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FINANCIAL DAMPENING

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ABSTRACT

We propose a novel mechanism, "financial dampening," whereby loan retrenchment by banks attenuates the effectiveness of monetary policy. The theory unifies an endogenous supply of illiquid local loans and risk-sharing among subsidiaries of bank holding companies (BHCs). We derive an IV-strategy that separates supply-driven loan retrenchment from local loan demand, by exploiting linkages through BHC-internal capital markets across spatially-separate BHC member-banks. We estimate that retrenching banks increase loan supply substantially less in response to exogenous monetary policy rate reductions. This relative decline has persistent effects on local employment and thus provides a rationale for slow recoveries from financial distress.

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1 Introduction

Monetary policy responded aggressively to the fallout caused by the 2008 financial crisis by cutting the Federal Funds rate all the way to zero, issuing forward guidance and conducting large-scale asset purchases. Yet despite these large, and unprecedented policy actions, the recovery from the Great Recession has been slow. This seemed to support the hypothesis that in the aftermath of financial crises, recoveries are typically sluggish. The basis of this "financial crises recoveries are different" hypothesis is typically cross-country empirical evidence as in Reinhart and Rogoff (2008) and Cerra and Saxena (2008). Yet, we currently lack a clear conceptual or empirical understanding of the mechanisms that might render recoveries after financial distress different from other recoveries.

We propose a novel mechanism that dampens the potency of monetary policy, particularly after financial crises. We focus on the phenomenon of loan retrenchment, commonly associated with financial distress, whereby banks seek to systematically reduce their exposure to non-tradable loan risks. We build on the framework of Froot and Stein (1998), which provides a unified perspective on risk management and capital structure in financial institutions. In our micro-founded model, loan retrenchment combined with loan liquidation costs reduces the pass-through from monetary policy rate changes to loan supply (the "Bank Lending Channel"), which attenuates the effectiveness of monetary policy.

To build intuition, consider the case were bank loans are completely illiquid, so retrenching banks cannot actively reduce their loan portfolio. Thus, their target loan exposure is less than their actual loan exposure. A reduction in the monetary policy rate does increase the target loan exposure of these banks, but so long as it is below the actual loan exposure no new loans will be forthcoming. By contrast, a bank that does not retrench will increase loan supply since its target loan exposure increased. The same logic also applies to monetary policy rate increases: a retrenching bank cannot reduce its loan exposure due to loan illiquidity, dampening the impact of monetary policy on loan supply, whereas an expanding bank can reduce new loan issuance. Thus, the degree of loan retrenchment is an important state variable influencing the effectiveness of monetary policy rate reductions, a mechanism we call "financial dampening."

We empirically investigate how financial dampening mitigates the transmission of monetary policy shocks on local lending. Like much of the empirical literature on financial frictions, we face an identification challenge since local loan volumes could be driven by local loan demand shocks, rather than changes in loan supply. To understand how to overcome this identification problem, we incorporate it into our model: a low sensitivity of loan quantities to monetary policy shocks can occur either because of supply-driven loan retrenchment or constrained local loan demand. Simple OLS estimates therefore do not correctly uncover financial dampening.

To show how our spatial IV-strategy can overcome this identification problem, our model also incorporates two previously documented features of U.S. banking. First, U.S. banking is very local as emphasized by Becker (2007). We independently document this local nature by showing that more than 50% of commercial banks essentially operate only in one county, 65% only in one metropolitan area, and over 95% only in one state. Second, commercial banks are typically part of larger financial conglomerates or bank holding companies (BHC). Furthermore, BHCs do not only own commercial banks from several distinct areas, but BHC-member banks share a single internal capital market (Houston, James, and Marcus, 1997; Campello, 2002). In the model, local banks use this internal capital market to insure against non-tradable risks from illiquid local loans.

These features imply that an increase in the BHC's internal capital cost imparts a common force for supply-driven loan retrenchment across all BHC-member banks, since now insurance against non-tradable risks becomes more expensive. Further, geographically-separate BHC-member banks are not subject to the same local demand constraints. Thus, average loan retrenchment at spatially-separate BHC-member banks can be used as an instrument for local loan retrenchment. We then show that if banks are small and demand shocks are spatially uncorrelated, then our instrument can consistently estimate the importance of supply-driven financial dampening.

We derive the empirical specification for our IV strategy from the model and estimate results consistent with our theory: in response to a -1% monetary policy shock, a bank at the 25^{th} percentile of the loan growth distribution increases its loan growth by 3.25 percentage points less than a bank at the 75^{th} percentile according to our baseline specification. We provide several robustness checks that our estimates are not biased by spatial correlation of local demand shocks, reverse causality from large BHC-member banks, or regulatory changes. We also show that financial dampening channel is distinct from other bank characteristics such as bank size (Kashyap and Stein, 2000), the level of leverage (Bernanke, Gertler, and Gilchrist, 1999; Van den Heuvel, 2005), and capital growth which can capture profitability or bank-specific weaknesses.

We then show that employment growth responds significantly less to monetary policy in counties with banks subject to supply-driven loan retrenchment. The employment effects of monetary policy are 0.52 percentage points lower after two years for counties at the 25^{th} percentile of the loan growth distribution compared to the median county. Assuming that the median county corresponds to aggregate employment effects, this renders monetary policy only half as effective at stimulating employment growth in counties at the 75^{th} percentile. We then apply these estimates to the U.S. economy, where loan growth in post-1990 recoveries was substantially slower, and the fraction of retrenching banks remained persistently higher, than in pre-1990 recoveries. These calculations imply that the financial dampening mechanism accounts for 0.85 percentage points slower employment growth in post-1990 recoveries. This suggests that financial dampening is likely an important mechanism in the aggregate, and a micro-founded and empirically-supported mechanism for why recoveries after financial distress may be slow.

This paper relates to at least five strands of literature. First, it emphasizes the role of financial intermediation in the propagation of monetary shocks, as in Kashyap and Stein

(1995, 2000), Campello (2002) and Landier, Sraer, and Thesmar (2013) among others. Relative to the existing literature we propose a novel mechanism—financial dampening—that affects the strength of this "bank lending channel." Van den Heuvel (2005) also emphasizes state-contingency of the credit channel when the *level* of leverage is close to the regulatory maximum.[1] Our mechanism instead emphasizes the desired *change* in loan holdings, which is not dependent on being close to a capital requirement. We provide empirical results showing that our financial dampening channel is distinct from regulatory capital considerations. First, we drop banks and BHCs close to regulatory capital requirements. Second, we control for leverage as well as leverage categories to separate Van den Heuvel's regulatory capital channel from financial dampening. While we find evidence consistent with Van den Heuvel (2005), our estimates of the financial dampening channel are unchanged, suggesting that it operates independently from his mechanism.

Second, our work is related to the empirical work on the link between financial shocks and real economic outcomes (Peek and Rosengren, 2000b; Chodorow-Reich, 2014; Amiti and Weinstein, 2013; Giroud and Mueller, 2015). Using lenders operating in multiple geographic areas to control for local loan demand is similar is spirit to Peek and Rosengren (2000a), Amiti and Weinstein (2013), Greenstone, Mas, and Nguyen (2014) and Mondragon (2014). These papers are either event studies of natural experiments or rely on annual variation. By contrast, we construct a quarterly panel dataset of lenders, which is better suited to analyze the impact of financial dampening on monetary policy transmission at business cycle frequencies. Furthermore, while this literature analyzes the real effects of financial shocks, we focus on the degree to which financial sector retrenchment dampens the real effects of monetary policy.

Third, our banking model features two key ingredients. We stress the connection of capital cushions and the optimal exposure to non-tradable loan risks following the theoret-

[1] In his model banks close to minimum capital requirements have non-monotonic lending behavior, by first retrenching and then gambling for resurrection. For medium values of leverage, banks reduce lending as they try to avoid hitting the minimum capital requirement. With a high level of leverage banks are very close to bankruptcy and optimally expand lending due to the fact that bankruptcy costs are limited.

ical framework of Froot and Stein (1998). Consistent with this framework, Cebenoyan and Strahan (2004) show that the subset of banks actively selling loans hold systematically less capital than other banks. We also follow a broad theoretical and empirical literature emphasizing the illiquidity of bank loans, which creates asymmetric loan portfolio adjustment costs (e.g, Diamond and Dybvig, 1983; Kashyap and Stein, 1995; Bianchi and Bigio, 2014, among many others). We do not provide a deep micro-foundation for illiquidity and instead appeal to existing work highlighting market and/or information frictions that generate illiquidity (e.g., Diamond, 1984; Holmstrom and Tirole, 1997; Afonso and Lagos, 2012). To the extent that liquidation costs are greater in times of financial distress, the financial dampening channel becomes more important. Thus, our results also relate to Coval and Stafford (2007), Campbell, Giglio, and Pathak (2011), Ellul, Jotikasthira, and Lundblad (2011) and Greenwood and Thesmar (2011) that empirically document how higher selling pressure leads to disproportional price discounts. Understanding asymmetries in financial market is also the focus recent dynamic equilibrium models with financial frictions (e.g., Brunnermeier and Sannikov, 2014; He and Krishnamurthy, 2013).

Fourth, our work shows that commercial banks may fail to increase loan growth, even if monetary policy reduces funding costs by lowering monetary policy rates. This suggests that financial dampening may be an important ingredient for quantitative business cycle models with financial frictions (e.g., Bernanke et al., 1999; Gertler and Karadi, 2011).[2] In these models, the effectiveness of monetary policy is increasing in the level of leverage, whereas financial dampening mechanism emphasizes the desired change in financial sector loan holdings. Thus, even if current leverage is high, as in the most recent recession (He, Khang, and Arvind, 2010; Ang, Gorovyy, and Van Inwegen, 2011), the effectiveness of monetary policy can be attenuated by the desire of the financial sector to retrench. We do not study the direct effect of financial sector retrenchment on economic activity, as is done by Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2012) and Mian, Rao, Sufi et al. (2013) among

[2] Bigio (2014) explores how asymmetric information can imply the failure of endogenous equity injections as a stabilizing force for financial intermediaries hit by negative shocks.

others.

Fifth, our results imply that the effectiveness of monetary policy is contingent on the state of the financial sector. Existing work has instead emphasized differential effectiveness in recessions and expansions (e.g., Angrist, Jordà, and Kuersteiner, 2013; Barnichon and Matthes, 2014; Tenreyro and Thwaites, 2013) or based on uncertainty (Vavra, 2013).

2 Model

2.1 Overview Our model is an extended version of the seminal analysis of Froot and Stein (1998), which provides a unified treatment of risk management and capital structure choice for financial institutions. We extend their framework in three ways to align the model with our specific empirical application. First, we model the behavior of local BHC subsidiaries, which are connected through a BHC internal capital market. Second, each local bank can choose to invest in either safe, liquid securities or create/liquidate illiquid, risky loans. Third, we allow for unobservable changes in local loan demand that will affect the responsiveness of banks to monetary policy and therefore complicate identification of a supply-driven financial-dampening channel. We directly derive our estimation equation and instrumental-variable strategy from this model.

2.2 Economic Environment and Timing Our exposition closely follows Froot and Stein (1998). Let $i \in \Omega_h$ index a local bank that is part of a bank holding company h. We assume for simplicity that each bank i is a small part of the BHC and each bank operates on a separate island. Each local bank i has the choice to invest in illiquid loans or liquid, safe securities. We denote these choices as $L_{i,h}$ and $S_{i,h}$ respectively. These investments are in turn funded by an exogenously given local deposit base $\widetilde{D}_{i,h}$ or capital provided by the BHC, denoted $K_{i,h}$. A local bank's balance sheet is therefore given by

$$L_{i,h} + S_{i,h} = \widetilde{D}_{i,h} + K_{i,h} \tag{1}$$

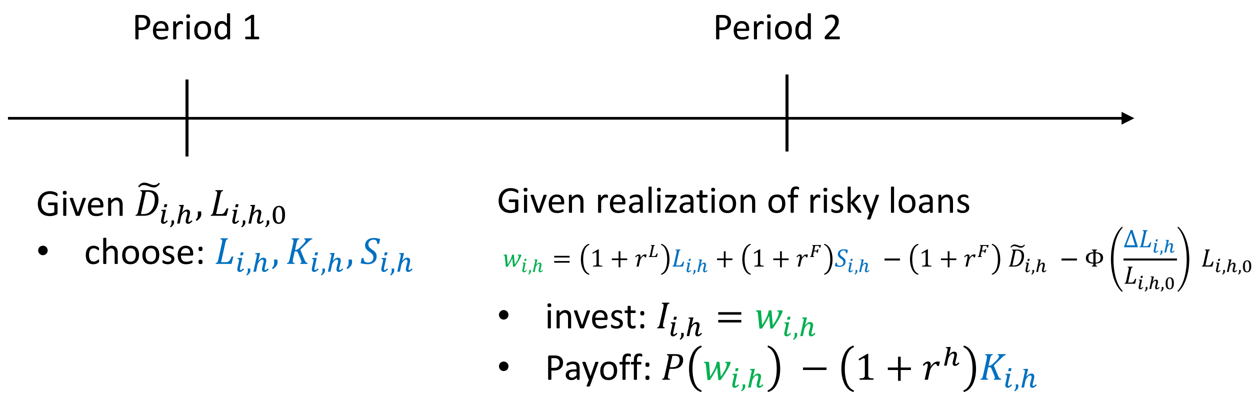


Figure 1 – Timing

The model has two subperiods as shown in figure 1. In period 1, local banks start with a given deposit base $\widetilde{D}_{i,h}$ and a given past loan portfolio $L_{i,h,0}$. Local banks decide how much to invest in loans and safe securities $L_{i,h}$ and $S_{i,h}$, while at the same time deciding how much capital $K_{i,h}$ to demand from the BHC internal capital market. Safe securities $S_{i,h}$ and deposits $\widetilde{D}_{i,h}$ pay the same safe return r^F, while loans $L_{i,h}$ pay a random return $r^L \sim N(\bar{r}^L, \sigma_\varepsilon^2)$.[3]

We assume throughout that banks' loan portfolio risks are untradable. This assumption can be relaxed following the original model of Froot and Stein (1998), where banks optimally hedge all tradable risks away so that only non-tradable risks remain on banks balance sheets. Our model can therefore be understood as a model of the net exposure to non-tradable loan risks, after tradable risks have been hedged using derivatives.

Since our model focuses on non-tradable loan portfolio risks, loans are subject to quadratic liquidation costs. Thus, to liquidate $x * 100$ percent of its initial loan portfolio, the bank has to pay a cost $\Psi(x)L_{i,h,0} = \frac{\psi}{2}x^2\mathcal{I}\left\{x < 0\right\}L_{i,h,0}$ as in Stein (1998), where $\mathcal{I}\{\bullet\}$ is an indicator function. Similar assumptions are typical in the literature (e.g., Diamond and Dybvig, 1983; Kashyap and Stein, 1995; Bianchi and Bigio, 2014).[4] The liquidation costs apply to total loan liquidations, and thus also apply to banks with a net increase in loan volumes if

[3] We can let deposit rates differ from the safe rate without affecting our derivations. E.g., Drechsler, Savov, and Schnabl (2014) emphasize that deposit rates are a function of a local bank's market power.

[4] Among others, Diamond (1984), Holmstrom and Tirole (1997), and Afonso and Lagos (2012) provide micro-founded mechanism for loan illiquidity.

gross liquidations are positive. To capture this potential excess of gross flows over net flows, we assume that between the initial loan stock $L_{i,h,0}$ and new choice $L_{i,h}$ a random fraction $\delta L_{i,h,0}$ of loans are paid off and $\chi L_{i,h,0}$ commitments are drawn. Let $z = \chi - \delta$ be the net percentage change in loans from drawn commitments and maturing loans.[5] The quantity z is observable by the bank at the time $L_{i,h}$ is chosen (but not by the econometrician who can only see $\frac{\Delta L_{i,h}}{L_{i,h,0}} = \frac{L_{i,h}-L_{i,h,0}}{L_{i,h,0}}$). Thus, the growth rate of bank loans is $x = \frac{\Delta L_{i,h}}{L_{i,h,0}} - z$ and the liquidation cost is[6]

$$\Psi\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}, z\right) L_{i,h,0} = \frac{\psi}{2}\left(\frac{\Delta L_{i,h}}{L_{i,h,0}} - z\right)^2 \mathcal{I}\left\{\frac{\Delta L_{i,h}}{L_{i,h,0}} < z\right\} L_{i,h,0} \tag{2}$$

In period 2, loan outcomes are realized so that overall profits from lending are

$$\begin{aligned} w_{i,h} &= (1+r^L)L_{i,h} - (1+r^F)\widetilde{D}_{i,h} + (1+r^F)S_{i,h} - \Psi\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}, z\right) L_{i,h,0} \\ &= (r^L - r^F)L_{i,h} + (1+r^F)K_{i,h} - \Psi\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}, z\right) L_{i,h,0} \end{aligned} \tag{3}$$

where the second line follows from the definition of the bank balance sheet.

Following Froot, Scharfstein, and Stein (1993) and Froot and Stein (1998), banks use their period 1 proceeds to invest in a non-stochastic investment opportunity, which we denote by $I_{i,h} = w_{i,h}$. As Froot and Stein (1998), we assume that returns in the non-stochastic investment are captured by a concave function $F(I)$.[7] After these returns are realized, banks pay capital back to the BHC, at a BHC specific capital rate $(1 + r^h) = (1 + \theta^h)(1 + r^F)$, where the BHC-premium θ^h is strictly positive and exogenous to the bank. This premium can be thought of as being determined by a potentially time-varying external financing costs for the BHC.

Two features of the set-up are particularly important. First, the curvature from $F(\bullet)$

[5] In line with this interpretation, Bassett, Chosak, Driscoll, and Zakrajšek (2014) stress that a the loan portfolio is not fully under a bank's control, because consumers and firms can draw on commitments (e.g., credit lines, credit cards) and expand the banks balance sheet. They show that this effect is particularly pronounced in the 2007-2009 recession.

[6] We assume that new commitments cannot be immediately liquidated.

[7] In Froot and Stein (1998), the bank is also able to raise additional equity at this stage, subject to a convex equity cost. We leave it out for simplicity since it does not affect our derivations.

endogenously creates risk aversion in financial institutions, as low realizations of $w_{i,h}$ imply high marginal returns $F'(w_{i,h})$, and vice versa. Second, since capital from the BHC, $K_{i,h}$, enters cash flows (3), it can be seen as insurance against low loan returns r^L. The higher the capital cushion $K_{i,h}$, the more the bank is protected against low loan return realizations, and the less risk averse the bank will be. This creates a positive demand for BHC-level capital despite its costly premium $\theta^h > 0$.

We now formally summarize this discussion.

2.2.1 Optimization Problems

Period 2 Payoffs

Period 2 investment decisions in the non-stochastic investment opportunity can be summarized as follows

$$
\begin{aligned}
P(w_{i,h}) &= \max_{I_{i,h}} F(I_{i,h}) \\
\text{s.t.} \qquad I_{i,h} &= w_{i,h}
\end{aligned}
$$

The final payoff as a function of realized period 1 investments is therefore the return from the investment opportunity net of equity repayment,

$$V(w_{i,h}, K_{i,h}) = P(w_{i,h}) - (1 + r^h)K_{i,h}$$

Period 1 Payoffs

As the return on loans, r^L, is a random variable, banks in period 1 optimally choose loans $L_{i,h}$ and capital $K_{i,h}$ to maximize expected utility:

$$
\begin{aligned}
&\max_{L_{i,h}, K_{i,h}} \quad E[V(w_{i,h}, K_{i,h})] \\
\text{s.t.} \qquad & w_{i,h} = (r^L - r^F)L_{i,h} + (1 + r^F)K_{i,h} - \Psi(\Delta L_{i,h}/L_{i,h,0}, z)L_{i,h,0} \\
& r^L = \bar{r}^L + \varepsilon \\
& \varepsilon \sim N(0, \sigma_\varepsilon^2)
\end{aligned}
$$

where, as before, we substituted for the bank balance sheet (1). Banks take all interest rates and returns as given.

2.2.2 Risk Aversion of Banks

To tractably describe risk aversion of banks under normal risks, we choose a linear-exponential payoff function for the non-stochastic investments:

$$F(I) = AI + B\left(1 - \frac{1}{g}e^{-gI}\right) \qquad \Rightarrow \qquad P(w) = Aw + B\left(1 - \frac{1}{g}e^{-gw}\right) \tag{4}$$

where $A, B > 0$, so that the marginal payoff of cash flows is always positive but decreasing. We also restrict $A \leq 1$, so that the demand for BHC-capital $K_{i,h}$ is always finite.

This functional form combines two attractive properties. First, it features decreasing risk aversion, so that banks with larger values of cash flows w_i will exhibit more risk-seeking behavior. For low values of cash flows w_i, the bank will exhibit risk aversion with an coefficient of absolute risk aversion g, while for large values of w_i, the bank will be risk-neutral. Second, due to its combination of linear and exponential utility terms, we are able to analytically solve for risk aversion once we combine this utility with normally distributed loan returns.

2.3 Optimal loan supply: level and responsiveness Under these parametric assumptions we can analytically characterize the optimal loan supply.

Proposition 1 *The optimal loan supply is given by*

$$L^S_{i,h}(z) = \frac{\bar{r}^L - r^F - \frac{\partial\Psi(\Delta L^S_{i,h}/L_{i,h,0},z)}{\partial\Delta L^S_{i,h}/L_{i,h,0}}}{G^h \cdot \sigma^2_\varepsilon} \tag{5}$$

where the absolute risk aversion coefficient is

$$G^h = \frac{g(1 - A + \theta^h)}{1 + \theta^h} > 0 \tag{6}$$

Proof See appendix A.1. ■

The numerator in (5) is the expected excess return, which consists of the expected loan premium and the marginal liquidation cost $\frac{\partial \Psi}{\partial \Delta L^S_{i,h}/L_{i,h,0}}$ (which may be zero). The denominator is the BHC-specific absolute risk aversion G^h and the variance of loan returns.

The second key result from this proposition is that bank risk aversion is determined by the BHC-level cost of capital. Intuitively, a low premium θ^h increases capital cushion $K_{i,h}$, which increases cash $w_{i,h}$ carried into period 2 for the non-stochastic investment opportunity. Since that investment opportunity is concave, variations in $w_{i,h}$ are less costly at higher levels of the capital cusion $K_{i,h}$. Thus, the bank becomes less risk averse the higher the capital on its books. Conversely, the higher the premium, the less capital the bank demands and the greater its risk aversion,

$$\frac{\partial G}{\partial \theta^h} = \frac{g \cdot A}{(1+\theta^h)^2} > 0$$

In equation (5) the actual liquidation costs are unobservable, so we can only estimate outcomes for the average loan supply $L^S_{i,h} = E_z L^S_{i,h}(z)$. This is equal to,[8]

$$L^S_{i,h} = \frac{\bar{r}^L - r^F - \Phi'(\Delta L^S_{i,h}/L_{i,h,0})}{G^h \cdot \sigma^2_\varepsilon} \tag{7}$$

where

$$\Phi'\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right) \equiv E_z\left[\frac{\partial \Psi(\Delta L^S_{i,h}/L_{i,h,0}, z)}{\partial \Delta L^S_{i,h}/L_{i,h,0}} \middle| \frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right]$$

Assuming a uniform distribution for z, $z \sim U[-a,a]$, in appendix B we show that the marginal liquidation cost has the properties $\Phi'(0) < 0$, $\Phi''(0) > 0$ and $\Phi'''(0) < 0$. Figure 2 plots a numerical example of the average marginal liquidation costs across banks. The key property for our analysis is that the marginal liquidation costs are asymmetric — they are higher the more loans are already sold.

[8] We cannot back out z from equation (5) because the excess loan return, the risk aversion, and the variance are not directly observable. One can interpret $L^S_{i,h}(z) - E_z L^S_{i,h}(z)$ as the structural error in our estimation equation.

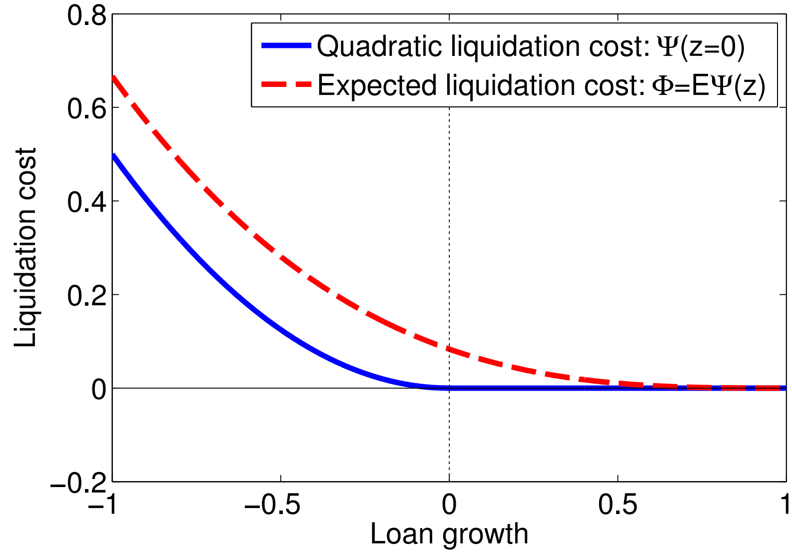


Figure 2 – Comparison of quadratic liquidation cost $\Psi\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}, z=0\right)$ with expected liquidation cost $\Phi\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right) \equiv E_z\left[\Psi\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}, z\right)\middle| \frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right]$. Parameterization: $z \sim U[-a,a]$, $a = \psi = 1$.

The advantage of incorporating the excess of gross flows over net flows through the random variable z, is that it smooths out the marginal liquidation costs as illustrated in figure 2. Thus, we gain the existence of a third derivative at 0, which allows us to summarize the asymmetry of loan liquidation costs at that point.

We next characterize the response of loan supply to monetary policy changes. We begin by discussing our assumptions on how changes in monetary policy rates affect the return on safe assets r^F and loans $\bar{r}^L$ in our model. First, we interpret monetary policy shocks as exogenous changes in the safe interest rate r^F. If one interprets the safe asset as Federal Funds, then the transmission is direct and one-for-one. More generally, the empirical literature on the term structure of interest rates has shown that short term interest rates respond strongly to changes in the Federal Funds rate, see Cook and Hahn (1989) and Kuttner (2001). If one instead focuses on the funding costs of banks, then the federal funds rate directly influences the interbank loan rate, and (through arbitrage) loan rates on close substitutes, such as money market funds and deposits.[9]

[9] Bianchi and Bigio (2014) emphasize this market as a source of funds for banks engaged in liquidity management.

Second, we assume that monetary policy does not fully pass through to the expected loan return $\frac{\partial \bar{r}^L}{\partial r^F} = \mu < 1$. Incomplete pass-through is consistent with the data (Fuster, Goodman, Lucca, Madar, Molloy, and Willen, 2013; Scharfstein and Sunderam, 2013) and, in the model, provides a mechanism for increases in loan supply following a reduction in monetary policy rates. Theoretically, this assumption can be motivated by adverse selection considerations as in Stiglitz and Weiss (1981), where increases in loan rates induce a selection of bad risks into the loan portfolio of banks and vice-versa. Such a view is consistent with the interpretation of our model as capturing the net exposure to non-tradable, illiquid loan risks.

We next characterize how loan supply responds to an exogenous change in the risk-free rate r^F.[10]

Proposition 2 *The response of loan supply to exogenous changes in the risk-free rate is approximately given by*

$$\frac{\partial \ln L_{i,h}^S}{\partial r^F} \approx -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2} \ln\left(\frac{L_{i,h}^S}{L_{i,h,0}}\right) \tag{8}$$

Proof See appendix A.2. ■

Proposition 2 captures the financial dampening mechanism that we try to measure. According to equation (8), banks that are in the process of reducing their risk-exposure to loans $L_{i,h}^S < L_{i,h,0}$ respond less to exogenous changes changes in monetary policy when loan liquidation costs are asymmetric, $\Phi'''(0) < 0$. Thus, banks will expand loans less to policy rate reductions, as well as contract loans less in response to policy rate increases.

To understand the key underlying intuition, consider the extreme case where banks cannot liquidate loans, so the marginal liquidation cost is infinite. In that case, banks that would want to contract loan supply (absent liquidations costs) to $L_{i,h}^S < L_{i,h,0}$, will simply

[10] We can also allow for changes in the loan risk, $\frac{\partial \ln \sigma^2}{\partial r^F} > 0$. Then equation (8) becomes,

$$\frac{\partial \ln L_{i,h}^S}{\partial r^F} \approx \underbrace{-\frac{1-\mu+\frac{\partial \ln \sigma^2}{\partial r^F}[\bar{r}^L - r^F - \Phi'(0)]}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)}}_{<0} + \underbrace{\frac{(1-\mu)\Phi'''(0) - \Phi''(0)\frac{\partial \ln \sigma^2}{\partial r^F}[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2}}_{<0} \ln\left(\frac{L_{i,h}^S}{L_{i,h,0}}\right),$$

and dampening effects arise even with complete loan-rate pass-through ($\mu = 1$).

keep their current loan portfolio $L^S_{i,h} = L_{i,h,0}$. A reduction in policy rates does raise the ideal loan supply $L^S_{i,h}$, but no new loans will be forthcoming so long as the ideal loan supply remains less than the original loan portfolio. The loan portfolio will be stuck at $L_{i,h,0}$ and the monetary transmission mechanism through bank lending is completely dampened. By contrast, a bank that does not want to liquidate loans is not subject to these liquidation costs and will increase loan supply. For finite marginal liquidation costs the loan supply response at retrenching banks is positive but dampened relative to banks not retrenching. Hence, we call this mechanism "financial dampening."

A corollary is that financial dampening becomes more important the higher the marginal liquidation costs are. We can measure the strength of the financial dampening channel as the ratio of the dampening coefficient to the base loan response (the intercept) in (8), $FD \equiv \frac{-\Phi'''(0)}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} > 0$. It is then straightforward to show that FD becomes larger as liquidation costs rise $\frac{\partial FD}{\partial \psi} > 0$. Thus, we expect financial dampening to be particularly important during times of financial distress when liquidation costs are particularly high (e.g, Coval and Stafford, 2007; Campbell et al., 2011; Ellul et al., 2011; Greenwood and Thesmar, 2011).

The mechanism applies equally to monetary policy rate decreases and increases. In the case where liquidation cost is infinite, a retrenching bank cannot further reduce its loan supply following an increase in the safe rate r^F. But a bank that already plans to increase loan supply can simply chose to do so less. While financial dampening does apply symmetrically, in what follows we will focus on interest rate decreases. This is because we expect this mechanism to be particularly important when the financial sector as a whole retrenches, which is also when central banks would want to counteract any adverse real effects with monetary policy rate reductions.

2.4 Local loan demand and identification Because loan supply is not directly observable, we cannot estimate equation (8). This creates an identification problem because realized loan volumes can be driven by either supply or demand. This is a standard concern in the literature and it also applies to our analysis of the responsiveness of loan volumes to monetary policy. We formalize this idea as follows. Local markets are subject to possible constrained loan demand, which captures variations in loan investment opportunities. In each location, denote $L^c_{i,h}$ as maximum possible loan supply. Realized loan volumes are then given by

$$\begin{aligned}\ln L_{i,h} &= \min\{\ln L^S_{i,h}, \ln L^c_{i,h}\} \\ &= \ln L^S_{i,h} + x_{i,h} \cdot (\ln L^c_{i,h} - \ln L^S_{i,h})\end{aligned}$$

where $x_{i,h} = \mathcal{I}\{\ln L^c_{i,h} < \ln L^S_{i,h}\}$ is an indicator whether a bank is constrained by local loan demand. In this demand constrained case, there is no response of loan quantities to monetary policy due to lacking loan demand. This channel is completely real and demand-driven and not related to the "lending view" of monetary transmission. We assume that banks are small relative to their local area, so that variation in local loan demand $\ln L^c_{i,h}$ determines whether the loan demand constraint $x_{i,h}$ binds, instead of changes in target loan supply moving a bank into a constraint. As a consequence $L^S_{i,h}$ and $x_{i,h}$ are independent random variables. We further discuss the importance of this assumption in the context of our IV strategy.

The response of loan volumes of bank i to changes in the policy rate r^F can be summarized as

$$\frac{\partial \ln L_{i,h}}{\partial r^F} = \begin{cases} -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2} \times \Delta \ln L_{i,h} & \text{if } \ln L^S_{i,h} \leq \ln L^c_{i,h} \\ 0 & \text{if } \ln L^S_{i,h} > \ln L^c_{i,h} \end{cases}$$

2.4.1 Endogeneity problem

The simplest version of our main estimation equation can be written as

$$\frac{\partial \ln L_{i,h}}{\partial r^F} = \alpha + \beta \Delta \ln L_{i,h} + u_{i,h} \tag{9}$$

where

$$\alpha = -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} \tag{10}$$

$$\beta = \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2} \tag{11}$$

$$u_{i,h} = x_{i,h}\left(-\alpha - \beta \times \Delta \ln L_{i,h}\right) \tag{12}$$

$$\Delta \ln L_{i,h} = \Delta \ln L^S_{i,h} + x_{i,h}\left(\Delta \ln L^c_{i,h} - \Delta \ln L^S_{i,h}\right) \tag{13}$$

The resulting OLS regression would therefore be a regression of loan growth at bank i on interest rate shocks ∂r^F and the interaction of interest rate shocks ∂r^F with lagged changes in loan growth. The problem is that even under the small bank assumption, unobserved variation in local loan demand will drive both local loan volumes (13) and the error term (12) through the constraint indicator $x_{i,h}$. Thus, even if $\beta = 0$, the OLS estimate is biased towards finding evidence for financial dampening, $E[\hat{\beta}^{OLS}] < 0$.[11] Intuitively, the OLS estimate also reflects that demand-constrained areas have low loan growth and low sensitivity of loan growth to changes in monetary policy rates.

2.4.2 Instrumental Variables Strategy

BHC common variation and instrument

To illustrate our instrumental variable strategy, we focus on variation in the in BHC specific costs of capital θ^h. This triggers common variation in loan supply across all BHC member banks, through the BHC-internal capital market.

$$\Delta \ln L^S_{i,h} = -\frac{G^{h\prime}}{G^h} d\theta^h$$

[11] Formally, if $\beta = 0$, then $\mathbb{C}\text{ov}(\Delta \ln L_{i,h}, u_{i,h}) = -\alpha \mathbb{C}\text{ov}(\Delta \ln L_{i,h}, x_{i,h}) < 0$ yielding a downward bias. When $\beta < 0$ then the bias can be either downward or upward, and, empirically, we find an upward bias.

Based on this common variation, we construct loan growth of BHC banks that are "elsewhere", i.e., not in the same location as bank i. This is defined as

$$\begin{aligned}
\Delta \ln L_{-i,h} &= \frac{1}{N}\sum_{j\neq i}\Delta \ln L_{j,h} \\
&= (1-\bar{x})\left(-\frac{G'}{G}d\theta^{BHC}\right) + \overline{x_{j,h}\Delta \ln L^{c}_{j,h}} \\
\implies \Delta \ln L_{-i,h} &= (1-\bar{x})\Delta \ln L^{S}_{i,h} + \overline{x_{j,h}\Delta \ln L^{c}_{j,h}}
\end{aligned}$$

where a bar over a variable denotes a cross-sectional average across all banks in BHC locations other than bank i. Elsewhere loan growth captures the common variation in BHC level risk premium θ^h, up to scale. It also captures the (unobserved) fraction of BHC member banks that is under loan demand constraints $\bar{x}$, so we cannot directly infer changes in optimal loan supply from loan growth of BHC member banks "elsewhere." However, an advantage of IV estimation is that we do not need this information. We only need the instrument to be correlated with the local loan supply and uncorrelated with local loan demand constraints.

Proposition 3 *If all banks are small in their local area and local loan demand shocks are uncorrelated across banks of the same BHC, then loan growth at other banks within the same BHC, $\Delta \ln L_{-i,h}$ is uncorrelated with the error term $u_{i,h}$ in estimating equation (9). Therefore the IV estimator*

$$\hat{\beta}^{IV} = \frac{\mathbb{C}ov\left(\frac{\partial \ln L_{i,h}}{\partial r^F}, \Delta \ln L_{-i,h}\right)}{\mathbb{C}ov(\Delta \ln L_{i,h}, \Delta \ln L_{-i,h})}$$

is consistent, and recovers the parameter β in (9).

Proof See appendix A.3. ■

We note that our IV-strategy identifies the parameter of interest even if loan retrenchment is not exogenous at the BHC level as we assumed above. For our purposes, it suffices that BHC level variation is not correlated with local demand conditions, conditional on (aggregate) controls we add to equation (9). In that sense, the source of variation at the BHC level is not important: any variation in BHC-level loan retrenchment that satisfies the exclusion restriction for the local banks, such as a higher BHC cost of capital, greater BHC risk aversion etc., will identify the structural parameter β.

Thus, our IV-strategy can overcome the identification problem and recover the importance of supply-driven financial dampening. In our empirical analysis we will pay particular attention that our results are not driven by correlated shocks across banks. The small bank assumption is less critical because violations of it create a bias against us. In particular, if it is violated, then banks with high loan growth are more likely to be demand-constrained, and then those banks will also exhibit weaker reactions to monetary policy shocks. By contrast, the financial dampening mechanism implies that banks with low loan growth will exhibit weaker sensitivity.[12]

3 Data

We next describe the data we use to construct our outcome variables and instrument.

Bank level data We use the Report of Condition and Income data available from the Federal Reserve Bank of Chicago and WRDS. It captures all commercial banks regulated by the Federal Reserve System, the Federal Deposit Insurance Corporation and the Comptroller of the Currency. The data are at a quarterly frequency from 1976 to 2010. This dataset has been previously used by Kashyap and Stein (2000) and Campello (2002) among others.[13] Our sample begins in 1986 onwards when the BHC consolidated statements are also available. We further restrict our analysis to banks whose head office is insured by either the FDIC, the National Credit Union Savings Insurance Fund, and/or its resident state. This removes U.S. branches of foreign banks as well as domestic national trusts. Whenever a bank merger

[12] Formally, the covariance between the instrument and the error term is positive, $\mathbb{C}\text{ov}(\Delta \ln L_{-i,h}, u_{i,h}) = -\alpha(1-\bar{x})\mathbb{C}\text{ov}(\Delta \ln L^S_{i,h}, x_{i,h}) > 0$, since absent the small bank assumption higher loan supply makes the constrained regime more likely, $\mathbb{C}\text{ov}(\Delta \ln L^S_{i,h}, x_{i,h}) > 0$. This generates an upward bias in the IV estimate.

[13] Goetz, Laeven, and Levine (2011) also exploit the geographic dispersion of banks to examine how mergers of geographically separate banks affect the riskiness of a BHC. Unlike us, they use the headquarter state to assign banks to locations. Drechsler et al. (2014) employ the same data to document that monetary transmission also works through a deposit channel.

occurs, we treat the resulting entity as a new bank. We identify mergers using the bank merger files available from the Federal Reserve Bank of Chicago website.

We match commercial banks to bank-holding-companies (BHCs) using the regulatory high-holder identifier (RSSD9348). We first check if the commercial bank regulatory data consistently aggregate, by comparing them with the BHC consolidated statements. In table 1 we document the ratio of total commercial bank assets, loans and capital at a BHC to the BHC-reported total assets, loans and capital. For most BHC-quarter observation that ratio is close to 1 for assets and loans, implying that the commercial bank data are consistent with the BHC data. The match is worse on bank and BHC book capital.

Table 1 – Consistency of Commercial Bank Balance Sheets with BHC Consolidated Statements

	1	5	10	25	50	75	90	95	99	N
$\frac{\sum \text{Bank Assets}}{\text{BHC Assets}}$	0.63	0.95	0.98	0.99	1.00	1.00	1.00	1.01	1.07	136370
$\frac{\sum \text{Bank Loans}}{\text{BHC Loans}}$	0.65	0.97	1.00	1	1	1	1.00	1.00	1.06	136369
$\frac{\sum \text{Bank Capital}}{\text{BHC Capital}}$	0.39	0.77	0.85	0.95	1.00	1.17	1.41	1.63	2.54	136370

Notes: Balance sheet variables of matched commercial banks are aggregated and divided by the corresponding variables in the BHC reports. A value of 1 indicates a perfect match. Data is at the BHC-quarter level. Source: Report of Condition and Income, BHC consolidated statements, and authors' calculations.

In table 2 we compare size and leverage of unmatched commercial banks (not part of a BHC) with those of matched banks. Among matched commercial banks we further distinguish between those that are the sole member of a BHC and those that are part of a multi-bank BHC. We find that unmatched and sole-member banks are both significantly smaller on average than commercial banks in multi-bank BHCs. Since our estimation strategy requires the presence of at least two banks in a BHC, we invariably select on banks that are larger than average.

We merge these data with the FDIC's Summary of Deposit survey. This dataset reports branch-level deposits as of June 30^{th} for all FDIC-insured institutions since 1994. It includes member banks, non-member banks and thrifts, among others. We exploit the exact coding of branch locations to determine a banks zone of operation. Let d_{iblt} be total deposits at

Table 2 – Average Bank Size and Leverage Comparison by BHC Membership

	Assets	Loans	Leverage	Obs.
Matched banks (1 bank in BHC)	235885.0	150858.7	11.3	582853
Matched banks (>1 bank in BHC)	1885055.7	1032120.6	11.9	390644
Unmatched banks	480872.0	192450.6	10.6	702425

Notes: Average across banks for assets, loans and leverage by category. "Obs." denotes the total number of observations in the asset category. Categories are banks not matched to a BHC (unmatched), banks that are the only member of a BHC (1 bank in BHC), and banks that are part of a multi-bank BHC (>1 bank in BHC). Observations are at the bank-quarter level. Source: Report of Condition and Income and authors' calculations.

branch b of bank i in location l at time t. For each bank we calculate its total yearly deposits in location l by summing over all local branches, $d_{ilt} = \sum_b d_{iblt}$. We consider four levels of geographical aggregation l: counties, micro- or metropolitan statistical areas (mSA/MSA), combined statistical areas (CSAs) and states. For each bank with at least one branch in location l, we construct the share of its deposits in that area for a given year $s_{ilt} = \frac{d_{ilt}}{\sum_l d_{ilt}}$. For counties that do not belong to mSA/MSAs we report the county deposit-share as part of the mSA/MSA and CSA level. For mSA/MSAs that are not part of a CSA we report the mSA/MSA share.

To illustrate the geographical concentration of banks we calculate the maximum deposit-share over all locations for a given bank-year, $s_{it}^{max} = \max_l s_{ilt}$. This gives us a single observation for each bank-year pair. Table 3 tabulates the percentiles of the s_{it}^{max}-distribution. Banking is already quite concentrated at the county level. Over half of our bank-year observations are located in a single county. Aggregating further we find that 65% of bank-years are located in a single mSA/MSA, 70% in one CSA, and more than 95% in a single state.

Table 3 – Distribution of Banks' Maximum Share of Deposits across Locations

Percentile	0.1	1	5	10	25	40	50	N
County level	0.11	0.23	0.42	0.53	0.77	0.96	1.00	195531
MSA level	0.15	0.28	0.49	0.60	0.87	1.00	1.00	195529
CSA level	0.17	0.30	0.51	0.64	0.93	1.00	1.00	195529
State level	0.34	0.66	1.00	1.00	1.00	1.00	1.00	195524

Notes: Observations are at the bank-year and calculated separately for each location level. Source: FDIC Summary of Deposit and authors' calculations.

We exploit this geographical concentration to match banks to locations. Our baseline rule is to assign banks to the smallest level of geographical aggregation such that 95% of all bank deposits are located within that area. For instance, a bank that is equally spread over 3 counties belonging to a single MSA, will be assigned to the MSA where it has 100% market share. We do not assign a location to banks that straddle state borders if it has less than 95% market share in a single state. We view our 95% rule as a sensible benchmark to capture essentially all major operations of a bank, while still allowing for minor presence elsewhere. In a robustness check we use a more conservative 100% threshold.

If a bank changes location (its deposit share drops below 95%), we do not assign a location to it throughout the sample. Thus, our definition of a location is a fixed attribute. For all banks present in 1994 we then backcast location to the beginning of the sample in 1986. A drawback is that we cannot assign a location to any bank that ceases to exist before 1994.

These location assignments are only sensible if banks also lend primarily where they have branches. While our data do not speak directly to this assumption, the local nature of commercial banking has been documented elsewhere. Brevoort, Holmes, and Wolken (2009) show that the median distance between a small business and a branch of its primary lender is between 3-4 miles. Further, more than 80% of a commercial banks' loans are made within a 30-mile radius even in the mid-2000s. Becker (2007) documents that cities with a demographically-induced high deposit supply also tend to have high local loan volumes. Nguyen (2015) also documents that the closing of a branch causes significant disruptions in local credit supply. This suggests that our location assignments capture a significant part of the banks area of operation.

In short, we obtain a set of commercial banks that operate in different locations but are owned by the same BHC. We use this spatial separation to construct our retrenchment measure that is independent of local demand shocks. Let L_{iht} be total loans at bank i matched to BHC h at time t. Total BHC loans are $L_{ht} = \sum_{i \in \Omega_h} L_{iht}$, where Ω_h is the set of banks in BHC h. We define total BHC assets that are spatially separate from location l of bank i ("elsewhere loans") as,

$$L_{-l,ht} = \sum_{k \in \Omega_h} L_{kht} \mathcal{I}\{s_{klt} < 0.05\} \tag{14}$$

where $\mathcal{I}\{s_{klt} < 0.05\}$ is an indicator that bank k in BHC h has fewer than 5% of its deposits in location l. This indicator is a substantive-presence test. We classify a bank's loans as essentially independent of local demand shocks in area l if its deposit share in l is sufficiently small—less than 5%. Note that this automatically excludes bank i, which has at least 95% of its deposits in location l. However, it can include national banks, so long as they only have a minor (relative) presence in location l.

We then sum over all banks in the BHC that pass this test, which creates a measure of total BHC level loans that are independent of shocks to area l. Our empirical strategy is then to instrument the degree of bank-level loan retrenchment, measured by local loan growth $\Delta \ln L_{iht}$, using elsewhere loan growth, $\Delta \ln L_{-l,ht}$. As a robustness check we use the more stringent presence test that a bank has zero deposits in location l.

Our instrumental variable strategy requires that we assign a bank to location l and that at least one other BHC-member bank does not operate in location l. Table 4 compares banks for which we can and cannot implement this strategy. Compared with the sample of banks in table 2 we still select among relatively large commercial banks, although we do drop some of the largest banks in the sample. This is because we cannot assign national banks to a single location.

Table 4 – Average Balance Sheet Size of Banks in Multi-Bank BHCs.

	Assets	Loans	Leverage	Obs.
Geographically-separate bank in BHC	1186385.0	725140.7	11.6	142993
No geographically-separate bank in BHC	3650195.8	2018798.8	11.5	82896

Notes: Average size and leverage for banks in multi-bank BHCs where we can construct a retrenchment measure excluding the current bank and average size and leverage for banks in multi-bank BHCs where we cannot do so. Source: Report of Condition and Income, FDIC Summary of Deposit and authors' calculations.

Because the bank regulatory data are very noisy we follow the existing literature (Kashyap and Stein, 2000; Campello, 2002) and remove extreme growth rates. For all variables we drop the top and bottom 0.5 percent of all observations. Table 5 tabulates cross-sectional summary statistics for our key variables of interest: asset growth, loan growth, leverage growth, and our instrument, the four-quarter growth rate of loans at BHC-member banks located elsewhere.

Table 5 – Commercial Bank Balance Sheets Summary Statistics

	Mean	SD	25 pctile	Median	75 pctile	Observations
Asset growth (one-quarter)	1.72	5.39	−1.04	1.21	3.74	122531
Loan growth (one-quarter)	2.11	6.24	−0.95	1.69	4.54	122067
Leverage growth (one-quarter)	−0.0086	7.78	−3.28	−0.41	2.78	122526
Loan growth (four-quarter)	9.46	17.3	0.70	7.34	14.9	121816
Elsewhere loan growth (four-quarter)	9.64	12.4	2.85	8.29	14.5	123627

Notes: Summary statistics for bank-level variables used in the baseline regressions. Elsewhere loan growth is the loan growth at spatially-separate banks of the same BHC. Growth rates are log changes multiplied by 100. Growth rates in the top and bottom 0.5 percentile were dropped. Source: Report of Condition, FDIC Summary of Deposit and Income and authors' calculations.

Monetary Policy Shocks We use the Romer and Romer (2004) monetary policy shock series ("Romer-shocks"). These are residuals from a regression of the federal funds rate on lagged values and the Federal Reserve's information set based on Greenbook forecasts. As argued by Romer and Romer (2004) these are plausibly exogenous with respect to the evolution of economic activity. We update the Romer-Romer shock series up to December 2007.[14] We sum the shocks to a quarterly frequency and merge them with the bank data.

The advantages of using a monetary shock relative to a time-series of nominal interest rates are threefold. First, it provides a closer match the theory, where the safe interest rate changes exogenously. Second, since monetary policy shocks are unanticipated, banks cannot adjust their portfolio in anticipation of these shocks, which matches our theoretical set-up. Third, endogenous changes in interest rates may be negatively correlated with BHC capital premia θ or loan risks σ_ε^2, so the total effect on loan supply is ambiguous, unlike for monetary policy shocks.

[14] These data are publicly available at https://sites.google.com/site/johannesfwieland/Monetary_shocks.zip.

4 Results

We add a lag structure to equation (9), which was found to be relevant in previous bank-level studies (Kashyap and Stein, 1995; Landier et al., 2013; Van den Heuvel, 2012). Hamilton (2008) argues that the lag structure reflects search frictions by prospective home owners, which causes a delays a change in mortgage loans. We estimate equation (9) with 8 lags as well as controls for the level of leverage and the un-interacted elsewhere loan growth,

$$\begin{aligned}\Delta \ln L_{i,h,t} =& \alpha_i + \gamma_t + \sum_{k=0}^{8} \beta_k \Delta r_{t-k} \Delta^4 \ln L_{i,h,t-1-k} + \sum_{k=0}^{8} \delta_k \Delta r_{t-k} \phi_{i,h,t-1-k} \\ &+ \sum_{k=0}^{8} \theta_{1k} \phi_{i,h,t-1-k} + \sum_{k=0}^{8} \theta_{2k} \Delta^4 \ln L_{i,h,t-1-k} \\ &+ \sum_{k=0}^{8} \theta_{3k} \Delta^4 \ln L_{-l,h,t-1-k} + \sum_{k=1}^{8} \gamma_{1k} \Delta \ln L_{i,h,t-k} + \delta \times \text{controls} + \varepsilon_{it}.\end{aligned} \tag{15}$$

Given the lag structure, we instrument nine endogenous variables, $\{\Delta r_{t-k} \Delta^4 \ln L_{i,h,t-1-k}\}_{k=0,\ldots,8}$, using nine instruments, $\{\Delta r_{t-k} \Delta^4 \ln L_{-l,h,t-1-k}\}_{k=0,\ldots,8}$.

The time fixed-effects absorb any correlation between the endogenous variables and instruments induced by aggregate business cycle variation (e.g., common demand shocks). Further, we interact the *contemporaneous* monetary policy shock with *lagged* loan growth. This implies that retrenching is pre-determined with respect to the monetary policy shock, which ensures that causality does not run from monetary policy to bank-level retrenching.

The fourth term in equation (15) interacts the monetary policy shock with leverage. We control for leverage to avoid conflating financial dampening with a standard financial accelerator or the capital adequacy channel of Van den Heuvel (2005). The final two terms control for bank-level dynamics in the dependent variable and other sources of bank-level heterogeneity. For example, bank size has been shown to affect monetary policy responsiveness (Kashyap and Stein, 2000), and differential capital growth rates can capture differences in bank profitability and its influence on responsiveness to monetary policy.

Table 6 – First-stage estimates for bank deleveraging interacted with the monetary shock

	Dependent variable: $\Delta r_{t-lag} * $ 4Q Loan Growth$_{t-lag-1}$								
	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta r_t *$ 4Q BHC Loan Growth$_{t-1}$	0.25***	−0.0028	−0.0033	0.011**	0.015***	−0.00061	0.0043	0.0068	0.0052
$\Delta r_{t-1} *$ 4Q BHC Loan Growth$_{t-2}$	−0.0032	0.26***	−0.00022	−0.0082	0.0093**	0.012**	0.0011	0.0048	0.0058
$\Delta r_{t-2} *$ 4Q BHC Loan Growth$_{t-3}$	0.000027	−0.0021	0.27***	0.0063	0.0012	0.0026	0.017***	−0.00040	0.0095*
$\Delta r_{t-3} *$ 4Q BHC Loan Growth$_{t-4}$	−0.0050	−0.00056	−0.00096	0.28***	0.0048	0.0065	0.0045	0.018***	−0.0049
$\Delta r_{t-4} *$ 4Q BHC Loan Growth$_{t-5}$	0.018***	−0.0028	−0.00077	−0.00036	0.28***	−0.0056	0.0072	0.0095*	0.018***
$\Delta r_{t-5} *$ 4Q BHC Loan Growth$_{t-6}$	0.0055	0.013***	−0.011**	−0.00055	−0.0034	0.30***	−0.0063	0.0044	0.0057
$\Delta r_{t-6} *$ 4Q BHC Loan Growth$_{t-7}$	−0.014***	0.0077*	0.015***	−0.012**	−0.0019	−0.0063	0.31***	−0.0048	−0.0029
$\Delta r_{t-7} *$ 4Q BHC Loan Growth$_{t-8}$	0.011**	−0.0093**	0.0083**	0.016***	−0.0074	−0.0011	−0.0040	0.31***	−0.0011
$\Delta r_{t-8} *$ 4Q BHC Loan Growth$_{t-9}$	0.000040	0.012***	−0.010***	0.0061	0.018***	−0.0055	−0.0036	−0.0023	0.33***
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sum: Δr * 4Q BHC Loan Growth	.27***	.28***	.27***	.29***	.31***	.3***	.33***	.35***	.36***
p-value	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.15	0.15	0.16	0.16	0.15	0.15	0.14	0.13	0.12
Observations	80,934	80,934	80,934	80,934	80,934	80,934	80,934	80,934	80,934

Notes: First-stage estimates of equation (15). The dependent variable is the Romer-Romer shock interacted with 4Q loan growth. The IV is the Romer-Romer shock interacted with 4Q loan growth at spatially separate banks of the same BHC. Lags refer to the lag of the dependent variable. Additional controls are bank leverage. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.1 First stage In table 6 we report the first stage estimates of equation (15), focussing on the coefficients on the instrument. The coefficient on the lag of BHC loan growth interacted with the Romer-shock corresponding to the same lag of of the dependent variable ranges from 0.25 to 0.33 at lags 0 through 8 and is highly statistically significant. All other instrument coefficients are at least an order of magnitude smaller and often statistically insignificant. This pattern likely reflects the lack of serial correlation of the monetary policy shocks.

The bottom part of the table reports the sum of the first-stage coefficients on the instruments, which ranges from 0.27 to 0.36. The F-test that the sum of coefficients equals zero is strongly rejected at the 0.1% level. Of course, a weak instrument test has to jointly test these restrictions across all equations, which we report along with our main results.

4.2 Main Results Table 7 presents our baseline IV estimates. The dependent variable is total loan growth of bank i at time t. For ease of exposition we only list the coefficients on the interaction of the Romer-shock with the loan growth variable, $\{\beta_k\}_{k=0}^{8}$. This quantity the cumulative effect of financial dampening on the bank lending channel. While the calculation ignores potential dynamic feed-back through lags of $\Delta \ln L_{i,h,t}$, in practice such effects are negligible. We report the sum of coefficients of this and other interactions at the bottom of the table together with the p-value of a χ^2-test that the sum is zero. All standard errors are robust and clustered at the bank level.

The first column presents IV estimates based on equation (15) controlling only for bank-level leverage. As predicted by the model, the individual coefficients on the interaction of monetary shocks with loan growth are consistently negative and highly significant. The sum of the coefficients is -22.9 and significant at the 0.1% level. The economic magnitude of this coefficient is large. It implies that a bank at the 25^{th} percentile of the loan growth distribution will expand its loan portfolio by 3.25 percentage points less relative to a bank at the 75^{th} percentile following one percentage point reduction in monetary policy rates. Thus, loan supply at retrenching bank is less sensitive to monetary policy shocks as implied by our

Table 7 – IV estimates for Loan Growth

	Dependent variable: 1Q Loan Growth			
	Baseline	Capital (Book) Controls	Capital & Portfolio Controls	Capital & Performance Controls
	(1)	(2)	(3)	(4)
$\Delta r_t * 4\text{Q Loan Growth}_{t-1}$	-0.96	-0.71	-1.53	-1.02
$\Delta r_{t-1} * 4\text{Q Loan Growth}_{t-2}$	-3.00	-4.01	-3.25	-2.09
$\Delta r_{t-2} * 4\text{Q Loan Growth}_{t-3}$	0.45	-0.73	0.024	-1.78
$\Delta r_{t-3} * 4\text{Q Loan Growth}_{t-4}$	-3.63	-4.70	-5.18	-3.46
$\Delta r_{t-4} * 4\text{Q Loan Growth}_{t-5}$	-3.89	-3.80	-3.31	-2.74
$\Delta r_{t-5} * 4\text{Q Loan Growth}_{t-6}$	-5.51^{**}	-6.52^{**}	-6.40^{**}	-8.98^{***}
$\Delta r_{t-6} * 4\text{Q Loan Growth}_{t-7}$	-3.76	-5.14^{*}	-6.20^{*}	-4.81
$\Delta r_{t-7} * 4\text{Q Loan Growth}_{t-8}$	2.22	1.56	2.84	2.56
$\Delta r_{t-8} * 4\text{Q Loan Growth}_{t-9}$	-4.96^{**}	-6.17^{**}	-6.94^{**}	-7.25^{**}
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Sum: Δr * 4Q Loan Growth	-23.05***	-30.21***	-29.96***	-29.59***
p-value	(0.001)	(0.001)	(0.001)	(0.003)
Sum: Δr * Leverage	2.08*	2.25**	2.74**	2.15*
p-value	(0.054)	(0.048)	(0.018)	(0.079)
Sum: Δr * 4Q Capital Growth		9.87**	10.28**	11.43**
p-value		(0.038)	(0.034)	(0.025)
Sum: Δr * Size		6.53	3.96	2.87
p-value		(0.288)	(0.533)	(0.662)
Sum: Δr * LTA			-4.5***	
p-value			(0.006)	
Sum: Δr * CTA			2.78	
p-value			(0.678)	
Sum: Δr * 4Q Allowance Change				-65.82
p-value				(0.568)
Sum: Δr * 4Q Charge-off Change				25.87
p-value				(0.754)
F-statistic	39.44	29.99	31.37	30.19
R^2	0.07	0.07	0.07	0.08
Observations	80,934	80,032	79,620	76,692

Notes: IV estimates of equation (15). The IV is the Romer-Romer shock interacted with 4Q loan growth at spatially separate banks of the same BHC. Additional controls are bank leverage, the banks median share in total assets (size), book capital growth from bank regulatory data, the median loan-to-asset ratio (LTA), the median cash-to-asset ratio (CTA), changes in the loan-loss allowance to loan ratio and changes in the charge-off to loan ratio. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

theory. The F-statistic is 38.71, which suggests that we do not suffer from a weak instrument problem.[15]

The economic magnitude of the financial dampening channel is comparable to other effects that have been highlighted in the existing literature. For instance, Kashyap and Stein (1995) show that loan growth at small banks rises by 0.3% more following a 1% reduction in interest rates than loan growth at large banks (their figure 2). In Kashyap and Stein (2000) the differential liquidity between the 10^{th} and 90^{th} generates a $0.8-5.3\%$ difference in loan growth after two years to the same monetary policy shock. Landier et al. (2013) show that the income gap difference between 25^{th} and 75^{th} percentile cause a 1.6% difference in loan growth after 4 quarters.

In the second column we add interactions of book capital growth and bank size with the monetary policy shock. As our measure of bank size we use a bank's median asset share over its lifetime. Controlling for book capital serves two purposes. First, in our baseline model we disallowed direct equity issuance by the bank (only internal capital markets where available), so holding equity fixed more closely approximates the model on that dimension. Second, it ensures that our estimates are not driven by unprofitable, weak banks that shrink their balance sheet because their capital is declining. We find that while these controls are significant, they only raise our coefficient of interest. This effect is largely driven by the capital growth control. It suggests that retrenching banks accumulate more capital to limit the decline in loan growth. By holding capital growth fixed we hold this mitigating factor fixed, which increases the estimated impact of financial dampening.

Another concern is that differential responses across banks are driven by differences in portfolio risks across banks. For example, the balance sheet of banks with a higher loan-to-asset ratio is likely more sensitive to monetary policy shocks, which may induce more

[15]The Stock and Yogo (2005) critical value for one endogenous variable and nine instruments is 36.19 and for two endogenous variables and nine instrument it is 27.51. The monotonicity implies that we clear the threshold for our just-identified setting with nine endogenous variables. Angrist and Pischke (2009) further argue that weak identification problems in just-identified IV manifest themselves in wide standard errors in the second stage but our second-stage coefficient are fairly precisely estimated.

volatile loan supply at these banks. In column 3 we add controls for the loan-to-asset and cash-to-asset ratio measured as averages over a banks lifetime. These controls also do not change our coefficient of interest, but we do find a greater sensitivity of loan quantities at banks with higher loan-to-asset ratios.

An alternative way to ensure that our results are not driven by potentially time-varying differences in bank profitability or portfolio selection is to control for loan charge-offs or loan-loss allowances, which capture the amount of non-performing loans at banks. In column 4, we use changes in the charge-off to loan ratio and the loan-loss allowance to loan ratio to again ensure that our estimates are again not driven by weak banks. As in the other columns, we still find consistent evidence for financial dampening.

We next explore on what other dimensions retrenching banks differentially adjust their balance sheets in response to monetary policy shocks. First, in table 8 we use total asset growth of bank i at time t as our dependent variable. The retrenchment effects are also present for asset growth. The sum of coefficients on the loan growth interaction range from -8 to -12, but they are at best borderline significant. Nevertheless, the economic magnitudes are large: according to column 1 a banks who's loan growth has been 10 percentage points slower will expand their asset growth by 0.88 percentage points less than the average bank following a 1 percentage point monetary policy rate reduction. Because the estimate is smaller than that for loan growth, it implies that a retrenching bank tilts its portfolio away from loans towards other assets compared to a bank that does not retrench. This suggests that retrenching banks adjust the portfolio composition of their assets to reduce riskiness as well as the overall size of their balance sheets. This is consistent with our theory.

While our model does not make a direct prediction about the change in leverage, this outcome is also of interest since deleveraging has accompanied historical episodes of financial retrenchment and, in particular, financial crises (Reinhart and Rogoff, 2008; Schularick and Taylor, 2012). We therefore estimate equation (15) using leverage growth as dependent variable and tabulate the estimates in table 9. The estimate in column 1 implies that a

Table 8 – IV estimates for Asset Growth

	Dependent variable: 1Q Asset Growth			
	Baseline	Capital (Book) Controls	Capital & Portfolio Controls	Capital & Performance Controls
	(1)	(2)	(3)	(4)
$\Delta r_t * 4\text{Q Loan Growth}_{t-1}$	-0.76	-1.58	-2.58	-0.50
$\Delta r_{t-1} * 4\text{Q Loan Growth}_{t-2}$	-0.41	-0.25	-0.36	-0.99
$\Delta r_{t-2} * 4\text{Q Loan Growth}_{t-3}$	0.57	1.43	2.37	1.24
$\Delta r_{t-3} * 4\text{Q Loan Growth}_{t-4}$	-1.92	-2.32	-2.27	-3.36
$\Delta r_{t-4} * 4\text{Q Loan Growth}_{t-5}$	0.16	1.30	1.35	1.74
$\Delta r_{t-5} * 4\text{Q Loan Growth}_{t-6}$	-2.94	-3.42	-3.90	-3.66
$\Delta r_{t-6} * 4\text{Q Loan Growth}_{t-7}$	-2.80	-3.53	-3.49	-3.11
$\Delta r_{t-7} * 4\text{Q Loan Growth}_{t-8}$	-0.98	-1.59	-0.91	-3.05
$\Delta r_{t-8} * 4\text{Q Loan Growth}_{t-9}$	0.29	-0.0030	-0.20	-0.43
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Sum: Δr * 4Q Loan Growth	-8.779	-9.96	-10	-12.12
p-value	(0.144)	(0.192)	(0.205)	(0.153)
Sum: Δr * Leverage	.66	.52	.53	1.03
p-value	(0.456)	(0.574)	(0.574)	(0.295)
Sum: Δr * 4Q Capital Growth		4.79	4.37	7.27*
p-value		(0.238)	(0.292)	(0.087)
Sum: Δr * Size		-1.31	-3.01	-1.07
p-value		(0.843)	(0.667)	(0.879)
Sum: Δr * LTA			2.94**	
p-value			(0.02)	
Sum: Δr * CTA			-3.65	
p-value			(0.56)	
Sum: Δr * 4Q Allowance Change				-6.34
p-value				(0.946)
Sum: Δr * 4Q Charge-off Change				89.12
p-value				(0.18)
F-statistic	40.59	27.95	33.14	35.89
R^2	0.11	0.11	0.11	0.11
Observations	79,913	79,102	78,706	75,822

Notes: IV estimates of equation (15). The IV is the Romer-Romer shock interacted with 4Q loan growth at spatially separate banks of the same BHC. Additional controls are bank leverage, the banks median share in total assets (size), book capital growth from bank regulatory data, the median loan-to-asset ratio (LTA), the median cash-to-asset ratio (CTA), changes in the loan-loss allowance to loan ratio and changes in the charge-off to loan ratio. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9 – IV estimates for Leverage Growth

	Dependent variable: 1Q Leverage Growth			
	Baseline	Capital (Book) Controls	Capital & Portfolio Controls	Capital & Performance Controls
	(1)	(2)	(3)	(4)
$\Delta r_t * 4\text{Q Loan Growth}_{t-1}$	5.36	5.07	4.64	4.95
$\Delta r_{t-1} * 4\text{Q Loan Growth}_{t-2}$	1.71	1.86	2.53	1.39
$\Delta r_{t-2} * 4\text{Q Loan Growth}_{t-3}$	-7.59^{*}	-9.77^{**}	-10.9^{**}	-9.93^{*}
$\Delta r_{t-3} * 4\text{Q Loan Growth}_{t-4}$	-3.76	-4.52	-4.10	-7.68
$\Delta r_{t-4} * 4\text{Q Loan Growth}_{t-5}$	1.27	1.87	1.77	2.43
$\Delta r_{t-5} * 4\text{Q Loan Growth}_{t-6}$	-3.01	-3.42	-3.83	-3.27
$\Delta r_{t-6} * 4\text{Q Loan Growth}_{t-7}$	-0.14	-0.20	0.65	0.18
$\Delta r_{t-7} * 4\text{Q Loan Growth}_{t-8}$	-5.77^{**}	-7.40^{**}	-7.96^{**}	-7.38^{*}
$\Delta r_{t-8} * 4\text{Q Loan Growth}_{t-9}$	-4.03	-4.93	-6.17^{*}	-5.61
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Sum: Δr * 4Q Loan Growth	-15.97*	-21.45*	-23.33**	-24.92**
p-value	(0.068)	(0.056)	(0.047)	(0.044)
Sum: Δr * Leverage	1.61	.8	.73	1.34
p-value	(0.27)	(0.593)	(0.639)	(0.393)
Sum: Δr * 4Q Capital Growth		16.36***	16.89***	17.41***
p-value		(0.008)	(0.009)	(0.008)
Sum: Δr * Size		3.24	4.38	8.08
p-value		(0.755)	(0.695)	(0.447)
Sum: Δr * LTA			3.27*	
p-value			(0.06)	
Sum: Δr * CTA			-5.01	
p-value			(0.618)	
Sum: Δr * 4Q Allowance Change				-79.12
p-value				(0.586)
Sum: Δr * 4Q Charge-off Change				52.99
p-value				(0.606)
F-statistic	40.56	27.87	33.07	35.88
R^2	0.12	0.13	0.13	0.13
Observations	79,911	79,101	78,705	75,821

Notes: IV estimates of equation (15). The IV is the Romer-Romer shock interacted with 4Q loan growth at spatially separate banks of the same BHC. Additional controls are bank leverage, the banks median share in total assets (size), book capital growth from bank regulatory data, the median loan-to-asset ratio (LTA), the median cash-to-asset ratio (CTA), changes in the loan-loss allowance to loan ratio and changes in the charge-off to loan ratio. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

1.32 percentage point reduction in leverage for a bank with 10 percentage point slower loan growth following a one percentage point monetary policy rate reduction. This is consistent with essentially all the reduction in asset growth being used to reduce leverage, as implied by our baseline model. Adding controls in columns 2 through 4 increases this estimate to the point where it is also statistically significant at conventional levels.

4.3 Robustness In table 10 we document additional results for loan growth to assess the robustness of our results. For brevity we only report the sum of coefficients on loan growth interacted with the Romer-Romer shock, their p-value and (if applicable) the first-stage F-statistic. The control sets are the same as in the previous tables. In the first row we tabulate the baseline estimates and in the second the OLS estimates for the same sample of banks. These are approximately one-half to one-quarter of the IV estimates, although still highly significant. This suggests, that if our instruments are weak in some specification, they are biased towards the OLS estimates and will underestimate the effect of financial dampening.

Interestingly, the OLS estimates for the full sample of banks, including national banks not assigned to a location, are quite similar to the OLS estimates for the sub-sample (not shown). Indeed, they are stable even when we only include banks whose balance sheet exceeds ten billion 2005 dollars. This is at least suggestive evidence that loan retrenchment is also important in the full sample, and that our IV estimates generalize beyond the sample of banks where we can implement the estimation strategy.

Our second set of exercises provides additional evidence for the exclusion restriction. In our theory, BHC-member banks are linked through common cost of capital. However, if there is a dominant bank in the BHC, then local demand conditions may affect portfolio decisions by other banks. In our baseline sample the median loan share in the BHC is 10.3%, but some banks do have a much larger loan share. We therefore exclude banks whose loan share in the BHC exceeds 20%. In this sub-sample the median loan share is 4.6% and our estimated coefficients are slightly larger, suggesting that our instrumental variable strategy is not confounded by banks with large BHC loan shares.

Table 10 – Robustness Exercises

	Dependent variable: 1Q Loan Growth			
	Baseline	Capital Controls	Capital & Portfolio Controls	Capital & Performance Controls
Baseline estimates				
Sum: Δr * 4Q Loan Growth	-23.05***	-30.21***	-29.96***	-29.59***
p-value	(0.001)	(0.001)	(0.001)	(0.003)
F-statistic	39.44	29.99	31.37	30.19
OLS Estimates (same sample)				
Sum: Δr * 4Q Loan Growth	-7.82***	-7.59***	-7.19***	-3.27
p-value	(0.000)	(0.002)	(0.005)	(0.192)
F-statistic				
Excluding banks with 20% or higher share of total BHC loans				
Sum: Δr * 4Q Loan Growth	-28.04***	-35.63***	-37.43***	-29.89**
p-value	(0.002)	(0.002)	(0.002)	(0.021)
F-statistic	22.14	18.09	17.23	17.07
Excluding banks in same mSA/MSA/CSA from BHC-instrument				
Sum: Δr * 4Q Loan Growth	-29.43***	-39.95***	-40.31***	-40.87***
p-value	(0.000)	(0.000)	(0.000)	(0.001)
F-statistic	33.47	24.21	24.32	20.97
Excluding banks in same State from BHC-instrument				
Sum: Δr * 4Q Loan Growth	-59.45***	-83.79***	-85.51***	-86.04**
p-value	(0.003)	(0.005)	(0.007)	(0.013)
F-statistic	6.65	4.12	3.69	3.23
Controlling for local loan growth				
Sum: Δr * 4Q Loan Growth	-21.41***	-28.35***	-28.73***	-26.95**
p-value	(0.006)	(0.004)	(0.004)	(0.014)
F-statistic	29.05	26.80	24.97	27.53

Notes: Robustness checks of equation (15). The IV is the Romer-Romer shock interacted with 4Q loan growth in matched banks operating elsewhere. Baseline and control specifications are as in table 7. "OLS estimates" report OLS estimates of equation (15). "Excluding banks with 20% or higher share of total BHC loans" excludes banks whose share of loans in the BHC exceeds 20%. "Excluding banks in same mSA/MSA/CSA from BHC-instrument" defines a bank's location as the largest of County/mSA/MSA/CSA and thus excludes any other bank in that location from the instrument. "Excluding banks in same State from BHC-instrument" defines a bank's location as its state (subject to the 95% rule) and thus excludes any other bank in the same state from the instrument. "Controlling for local loan growth" adds a control for loan growth at the banks' location excluding the current bank. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11 – Robustness Exercises (continued)

	Dependent variable: 1Q Loan Growth			
	Baseline	Capital Controls	Capital & Portfolio Controls	Capital & Performance Controls
Excluding banks near regulatory threshold				
Sum: Δr * 4Q Loan Growth	-28.59***	-31.95***	-33.16***	-29.63**
p-value	(0.004)	(0.004)	(0.005)	(0.021)
F-statistic	19.33	24.52	26.32	28.54
Excluding BHCs with $>20\%$ of loans at banks near regulatory threshold				
Sum: Δr * 4Q Loan Growth	-36.61***	-38.71***	-39.44***	-36.61***
p-value	(0.002)	(0.002)	(0.002)	(0.009)
F-statistic	27.41	29.00	27.61	28.07
Leverage categories ($20, 40, 60, 80, 98, 99.5$ percentiles)				
Sum: Δr * 4Q Loan Growth	-24.62***	-31.95***	-31.8***	-31.01***
p-value	(0.000)	(0.000)	(0.000)	(0.001)
F-statistic	42.38	32.90	34.04	33.67
Dependent variable: 1Q Loans and Unused Commitments Growth				
Sum: Δr * 4Q Loan Growth	-22.62***	-30.38***	-30.78***	-29.55***
p-value	(0.001)	(0.001)	(0.001)	(0.004)
F-statistic	37.39	28.07	30.28	31.01
Starting sample in 1994				
Sum: Δr * 4Q Loan Growth	-19.51**	-26.47**	-25.98**	-29.42**
p-value	(0.021)	(0.021)	(0.029)	(0.019)
F-statistic	21.50	22.04	21.16	19.73
Using 100% deposit share to assign location and 0% in major-presence test				
Sum: Δr * 4Q Loan Growth	-29.23***	-36.89***	-36.41***	-36.19***
p-value	(0.000)	(0.000)	(0.000)	(0.001)
F-statistic	25.57	19.97	31.43	25.62

Notes: Robustness checks of equation (15). The IV is the Romer-Romer shock interacted with 4Q loan growth in matched banks operating elsewhere. Baseline and control specifications are as in table 7. "Excluding banks near regulatory threshold" excludes banks for which the regulatory indicator (RCFD6056) is zero or (if unavailable) the risk-adjusted capital ratio is below 12.5%. "Excluding BHCs with $>20\%$ of loans at banks near regulatory threshold" excludes banks whose BHC-loan-weighted average of the regulatory indicator exceeds 0.2. "Leverage categories ($20, 40, 60, 80, 98, 99.5$ percentiles)" replaces the linear leverage control with leverage categories with cut-offs at the $20, 40, 60, 80, 98$ and 99.5 percentiles. "Dependent variable: 1Q Loans and Unused Commitments Growth" adds unused loan commitments to the dependent variable. "Starting sample in 1994" starts the estimation in 1994 when the FDIC Summary of Deposits is first available. "Using 100% deposit share to assign location and 0% in major-presence test" only assigns banks to locations if all their deposits are located their (rather than 95% in the baseline), and replaces the 5% threshold of the major-presence test (14) with a 0% threshold. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we investigate if our results are driven by correlated demand shocks across banks within the same BHC. We first exclude all banks from the BHC instrument that are located in the same local labor market, defined as the largest of the County/mSA/MSA/CSA that the local bank is part of. This removes 8% of banks from our baseline sample and should eliminate any correlation from common shocks within these local labor markets from our instrument. However, if anything we estimate larger effects from financial dampening.

A more aggressive strategy is to repeat this exercise defining the local labor market using state-delineations. This removes 51% of all banks from our baseline sample, which is reflected in our lower F-statistics. But even so, we still find statistically significant effects from financial dampening in this specification.

As a second check, we construct local loan growth excluding the current bank to capture common unobserved local demand shocks. We sum up all assets at banks in location l of bank i but not including bank i. When there are no such banks we move up to the next geographical level until this set is non-empty. If all banks at the same location are similarly affected by local demand conditions, then this strategy would help us control for local demand. Adding this control has little effect on the strength of financial dampening. Overall, these results suggests that our instrument is largely orthogonal to local demand shocks as required by proposition 3.

In table 11 we next examine whether our estimates could be driven by regulatory limits. For example, the regulator may force banks to shed loans and simultaneously limit new loan creation. Retrenching banks could be close to regulatory capital requirements and thus less able to issue more loans following a reduction in monetary policy rates. Examining this hypothesis is somewhat limited by data availability. From the call reports we can construct the risk-adjusted capital ratio (Tier1 plus Tier 2 capital divided by risk-adjusted assets) only from 1996 onwards. The call data from 1990 to 2001 also contains a regulatory indicator (RCFD6056) if total capital exceeds 8% of adjusted total assets. We therefore splice the data as follows: we use the regulatory indicator whenever available. When it is not available, we set it to 0 if the risk-adjusted capital ratio is below 12.5%. For the overlap period, this threshold corresponds to the 80^{th} percentile of the risk-adjusted capital ratio when the regulatory indicator is 0 and the 21^{st} percentile when the regulatory indicator is 1. We then exclude banks from the sample whenever the regulatory indicator is zero. For this sub-sample we find, if anything, stronger effects from financial dampening.

We then check if this mechanism could apply at the BHC level. For example, the regulator may force all BHC member banks to shed loans and limit new loan creation. To capture this possibility, we measure what fraction of BHC loans are at banks close to the regulatory limit by weighting the bank regulatory indicator with the bank's loan share in the BHC. We then exclude all banks/BHCs from the sample for which more than 20% of loans are at BHC-member banks close to regulatory limits. Again, our estimates increase slightly. This suggests, that our results suggests that we do not conflate financial dampening with regulatory policies.

A particular model of how banks respond to regulatory minimums is Van den Heuvel (2005), which predicts that bank lending exhibits non-monotonic behavior in leverage. We therefore replace our linear leverage control with categorical variables. We use leverage quintiles supplemented with separate categories for the top 2% and top 0.5% of bank leverage. We find that banks with relatively low leverage (below the 98^{th} percentile) have the strongest response; banks with high leverage (between the 99.5^{th} and 98^{th} percentile) have the weakest response; and banks with very high leverage (top 0.5^{th} percentile) have an intermediate response to monetary policy. This non-monotonicity is consistent with Van den Heuvel's implication that high-leverage financial intermediaries may retrench and very-high-leverage banks may gamble for resurrection. However, this mechanism is distinct from financial dampening as adding these controls does not affect our estimates of the financial dampening effect.

Next we examine if retrenching banks replace on-balance sheet loans with off-balance sheet commitments, which may also be indicative of regulatory arbitrage. Alternatively, retrenching banks may also reduce their exposure to unused commitments as emphasized by Bassett et al. (2014) for the 2007-2009 recession. Thus, our outcome variable is now the growth rate of loans and unused commitments. Our estimates are almost unchanged relative to our baseline model, which suggests that banks reduce their off-balance sheet portfolio proportionally with on-balance sheet loans. This is consistent with our interpretation of loan retrenching.

In the construction of bank locations we only have FDIC deposit data from 1994 onwards, and we assume that a bank's location in 1994 is also its location before 1994. We think this is a sensible assumption since location concentration was likely decreasing over time, but in table 11 we also present results using sample after 1994. These estimates are very similar to the whole sample, although our F-statistics are somewhat smaller than in our baseline. Thus, this assumption is not driving our results. Further, the regulatory regime has changed considerably over the 1980s, with, for instance, the abolition of Regulation Q and relaxation on interstate banking restrictions (Goetz et al., 2011; Van den Heuvel, 2012). That our estimates are essentially unchanged after 1994 is further evidence that financial dampening is present across regulatory regimes.

Finally, we use a more stringent location assignment, that matches banks only to locations with 100% of their total deposits rather than 95% in the baseline. Further, in the construction of our instrument we only include banks that have no deposits in the current location rather than less than 5% (equation (14)). Our results are not sensitive to this choice.

In short, we find that financial dampening is a robust feature of bank responses to monetary policy shocks.

4.4 Local outcomes We next determine if other commercial banks in a location offset the financial dampening effect at retrenching banks. This is likely a necessary condition for financial dampening to have real effects.[16]

[16] We can only test for substitution in credit quantities. Our data do not allow us to check to what extent such loan substitutions have the same interest rate.

We first collapse the balance sheet information to the county level. For banks that operate in multiple counties, we apportion the balance sheet using the fraction of the banks' deposits located in the county in the previous year. The implicit assumption is that a bank's loan growth within a year is the same in each county l it operates, $\Delta \ln L_{ilt} = \Delta \ln L_{it}$. For the following year the county-weights adjust based on local deposit changes and we assume that these capture changes in local loan growth. If these assumptions are incorrect, then our outcome variable will be more noisy, but it should not bias our coefficients of interest.

We weigh each bank in a county by its local deposit share in the previous year, $\tilde{s}_{il,t-1} = \frac{d_{il,t-1}}{d_{l,t-1}}$. We then construct two measures of loan growth. The first only includes banks in our baseline sample ("in-sample"), which are banks assigned to a location for which we can construct the elsewhere loan growth instrument. The second measure ("all") are all commercial banks with a presence in location l,

$$\Delta \ln L_{lt}^{\text{type}} = \frac{\sum_{i \in \text{type}} \tilde{s}_{il,t-1} \Delta \ln L_{it}}{\sum_{i \in \text{type}} \tilde{s}_{il,t-1}}, \quad \text{type} \in \{\text{in-sample, all}\}$$

The "in-sample" banks account, on average, for 30.9% of county-level deposits. The banks in the "all" loan growth measure, on average account for 80.4% of local deposits. Thrifts account for the remaining share.

We repeat the same calculations to obtain two measures of local loan growth, $\Delta \ln L_{lt}^{\text{type}}$, and elsewhere loan growth $\Delta \ln L_{-l,t}^{\text{type}}$. With these data we estimate our baseline specification (15) at the county level.

The first column of table 12 is a regression analogous to the results in table 7, except that all variables are measured at the county level rather than at the bank level. We have the same outcome variable, $\Delta \ln L_{lt}^{\text{in-sample}}$, the same IV strategy, and the same sample of banks.[17] One difference is that the county-level regression weighs banks based on their local importance. Nevertheless, the estimates in column (1) of table 12 are quite close to our bank-level results.

[17] As in our baseline regressions, we trim the top 0.5% and bottom 0.5% of the balance sheet variables. For employment growth, which is less noisy, we trim the top and bottom 0.01%.

In column (2) of table 12 the outcome variable is loan growth at all commercial banks, $\Delta \ln L_{lt}^{\text{all}}$. This regression captures if other banks compensate for the relative reduction in local loan growth due to financial dampening at the in-sample banks. The total effect in column (2) is of similar size as in column (1), suggesting that there is little substitution to other banks and that financial dampening does affect local loan growth.

Table 12 – IV estimates at County level

Dependent variable:	1Q Loan Growth		1Q Employment Growth
	Banks in-sample	All banks	Local employment
	(1)	(2)	(3)
$\Delta r_{t-0} * \text{4Q Loan Growth}_{t-1}$	0.20	2.87	-3.22
$\Delta r_{t-1} * \text{4Q Loan Growth}_{t-2}$	-3.95	-3.38^{**}	-0.33
$\Delta r_{t-2} * \text{4Q Loan Growth}_{t-3}$	-2.63	-2.00	-3.36^{*}
$\Delta r_{t-3} * \text{4Q Loan Growth}_{t-4}$	1.39	-0.96	3.13
$\Delta r_{t-4} * \text{4Q Loan Growth}_{t-5}$	-0.63	-1.17	-6.15^{***}
$\Delta r_{t-5} * \text{4Q Loan Growth}_{t-6}$	2.34	1.07	1.62
$\Delta r_{t-6} * \text{4Q Loan Growth}_{t-7}$	-5.87^{***}	-3.89^{***}	-2.34
$\Delta r_{t-7} * \text{4Q Loan Growth}_{t-8}$	4.27^{*}	2.85^{*}	3.16
$\Delta r_{t-8} * \text{4Q Loan Growth}_{t-9}$	-11.6^{***}	-6.95^{***}	-1.25
Time FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Sum: Δr * 4Q Loan Growth	$-16.46{*}{*}{*}$	$-11.57{*}{*}{*}$	$-8.74{*}$
p-value	(0.009)	(0.005)	(0.078)
Sum: Δr * Leverage	0.31	$-.01$	$1.91{*}{*}$
p-value	(0.776)	(0.994)	(0.039)
F-statistic	42.80	43.81	35.64
R^2	0.06	0.15	0.11
Observations	96.535	96.535	96.332

Notes: IV estimates of equation (15) at the County level. The dependent variable is in the table header. In-sample banks are banks for which we can construct the instrument based on BHC-member banks located elsewhere. All banks are all commercial banks in the bank regulatory data. The employment regressions are weighted by the County deposit-share of in-sample banks. The IV is the Romer-Romer shock interacted with 4Q loan growth in matched banks operating elsewhere. Standard errors are clustered at the County level. Additional controls are 8 lags of the dependent variable and 8 lags of leverage and its interaction with the Romer-Romer shock.

To determine whether financial dampening also affects real economic outcomes at the county level, in column (3) we use county employment growth as an outcome variable. The regression equations are otherwise identical to columns (1) and (2). We weigh observations by the deposit share of in-sample banks to capture how important our retrenching variable is for the county.[18] We find that the effect of financial dampening on local employment is sizable, persistent and statistically significant. Figure 3 plots the implied lower employment growth in a county at the 25^{th} percentile of the loan growth distribution compared to a county at the 50^{th} percentile following a -1% monetary policy shock, along with the 95% confidence interval. The differential effect amounts to an annualized 0.52 percentage points weaker employment growth over two years. To put our quantitative results in perspective, for the U.S. economy as a whole, a -1% monetary policy shock leads to a peak increase in employment of 1% after 29 months.[19] If the aggregate effect applies at the median county, then the peak response is only -0.48% at the 25^{th} percentile of the county loan growth distribution. Thus the stimulative effect of monetary policy is almost cut in half in counties with moderate loan retrenchment. This relative slowdown in employment growth suggests that financial dampening could be an important contributor to slow recoveries from recessions featuring loan retrenchment by the financial sector.

To gauge the aggregate implications of our estimates, we apply them to differential loan retrenchment in pre-1990 and post-1990 recessions. Figure 4a displays the time-variation in financial sector real loan growth from the flow of funds averaged around pre-1990 recessions and post-1990 recessions. Real loan growth falls significantly more in post-1990 recessions: during and after the recession it is on average 3.83 percentage points lower than in pre-1990 recessions. Figure 4b shows that this correlates with weaker employment growth post-1990.

The decline in aggregate loan growth in post-1990 is also accompanied with a greater incidence of loan retrenchment among banks. From the call report data we construct the share of banks whose real four-quarter loan growth is negative and plot the time series in

[18] Alternatively, we could regress local employment growth on local loan growth instrumenting with elsewhere loan growth and elsewhere loan growth interacted with the monetary policy shock. Results are qualitatively similar in that case. A disadvantage of this second specification is that we cannot directly test for the dampening effect since we cannot separate the effect of elsewhere loan growth from its interaction with the monetary policy shock.

[19] This statement is based on regressing aggregate employment growth on the monetary policy shock, $\Delta \ln e_t = \alpha + \sum_{j=0}^{36} \beta_j r_{t-j} + \varepsilon_t$ and reporting the peak impact at 29 months, $\sum_{j=0}^{29} \beta_j$.

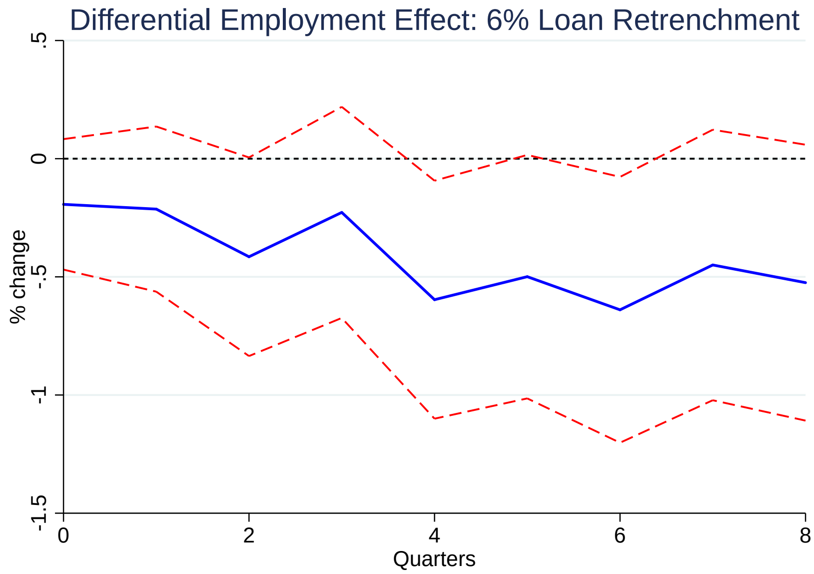
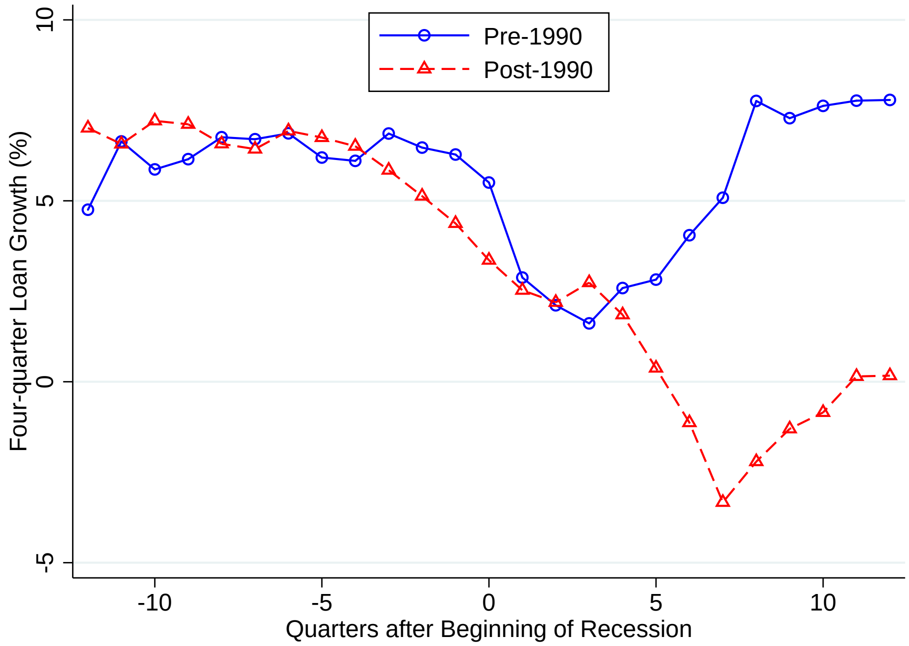


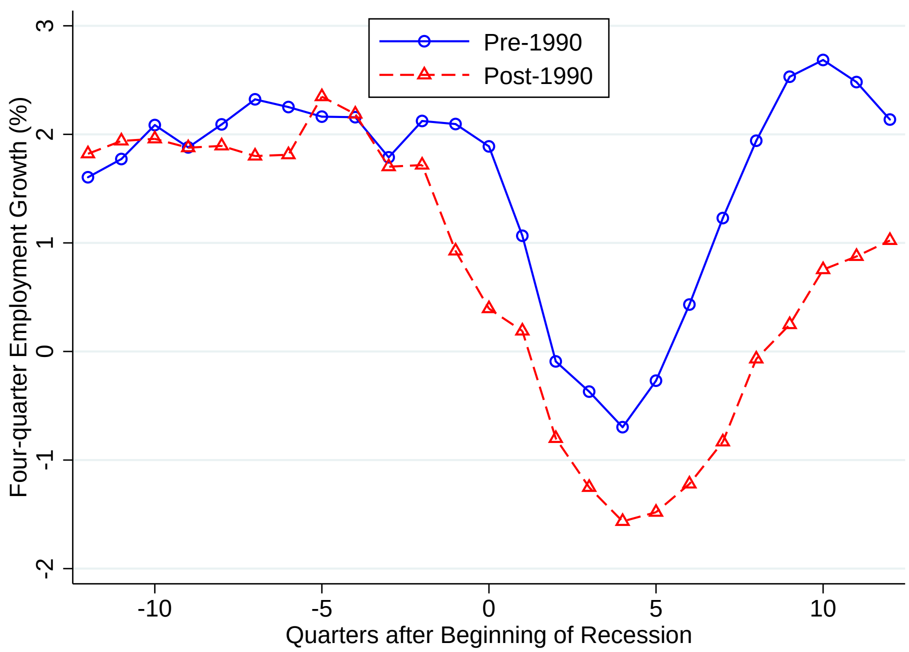
Figure 3 – Differential employment growth following a -1% monetary policy shock in a county at the 25^{th} percentile of the loan growth distribution compared to a county at the 50^{th} percentile. Dashed lines represent the 95% confidence interval.

figure 5. The data show that there is a persistent increase in the share of retrenching banks in post-1990 recessions. By contrast, following the 1981-2 recession that share dropped quickly. Along with the aggregate quantities, this fact also suggests that financial dampening is likely a much more important mechanism in post-1990 recessions than before.

Applying our estimates to the differential loan growth in post-1990 recessions implies an annualized 0.167 percentage point slower employment growth over two years for each percentage point of lower monetary policy rates. Since the Federal Funds Rate has fallen on average by 5.1 percentage points in post-1990 recessions, the cumulative effect is to reduce annual employment growth by 0.85 percentage point over two years. For comparison, average employment growth was 0.7% per year in post-1990 recoveries and 2% per year in pre-1990 recoveries, suggesting that financial dampening can potentially explain up to two thirds of the slowdown in recovery speed after 1990. Thus, extrapolating from our micro-evidence suggests that financial dampening may also be quantitatively important at the aggregate level. More generally, it provides a microfounded and empirically-supported mechanism for why recoveries after financial crises may be slow.



(a) Four-quarter real loan growth



(b) Four-quarter employemnt growth

Figure 4 – Four-quarter real loan growth rate for the U.S. financial sector and four-quarter civilian employment growth rate for the U.S. economy averaged over pre- and post-1990 recessions and centered around recession start dates. Loan growth is deflated using the U.S CPI. Source: U.S. Flow of Funds and FRED.

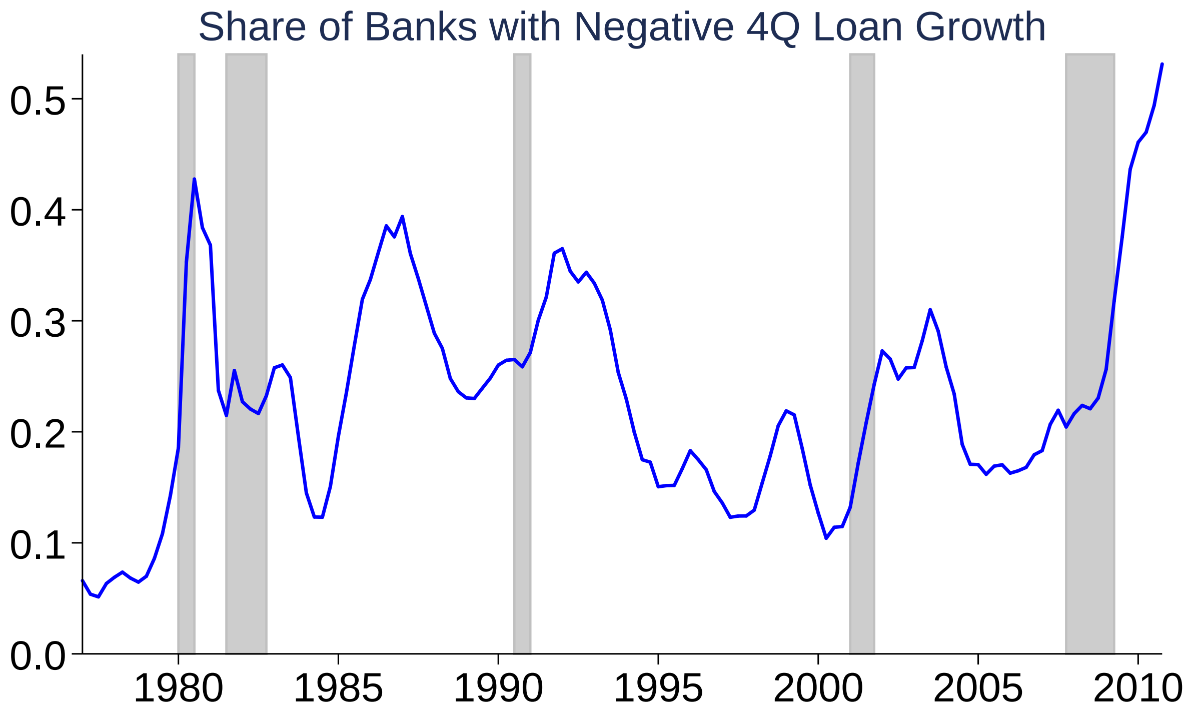


Figure 5 – Fraction of U.S. commercial bank with negative four-quarter loan growth. Loan growth is deflated using the U.S CPI. Source: U.S. Call Report Data and FRED

A limitation of these calculations is that they take monetary policy as given. But, in principle, the central bank could simply cut interest rates more aggressively to compensate for financial dampening. In our view there are two reasons why such a response is likely limited in practice. First, the central bank must have been aware of the degree of financial dampening present. To the extent that it has relied on models that do not incorporate this channel it is unlikely that its past responses were fine-tuned to the financial dampening channel. This conjecture is also supported by the persistence of loan retrenchment at a substantial fraction of banks in post-1990 recessions. Second, the zero-lower bound may constrain the central bank's ability to compensate for financial dampening. Indeed, since financial dampening renders monetary policy rate reductions less effective, the central bank may run into this constraint precisely at the time when monetary policy rates need to be cut the most to stimulate the economy to a desired effect. Thus, in our view the calculations assuming no central bank response to financial dampening are a reasonable starting point.

5 Conclusion

We document new evidence suggesting that loan retrenchment by banks attenuates the effectiveness of monetary policy, a mechanism we call financial dampening. We derive conditions under which financial dampening arises in a model of BHC member banks that share an internal capital market. The key ingredients are the usage of capital as cushion against non-tradable loan risks and loan liquidation costs. Our theory implies that retrenching banks, which face higher marginal liquidation costs, will expand loan supply less in response to a reduction in monetary policy rates compared to banks that do not retrench.

We test our baseline theory with micro-data on financial intermediation and Romer and Romer (2004) monetary policy shocks. A key obstacle is to separate the loan supply effects from loan demand. We derive an IV-strategy from our model, which exploits exploit the spatial concentration of U.S. banks and linkages across banks through common BHC-internal capital markets. We instrument loan retrenchment at a bank with average retrenchment at banks belonging to the same controlling BHC, but operating in a separate geographical area. We find that this instrument has significant predictive power. Our estimates imply that in response to a 1% monetary policy shock, a bank at the 25^{th} percentile of the retrenchment distribution increases its loan growth by 3.25 percentage points more than a bank at the 75^{th} percentile.

At the county level we do not find evidence that the financial dampening effect on loan supply is offset by other local banks. Instead, we estimate that counties with lower loan growth from financial dampening have persistently lower employment growth. Applying our estimates to the differential deleveraging patterns in pre-1990 and post-1990 recessions suggest that financial dampening may be a quantitatively important factor in slow post-1990 recoveries. This evidence provides a microfounded and empirically supported rationale for why recoveries from financial sector retrenchment, such as deep financial crises, may be slow.

Our results also suggest policy implications that we did not focus on in this paper. In particular, monetary policy may want to cut monetary policy rates more aggressively in recessions accompanied by financial sector retrenchment than in other recessions. Furthermore, if the zero-lower bound is a binding constraint on monetary policy, then our analysis suggests how non-traditional monetary policy tools working through bank balance sheets may support the traditional interest rate channel. On the asset side, direct purchases of bank loans such as during the TARP program, will mitigate financial dampening by reducing the loan liquidation costs ψ. On the liability side, capital subsidies can reduce risk premia θ^h, lower bank risk aversion, and thereby reduce loan retrenchment. We leave a more detailed study of these policy implications for future work.

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A Proofs

A.1 Proof of Proposition 1 For convenience, we restate the optimization problem of period 1 here:

$$\begin{aligned}
&\max_{L_{i,h},K_{i,h}} \quad E[V(w_{i,h},K_{i,h})] \\
\text{s.t.} \quad & w_{i,h} = (r^L - r^F)L_{i,h} + (1+r^F)K_{i,h} - \Psi(\Delta L_{i,h}/L_{i,h,0}, z)L_{i,h,0} \\
& r^L = \bar{r}^L + \varepsilon \\
& \varepsilon \sim N(0, \sigma_\varepsilon^2) \\
& V(w_{i,h},K_{i,h}) = P(w_{i,h}) - (1+r^h)K_{i,h}
\end{aligned}$$

The first order condition with respect to BHC capital $K_{i,h}$ is given by

$$E[P'(w_{i,h})](1+r^F) - (1+r^h) = 0 \tag{16}$$

The first order condition with respect $L_{i,h}$ is given by

$$E\left[P'(w_{i,h})\left(r^L - r^F - \frac{\partial\Psi(\Delta L_{i,h}/L_{i,h,0},z)}{\partial\Delta L_{i,h}/L_{i,h,0}}\right)\right] = 0 \tag{17}$$

Manipulating this first order condition (17)

$$\begin{aligned}
\frac{\partial E[P(w_{i,h})]}{\partial L_{i,h}} &= E\left[P'(w_{i,h})\cdot\frac{\partial w_{i,h}}{\partial L_{i,h}}\right] \\
&= E\left[P'(w_{i,h})\right]\cdot E\left[\frac{\partial w_{i,h}}{\partial L_{i,h}}\right] + \mathbb{C}\text{ov}\left(P'(w_{i,h}), \frac{\partial w_{i,h}}{\partial L_{i,h}}\right) \\
&= E\left[P'(w_{i,h})\right]\cdot E\left[\frac{\partial w_{i,h}}{\partial L_{i,h}}\right] + E[P''(w_{i,h})]\mathbb{C}\text{ov}\left(w_{i,h}, \frac{\partial w_{i,h}}{\partial L_{i,h}}\right) \\
&= E\left[P'(w_{i,h})\right]\cdot E\left[r^L - r^F - \tfrac{\partial\Psi(\Delta L_{i,h}/L_{i,h,0},z)}{\partial\Delta L_{i,h}/L_{i,h,0}}\right] \\
&+ E[P''(w_{i,h})]\mathbb{C}\text{ov}\left(w_{i,h}, r^L - r^F - \tfrac{\partial\Psi(\Delta L_{i,h}/L_{i,h,0},z)}{\partial\Delta L_{i,h}/L_{i,h,0}}\right) \\
&= E\left[P'(w_{i,h})\right]\cdot\left[\bar{r}^L - r^F - \tfrac{\partial\Psi(\Delta L_{i,h}/L_{i,h,0},z)}{\partial\Delta L_{i,h}/L_{i,h,0}}\right] + E[P''(w_{i,h})]L_{i,h}\sigma_\varepsilon^2
\end{aligned}$$

where from the second to the third line, we used the fact that $\mathbb{C}\text{ov}(f(x),y) = E[f'(x)]\mathbb{C}\text{ov}(x,y)$

for normally distributed random variables. Defining risk aversion as

$$
\begin{aligned}
G^h &= -\frac{E[P''(w_{i,h})]}{E[P'(w_{i,h})]} \\
&= \frac{g(1 - A + \theta^h)}{1 + \theta^h}
\end{aligned}
$$

where the second line follows from the definition of $P(w)$ in (4) and the first order condition (16) and the definition of the BHC capital premium $1 + \theta^h = \frac{1+r^h}{1+r^F}$.

Therefore, the optimal loan supply is given by

$$
L^S_{i,h}(z) = \frac{\bar{r}^L - r^F - \frac{\partial \Psi(\Delta L_{i,h}/L_{i,h,0}, z)}{\partial(\Delta L^S_{i,h}/L_{i,h,0})}}{G^h \cdot \sigma^2_\varepsilon}
$$

A.2 Proof of Proposition 2 We differentiate (7) with respect to r^F to obtain:

$$
\begin{aligned}
\frac{\partial \ln L^S_{i,h}}{\partial r^F} &= -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(\Delta L_{i,h}/L_{i,h,0})} - \frac{(1 + \Delta L_{i,h}/L_{i,h,0})\Phi''(\Delta L_{i,h}/L_{i,h,0})}{\bar{r}^L - r^F - \Phi'(\Delta L_{i,h}/L_{i,h,0})} \frac{\partial \ln L^S_{i,h}}{\partial r^F} \\
&= -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(\Delta L_{i,h}/L_{i,h,0}) + (1 + \Delta L_{i,h}/L_{i,h,0})\Phi''(\Delta L_{i,h}/L_{i,h,0})}
\end{aligned}
$$

We then approximate around $L_{i,h} = L_{i,h,0}$:

$$
\frac{\partial \ln L^S_{i,h}}{\partial r^F} \approx -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2} \ln\left(\frac{L_{i,h}}{L_{i,h,0}}\right)
$$

Our micro-foundation for the asymmetric adjustment costs (appendix B) imply $\Phi'(0) < 0$, $\Phi''(0) > 0$, $\Phi'''(0) < 0$, so that the loan supply response is given by

$$
\frac{\partial \ln L_{i,h}}{\partial r^F} \approx -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2} \ln\left(\frac{L_i}{L_{i,0}}\right) \qquad (18)
$$

A.3 Proof of Proposition 3 For convenience, we restate our core estimating equation again:

$$\frac{\partial \ln L_{i,h}}{\partial r^F} = \alpha + \beta \Delta \ln L_{i,h} + u_{i,h}$$
$$\alpha = -\frac{1-\mu}{\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)}$$
$$\beta = \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F - \Phi'(0) + \Phi''(0)]^2}$$
$$u_{i,h} = x_{i,h}\left(-\alpha - \beta \times \Delta \ln L_{i,h}\right)$$

The instrumental variables estimator is defined as

$$\begin{aligned}
\hat{\beta}^{IV} &= \frac{Cov\left(\frac{\partial \ln L_{i,h}}{\partial r^F}, \Delta \ln L_{-i,h}\right)}{Cov\left(\Delta \ln L_{i,h}, \Delta \ln L_{-i,h}\right)} \\
&= \frac{Cov\left(\alpha + \beta \times \Delta \ln L_{i,h} + u_{i,h}, \Delta \ln L_{-i,h}\right)}{Cov\left(\Delta \ln L_{i,h}, \Delta \ln L_{-i,h}\right)} \\
&= \beta + \frac{Cov\left(u_{i,h}, \Delta \ln L_{-i,h}\right)}{Cov\left(\Delta \ln L_{i,h}, \Delta \ln L_{-i,h}\right)}
\end{aligned}$$

where the key term is

$$\begin{aligned}
&Cov\left(\Delta \ln L_{-i,h}, u_{i,h}\right) \\
&= Cov\left((1-\bar{x})\Delta \ln L^S_{i,h} + \overline{x_{j,h} \cdot \Delta \ln L^c_{j,h}}\ ,\ x_i \cdot \left(-\alpha - \beta \cdot \left[\Delta \ln L^S_{i,h} + x_{i,h} \cdot \left(\Delta \ln L^c_{i,h} - \Delta \ln L^S_{i,h}\right)\right]\right)\right) \\
&= Cov\left((1-\bar{x})\Delta \ln L^S_{i,h}\ ,\ x_{i,h} \cdot \left(-\alpha - \beta\left[\Delta \ln L^S_{i,h} + x_{i,h} \cdot \left(\Delta \ln L^c_{i,h} - \Delta \ln L^S_{i,h}\right)\right]\right)\right) \\
&= -\alpha(1-\bar{x})\underbrace{Cov\left(\Delta \ln L^S_{i,h}, x_{i,h}\right)}_{=0} - (1-\bar{x})\beta\underbrace{E[x_{i,h}(1-x_{i,h})]}_{=0} Var[\Delta \ln L^S_{i,h}] \\
&- (1-\bar{x})\beta\underbrace{Cov\left(\Delta \ln L^S_{i,h}, x_i^2 \Delta ln L^c_{i,h}\right)}_{=0} \\
&= 0
\end{aligned}$$

where the second line uses that demand constraints are uncorrelated across banks in different locations and the third line uses the independence of $x_{i,h}$ from $\Delta \ln L^S_{i,h}$ (small bank assumption).

B Expected liquidation costs

In the equation (5) the actual marginal adjustment costs are unobservable, because z is unobserved by the econometrician. Thus, we can only capture the average cost of liquidations for a given observed change in loan exposure. Assuming a uniform distribution for z, $z \sim U[a,b]$, the average marginal liquidation cost for a bank is,

$$\begin{aligned}
\Phi'\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}\right) &= E_z\left[\frac{\partial \Psi}{\partial \frac{\Delta L_{i,h}}{L_{i,h,0}}}\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}, z\right)\right] \\
&= E_z\left[\psi\left(\frac{\Delta L_{i,h}}{L_{i,h,0}} - z\right)\mathcal{I}\left\{\frac{\Delta L_{i,h}}{L_{i,h,0}} - z < 0\right\}\right] \\
&= \psi\frac{\Delta L_{i,h}}{L_{i,h,0}}\mathbb{P}\mathrm{r}_z\left(\frac{\Delta L_{i,h}}{L_{i,h,0}} - z < 0\right) - \psi E_z\left[z\mathcal{I}\left\{\frac{\Delta L_{i,h}}{L_{i,h,0}} < z\right\}\right] \\
&= \psi\frac{\Delta L_{i,h}}{L_{i,h,0}}\frac{b - \frac{\Delta L_{i,h}}{L_{i,h,0}}}{b-a} - \psi\frac{b^2 - \left(\frac{\Delta L_{i,h,0}}{L_{i,h,0}}\right)^2}{2(b-a)}
\end{aligned}$$

where $\mathcal{I}\{\bullet\}$ is an indicator function and the last line assumes that observed loan growth is within the bounds $b > \frac{\Delta L_{i,h}}{L_{i,h,0}} > a$. Crucial for our purposes, the adjustment costs are asymmetric

$$\begin{aligned}
\Phi'\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}\right) &= -\frac{\psi}{2}\frac{\left(b - \frac{\Delta L_{i,h}}{L_{i,h,0}}\right)^2}{b-a} < 0 \\
\Phi''\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}\right) &= \frac{\psi(b - \frac{\Delta L_{i,h}}{L_{i,h,0}})}{b-a} > 0 \\
\Phi'''\left(\frac{\Delta L_{i,h}}{L_{i,h,0}}\right) &= \frac{-\psi}{b-a} < 0
\end{aligned}$$

Evaluated at zero:

$$\begin{aligned}
\Phi'(0) &= -\frac{\psi b^2}{2(b-a)} < 0 \\
\Phi''(0) &= \frac{\psi b}{b-a} > 0 \\
\Phi'''(0) &= -\frac{\psi}{b-a} < 0
\end{aligned}$$

With a symmetry, $a = -b$, we have $\Phi'(0) = -\frac{\psi a}{4}$, $\Phi''(0) = \frac{\psi}{2}$, and $\Phi'''(0) = -\frac{\psi}{2a}$.