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 (2014) 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 define non-tradable risks as any risk that a bank cannot hedge against using traded financial instruments.[1] We build on Froot and Stein (1998), which provides a unified framework 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, 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 loan exposure is above their target 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

[1]In particular, some types of lending, such as loans to small businesses might be highly reliant on soft information that cannot be easily summarized by measures such as credit ratings and would therefore face severe illiquidity, when securitized. Additionally, these types of loans might also require continuous monitoring to perform well. Consequently, any counterparty that might provide for example credit-default swaps would risk to undermine monitoring efforts by the loan-originating bank.

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 a 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 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. These cross-sectional effects are quantitatively large and comparable to the size and liquidity effects identified by Kashyap and Stein (1995, 2000).

We provide a battery of robustness checks to validate the exclusion restriction and address several potential threats to identification. First, we control for loan demand at other local banks and for local house prices. Second, to address concerns about spatially correlated demand shocks we exclude banks from the instrument that are closely located in the same MSA or State. Third, we exclude banks with a sizable loan share within the BHC that could create causality from local demand shocks to the instrument. In each case our results are quantitatively similar or strengthen.

Next, we address identification threats stemming from bank portfolio specialization. First, BHCs may select into areas with specific industrial compositions that differ in their sensitivity to a monetary shock, in which case a monetary policy shock can generate differential loan demand shocks across BHC. We account for this issue by controlling for local industry composition. Second, BHCs might select into certain types of lending within each area, such as small business lending. If loan demand at small business is more sensitive to monetary policy this can threaten identification. We therefore include several bank portfolio controls, including the extent of small business lending and balance sheet liquidity. Again these controls result in quantitatively similar or stronger estimates.

Finally, we show that our results are distinct from other well-known determinants of the bank lending channel, such as bank liquidity (Kashyap and Stein, 2000), banks size (Kashyap and Stein, 1995), the level of leverage (Bernanke, Gertler, and Gilchrist, 1999), regulatory capital constraints (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 25^{th} percentile. This suggests that financial dampening may be important mechanism for the real economy, and an empirically supported mechanism for why recoveries after financial distress may be slow.

This paper relates to at least four 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 (2015), among many 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) emphasizes state-contingency of the credit channel when the *level* of leverage is close to the regulatory maximum. Our mechanism instead emphasizes the desired *change* in loan holdings, which is not dependent on being close to a capital requirement. Our study is also related to recent empirical work on the monetary transmission mechanism for Quantitative Easing (QE) operations as opposed to conventional policy rate changes. In particular, Luck and Zimmermann (2018) argue that large-scale asset purchases during QE1 and QE3 increased loan supply the most at banks with a high exposure to mortgage-backed securities (MBS). Their findings can be understood as mirroring our financial dampening mechanism, since in their work, central bank policies are targeted at the most distorted banks are most successful at expanding loan supply. In contrast, since the conventional monetary policy changes we analyze do not target the allocation of BHC internal capital markets, policy rate changes are least effective at local banks that are most affected by BHC-level capital scarcity.

Second, our work is related to the empirical work on the link between financial shocks and real economic outcomes (e.g., Peek and Rosengren, 2000; Chodorow-Reich, 2014; Bassett, Chosak, Driscoll, and Zakrajšek, 2014; Amiti and Weinstein, 2018). Using lenders operating in multiple geographic areas to control for local loan demand is similar is spirit to Peek and Rosengren (2000); Greenstone, Mas, and Nguyen (2017); Amiti and Weinstein (2018), and Mondragon (2018). 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.

Third, 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; Cúrdia and Woodford, 2016). In these models, the effectiveness of monetary policy is increasing in the level of leverage, whereas the 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 Krishnamurthy, 2010; Ang, Gorovyy, and Van Inwegen, 2011), the effectiveness of monetary policy can be attenuated by the desire of the financial sector to retrench. This implies that the effectiveness of monetary policy is likely contingent on the state of the financial sector. Existing work has instead emphasized differential effectiveness based on firm balance sheets (Gertler and Gilchrist, 1994), based on whether the economy is in a recessions and expansions (e.g., Angrist, Jordà, and Kuersteiner, 2018; Barnichon and Matthes, 2015; Tenreyro and Thwaites, 2016), or based on uncertainty (Vavra, 2014).

Fourth, our work is related to studies analyzing how internal capital markets shape investment choices (Stein, 1997; Scharfstein and Stein, 2000). Houston et al. (1997) and Campello (2002) also focus on how internal capital markets shape lending behavior at BHCs, but they proxy for financial constraints using cash-flow sensitivities whereas we derive an IV-strategy to estimate loan supply as a function of scarcity in the internal capital market. Our model builds on Froot and Stein's integrated view of capital budgeting and loan risk management.[2] Consistent with the model, Begenau, Piazzesi, and Schneider (2015) find that loan risk is not hedged with BHC-level derivative positions and Cebenoyan and Strahan (2004) show that the subset of banks actively selling loans hold systematically less capital than other banks.

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, bank loans are illiquid and subject to non-linear liquidation costs. This implies that the interest rate elasticity of loan supply will depend on the bank's existing exposure to non-tradable loan risk relative to the bank's desired risk. This new ingredient allows us to formalize financial dampening. Second, we allow for unobservable changes in local loan demand that can potentially affect the responsiveness of banks to monetary policy, and thereby complicate identification of a supply-driven financial dampening channel. A third, more incremental, extension of Froot and Stein (1998) is that we model the behavior of local BHC subsidiaries, which are connected through a BHC internal capital market. This allows us to derive our estimation equation and IV-strategy directly from our model.

[2] Rampini and Viswanathan (2010) provide an alternative framework where collateralization constraints connect capital budgeting and risk management to net wealth. We conjecture that our results can be recast in that framework with BHC-collateral constraints taking the role of the BHC-level capital cost in our framework. However, even such a model would need loan liquidation costs to generate financial dampening effects discussed here.

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 that each bank i is a small part of the BHC and each bank operates on a separate island. The bank has a choice of investing in illiquid, risky loans $L_{i,h}$ or in liquid, safe securities $S_{i,h}$. These investments are in turn funded by an exogenously given local deposit base $\widetilde{D}_{i,h}$ and capital provided by the BHC, denoted $K_{i,h}$. The balance sheet is therefore

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

The model has two subperiods. 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 that banks' loan portfolio risks are non-tradable. This assumption can be relaxed following Froot and Stein (1998), in which banks optimally hedge all tradable risks away so that only non-tradable risks remain on the balance sheet. Begenau et al. (2015) provide evidence for the existence of non-tradable loan risk on balance sheets of local banks in call report data.

Since our model focuses on non-tradable loan portfolio risks, loans are subject to quadratic liquidation costs. To liquidate $x * 100$ percent of its initial loan portfolio, the bank has to pay a cost $\Psi(x)L_{i,h,0} = \frac{\psi}{2}x^2\mathcal{I}\{x<0\}L_{i,h,0}$ 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, 2018).[4] Thus, the liquidation cost is,

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

[3] We can let deposit rates differ from the safe rate without affecting our derivations.

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

Following Froot, Scharfstein, and Stein (1993) and Froot and Stein (1998), banks use their period 1 cash flows to invest in a non-stochastic investment opportunity. As Froot and Stein (1998), we assume that the payoff is given by the concave function,[5]

$$P(w) = Aw + B\left(1 - \frac{1}{g}e^{-gw}\right) \tag{3}$$

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 implies decreasing risk aversion, so that banks with larger values of cash flows w_i will exhibit more risk-seeking behavior. For low values of 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.

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 $P(\bullet)$ creates risk aversion in banks, as low realizations of $w_{i,h}$ imply high marginal returns $P'(w_{i,h})$, and vice versa. Second, since capital from the BHC, $K_{i,h}$, are part of cash flows $w_{i,h}$, it acts as insurance against low loan returns. 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 $\theta^h > 0$.

2.3 Payoffs The final payoff in period 2 is the return from the investment opportunity $P(w_{i,h})$ net of equity repayment, $V(w_{i,h}, K_{i,h}) = P(w_{i,h}) - (1 + r^h)K_{i,h}$.

As the return on loans, r^L, is a random variable, banks in period 1 optimally choose

[5] 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.

loans $L_{i,h}$ and capital $K_{i,h}$ to maximize expected utility:

$$\max_{L_{i,h},K_{i,h}} \quad E[V(w_{i,h}, K_{i,h})]$$

$$\text{s.t.} \qquad w_{i,h} = (r^L - r^F)L_{i,h} + (1 + r^F)K_{i,h} - \Psi(\Delta L_{i,h}/L_{i,h,0})L_{i,h,0}$$

$$r^L = \bar{r}^L + \varepsilon, \qquad \varepsilon \sim N(0, \sigma_\varepsilon^2)$$

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

Proposition 1 *The optimal loan supply is given by*

$$L_{i,h}^{S*} = \frac{\bar{r}^L - r^F - \Psi'(\Delta L_{i,h}^{S*}/L_{i,h,0})}{G^h \cdot \sigma_\varepsilon^2} \tag{4}$$

where the absolute risk aversion coefficient is

$$G^h = \frac{g(1 - A + \theta^h)}{1 + \theta^h} > 0 \tag{5}$$

Proof See appendix A.1. ■

The numerator in (4) is the expected excess return, which consists of the expected loan premium and the marginal liquidation cost Ψ' (which may be zero). The denominator is the BHC-specific absolute risk aversion G^h and the variance of loan returns.

A 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,

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

We assume that the econometrician observes loan supply only with measurement error, $L^S_{i,h} = L^{S*}_{i,h} + \varepsilon L_{i,h,0}$. The measurement error $\varepsilon \perp\!\!\!\perp L^{S*}_{i,h}$ is bank-specific and scales with bank size $L_{i,h,0}$. The average loan supply $E_\varepsilon[L^{S*}_{i,h}|L^S_{i,h}]$ is then equal to,

$$E_\varepsilon[L^{S*}_{i,h}|L^S_{i,h}] = \frac{\bar{r}^L - r^F - \Phi'(\Delta L^S_{i,h}/L_{i,h,0})}{G^h \cdot \sigma^2_\varepsilon} \tag{6}$$

where

$$\Phi'\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right) \equiv E_\varepsilon\left[\left.\frac{\partial\Psi(\Delta L^{S*}_{i,h}/L_{i,h,0})}{\partial \Delta L^{S*}_{i,h}/L_{i,h,0}}\right| \frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right]$$

Incorporating measurement error through the random variable ε smooths out the marginal liquidation costs. We gain the existence of a third derivative at 0, which later allows us to linearize at that point and derive a linear estimation equation for the financial dampening effect.[6] In what follows, we assume a uniform distribution for ε, $\varepsilon \sim U[-a, a]$. In appendix B we show that the marginal liquidation cost then has the properties $\Phi'(0) < 0$, $\Phi''(0) > 0$ and $\Phi'''(0) < 0$.

2.4 Optimal loan supply: responsiveness We next characterize the response of measured loan supply to monetary policy changes. We interpret monetary policy shocks as exogenous changes in the safe interest rate r^F.[7]

To ensure that changes in r^F affect loan supply, we assume that there is imperfect pass through to the expected loan return $\frac{\partial \bar{r}^L}{\partial r^F} = \mu < 1$.[8] Incomplete pass-through is consistent

[6] Alternatively, we could use the fact that a banks gross changes in asset positions typically exceed net changes in asset positions, due to the take-up of commitments and the payment of existing loans. Thus, even banks with positive net changes in total loans would be subject to loan liquidation costs because of some gross liquidations. In that set-up ε would reflect the imperfect mapping from net total loan changes to gross liquidations.

[7] 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 (Bianchi and Bigio, 2018).

[8] Alternatively, endogenous changes in loan risk, $\frac{\partial \ln \sigma^2}{\partial r^F} > 0$, achieve the same outcome.

with the data (Fuster, Goodman, Lucca, Madar, Molloy, and Willen, 2013; Scharfstein and Sunderam, 2016) 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), in which increases in loan rates induce a selection of bad risks into the loan portfolio of banks and vice-versa.

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

$$\frac{\partial \ln L_{i,h}^S}{\partial r^F} \approx -\frac{1-\mu}{\bar{r}^L - r^F + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F + \Phi''(0)]^2} \ln\left(\frac{L_{i,h}^S}{L_{i,h,0}}\right) \tag{7}$$

Proof See appendix A.2. ■

Proposition 2 captures the financial dampening mechanism that we try to measure. According to equation (7), 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 mechanism, consider the extreme case where banks cannot liquidate loans, so the marginal liquidation cost is infinite. Then banks that would want to contract loan supply (absent liquidations costs) to $L_{i,h}^S < L_{i,h,0}$, will simply keep their current loan portfolio $L_{i,h}^S = L_{i,h,0}$. A reduction in policy rates does raise the ideal loan supply $L_{i,h}^S$, 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."

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 the intuition for interest rate decreases.

2.5 Local loan demand Because loan supply is not directly observable, we cannot estimate equation (7). This creates an identification problem because realized loan volumes can be driven by either supply or demand. We formalize this idea as follows. Local markets may be subject to constrained loan demand, which captures variations in investment opportunities. Denote $L^c_{i,h}$ as maximum possible loan demand in the location of bank i. Realized loan volumes are then given by

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

where $x_{i,h} = \mathcal{I}\{\ln L^c_{i,h} < \ln L^S_{i,h}\}$ is an indicator of whether a bank is constrained by local loan demand. In this demand-constrained case, there is no response of loan quantities to monetary policy. Thus, while reduced-form, this demand equation captures the key concern that weak loan quantity responses may come from the demand-side rather than the supply side.

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. As we discuss below, a violation of this assumption creates a bias against us in our IV strategy.

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

$$\frac{\partial \ln L_{i,h}}{\partial r^F} = \alpha + \beta \Delta \ln L_{i,h} + u_{i,h} \tag{8}$$

where

$$\alpha = -\frac{1-\mu}{\bar{r}^L - r^F + \Phi''(0)} \tag{9}$$

$$\beta = \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F + \Phi''(0)]^2} \tag{10}$$

$$u_{i,h} = x_{i,h}\left(-\alpha - \beta \times \Delta \ln L_{i,h}\right) \tag{11}$$

$$\Delta \ln L_{i,h} = \Delta \ln L^S_{i,h} + x_{i,h}\left(\Delta \ln L^c_{i,h} - \Delta \ln L^S_{i,h}\right) \tag{12}$$

The resulting OLS regression would therefore be a regression of loan growth at bank i, $\partial \ln L_{i,h}$, 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 affect both local loan volumes (12) and the error term (11) through the constraint indicator $x_{i,h}$. Thus, even if $\beta = 0$, the OLS estimate is biased towards finding evidence for financial dampening, $E[\hat{\beta}^{OLS}] < 0$.[9] 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.

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

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

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

$$\begin{aligned}\Delta \ln L_{-i,h} &= \frac{1}{N}\sum_{j\neq i} \Delta \ln L_{j,h} \\ &= (1-\bar{x})\Delta \ln L^S_{i,h} + \overline{x_{j,h}\Delta \ln L^c_{j,h}}\end{aligned}$$

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

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.[10] 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 (8). 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 (8).

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 controls we add to equation (8). 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

[10] Our identification strategy does require that BHC capital costs get passed through perfectly to local banks. For example, distortions in the BHC internal capital markets could lead to an incomplete pass-through of BHC capital costs to local banks (Scharfstein and Stein, 2000; Rajan, Servaes, and Zingales, 2000). This would weaken our instrument because loan growth at other BHC-member banks is less informative about capital costs at the local bank, but it would not violate the exclusion restriction.

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.[11]

3 Data

Our identification strategy requires knowledge of which BHCs own which banks, the amount of loans made by banks, and in which local area a given bank operates. In brief, we use the bank call report data to determine how many loans a bank has made and which BHC owns the bank. This knowledge allows us to determine the ownership structure of banks across BHCs. We use the location of physical branches of a bank to determine the area in which a given bank makes loans.

For example, the bank New York Commercial Bank is owned by the multi-bank BHC New York Community Bancorp. The call reports tell us how many loans New York Commercial Bank has made. New York Commercial Bank also operates 30 physical branches in metropolitan New York (but not elsewhere). We therefore assume that New York Commercial Bank only makes loans in the New York metropolitan area.

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

[11]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.

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.

been previously used by Kashyap and Stein (2000) and Campello (2002) among others.[12] 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 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.

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 strat-

[12] Goetz, Laeven, and Levine (2013) 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.

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.

egy 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 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.

This geographic concentration of banking activity is likely rooted in historical restrictions

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.

on interstate banking due to the National Bank Act of 1863 and the McFadden Act of 1927, which substantially curtailed geographic diversification of banks. These restrictions were then gradually lifted during the 1980s and 1990s resulting in the deregulation of interstate banking studied in Goetz et al. (2013).

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 (2019) 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,

$$L_{-l,ht} = \sum_{k \in \Omega_h} L_{kht} \mathcal{I}\{s_{klt} < 0.05\} \tag{13}$$

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

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.

Table 5 – Commercial Bank Balance Sheets Summary Statistics

	Mean	SD	25 pctile	Median	75 pctile	Observations
Asset growth (one-quarter)	1.74	5.46	−1.04	1.19	3.72	87262
Loan growth (one-quarter)	2.23	6.25	−0.83	1.75	4.57	86834
Leverage growth (one-quarter)	−0.096	7.77	−3.35	−0.43	2.77	87261
Loan growth (four-quarter)	9.68	17.6	0.92	7.31	14.8	86726
Elsewhere loan growth (four-quarter)	9.93	12.2	3.25	8.45	14.5	88027

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.

of the largest banks in the sample. This is because we cannot assign national banks to a single location.

Because the bank regulatory data are 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.

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.[13] 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.

4 Results

We add a lag structure to equation (8), which was found to be relevant in previous bank-level studies (Kashyap and Stein, 1995; Landier et al., 2015; 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 (8) with 8 lags as well as controls for the level of leverage and the non-interacted elsewhere loan growth,

$$\begin{aligned}\Delta \ln L_{i,h,t} =& \alpha_i + \gamma_t + \sum_{k=0}^{8} \beta_k \Delta r_{t-k} \Delta^4 \ln L_{i,h,t-1-k} + \sum_{k=0}^{8} \delta_k \Delta r_{t-k} \phi_{i,h,t-1-k} \\ &+ \sum_{k=0}^{8} \theta_{1k} \phi_{i,h,t-1-k} + \sum_{k=0}^{8} \theta_{2k} \Delta^4 \ln L_{i,h,t-1-k} \\ &+ \sum_{k=0}^{8} \theta_{3k} \Delta^4 \ln L_{-l,h,t-1-k} + \sum_{k=1}^{8} \gamma_{1k} \Delta \ln L_{i,h,t-k} + \delta \times \text{controls} + \varepsilon_{it}.\end{aligned} \tag{14}$$

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, $\{\Delta r_{t-k} \Delta^4 \ln L_{-l,h,t-1-k}\}_{k=0,\ldots,8}$.

Note that the timing here is analogous to equation (8) multiplied through by ∂r^F, $\partial \ln L^S_{i,h} = \alpha \partial \ln L^S_{i,h} + \beta \Delta \ln L_{i,h} \partial r^f + v_{i,h}$. The latter characterizes the response of loan growth $\partial \ln L^S_{i,h}$ as a function of the interaction of an exogenous change in interest rates

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

∂r^F and the pre-existing distance of loan supply from the initial loan supply $\Delta \ln L_{i,h}$. In discrete time we adopt this timing by measuring the growth rate of loans $\partial \ln L^S_{i,h}$ for the time horizon $t-1$ to t, while measuring the pre-existing distance of loan supply from the initial loan supply $\Delta \ln L^S_{i,h}$ using loan volume changes from $t-2$ to $t-1$.

We further add time fixed-effects to absorb any correlation between the endogenous variables and instruments induced by aggregate business cycle variation (e.g., common demand shocks). Also, 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 (14) 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^{***}	-0.003	-0.003	0.011^{**}	0.015^{***}	-0.001	0.004	0.007	0.005
$\Delta r_{t-1} *$ 4Q BHC Loan Growth$_{t-2}$	-0.003	0.26^{***}	-0.000	-0.008	0.009^{**}	0.012^{**}	0.001	0.005	0.006
$\Delta r_{t-2} *$ 4Q BHC Loan Growth$_{t-3}$	0.000	-0.002	0.27^{***}	0.006	0.001	0.003	0.017^{***}	-0.000	0.010^{*}
$\Delta r_{t-3} *$ 4Q BHC Loan Growth$_{t-4}$	-0.005	-0.001	-0.00096	0.28^{***}	0.005	0.007	0.005	0.018^{***}	-0.005
$\Delta r_{t-4} *$ 4Q BHC Loan Growth$_{t-5}$	0.018^{***}	-0.003	-0.001	-0.0004	0.28^{***}	-0.006	0.007	0.010^{*}	0.018^{***}
$\Delta r_{t-5} *$ 4Q BHC Loan Growth$_{t-6}$	0.006	0.013^{***}	-0.011^{**}	-0.001	-0.003	0.30^{***}	-0.006	0.004	0.006
$\Delta r_{t-6} *$ 4Q BHC Loan Growth$_{t-7}$	-0.014^{***}	0.008^{*}	0.015^{***}	-0.012^{**}	-0.002	-0.006	0.31^{***}	-0.005	-0.003
$\Delta r_{t-7} *$ 4Q BHC Loan Growth$_{t-8}$	0.011^{**}	-0.009^{**}	0.008^{**}	0.016^{***}	-0.007	-0.001	-0.004	0.31^{***}	-0.001
$\Delta r_{t-8} *$ 4Q BHC Loan Growth$_{t-9}$	0.000	0.012^{***}	-0.010^{***}	0.006	0.018^{***}	-0.006	-0.004	-0.002	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)
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 (14). 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 (14), 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 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 (14) 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 -23.1 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 (14). 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 39.44, which suggests that we do not suffer from a weak instrument problem.[14]

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. (2015) 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

[14] 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. 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. 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, 2014; Schularick and

Table 8 – Other Outcome Variables

	Baseline	Capital Controls	Capital & Portfolio Controls	Capital & Performance Controls
Dependent variable: Asset Growth				
Sum: Δr * 4Q Loan Growth	-8.779	-9.96	-10	-12.12
p-value	(0.144)	(0.192)	(0.205)	(0.153)
F-statistic	40.59	27.95	33.14	35.89
Dependent variable: Leverage Growth				
Sum: Δr * 4Q Loan Growth	-15.97*	-21.45*	-23.33**	-24.92**
p-value	(0.068)	(0.056)	(0.047)	(0.044)
F-statistic	40.56	27.87	33.07	35.88
Dependent variable: 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
Dependent variable: Real Estate Loan Growth				
Sum: Δr * 4Q Loan Growth	-17.14**	-24.56**	-23.76**	-28.66**
p-value	(0.041)	(0.028)	(0.039)	(0.02)
F-statistic	39.66	34.53	31.90	34.37
Dependent variable: C&I Loan Growth				
Sum: Δr * 4Q Loan Growth	-6.8	-13.09	-12.1	-17.13
p-value	(0.726)	(0.624)	(0.653)	(0.553)
F-statistic	38.73	28.71	29.29	28.65

Notes: Alternative dependent variables in equation (14). Baseline and control specifications are as in table 7. In each case we include eight lags of four-quarter growth of the new outcome variable as a control. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Taylor, 2012). We therefore estimate equation (14) using leverage growth as dependent variable and tabulate the estimates in table 8. The estimate in column 1 implies that a 1.60 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.

Finally, we examine the margins of adjustments within the loan portfolio. We do find that including unused commitments in our measure of loans has very little impact on our estimates of loan retrenchment (table 8). This suggests that banks are also shrinking off-balance-sheet items, rather than merely shifting loans off of the balance sheet. We also find a significant decline in real estate loans, which include both commercial and residential loans. However, our estimates for C&I loans are very noisy, so it is difficult to say whether financial dampening disproportionally affects one type of loan relative to another. Unfortunately, limited call report data prevent us from studying further disaggregated categories.

5 Validating the Identification Strategy

In tables 9 and 10 we document additional results for loan growth to validate our identification strategy and further illustrate the robustness of our results.

5.1 Spatial correlation of demand We first focus on the concern that loan demand shocks may be spatially correlated at BHC-member banks. This would violate the exclusion restriction since a common loan demand shock would determine both local and BHC-level loan quantities.

We perform three exercises to show that this concern does not drive our results. We first 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. We interact this local loan growth variable with the monetary policy shock and include it in the regression. This has little effect on the strength of financial dampening.

An alternative approach, we follow Beraja, Fuster, Hurst and Vavra (2018) who show significant effects of local house price growth on the demand for refinancing and mortgage lending. We therefore interact MSA-level house price indexes from the Federal Housing Finance Agency (FHFA) with our monetary policy shock and include this variable as a control. Using the FHFA data considerable reduces the sample size of our data, since many MSAs were not covered before the early 1990s. This reduction in sample size substantially reduces our first stage F-statistics. However, our financial dampening effects in table 9 are still relatively precisely estimated and the magnitudes become even stronger, which provides additional support that our baseline results are supply-driven rather than demand-driven.

Second, if there is a dominant bank in the BHC, then a local demand shock may affect portfolio decisions by other banks, so the instrument for the dominant bank will be invalid. 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.

Third, we drop banks in the construction of the instrument that are near the local bank and thus more likely to be subject to the same loan demand shock. We first exclude all banks from the 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. These results suggest that our results are not driven by spatially correlated demand shocks.

5.2 Portfolio selection effects Next we focus on the concern that specialization by the BHC creates generates correlated demand shocks among BHC-member banks. We have already included several portfolio controls that will account for some of these choices. Here we further extend this analysis.

First, we directly control for the possibility that BHCs select into location with particular industry compositions. For example, the construction sector may be disproportionally affected by a national demand shock, so that BHCs operating in areas with a high employment share in construction are particularly affected by loan demand constraints. To address this issue, we also separately interact the local employment shares of mining, manufacturing and construction with the monetary policy shock and include them as controls. These controls therefore capture the possibility that some areas' loan demand is more sensitive to monetary policy because of its industry composition. As can be seen in table 9, our results with these additional controls are very similar to our baseline.

Second, after 1994 we also have data on the small business loan exposure of banks. For each bank we calculate the median value share of business and industrial loans secured by real estate that had an origination value of less and \$100,000 and less then \$1,000,000. We then interact both shares with the monetary policy shock and add this controls to our estimation. The coefficients in table 10 remain very similar our baseline estimates and particularly to the post-1994 results shown later, again showing that the financial dampening channel we identify is not an artifact of bank portfolio specialization.

Importantly we only control for bank-level portfolio choices not BHC-level portfolio choices (excluding the current bank), because only the former create a threat to our identification. For example, suppose some BHCs specialize in small business loans. If loan demand at small businesses is more sensitive to monetary policy shocks, then all BHC-member banks may see lower loan demand, even if they operate in distinct locations. However, to address this concern, it is sufficient to include only controls for local bank portfolios. Consider the case of two local banks one specializing in small business loans and the other not specializing. By controlling for the banks' small business loan exposure, we purge differences in (local) bank loan demand stemming from such specialization. Conditional on these controls, any differential exposure to small business loans at the corresponding BHCs could only affect local loan quantities through the BHC internal capital market. Since this variation is exogenous to "purged" local loan demand, our IV-strategy remains valid subject to only including bank-level portfolio controls. As we have just shown, these controls, if anything, strengthen our results.

5.3 Regulatory capital requirements In table 10 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

Table 9 – Identification Validation and Robustness Exercises

	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
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
Controlling for local house price growth				
Sum: Δr * 4Q Loan Growth	-32.53***	-37.33***	-36.81**	-30.3**
p-value	(0.003)	(0.005)	(0.01)	(0.034)
F-statistic	15.79	13.88	13.51	11.64
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 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 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 employment composition				
Sum: Δr * 4Q Loan Growth	-22.76***	-28.86***	-28.59***	-28.17***
p-value	(0.001)	(0.001)	(0.002)	(0.005)
F-statistic	35.34	28.72	29.97	28.56

Notes: Robustness checks of equation (14). Baseline and control specifications are as in table 7. “Controlling for local loan growth” adds a control for loan growth at the banks’ location excluding the current bank interacted with the monetary policy shock. “Controlling for local house price growth” adds a control for house price growth for the MSA in which the bank is located. “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 employment composition” adds the employment share of construction, manufacturing, and mining each interacted with the monetary policy shock. Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10 – Identification Validation and Robustness Exercises (continued)

	Baseline	Capital Controls	Capital & Portfolio Controls	Capital & Performance Controls
Controlling for share of small business loan (starting in 1994)				
Sum: Δr * 4Q Loan Growth	-17.79**	-24.17**	-23.76*	-26.21**
p-value	(0.044)	(0.042)	(0.05)	(0.04)
F-statistic	20.45	20.22	19.54	18.55
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
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
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
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)

Notes: Robustness checks of equation (14). Baseline and control specifications are as in table 7. "Controlling for share of small business loan" interacts the shares of small business loans ($< 100,000$ and $< 1,000,000$) secured by real estate with the monetary policy shock. "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" replaces the linear leverage control with leverage categories with cut-offs at the $20, 40, 60, 80, 98$ and 99.5 percentiles. "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 (13) with a 0% threshold. "Starting sample in 1994" starts the estimation in 1994 when the FDIC Summary of Deposits is first available. "OLS estimates" report OLS estimates of equation (14). Standard errors are clustered at the bank level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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 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 pattern 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 main estimates.

5.4 Sample construction robustness Finally, we perform robustness checks on our sample construction. First, 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 (13)). Our results are not sensitive to this choice.

Second, 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 10 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., 2013; Van den Heuvel, 2012). That our estimates are essentially unchanged after 1994 is further evidence that financial dampening is present across regulatory regimes.

Third, 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.

In short, we provide a battery of checks to validate the exclusion restriction, and show that the financial dampening channel is a quantitatively robust feature of bank responses to monetary policy shocks.

6 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.[15]

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 weight 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 (14) at the county level.

The first column of table 11 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.[16] One difference is that the county-level regression weighs banks based on their local

[15] Our data do not allow us to check to what extent such loan substitutions carry the same interest rate.

[16] 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%.

importance. Nevertheless, the estimates in column (1) of table 11 are quite close to our bank-level results.

In column (2) of table 11 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.

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 weight observations by the deposit share of in-sample banks to capture how important our retrenching variable is for the county.[17] We find that the effect of financial dampening on local employment is sizable, persistent and statistically significant.

Figure 1 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.[18] 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

[17] 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.

[18] 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, $\sum_{j=0}^{29} \beta_j$.

Table 11 – IV estimates at County level

Dependent variable:	1Q Loan Growth		1Q Employment Growth
	Banks in-sample	All banks	Local employment
	(1)	(2)	(3)
$\Delta r_{t-0} * 4\text{Q Loan Growth}_{t-1}$	0.20	2.87	−3.22
$\Delta r_{t-1} * 4\text{Q Loan Growth}_{t-2}$	−3.95	−3.38**	−0.33
$\Delta r_{t-2} * 4\text{Q Loan Growth}_{t-3}$	−2.63	−2.00	−3.36*
$\Delta r_{t-3} * 4\text{Q Loan Growth}_{t-4}$	1.39	−0.96	3.13
$\Delta r_{t-4} * 4\text{Q Loan Growth}_{t-5}$	−0.63	−1.17	−6.15***
$\Delta r_{t-5} * 4\text{Q Loan Growth}_{t-6}$	2.34	1.07	1.62
$\Delta r_{t-6} * 4\text{Q Loan Growth}_{t-7}$	−5.87***	−3.89***	−2.34
$\Delta r_{t-7} * 4\text{Q Loan Growth}_{t-8}$	4.27*	2.85*	3.16
$\Delta r_{t-8} * 4\text{Q Loan Growth}_{t-9}$	−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 (14) 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.

important contributor to slow recoveries from recessions featuring loan retrenchment by the financial sector.

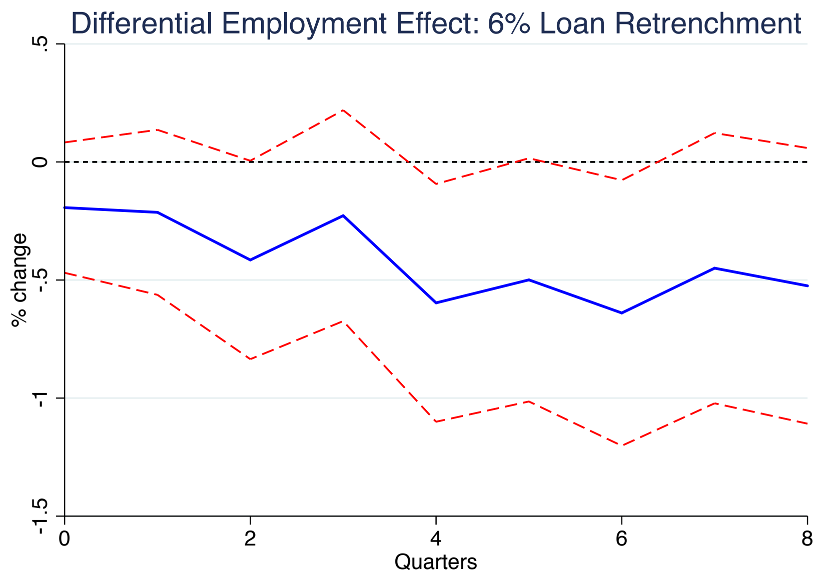

Figure 1 – Differential employment growth following a -1% monetary policy shock in a county at the 25^{th} percentile of the loan growth distribution compared to a county at the 50^{th} percentile. Dashed lines represent the 95% confidence interval.

7 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. We provide a battery of robustness checks to validate our identification strategy and demonstrate the quantitative importance of financial dampening at the bank level.

At the county level we do not find evidence that the financial dampening effect on loan supply is offset by other banks. Instead, we estimate that counties with lower loan growth from financial dampening have persistently lower employment growth. 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:

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

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

$$E[P'(w_{i,h})](1+r^F) - (1+r^h) = 0 \tag{15}$$

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

$$E\left[P'(w_{i,h})\left(r^L - r^F - \frac{\partial\Psi(\Delta L_{i,h}/L_{i,h,0})}{\partial\Delta L_{i,h}/L_{i,h,0}}\right)\right] = 0 \tag{16}$$

Manipulating this first order condition (16)

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

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

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 (3) and the first order condition (15) 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

$$L_{i,h}^{S*} = \frac{\bar{r}^L - r^F - \frac{\partial \Psi(\Delta L_{i,h}^{S*}/L_{i,h,0})}{\partial(\Delta L_{i,h}^{S*}/L_{i,h,0})}}{G^h \cdot \sigma_\varepsilon^2}$$

A.2 Proof of Proposition 2 We differentiate (4) with respect to r^F to obtain:

$$\begin{aligned} \frac{\partial \ln L_{i,h}^{S*}}{\partial r^F} &= -\frac{1-\mu}{\bar{r}^L - r^F - \Psi'\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)} - \frac{\left(1+\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)\Psi''\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)}{\bar{r}^L - r^F - \Psi'\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)} \frac{\partial \ln L_{i,h}^{S*}}{\partial r^F} \\ &= -\frac{1-\mu}{\bar{r}^L - r^F - \Psi'\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right) + \left(1+\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)\Psi''\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)} \\ &= -\frac{1-\mu}{\bar{r}^L - r^F + \Psi''\left(\frac{\Delta L_{i,h}^{S*}}{L_{i,h,0}}\right)} \end{aligned}$$

where the last line uses that Ψ is a quadratic function, so $x\Psi''(x) = \Psi'(x)$.

We then substitute $L_{i,h}^S = L_{i,h}^{S*} + \varepsilon L_{i,h,0}$,

$$\frac{\partial \ln L_{i,h}^S}{\partial r^F} \frac{L_{i,h}^S}{L_{i,h}^S - \varepsilon L_{i,h,0}} = -\frac{1-\mu}{\bar{r}^L - r^F + \Psi''\left(\frac{\Delta L_{i,h}^S}{L_{i,h,0}} - \varepsilon\right)}$$

and take expectations over the measurement error ε conditional on $\Delta L_{i,h}^S / L_{i,h,0}$,

$$\begin{aligned} \frac{\partial \ln L_{i,h}^S}{\partial r^F} E_\varepsilon\left[\bar{r}^L - r^F + \Psi''\left(\frac{\Delta L_{i,h}^S}{L_{i,h,0}} - \varepsilon\right) \middle| \frac{\Delta L_{i,h}^S}{L_{i,h,0}}\right] &= E_\varepsilon\left[\frac{-(1-\mu)(L_{i,h}^S - \varepsilon L_{i,h,0})}{L_{i,h}^S} \middle| \frac{\Delta L_{i,h}^S}{L_{i,h,0}}\right] \\ \Rightarrow \frac{\partial \ln L_{i,h}^S}{\partial r^F} &= -\frac{1-\mu}{\bar{r}^L - r^F + \Phi''\left(\frac{\Delta L_{i,h}^S}{L_{i,h,0}}\right)} \end{aligned}$$

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

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

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

$$\frac{\partial \ln L^S_{i,h}}{\partial r^F} \approx -\frac{1-\mu}{\bar{r}^L - r^F + \Phi''(0)} + \frac{(1-\mu)\Phi'''(0)}{[\bar{r}^L - r^F + \Phi''(0)]^2} \ln\left(\frac{L^S_{i,h}}{L_{i,h,0}}\right) \tag{17}$$

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

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

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

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

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 (4) the actual marginal adjustment costs are unobservable, because the measurement error ε 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 ε, $\varepsilon \sim U[a,b]$, the average marginal liquidation cost for a bank is,

$$
\begin{aligned}
\Phi'\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right) &= E_\varepsilon\left[\frac{\partial \Psi}{\partial \frac{\Delta L^{S*}_{i,h}}{L_{i,h,0}}}\left(\frac{\Delta L^{S*}_{i,h}}{L_{i,h,0}}\right)\middle| \frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right] \\
&= E_\varepsilon\left[\psi\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}} - \varepsilon\right)\mathcal{I}\left\{\frac{\Delta L^S_{i,h}}{L_{i,h,0}} - \varepsilon < 0\right\}\right] \\
&= \psi \frac{\Delta L^S_{i,h}}{L_{i,h,0}} \mathbb{P}\mathrm{r}_\varepsilon\left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}} - \varepsilon < 0\right) - \psi E_\varepsilon\left[\varepsilon \mathcal{I}\left\{\frac{\Delta L^S_{i,h}}{L_{i,h,0}} < \varepsilon\right\}\right] \\
&= \psi \frac{\Delta L^S_{i,h}}{L_{i,h,0}} \frac{b - \frac{\Delta L^S_{i,h}}{L_{i,h,0}}}{b-a} - \psi \frac{b^2 - \left(\frac{\Delta L^S_{i,h}}{L_{i,h,0}}\right)^2}{2(b-a)}
\end{aligned}
$$

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

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

Evaluated at zero:

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

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