2005) and Gorodnichenko and Weber (2016). The idea is to isolate the unexpected (surprise) policy change that can generate market response. These series are constructed by measuring the reaction of the implied Fed funds rate from a current-month Federal funds future contract during the window from 15 minutes before to 45 minutes after the release of the announcement of the Federal Open Market Committee (FOMC) meetings. Further details can be found in Appendix section A.A1.

Given the bank-data characteristics, my empirical strategy is based on panel data regression and a local forecasting method proposed by Jordà (2005) to estimate impulse responses. Second, given the results (i.e., that the response depends on the capitalization rate), I tested the "liquidity view" and "market power view" of the bank lending channel mentioned in the motivation part by including an additional interaction between bank size, liquidity, market power on deposits, and monetary policy. Third, I decompose total loans and analyze the response of different types of loans instead of overall loan growth. I find higher-capitalization banks react more across different types of loans than lower-capitalization banks after a monetary policy tightening. Fourth, I analyze how loan-portfolio composition and riskiness is conditional on bank capitalization. Fifth, I analyze the relationship between bank capitalization and default rates for different types of loans over the business cycle, and find no evidence of significant differences in cyclicality of customers with different capitalization rates. Finally, I propose a mechanism that explains my findings and is consistent with how the overall components of a bank's balance sheet move after a tightening. The following subsections describe these results.

A. Fact 1

DYNAMIC RESPONSE: HETEROGENEOUS RESPONSES TO MONETARY POLICY SHOCK

This section documents the heterogeneity impact of monetary policy shocks on bank lending. First, I answer my main question with a linear specification by focusing on the estimation of the interaction coefficient between the capitalization rate and a monetary policy shock on bank lending. Second, I study the dynamic version of my linear specification in order not only to assess the moment of the policy shock, but also the dynamic behavior of the interaction coefficient at some horizon in the future in response to a change in policy today.

Baseline specification: I begin by estimating the following specification:

$$(1) \quad \Delta log\text{loan}_{i,t} = \alpha_i + \alpha_{st} + \delta_1 \text{MPShock}_t + \delta_2 X_{i,t-1} + \beta(\text{MPShock}_t * X_{i,t-1}) + \Gamma_1' \text{macro}_{t-1} + \Gamma_2' Y_{i,t-1} + \epsilon_{i,t} \ ,$$

where $\Delta log\text{loan}_{i,t}$ is the log change in a given balance sheet component (e.g., loans) of bank i from date t to $t+1$, α_i is a bank's i fixed effect[3], α_{st} is a state s-by-quarter t fixed effect,[4] MPShock_t is the monetary policy shock, $X_{i,t-1}$ represents a set of explanatory variables under consideration for a given specification, such as bank capitalization, liquidity[5], and market power. $Y_{i,t-1}$ is a vector of bank-level controls such as age, size, liquidity, capitalization, loan loss, deposit over liabilities, and wholesale funding over liabilities. macro_{t-1} represents a set of macroeconomic variables in the previos quarter such a real GDP growth, inflation, unemployment rate, change in the VIX index. $\delta_1, \delta_2, \Gamma_1$, and Γ_2 are regression coefficients. The main coefficient of interest in the regression (1) is β, which measures the semi-elasticity of loans with respect to a monetary policy shock depending on a bank's capitalization rate.[6] Note I use the lag of the explanatory and control variables to ensure they are predetermined at the time of the monetary policy shock.[7] I cluster standard errors at the bank and time level. I also do size-weighted regressions due to the skewed size distribution of banks. $\beta < 0$ implies banks with a higher capitalization rate reduce their lending more than banks with a lower capitalization rate after a positive monetary policy surprise.

TABLE 2—HETEROGENEOUS EFFECTS OF MONETARY POLICY ON BANK LENDING

	(1)	(2)	(3)	(4)
	Loan Growth			
Capitalization× MPshock	-0.758***	-0.769***	-0.936***	-0.825***
	(0.27)	(0.26)	(0.26)	(0.26)
MPshock			0.607	0.925**
			(0.46)	(0.39)
Observations	642311	642303	642303	642303
R^2	0.281	0.295	0.275	0.278
Bank controls	no	yes	yes	yes
Time sector FE	yes	yes	no	no
Macro control	no	no	no	yes
Bank,Time clustering	yes	yes	yes	yes

Robust standard errors in brackets
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: The sample is quarterly from 1990 to 2007. The regressions include bank fixed-effects.

Table 2 shows the results from the estimation of equation (1). The four columns in the table show a negative coefficient $\beta < 0$, which implies higher-capitalized banks reduce their lending more than lower-capitalized banks after a positive monetary policy surprise. Column (1) reflects that banks with one standard deviation of capitalization rate above the mean in the capitalization-rate dis-

[3] Bank-fixed effects capture permanent differences in lending behaviour across banks.
[4] State-by-quarter fixed effects capture differences in how broad states are exposed to aggregate shocks.
[5] Liquidity is defined as the ratio of securities and fed funds contracts sold to total assets
[6] Alternately, β measures the importance of variable $X_{i,t}$ on predicting heterogeneity in bank lending response.
[7] Note a positive monetary policy shock represents a Fed funds rate increase, and a negative β (interaction coefficient) reflects that banks with a greater explanatory variable (X_i, t) prior to the shock experience smaller loan growth (or a larger contraction) after a contractionary shock.

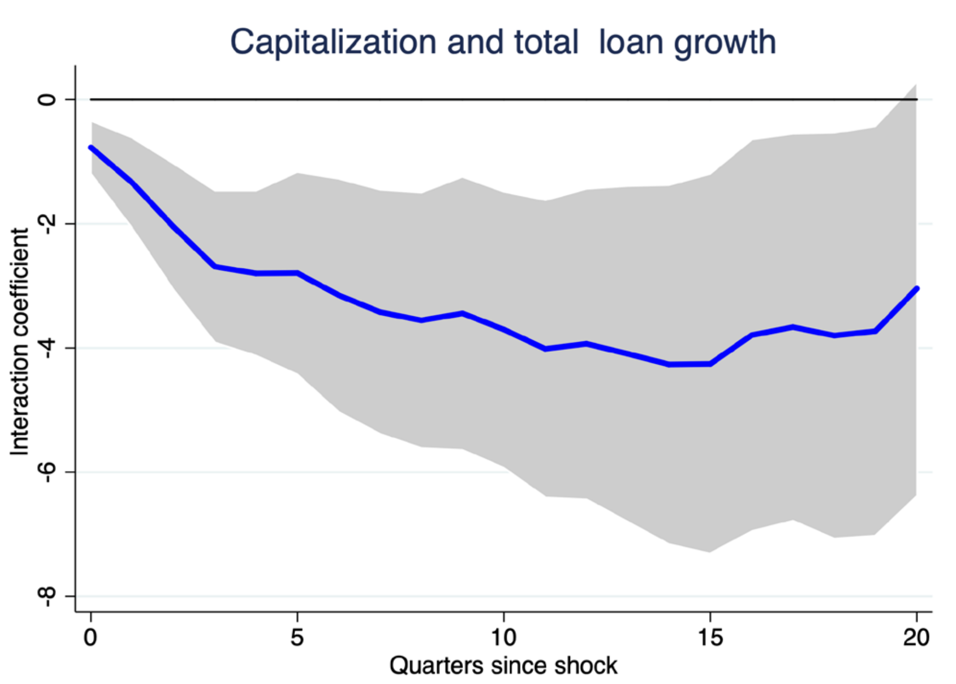
tribution react, on average, 0.75 percentage points more than a bank located at the mean of the capitalization-rate distribution. Columns (3) and (4) drop the time fixed effect, so I can estimate the average effect of monetary policy. This coefficient in column (4), which is statistically significant, indicates that a 1% increase in the policy rate increases loan growth by around 0.9%. I find that the average effect is sensitive to the set of aggregate controls. Therefore, I only focus on the heterogeneous responses across banks, which are robustly estimated across different specifications.

To estimate the **dynamic** response across banks, I estimate the Jordà (2005) local projection specification:

$$(2)\qquad \Delta log \text{loan}_{i,t+h} = \alpha_i^h + \alpha_{st}^h + \delta_1^h \text{MPShock}_t + \beta^h (X_{i,t-1} \cdot \text{MPShock}_t) + \delta_2^h X_{i,t-1} + \Gamma'^h Y_{i,t-1} + \Gamma_2^h \text{macro}_{t-1} + \epsilon_{i,t+h}\ ,$$

where $h \geq 0$ is the forecast horizon. Now β^h indicates the cumulative response of lending in quarter $t+h$ to a monetary policy shock in quarter t, which depends on the bank capitalization rate.

FIGURE 1. DYNAMICS OF DIFFERENTIAL RESPONSE TO MONETARY SHOCKS: CAPITALIZATION



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (2). The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

Figure 1 shows the dynamic response. The estimated interaction coefficient $\beta^h < 0$ implies higher-capitalized banks are more responsive to monetary policy shocks at the time of a contractionary monetary policy shock over horizon h. The point estimate is negative and statistically significant over the horizon until quarter 20.[8] This result is in contrast to the capital approach proposed by Van den Heuvel (2002) in the sense that lower-capitalized banks are more

[8]This result is robust if we use the tier1 capital-to-asset ratio or the tier 1 capital to risk-weighted-assets ratio.

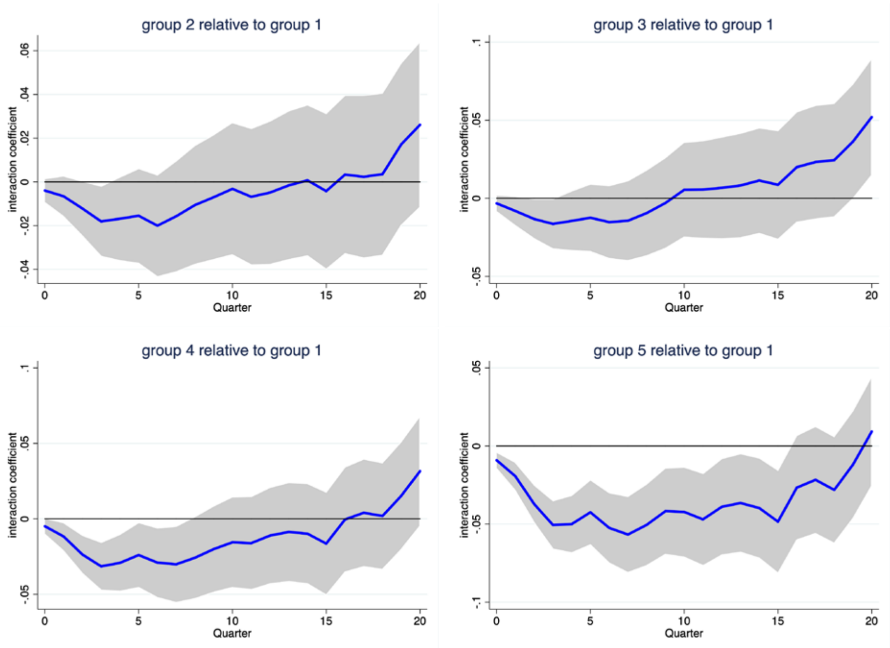
responsive to a monetary policy shock. The main difference with respect to him is the data limitation, specifically the type of data. He is using state-level data and I have bank-level data. Also, his econometric specification is different. Therefore, the analysis of the heterogeneity at the bank level is lost, and the relation can be misleading. Table 3 shows the main differences with respect to his paper in terms of econometric specification, period of sample, and measure of monetary policy. The advantages of using local projection (LP) instead of VAR are simplicity and bias. First, for simplicity, LP does not have to assume anything about invertibility, allow easily modified to estimate certain kinds of nonlinearities, and generalizes easily to panel data settings compare to traditional VAR. Second, for bias, using VAR the impulse response functions for horizon greater than the order of lag are biased. Theoretically, Plagborg-Møller and Wolf (2021) show that if the shock is unpredictable, then the traditional SVAR with order p and LP impulses responses coincide for horizons $h = 0, 1, 2, \dots p$ and they generally differ for $h > p$. If the shock is not unpredictable, then SVAR and LP impulses responses generally differs at all horizons but the differences is typically negligible for small horizons.

Alternative specification: As a robustness check, I use a non-linear specification as follows:

$$(3) \qquad \Delta log\text{loan}_{i,t+h} = \alpha_i^h + \alpha_t^h + \sum_{g=1}^{G-1} \alpha_g^h \times D_{gi,t}^h + \sum_{g=1}^{G-1} \beta_g^h \times D_{gi,t}^h \times \text{MPshock} + \delta^h \text{MPshock} + \Gamma'^h Y_{i,t-1} + \epsilon_{i,t+h} \, ,$$

where α_i^h, and α_t^h bank fixed effects and time fixed effects, and D_g is a dummy for a group of capitalization rates in the previous quarter. I divide the sample into quintiles where banks are ranked by capitalization rate and each group represents 20% of total assets in the sample. $Y_{i,t-1}$ is the banks' control, which

FIGURE 2. NON-LINEAR RESPONSE



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (3). The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

are the same in the previous specification. MPshock is the monetary policy shock at time t. Again, the coefficient of interest is β_g^h, which is the impulse response for a group g at forecast horizon h. Finally, the standard errors are clustered by banks. Figure 2 shows the results of the non-linear specification. The first group, the lowest-capitalization-rate quantile, is omitted. Therefore, the coefficient of interest, β_g^h, is interpreted as the response relative to group 1. Figure 2 shows the response of group 5 (higher capitalization rate) relative to group 1 (lower capitalization) is negative and statistically significant on impact and over some horizon going forward. Finally, I also perform robustness checks regarding bank-level heterogeneity, including the lag of the dependent variable as explanatory variable in the equation 1 and 2 see table J1 and figure J1 in the online appendix.

Testing different channels

In this section, I tested the other approaches found in the empirical literature about the response of bank lending to monetary policy. So far, the literature has two main channels, namely, the "liquidity view" and "market power view" to the bank lending channel mentioned in the motivation part. The idea is to include an additional interaction between bank size, liquidity, market power on deposits, and monetary policy in my main specification. The specification is as follows:

$$\Delta log\text{loan}_{i,t+h} = \alpha_i^h + \alpha_{st}^h + \delta_1^h \text{MPShock}_t + \delta_2^h X_{i,t-1} + \beta^h (X_{i,t-1} \cdot \text{MPShock}_t) + \Gamma'^h Y_{i,t-1} + \epsilon_{i,t+h} \quad (4)$$

where $X^1 = \{\text{capitalization, size}\}$, $X^2 = \{\text{capitalization, liquidty}\}$, and $X^3 = \{\text{capitalization, Market Power}\}$.

This specification will allow me to answer a sub-question: Does my result survive controlling for the interaction between bank size (or liquidity or market power) and monetary policy shock? I find the capitalization rate is still significant when I test the other channel at the same time.

First, the "liquidity view" of bank lending proposed by Kashyap and Stein (2000) suggests a tightening of monetary policy reduces lending more in less liquid banks, because they cannot sell assets to meet reserve requirements. Additionally, they claim the sensitivity of the contraction to liquidity is stronger for small banks. Figure 3 shows the results of the dynamic response by controlling the double interaction with the size of banks. The figures show the effect of size is not statistically significant. Figure 4 shows the result by controlling the double interaction with liquidity. Both figures show the effect of the capitalization rate is negative and statistically significant. The figures show the effect of liquidity as well, but it becomes less important going forward.

Second, the "market power view" of bank lending proposed by Drechsler, Savov and Schnabl (2017) suggests banks with more market power are more responsive to a monetary policy tightening. They can keep interest rates on deposits low when monetary policy tightens, thus increasing spreads. Figure 5 shows the result by controlling the double interaction with bank market power on deposits and a monetary policy shock. I find the effect of market power is not significant once I control for bank capitalization rate.[9]

Table 3 summarizes the main differences concerning the main empirical literature on the heterogeneous response across banks with different capitalization rates, market power on deposits, and liquidity in the U.S. economy (see appendix B for more details). I view these findings as reflecting that once I also

[9] All the methodological differences between my specification and their specification are in the appendix. Appendix B analyzes in detail the differences in my results with previous studies.

allow for these different channels jointly, I do not find the market-power view to be statistically significant, and liquidity channel is there, but is less important. Therefore, heterogeneity in bank capitalization rates plays a crucial role in the transmission of monetary policy to bank lending.

DYNAMIC RESPONSE FOR TYPES OF LENDING

This section documents the lending response across different types of loans instead of overall loan growth. The specification is the same as in equation (2), but the dependent or endogenous variables are loan growth rates for different types of loans: commercial and industrial (C&I), real estate, and personal loans. I find higher-capitalization banks react more in reducing their loans across different types of loans than lower-capitalization banks after a monetary

FIGURE 3. DYNAMICS: JOINT REGRESSION CAPITALIZATION RATE AND SIZE

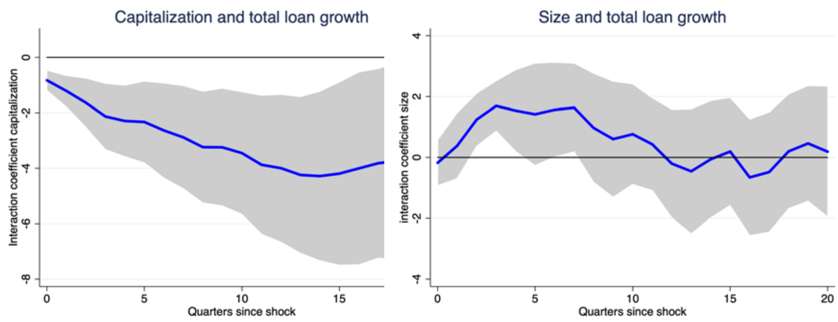


FIGURE 4. DYNAMICS: JOINT REGRESSION CAPITALIZATION AND LIQUIDITY

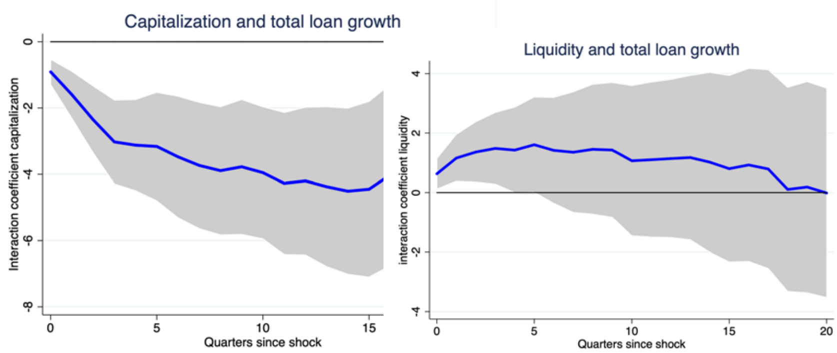
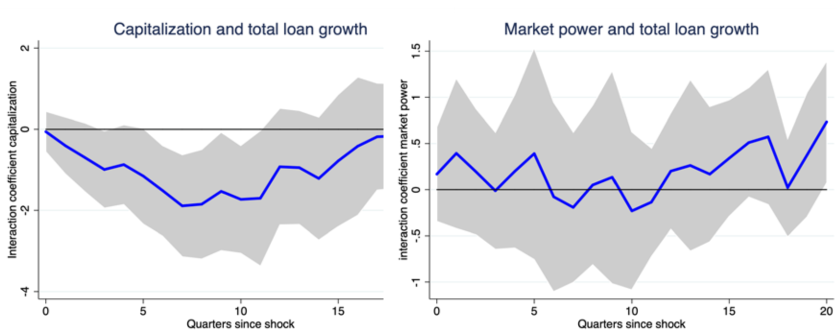


FIGURE 5. DYNAMICS: JOINT REGRESSION CAPITALIZATION AND MARKET POWER



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (4). The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

shock. The effect is negative, statistically significant, and lasts several quarters after the shock. Figure 6 shows the results for each type of loan. I find the C&I loans are more sensitive on average than real estate loans to monetary shocks. Therefore, my main result holds for all types of loans. These results allow me to conclude no sectoral-driven or sectoral-risk history exists; that is is not the type of loan that matters, because my results hold across different types of loans.

TABLE 3—COMPARISON WITH MAIN EXISTING EMPIRICAL LITERATURE

	Monetary-Policy Measure	**Sample Period** and **frequency**	**Individual Analysis**	**Econometric Specification**
Paz (2020)	High-frequency identification	1990-2007 quarterly	Bank Level	-Linear regression with bank controls, interaction term, bank fixed effect, state X times fixed effects. Standard errors are clustered at bank and time level, macro controls. -Dynamic: Local projection Method -Robustness: Non-linear regression
Drechsler, I., Savov, A., and Schnabl, P. (2017, QJE)	Change in Fed funds	1994-2013 quarterly	Bank Level	Linear regression with interaction term, bank fixed effect, and quarter fixed effects. Standard errors are clustered by bank.
Van den Heuvel, (2012,BEJM)	Change in Fed funds, Bernanke-Mihov indicator	1969-1995 annual	State Level	Linear regression with interaction term, with state fixed effects.
Kashyap, A. K. and Stein, J. C. (2000, AER)	Change in Fed funds, Bernanke-Mihov indicator	1973-1996 quarterly	Bank Level	Two-Step regression for different size class.

BANK BALANCE SHEETS AND MONETARY POLICY: DEPOSITS AND SECURITIES

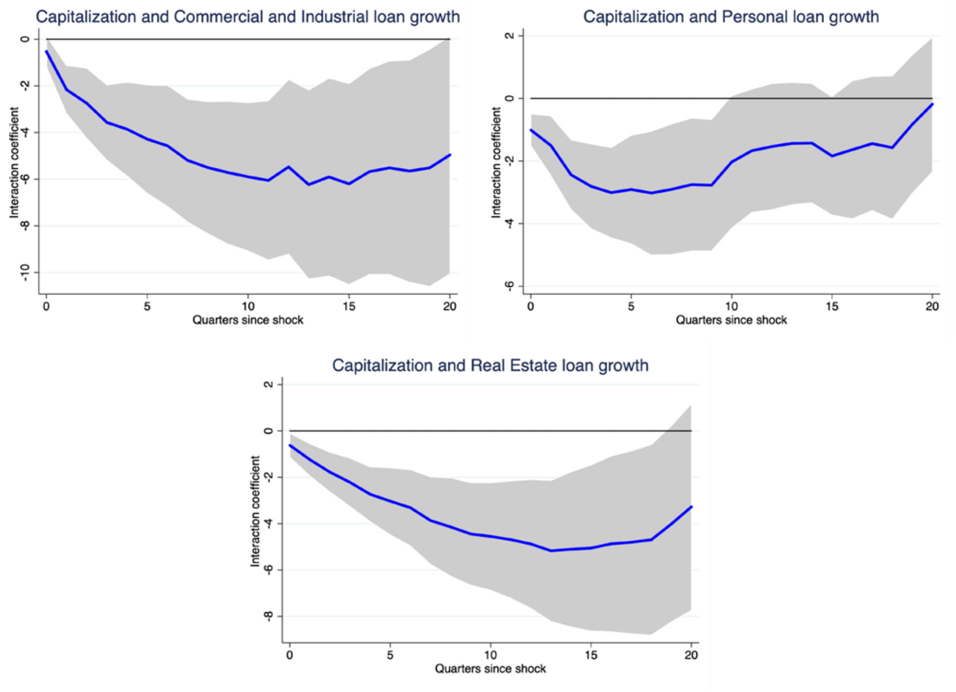
This section documents the response of other banks' balance-sheet variables, such as deposits and securities, after a monetary shock. First, the top part of Figure 7 shows bank deposits' response to a monetary shock. I find higher-capitalized banks reduce their deposits more than lower-capitalized bank. Second, the bottom part of Figure 7 shows bank securities' response to a monetary shock. I find securities' response, on average (blue line), is systematically below zero and the gray band is wide, meaning highly capitalized banks also reduce security holdings. In sum, highly capitalized banks reduce deposits, securities, and loans; that is, the overall balance sheet shrinks.

B. Fact 2

DEFAULT RATES, BANK CAPITALIZATION RATE, AND MONETARY POLICY

This section documents the relation between default rates and a monetary shocks. Given the aggregate data in delinquency rates (charge-off rates for each category of loans), I document the response of a proxy of default rates to a monetary policy shock. Figure 8 shows the response of delinquency rates to a monetary shock for each type of loan (main fact 2). I find delinquency rates (proxy of default) goes up for all types of loans. In particular, default rates increase over two years after a monetary tightening (see online Appendix C for the charge-off responses). This evidence suggests that loans are intrinsically riskier by themselves. It is not the case loans becomes riskier after a monetary policy shock. In addition, note that central banks tighten monetary conditions when the economy is doing well (a context that should have few defaults). However, after tightening occurs, more defaults will occur, so the effect of tightening on the cost of financing these types of sectors matters. Therefore, a first-order effect arises that leads to an increase in default rates from the monetary tightening.

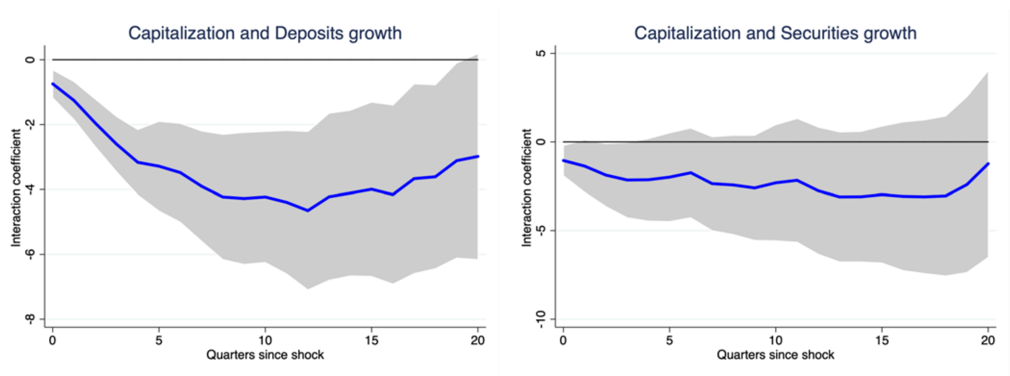
FIGURE 6. DYNAMIC RESPONDS ON BANKS' LOAN PORTFOLIO BY TYPE



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (2) for each type of loan. The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

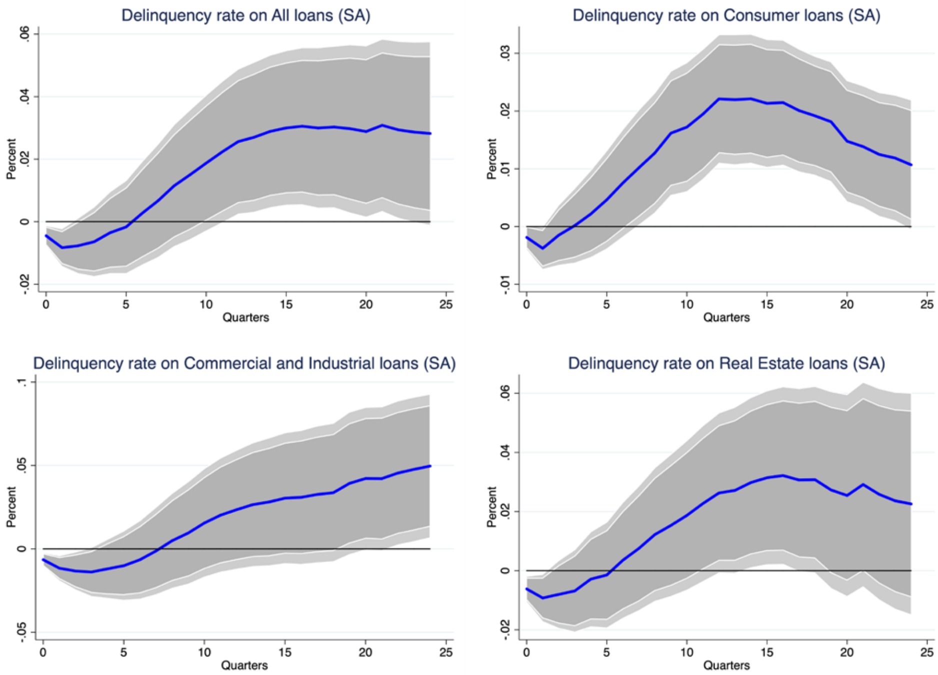
Additional Empirical Results. Online Appendix C contains two set of additional exercises related to fact 2. The first set of additional results contains the charge-off rate for each category of loans across percentiles of bank capitalization at the cross-sectional bank-level data. Figure C2 shows that there is no clear pattern in default rates exists across capitalization rates. In the second set of results, I analyze (conditional on loan types) whether the response of default rates to a monetary shock depends on capitalization rates. Figure C3 shows that within a given sector (e.g., real estate), high- and low-capitalized banks have statistically the same defaults rates. A suitable interpretation is that high- and low-capitalized banks tend to have similar borrowers; that is, credit risk is similar for both. In addition, online appendix D1 documents the relationship between bank capitalization rates, default rates, and business cycles. I find a

FIGURE 7. BANK BALANCE SHEETS AND MONETARY POLICY: DEPOSITS AND SECURITIES



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (2) for deposit growth and securities as a dependent variables. The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

FIGURE 8. AGGREGATE: DELINQUENCY RESPONSES TO MONETARY POLICY SHOCK



Note: The figure reports the response of the delinquency rates to monetary policy shocks for each type of loans. The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

negative relation between default rates and GDP growth, but the effect across banks for each type of loan is not statistically different. Therefore, I could rule out the demand-driven story whereby one bank type lends more cyclically than the other.

C. Fact 3

RISKINESS OF TYPES OF LOAN

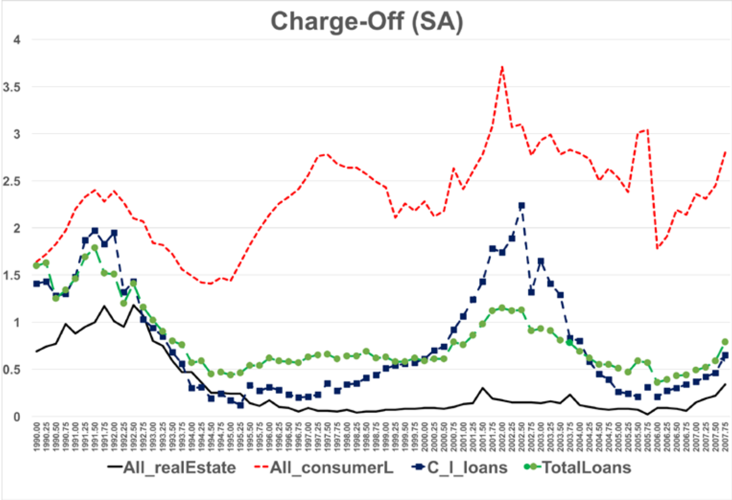
This section analyzes which types of loans are riskier. I define riskiness as a higher frequency of default. I consider charge-off rates for each loan category a proxy for default rates. Figure 9 shows the evolution of the aggregate data for charge-off and delinquency rates (proxy of default) for total loans and each loan category in all U.S. commercial banks. I show that, in the period of analysis, the charge-off rates are lower for real estate loans.

In addition, I use cross-sectional data to study the relative effect of risk between loan types using a charge-off rate for each category. The empirical strategy is regressing the charge-off rate for each bank against a charge-off indicator:

$$y_{ikt} = \alpha_i + \beta^p \times 1_{\{k=p\}} + \beta^{ci} \times 1_{\{k=ci\}} + \beta^{ag} \times 1_{\{k=ag\}} + \gamma' x_{i,t} + \epsilon_{i,t} \ , \qquad (5)$$

where y_{ikt} is the charge-off rate (proxy for default) of bank i with loan type k at time t, $x_{i,t}$ are bank control variables, $1_{\{k=\tau\}}$ is an indicator for the charge-off rate, $\tau = \{p, ci, ag\}$, where $1_{\{k=re\}}$ serves as the omitted category, and β^k represent the riskiness of loan type k relative to real estate loans. Table 4 shows the result of the estimation of the equation 5. The coefficient β reflects how risky loan type k is relative to real estate loans, where $k = \{\text{C\&I}, \text{personal}\}$. I find personal and C&I loans are riskier than real estate loans.

FIGURE 9. AGGREGATE CHARGE-OFF RATES



Note: The figure shows the aggregate charge-off rate for C&I, personal, real estate loans, and total loans over the time of the commercial banking sector..

TABLE 4—RELATIVE RISK OF LOAN TYPES OVER THE REAL ESTATE LOAN

VARIABLES	(1) Charge-off rate	(2) Charge-off rate
β^{ci}	0.341***	0.346***
	[0.006]	[0.006]
β^{p}	0.530***	0.535***
	[0.006]	[0.006]
β^{ag}	0.014**	0.012**
	[0.006]	[0.006]
constant	0.105***	0.022*
	[0.004]	[0.013]
Bank fe	Y	Y
Bank controls	N	Y
Obs	1,205,998	1,205,998
R^2	0.0874	0.091

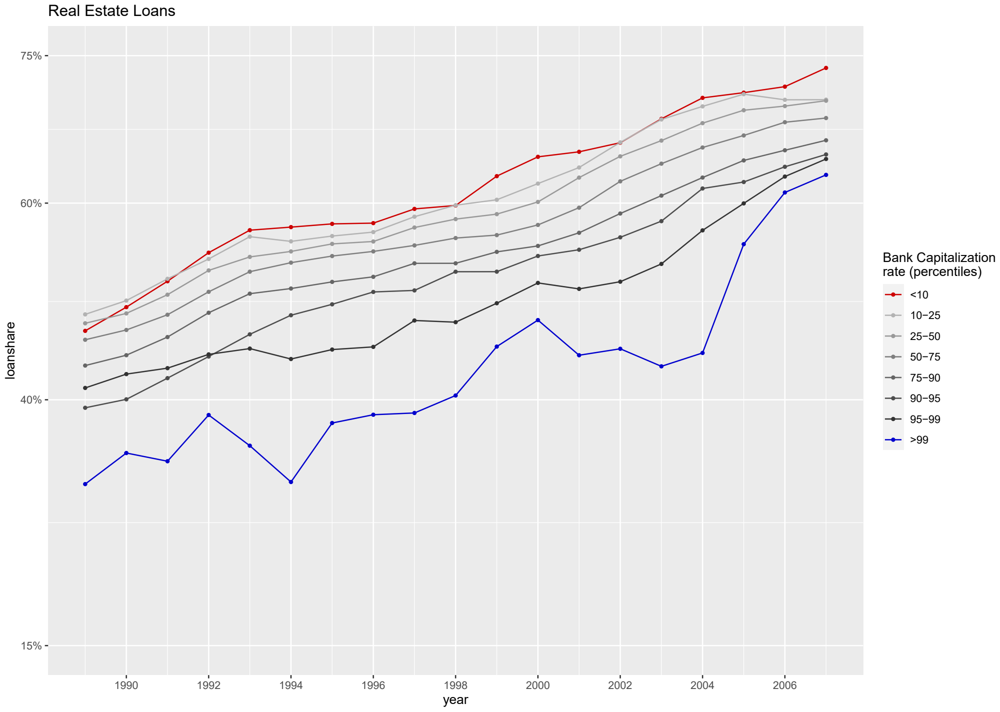
Robust standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

BANKS' LOAN-PORTFOLIO COMPOSITION

In this section, given that the response is different across loan types, I document the loan-portfolio composition for banks with different capitalization rates. First, Figure 10 shows the average loan portfolio across bank-capitalization-rate percentiles for real estate loans. I find higher-capitalized banks have a lower share of real estate loans than lower-capitalized banks. Second, whereas the evidence of Figure 10 suggests that the portfolio composition of banks with higher-capitalization rates is less oriented toward real estate loans, see online appendix E1 for other types of loans. Note that bank size, or the state-fixed effects, may be the driving force of the result. I calculate the trend in average bank capitalization after controlling for bank size, state, and size-state interactions. The empirical strategy is regressing the portfolio share associated with each category against different percentiles of bank capitalization rates:

(6) $$y_{jbt} = \sum_{i \in I} \beta_i^j 1_{\{bt \in i\}} + \Gamma^j Z_t + \delta_t + \delta_{\text{state}} + \epsilon_{jbt} \ ,$$

FIGURE 10. AVERAGE PORTFOLIO SHARE FOR REAL ESTATE LOAN ACROSS BANK-CAPITALIZATION PERCENTILES

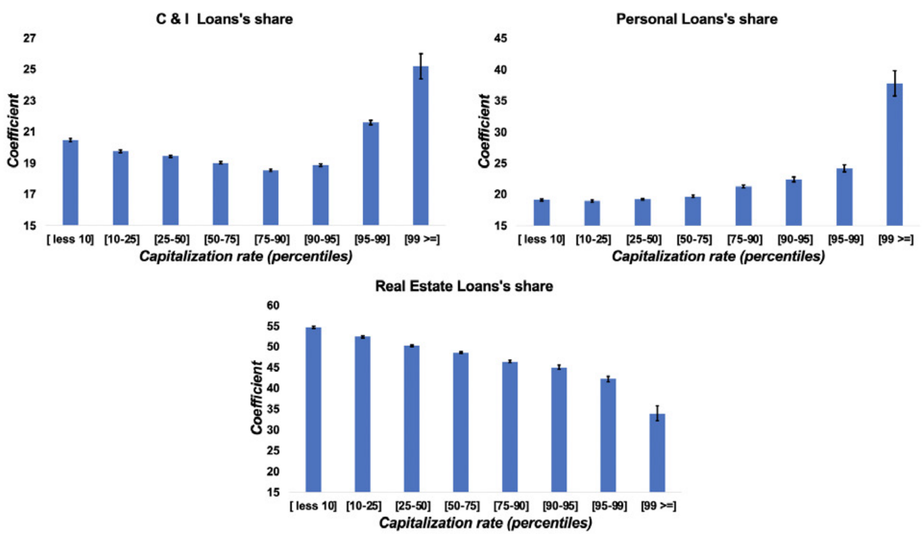


Note: The figure shows that average loan portfolio across bank-capitalization-rate percentiles for real estate loans.

where y_{jt} is the bank's loan-type share, j is loan type {C&I, personal, real estate}, $I$is percentiles groups i , $Z_t$are bank size, as a control variable. Therefore, the coefficient of interest is β_{cap}. I find that, on average, higher-capitalized banks have a higher average share of C&I and personal loans, and lower-capitalized banks have more real estate loans.

Figure 11 shows the coefficient of interest β_{cap} from the estimation of the equation 6 for C&I, personal and real estate loans. I find higher-capitalization banks have a higher portfolio of personal loans (the same for C&I loans). By contrast, lower-capitalization banks have a higher portfolio of real estate loans.

FIGURE 11. ESTIMATION: AVERAGE-PORTFOLIO-SHARE PARAMETERS β_{cap}



Note: The figure shows the average portfolio share parameter from the estimation of the equation 6 for C&I, personal and real estate loans.

D. Inspecting the mechanism:

Against this backdrop, I set out to explore the mechanisms underpinning my findings. A framework intending to study the heterogeneous transmission of monetary policy to the economy through the banking sector should include several features absent in conventional macro-finance models. The main facts about banks' loan portfolios and the response of bank lending to a contractionary monetary shock (positive-monetary policy surprise) are the following:

1) Portfolio composition and loan risk: Higher-capitalized banks have a higher share of C&I and personal loans. These types of loans are riskier than real estate loans, as measured by charge-off rates.

2) Response to monetary tightening: default rates increase.

3) Response to monetary tightening: higher-capitalized banks reduce lending more. This response holds across all types of loans (C&I, personal, and real estate). In addition, they contract their balance sheet more (i.e., deposits and securities fall).

A mechanism proposed is than an unanticipated increase in the Fed funds rate increases the probability of loan default. Therefore, banks reduce their exposure to all risky assets. In particular, in terms of portfolio composition and riskiness, higher-capitalized banks have a higher share of risky loans than lower-capitalized banks, and because they have a risk-sensitive capital requirement, they reduce loans even more than lower-capitalized banks. Thus, higher-capitalized banks reduce their overall loans more than lower-capitalized banks. This effect on lending will have a negative impact on economic activity.

III. Baseline model

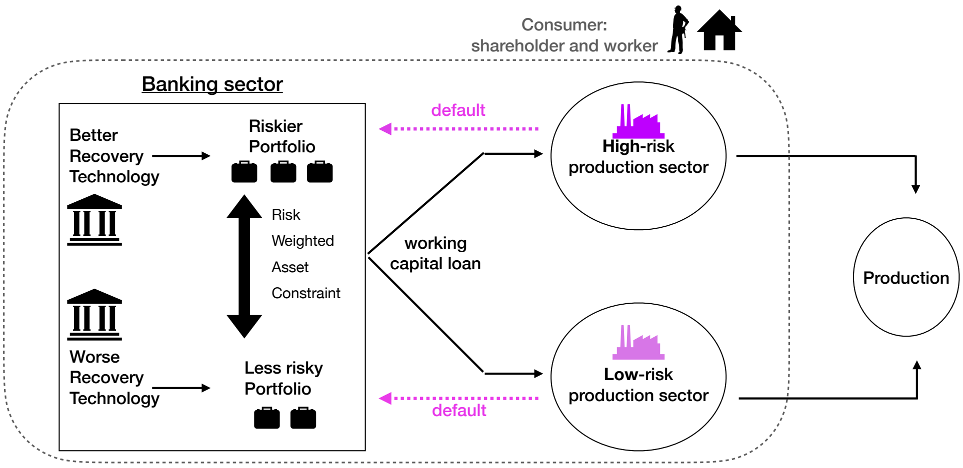
In the second half of the paper, I develop a heterogeneous-bank model that considers risk-sensitive capital requirements to rationalize the empirical facts. This dynamic stochastic general equilibrium model is based on the Elenev, Landvoigt and Van Nieuwerburgh (2021) framework. The proposed model has three key elements. First, it has two banks that are heterogeneous in the recovery rates on defaulting loans and face capital regulation with a risk-weighted asset constraint. This assumption implies an endogenous difference in capitalization rates and portfolio composition. Second, it has two risky production sectors, with heterogeneous volatility in idiosyncratic productivity shocks on each sector. Additionally, these firms have a CES demand for loans, which implies differences in steady-state default rates and in lending responses to monetary shocks. Third, the aggregate fluctuations are driven by the monetary shock, where the deposit rate is given and follows a standard order-1 autoregressive process.

Figure 12 provides an overview of the model. The banking sector is composed by two banks. Additionally, two productive sectors exists. One of them has higher idiosyncratic volatility than the other (high- and low-risk sectors). Banks are heterogeneous in the ability to recover losses from loans, face a regulatory constraint (a Basel I capital requirement with risk-weighted assets), and maximize the present-value dividends paid to their shareholders. They take the interest rate as given and can issue equity from consumers and extend loans to both production (non-financial) sectors. Banks cannot default. Importantly, banks extend high-risk lending to the firms in the high-risk productive sector and less risky lending to the firms in the low-risk sector. The bank lending is in the form of working-capital loans. Both productive sectors can default on their loans to the banks. Producers maximize profits and operate a production technology using labor and capital. They are funded by working-capital loans from banks. They also buy capital from consumers. Finally, consumers maximize inter-temporal expected utility, work for the firms (the labor supply is inelastic), and own firms and banks.

A. *Environment*

The model is formulated in discrete time over an infinite horizon and has three agents: consumers, firms, and banks. I develop a heterogeneous-bank model in order to interpret the cross-sectional empirical evidence and understand monetary policy transmission to bank lending considering the heterogeneity in bank capitalization rates. I describe the model in three blocks: (1)

FIGURE 12. OVERVIEW OF THE MODEL



two sectors firm block, which captures the difference in default rates; (2) banking block, which generates the differences in capitalization rates, portfolio composition, and lending responses to a monetary shock; and (3) a representative consumer or household, which closes the model.

TWO RISKY PRODUCTION SECTOR BLOCK

Two types of firms $j \in \{H, L\}$ exist with heterogeneous risk. Each sector contains a continuum of firms facing an idiosyncratic productivity shock. I assume there is perfect risk-sharing. This assumption implies a representative firm exists in each sector with a default rate in equilibrium. Each risky productive sector uses a Cobb-Douglas production function with capital and labor ℓ:

$$Y_{t,j} = \omega_{t,j} K_{t,j}^{1-\alpha} \ell_j^{\alpha},$$

where $\omega_{t,j}$ is drawn i.i.d. from c.d.f. gamma distribution , $E[\omega_{t,j}] = 1$, and $\sigma_{\omega_H} > \sigma_{\omega_L}$. Firm j issues debt to finance working capital to bank i, at interest rate $R^i_{t,j} = 1/q^i_{t,j}$. The firm's problem in each sector can be explained in two stages.

Stage I: Given the interest rates, firms determine what fraction of loans to borrow from each bank. I assume the representative firm has a preference for a variety for loans (multiple relationship). This assumption has an empirical counterpart; for example, for emerging markets, Khwaja and Mian (2008) present empirical evidence in the case of Pakistan that 60% of firms borrow from multiple banks, and 56% of lending is in the form of working capital. In an example for developed countries, in this case, Japan, Amiti and Weinstein (2018) show the median firm borrows from seven banks, and 97% of the firms in their sample borrowed from more than one bank.

Formally, the firm will solve a standard problem and I assume loans are differentiated by sector according to a CES functional form[10]:

$$\max_{\{L_j^1, L_j^2\}} \text{WC}_{t,j} = \left(\sum_{i=1}^{2} (\nu_j)^{\frac{1-\sigma}{\sigma}} (L_j^i)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \quad s.t. \quad \left(\frac{1}{q_j^1}\right) L_j^1 + \left(\frac{1}{q_j^2}\right) L_j^2 = \left(\frac{1}{Q_j}\right) \hat{\text{WC}}_j,$$

where ν_j is a weight parameter, σ is the elasticity of substitution between the two types of loans, L_j^i denotes bank $i \in \{1,2\}$ loans in sector $j \in \{H, L\}$, $\hat{\text{WC}}_j$ is the amount of working capital needed for firm j, and Q_j is the aggregate-loan-price index of both banks' loans prices for firm j

The solution to this problem provides the demand for loans as:

$$L_{t,j}^i = \overbrace{\left(\frac{\frac{1}{Q_{t,j}}}{\frac{1}{q_{t,j}^i}} \right)^{\sigma} (\nu_j)^{1-\sigma} \times \underbrace{\phi^j w_{t,j} \bar{l}_{t,j}}_{\text{working capital } (\bar{\text{WC}}_{t,j})}}^{\text{Loan's firm j (sector) demand for bank } j},$$

Fundamentally, this assumption allows me to endogenously determine what fraction of working capital is provided by each bank. This fraction will depend on the interest rate, which in turn will depend on the recovery value of each bank, which is a technology parameter. Additionally, in equilibrium, banks coexist with an interior solution of portfolio composition.

Stage II: Given borrowing decisions, firms hire labor and buy capital at price p_{jt}^K to maximize the present discounted value of dividends paid to shareholders and produce final goods using the Cobb-Douglas production function. Failed producers are replaced by new producers.

The flow of profit for the firm is:

$$\underbrace{\omega_j k_j^{1-\alpha} l^{\alpha} - (1-\phi) w_j l - \frac{1}{Q_j} \text{wc}_j}_{\text{profit flow}}, \tag{7}$$

Producers with a negative profit flow are in default and shut down. Alternatively, a firm defaults if its sales do produce enough cash to pay back working-capital loans. The equation 7 implies a default threshold:

$$\omega_j^* = \frac{(1 + \phi^j (\frac{1}{Q_j} - 1)) w_j \bar{l}_j}{y_j}, \tag{8}$$

Note that firms with low idiosyncratic shock $\omega_{t,j} < \omega_{t,j}^*$ default.
The firm's recursive problem is

$$V_j(n_j) = \max_{k'} div_j + \mathbb{E}_t [\mathcal{M}_{t,t+1} \tilde{V}_j(k_j')], \tag{9}$$

[10]This preference for a variety of goods is very common in the international trade literature.

$$\overbrace{n_j - p^{k_j} k'_j + \underbrace{\mathrm{wc}_j}_{\text{new debt}}}^{\mathrm{div}^j_{ft}} \geq 0, \tag{10}$$

$$n_j = \underbrace{\omega_j k_j^{1-\alpha} l^{\alpha} - (1-\phi) w_j l - \frac{1}{Q_j} \mathrm{wc}_j}_{\text{profit flow}} + p^{k_j}(1-\delta^{k_j}) k_j, \tag{11}$$

where $\mathcal{M}_{t,t+1}$ is the stochastic discount factor for the firm, and

$$\tilde{V}_j(k_j) = \max_{l_j} [\Omega(\omega_j^*) \mathbb{E}_t(V_j(n_j) | \omega_j > \omega_j^*)], \tag{12}$$

Note that a firm hires labor before the idiosyncratic shock occurs. Thus equation (12) implies the firm chooses labor with the expected value of the firm's idiosyncratic productivity conditional on not defaulting. The complete solution of the firm problem is in online Appendix E.E2.

BANKING-SECTOR BLOCK

The banking-sector block consists of two banks $i \in \{1, 2\}$ that are intermediaries and grant loans to both sectors (high and low risk). The supply of deposits is perfectly elastic to the policy rate. These banks are owned by consumers and face equity-issuance costs. Banks are required to pay a fraction ϕ_0 of equity as dividend each period, but they can deviate from this target by issuing equity e_t^i at a convex cost $\Psi^i(e_t^i)$. These two banks are heterogeneous in their default recovery rates $(1 - \zeta_j^i)$. They will receive a coupon payment on performing loans $\Omega(\omega_{t,j}^*) L_{t,L}^i$, and firms that default go into liquidation and banks repossess them, sell the current period's output, pay the current period's wage, and sell off the assets. Therefore, the total payoff per loan type unit j is:

$$\tilde{M}_{t,j}^i = \underbrace{\Omega(\omega_{t,j}^*)}_{\text{No default}} + \underbrace{\frac{(1 - \Omega(\omega_{t,j}^*))}{L_{t,j}^i / q_{t,j}^i} \left[\varpi_{t,j}^i (1 - \zeta_j^i) \left(\mathbb{E}_\omega[\omega < \omega^*] Y_t + ((1 - \delta_j^k) p_t^{K_j}) K_{t,j}\right) - \varpi_{t,j}^i w_{t,j} \bar{l}_j\right]}_{\text{default (recovery value)}}, \tag{13}$$

where ζ is the fraction of firm assets and output lost to banks in bankruptcy.

The bank portfolio consists of choosing the loan interest rate for each type of firm, subject to bank-capital regulation, that is a risk-weighted capital constraint:

$$\mathrm{Networth}^i \geq \theta \underbrace{(\varpi_H L_{H,t}^i + \varpi_L L_{L,t}^i)}_{\text{risk weighted assets}},$$

where ϖ_H, ϖ_L, are the risk weights for each type of loan.

The bank problem is:

(14)

$$V^i(N_t^i) = \max_{q_{Ai,t}, D_t^i, e_t^i} \underbrace{div_t^i - e_t^i}_{Netdiv_t^i} + E_t[\mathcal{M}_{t+1,t}^B V^i(N_{t+1}^i)]$$

$$N_{t-1}^i + D_t^i + e_t^i = L_{t,H}^i + L_{t,L}^i + div_t^i + \Psi^i(e_t^i) \qquad \text{(budget constraint)}$$

$$D_t^i \leq \xi_H L_{t,H}^i + \xi_L L_{t,L}^i \qquad \text{(leverage constraint)}$$

$$\pi_t^i = (\frac{\tilde{M}_{t,j}^i}{q_{t,H}^i} - 1)L_{t,H}^i + (\frac{\tilde{M}_{t,j}^i}{q_{t,L}^i} - 1)L_{t,L}^i - (R_t - 1)D_t^i \qquad \text{(profit flow)}$$

$$N_t^i = N_{t-1} + \underbrace{\pi_t^i - div_t^i + e_t^i - \Psi^i(e_t^i)}_{\text{retaining earnings + equity injections}} \qquad \text{(Law of motion of net worth)},$$

where $div_t^i = \phi_0 e_t^i$. The complete solution to the bank problem is in online appendix E.E3.

Representative household

A representative household with log-utility preferences over consumption is represented by an expected utility function:

$$\mathbb{E}\left[\sum_{t=0}^{\infty} \beta^t \left[log(C_t)\right]\right], \tag{15}$$

where β is the discount factor. The representative households are the owners of firms and banks. This implies that he owns equity capital of the firms and banks, and received the aggregate dividend payments from producers and banks, see online appendix G for the consistency in the resources constraint in equilibrium[11]. They provide labor in fixed supply and choose consumption and investment in both sectors subject to a budget constraint. The consumer problem is:

$$\max_{C_t, X_t^A, X_t^M} \mathbb{E}_t\left[\sum_{t=0}^{\infty} \beta^t \left[log(C_t\right]\right]$$

s.t.

$$C_t + \sum_{i=1}^{2}(X_t^j + \Psi(X_t^j, K_t^j)) \leq w^j \bar{L} + \sum_{j=1}^{2} \text{div}_t^j + \sum_{i=1}^{2} \text{Netdiv}_t^i + \sum_{j=1}^{2} p_t^{Kj} X_t^j$$

$$K_{t+1}^j = (1 - \delta_K)K_t^j + X_t^j \qquad j \in \{H, L\},$$

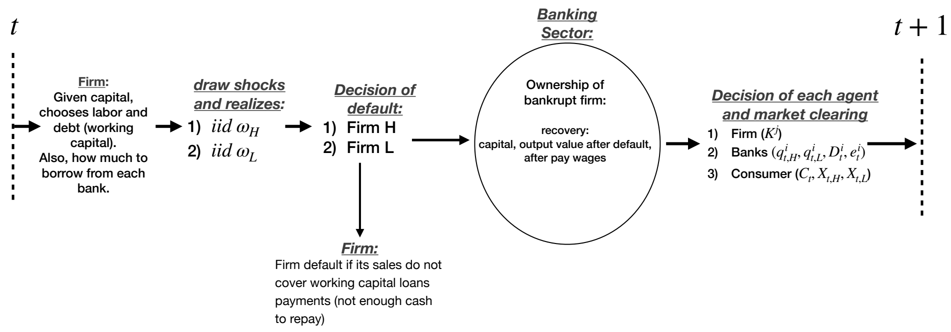
The complete solution of the consumer problem is in online appendix F.

Timing:

At the beginning of period t, given capital, firms choose labor and working capital. Firms also decide how much to borrow from each bank. Idiosyncratic productivity shocks for intermediate-good producers are realized in each sector and then their production occurs. Firms default if their sales do not cover working-capital loans payments or they do not have enough cash to repay. Banks assume ownership of bankrupt firms. Firms decide how much of the capital to take. All agents solve their consumption and portfolio choice problems. The market clears and all agents consume. Figure 13 summarizes the timing of the model.

[11] Note that banks and firms have discount factors that depend of the household discount factor, see the appendix for each agent problem to see the discount factor for each agent

FIGURE 13. TIMING



COMPETITIVE EQUILIBRIUM

Equilibrium is defined in the standard way. Competitive equilibrium is a sequence of monetary policy shocks $\{\epsilon_t^{MP}\}$, and an idiosyncratic productivity shock $\{\omega_{t,j}\}$ for each sector $j \in \{H, L\}$, and an allocation of:

- $\{C_t, X_{t,H}, X_{t,L}\}$ for consumers
- $\{K_{t,j}\}$ for firms $j \in \{H, L\}$
- $\{D_{t,i}, e_{t,i}, q^j_{t,i}\}$ for banks i in $\{1, 2\}$
- A set of prices $\{p_H^K, p_L^K, w_H, w_L\}$

Such that given prices:

1) Consumers maximize life-time utility subject to their constraint.
2) Producers in each sector maximize dividends subject their constraints.
3) Banks maximize net dividends subject to their constraints.
4) Markets clears: Loan markets, capital markets, labor market, and consumption market.

B. Mechanism

This section explains how the primitive model delivers the qualitative results that I show in the empirical-evidence section.

First, I explain the relationship between recovery rates and risky portfolio share. Higher-recovery banks wish to lend more. In particular, they allocate a higher share of their portfolio to the riskier sector. Additionally, as these banks grant more loans, they need more funds to provide more loans (both deposit and equity issuance). The underlying idea is comparative advantage.

Second, I explain the recovery and capitalization rates. The financing constraint is a function of risk-weighted assets. The regulator does not understand one bank has better technology than the other (i.e., they do not know the recovery rates for each bank) and imposes the same risk-weighted constraint on both banks. Therefore, banks with better skills or with higher recovery rates are able to invest in risky firms (or risky sectors), but they might not have the necessary capital to do so. Therefore, they need to be better capitalized. Note that,

in my model, the recovery rate is not a property of the asset: it is a property of the bank, namely its technology.
The following example can illustrate the situation: Two banks exist. One of them has a comparative advantage in asset management, but it is mandated to deploy the same amount of capital as a less efficient bank. In a two-sector economy, the better bank is able to manage the riskier sector better; that is, it is willing to invest more in the risky sector because it has a comparative advantage, which makes its portfolio riskier. The regulator mandates a higher capital requirement on this bank than on the bank that invests in safer assets (less risky portfolio). Providing the capital is costly for the more efficient bank, so imposing the risk-weighted constraint actually pushes it away from the risky sector. This constraint affects the better bank more than proportionally, because it is investing more in the risky sector. Therefore, the bank with portfolio riskier will tend to withdraw more intensively away from the riskier sector, but to the extent that it equalizes its portfolio composition with the worse bank. The better bank will actually push the portfolio composition to the same structure as the worse bank. Therefore, now they will face the same collateral constraint (or regulatory constraint), because they have the same asset composition. However, the better bank has the same constraint, but the advantage of managing the riskier sector; therefore, it would still be willing to invest more in the riskier sector, but would need to be better capitalized to do so.

To summarize, the bank with better recovery technology has a comparative advantage in lending to riskier firms, but in order to do so, the firm must provide more capital to satisfy the RWA constraint, so it ends up appearing as better capitalization.

Third, considering the sensitivity of well-capitalized banks to monetary policy shocks is important. The sequence is as follows: increase in the policy interest rate, increase in loan rates, the firm's loan default probabilities increase. All banks respond by reducing their lending, but higher capitalized banks- the ones with riskier assets- do so by more.

C. Parameterization and Results

In this section, I use the model to analyze in detail the novel channel of heterogeneous transmission of monetary policy shocks through differences in capitalization rates. I calibrate the model under the assumption of bank heterogeneity on recovery defaulting loans, as primitive parameter, that face risk-weighted capital requirement. Then, I compute the deterministic steady state, and I shock the economy with a positive monetary policy shock to verify the model performance in terms of my key features of the micro data.

Calibration

Household preferences and production function. For simplicity, I assume standard preferences for the consumer $u(C) = logC$ or I set the intertemporal elasticity of substitution (IES) to 1. The consumer's discount factor β is set to 0.85. On the production side, the labor share α in the final good is set to 0.71, which is a standard value in the business-cycle literature. For the investment sector, I also assume standard quadratic specification for the investment adjustment cost, and I set the marginal adjustment-cost parameter ψ to 2 to match the adjustment cost and its first derivative to zero in the steady-state. For the working capital loan, the corporate-finance literature shows a firm requires to cover its cash-flow mismatch between the payments made at the beginning of the period and the realization of revenues; see Mahmoudzadeh, Nili and Nili (2018). I set the working capital parameters to 0.8, which is in line with Galindo Gil (2021) and Christiano, Trabandt and Walentin (2010). In the case of the CES functional form to the firm, I set an elasticity of substitution between loans $\sigma = 7$, implying a standard elasticity between these banks typically used between monopolistically competitive goods. Also, I set the weighting parameters $\nu_1 = 1.12$ and $\nu_2 = \left(1 - \nu_1^{1-\sigma}\right)^{\frac{1}{(1-\sigma)}}$ so banks hold 50 % of the loans in equilibrium when no heterogeneity exists in recovery rates.

Idiosyncratic Productivity. Idiosyncratic shocks are assumed to be gamma distributed with parameters μ_ω and σ_ω. I normalize the mean of idiosyncratic productivity at $\mu_\omega = 1$ for both sector $j \in \{H, L\}$. In the case of the low-risk productive sector, the cross-sectional standard deviation of the idiosyncratic productivity $\sigma_{\omega,L}$ targets the unconditional mean of the default rate. The model-implied average default rate of 2% is similar to the data corresponding to the average delinquency rate of 2% for the residential real estate loans. In the case of the high-risk productive sector, the cross-sectional standard deviation of the idiosyncratic productivity $\sigma_{\omega,H}$ targets the unconditional mean of the default rate. The model-implied average default rate of 3% is similar to the data corresponding to the average delinquency rate of 3% for the commercial and industrial loans.[12]

Banking sector. The intermediaries face the risk-weighted capital constraint. The capital requirement or minimum regulatory equity-capital requirement θ is set to 8% of risk-weighted assets, the risk weights for the riskier type of loan is set ϖ_H set to 1, and risk weight to less risky type of loan is set ϖ_H set to 0.8, consistent with the general requirement for banks under Basel I regulatory framework (BCBS (1998)). The dividend target of banks ϕ_0 and the marginal bank equity-issuance cost ϕ_1 are set to 0.096 and 7, respectively, as in Elenev, Landvoigt and Van Nieuwerburgh (2021). Two parameters drive the heterogeneity in the banking sector, namely, the recovery rates on defaulting loans. For bank 2, I set the recovery rates on defaulting loans in the low-risk sector to for 0.2 and high-risk sector to 0.5. This values are in line with Elenev, Landvoigt and Van Nieuwerburgh (2021). For the bank 1, I set 0.8 for both sectors. I calibrated

TABLE 5—PARAMETERS OF THE MODEL

Parameter	Name	Value	Target/Sources
	Preferences		
β	Discount factor	0.85	See text
	Technology $j \in \{H, L\}$		
α	labor share	0.71	Standard
ψ	capital-adjustment cost	2	Standard
δ_K	depreciation rate	8.25%	Standard
ϕ_K	working-capital parameter	0.8	Christiano et al. (2010)
σ	elasticity of substitution	7	See text
ν	weighting parameter	1.12	See text
	Banking: Banks $i \in \{1, 2\}$		
$[1-\zeta_H^1, 1-\zeta_L^1]$	bank 1 recovery rates on defaulting loans	[0.8,0.8]	See text
$[1-\zeta_H^2, 1-\zeta_L^2]$	bank 2 recovery rates on defaulting loans	[0.2,0.5]	Elenev et al. (2020)
ϕ_0	target bank dividend	0.096	Elenev et al. (2020)
ϕ_1	bank equity-issuance cost	7	Elenev et al. (2020)
θ	regulatory constraint	0.08	Basilea I
$[\varpi_H, \varpi_L]$	risk weights to each type loan	[1, 0.8]	Basilea I
	Shock parameters or shock structure		
ρ_R	persistence of policy rate	0.7	Standard
σ_R	volatility of policy rate	0.01	Standard
σ_{ω_L}	volatility idiosyncratic low-risk sector	0.03	Default rate 2%
σ_{ω_H}	volatility idiosyncratic high-risk sector	0.05	Default rate rate 3%

[12]From the Federal Reserve Board of Governors, I obtained delinquency rates on Residential Real Estate, and Commercial and Industrial loans by U.S. Commercial Banks for the period 1990-2007.

this value using a proxy for recovery rate with the bank-level data. This proxy is a ratio of recoveries on allowances for loan and lease losses to charge-offs on allowances for loan and lease losses. Details are provided in the section III.D. Note that I assume bank 1, has a higher recovery rate in both sectors equal to 0.8, and bank 2 has a lower recovery rate of 0.2 in the high-risk sector and 0.5 in the low-risk sector. I do this to generate a higher relative differences in recovery rates for bank 1 with respect to bank 2 between sectors.

Finally, Christiano, Trabandt and Walentin (2010) suggest that the persistence and the standard deviation of the interest-rate shock driven by variation in monetary policy are 0.87 and 0.51, respectively. However, not all the volatility of the monetary shock is transmitted to the interest rate of loans. As a result, I assume the relevant volatility of the interest rate shock for the firm is one fifth of the corresponding to monetary policy $\sigma_R = 0.01$ and less the persistence $\rho_R = 0.7$.

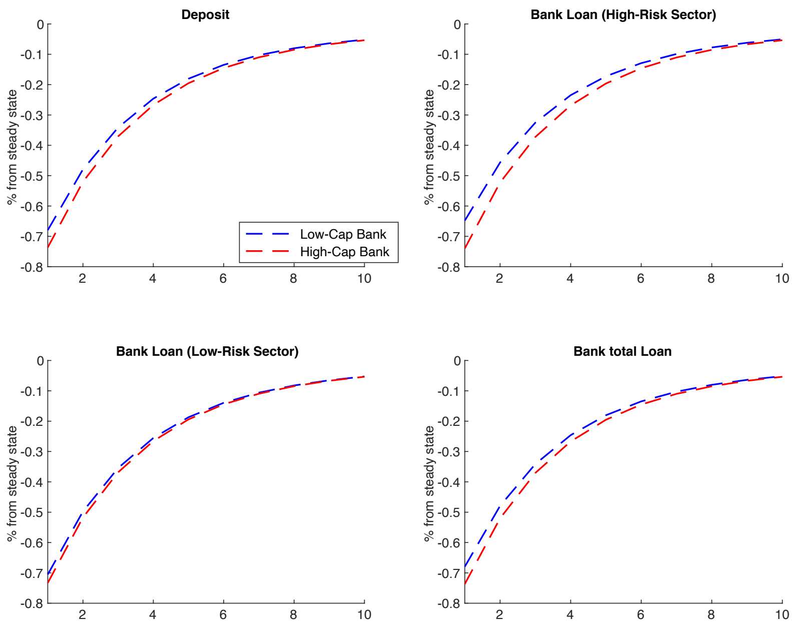
STEADY STATE AND MONETARY POLICY ANALYSIS

Table 6 shows the portfolio composition in the steady state. I find that higher-capitalized banks have a higher portfolio share of risky assets than lower-capitalized banks. This finding proves a qualitative result that I find in my empirical exercise. Figures 14 and 15 show the response of variables such as deposits, loans, and default rates after a one-percentage-point increase in the interest rate.

TABLE 6—PORTFOLIO COMPOSITION, **FACT 3**

Steady State		
	Portfolio Composition	
2-3	High-risk sector	Low-risk sector
2-3		
High-cap bank	53%	47%
Low-cap bank	45%	55%

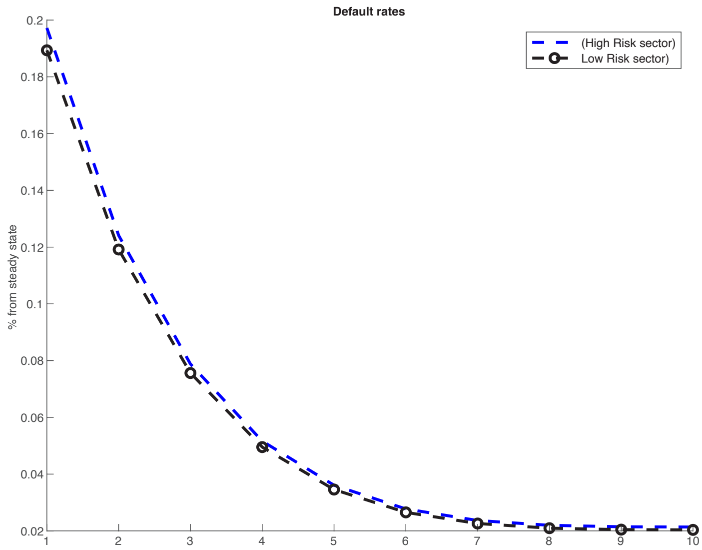
FIGURE 14. EXPERIMENT: MONETARY POLICY SHOCK AND FACT 1



D. *Model vs. Data*

This section compares the empirical regression on impact to the model, and show some evidence on the link between capitalization rate and recovery rates.

FIGURE 15. EXPERIMENT: MONETARY POLICY SHOCK AND FACT 2



BANKS' LENDING RESPONSE VS. CROSS-SECTIONAL INTERACTION COEFFICIENTS

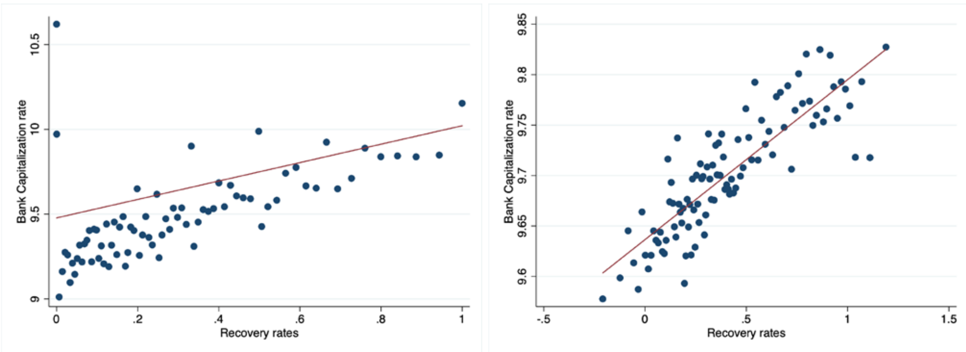
This section discusses how the model captures the interaction coefficient from the empirical evidence in terms of the sensitivity of the response to a monetary shock as a function of the capitalization rate. First note that from the data, a standard deviation of the bank capitalization rate is 4.5 percentage points, and banks with a capitalization rate of one standard deviation above the mean reduce lending by $\beta^{\text{micro}} = -0.76$ percentage points.

In the model, the steady-state difference between high and low bank capitalization rates is $\Delta_{HL}^{model} = 0.2$ percentage points. At this point, I perform an exercise to compare the lending response of banks whose capitalization rates differ by as much as the capitalization rate in the model. First, the high-capitalization relative response of lending, normalized to the dispersion in the capitalization rates in the model is $\frac{\beta^{\text{micro}}}{SD_{data}} \times \Delta_{HL}^{model}$ =-0.033 percentage points. Second, the model's high-capitalization relative response of lending: a 100-basis-point increase in the interest rate leads to a high-capitalization relative response of -0.0565 percentage points. Therefore, the model generates comparable sensitivity in the response to capitalization rates to the one observed in the data, but not enough dispersion in capitalization rates.

PROXY OF RECOVERY RATES AND CAPITALIZATION RATES IN THE DATA

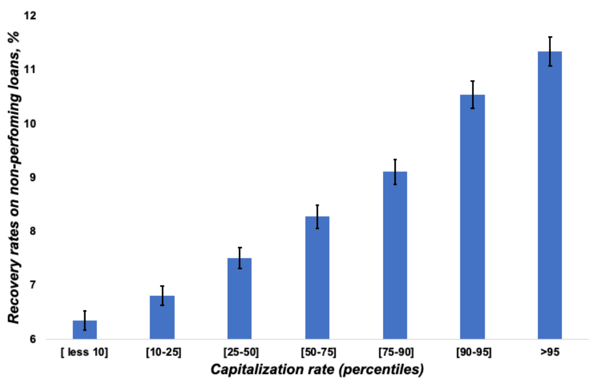
In this subsection, I provide direct evidence on the relation between recovery rates and bank capitalization rates. In the model, I assume recovery rates on defaulting loans generate heterogeneity in capitalization rates. From the data, I construct a proxy of banks' recovery rates as a ratio of recoveries on allowances for loan and lease losses to charge-offs on allowances for loan and lease losses.[13] Over my period of analysis, the top 75th percentile of bank's recovery rates in $C\&I$ loans and real estate loans are, on average, 0.8 and 0.5, respectively, over the sample. The left panel of Figure 16 presents a bin scatter plot of the bank capitalization rate against my proxy for bank recovery rates. It shows a positive relation between bank recovery rates and bank capitalization rates. This result is in line with the prediction of my model. Therefore, banks that are better at recovery tend to have a higher capitalization rate. The right panel is the same bin-scatter plot including bank fixed effects. This relation is strongly positive. This evidence strengthens the rationale of the proposed mechanism. See online appendix H1,H2,H3 for further details and the same analysis by loan type.

FIGURE 16. PROXY FOR RECOVERY RATES AND CAPITALIZATION RATE



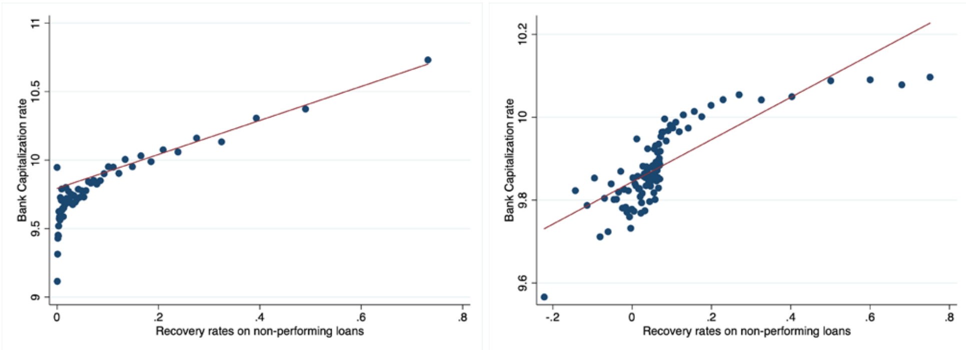
Alternatively, I construct another proxy for recovery rates based on ratio of recovery rates to non-performing loans (past due 90 plus non-accrual). This information is available for my period of analysis at the Call Reports, but not for the full period in the case of loan type. See online appendix I1,I2, I3 for further details. Figure 17 presents the average of the recovery rates on non-performing loans ratio by each capitalization-rate percentile group in the full sample. I show a positive relation between recovery rates and bank capitalization rate. Higher-capitalization-rate banks have, on average, a higher recovery rates on non-performing loans. In addition, Figure 18 presents bin-scatter plots of the bank capitalization rate against my proxy of banks' recovery rates on non-performing loans.

FIGURE 17. RECOVERY RATES AND CAPITALIZATION RATE



[13] Recoveries on allowance for loan and lease losses(*RIAD4605*) and charge-offs on allowance for loan ans lease losses(*RIAD4265*) on the "Call Reports" data base. For further references, see The Fed- Micro Data Reference Manual.

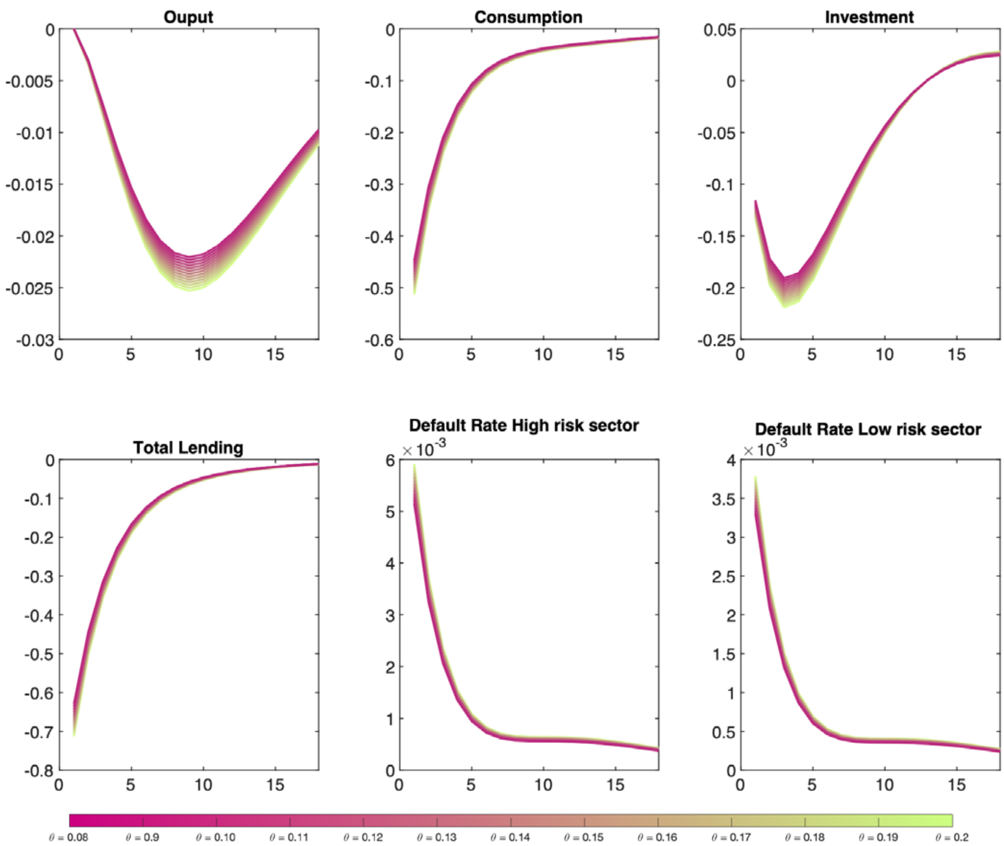
FIGURE 18. RECOVERY RATES AND CAPITALIZATION RATE



E. Sensitivity Analysis

This section discusses the effect of changing capital requirements. Figure 19 shows the effect on aggregate economic variables such as consumption, output, investment, total lending, and default rates. The dark red line represents the baseline case in which the capital requirement is 0.08, and the green line represents 0.2 of the minimum capital requirement. I find that as the capital requirement increases, the effects of a monetary shock are more adverse; that is, higher capital requirements amplify the effects of a monetary policy shock.

FIGURE 19. AGGREGATE: DELINQUENCY RESPONSES TO MONETARY POLICY SHOCK



IV. Conclusion

In this paper, I assess the role of heterogeneity in bank capitalization in the pass-through of monetary policy to bank lending. I provides new empirical evidence using bank-level data, where I find the capitalization rate plays a crucial role in the transmission of monetary policy to bank lending. Highly capitalized banks have a higher share of commercial and industrial loans and personal loans, which are riskier than real estate loans. Highly capitalized banks contract more after a monetary policy tightening, in contrast to the "capital view" Van den Heuvel (2002). I also propose a theoretical mechanism to support the empirical evidence, based on the default channel and the risk composition of banks' portfolios. In addition, I develop a dynamic macro model with a novel bank-heterogeneity feature in the recovery rates for defaulting loans and the interaction with a risk-weighted asset constraint. Finally, I show in a counterfactual exercise that a higher capital requirement amplifies the effects of monetary policy.

For future work, I hope to explore other extensions. One possible extensions include a distinctive feature of the financial sector not included in my counterfactual analysis. Given the RWA constraint differs across loan types through risk weights but not across banks, I would like to use the model to conduct a policy experiment of allowing for heterogeneity in RWAs based on bank type. This underscores that, even though some banks have a better technology than others, or have different recovery rates, the regulator imposes the same RWA constraint on all banks. As a result, banks with riskier loans need to be more capitalized to comply with regulation, thereby raising concerns about the efficiency of banking regulation; i.e., imposing the same constraint on banks with heterogeneous technologies is sub-optimal.

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A1. Empirical Appendix

MONETARY POLICY SHOCK

The measure of monetary shocks is using the high-frequency movements in the Federal funds rate in a short window of time around the FOMC announcements or policy meeting (known as an event-study approach). Following Gurkaynak (2005), Gorodnichenko and Weber (2016), Wong et al. (2019), and Ottonello and Winberry (2020). The monetary policy shock is constructed as

$$\epsilon_t^{MP} = \frac{M}{M-t}\left(r_{t+\Delta^+}^{FFR} - r_{t-\Delta^-}^{FFR}\right),$$

where M is the number of days in a month, t is the time of the monetary announcement, r_t^{FFR} is the average Fed funds rate in the month based on Fed funds futures contract rate up to time t[14], Δ^- is 15 minutes before the policy announcement, and Δ^+ is 45 minutes after the announcement. The shock series begins, in 1990 and ends in 2007 in order to focus on conventional monetary policy. Table A1 shows some moments of the shocks. First, the raw data have 164 shocks with a mean of approximately zero and a standard deviation of 9 basis points. Second, the second column of the table shows the statistics of the monetary policy shock smoothed , as, for example, in Ottonello and Winberry (2020). I construct a moving average of the raw shocks weighted by the number of days in the quarter after the shock occurs. Third, I show the statistics of monetary policy shocks by simply summing all the shocks that occur within a quarter, as, for example, in Wong et al. (2019). Figure A1 shows a time-series graph of the monetary policy shocks for different time aggregations. All my results are based on the monetary policy shocks, using the time aggregation of simply summing all the shocks within any quarter. For robustness, I also use the alternative time aggregation of monetary policy shock smoothed. My results using these alternative shocks do not significantly differs.

COMPARISON TO EXISTING EMPIRICAL LITERATURE

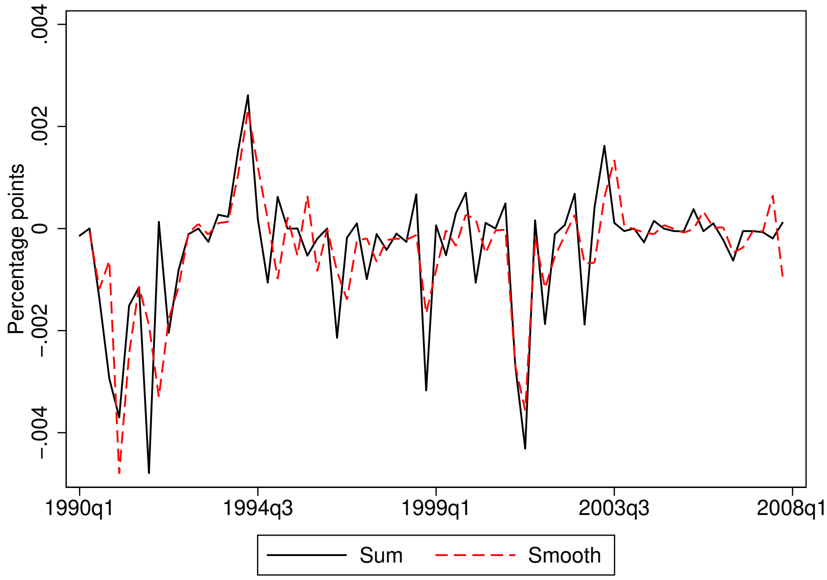
This subsection relates my findings to empirical studies documenting heterogeneous responses across banks with different market power on deposits.

TABLE A1—SUMMARY STATISTICS OF MONETARY-POLICY SHOCK

	high frequency	smoothed(quarterly)	Sum(quarterly)
mean	-0.019	-0.043	-0.042
median	0	-0.0127	-0.0051
std	0.086	0.108	0.124
min	-0.463	-0.480	-0.479
max	0.152	0.233	0.261
num	164	71	72

[14] Fed funds futures have been traded on Chicago Board of Trade since 1988. The contract for a particular month that pays the average of the effective Federal funds rate over the month.

FIGURE A1. MONETARY POLICY SHOCKS



Subsection B.B1 replicates the results of Drechsler, Savov and Schnabl (2017) with my sample and shows that including their measure of market power does not affect my results. Subsection B.B2 reconciles the empirical evidence of Van den Heuvel (2002) regarding the capitalization rate. Subsection B.B3 reconciles the empirical evidence of Kashyap and Stein (2000) regarding the liquidity variable. Note my results differ from the above-mentioned due to three main characteristics: (1) I use an identified monetary policy shock instead of changes on the Fed funds rate;[15] (2) I use a different sample period; and (3) the econometric specification is a panel-data regression. Table 3 in the main part summarizes the main differences concerning the main empirical literature that studies the heterogeneous response across banks with different capitalization rates, market power on deposits, and liquidity in the U.S. economy.

B1. Relation for Drechsler, Savov and Schnabl (2017) and market power on deposits

Drechsler, Savov and Schnabl (2017) show banks with more market power are more sensitive to changes in the Fed funds rate. First, I replicate their result using my bank-level data, their measure of market power on deposits, and their specification. Table B1 shows my results, which are consistent with Table VIII in Drechsler, Savov and Schnabl (2017). Note the data are at the bank-quarter level and cover all commercial banks from January 1994 to December 2013. My estimates are consistent with their paper. Second, I replicate the same table, but I consider standard errors clustered at the time and bank levels on the regression.[16] Table B2 shows the results where I consider standard errors clustered at the time and bank levels. The results on the deposit side are still negative and significant. Still, the result on the asset side, particularly for total loans and real estate loans, is not significant. Third, I want to be able to compare my results with their table. Therefore, I replicate the same table,

[15]The Fed's action creates a well known endogeneity problem in response to changes in economic conditions.

[16]Clustering at the bank level allows for fully flexible dependence in the error terms across time within each bank, thereby affecting the estimated standard error. To provide the most conservative confidence intervals, I also cluster at the time level. Without doing so, any confidence intervals on estimates presented tend to be considerably narrower.

but considering my sample period until 2007, because I focus only on conventional monetary policy and end the sample before the GFC. Additionally, after 2008, monetary policy is not based on the interest rate, but on unconventional monetary policy such as QE and forward guidance. Therefore, using the interaction with the Fed-funds-rate changes could yield misleading results, because it was not the main monetary policy tool after 2008. Tables B3 and B4 show the results considering the pre-crisis period, but for the case standard errors clustered at the bank level and the case standard errors at the time and bank levels, respectively. In the case of deposits, the interaction coefficient is negative and statistically significant. Banks with higher market power are more sensitive to monetary policy tightening measures by changes in the Fed funds rate. In addition, in the case of loans, the interaction coefficient is positive and not statistically significant. I use this coefficient interaction to compare with my result at impact response and the dynamic response.

TABLE B1—BANK-LEVEL RESULTS REPLICATION OF DEPOSIT CHANNEL - BANK LIABILITIES AND LENDING,1994-2013

VARIABLES	ΔTotal deposit	Δ Deposit spreads	Δ Savdep	Δ Time deposit	Δ Wholesale	Δ Tot liab
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-1.493***	0.063***	-1.212***	-2.181***	2.403**	-1.296***
	[0.145]	[0.009]	[0.244]	[0.213]	[0.947]	[0.139]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	N	N	N	N	N	N
Observation	565,341	565,341	565,341	565,341	565,341	565,341
R^2	0.160	0.364	0.078	0.166	0.033	0.172
VARIABLES	Δ Total assets	Δ Cash	Δ Securities	Δ Total loans	Δ Real estate loans	Δ C&I loans
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-1.215***	-2.393***	-0.948***	-0.491***	-0.878***	-0.973***
	[0.124]	[0.664]	[0.337]	[0.152]	[0.200]	[0.353]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	N	N	N	N	N	N
Observation	565,341	565,341	565,341	565,341	565,341	565,341
R^2	0.173	0.050	0.062	0.219	0.172	0.060

*** p<0.01, ** p<0.05, * p<0.1

TABLE B2—BANK-LEVEL RESULTS REPLICATION OF DEPOSIT CHANNEL - BANK LIABILITIES AND LENDING, 1994-2013

VARIABLES	ΔTotal deposit	Δ Deposit spreads	Δ Savdep	Δ Time deposit	Δ Wholesale	Δ Tot liab
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-1.493***	0.063***	-1.212	-2.181***	2.403	-1.296***
	[0.506]	[0.020]	[0.939]	[0.447]	[2.822]	[0.460]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	Y	Y	Y	Y	Y	Y
Observation	565,341	565,341	565,341	565,341	565,341	565,341
R^2	0.160	0.364	0.078	0.166	0.033	0.172
VARIABLES	Δ Total assets	Δ Cash	Δ Securities	Δ Total loans	Δ Real estate loans	Δ C&I loans
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-1.215***	-2.393**	-0.948	-0.491	-0.878	-0.973**
	[0.408]	[1.072]	[0.738]	[0.502]	[0.549]	[0.462]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	Y	Y	Y	Y	Y	Y
Observation	565,341	565,341	565,341	565,341	565,341	565,341
R^2	0.173	0.050	0.062	0.219	0.172	0.060

*** p<0.01, ** p<0.05, * p<0.1

TABLE B3—BANK-LEVEL RESULTS REPLICATION OF DEPOSIT CHANNEL - BANK LIABILITIES AND LENDING, 1994-2007

VARIABLES	ΔTotal deposit	Δ Deposit spreads	Δ Savdep	Δ Time deposit	Δ Wholesale	Δ Tot liab
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-0.676***	0.087***	0.421	-2.112***	4.656***	-0.475***
	[0.156]	[0.011]	[0.272]	[0.257]	[1.118]	[0.152]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	N	N	N	N	N	N
Observation	416,901	416,901	416,901	416,901	416,901	416,901
R2	0.159	0.309	0.079	0.146	0.028	0.169
VARIABLES	Δ Total assets	Δ Cash	Δ Securities	Δ Total loans	Δ Real estate loans	Δ C&I loans
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-0.465***	-3.079***	0.113	0.195	0.143	-0.148
	[0.135]	[0.644]	[0.380]	[0.195]	[0.255]	[0.428]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	N	N	N	N	N	N
Observation	416,901	416,901	416,901	416,901	416,901	416,901
R2	0.170	0.057	0.058	0.199	0.150	0.050

*** p<0.01, ** p<0.05, * p<0.1

TABLE B4—BANK-LEVEL RESULTS REPLICATION OF DEPOSIT CHANNEL - BANK LIABILITIES AND LENDING, 1994-2007

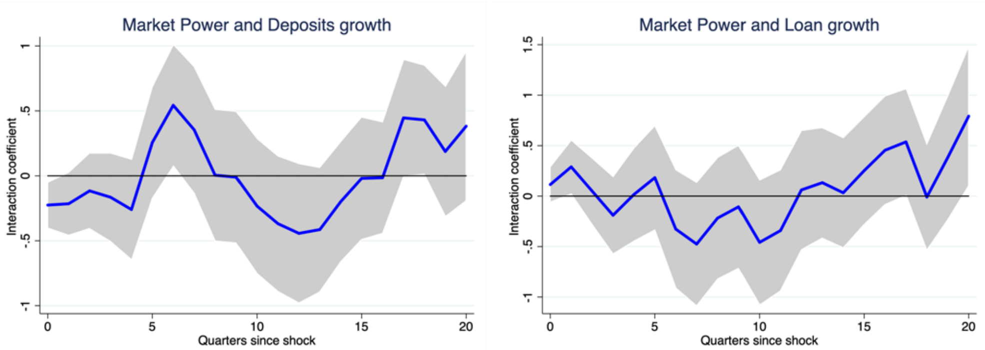
VARIABLES	ΔTotal deposit	Δ Deposit spreads	Δ Savdep	Δ Time deposit	Δ Wholesale	Δ Tot liab
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-0.676	0.087***	0.421	-2.112***	4.656	-0.475
	[0.509]	[0.015]	[0.884]	[0.550]	[3.760]	[0.408]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	Y	Y	Y	Y	Y	Y
Observation	416,901	416,901	416,901	416,901	416,901	416,901
R2	0.159	0.309	0.079	0.146	0.028	0.169
VARIABLES	Δ Total assets	Δ Cash	Δ Securities	Δ Total loans	Δ Real estate loans	Δ C&I loans
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta FF\times$ bank HHI	-0.465	-3.079**	0.113	0.195	0.143	-0.148
	[0.334]	[1.520]	[0.794]	[0.618]	[0.477]	[0.532]
Bank f.e.	Y	Y	Y	Y	Y	Y
Quarter f.e.	Y	Y	Y	Y	Y	Y
Cluster Bank Level	Y	Y	Y	Y	Y	Y
Cluster Time Level	Y	Y	Y	Y	Y	Y
Observation	416,901	416,901	416,901	416,901	416,901	416,901
R2	0.170	0.057	0.058	0.199	0.150	0.050

*** p<0.01, ** p<0.05, * p<0.1

In this section, I show my results using the main econometric specification used in the paper, with my measure of monetary policy shocks for the dependent variables, deposit growth and loan growth. First, for the case of deposit growth, the top part of Figure B1 shows the response of deposit growth to monetary policy-shock considering the interaction with market power. I find that banks with higher market power reduce their deposit on impact more than banks with lower market power. I conclude this finding is consistent with the deposit channel's replication Table B3, which considers the sample until 2007. Second, for the dependent variable loan growth, I find the loan response is positive and not significant on impact. Again, I conclude this finding is consistent with the deposit channel's replication Table B3.[17]

[17] This result shows my specification and my measure of monetary policy shock are consistent with the effect on impact on the QJE's paper for deposit growth and loan growth.

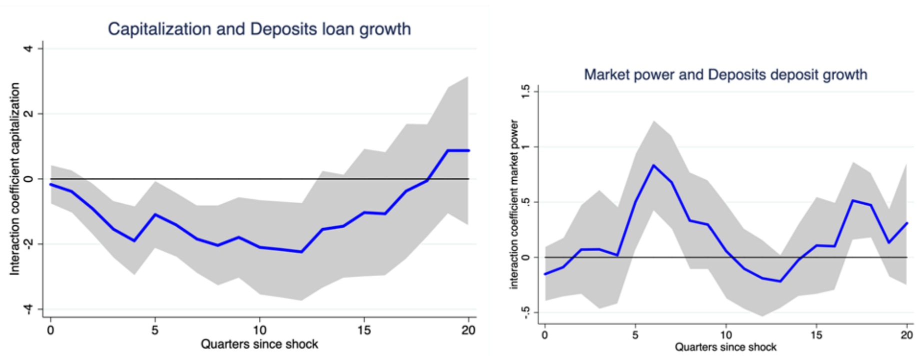
FIGURE B1. DYNAMICS OF DIFFERENTIAL RESPONSE TO MONETARY SHOCKS: MARKET POWER



Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

Now, I show whether the above result survives considering the capitalization rate jointly with market power. First, in the case of deposit growth, the top part of Figure B2 shows the coefficient of interaction associated with the capitalization rate and monetary policy shock, and the bottom part of the figure shows the coefficient of interaction associated with market power and monetary policy shock. I find the market power's effect on deposit growth disappears or is not statistically significant on impact. Also, the effect of the capitalization rate is negative on impact, and then persistently negative and statistically significant going forward. Therefore, the effect of the capitalization rate is important. Second, in the case of loan growth, the top part of Figure B3 shows the coefficient of interaction associated with the capitalization rate and monetary policy shock, and the bottom part of the figure shows the coefficient of interaction associated with market power and monetary policy shock. I find the effect on loan growth of market power disappears or is not statistically significant on impact and going forward. Also, the effect of the capitalization rate is, on average, negative and persistently negative going forward. Therefore, the effect of the capitalization rate is essential.

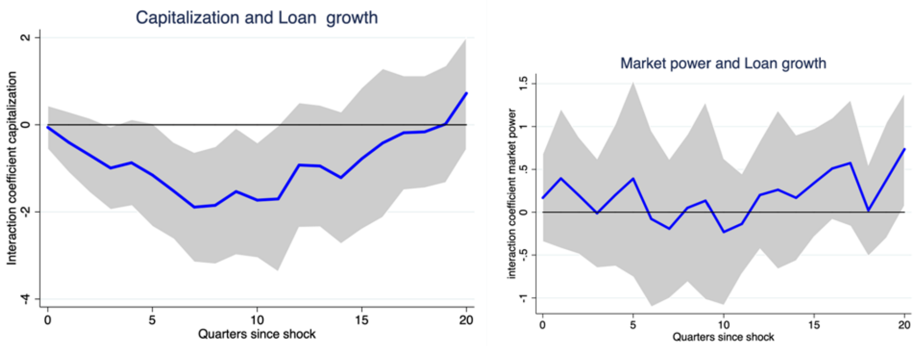
FIGURE B2. DYNAMICS OF DIFFERENTIAL RESPONSE TO MONETARY SHOCKS: MARKET POWER



Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

Finally, I reproduce the same econometric specification for the dynamic response but using Fed funds rate change as a measure of monetary policy shock, following Drechsler, Savov and Schnabl (2017). Figure B4 shows the result considering only market power for the dependent variable of deposits and loan growth. Figure B5 considers the double interaction of market power and the capitalization rate for the dependent variable of deposit growth. Similarly, I find market power's effect on deposit growth disappears or is not statistically significant on impact, and the effect of the bank capitalization rate is negative and statistically significant and persistently negative going forward. Therefore, again, the effect of the capitalization rate is important. Figure B6 considers the

FIGURE B3. DYNAMICS OF DIFFERENTIAL RESPONSE TO MONETARY SHOCKS: MARKET POWER

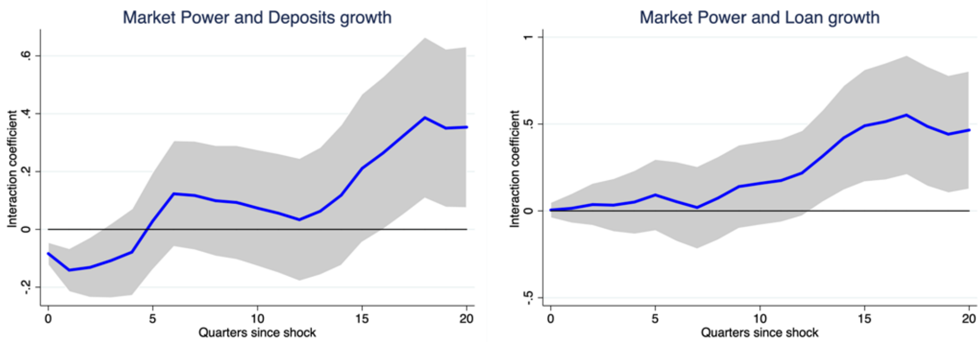


Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

double interaction of market power and the capitalization rate for the dependent variable of loan growth. I find my results hold qualitatively on impact, but the dynamic results are different using their monetary policy tightening measure.

I view these findings as reflecting that the market-power mechanism loses significance or power for explanation when I consider bank capitalization in the regressions.

FIGURE B4. DYNAMICS OF DIFFERENTIAL RESPONSE TO FED FUNDS RATE: MARKET POWER

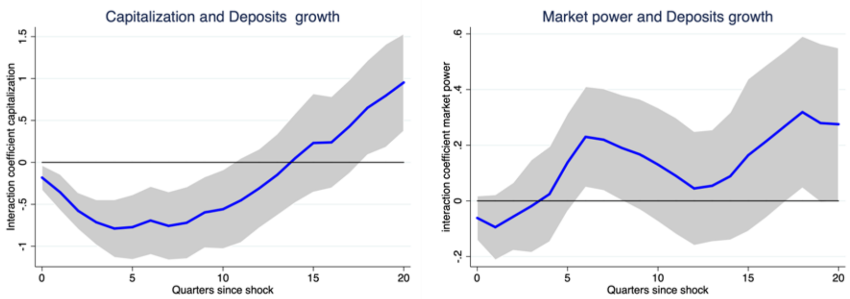


Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

B2. Relation to Van den Heuvel (2012)

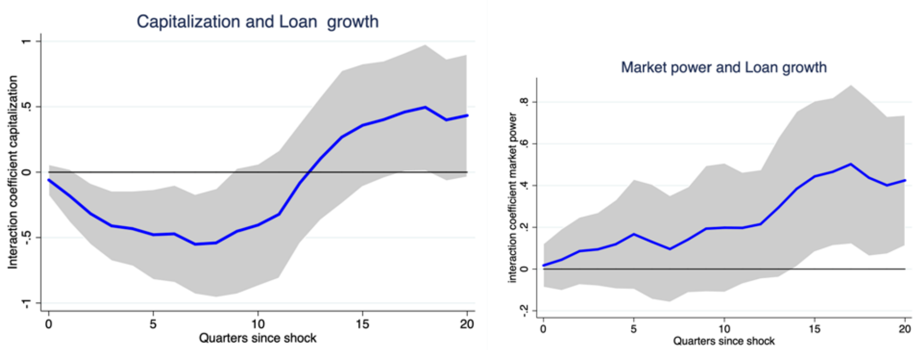
In this subsection, I explain the main differences between my paper and Van den Heuvel (2012). Van den Heuvel (2012) shows lending in states with less-capitalized banks are more sensitive to monetary policy. First, the main difference is the data limitation, specifically the type of data. His data set is at the state-level and not the individual bank-level. Second, his econometric specification is different. His analysis is at the state level; therefore, the analysis of the heterogeneity at the bank level is lost. Third, period of sample is different and the frequency of the data is annually. I do quarterly. Finally, the measure of monetary policy shocks is not the same. I rely on high frequency identification.

FIGURE B5. DYNAMICS OF DIFFERENTIAL RESPONSE TO FED FUNDS RATE: CAPITALIZATION RATE AND MARKET POWER



Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

FIGURE B6. DYNAMICS OF DIFFERENTIAL RESPONSE TO FED FUNDS RATE: CAPITALIZATION RATE AND MARKET POWER



Notes: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time.

Given the differences with Van den Heuvel (2012). I start by estimating his econometric specification with my bank-level data. It implies that I aggregate the bank level data to state level, I aggregate from quarterly level to annual level, and I use the fed funds rate change as measure of monetary policy indicator. His main econometric specification is the following:

$$\text{(B1)} \qquad \Delta y_{it} = \alpha_i + \sum_{j=0}^{1}(\beta_{usj} + \delta_{usj}c_{it-j-1})\Delta y_{ust-j} + \sum_{j=0}^{1}(\beta_{Mj} + \delta_{Mj}c_{it-j-1})\Delta M_{t-j}$$
$$+ (\beta_{y1} + \delta_{y1}c_{it-2})_{it-1} + \sum_{j=1}^{2}\delta_{cj}c_{it-j} + \epsilon_{it}$$

where Δy_{it} is lending growth of state i in year t,Δy_{ust} is the output growth for US, ΔM_t is an indicator of the change in the stance of monetary policy. Van den Heuvel (2012) normalize the sign of the change of fed funds rate so that a positive value correspond to a loosening of monetary conditions, α_i is a fixed effect for state i, and c_{it-1} is some transformation of the aggregate capital asset ratio of all commercial banks in state i at end of the year $t-1$. Table B5 shows the results for the interaction coefficient between capitalization rate and the change in the stance of monetary policy. Column (1) estimate the interaction coefficient using the change in the Fed Funds rate as in Van den Heuvel (2012). I find this coefficient is statistically significant. Otherwise, Column (2) estimate the interaction coefficient using the high-frequency identification of monetary

TABLE B5—STATE-LEVEL RESULTS REPLICATION OF CAPITAL VIEW OF VAN DEN HEUVEL (2012), 1990-2007 ANNUALLY

Variable:	(1) Δ Total loans 2[1]*(using 2[1]**Fed Funds rate)*	(2) Δ Total loans 2[1]**(using High-frequency* 2[1]**identified monetary policy Shocks)*
$c_{it-1} \times \Delta M_t$	2.406*** (0.88)	2.608 (4.71)
Observation	784	784
R^2	0.095	0.091

*** p<0.01, ** p<0.05, * p<0.1

policy as in my paper. I find this coefficient becomes not statistically significant. I view these findings as reflecting the fact that the main difference is the measure of monetary policy shock. So there is a well know endogeneity problem of using fed funds rate in the sense that the action of the fed does, is in response to changes in economic conditions.

B3. Relation to Kashyap and Stein (2000)

In this subsection, I explain the main differences between this paper and Kashyap and Stein (2000). Kashyap and Stein (2000) shows bank lending contracts when monetary policy tightens, the contraction is stronger for less liquid banks, and the sensitivity of the contraction to liquidity is stronger for small banks. This traditional result comes from a close connection between reserves and deposits, and the idea is that a bank has a reserve requirement. A contractionary monetary policy reduces the amount of reserves, which then has an impact on deposits, unless banks have sufficient liquidity or sufficient capacity to replace deposits with other types of funds. Therefore, if a bank is less liquid, it contracts its lending more. The main differences in my paper are the following: First, I used an identified monetary policy shock using high-frequency data. They instead use the Fed funds rate, Bernanke and Mihov, and Boschen-Mills indexes as different monetary measures, respectively. Second, I used bank-level quarterly data for the period 1990-2007, focusing on all commercial banks in the sample. They also use bank-level data, but the period of analysis is 1973-1996 quarterly, and they split banks into three size groups ($<$95th percentile, 95th$-$99th percentile, $>$ 99th percentile) and the measure of liquidity is the ratio of securities and Fed funds contracts sold to total assets.

Third, my econometric specification is more general and considers a more recent identification strategy of the measure of monetary policy shock. My baseline dynamic model is robust to bank controls, bank fixed effects, state-time fixed effect, and size-weighted regression, and clustered at the bank and time level. Kashyap and Stein (2000) have a different econometric specification, which consists of running a two-part regression. First, for all t in their sample and for each size group g, they individually estimate:

$$\Delta log(L_{it}) = \sum_{j=1}^{4} \alpha_{gtj} \Delta log(L_{i,t-j}) + \beta_{gt} B_{it-1} + \sum_{k=1}^{12} \Psi_{gkt} FRB_{ik} + \epsilon_{it}$$

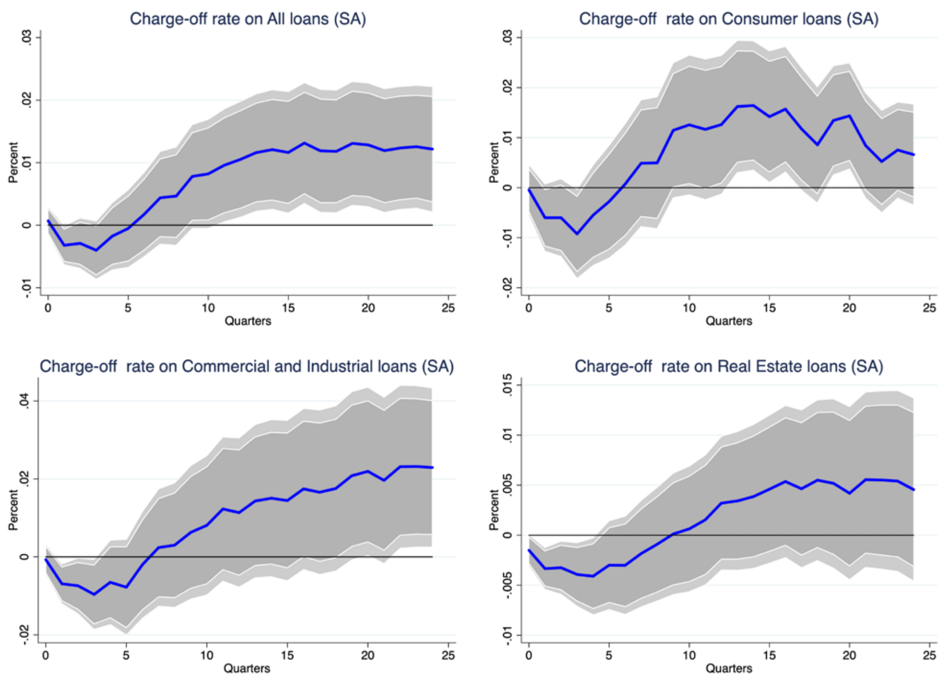
where $\beta_{g,t}$ captures the sensitivity of lending changes to liquidity for size group g in period t, L_{it} is total lending, and B_{it-1} liquidity . Then, they estimate

$$\hat{\beta}_{g,t} = \eta_g + \sum_{j=0}^{4} \phi_{j,g} \Delta M_{t-j} + \delta_g t + u_{g,t}$$

where M_t is the measure of monetary policy, and $\sum_{j=0}^{4} \phi_{j,g}$ captures the correlation between lagged monetary policy and lending sensitivity to liquidity for size group g. They also try a 'bivariate' regression, where they add a four-quarter flexible-form-distributed lag function on GDP growth. This technique is a precursor of modern empirical macro literature.

DEFAULT RATES AND MONETARY POLICY

FIGURE C1. AGGREGATE: CHARGE-OFF RESPONSES TO MONETARY POLICY SHOCK



RELATIONSHIP BETWEEN BANK CAPITALIZATION, DEFAULT RATES, AND BUSINESS CYCLES

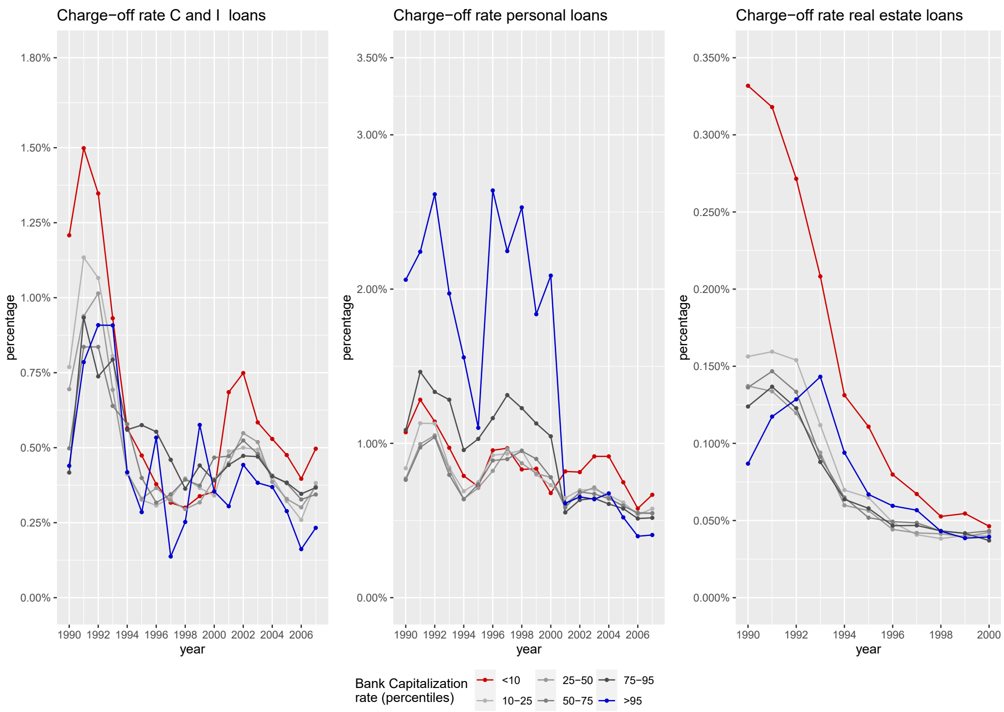
This section documents the the between relationship bank capitalization rate, default rates, and business cycles. First, I study how GDP growth affects the default rate of lower-capitalization banks minus the default rate of higher-capitalization banks. I find a negative relation between the default rate and GDP growth, but the effect across banks is not statistically different.

Second, I study the same question but now with the following especification that allows me to control for banks fixed effects and state fixed effects. The empirical model is as follows:

$$y_{i,t} = \sum_{j \in J} (\beta_j + \alpha_j \Delta \text{GDP}_t)\, 1_{\{i=J\}} + \sum_{s \in S} (\gamma_s + \delta_s \Delta \text{GDP}_t)\, 1_{\{i=S\}} + \epsilon_{i,t} \quad \text{(D1)}$$

where i identified a bank, and t a quarter. The dependent variable $y_{i,t}$ is the year-on-year change in the charge-off rate. The set J defines a capitalization-

FIGURE C2. CROSS-SECTIONAL: CHARGE-OFF RATES FOR LOAN TYPES ACROSS BANK CAPITALIZATION RATES



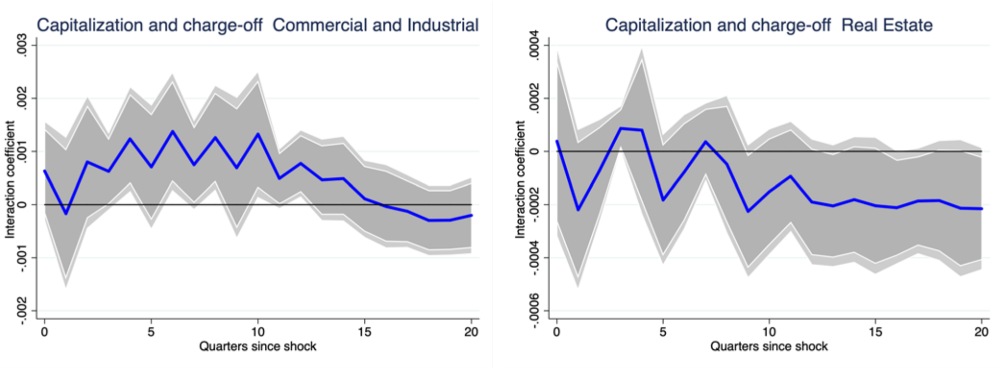
Note: The figure shows the average of charge-off rate for C&I, personal, and real estate loans across capitalization rates over the time of the commercial banking sector. The blue line is the highest capitalized banks and the red lines are the worst capitalized banks.

rate group, I define five groups and each group has a 20% of assets. Moreover, $\Delta \text{GDP}_t = log(\frac{GDP_t}{GDP_{t-4}})$ is the year-on-year growth rate of GDP, and S is a set of U.S. states. Table D1 shows GDPgrowth does not affect the default rates across capitalization rates and across types of loans. There is only statistically significant for lower-capitalization banks at the bottom of the distribution.

TABLE D1— REGRESSION OF CHARGE-OFF RATES ON GDP GROWTH FOR BANKS

	(1)	(2)	(3)
[10-25]x GDP growth	0.035***	0.004	0.012
	(0.01)	(0.00)	(0.01)
[25-50]x GDP growth	0.034**	0.003	0.015*
	(0.01)	(0.00)	(0.01)
[50-75]x GDP growth	0.036**	0.007**	0.009
	(0.01)	(0.00)	(0.01)
[75-90]x GDP growth	0.061***	0.002	0.011
	(0.02)	(0.00)	(0.01)
[90-95]x GDP growth	0.033	0.005	0.043**
	(0.02)	(0.00)	(0.02)
[¿95,100]x GDP growth	0.010	0.003	0.039
	(0.04)	(0.00)	(0.03)
GDPgrowth	-0.114***	-0.006	-0.042**
	(0.03)	(0.00)	(0.02)
Observations	216108	392147	216879
R^2	0.041	0.043	0.056
State controls	yes	yes	yes
Bank fixed effects	yes	yes	yes
Quarter fixed effects	yes	yes	yes
Bank Time clustering	yes	yes	yes

FIGURE C3. CROSS-SECTIONAL: CHARGE-OFF RESPONSES TO A MONETARY SHOCK ACROSS CAPITALIZATION RATES



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (2) for charge-off rates as a dependent variable. The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

FIGURE D1. DIFFERENCE BETWEEN LOW AND HIGH CAPITALIZATION OF CHARGE-OFF RATES AND YEAR-ON-YEAR GDP GROWTH

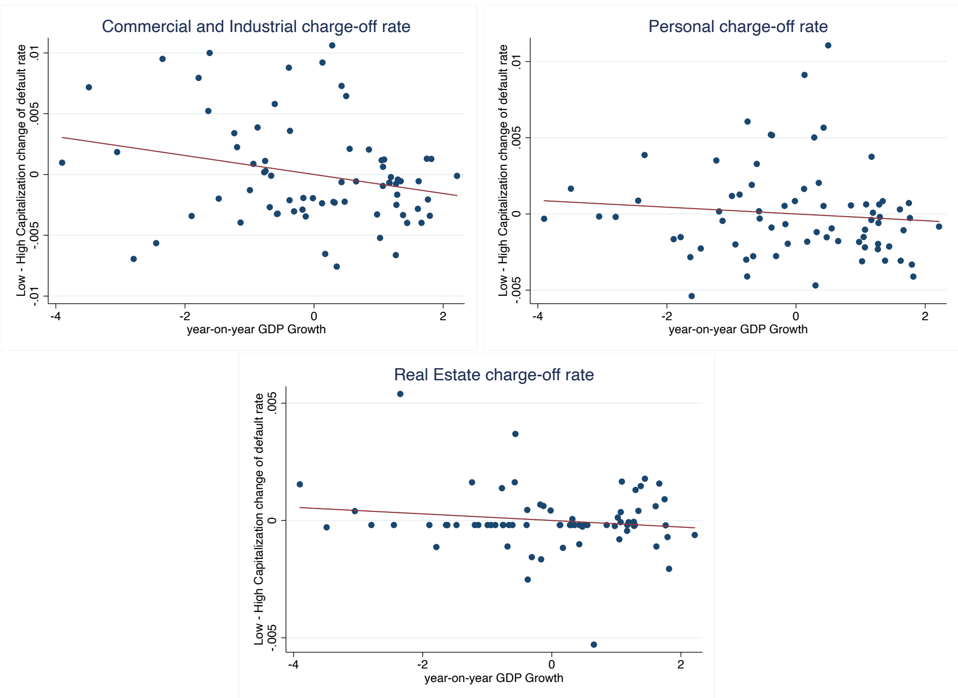
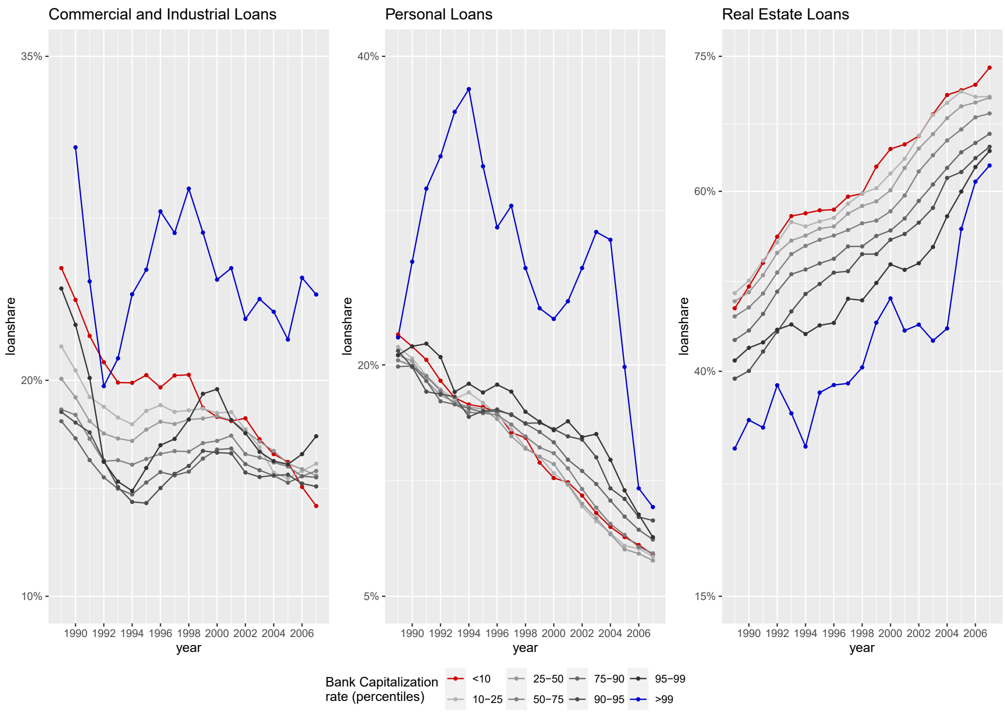


FIGURE E1. AVERAGE PORTFOLIO SHARE FOR REAL ESTATE LOAN ACROSS BANK CAPITALIZATION PERCENTILES



E1. Baseline Model

E2. Firm problem

$$V(n;q^a) = \max_{k'} div + \mathbb{E}_t[\mathcal{M}^B_{t,t+1}\tilde{V}(k';q^{a'})]$$

$$\text{div}(k,k',l;q^a,\omega) = \underbrace{\omega k^{1-\alpha}l^{\alpha}}_{\text{Revenues}} - \underbrace{(k' - (1-\delta_k)k)}_{\text{investment}} - [(1-\phi)wl + a(\frac{1}{q^a})]$$

$$a = \phi wl$$

$$\omega^* = \frac{(1+\phi(\frac{1}{q^a_t}-1))w_t l_t}{k^{1-\alpha}l^{\alpha}}$$

$$\tilde{V}(k;q^a) = \max_{l_t}[\Omega_A(\omega^*_t)\mathbb{E}_t(V(n;q^a)|\omega_t > \omega^*_t)]$$

Solution:

$$\tilde{V}(k;q^a) = \max_{l}[\Omega_A(\omega^*_t)\mathbb{E}_t(V(n;q^a)|\omega_t > \omega^*_t)] = \max_{l_t}[\Omega_A(\omega^*_t)v(q^a)\mathbb{E}_t(n|\omega > \omega^*)]$$

$\Omega_A(\omega^*) = 1 - F(\omega^*)$ where F is the probability of default.
$n = \omega k^{1-\alpha}l^{\alpha} - (1-\phi)wl - (\frac{1}{q^a})a + (1-\delta_k)k$
Note:

$$\mathbb{E}_t(n|\omega > \omega^*) = \mathbb{E}_t\left(\left[\omega k^{1-\alpha}l^{\alpha} - (1-\phi)wl - (\frac{1}{q^a})a + (1-\delta_k)k\right]|\omega_t > \omega^*_t\right)$$

$$\mathbb{E}_t(n_t|\omega_t > \omega_t^*) = y\left(\omega^+ - \omega^*\right) + (1-\delta_k)k$$

Thus, $V(n)$ is a homogeneous of degree 1 in n.
The first order condition with respect to l_t:

$$\frac{\partial[\Omega_A(\omega_t^*)v(q^a)\mathbb{E}_t(n|\omega > \omega^*)]}{\partial l} = 0$$
$$\frac{\partial[\Omega_A(\omega_t^*)]}{\partial l}\mathbb{E}_t(n|\omega > \omega^*) + \Omega_A(\omega_t^*)\frac{\partial[\mathbb{E}_t(n|\omega > \omega^*)]}{\partial l} = 0$$
$$(-f_{\omega^*})\frac{\partial \omega_t^*}{\partial l_t}\mathbb{E}_t(n_t^P|\omega_t > \omega_t^*)] + \Omega_A(\omega_t^*)\frac{\partial[\mathbb{E}_t(n|\omega > \omega^*)]}{\partial l} = 0$$

Using $\frac{\partial[\mathbb{E}_t(n|\omega>\omega^*)]}{\partial l}$ and $\frac{\partial \omega_t^*}{\partial l_t}$, I have:

$$\text{MPL} = w_t\left(\frac{\left[\Omega_A(\omega_t^*) + \frac{f_\omega^*[y(\omega^+-\omega^*)+(1-\delta_k)k]}{y}\right]}{\left[\Omega_A(\omega_t^*)(\omega_t^+) + f_\omega^*\frac{\omega^*[y(\omega^+-\omega^*)+(1-\delta_k)k]}{y}\right]}\left(1+\phi(\frac{1}{q_t^a}-1)\right)\right)$$

The first order condition with respect to k':

$$1 - E_t[\mathcal{M}^B v(q^{a'})\left((-f_{\omega^{*'}})\frac{\partial \omega^{*'}}{\partial k'}[y'\left(\omega_{t+1}^+ - \omega_{t+1}^*\right) + (1-\delta_k)p_{t+1}^K k']\right.$$
$$+\Omega_A(\omega^{*'})\frac{\partial[\mathbb{E}_t(n'|\omega' > \omega^{*'})]}{\partial k'} = 0$$

Using $\frac{\partial[\mathbb{E}_t(n|\omega>\omega^*)]}{\partial k'}$, $\frac{\partial \omega^{*'}}{\partial k'}$, and define $\mathcal{M}^P = \mathcal{M}^B v(q^{a'})$

$$1 = E_t[\mathcal{M}^P\left(\Omega_A(\omega^{+'})\left(\omega^{*'}\text{MPK}' + (1-\delta_K)\right) + f_{\omega^{*'}}\left(\frac{\text{MPK}'\omega^{*'}}{y'}\right)[y'\left(\omega_{t+1}^+ - \omega_{t+1}^*\right)\right.$$
$$+ (1-\delta_k)p_{t+1}^K k']$$

In the standard RBC without adjustment cost, the optimal investment:

$$1 = \beta E(\text{MPK}' + (1-\delta_K))$$

Firm's problem stage I:
CES:

$$A_t^{P_A} = \left((\nu_A^F)^{\frac{1-\sigma_A^F}{\sigma_A^F}} A_{1t}^{\frac{\sigma_A^F-1}{\sigma_A^F}} + (1-\nu_A^F)^{\frac{1-\sigma_A^F}{\sigma_A^F}} A_{2t}^{\frac{\sigma_A^F-1}{\sigma_A^F}}\right)^{\frac{\sigma_A^F}{\sigma_A^F-1}}$$

Loan's firm(sector) A demand for each bank:

$$A_{1t} = \left(\frac{\frac{1}{Q_t^a}}{\frac{1}{q_{1t}^a}}\right)^{\sigma_A^F}(\nu_A^F)^{1-\sigma_A^F}A_t^{P_A}$$
$$A_{2t} = \left(\frac{\frac{1}{Q_t^a}}{\frac{1}{q_{2t}^a}}\right)^{\sigma_A^F}(1-\nu_A^F)^{1-\sigma_A^F}A_t^{P_A}$$

where

$$Q_t^a = 1/\left(\left(\frac{\nu_A^F}{q_{1t}^a}\right)^{1-\sigma_A^F} + \left(\frac{1-\nu_A^F}{q_{2t}^a}\right)^{1-\sigma_A^F}\right)^{\frac{1}{1-\sigma_A^F}}$$

$$A_t^{P_A} = \phi^A w_t^A L_t^A$$

$$V_j(n_j) = \max_{k'} div_j + \mathbb{E}_t[\mathcal{M}_{t,t+1}\tilde{V}_j(k_j')]$$

$$\overbrace{n_j - p^{k_j}k_j' + \underbrace{\text{wc}_j}_{\text{new debt}}}^{\text{div}_{ft}^j} \geq 0$$

$$n_j = \underbrace{\omega_j k_j^{1-\alpha} l^\alpha - (1-\phi)w_j l - \frac{1}{Q_j}\text{wc}_j}_{\text{profit flow}} + p^{k_j}(1-\delta^{k_j})k_j$$

$$\omega_j^* = \frac{(1+\phi^j(\frac{1}{Q_j}-1))w_j\bar{l}_j}{y_j} \quad , \quad \tilde{V}_j(k_j) = \max_{l_j}[\Omega(\omega_j^*)\mathbb{E}_t(V_j(n_j)|\omega_j > \omega_j^*)]$$

E3. Bank problem

The bank problem is the following:

$$V^i(N_t^i, \mathcal{S}_t) = \max_{q_{Ai,t}, D_t^i, e_t^i} div_t^i - e_t^i + E_t[\mathcal{M}_{t+1,t}^B V^i(N_{t+1}^i)]$$

s.t

$$N_t^i + D_t^i + e_t \geq L_{At}^i + div_t^i + \Psi^i(e_t^i)$$

$$D_t^i \leq \xi_A L_{At}^i$$

$$N_{t+1}^i = (\frac{\tilde{M}_{t+1}^A}{q_{Ai,t}})L_{A,t}^i - (R_t)D_t^i$$

where:

$$div_t^i = \phi_0 N_t^i \quad \Psi^i(e_t^i) = \frac{\phi_1^i}{2}(e_t^i)^2$$

$$L_{At}^i = \left(\frac{\frac{1}{Q_A}}{\frac{1}{q_{Ai}}}\right)^\sigma (\nu)^{1-\sigma}\bar{A}$$

$$\tilde{M}_t = \underbrace{\Omega(\omega_t^*)}_{\text{No default}} + \underbrace{\frac{(1-\Omega(\omega_t^*))}{L_t^i/q_{Ai,t}}\left[\varpi^i(1-\zeta^i)\left(\mathbb{E}_{\omega,t}[\omega < \omega^*]Y_t + ((1-\delta^k)p_t^K)K_t\right) - \varpi^i w_t \bar{L}\right]}_{\text{default (recovery value)}}$$

Assumptions:

- Everything that has a t subscript is known at time t, and everything that has a $t+1$ subscript is not known at time t.

- In the law of motion of net worth, at time t, the bank decides how much to charge $q_{Ai,t}$, but the return on the loan is uncertain, because it depends of the firm default or not. For this reason, $\tilde{M}^A_{t+1}$ has a $t+1$ subscript. On the other hand, the payment on D_t is known at time t, so we have R_t not R_{t+1}.

- In the equation for N^i_{t+1}, N^i_{t+1} would be banks $t+1$ net worth N^i_{t+1}, that would be used for next-period lending. Now the action today affects tomorrow state N^i_{t+1}.

Note $L^i_{At} = \left(\frac{\frac{1}{Q_A}}{\frac{1}{q_{A1}}}\right)^{\sigma} (\nu)^{1-\sigma} \bar{A}$ and $\varpi^i = \frac{\frac{1}{q_{Ai}} L^i_{At}}{\frac{1}{Q_A} \bar{A}_t}$

STEP 1:

$$V^i(N^i_t) = \phi_0 N^i_t - e^i_t + E_t[\mathcal{M}^B_{t+1,t} V^i(N^i_{t+1}, \mathcal{S}_t)] + \lambda_t[(1-\phi)N_t + e_t - \Psi(e_t) - L^i_{Ai} - D_t] + \mu_t[\xi_A L^i_{At} - D^i_t],$$

where: $N^i_t = (\frac{\tilde{M}^A_t}{q_{Ai,t}})L^i_{At} - (R_t)D^i_t$, $L^i_{At} = (\frac{q_{Ai}}{Q_A})^2 \bar{A}_t$, $\Psi^i(e^i_t) = \frac{\phi^i_1}{2}(e^i_t)^2$, $\varpi^i = \frac{\frac{1}{q_{Ai}} L^i_{At}}{\frac{1}{Q_A} \bar{A}_t}$

$$\tilde{M}_t = \underbrace{\Omega(\omega^*_t)}_{\text{No default}} + \underbrace{\frac{(1-\Omega(\omega^*_t))}{L^i_t / q_{Ai,t}} \left[\varpi^i(1-\zeta^i)\left(\mathbb{E}_{\omega,t}[\omega < \omega^*]Y_t + ((1-\delta^k)p^K_t)K_t\right) - \varpi^i w_t \bar{L}\right]}_{\text{default (recovery value)}}$$

The first order condition with respect to q_{Ai}:

$$\frac{1}{q_{Ai}} = \underbrace{\left(\frac{\frac{\partial L_{Ai}}{\partial q_{Ai}} \frac{q_{Ai}}{L_{Ai}}}{\frac{\partial L_{Ai}}{\partial q_{Ai}} \frac{q_{Ai}}{L_{Ai}} - 1}\right)}_{\left(\frac{\sigma}{\sigma-1}\right)} \left(\frac{1-\tilde{\mu}\xi_A}{\frac{\mathcal{M}^I_t}{\mathcal{M}^B_t}}\right) \frac{1}{\left(\Omega(\omega^*_t) + (1-\Omega(\omega^*_t))\frac{(X_t - Z_t)}{\frac{1}{Q_A}\bar{A}}\right)}$$

where: $X_t = (1-\zeta^i)\left(\mathbb{E}_{\omega,t}[\omega < \omega^*]Y_t + ((1-\delta^k)p^K_t)K_t\right)$ and $Z_t = w_t \bar{L}$

The first order condition with respect to e_t:

$$-1 + \lambda_t(1 - \Psi_e(e)) = 0 \Rightarrow \lambda_t = \frac{1}{1 - \Psi_e(e)}$$

FOC of N_t:

$$\frac{\partial V}{\partial N} = \phi_0 + (1-\phi_0)\lambda_t \Rightarrow \frac{\partial V_{t+1}}{\partial N_{t+1}} = \phi_0 + (1-\phi_0)\lambda_{t+1}$$

Define: $\mathcal{M}^I_{t+1,t} \equiv \mathcal{M}^B_{t+1,t} \frac{\partial V_{t+1}}{\partial N_{t+1}} \frac{1}{\lambda_t}$ and define $\tilde{\mu} = \frac{\mu}{\lambda}$ to simplify the notation.

The first order condition with respect to D_{it}:

$$1 = \tilde{\mu}_t + E_t[\mathcal{M}^I_{t+1,t}]R_t$$

$$\max_{C_t, X_t^A, X_t^M} \mathbb{E}_t \left[\sum_{t=0}^{\infty} \beta^t \left[log(C_t) \right] \right]$$

s.t.

$$C_t + \sum_{i=1}^{2} (X_t^j + \Psi(X_t^j, K_t^j)) \leq w^j \bar{L} + \sum_{j=1}^{2} \text{div}_t^j + \sum_{i=1}^{2} \text{Netdiv}_t^i + \sum_{j=1}^{2} p_t^{K^j} X_t^j$$

$$K_{t+1}^j = (1 - \delta_K) K_t^j + X_t^j$$

RESOURCE CONSTRAINT DERIVATION

Resource-constraint derivation:
Consumer budget constraint:

$$\begin{aligned} C^B &= w^B \bar{L}^B + Div_t^P + NetDiv_t^1 + NetDiv_t^2 + pX_t - X_t - \Psi(X, K) \\ A_{1,t}^I - D_{1t}^I &= N^{I_1} - \phi_0^I N^{I_1} + e^{I_1} - \Psi^{I_1}(.) \quad \text{Bank 1's Budget constraint} \\ A_{2,t}^I - D_{2t}^I &= N^{I_2} - \phi_0^I N^{I_2} + e^{I_2} - \Psi^{I_2}(.) \quad \text{Bank 2's Budget constraint} \end{aligned}$$

This implies:

$$\begin{aligned} C^B + (A_{1,t}^I + A_{2,t}^I) - (D_{1t}^I + D_{2t}^I) = {} & w^B \bar{L}^B + Div_t^P + NetDiv_t^1 + NetDiv_t^2 + pX_t - X_t \\ & - \Psi(X, K) + N^{I_1} - \phi_0^I N^{I_1} + e^{I_1} - \Psi^{I_1}(.) + \\ & + N^{I_2} - \phi_0^I N^{I_2} + e^{I_2} - \Psi^{I_2}(.) \end{aligned}$$

Using: $A^P = \phi w L$, $A_{i,t}^I = \left(\frac{\frac{1}{Q_A}}{\frac{1}{q_{Ai}}} \right)^{\sigma} (\nu)^{1-\sigma} A^P$, $NetDiv_{it}^I = N_i^I \phi_0^I - e_i^I$ for $i = \{1, 2\}$

$$\begin{aligned} Div_t^P &= N^P - (p_t K_{t+1}) + A_t^P - F(\omega^*) n^0 \\ K_{t+1} &= (1 - \delta_K) K_t + X_t \end{aligned}$$

$$\begin{aligned} C^B + X_t + \Psi(X, K) + \Psi^{I_2}(.) + \Psi^{I_1}(.) = {} & w^B \bar{L}^B + N^P - (1 - \delta_K) p_t K_t \\ & + (A_t^P - (A_{1,t}^I + A_{2,t}^I)) - (1 - \Omega(\omega^*)) n^0 + N^{I_1} + N^{I_2} + (D_{1t}^I + D_{2t}^I) \end{aligned}$$

Using:

$$\begin{aligned} N^P = {} & \left[\Omega(\omega^*) E(\omega | \omega > \omega^*) Y - \Omega(\omega^*) w^B \bar{L}^B - \Omega(\omega^*) (\frac{1}{Q_A}) A^P \right] \\ & + (\Omega(\omega^*))(1 + \delta_K) p_t K_t + (1 - \Omega(\omega^*)) n^0 \\ N_t^{I_i} = {} & (\frac{\tilde{M}_t^{Ai}}{q_{Ai,t}}) L_{At}^1 - (R_t) D_t^1 \text{for} i \in \{1, 2\} \end{aligned}$$

n^0 is an initial net worth.

$$\tilde{M}_t^{A1} = \underbrace{\Omega(\omega_t^*)}_{\text{No default}} + \underbrace{\frac{(1-\Omega(\omega_t^*))}{L_t^1/q_{A1,t}}\left[\varpi^1(1-\zeta^1)\left(\mathbb{E}_{\omega,t}[\omega<\omega^*]Y_t+((1-\delta^k)p_t^K)K_t\right)-\varpi^1 w_t\bar{L}\right]}_{\text{default (recovery value)}}$$

$$\tilde{M}_t^{A2} = \underbrace{\Omega(\omega_t^*)}_{\text{No default}} + \underbrace{\frac{(1-\Omega(\omega_t^*))}{L_t^2/q_{A2,t}}\left[\varpi^2(1-\zeta^2)\left(\mathbb{E}_{\omega,t}[\omega<\omega^*]Y_t+((1-\delta^k)p_t^K)K_t\right)-\varpi^2 w_t\bar{L}\right]}_{\text{default (recovery value)}}$$

Define:

$$\Sigma(\zeta^i) = \left[(1-\zeta^i)\left(\mathbb{E}_{\omega,t}[\omega<\omega^*]Y_t+((1-\delta^k)p_t^K)K_t\right)-w_t\bar{L}\right] \quad \text{for } i \in \{1,2\}$$

$$N_t^{I_1} = \Omega(\omega_t^*)\frac{L_{At}^1}{q_{A1,t}} + (1-\Omega(\omega_t^*))\varpi^1\Sigma(\zeta^1) - (R_t)D_t^1 \quad \text{for} i \in \{1,2\}$$

$D \equiv D_{1t}^I + D_{2t}^I$ The resource constraint becomes:

$$C^B + X_t + \Psi(X,K) + \Psi^{I_2}(.) + \Psi^{I_1}(.) + DWL + D(R-1) = Y$$
$$+ A_t^P(1-\frac{\Omega(\omega^*)}{Q_A}) - A_{1,t}^I(1-\frac{\Omega(\omega_t^*)}{q_{A1,t}}) - A_{2,t}^I(1-\frac{\Omega(\omega_t^*)}{q_{A2,t}})$$

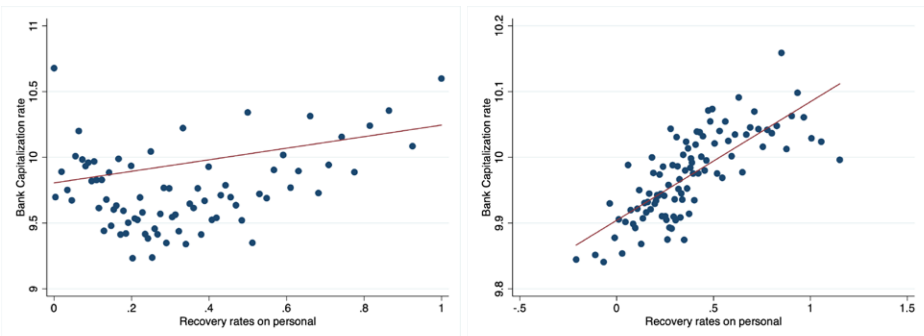
where:

$$\text{DWL} = (1-\Omega(\omega_t^*))\left[\mathbb{E}_{\omega,t}[\omega<\omega^*]Y_t+((1-\delta^k)p_t^K)K_t\right](\varpi^1\zeta^1+\varpi^2\zeta^2))$$

Recovery Rates and Capitalization Rates in the Data

This subsection describes the bank-level variables used to calculate the relation between recovery rates for each type of loan and bank capitalization rates, based on Call Reports. First, I construct a proxy for banks' recovery rates using the variable recoveries on allowance for loan and lease losses. First, in the case of recoveries on commercial loans, recoveries on loans to individual for households, and recoveries on real estate loans, I use *riad4608,riad4609*, and *riad4257*, respectively. Second, charge-offs on allowance for loan and lease losses for commercial loans, individual for households, real estate loans are

Figure H1. Recovery rates on personal loans and capitalization rate



riad4638,*riad4639*, and *riad4256*, respectively. I divide t. Then, I winsorize the observation for the proxy of banks' recovery rates to have a recovery rate on the interval [0,1]. Figure 16 presents bin-scatter plots of the bank capitalization rate against my proxy of banks' recovery rates for each loan type.

FIGURE H2. RECOVERY RATES ON REAL ESTATE LOANS AND CAPITALIZATION RATE

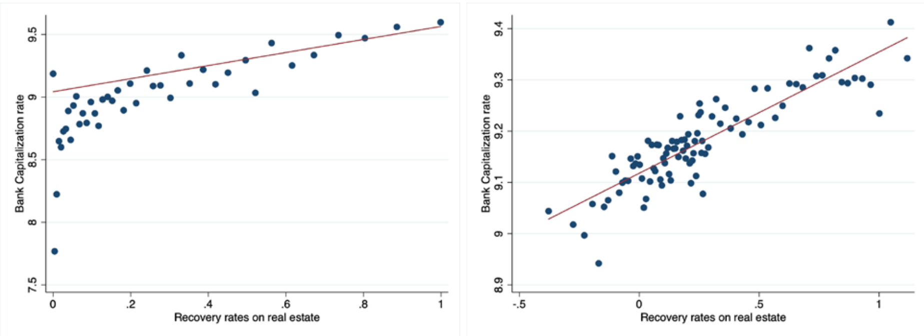
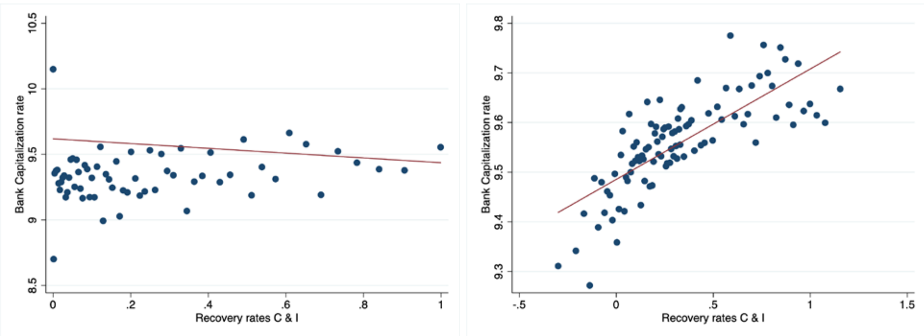


FIGURE H3. RECOVERY RATES ON COMMERCIAL AND INDUSTRIAL LOANS AND CAPITALIZATION RATE



ALTERNATIVE MEASURE OF RECOVERY RATES

First, in the case of non-accrual on total loans and lease, I use *rcfd1403*. Second, for total loans and lease past 90 or more and still accruing, I use *rcfd1407*. I sum them and define them as non-performing loans. Then, I construct a proxy for the recovery rate by summing the recovery of each loan type. Finally, I divide them. Then, I winsorize the observation for the proxy for banks' recovery rates to have the recovery rate on the interval [0,1]. Figure 16 presents bin-scatter plots of the bank capitalization rate against my proxy for banks' recovery rates for each loan type.

This subsection describes the bank-level variables used to calculate the relation between recovery rates and bank capitalization rates, based on Call Reports. First, in the case of non-accrual on C&I loans, non-accrual loans to individual for households, non-accrual loans secured by real estate, I use*rcfd1608*, *rcfd1981*,and *rcfd1423*, respectively. Second, for loans past 90 or more and still accruing on C&I loans, non-accrual loans to individuals for households, and non-accrual loans secured by real estate, I use *rcfd1607*, *rcfd1979*, and *rcfd1422*, respectively. I sum them and define them as non-performing loans. Then, I use the recovery rate for each loan type for a given bank and I divide them. Then, I winsorize the observation for the proxy for banks' recovery rates to have the recovery rate on the interval [0,1]. Figure 16 presents bin scatter plots of the bank capitalization rate against my proxy for banks' recovery rates for each loan type.[18]. Then I winsorize the observation of bank's recovery rates to have recovery rate on the interval [0,1]. Figure 16 presents bin-scatter plots of the bank capitalization rate against my proxy of banks' recovery rates for each loans type.

Additional Empirical Results

FIGURE I1. RECOVERY RATES ON COMMERCIAL AND INDUSTRIAL LOANS AND CAPITALIZATION RATE

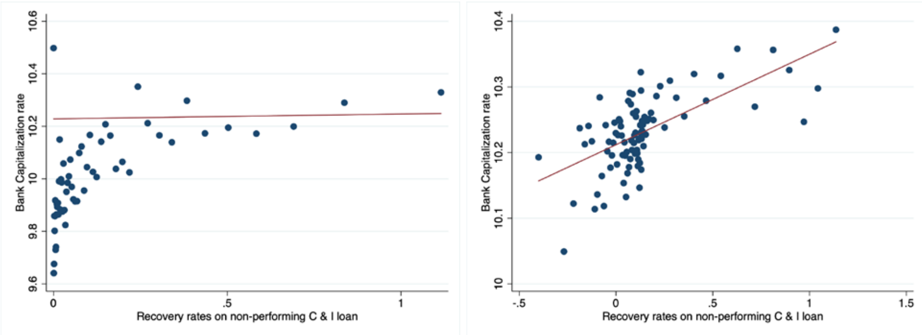


FIGURE I2. RECOVERY RATES ON REAL ESTATE LOANS AND CAPITALIZATION RATE

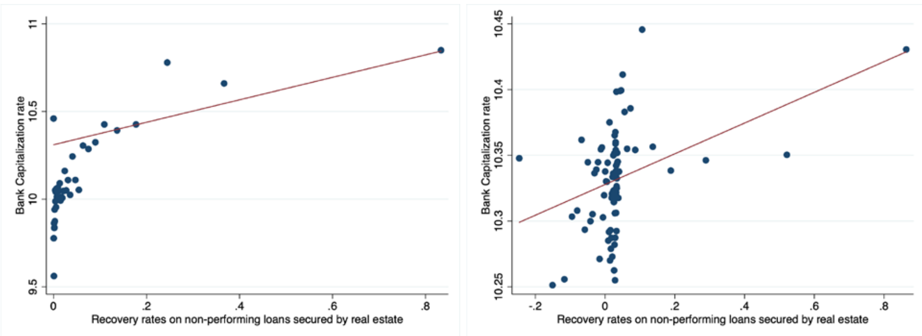
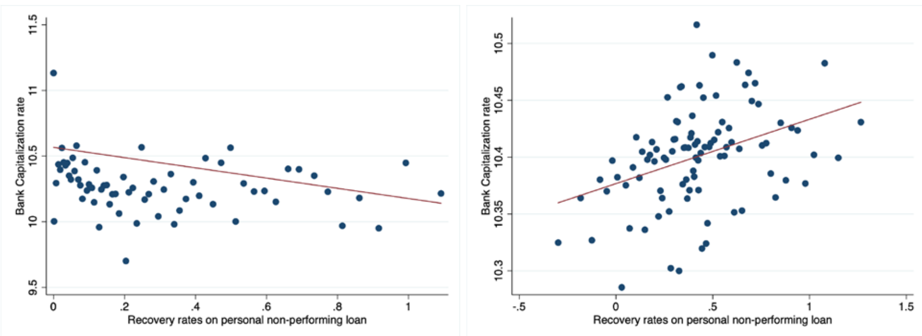


FIGURE I3. RECOVERY RATES ON PERSONAL LOANS AND CAPITALIZATION RATE



DYNAMIC PANEL MODEL

I also perform robustness checks regarding bank-level heterogeneity, including controlling for lagged dependent variable as explanatory variable. When we introduce the lagged value of dependent variable, the model is estimated using the system-GMM methods, due to the correlation between the past realization of the dependent variable and error term. When we only use difference

[18] For further references, see The Fed- Micro Data Reference Manual.

of residuals in the moment conditions, the estimator is similar to the one proposed and used by Arellano and Bover (1995), and Bludndell and Bond (1998). The system-GMM estimator improves the efficiency by incorporating in the moment conditions the lagged levels and differences of the dependent variable as instruments for the equations in levels, as well as it considers the optimal weighting matrix of the instruments. The empirical specification is the following:

$$\Delta log\text{loan}_{i,t} = \rho \Delta log\text{loan}_{i,t-1} + \alpha_i + \alpha_{st} + \delta_1 \text{MPShock}_t + \delta_2 X_{i,t-1} + \beta(\text{MPShock}_t * X_{i,t-1}) + \Gamma_1' \text{macro}_{t-1} + \Gamma_2' Y_{i,t-1} + \epsilon_{i,t} \,, \quad \text{(J1)}$$

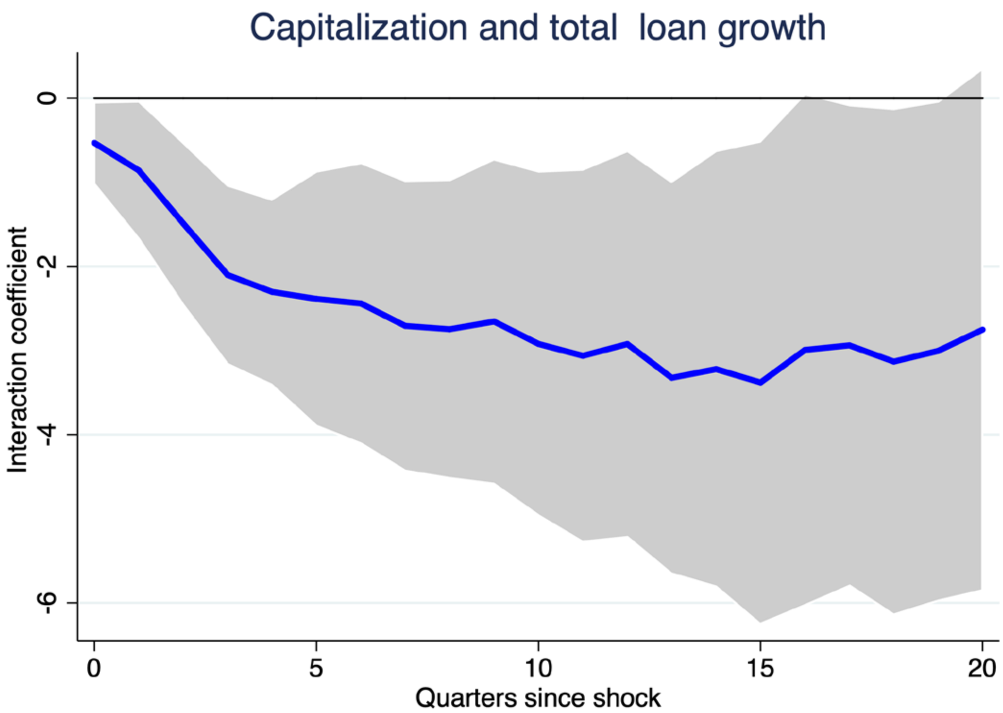
Table J1 reports the results from estimating the dynamic panel model **??**. I focus in the main coefficient of interest in the paper, and I still find a negative coefficient $\beta < 0$, which implies higher-capitalized banks reduce their lending more than lower-capitalized banks after a positive monetary policy surprise.

TABLE J1—HETEROGENEOUS EFFECTS OF MONETARY POLICY ON BANK LENDING

	(1)	(2)	(3)	(4)
Capitalization× MPshock	-0.034	-0.563***	-0.563***	-0.563***
	(0.08)	(0.09)	(0.09)	(0.09)
Observations	627637	627632	627632	627632
R^2				
Bank controls	no	yes	yes	yes
MP shock	no	no	yes	yes
Macro controls	No	no	no	yes

Note: The sample is quarterly from 1990 to 2007. The dynamic panel model is estimated using the System-GMM estimator due to the correlation between the past realization of the dependent variable and error term. I consider lags of the dependent variable as instruments, also the lags of the capitalization rate, and lags of the interaction term between monetary policy shock and capitalization rates.

FIGURE J1. DYNAMICS OF DIFFERENTIAL RESPONSE TO MONETARY SHOCKS: CAPITALIZATION



Note: Dynamics of the interaction coefficient between the capitalization rate and monetary shocks over time. The figure reports the coefficient β^h from equation (2). The grey shading represents the means 90% confidence interval. Confidence interval is constructed based on two-way clustered standard errors at bank and time levels.

I also perform robustness checks relating to **dynamic** response across banks, but now controlling for lagged dependent variable as explanatory variables, similar to the standard VAR. The local projection specification is the following:

$$\text{(J2)} \quad \Delta log\text{loan}_{i,t+h} = \alpha_i^h + \alpha_{st}^h + \delta_1^h \text{MPShock}_t + \beta^h (X_{i,t-1} \cdot \text{MPShock}_t) + \delta_2^h X_{i,t-1} + \Gamma'^h Y_{i,t-1} + log\text{loan}_{i,t-1} + \Gamma_2^h \text{macro}_{t-1} + \epsilon_{i,t+h} ,$$

Figure J1 shows that dynamic response from the equation 2. I find similar results from the baseline model specification.

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