Firm Financial Constraints and the Impact of Monetary Policy: Evidence from Financial Conglomerates

Adam B. Ashcraft  
Banking Studies  
Federal Reserve Bank of New York  
Adam.Ashcraft@ny.frb.org  
(212) 720-1617

Murillo Campello  
Department of Finance  
Michigan State University  
campello@bus.msu.edu  
(517) 353-2292

February 12, 2002

Abstract

Building on recent evidence on the functioning of internal capital markets in financial conglomerates, this paper conducts a novel test of the balance sheet channel of monetary policy. It does so by comparing monetary policy responses of small banks that are affiliated with the same bank holding company, and thus arguably face similar constraints in accessing internal/external sources of funds, but that operate in different geographical regions, and thus face different pools of borrowers. Because these subsidiaries typically concentrate their lending with small local businesses, we can use cross-sectional differences in state-level economic indicators at the time of changes of monetary policy to study whether or not the strength of borrowers’ balance sheets influences the response of bank lending. We find evidence that the negative response of bank loan growth to a monetary contraction is significantly stronger when borrowers have weak balance sheets. Our evidence suggests that the monetary authority should consider the amplification effects that financial constraints play following changes in basic interest rates and the role of financial conglomerates in the transmission of monetary policy.

JEL Codes: E50, E51, G22. Keywords: monetary policy, balance sheet channel, financial conglomerates, internal capital markets.

*Preliminary and incomplete. Sincere thanks to Ken Kuttner, Charles Himmelberg, Mark Gertler. Any remaining errors are our own, and the opinions expressed here do not necessarily reflect the views of the Federal Reserve Bank of New York or the Federal Reserve System.
1 Introduction

How does monetary policy affect the real economy? The textbook story, often referred to as the interest rate or money channel, is that the Federal Reserve uses open-market operations to enforce a target for the federal funds rate by managing the aggregate supply of commercial bank reserves. The absence of arbitrage requires that changes in policy interest rates induce similar changes in other short-term interest rates. In the presence of sticky prices, these real changes in the cost of capital drive changes in the interest-sensitive components of demand. The response of real output to monetary policy should depend on how far interest rates move and how elastic spending is to interest rates. In practice, however, it has been very difficult reconcile the observed large and prolonged output responses to small and temporary changes in interest rates, particularly in light of the weak evidence of cost of capital effects on private spending.\(^1\)

The excessive sensitivity of output to monetary policy has prompted economists to look for a financial mechanism — often referred to as the credit channel — through which policy-induced changes in short-term interest rates are greatly amplified. These theories generally emphasize the importance of information frictions in creating financial constraints through increases in the marginal cost of external finance.\(^2\) There are two main views on the credit channel. The *lending channel* presumes that monetary policy directly affects bank loan supply. Draining deposits from banks will reduce lending if banks face financial constraints when attempting to smooth these outflows by issuing uninsured liabilities. When long-standing relationships provide banks with information advantage about the quality of their borrowers, firms find the credit offered by other banks to be an imperfect substitute. A policy-induced monetary contraction therefore has much larger effects on the investment of bank-dependent firms than what is implied by the actual change in interest rates. The *balance sheet channel*, on the other hand, hypothesizes that monetary policy affects loan demand through its effect on firms’ net worth. Higher interest rates increase debt service and erode firm cash flow (or the present value of future profits), thereby exacerbating conflicts of interest between lenders and high information/agency cost borrowers. Higher rates are also typically accompanied by declining asset prices, which depress the value of borrowers’ collateral. This deterioration in firm creditworthiness increases the external finance premium and squeezes firm demand for credit.

A growing number of empirical studies try to assess whether financial constraints indeed play

\(^1\)See Caballero (1997) for a survey of the literature on the sensitivity of investment to the cost of capital.

\(^2\)See Hubbard (1994) or Bernanke and Gertler (1995) for a review of this literature.
a significant role in the transmission mechanism of monetary policy. Assuming that firm (or bank) size should be correlated with the types of informational frictions that constrain access to credit markets, most of those studies compare how firms and banks in different size categories change their investment (or lending) behavior following changes in monetary policy.\(^3\) Unfortunately, one important limitation of the existing research is that it does not distinguish between the role of financial constraints in firms that would correspond to balance sheet channel and those in banks that would correspond to the lending channel. Since small, financially constrained firms are typically bank-dependent, any observation that small firms are hurt the hardest by a monetary contraction cannot distinguish between this being driven by a deterioration in firm creditworthiness or by a contraction in the supply of credit by financially constrained banks. Assessing the impact of monetary policy purely along the lines of the size of firms and banks is further complicated in light of well-documented evidence suggesting that large banks tend to concentrate their lending with large firms: one cannot distinguish a differential response of loan demand across firm size from a differential response of loan supply across bank size following monetary policy shocks.\(^4\)

The ideal strategy for identifying the lending channel is to look at cross-sectional variation in commercial banks’ ability to smooth policy-induced deposit outflows holding constant the characteristics of those banks’ loan portfolios. Recent research indicates that banks that are affiliated with large multi-bank holding companies (BHCs) are effectively ‘larger’ than their actual size indicates with respect to the ease in which they smooth Fed-induced deposit outflows (see Campello (2002) and Ashcraft (2001)). Consistent with Kashyap and Stein’s (2000) evidence on the behavior of large banks, those studies show that BHC-affiliate lending is less sensitive to monetary contractions than comparable independent banks. This should happen because, differently from independent banks, members of large BHCs can resort to funds available from conglomerate’s internal capital markets to fund their loans even during a Fed tightening. The most straightforward mechanism through which internal capital markets work is that holding company could issue uninsured debt on cheaper

\(^3\)Gertler and Gilchrist (1994) and Bernanke, Gertler, and Gilchrist (1996) show that small and large firms have significantly different investment, growth, and inventory responses following monetary contractions. Similar findings are reported by Kashyap, Lamont, and Stein (1994), Oliner and Rudebush (1996), and Gilchrist and Himmelberg (1998). Using data from banks, Kashyap and Stein (1995, 2000) show that the lending of large commercial banks is significantly less sensitive to monetary policy than that of small banks. The authors attribute this finding to the ability of large banks to issue uninsured liabilities at low cost (relatively to smaller banks) when the Fed tightens the money supply. Kishan and Opiela (2000) observe that the response of lending to monetary policy is amplified by bank leverage, another measure of financial constraints.

\(^4\)Ashcraft (2001) highlights the differences in small loan concentration — often used as a proxy for borrower size — across bank size categories. As of 1996, a typical small bank had 70 percent of its loan portfolio composed of small loans (face value of less than $250,000), compared to 30 percent for large banks. Peek and Rosengren (1997) establish a similar connection between loan size and the size of the borrower.
terms than the subsidiary bank and then downstream funds to the bank. Internal capital markets can also affect the ability of the bank to raise external finance because of the parent company’s obligation to assist a troubled subsidiary under the Federal Reserve’s source of strength doctrine. Overall, the evidence from financial conglomerates show that bank financial constraints are important in amplifying the effect of monetary policy on bank lending.

On the flip side, the ideal strategy for identifying the balance sheet channel is to examine cross-sectional differences in firms’ financial constraints holding constant the characteristics influencing policy-sensitivity of the banks from which those firms borrow. This paper builds on the insight that internal capital markets in BHCs translate into similar financial constraints for the members of the same conglomerate to conduct a novel test of the balance sheet channel. It does so by comparing policy responses of similar size banks that are affiliated with the same BHC but that face different pools of borrowers. We separate these borrowing clienteles by looking at the lending of (same-BHC) small affiliates that reside in different states. Because these subsidiary banks typically concentrate their lending with small local businesses whose fortunes are tied to the local economy, it follows that we can use cross-sectional differences in local economic indicators at the time of changes of monetary policy to study whether borrowers’ balance sheet strength influence the volume of bank lending.

Implementing this strategy in bank microdata, we first check whether there is evidence consistent with significant variations in borrowers’ balance sheet strength for the banks in our sample. We do this by looking at the correlation between the business conditions in the localities where subsidiary banks in our sample reside and the proportion of non-performing loans they report. Using Hodrick-Prescott-filtered series on state income gap for every US state, we find that differences in local economic conditions across states generate significant differences in the fraction of non-performing loans across same-BHC subsidiaries of multi-state holding companies. We then design a test of monetary policy transmission by relating the sensitivity of bank lending to local economic conditions and the stance of monetary policy over a 22-year long period. We find that the negative response of loan growth to contractionary monetary policy for subsidiaries operating during state-recessions is much stronger than subsidiaries of the same holding company that operate in state-booms. Our results hold for a number of different proxies for the stance of monetary policy, and our conclusions are robust to changes in the specification of our empirical models.

This could be done either through deposits or by purchasing existing loans from the bank, but in either case the transaction would tend to offset the impact of insured deposit outflows, reducing any need for the bank to turn to large CDs as a source of finance. Ashcraft (2001) and Mayne (1980) show some evidence of BHC fund channeling along those lines.
We design our tests so that usual concerns about the endogeneity of lending/borrowing decisions and financial constraints are minimized. This contrasts with most similar empirical studies, which have to rely on a series of auxiliary tests to address those concerns.\(^6\) However, one potential source of concern for our tests is sample selection. We collect data from banks belonging to certain types of financial conglomerates to identify the balance sheet channel of monetary policy. To the extent that financial institutions choose to organize their business in particular ways (e.g., choose to operate in various geographical regions at the same), one can argue that our data does not come from a random sample of banks and that our inferences are biased. For instance, a selection bias story can be argued along the following lines. Expansionary monetary policies might prompt BHCs to enter new, fast growing markets (states). If a given BHC based (and restricted to) state A sees an opportunity to enter the fast growing lending market of state B when access to reserves is easy, it may change its status from a single-state BHC to a multi-state BHC and thus enter our sample, possibly contaminating our results. We address this and other scenarios in which sampling could be a source of concern for our empirical strategy in a number of ways. In all cases, we find that our principal findings on the balance sheet channel remain unchanged.

A cautious interpretation of our findings would indicate that there is an asymmetry in the effectiveness of monetary policy over the business cycle with policy being more effective when the economy is in recession than in a boom. As this asymmetry appears to be driven by the creditworthiness of borrowers, we choose to interpret these findings as consistent with an active and independent balance sheet channel in the transmission mechanism of monetary policy. Such an interpretation would suggest that when engaging in monetary policy, the central bank should consider the amplification of changes in the federal funds rate on the real economy created by firm-level financial constraints. Our findings also add to the growing literature on the role internal capital markets play in the allocation of funds within conglomerate firms, particularly in financial conglomerates. This in turn points at need to understand in more detail the influence of conglomereration (and merger waves) on the impact of Federal Reserve policies on bank lending activity.

The remainder of the paper is organized as follows. In Section 2, we sketch a simple model describing the most relevant theoretical questions addressed in the empirical analysis. Section 3 provides a description of the data and our sampling criteria. Our results are presented in Section 4.

\(^6\)A good example is Kashyap and Stein (2000), who measure the monetary policy responses of bank loan-liquidity sensitivity. The problem is that both lending and liquidity management are choice variables to the bank. As the authors suggest, while an increase in the loan-liquidity sensitivity following a monetary contraction might be consistent with the bank lending channel, one must recognize the possibility that the same result would obtain if risk-averse banks, who accumulate more liquidity, choose to ration cyclical borrowers following the contraction.
A number of robustness checks for our main results are conducted in Section 5. Section 6 concludes the paper.

2 Theory

In this section, we analyze a bare bones model that captures the essential elements of the balance sheet channel of monetary policy. While this is largely an applied paper, we feel the following framework is an important contribution to the literature. The existing microfoundations for the balance sheet channel sketched do not necessarily imply that firm-level financial constraints amplify the effect of policy-induced changes in short-term interest rates. To our knowledge, this is the first treatment of firm-level financial constraints which implies that firm creditworthiness (measured by collateral) necessarily mitigates the response of lending to monetary policy.

We first describe a loan market where private information about the probability of failure creates adverse selection. We then solve for the equilibrium of the model, showing how firms with different failure probabilities and collateral levels are allocated between two types of secured loan markets. Finally, we study how the volume of bank lending responds to monetary policy. Since our later empirical approach is of a reduced-form that does not rely on estimating structural equations, we do not hesitate to make simplifying assumptions that facilitate the exposition of our main arguments.

2.1 Structure

The representative firm can produce one unit of output at time 0, but has to pay its workers’ wages \( w \) at time 0 before revenues \( y \) are realized at time 1. Firms are endowed with pledgable assets (collateral). Collateral values are either \( c_l \) or \( c_h \), with \( c_h > c_l \). In this world, workers will not work unless paid in full and production does not take place unless workers contribute with their input. This problem underlies the firm’s demand for credit. In the absence of internal funds, the firm will borrow the amount \( w \) from a lender (which we call a bank) at time 0 with a promise to repay the amount \( w(1 + r_b) \) at time 1.

We assume uncertainty over conditions in the product market at time 1. Firm revenues, \( y \), equal \( y_h \) with probability \( q \), and \( y_l \) with probability \( 1 - q \), where \( y_h > y_l \). Contracting with a lender is complicated by the presence of asymmetric information over the probability distribution of firm revenues across the two income states. In particular, we assume that the entrepreneur has private

---

7 This critique applies to the simple model proposed by Bernanke, Gertler, and Gilchrist (1996).
8 Differently from Bernanke and Gertler (1989) and others of the same genre, our model is not borne out a simple modification of the standard IS-LM framework.
information about this distribution and thus knows $q$ at time 0. The bank, on the other hand, only has a noisy forecast of $q$, denoted by $E[q]$. When $y < w(1 + r_b)$ the firm defaults on its loan. In this case, the bank shuts the firm down and claims its assets. Otherwise, the firm repays the loan and collects the profits. To make the problem interesting, we suppose that the firm always defaults in the low revenue state. This is consistent with the following parameter restriction: $(1 + r_f) > \frac{M + c}{w}$, where $(1 + r_f)$ is the risk-free rate.

We introduce firm heterogeneity by permitting differences not only in the value of collateral firms have, but also in the value of their revenues in the good state $y_h$. We further suppose that the probability of the high state, $q$, takes on two values, $q_h$ and $q_l$, with $q_h > q_l$. These latter assumptions are necessary in order for small changes in interest rates to have an effect on the volume of lending.

2.2 Equilibrium

Characterizing the equilibrium conditions in the loan market is complicated by the possibility that firms with collateral $c_h$ are able to liquidate some of their pledgable assets and thus look like firms with collateral $c_l$ to lenders.\(^9\) There are two types of equilibria in the market for bank loans: a semi-separating and a pooling equilibrium. We describe the properties of these equilibria in turn.

Semi-separating equilibrium. There are two secured loan markets, each differentiated by the level of collateral. Firms with high collateral $c_h$ will choose the type of loan market according to the probability of success $q$. Those firms with higher probability of the good state $q_h$ will borrow in the well-collateralized loan market. In contrast, those with smaller probability of the good state $q_l$ will liquidate their pledgable assets and borrow in the less collateralized loan market so long as the collateral posted in the well-collateralized market is sufficiently large. Finally, firms with low collateral $c_l$ are forced to borrow in the less collateralized loan market.

In characterizing the semi-separating equilibrium, let us first demonstrate that firms with the high probability of the good state $q_h$ and with high collateral $c_h$ (henceforth, $(q_h, c_h)$-types) will choose to borrow in the well-collateralized loan market. Define $E[q|c]$ as the average probability of the high state given collateral $c$. A risk-neutral bank with an opportunity cost equal to the risk-free rate will price a loan of $w$ to the entrepreneur at the risky interest rate $(1 + r_b)$ according to the following pricing rule,

---

\(^9\)This is motivated by the so-called paradox of liquidity described in Meyers and Rajan (1998). While liquid assets can be used to mitigate financial constraints, they can create agency problems between ownership and management.
\[ (1 + r_b) = \frac{(1 + r_f)w - (1 - E[q|c])(y_l + c)}{E[q|c]w}. \] (1)

There is a natural ceiling on this interest rate at \( \frac{w}{w} \), but it is easy to show that this constraint will not bind unless \( c \) is sufficiently small. Inserting this pricing rule into the entrepreneur’s net profit function, conditional on the probability \( q \) and the level of collateral \( c \), yields the following useful expression:

\[ \pi(q, c) = q(y_h - y_l) - \frac{q}{E[q|c]}[(1 + r_f)w - y_l - c] - c. \] (2)

Using the fact that \( E[q|c = c_h] = q_h \), one can write the difference from borrowing in the well-collateralized loan market versus less collateralized loan market as,

\[ \pi(q_h, c_h) - \pi(q_l, c_l) = \frac{q_h - E[q|c = c_l]}{E[q|c = c_l]}[(1 + r_f)w - y_l - c_l] > 0. \] (3)

The inequality follows from the parameter restriction ensuring that the firm defaults in the bad state. It follows that \((q_h, c_h)\)-types prefer to use their collateral and consequently borrow in the well-collateralized market.

The next step is to ensure that the firm’s participation constraint is met so that \( \pi(q, c) \geq 0 \). This constraint can be written in terms of the value of firm revenue in the good state,

\[ y_h \geq y^*_h = \frac{(1 + r_f)w - y_l - c}{E[q|c]} + y_l + \frac{c}{q}. \] (4)

Notice that this constraint defines the minimum value of \( y_h \) that will be funded by the bank for each combination of \( c \) and \( q \). Importantly, \( y_h \) is increasing in the risk-free rate of interest. Evaluated at \( q = q_h \) and \( c = c_h \), so that \( E[q|c = c_h] = q_h \), this equation defines the volume of lending in the well-collateralized loan market. Given a cross-sectional distribution \( G \) over \( y_h \) that is independent of \( q \), aggregate borrowing in the well-collateralized loan market is simply,

\[ L(q_h, c_h) = \int_{-\infty}^{+\infty} 1(y_h \geq y^*_h) dG(y_h). \] (5)

Now let us demonstrate that firms with the lower probability of the good state \( q_l \) will choose to borrow in the less collateralized loan market. In order to facilitate the algebra, define the ratio of \( c_h \) to \( c_l \) as \( \beta \), and further define \( \alpha_l \) as the ratio of \( c_l \) to \([1 + r_f]w - y_l \). Using these definitions one can write the difference in profits from borrowing in the well-collateralized versus poorly collateralized market as,
\[ \pi(q_l, c_h) - \pi(q_l, c_l) = \frac{(1 + r_f)w - y_l}{q_h E[q|c = c_l]} [(\alpha_l \beta - 1)q_l (E[q|c = c_l] - q_h) + \alpha_l (1 - \beta) q_h E[q|c = c_l]] \quad (6) \]

This expression is negative so long as,

\[ \frac{\alpha_l (\beta - 1)}{1 - \alpha_l \beta} \geq q_l \left[ \frac{1}{E[q|c = c_l]} - \frac{1}{q_h} \right] \quad (7) \]

where we used the fact that \( 1 - \alpha_l \beta < 0 \) given \( (1 + r_f)w - y_l - c_h > 0 \). The left-hand side of this inequality is increasing in the ratio of high to low collateral \( \beta \) as long as \( \alpha_l < 1 \). It follows that \((q_l, c_h)\)-types will prefer to act like firms with low collateral \( c_l \) as long as the ratio of high to low collateral \( \beta \) is sufficiently large.

The final step is to ensure that the \((q_l, c_h)\) type’s participation constraint is met. This is done by evaluating Eq. (4) at \( q = q_l \) and \( c = c_l \), which simply defines the cutoff level of high state revenues \( y_h^* \) such that the firm chooses to borrow. Firms that are endowed with low levels of collateral \( c_l \) borrow in less collateralized loan market, again subject to the participation constraint.

**Pooling equilibrium.** When \( \beta \) is less than the cutoff value in Eq. (7), there is a pooling equilibrium in each the well-collateralized and less collateralized loan markets. As before, entrepreneurs with the higher probability of the good state will always use their collateral. Using the fact that \( E[q|c = c_h] = E[q|c = c_l] \) we can show that

\[ \pi(q_h, c_h) - \pi(q_h, c_l) = c_l (\beta - 1) \frac{q_h - E[q|c = c_h]}{E[q|c = c_h]} > 0. \quad (8) \]

This inequality is met since \( \beta > 1 \), implying that \((q_h, c_h)\)-types choose to use their high level of collateral.

The \((q_l, c_h)\)-types, in contrast, will employ a mixed strategy between the two loan markets. The mixed strategy can be inferred by equalizing the expected returns of borrowing in each of the loan markets. Following a strategy similar to the one above, the equilibrium allocation of this borrower type across the two loan markets can be defined by

\[ \frac{\alpha_l (\beta - 1)}{1 - \alpha_l \beta} = q_l \left[ \frac{1}{E[q|c = c_l]} - \frac{1}{E[q|c = c_h]} \right]. \quad (9) \]

Recall that the pooling equilibrium exists when the left-hand side of this equation is too small relative to the value of the right-hand side in the semi-separating equilibrium. The only way this equation can be met is by reducing the value of the right-hand side. This is accomplished by
increasing the fraction of \((q_l, c_h)\)-types that borrow in the well-collateralized market, which increases \(E[q|c = c_l]\) and decreases \(E[q|c = c_h]\). Note that since only a fraction of those with \(q = q_l\) choose to borrow in the well-collateralized loan market, it follows that the average \(q\) in the well-collateralized loan market is larger than that in poorly-collateralized loan market.

### 2.3 The Balance Sheet Channel of Monetary Policy

Let us now analyze the impact of monetary policy on the loan market equilibrium. We first study the semi-separating equilibrium. Recall that firms having both collateral and a high probability of the good state borrow in the well-collateralized loan market, where their type is perfectly revealed to the bank. The effect of a change in the risk-free rate on the loan interest rate is thus,

\[
\frac{\delta(1 + r_h)}{\delta(1 + r_f)} = \frac{1}{q_h}. \tag{10}
\]

Here an increase in the risk-free rate simply increases the promised payment by the firm, but since this only occurs in the good state this change is scaled by the probability of that state, \(q_h\). Importantly, note that Eq. (10) implies that as these firms become riskier or less creditworthy (i.e., \(q_h\) decreases), their loan rate will have a larger response to monetary policy.

The remaining firms are borrowing in a poorly-collateralized loan market where their type is not fully revealed to the bank. In this case, the response of the equilibrium loan rate to an increase in the risk-free rate is simply,

\[
\frac{\delta(1 + r_h)}{\delta(1 + r_f)} = \frac{1}{E[q|c = c_l]}. \tag{11}
\]

This expression shows that the response of the loan rate to monetary policy will be larger in the unsecured market so long as borrowers in the secured market have a larger average probability of the good state.

Looking now the impact of monetary policy on loan interest under the pooling equilibrium, recall that the average probability of the good state is larger in the well-collateralized loan market than in the unsecured loan market. This suggests that monetary policy has a larger effect on the loan rate of unsecured borrowers. Note also that there is an additional effect working in the same direction: an increase in the risk-free rate also increases losses in default states, implying there is an decrease in \(\alpha_l\). Since the left-hand side of Eq. (9) is increasing in \(\alpha_l\), this requires an adjustment in the fraction of low probability types that choose to borrow in the well-collateralized loan market. A reduction in \(\alpha_l\) reduces the left-hand side of Eq. (9), implying that we must find a way to reduce
the right-hand side of this equation. As before, this is only accomplished by a larger fraction of low probability firms shifting from the secured to unsecured loan market, an effect that amplifies the effect of monetary policy on unsecured borrowing.

It is now a straightforward task to evaluate how monetary policy affects the volume of lending in our model. First, reconsider the participation constraint in Eq. (4). It should be clear that an increase in the risk-free rate increases the lower bound on $y_h$, which implies that the volume of lending will decrease. At the same time, note that the response of lending is proportional to $\frac{1}{E[q|c]}$, implying that the volume will fall by more in response to a monetary contraction in markets where $E[q|c]$ is smaller. Recall that both the pooling and semi-separating equilibria had the property that the well-collateralized loan market had a larger $E[q|c]$. This implies that collateral tends to mitigate the response of lending to interest rates. In other words, the equilibrium of our model predicts that borrowers’ creditworthiness will influence the response of bank lending volume to monetary policy shocks precisely along the of the balance sheet channel: higher basic interest rates will reduce the borrowings of all firms, but will affect those firms with low collateral values particularly more.

In the empirical investigation that follows we focus on borrowers for which the implications of information-based theories fit well with the observed structure of financing arrangements. In particular, we examine the relationship of financial intermediaries with borrowers that are likely to characterize the entrepreneur with a single idiosyncratic project and whose business demands intensive monitoring. These are primarily small firms and individuals. Most of the small firm financing in the U.S. is intermediated, with the majority of the credit being provided by commercial banks. Note also that the use of collateral, covenants, and other guarantees are present in nearly all of the financing contracts between banks and small firms and individuals. Similarly to Bernanke, Gertler, and Gilchrist (1996), we argue that examining data on bank loans geared towards this type of borrowers will provide for the best way to identify the workings of the balance sheet channel in practice.

Before we conclude let us emphasize the importance of the role imperfect information (alternatively, high agency costs) plays in the transmission mechanism by considering the response of the loan rate and volume to monetary policy across the amount of collateral in the absence of private information about $q$. This would imply that $E[q|c] = q$, which means that loans are priced in a manner such that firm payoffs are independent of collateral. Rewriting Eq. (2),

$$\pi(q,c) = q(y_h - y_l) - [(1 + r_f)w - y_l].$$  \hspace{1cm} (12)
In this world, each firm is indifferent between borrowing in either loan market, so there should be no equilibrium correlation between the amount of collateral and probability of the good state. It follows that as the cutoff value $y^*_h$ no longer depends on the amount of collateral, there are no longer differential effects of loan volume to monetary policy across $c$. It follows that a useful test of the importance of financial constraints in the transmission mechanism is to consider whether or not the response of lending to monetary policy is mitigated by the value of collateral.

3 Sampling Methodology

In order to identify the response of a loan demand to monetary policy it is necessary to eliminate any differences in financial constraints across banks that would drive a differential policy-response of loan supply. Such an analysis requires one to use banks that face similar financial constraints, but experience differential strength in their borrowers’ balance sheets. Our study uses such a strategy to look for evidence on the balance sheet channel of monetary policy. Here we describe the identification problem and our approach in detail, and then discuss the data employed.

3.1 Identification

We model the differential response of bank lending to monetary policy across banks by explicitly separating demand and supply-side effects of monetary policy. Let $r_t$ denote the stance of monetary policy as of time $t$, Eq. (13) writes the response of loan growth to policy for an individual bank $i$ that is part of holding company $j$ at time $t$,

$$\frac{\delta \Delta \ln (\text{Loans})_{ijt}}{\delta r_t} = \alpha_0 + \alpha_1 A_{ijt} + \alpha_2 B_{ijt} + \alpha_3 X^\text{bank}_{ijt} + \alpha_4 X^\text{BHC}_{ijt} + v_{ijt}. \quad (13)$$

Differences in the response of loan demand across banks are captured by $A_{ijt}$ and $B_{ijt}$, which correspond to balance sheet and non-balance sheet effects, respectively. The first of these demand effects can be understood in the spirit of our model, where the demand for loans by firms with poor balance sheets and limited collateral will decline following a monetary contraction. The second refers to changes in loan demand that are not related to firm financial strength. Firms involved in the manufacture of durable goods, for example, have product demand that is more sensitive to monetary policy than other firms. One should thus expect to see relatively more policy-sensitive lending by banks that concentrate their business with these firms. Differences in the response of loan supply across banks are caused by differences in the severity of financial constraints they face.
at the bank-level, $X_{ijt}^{bank}$, or the holding company-level, $X_{ijt}^{BHC}$.

These controls are meant to capture lending channel effects where financial constraints affect the ability of banks to replace an outflow of insured deposits with other funds.

Given the appropriate data on each of these regressors, estimating Eq. (13) via Ordinary Least Squares would recover the correlation of firm balance sheet strength with the response of bank lending to monetary policy through the estimate of $\alpha_1$. The problem with this strategy, however, is lack of data on all of the relevant dimensions of each of these regressors. In particular, there are likely to be unobserved components of $B_{ijt}$, $X_{ijt}^{bank}$, or $X_{ijt}^{BHC}$ that are correlated with the observed dimensions of firm balance sheet strength $A_{ijt}$, in which case the OLS estimation will be compromised by omitted variables bias.

We attempt to minimize this problem using several devices. First, we restrict our sample to banks that are affiliated with large multi-bank holding companies. This follows from the evidence on recent research on the bank lending channel. Kashyap and Stein (2000) show that large commercial banks are mostly insensitive to monetary policy shocks, as their ability to tap on non-reservable sources of funds at low cost allows them to shield their lending from Fed-induced contractions. Campello (2002) and Ashcraft (2001) further demonstrate that, just like large banks, subsidiaries of large BHCs are far less constrained than comparable independent banks. Based on these findings, that sample restriction alone should all but eliminate the importance of bank (supply-side) financial constraints in explaining the response of lending to monetary policy, allowing us to disregard $X_{ijt}^{bank}$ and $X_{ijt}^{BHC}$. We, however, weaken such an assumption and estimate Eq. (13) including a set of $x_{ijt}$ variables that, according to the lending channel literature, should exhaust the sources of variation in bank-level financial constraints: capitalization, size, and liquidity. In the end, $\alpha_3$ and $\alpha_4$ should be very small — if not zero — so that even if there are unobserved dimensions of bank/BHC financial constraints, any correlation of these unobservables with firm balance sheet strength is mitigated.

The second device we employ to mitigate omitted variables bias is to focus the analysis on the difference between a subsidiary’s response to monetary policy and the average response of all of the other banks affiliated with the same holding company. Focusing on within-conglomerate comparisons is useful because it eliminates financial constraints at the BHC-level from the equation, purging one potential source of bias. Define $\Omega_{ijt}$ as the difference between a subsidiary’s $x_{ijt}$ and

---

10Dependence on holding company-level financial health is induced by regulation requiring that financial conglomerates must operate on consolidated basis. See Houston, James, and Marcus (1997) for a discussion.

11Recall that omitted variables bias depends on both the correlation of the omitted variable with the variable of interest and the coefficient on the omitted variable in the original model. As this coefficient goes to zero, the bias created by any correlation with the variable of interest also goes to zero.
its holding company mean in a given quarter. We can re-write Eq. (13) in differences from the holding company mean as follows,

\[
\frac{\delta \Omega^{Loans}_{ijt}}{\delta r_t} = \alpha_1 \Omega^A_{ijt} + \alpha_2 \Omega^B_{ijt} + \alpha_3 \Omega^{bank}_{ijt} + v_{ijt}.
\] (14)

Once we have minimized bank-driven differences in loan-policy responses, the next device we use to reduce the influence of biases is to isolate sources of cross-sectional variations in borrower balance sheet strength which are presumably uncorrelated with the other omitted variables. We lack data on every borrower of every bank in our sample of BHC subsidiaries. Nonetheless, we have a rich dataset describing the markets (or local business conditions) where loans are made. Arguably, depressed economic activity within a state will lead to a deterioration in local borrowers’ balance sheets, as small, local businesses fortunes (cash flows, collateral values, etc.) are intrinsically tied to the local economy. Our identification scheme is complete if we can assume that these borrowers concentrate most of their lending with small banks.\footnote{Such an assumption is strongly supported by extensive research on business lending practices of small and large banks. See, among others, Nakamura (1994), Strahan and Weston (1998), Berger, Saunders, Scalise and Udell (1998), di Patti and Gobbi (2001), and Sapienza (2002).}

We thus isolate differences in borrowers’ strength across members of a given conglomerate (\(\Omega^A_{ijt}\)) by looking at data from small subsidiaries of large multi-state conglomerates.

Our approach is sound if we isolate from \(A_{ijt}\) those unobserved components that are likely to be correlated with \(B_{ijt}\). This is not an obvious task. The solution involves the observation that variations in \(A_{ijt}\) can be broken out into both high-frequency and low-frequency components. The low frequency component is potentially correlated with \(B_{ijt}\).\footnote{Recall, \(B_{ijt}\) drives differences in the response of loan demand to monetary policy that are not created by borrower financial constraints, but by underlying characteristics of the borrowers in a market (or state), such as the sensitivity of product demand to monetary policy. It seems plausible to think that such characteristics (e.g., industrial structure) evolves quite slowly over time and are essentially fixed over short periods of time.}

The high-frequency component of \(A_{ijt}\), on the other hand, is plausibly independent of non-balance sheet factors. In implementing our tests, we exploit the high-frequency variation in firm balance sheets that is induced by short-run changes local business conditions. In essence, our identifying assumption is that short-term deviations from long-run economic trends at the state level are uncorrelated with non-balance sheet drivers of the response of bank lending to monetary policy, \(B_{ijt}\), and unobserved measures of bank-level financial constraints, \(X^{bank}_{ijt}\).
We collect quarterly accounting information on the population of insured commercial banks from the Federal Reserve’s *Call Report of Income and Condition* over the 1976:I-1998:II period, using a version of the data that was cleaned by the Banking Studies Function of the Federal Reserve. After an initial screening, we retain only bank-quarters with positive values for total assets, total loans, and deposits. Details about the construction of the panel data set and formation of consistent time series are provided in Appendix A.\textsuperscript{14}

The single most important bank-level variable used in our analysis is loan growth. This variable is defined as the quarterly time series difference in the log of total loans. We use the bank merger file published online by the Federal Reserve Bank of Chicago to remove any quarter in which the bank makes an acquisition, which helps reducing data measurement problems with the differenced data. In addition, we eliminate any quarter in which bank loan growth is more than 5 standard deviations from the mean in absolute value. Since the regressions below include four lags of loan growth as explanatory variables, the sample is implicitly limited to banks having at least five consecutive quarters of data. The first five quarters of the data are lost in order to construct lagged dependent variables and appropriate differences.

Our analysis focuses on the lending of small banks. This sample restriction is made in order to best match the state in which the bank is chartered with local business conditions.\textsuperscript{15} Consistent with previous studies, we define as ‘small’ banks those bank-quarters in the bottom 95\textsuperscript{th} percentile of the assets size distribution of all observations in a given quarter.\textsuperscript{16} There are 926,845 small bank-quarters contained in the 1977:II-1998:II period. The first restriction we impose on the data is to retain only small banks that are part of multi-bank holding companies which control at least one large bank (i.e., a bank in the top 5\textsuperscript{th} percentile of the asset distribution). This drops the number of bank-quarters down to 94,333. Next, we require that small banks must be affiliated with holding companies that have subsidiaries residing in at least two different U.S. states during the same quarter. These restrictions leave 38,599 bank-quarters in our panel dataset. The time distribution of the number of observations in this ‘raw’ sample of multi-state BHC subsidiaries is reported in Table 1. The table shows a steady increase in the number of observations in each quarter until the advent of problems in the banking industry in the late 1980s. During the last...
decade, consolidation within the industry (and within BHCs) has greatly reduced the number of small banks affiliated with large BHCs to currently approximately one-third of its peak number in 1988.\textsuperscript{17} 

The first column of Table 2 reports the mean and standard deviation of the variables used in our analysis. The statistics in the first column of the table are for the small banks that are included in the sample. The figures for basic balance sheet information such as size, loan growth, leverage, etc. are similar to those reported in similar studies on small banks (see, e.g., Campello (2002)). Banks in our final sample display a quarterly loan growth average of 1.57 percent with a standard deviation of 7.6 percent. Note that the standard deviation of long-run loan growth and non-performing loans are similar in magnitude to the long run means, implying that there are large differences across banks in long-run average loan growth and non-performing loans.

As we discuss below, we must be concerned with the fact that our data selection criteria may create sample biases that affect our inferences. To check whether the observations in our sample are “unique” in some obvious sense, we also compute descriptive statistics for the variables of interest using those small banks that are left out of our final sample. Comparisons based on those statistics suggest that one would have a difficult time arguing that small subsidiaries of multi-state BHCs operate very differently from other banks in the same size category.

Finally, our analysis also necessitates data on the stance of monetary policy and on the business environment in which the small affiliate banks in our sample operate. The measures of monetary policy we use are fairly standard and are described in detail in Appendix B. Most of these policy measures are constructed with series available online from FRED at the Federal Reserve Bank of St. Louis. In order to measure local business conditions we use the nominal state income series available online from the Bureau of Economic Analysis. Deviations from the long-run economic growth trend in each state are used to characterize state-recessions and state-booms. Specifically, a state ‘income gap’ (\textit{YGap}) is constructed by applying an Hodrick-Prescott filter (bandwidth of 1600) to the time series difference of the log of total state income for each state and the District of Columbia.

\textsuperscript{17}Without weighting these trends in the number of observations, statistics constructed on this sample would place an unusual amount of weight on the first decade of data. As the analysis below is done quarter by quarter, this will not be a concern, but the descriptive statistics displayed in Table 2 would inherit this property.
4 Empirical Results

4.1 Local Business Conditions and Bad Loans

In order to substantiate our testing strategy we need to find evidence that depressed economic activity actually depresses borrowers’ balance sheets. To our knowledge, there are not public available data on individual firms’ borrowings that serve our purposes. On the other hand, we do have data on the loan portfolio of their banks. In establishing a link between local economic conditions and firm balance sheets, we argue that an unexpected deterioration in firm balance sheets should show up in the quality their banks’ loan portfolio. We examine this working hypothesis in turn.

For each individual bank \( i \) affiliated with the holding company \( j \) at time \( t \), let \( \Omega^\text{dl}_{ijt} \) denote the difference between a subsidiary’s bad loans (i.e., non-performing loans) and the average bad loans of all other small banks in the holding company. Similarly, define \( \Omega^\text{YGAP}_{ijt} \) as the difference between a subsidiary’s state income gap and the average income gap of all small banks in the holding company,

\[
\Omega^\text{BadLoans}_{ijt} = \text{BadLoans}_{ijt} - \overline{\text{BadLoans}}_{jt},
\]

\[
\Omega^\text{YGAP}_{ijt} = \Delta \ln(Y\text{Gap}_{ijt}) - \Delta \ln(Y\text{Gap}_{jt}).
\]

The issue of interest is whether subsidiaries operating in state-quarters with relatively poor economic conditions report a greater fraction of loans gone bad. We use the following empirical model to address this question:

\[
\Omega^\text{BadLoans}_{ijt} = \eta + \sum_{k=1}^{\lambda} \Omega^\text{YGAP}_{ijt-k} + \sum_{t} \Omega^X_{ijt-k} + \alpha_t 1_t + \varepsilon_{ijt}.
\]

The set of controls included in \( X \) is composed of lagged of log assets, the lagged bank equity ratio, and the lag of bank liquid assets. The \( \alpha \) coefficients absorb time-fixed effects. The four lags of log changes in the relative-to-BHC state income gap (\( \Omega^\text{YGAP}_{ijt} \)) are meant to capture the relative strength of the balance sheets of the borrowers of the subsidiary bank. We are, of course, interested in the relationship between a small subsidiary’s (relative-to-BHC) ratio of bad loans and the financial status of the businesses in its market, captured by \( \lambda \).

We report the estimates returned for \( \lambda \) in Table 3 (standard errors are corrected for clustering and heteroskedasticity). Panel A simply uses the state income gap \( \Delta \ln(Y\text{Gap}_{ijt}) \), while Panel B uses \( \Omega^\text{YGAP}_{ijt} \). These pooled cross-section times series regressions are estimated both with and without bank fixed-effects. The coefficients on \( \lambda \) range from \(-0.025\) to \(-0.04\) and imply that an increase in
the state income gap by one standard deviation of the income gap (about 2.4 percentage points) reduces the fraction of bad loans in a small bank’s loan portfolio by about 6 to 10 basis points. While these effects are statistically significant, this may seem like a relatively small deterioration in bank loan credit quality, representing less than 10 percent of the sample mean. Notice, however, that this estimate represents the impact of a slowdown in state income on bad loans in the current quarter, and that the cumulative deterioration in firm credit quality could be several times as large over a longer time horizon.

One potential limitation with this specification is that it exploits both permanent and transitory differences in the fraction of bad loans across subsidiaries. In principle, we are interested in bad loans created by what are temporary changes in local economic conditions, so it makes sense to eliminate long-run individual bank effects. This can be accomplished by differencing out any bank-level long-run differences relative to the holding company, defining $\Omega^B_{ijt}BadLoans$ as follows:

$$\Omega^B_{ijt}BadLoans = \Omega^B_{ijt}BadLoans - \Omega^B_{ijt}BadLoans$$

We re-examine the question of relative loan performance, now only exploiting transitory differences in bad loans across subsidiaries, by estimating the following equation:

$$\Omega^B_{ijt}BadLoans = \eta + \sum_{k=1}^{X^i} \lambda_k \Omega^{YGap}_{ijt-k} + \beta \Omega^X_{ijt} + \alpha_t \Omega^1_t + \varepsilon_{ijt}.$$  \hfill (19)

The results from this last estimation are reported in Table 3. The first panel uses state income gap while the second uses the equivalent relative-to-BHC measure ($\Omega^{YGap}_{ijt}$). There continues to exist clear evidence that differences in the state income gap drive temporary differences in bad loans across bank subsidiaries. We interpret these results as motivating evidence for using the state income gap as a proxy for borrower creditworthiness.

### 4.2 Local Business Conditions and Asymmetric Monetary Policy Effects

We have established that cross-sectional differences in economic conditions of the various markets in which a conglomerate operate drive differences in the loan quality (indicative of borrowers’ financial strength) among the various subsidiaries of the same conglomerate. We now turn to the main question of the paper: Whether there’s a balance sheet channel of monetary policy.

To investigate this transmission mechanism we use a two-step approach which resembles that of Kashyap and Stein (2000). The idea is to relate the sensitivity of bank lending to local economic
conditions and the stance of monetary policy by combining cross-sectional and times series regressions. The approach sacrifices estimation efficiency, but reduces the likelihood of Type I inference errors — i.e., it reduces the odds of concluding that borrowers’ finances matter when they really do not.18

Define $\Omega_{ijt}^{Loans}$ as the difference between subsidiary lending and the average loan growth of all other small banks in the conglomerate. The first step of our procedure consists of running the following cross-sectional regression for every quarter $t$ in the sample:

$$
\Omega_{ijt}^{Loans} = \eta + \pi_k \Omega_{ijt-k}^{Loans} + \gamma_k \Omega_{ijt-k}^{Y\text{Gap}} + \beta \Omega_{ijt-1}^{X} + \epsilon_{ijt}. \quad (20)
$$

To explicitly account for the idiosyncratic long-run effects discussed above, we also estimate the following ‘double-differenced’ equation:

$$
\Omega_{ijt}^{\text{ans}} = \eta + \pi_k \Omega_{ijt-k}^{\text{ans}} + \gamma_k \Omega_{ijt-k}^{\text{Gap}} + \beta \Omega_{ijt-1}^{X} + \epsilon_{ijt}, \quad (21)
$$

where $\Omega_{ijt}^{\text{ans}} = \Omega_{ijt}^{Loans} - \Omega_{ijt}^{\text{Loans}}$, $\Omega_{ijt}^{\text{Gap}} = \Omega_{ijt}^{Y\text{Gap}} - \Omega_{ijt}^{Y\text{Gap}}$, and $\Omega_{ijt}^{X} = \Omega_{ijt}^{X} - \Omega_{ijt}^{X}$.

From each sequence of cross-sectional regressions, we collect the coefficients returned for $\gamma$ and ‘stack’ them into the vector $\Psi_t$, which is then used in the following (second stage) time series regression:19

$$
\Psi_t = \alpha + \phi_k MP_{t-k} + \mu_k \Delta \ln(GDP)_{t-k} + \sigma_k Q_k + \rho t + \omega_t. \quad (22)
$$

Of course, we are interested in gauging the influence of monetary policy, $MP$, on the sensitivity of loan growth to borrower balance sheet strength. The economic and the statistical significance of the impact of monetary policy in Eq. (22) can be gauged from the sum of the coefficients for the eight lags of the monetary policy measure ($\sum \phi$) and from the $p$-value of this sum. Because policy changes and other macroeconomic movements often overlap, we must distinguish between

18 An alternative one-step specification — with Eq. (22) below nested in Eq. (20) — would impose a more constrained parametrization and have more power to reject the null hypothesis of borrowers finances irrelevance. However, tests of coefficient stability indicate that the data strongly rejects those parameter restrictions. Another advantage of the two-step approach is that it allows for cross-sectional variations in local demand conditions to be accounted for in every period.

19 To see how this procedure accounts for the error contained in the first-step, assume that the true $\Psi_t^*$ equals what is estimated from the first-step run ($\Psi_t$) plus some residual ($\nu_t$): $\Psi_t^* = \Psi_t + \nu_t$. One would like to estimate Equation (22) as $\Psi_t^* = \alpha + X \theta + \omega_t$, where the error term would only reflect the errors associated with the specification of the model. However, the empirical version of Equation (22) uses $\Psi_t$ (rather than $\Psi_t^*$) on the right hand-side. Consequently, so long as $E[X']\nu = 0$, $\alpha$ will absorb the mean of $\nu_t$, while $ut$ will be a mixture of $\nu_t$ and $\omega_t$. That is, the measurement errors of the first-step will increase the total error variance in the second-step, but will not bias the coefficient estimates in $\theta$. 

18
financial and real explanations for the observed relationship between bank lending and borrower strength. To check whether the measure of monetary policy retains significant predictive power after conditioning on macroeconomic factors we include eight lags of the log change in real GDP in the specification. The variable $Q$ corresponds to quarter dummies, and $t$ represents a time trend.

Since there is little consensus on the most appropriate measure of the stance of monetary policy we use four alternative measures in all estimations performed: a) the Fed funds rate (Fed Funds); b) the spread between the Fed funds rate and the rate paid on 10-year Treasury bills (Funds-Bill); c) the spread between the rates paid on six-month prime rated commercial paper and 180-day Treasury bills (CP-Bill); and d) Strongin’s (1995) measure of unanticipated shocks to reserves (Strongin). All monetary policy measures are transformed so that increases in their levels represent Fed tightenings.

Figure 1 plots the empirical distribution of the coefficient of interest from the first stage regressions, $P^\gamma$. This empirical distribution is constructed using a kernel density estimator, which is essentially a non-parametric estimator for a continuous probability distribution. We perform the first stage estimations of our two-step procedure in four different ways (see below), yielding a total of 364 realizations. As expected, those estimations return a positive coefficient for $P^\gamma$ in most runs. The mean (median) of those coefficients equals 0.078 (0.027) and is statistically different from zero at the 0.1 (0.1) percent level. A positive coefficient indicates that there is more demand for credit by firms in states where business conditions are favorable and unconstrained banks are able to provide financing. Of course, these univariate results alone don’t say much about the dynamics of the transmission of monetary policy.

The main results of the paper are reported in Table 4. The table reports the sum of the coefficients for the eight lags of the monetary policy measure ($P^\phi$) from Eq. (22), along with the $p$-values for the sum. Heteroskedasticity- and autocorrelation-consistent errors are computed with Newey-West lag window of size eight in all regressions. The table summarizes the results of 16 two-step estimations (four different first stage regressions $\times$ four monetary policy measures). The results in Panel A use the state income gap $\Delta ln(YGap_{ijt})$ as the proxy for local borrowers’ financial status, while those in Panel B use $\Omega_{ijt}^{YGap}$ (the difference between the income gap facing a subsidiary and the average gap facing all other small subsidiaries of the same BHC) as the relevant proxy. The first row of each panel reports results from regressions that use $\Omega_{ijt}^{Loans}$ (the relative-to-BHC subsidiary loan growth) as the dependent variable (see Eq.(20)), while those in the second row use

---

$^{26}$Notice that we are not claiming that the $\gamma$ realizations are independent across runs.
\( \Omega_{ijt}^{\text{loans}} \) (the double-differenced \( \Omega_{ijt}^{\text{loans}} \)) as the dependent variable (Eq. (21)).

All of the coefficients in the table have the expected sign, and most measures of monetary policy return statistically significant coefficients. This is remarkable given well-documented differences in the time series properties of policy measures based on the interest rates and those based on monetary aggregates. Of these coefficients, twelve (seven) are significant at the 9.6 (3.9) percent level or better. The coefficients for the most conventional measure, the federal funds rate, are all significant at better than the 6.5 percent level.

In order to interpret the economic significance of those estimates, it is necessary to select a baseline policy experiment. Consider the scenario in which the central bank increases the funds rate by 25 basis points and keeps it there for eight quarters, implying a 200 basis point change over the entire horizon. Using the most conservative of our fed funds rate estimates (0.031), a one standard deviation deterioration in the state income gap (0.025) faced by a subsidiary would amplify the impact of this monetary contraction on bank loan growth by some 15 basis points in the current quarter alone. To see what this result would imply in dollar terms, consider two subsidiaries of the same BHC, both with a loan portfolio equal to $100 million (about the average figure for banks in our sample as of 1998:II). Suppose one of the subsidiaries operates in a state where the income gap is one standard deviation above average and the other operates in a state where the income gap is one standard deviation below average. Then a 25 basis point increase in the fed funds rate sustained over eight quarters would lead the loan portfolio of the bank facing a local slump to cut back on lending by $300,000 more in the current quarter than the first bank facing a local boom.

Table 5 illustrates the complete ‘impulse-response’ of balance sheet amplification using the federal funds rate as a measure of monetary policy. The rows of the table are similar to the previous table, while the columns correspond to the point estimate and \( p \)-value for sum of coefficients across lags of the funds rate. The time pattern describes an initial effect of 1.5 to 2 percent on the current quarter that increases to 3 to 4 percent after eight quarters. These estimates imply that the bulk of the amplification effects implied by the balance sheet channel of monetary policy takes place immediately after a policy change. They also show that the effects of monetary policy on bank lending that are induced by borrowers’ financial weakening is very persistent through time. The timing and duration of balance sheet effects over the business cycle we uncover are roughly similar to those Gertler and Gilchrist (1994) find using aggregate times series data from small manufacturing firms. These patterns suggest that the presence of firm-level financial constraints could help explain
the excessive sensitivity of output to short-term interest rates. Moreover, in the presence of a strong balance sheet channel there are important asymmetries in the transmission mechanism of monetary policy over the business cycle that need to be acknowledged both in forecasting future economic performance and in the design of policy.

The analysis of this section established that there are important differences in the response of bank loan growth to monetary policy over the state business cycle. We want rely on the evidence that movements in the state economic conditions are correlated with movements in the credit-worthiness of local borrowers in order to interpret our findings as consistent with a balance sheet channel of monetary policy. Before we conclude, however, we discuss some potential weaknesses with the evidence above.

5 Robustness

Although we use an approach that resembles that of Kashyap and Stein’s (2000) two-step procedure, our analysis is far less subject to the simultaneity biases discussed in their paper. Specifically, while our second-stage times series regressions are similar to those of Kashyap and Stein, their paper’s first-stage regressions involve estimating the sensitivity of a bank’s choice variable (lending) to another endogenous variable (liquidity). Our first-stage regressions, in contrast, involves estimating the sensitivity of loan growth to local economic conditions, which are exogenous to the bank’s decision set. This relieves us from having to consider whether our results could be explained away under various scenarios in which banks may choose to behave in a specific way (say, they may hold more liquid assets) when they know their borrowers to be particularly sensitive to monetary policy or business cycles. Our approach, on the other hand, is subject to different types of criticisms.

5.1 Sample Selection: Heckman Correction

One potential source of concern for our tests is sample selection. In particular, we select from the population of insured commercial banks only those small banks belonging to certain types of financial conglomerates. To the extent that financial institutions choose to organize their business as multi-bank firms and may decide whether or not to operate in various geographical regions, one could argue that our data does not come from a random sample of banks. If this sample of banks was constant over the complete time period, this would not be a problem as inference could simply be done conditional on the sample. The potential selection problem is that the sample changes in non-random ways over time as bank holding companies acquire other institutions and consolidate
their subsidiaries into large banks.

Recall that the first stage measures the sensitivity of lending to state-level economic conditions. If there are unobserved financial constraints across banks, changing the number of banks in the holding company will change the average sensitivity of lending to economic conditions unless the holding company adds a bank with a sensitivity exactly at the holding company mean. Note that the lending of more financially constrained banks should be more sensitive to economic conditions, and that the balance sheet channel implies that a monetary expansion should reduce the sensitivity of lending to firm-level financial constraints proxied for by state business conditions. Thus the main threat to identification from sample selection is that during a monetary expansion holding companies are acquiring small banks that are financially unconstrained in unobserved dimensions relative to banks in the holding company. Similarly it would be a problem if the holding company would be acquiring small banks that are financially constrained relative to banks in the holding company during a monetary contraction. Of course, such a story would require a bank’s acquisition strategy to quickly reverse itself as the stance of monetary policy changes, which seems unlikely. However, a more general argument linking geographic diversification to local economic conditions and the monetary policy cycle could pose a challenge to our main conclusions.

Our first line of defense against this argument comes from the fact that the secular movements towards deregulation of conglomerate activities and mergers are already captured in our second stage regression through the included trend. As it turns out, this variable never shows any statistical significance. Our second (more formal) strategy in addressing that argument consists of a couple of Heckman-type corrections for sample selection. We explain the details in turn.

Let \( y_i \) correspond to the sensitivity of loan growth to interest rates. We are interested in how this sensitivity changes in response to the state income gap, which is in the subset of regressors \( x_i \)

\[
y_i = \beta x_i + \varepsilon_i. \tag{23}
\]

Our problem in estimating Eq. (23) is that we do not have a random sample of banks and it is possible that bank holding companies only acquire banks that are operating under a specific set of circumstances (e.g., during state economic booms).

Define \( z_i^* \) an indicator function for being part of the sample, and \( w_i \) the vector of variables which affect this probability

\[
z_i^* = 1(\gamma w_i + u_i > 0). \tag{24}
\]
It is standard to assume \( u_i \) and \( \varepsilon_i \) as bivariate normal random variables with zero mean, variances \( \sigma_u \) and \( \sigma_\varepsilon \), respectively, and correlation \( \rho \). It is also straightforward to demonstrate that the conditional expectation of \( y_i \) for the observations in our sample can be written as

\[
E[y_i | z_i^* > 0] = \beta x_i + E[\varepsilon_i | z_i^* > 0] = \beta x_i + \beta \lambda_i(\gamma w_i),
\]

where \( \lambda_i(z) = \frac{\phi(z)}{1-\Phi(z)} \).

This formulation is important because we are interested in the average marginal effect of \( x_{ik} \) on \( y_i \), but do not observe the variable \( \lambda_i(\gamma w_i) \). The equation below indicates that an OLS regression suffers from omitted variables bias if there is any correlation (or overlap) between regressors in the two equations

\[
\frac{\delta E[y_i | z_i^* > 0]}{\delta x_{ik}} = \beta_k - \gamma_k \rho \sigma_\varepsilon [\gamma^2 w_i - \gamma w_i \lambda_i(\gamma w_i)].
\]

The Heckman (1979) correction for this problem consists a first-stage probit of a dummy indicating selection into the sample on a vector of variables driving selection. From this selection equation it is possible to estimate the omitted variable in Eq. (25) using \( \lambda_i(\gamma w_i) \). With this predicted value in hand, we simply estimate the original equation with this additional regressor for consistent estimates of \( \beta \).

We employ two strategies to deal with sample selection. First, we try to capture the impact on deregulation on geographic diversification and sample inclusion. Several states did not permit multi-bank holding companies to operate in the state until the mid-1980s, and until the mid to late 1980s there were several restrictions on BHC’s ability to acquire out-of-state banks. As we noted above, the U-shaped pattern in the number of banks in the sample (see Table 1) is plausibly explained by deregulation in the 1980s which permitted banks to become affiliated with large multi-state financial conglomerates and then consolidate their subsidiaries into one bank in the 1990s. We correct for these trends in BHC consolidation using a selection equation that includes a full set of state effects, a full set of time effects, and dummy variables indicating that a state has deregulated its branching regulation.\(^{21}\) Our second approach speaks directly to the influence of the monetary policy cycle on sample inclusion. We estimate a Heckman-corrected procedure that includes eight lags of the federal funds rate in the selection equation. In both the deregulation and federal funds Heckman procedures, we use the selection equation to predict inclusion in the sample, and then use this predicted inclusion variable as a control in the first-stage of our two-step estimations.

\(^{21}\)Our branching deregulation proxies are base on Strahan’s (2001).
The results for the Heckman corrected estimations are displayed in Table 6. In both cases, they consistently indicate that changes in the number of banks over the sample period are unlikely to exert any significant influence on our conclusions.

5.2 Non-Random BHC Assignments

The second selection bias we consider as potentially affecting our inferences comes from the non-randomness in the process through which bank affiliates are assigned to their particular BHCs. Mergers and acquisitions are not random events, and are thought to occur whenever it ‘makes economic sense’ to combine certain businesses in specific ways. The banking industry is no exception. Although it is still a matter of debate what is economically sensible in the conglomeration trend in the US banking industry, conceivably, multi-bank conglomerates operate in such a way that could explain why their subsidiaries display different responses to monetary policy shocks. Of course, the only circumstance in which this may be concerning to our conclusions is under a scenario in which underlying reasons why subsidiaries display different responses to monetary policy seem to be correlated — but are not caused by — the financial constraints of their borrowers. While it is difficult to specify a mechanism that could bias our results in a systematic way along those lines, we try to address this possibility (and other similar stories) in a very general way.

Again, the claim is that our inferences are based on the specific sample we have and that the way the data are endogenously presented — rather than the workings of internal capital markets favoring bank affiliates with best borrowers — is responsible for our results. To see whether the patterns in (relative-to-BHC) affiliate loan growth we observe are robust to changes in the structure of the data we “intervene” in the formation of the BHCs by way of a randomization procedure. This consists of randomly re-assigning affiliates in the sample to different conglomerates and estimating our two-step procedure on the randomized parent-affiliate matching. We implement this as follows. First, at each quarter, we compile a basic record of the conglomerates in our sample, which consists of the number of conglomerates and the number of subsidiaries assigned to each of these entities. The next step consists of randomly ‘re-assigning’ the affiliates in each time period to different conglomerates, maintaining the same profile of conglomerates and affiliates for that period. For example, in 1990:IV our sample contains 344 individual bank subsidiaries assigned to 58 different BHCs. Ten of those BHCs controlled four banks, nine controlled three banks, and so on. Our procedure reassigns all of the affiliate banks while maintaining the same conglomerate structures.

The results from the in-sample randomization procedure are presented in Table 7, which has
the same structure of Table 4 above. The $P \phi_k$ estimates have the same sign and level of statistical significance of those displayed in Table 4 and point us to similar conclusions about a dimension of the balance sheet channel of monetary policy that is identified through data from financial conglomerates.

6 Conclusions

The analysis of this paper shows that there are important differences in the response of bank loan growth to monetary policy over the state business cycle. We argue that our evidence is consistent with a balance sheet channel of monetary policy. Our results have a number of implications for the monetary authority. For example, they suggest that when engaging in monetary policy, the central bank should consider the amplification of changes in the federal funds rate on the real economy created by firm-level financial constraints. In particular, barring the presence of other asymmetries in the transmission mechanism (which we don’t dispute), expansionary monetary policy should generally be more restrained during a recession than contractionary monetary policy during a boom. Our findings also add to the growing literature on the role internal capital markets play in the allocation of funds within conglomerate firms, particularly in financial conglomerates. This in turn points at need to understand in more detail the influence of conglomerate (and merger waves) on the impact of Federal Reserve policies on bank lending activity.

The big question, of course, is whether or not firm-level financial constraints are important enough to explain the aforementioned excessive sensitivity of the real economy to monetary policy. In order to develop evidence on this question, we plan to extend this research by studying the response of state income to monetary policy across state-level measures of firm balance sheet strength.
References


Appendix A: Construction of Panel Bank Microdata

All of the bank-level data used in the analysis is derived from the Federal Reserve’s *Report of Condition and Income (Call Reports)*. We employ a version of the *Call Reports* cleaned by the Banking Studies Function of the Federal Reserve, and thus may differ from the data made publicly available online at the Federal Reserve Bank of Chicago. We collect quarterly data on insured commercial banks over 1976:I-1998:II, where our definition of a commercial bank is similar to that employed by the Banking Studies Section of the Federal Reserve Bank of New York. This requires the bank type (RSSD9331) be identified as a “commercial bank” by having a value equal to one and the reporting level code (CALL8786) identified as “Not Applicable” by having a value equal to zero. FDIC-insured banks are identified by the deposit insurance status (RSSD9424) reflecting the FDIC as the bank’s insurer by having a value of 1. In order to match banks to local economic conditions, it is necessary to eliminate banks which are chartered outside of the 50 states or the District of Columbia. This is done by eliminating banks which have a state code (RSSD9210) greater than 57.

There are many well-known reporting discontinuities in the data and rely on notes by Anil Kashyap and Jeremy Stein published online by the Federal Reserve Bank of Chicago to construct consistent times series. Each of the variables used in our analysis are constructed as follows:

**Loans.** The aggregate gross book value of total loans and leases before deduction of valuation reserves (RCFD1400) includes: (a) acceptances of other banks and commercial paper purchased in open market; (b) acceptances executed by or for account of reporting bank and subsequently acquired by it through purchase or discount; (c) customers’ liability to reporting bank on drafts paid under letter of credit for which bank has not been reimbursed; and (d) “cotton overdrafts” or “advances”, and commodity or bill of lading drafts payable upon arrival of goods against which drawn for which reporting bank has given deposit credit to customers. Also includes: (a) paper rediscouned with Federal Reserve or other banks; and (b) paper pledged as collateral to secure bills payable, as marginal collateral to secure bills rediscouned, or for any other purpose. Before 1984:I, this item does not include lease-financing receivables, so in order to ensure continuity, total loans must be computed as the sum of total loans (RCFD1400) and lease-financing receivables (RCFD2165) for the period prior to 1984:I.

**Bad Loans.** The measure of loan performance employed avoids managerial discretion in reporting losses, and is similar to the proxy is used by Lucas and McDonald (1992). Bad loans are defined as the ratio of the sum of loans not accruing (RCFD1403) and loans over 90 days late (RCFD1407), divided by total loans. Loans not accruing (RCFD1403) measures the outstanding balances of loans and lease financing receivables that the bank has placed in nonaccruing status. Also includes all restructured loans and lease financing receivables that are in nonaccrual status. Loans
and lease financing receivables are to be reported in nonaccrual status if: a) they are maintained on a cash basis because of deterioration in the financial position of the borrower, or b) principal or interest has been in default for a period of 90 days or more unless the obligation is both “well secured” and “in the process of collection”. Loans over 90 days late (RCFD1407) measures loans and lease financing receivables on which payment is due and unpaid for 90 days or more. The measure includes all restructured loans and leases after 1986:II, which was reported separated as Renegotiated “Troubled” Debt (RCFD1404).

Capitalization. The capital-to-asset ratio is computed as equity (RCFD3210) divided by total assets (RCFD2170). Equity capital (RCFD3210) is the sum of “Perpetual Preferred Stock and Related Surplus”, “Common Stock”, “Surplus”, “Undivided Profits and Capital Reserves”, “Cumulative Foreign Currency Translation Adjustments” less “Net Unrealized Loss on Marketable Equity Securities”.

Deposits. Total deposits are measured using item RCFD2200.

Bank Size. At each quarter, all banks in the data are ranked according to their total assets (RCFD2170). Small and large banks are identified using the 95th percentile of the asset distribution as a size cut-off.

Multi-Bank Holding Company Affiliation. Affiliation with a multi-bank holding company is identified the number of insured commercial banks that have a common regulatory direct holder (RSSD9348) or high holder (RSSD9379) being larger than one.

Large Multi-Bank Holding Company Affiliation. Affiliation with a large multi-bank holding company is determined by the holding company owning more than one bank and either the regulatory direct holder or regulatory high holder owning at least one subsidiary considered to be a large commercial bank.

Large Multi-State Bank Holding Company Affiliation. Affiliation with a large multi-state bank holding company is determined by the holding company being a large multi-bank holding company that has two small subsidiaries operating in separate states (RSSD9210).
Appendix B: Measures of Monetary Policy

The monetary policy measures we use are standard in the literature. All of our policy measures are constructed with series available from the Federal Reserve system’s data bank.

Fed Funds. We use the monthly series of effective annualized Fed funds rates from the Board of Governors’ Release H.15. Bernanke and Blinder (1992) argue that this rate captures the stance of monetary policy well because it is sensitive to shocks to the supply of bank reserves. The Fed funds rate is the prevalent measure of monetary policy in related empirical work. However, the adequacy of this proxy has been questioned for periods when the Fed’s operating procedures were modified (e.g., the Volker period).

Funds–Bill. Motivated by Bernanke and Blinder (1992), this is computed as the difference between the effective annual Fed funds rate and the rate on 10-year Treasury bills. These series are gathered from Board of Governors’ Release H.15.

CP-Bill. This is computed as the difference between the rates paid on six-month prime rated commercial papers and 180-day Treasury bills. These series are also available from Board of Governors’ Release H.15, but the paper series is discontinued in 1997:I. The paper rates are given as discount rates and the Treasury bill as coupon equivalent rates. We transform both series into effective yield rates before computing the difference. Bernanke (1990) argues that CP-Bill increases capture Fed tightenings since banks will cut loans and corporations are forced to substitute commercial paper for bank loans.

Strongin. Strongin (1995) argues that previous studies attempting to identify the stance of monetary policy fail to properly address the Fed’s strategy of accommodating reserve demand shocks. Strongin measures the portion of non-borrowed reserves growth that is orthogonal to total reserve growth. It equals the residual of a linear regression of total reserves on non-borrowed reserves, where both series are normalized by a 24-month moving average of total reserves prior to the estimation. We perform this computation using data from the Federal Reserve’s FRED data bank.
Table 1: Banks Part of Large Multi-State Holding Companies

<table>
<thead>
<tr>
<th>Year</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>77</td>
<td>0</td>
<td>195</td>
<td>194</td>
<td>195</td>
<td>584</td>
</tr>
<tr>
<td>78</td>
<td>195</td>
<td>195</td>
<td>196</td>
<td>196</td>
<td>782</td>
</tr>
<tr>
<td>79</td>
<td>196</td>
<td>196</td>
<td>198</td>
<td>197</td>
<td>787</td>
</tr>
<tr>
<td>80</td>
<td>198</td>
<td>199</td>
<td>199</td>
<td>200</td>
<td>796</td>
</tr>
<tr>
<td>81</td>
<td>202</td>
<td>202</td>
<td>204</td>
<td>195</td>
<td>803</td>
</tr>
<tr>
<td>82</td>
<td>197</td>
<td>197</td>
<td>198</td>
<td>198</td>
<td>790</td>
</tr>
<tr>
<td>83</td>
<td>208</td>
<td>213</td>
<td>206</td>
<td>195</td>
<td>822</td>
</tr>
<tr>
<td>84</td>
<td>206</td>
<td>189</td>
<td>200</td>
<td>189</td>
<td>784</td>
</tr>
<tr>
<td>85</td>
<td>237</td>
<td>234</td>
<td>293</td>
<td>286</td>
<td>1,050</td>
</tr>
<tr>
<td>86</td>
<td>320</td>
<td>357</td>
<td>411</td>
<td>576</td>
<td>1,664</td>
</tr>
<tr>
<td>87</td>
<td>665</td>
<td>778</td>
<td>739</td>
<td>801</td>
<td>2,983</td>
</tr>
<tr>
<td>88</td>
<td>892</td>
<td>883</td>
<td>854</td>
<td>823</td>
<td>3,452</td>
</tr>
<tr>
<td>89</td>
<td>862</td>
<td>859</td>
<td>871</td>
<td>849</td>
<td>3,441</td>
</tr>
<tr>
<td>90</td>
<td>835</td>
<td>800</td>
<td>794</td>
<td>751</td>
<td>3,180</td>
</tr>
<tr>
<td>91</td>
<td>733</td>
<td>762</td>
<td>745</td>
<td>722</td>
<td>2,962</td>
</tr>
<tr>
<td>92</td>
<td>693</td>
<td>713</td>
<td>724</td>
<td>717</td>
<td>2,847</td>
</tr>
<tr>
<td>93</td>
<td>684</td>
<td>737</td>
<td>717</td>
<td>713</td>
<td>2,851</td>
</tr>
<tr>
<td>94</td>
<td>695</td>
<td>706</td>
<td>631</td>
<td>656</td>
<td>2,688</td>
</tr>
<tr>
<td>95</td>
<td>596</td>
<td>597</td>
<td>599</td>
<td>575</td>
<td>2,367</td>
</tr>
<tr>
<td>96</td>
<td>578</td>
<td>520</td>
<td>490</td>
<td>480</td>
<td>2,068</td>
</tr>
<tr>
<td>97</td>
<td>468</td>
<td>430</td>
<td>0</td>
<td>0</td>
<td>898</td>
</tr>
<tr>
<td>Total</td>
<td>9,660</td>
<td>9,962</td>
<td>9,463</td>
<td>9,514</td>
<td>38,599</td>
</tr>
</tbody>
</table>
Table 2: Descriptive Statistics on Small Banks

<table>
<thead>
<tr>
<th></th>
<th>In the Sample</th>
<th>Not in the Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta \ln(\text{Loans})_{ijt}$</td>
<td>0.0157</td>
<td>0.0211</td>
</tr>
<tr>
<td></td>
<td>(0.0764)</td>
<td>(0.0680)</td>
</tr>
<tr>
<td>$\text{BadLoans}_{ijt}$</td>
<td>0.0144</td>
<td>0.0156</td>
</tr>
<tr>
<td></td>
<td>(0.0259)</td>
<td>(0.0267)</td>
</tr>
<tr>
<td>$\ln(\text{Assets})_{ijt-1}$</td>
<td>11.4992</td>
<td>10.3804</td>
</tr>
<tr>
<td></td>
<td>(0.8750)</td>
<td>(0.9803)</td>
</tr>
<tr>
<td>$(\text{Equity}/\text{Assets})_{ijt-1}$</td>
<td>0.0811</td>
<td>0.0912</td>
</tr>
<tr>
<td></td>
<td>(0.0406)</td>
<td>(0.0340)</td>
</tr>
<tr>
<td>$(\text{Securities}/\text{Assets})_{ijt-1}$</td>
<td>0.2378</td>
<td>0.2987</td>
</tr>
<tr>
<td></td>
<td>(0.1406)</td>
<td>(0.1447)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Loans})_{ij}$</td>
<td>0.0240</td>
<td>0.0245</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0189)</td>
</tr>
<tr>
<td>$\text{BadLoans}_{ij}$</td>
<td>0.0118</td>
<td>0.0148</td>
</tr>
<tr>
<td></td>
<td>(0.0143)</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>$\Delta \ln(\text{Loans})<em>{ijt} - \Delta \ln(\text{Loans})</em>{ij}$</td>
<td>-0.0084</td>
<td>-0.0034</td>
</tr>
<tr>
<td></td>
<td>(0.0748)</td>
<td>(0.0668)</td>
</tr>
<tr>
<td>$\text{BadLoans}<em>{ijt} - \text{BadLoans}</em>{ij}$</td>
<td>0.0026</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0235)</td>
</tr>
<tr>
<td>$\Delta \ln(YGapijt) - \Delta \ln(YGapij)$</td>
<td>0.0006</td>
<td>0.0008</td>
</tr>
<tr>
<td></td>
<td>(0.0245)</td>
<td>(0.0265)</td>
</tr>
<tr>
<td>$\Omega^{\text{Loans}}_{ijt}$</td>
<td>-0.0009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0672)</td>
<td></td>
</tr>
<tr>
<td>$\Omega^{\text{BadLoans}}_{ijt}$</td>
<td>-0.0001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0211)</td>
<td></td>
</tr>
<tr>
<td>$\Omega_{ijt}^{\text{Loans}}$</td>
<td>-0.0005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0631)</td>
<td></td>
</tr>
<tr>
<td>$\Omega_{ijt}^{\text{BadLoans}}$</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0163)</td>
<td></td>
</tr>
</tbody>
</table>

$N$ = 38,599, 926,845

*Table Notes:* The table refers to the sample mean and standard deviation for a variety of variables in the population of small insured commercial banks. The first column refers to small banks that are part of large multi-state bank holding companies while the second column refers to all other small banks. Panel A includes quarterly loan growth, bad loans as a fraction of total loans, one lag of log bank assets, one lag of bank leverage, one lag of bank liquidity, average quarterly loan growth and bad loans for the bank, the difference in quarterly loan growth and bad loans from its long-run average, and the state income gap. Panel B contains the sample mean and standard deviation for variables that are involved in differencing bank-level variables from the average subsidiary in the holding company. Reading down, the measures include loan growth and bad loans differenced from their holding company subsidiary mean, the long-run average difference in loan growth and bad loans across subsidiaries, and finally the difference between these previous two measures.
### Table 3: Local Economic Conditions and Bank Loan Quality

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>$\Omega_{ijt}^{BadLoans}$</th>
<th>$\Omega_{ijt}^{BG\text{Loans}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>A. Borrower’s Balance Sheet proxyed by $\Delta \ln (\text{YGap}_{ijt})$</td>
<td>-0.0244 (0.0141)</td>
<td>-0.0295 (0.0083)</td>
</tr>
<tr>
<td>B. Borrower’s Balance Sheet proxyed by $\Omega_{ijt}^{YGap}$</td>
<td>-0.0420 (0.0168)</td>
<td>-0.0267 (0.0108)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bank Fixed Effects</th>
<th>No</th>
<th>Yes</th>
<th>No</th>
<th>Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>36,090</td>
<td>36,090</td>
<td>36,090</td>
<td>36,090</td>
</tr>
</tbody>
</table>

**Table Notes:** The table refers a regression of a function of bank-level bad loans on state economic activity and other covariates. This measure of economic activity includes the state income gap in Panel A and the difference in state income gap from the average gap faced by banks in the subsidiary in Panel B. In the first three columns the dependent variable is the difference in bad loans from the holding company mean while in the final three columns it is this variable differenced again against its long-run mean. The coefficient on state economic activity is reported as well as standard errors, which have been corrected for heteroskedasticity and are clustered at the bank level in specifications that do not use bank-fixed effects.
Table 4: Monetary Policy and the Balance Sheet Channel

<table>
<thead>
<tr>
<th>First Stage Measure of Monetary Policy</th>
<th>CP-Bill</th>
<th>Fed Funds</th>
<th>Funds-Bill</th>
<th>Strongin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A. Borrower’s Balance Sheet proxyed by $\Delta ln(YGap_{ijt})$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega^{Loans}_{ijt}$</td>
<td>0.200</td>
<td>0.041</td>
<td>0.036</td>
<td>0.793</td>
</tr>
<tr>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.036)</td>
<td>(0.015)</td>
<td></td>
</tr>
<tr>
<td>$\Omega^{G_{loans}}_{ijt}$</td>
<td>0.143</td>
<td>0.042</td>
<td>0.054</td>
<td>0.931</td>
</tr>
<tr>
<td>(0.027)</td>
<td>(0.009)</td>
<td>(0.039)</td>
<td>(0.181)</td>
<td></td>
</tr>
<tr>
<td>B. Borrower’s Balance Sheet proxyed by $\Omega^{YGap}_{ijt}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega^{Loans}_{ijt}$</td>
<td>0.215</td>
<td>0.032</td>
<td>0.039</td>
<td>1.070</td>
</tr>
<tr>
<td>(0.024)</td>
<td>(0.063)</td>
<td>(0.323)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>$\Omega^{G_{loans}}_{ijt}$</td>
<td>0.100</td>
<td>0.031</td>
<td>0.055</td>
<td>0.942</td>
</tr>
<tr>
<td>(0.266)</td>
<td>(0.065)</td>
<td>(0.124)</td>
<td>(0.096)</td>
<td></td>
</tr>
</tbody>
</table>

Table Notes: The table refers to the second stage regression described in the text. The dependent variable is the average sensitivity of bank loan growth to the state economic activity, while explanatory variables include 8 lags of monetary policy measures, 8 lags of aggregate output growth, a time trend, and quarter effects. The table reports the sum of coefficients on the 8 lags of each measure of monetary policy and the $p$-value for the hypothesis test that this sum is no different from zero. Each of the last five columns refers to specifications characterized by the employed measure of monetary policy. In Panel A, borrowers’ balance sheet strength is proxyed by $\Delta ln(YGap_{ijt})$, while in Panel B the relevant proxy is $\Omega^{YGap}_{ijt}$. 

34
Table 5: Cumulative Balance Sheet Effect of the Funds Rate on Lending

<table>
<thead>
<tr>
<th>First Stage Cumulative Lags of the Funds Rate</th>
<th>Dependent Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Borrower’s Balance Sheet proxyed by $\Delta \ln(Y_{Gap_{ijt}})$</td>
<td>$\Omega_{\text{Loans}_{ijt}}$</td>
<td>0.017</td>
<td>0.024</td>
<td>0.021</td>
<td>0.024</td>
<td>0.026</td>
<td>0.029</td>
<td>0.039</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.175)</td>
<td>(0.144)</td>
<td>(0.239)</td>
<td>(0.173)</td>
<td>(0.142)</td>
<td>(0.102)</td>
<td>(0.034)</td>
<td>(0.020)</td>
</tr>
<tr>
<td></td>
<td>$\Omega_{\text{Loans}_{ijt}}$</td>
<td>0.016</td>
<td>0.023</td>
<td>0.022</td>
<td>0.026</td>
<td>0.026</td>
<td>0.030</td>
<td>0.039</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.149)</td>
<td>(0.107)</td>
<td>(0.162)</td>
<td>(0.124)</td>
<td>(0.137)</td>
<td>(0.112)</td>
<td>(0.028)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>B. Borrower’s Balance Sheet proxyed by $\Omega_{Y_{Gap}}$</td>
<td>$\Omega_{\text{Loans}_{ijt}}$</td>
<td>0.023</td>
<td>0.024</td>
<td>0.019</td>
<td>0.025</td>
<td>0.027</td>
<td>0.029</td>
<td>0.036</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.133)</td>
<td>(0.158)</td>
<td>(0.299)</td>
<td>(0.157)</td>
<td>(0.087)</td>
<td>(0.049)</td>
<td>(0.049)</td>
<td>(0.063)</td>
</tr>
<tr>
<td></td>
<td>$\Omega_{\text{Loans}_{ijt}}$</td>
<td>0.019</td>
<td>0.020</td>
<td>0.017</td>
<td>0.022</td>
<td>0.022</td>
<td>0.025</td>
<td>0.033</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.118)</td>
<td>(0.147)</td>
<td>(0.327)</td>
<td>(0.223)</td>
<td>(0.210)</td>
<td>(0.160)</td>
<td>(0.083)</td>
<td>(0.065)</td>
</tr>
</tbody>
</table>

Table Notes: The table refers to the second-stage regression described in the text. The dependent variable is the average sensitivity of bank loan growth to the state economic activity, while explanatory variables include 8 lags of monetary policy measures, 8 lags of aggregate output growth, a time trend, and quarter effects. The table reports the sum of coefficients on lags of the funds rate and the $p$-value for the hypothesis test that this sum is no different from zero. Each of the last eight columns refers to statistics characterized by the number of lags over which to sum. In Panel A, borrowers’ balance sheet strength is proxyed by $\Delta \ln(Y_{Gap_{ijt}})$, while in Panel B the relevant proxy is $\Omega_{Y_{Gap}}$. 
Table 6: Heckman Sample Selection Correction

<table>
<thead>
<tr>
<th>First Stage Measure of Monetary Policy</th>
<th>CP-Bill</th>
<th>Fed Funds</th>
<th>Funds-Bill</th>
<th>Strongin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### A. Branching Variables in Selection Equation

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega_{ij,t}^{Loans}$</td>
<td>0.212</td>
<td>0.039</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.047)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>$\Omega_{ij,t}^{g}$</td>
<td>0.157</td>
<td>0.032</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td>(0.093)</td>
<td>(0.094)</td>
<td>(0.089)</td>
</tr>
</tbody>
</table>

### B. Lagged Funds Rate in Selection Equation

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Omega_{ij,t}^{Loans}$</td>
<td>0.145</td>
<td>0.034</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td>(0.024)</td>
<td>(0.259)</td>
</tr>
<tr>
<td>$\Omega_{ij,t}^{g}$</td>
<td>0.111</td>
<td>0.029</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>(0.155)</td>
<td>(0.047)</td>
<td>(0.204)</td>
</tr>
</tbody>
</table>

**Table Notes:** The table refers to the second stage regression described in the text. The dependent variable is the average sensitivity of bank loan growth to the state economic activity, while explanatory variables include 8 lags of monetary policy measures, 8 lags of aggregate output growth, a time trend, and quarter effects. The table reports the sum of coefficients on the 8 lags of each measure of monetary policy and the p-value for the hypothesis test that this sum is no different from zero. Each of the last five columns refers to specifications characterized by the employed measure of monetary policy. Each specification uses the state income gap in the first-stage regression. In Panel A we use dummies for state branching deregulation in the selection equation while in Panel B we use eight lags of the federal funds rate.
Table 7: Random Assignment of Bank Holding Companies

<table>
<thead>
<tr>
<th>First Stage Measure of Monetary Policy</th>
<th>CP-Bill</th>
<th>Fed Funds</th>
<th>Funds-Bill</th>
<th>Strongin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. Variable</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A. Borrower’s Balance Sheet proxyed by $\Delta ln(YGap_{ijt})$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega_{ijt}^{Loans}$</td>
<td>0.214</td>
<td>0.038</td>
<td>0.038</td>
<td>1.890</td>
</tr>
<tr>
<td>(0.061)</td>
<td></td>
<td>(0.023)</td>
<td>(0.099)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$\Omega_{ijt}^{Yloans}$</td>
<td>0.241</td>
<td>0.041</td>
<td>0.077</td>
<td>2.577</td>
</tr>
<tr>
<td>(0.075)</td>
<td></td>
<td>(0.022)</td>
<td>(0.130)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>B. Borrower’s Balance Sheet proxyed by $\Omega_{ijt}^{YGap}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Omega_{ijt}^{Loans}$</td>
<td>0.240</td>
<td>0.043</td>
<td>0.028</td>
<td>1.869</td>
</tr>
<tr>
<td>(0.041)</td>
<td></td>
<td>(0.014)</td>
<td>(0.036)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>$\Omega_{ijt}^{Yloans}$</td>
<td>0.265</td>
<td>0.045</td>
<td>0.073</td>
<td>2.526</td>
</tr>
<tr>
<td>(0.056)</td>
<td></td>
<td>(0.015)</td>
<td>(0.146)</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

Table Notes: The table refers to the second stage regression described in the text. The dependent variable is the average sensitivity of bank loan growth to the state economic activity, while explanatory variables include 8 lags of monetary policy measures, 8 lags of aggregate output growth, a time trend, and quarter effects. The table reports the sum of coefficients on the 8 lags of each measure of monetary policy and the $p$-value for the hypothesis test that this sum is no different from zero. Each of the last five columns refers to specifications characterized by the employed measure of monetary policy. In Panel A, borrowers’ balance sheet strength is proxyed by $\Delta ln(YGap_{ijt})$, while in Panel B the relevant proxy is $\Omega_{ijt}^{Y$.
Figure 1: First-Stage Estimates of Gamma