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THE RESERVE SUPPLY CHANNEL OF UNCONVENTIONAL MONETARY POLICY

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ABSTRACT

We find that central bank reserves injected by QE crowd out bank lending. We estimate a structural model with cross-sectional instrumental variables for deposit and loan demand. Our results are determined by the elasticity of loan demand and the impact of reserve holdings on the cost of supplying loans. The reserves injected by QE raise loan rates by 8.2 basis points, and each dollar of reserves reduces bank lending by 8.1 cents. Our results imply that a large injection of central bank reserves has the unintended consequence of crowding out bank loans because of bank balance sheet costs.

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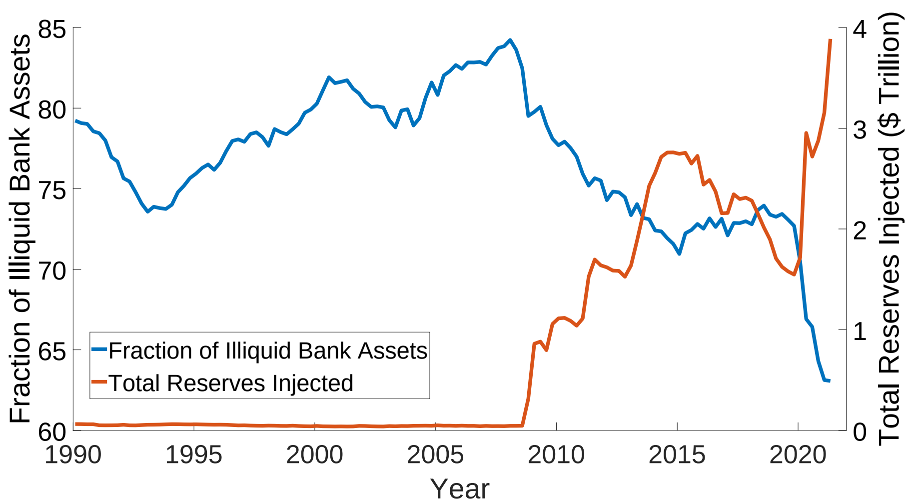
1 Introduction

There has been a massive expansion of central bank reserves in the last 15 years. In the US, reserves amounted to less than \$50 billion in 2008Q1, but reached \$2.8 trillion in 2015 and exceeded \$3 trillion in 2021 (Figure 1). These reserves were created in the aftermath of the 2008–2009 financial crisis and the 2020 Covid-19 pandemic, when the Federal Reserve conducted trillions of dollars worth of Quantitative Easing (QE). In QE, the Federal Reserve buys assets such as Treasuries, which are primarily held outside of the banking sector.[1] The Federal Reserve then pays with reserves, which are an interest-bearing asset that can only be held within the banking system. QE therefore results in a net injection of liquid assets to bank balance sheets. While a large literature has studied the effect of QE's asset purchases, less is known about how QE's injection of reserves impacted the functioning of the banking system. We document the unintended consequence that reserves crowd out bank lending to the real economy, i.e., the "reserve supply channel".

In principle, an increase in the supply of central bank reserves could either increase or decrease bank lending, motivating the need for empirical analysis. If holding illiquid assets like mortgages and loans funded by runnable deposits raises the risk of a bank run, increasing the supply of liquid reserves could reduce the risk of runs and increase banks' ability to lend. Conversely, regulatory constraints like the leverage ratio can make it costly for banks to expand their asset holdings so that a bank which holds more reserves will want to reduce its lending.

Figure 1: Supply of Central Bank Reserves and Bank Asset Illiquidity

This figure plots the total reserves of US depository institutions and their ratio of illiquid to total assets from 1990 to 2021. Illiquid assets include all assets except for cash, reserves, Fed funds, repos, Treasury securities and agency securities. Data is from FRED.



[1] In 2008Q1, only 1.1% of Treasuries outstanding were held by US banks.

Aggregate time series evidence suggests that QE's injection of reserves crowded out bank lending. As reserves increased from $0.02 trillion in 2006Q1 to $3.88 trillion in 2021Q1, the proportion of illiquid assets such as loans on bank balance sheets declined from 83% to 63% (see Figure 1). However, QE was implemented to stimulate the economy during recessions. Thus, the observed substitution away from illiquid assets could simply reflect a low demand for bank loans rather than being the direct result of QE itself.

Instead of directly using time series data, we estimate a structural model with plausibly exogenous instruments to quantify the impact of QE's reserve injection. On the demand side, banks compete in imperfectly competitive markets to provide deposits, loans, and mortgages. The supply side of our model is novel since it features flexible interactions between a bank's costs of borrowing, lending, and holding securities. In particular, our specification allows a bank's cost of lending to depend on the quantity of reserves it holds. Thus, our framework is ideally suited to estimating how the banking system's overall cost and capacity of providing loans changes when it is forced to hold additional reserves.

With our estimated model, we show that each dollar of reserves injected during QE from 2007 to 2018 crowded out 8.1 cents of bank lending, so the reserve supply channel suggests a counterproductive reduction in the supply of bank loans. We note that this crowding out exists in addition to the effects of asset purchases that have been identified in the literature. Hence, the reserve supply channel is important in understanding the true effectiveness of QE.

To estimate the demand side of our model, we need to observe how the quantities demanded from a bank vary when it exogenously changes its interest rates. We apply an instrument from the reduced-form literature based on banks' reallocation of funds in their internal capital markets after a natural disaster. As Cortés and Strahan (2017) show, loan demand in a region increases after it is hit by a disaster. Banks reallocate funds away from non-disaster regions to provide funds to the disaster region, and this creates an exogenous shock to the interest rates the bank chooses in non-disaster regions. This reallocation provides precisely the exogenous interest rate shock needed to estimate a bank's loan, mortgage, and deposit demand curves, assuming that natural disasters do not impact the demand for borrowing and lending far away from the regions where they occur.

Our estimates show that the demand for bank loans is more interest-rate sensitive than the demand for deposits and mortgages. If all banks in a market raise their corporate loan interest rates by 10 basis points in 2007, the quantity of corporate loans demanded falls by 10.9%. In comparison, a 10 basis point increase in interest rates would raise deposit demand by 0.6% and would lower mortgage demand by 3.2%. If banks change their deposit, loan, and mortgage interest rates by similar amounts, their loan quantities will respond by a larger amount than their mortgage or deposit quantities. This explains why we find that corporate loan quantities respond most to a larger reserve supply.

Next, we estimate the supply side of our model. We need to know how a bank's costs depend on the quantities of loans, mortgages, deposits, and liquid securities on its balance sheet. Estimating this cost function is challenging because a bank can simultaneously adjust several components of its balance sheet in response to a demand shock. We solve this problem by first running a series of reduced-form regressions of a bank's marginal costs and balance sheet quantities on two distinct exogenous demand shocks. In addition to the disaster instrument mentioned above, we use a Bartik-style instrument for deposit demand using cross-sectional variation in deposit growth across regions of the country.[2] We separately estimate banks' cost of holding liquid securities using daily changes in reserves held in the Treasury General Account (TGA). Finally, we choose the remaining cost function parameters to match our reduced-form regressions.

Our estimates imply that increasing a bank's reserve holdings crowds out lending and crowds in deposit issuance. In other words, reserves and bank lending are substitutes rather than complements for banks. One reason could be that bank balance sheet space is costly due to regulation. Acharya and Rajan (2021) argue that reserves may amplify liquidity strains during stress episodes, which may also render lending more costly. Quantitatively, a \$100 million increase in reserves held by a bank branch increases its marginal cost of providing mortgages and loans by 39 bps. At the same time, the marginal cost of deposits decreases by 70 bps.

Finally, we run a counterfactual simulation using our estimated model to quantify how increases in reserve supply affects lending and deposit-taking by the banking system. We first shock the reserve supply, allow each bank to trade reserves and adjust its deposit, loan, and mortgage rates, and then determine its quantities of loans, mortgages, and deposits using the demand system. We find that reserve injections affect the interest rates on loans, mortgages, and deposits to a similar extent. However, a larger reserve supply predominantly crowds out bank lending to firms, while the effect on mortgage and deposit quantities is more muted. We estimate that the reserve injections due to QE from 2008 to 2017 crowded out 8.1 cents of bank lending per dollar of reserves injected, reducing total lending by \$141 billion per year. Further, we find that the spread between the interest paid on reserves and risk-free rates available to non-bank investors generated by the model matches the magnitude and dynamics of a proxy for this spread in the data. Taken together, our findings imply that requiring banks to hold the trillions in reserves created by QE

[2]In appendix D, we show that for a firm that sells goods in multiple markets, demand shocks in one market can be used to estimate both the demand curves the firm faces in other markets as well as the firm's marginal cost curve.

causes a counterproductive reduction in bank lending.

Relation to Literature

Our structural model belongs to a growing recent literature on structural estimation in banking. Wang, Whited, Wu, and Xiao (2020) use a structural model of banking to study conventional monetary policy transmission, while our structural model estimates the effect of reserve injections from unconventional monetary policy on the banking system. Several other papers estimate models of imperfect competition in banking similar to ours (Egan, Hortaçsu, and Matvos, 2017; Xiao, 2020; Buchak, Matvos, Piskorski, and Seru, 2018; Albertazzi, Burlon, Jankauskas, and Pavanini, 2022), while others estimate models of networks and matching (Akkus, Cookson, and Hortacsu, 2016; Schwert, 2018; Craig and Ma, 2018). Our application of demand systems in banking complements work that applies demand systems in other financial markets (Koijen and Yogo, 2019, 2020; Koijen, Richmond, and Yogo, 2020; Bretscher, Schmid, Sen, and Sharma, 2020; Jiang, Richmond, and Zhang, 2020). In particular, Koijen, Koulischer, Nguyen, and Yogo (2021) quantify the effect of asset purchases from QE using a demand system, whereas our focus is on the reserves injected by QE.

This paper also contributes to the empirical literature on how QE impacts the banking system. Existing work in this literature has mostly focused on the effect of asset purchases. For example, Rodnyansky and Darmouni (2017) and Chakraborty, Goldstein, and MacKinlay (2020), focus on the mortgage-backed securities purchased in QE and show that banks with more mortgage-backed securities increase their mortgage lending by more relative to those that hold fewer mortgage-backed securities. Another set of papers study the effect of asset purchases on flattening the long-term yield curve (Gagnon, Raskin, Remache, and Sack, 2010; Krishnamurthy and Vissing-Jorgensen, 2011).

The effect of reserves supplied by QE has been the focused of a much smaller literature. Theoretical work by Acharya and Rajan (2021) argue for the unintended consequence that reserve injections exacerbate liquidity shortages during financial crises. Christensen and Krogstrup (2019) find empirically that long-term government yields are directly impacted by the supply of reserves in QE. Kandrac, Kokas, and Kontonikas (2021) show that banks whose reserve holdings are more sensitive to aggregate reserve supply lend more than other banks after QE. Kandrac and Schlusche (2021) show that in a change to deposit insurance fees that raises the cost of non-deposit borrowing, treated banks decrease their lending and reserve holding relative to other banks. Unlike previous work comparing reserve holding and lending across banks, our paper is the first to quantify the aggregate effect of central bank reserve injection on the US banking system. We do so with a counterfactual simulation in our estimated structural model, ensuring that our results arise only from a change in the aggregate reserve supply like in QE. The "reserve supply channel" we identify points to an important unintended consequence of central bank reserves in crowding out bank lending from bank balance sheets that complements the transmission channels from asset purchases in the literature. Elenev, Landvoigt, Shultz, and Van Nieuwerburgh (2021) and Acharya and Rajan (2021) also find evidence consistent with our reserve supply channel.

Our work also relates to a recent literature demonstrating the role of imperfect competition in deposit markets (Drechsler, Savov, and Schnabl, 2017; Li, Ma, and Zhao, 2019) and mortgage markets (Scharfstein and Sunderam, 2016) in the transmission of conventional monetary policy. Our work shows that demand elasticity is an important determinant of the reserve supply channel, since highly price-elastic corporate loan demand is impacted much more by reserve supply than deposit and mortgage demand.

Finally, our results relate to the core idea in banking theory that it is optimal for banks to simultaneously provide deposits and loans (Diamond and Rajan, 2000; Kashyap et al., 2002; Hanson et al., 2015; Diamond, 2019). Our estimate of a bank's costs function quantifies the gains from deposits and loans coming from the same institution rather than from separate ones.

2 A Model of Bank Balance Sheets

This section introduces the theoretical framework that guides our structural analysis. The goal of the model is to quantify how the banking system responds to policy interventions, such as an increase in reserve supply caused by QE. This response depends on two key model components: the demand that banks face and the balance sheet costs that banks incur in supplying loans, mortgages, and deposits. We first provide a graphical illustration of our model in Subsection 2.1. Then, in Subsection 2.2, we formally set up the model and derive the banking sector's response to an increase in reserve supply.

2.1 A Graphical Illustration

We first present a simplified, visual depiction of our model using a single bank as an illustration. In the model, banks provide loans, mortgages, and deposits in imperfectly competitive markets. Each bank faces a demand curve that determines quantities given the interest rate they choose in each market. In Figure 2, the loan demand for a given bank, i.e., the green line, pins down the loan quantity Q_L based on the loan rate R_L it chooses. Like any firm facing a downward-sloping demand curve, banks choose their interest rate so that the marginal cost equals the marginal revenue. In Figure 2, the bank chooses the loan rate R^L at which its marginal cost of supplying loans, i.e., the red line, equals the marginal revenue from loans lending, i.e., the blue line.

Banks' holdings of liquid reserves may impact their marginal cost of lending. Having more liquid assets may prevent fire-sales of illiquid assets and help comply with liquidity regulations. For example, Afonso, Giannone, La Spada, and Williams (2022b) show that banks' demand for reserves has increased over the last decade. However, a larger supply of reserves also uses up balance sheet space and may add to the cost of meeting capital requirements when bank equity is costly. For example, Afonso, Cipriani, and La Spada (2022a) show that when reserves were added back to the consideration of leverage ratios after the Covid-19 crisis, banks attempted to reduce their funding size to reduce balance sheet costs. We will formally set up and estimate a cost function, but for now, suppose that the increase in reserve supply shifts the marginal cost of lending as illustrated in Figure 2, then the bank would raise its loan rate to $R^{L'}$, at which the new marginal cost meets the marginal revenue. In the new equilibrium, the quantity of loans supplied by the bank would drop to Q'_L, as implied by the loan demand curve at the new loan rate, $R^{L'}$. Hence, the increase in loan rate and the drop in loan volume as a result of reserve injection would be $R^{L'} - R^L$ and $Q_L - Q'_L$, respectively.

Our empirical approach to quantify the banking system's response to an increase in reserves is similar to the framework in Figure 2. We first estimate the loan demand curve, which determines the marginal revenue. In the full model, banks compete with each other so we extend the loan demand curve for a single bank to a demand system that captures how banks' chosen loan rates affect their own and each other's quantities. Next, we estimate a bank's cost of lending as a function of its balance sheet composition, i.e., its volume of loans, mortgages, securities, and deposits. Then, we can infer how an increase in reserve supply shifts the bank's marginal cost curve to trace out the equilibrium change in loan rates and volumes. The same estimation is performed for deposits and mortgages.

2.2 Model

We consider a set of banks indexed by m that operate in a set of markets indexed by n at each time t. Banks invest in loans, L, mortgages, M, and liquid securities, S, backed by deposits, D. Each bank m chooses market-specific rates $R_{D,nmt}$, $R_{M,nmt}$, and $R_{L,nmt}$ for its deposits, mortgages, and loans, respectively. Taking the vector of rates chosen by their competitor banks as given, banks choose their own rates to maximize their profits. In terms of loans, for example, bank m takes the rates of its competitor banks $-m$, $R_{L,n(-m)t}$, as given. The quantity of funds it lends is given by the residual demand curve $Q_{L,nmt}(R_{L,nmt}, R_{L,n(-m)t})$. Similarly, its residual demand curves for mortgages and deposits are $Q_{M,nmt}(R_{M,nmt}, R_{M,n(-m)t})$ and $Q_{D,nmt}(R_{D,nmt}, R_{D,n(-m)t})$. For

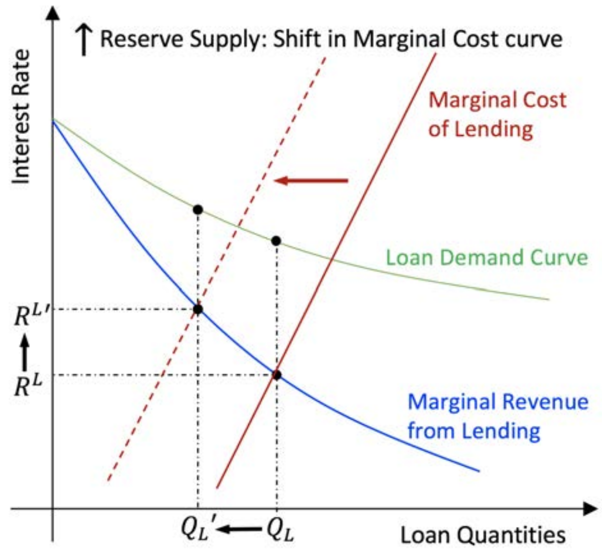


Figure 2: This figure illustrates the effect of an increase in reserves on the loan market. An increase in reserve supply shifts the bank's marginal cost curve for lending. This results in a new intersection with the marginal revenue curve, yielding a new interest rate, $R^{L'}$. The new loan quantity, Q'_L, is then pinned down by the demand curve.

simplicity, we suppress the arguments of the residual demand functions, writing $Q_{L,nmt}$, $Q_{M,nmt}$, and $Q_{D,nmt}$ going forward. Liquid securities, $Q_{S,mt}$, trade in a competitive market at an interest rate $R_{S,t}$. Loans, mortgages, deposits, and securities have cash flows that are discounted at rates $R_t^{L,m}$, $R_t^{M,m}$, $R_t^{D,m}$, and $R_t^{S,m}$ reflecting their respective riskiness.

Banks face a cost $C(\Theta_{mt})$ of providing loans, deposits, and mortgages that depends on all of the items Θ_{mt} on its balance sheet. Θ_{mt} is a vector of bank m's balance sheet components, $Q_{D,nmt}$, $Q_{M,nmt}$, $Q_{L,nmt}$, and $Q_{S,mt}$. In general, this cost function quantifies the various ways that a bank's decisions for one part of its balance sheet can impact its costs for another. For example, having more liquid securities on balance sheets may reduce the cost of selling illiquid loans or mortgages in the event of large deposit withdrawals in a bank run (Diamond and Dybvig, 1983). In addition, bank regulations such as the Supplementary Leverage Ratio (which constrains a bank's leverage) and the Liquidity Coverage Ratio (which constrains the mismatch between a bank's holding of illiquid assets and issuance of liquid deposits) impose costs that depend on multiple balance sheet components. We show in Section 4 how the bank's overall cost depends on the composition of its balance sheet.

In this setting, bank m chooses its rates $R_{D,nmt}$, $R_{M,nmt}$, and $R_{L,nmt}$ and security quantities $Q_{S,mt}$ at time t to maximize the expected present value of its profits at $t+1$ in all markets n, which are given by

$$\max_{(R_{D,nmt},R_{M,nmt},R_{L,nmt},Q_{S,mt})} \sum_n Q_{L,nmt}(R_{L,nmt} - R_t^{L,m}) + \sum_n Q_{M,nmt}(R_{M,nmt} - R_t^{L,m})$$
$$+Q_{S,mt}(R_{S,t} - R_t^{S,m}) - \sum_n Q_{D,nmt}(R_{D,nmt} - R_t^{D,m}) - C(\Theta_{mt}). \tag{1}$$

In words, bank m's profits are the sum of its revenue from loans, mortgages, and securities, less the nominal cost of deposit funding and the balance sheet costs $C(\Theta_{mt})$. The first order conditions of bank profits with respect to the choice variables, $R_{D,nmt}$, $R_{M,nmt}$, $R_{L,nmt}$, and $Q_{S,mt}$, are

$$\overbrace{\frac{\partial}{\partial R_{D,nmt}}[Q_{D,nmt}(R_t^{D,m} - R_{D,nmt})]}^{\text{Marginal Revenue}} = \overbrace{\frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}} \frac{\partial Q_{D,nmt}}{\partial R_{D,nmt}}}^{\text{Marginal Cost}}, \tag{2}$$
$$\frac{\partial}{\partial R_{M,nmt}}[Q_{M,nmt}(R_{M,nmt} - R_t^{M,m})] = \frac{\partial C(\Theta_{mt})}{\partial Q_{M,nmt}} \frac{\partial Q_{M,nmt}}{\partial R_{M,nmt}}, \tag{3}$$
$$\frac{\partial}{\partial R_{L,nmt}}[Q_{L,nmt}(R_{L,nmt} - R_t^{L,m})] = \frac{\partial C(\Theta_{mt})}{\partial Q_{L,nmt}} \frac{\partial Q_{L,nmt}}{\partial R_{L,nmt}}, \tag{4}$$
$$R_{S,t} - R_t^{S,m} = \frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}}. \tag{5}$$

The left-hand side of equations (2) to (4) is the marginal revenue from changing each of the bank's interest rates (the blue curve in Figure 2). This is because the bank's "revenue" from loans, for example, can be seen as the quantity $Q_{L,nmt}$ of loans times its interest rate spread $R_{L,nmt} - R_t^{L,m}$ above the loan discount rate $R_t^{L,m}$. On the right-hand side of equations (2) to (5), we have the marginal costs from changing each of the bank's interest rates. Liquid securities are traded in a competitive market, so the first order condition for securities holdings $Q_{S,mt}$ in equations (5) sets price $R_{S,t} - R_t^{S,m}$ equal to marginal cost of holding these securities $\frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}}$. Based on equation (5), we refer to $\frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}}$ as the "reserve spread"—the difference between risk-free rates $R_{S,t}$ available only to banks and risk-free rates $R_t^{S,m}$ available to non-bank investors as well.

When the supply of liquid securities increases, as in the increase in reserve supply from QE, banks respond by optimally changing their interest rates in all markets as well as their securities holdings. The interest rates they choose still satisfy the first order conditions in equations (2) to (5), which allows us to solve for the equilibrium quantities of loans, mortgages, and deposits. Specifically, the comparative statics with respect to a change in bank m's liquid security holdings

$Q_{S,mt}$ are

$$\frac{\partial \left(R_t^{D,m} - R_{D,nmt} - \frac{Q_{D,nmt}}{\partial Q_{D,nmt}/\partial R_{D,nmt}}\right)}{\partial Q_{D,nmt}} \frac{\partial Q_{D,nmt}}{\partial Q_{S,mt}} = \frac{\partial^2 C(\Theta_{mt})}{\partial Q_{D,nmt}\partial \Theta_{mt}} \cdot \frac{\partial \Theta_{mt}}{\partial Q_{S,mt}}, \tag{6}$$

$$\frac{\partial \left(R_t^{M,m} - R_{M,nmt} - \frac{Q_{M,nmt}}{\partial Q_{M,nmt}/\partial R_{M,nmt}}\right)}{\partial Q_{M,nmt}} \frac{\partial Q_{M,nmt}}{\partial Q_{S,mt}} = -\frac{\partial^2 C(\Theta_{mt})}{\partial Q_{M,nmt}\partial \Theta_{mt}} \cdot \frac{\partial \Theta_{mt}}{\partial Q_{S,mt}}, \tag{7}$$

$$\frac{\partial \left(R_t^{L,m} - R_{L,nmt} - \frac{Q_{L,nmt}}{\partial Q_{L,nmt}/\partial R_{L,nmt}}\right)}{\partial Q_{L,nmt}} \frac{\partial Q_{L,nmt}}{\partial Q_{S,mt}} = -\frac{\partial^2 C(\Theta_{mt})}{\partial Q_{L,nmt}\partial \Theta_{mt}} \cdot \frac{\partial \Theta_{mt}}{\partial Q_{S,mt}}, \tag{8}$$

$$\frac{\partial Q_{S,mt}}{\partial Q_{S,mt}} = 1, \tag{9}$$

where $\frac{\partial Q_{D,nmt}}{\partial Q_{S,mt}}, \frac{\partial Q_{M,nmt}}{\partial Q_{S,mt}}, \frac{\partial Q_{D,nmt}}{\partial Q_{S,mt}}$ are the responses of each individual bank branch quantity to the reserve increase, and Θ_{mt} is the vector of balance sheet quantities $(Q_{D,nmt}, Q_{M,nmt}, Q_{L,nmt}, Q_{S,mt})$. Please see Appendix A.1 for detailed derivations.

To determine the equilibrium response of the banking system to a change in the supply of liquid securities, we need empirical estimates of the components of equations (6) to (8). The left-hand side is determined by the bank's loan, mortgages, and deposit demand curves. In Section 3, we estimate this term with an industrial organization style demand system by observing how each bank's quantities respond to shocks to the interest rates they and other banks choose.[3] On the right-hand side is an expression reflecting how a bank's marginal cost of borrowing or lending in a market changes with the composition of its entire balance sheet. We therefore need to estimate how a bank's marginal costs of lending and borrowing depend on the different components its balance sheet. In Section 4, we develop and apply a novel econometric approach to estimate this cost function. Taken together, our estimates of the demand for a bank's services and its cost of providing them allow us to infer the aggregate effect of an increased supply of reserves caused by QE—the policy we intend to analyze.

3 Demand Systems

This section estimates the demand systems for deposits, mortgages, and loans. Section 3.1 introduces a modified version of a logit demand system that can be estimated without observing an outside good. Section 3.2 details the data and instruments we use for estimating our demand systems. The estimation results are reported in Section 3.3.

[3]This section considers a single bank in isolation, while our full model allows for competition between banks. Thus, we need to estimate a demand system across all banks rather than just a demand curve faced by an individual bank.

3.1 Estimation Strategy

Our first step is to estimate the demand curves that individual banks face in deposit, loan, and mortgage markets. Depositors can either invest in deposits at banks $m > 0$ that have branches in the market or an unobserved outside option $m = 0$. This outside option reflects the availability of investment options other than deposits that are not in our data such as money market fund shares. An observed quantity $Q_{D,nmt}$ of deposits is invested in bank m's branches in market n in time t. In the standard approach to demand estimation, it is necessary to observe the quantity invested in the outside option. For our deposit and mortgage markets, we present a small modification of a logit demand system that can be consistently estimated only using linear regressions without observing the outside option quantity. For loans, we apply the standard logit demand system and assume that the quantity $Q_{L,nm0}$ invested in the loan market outside option is observed.

Preferences of borrowers and depositors for observed goods are like those in a standard logit demand system (Berry, 1994; McFadden, 1974). Depositor j investing in bank m in market n has the following utility:[4]

$$u_{D,jnmt} \quad = \quad \alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt} + \varepsilon_{D,jnmt}. \tag{10}$$

The first term is the interest rate $R_{D,nmt}$ paid on deposits times the depositor's preference for receiving interest, α_D. We expect the price disutility parameter for deposits, α_D, to be positive because depositors should prefer a higher deposit rate, all else equal. In contrast, we expect the corresponding price disutility parameter for mortgage and loan borrowers to be negative because they prefer a lower funding cost. Depositors' utility is also affected by the desirability of bank m's deposits, which depends on a vector of observed characteristics, $X_{D,nmt}$, preferences for observed characteristics, β_D, and unobserved characteristics, $\delta_{D,nmt}$. Finally, the error term, $\varepsilon_{D,jnmt}$, is assumed to be i.i.d. across depositors j and to follow a type one extreme value distribution. In addition, the outside good $m = 0$ provides utility

$$u_{D,jn0t} \quad = \quad \delta_{D,jn0t} + \varepsilon_{D,jn0t}, \tag{11}$$

where $\varepsilon_{D,jn0t}$ is also type one extreme value and independent of all other random variables. The additional variable $\delta_{D,jn0t}$ is i.i.d. across depositors j and has a measure given by the density $f(\delta_{D,jn0t}) = \overline{F}_{D,nt} \exp(\beta_{D,o}\delta_{D,jn0t})$, where $\overline{F}_{D,nt}$ is a constant that determines the size of each market. The coefficient $\beta_{D,o}$ determines how the total quantity of deposits in a market changes when the utility $u_{D,nmt}$ of all banks' deposits m increases. For loans, where we observe an outside

[4]The demand curves for mortgages and loans are defined similarly. We use the subscript M for mortgages and L for loans to describe these demand systems.

option quantity, we follow the standard practice in a logit demand model and normalize $\delta_{L,jn0t} = 0$ in all loan markets.

Conditional on a value of $\delta_{D,jn0t}$, the probability $P_{D,nmt|\delta_{D,jn0t}}$ of agent j choosing to invest in the branch of bank m in market n at time t satisfies

$$P_{D,nmt|\delta_{D,jn0t}} = \frac{\exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\exp(\delta_{D,jn0t}) + \sum_{m'} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} \quad (12)$$

according to equation (10) in McFadden (1974). In appendix A.2.1 we show that integrating $P_{D,nmt|\delta_{D,jn0t}}$ over the distribution of $\delta_{D,jn0t}$ gives the following expression for the quantity $Q_{D,nmt}$ chosen from bank m in market n at time t

$$\log Q_{D,nmt} = \log(U_{D,nt}) + \alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt}. \quad (13)$$

Here, $log(U_{D,nt})$ is a market-time specific term that is the same across banks m given in appendix equation (A10) . The demand curve between the quantity $Q_{D,nmt}$ provided by bank m in market n at time t and its interest rate $R_{D,nmt}$ is given by

$$\frac{\partial \log Q_{D,nmt}}{\partial R_{D,nmt}} = \frac{\partial \log(U_{D,nt})}{\partial R_{D,nmt}} + \alpha_D. \quad (14)$$

To identify this demand curve, we first use the linear expression in equation 13 to estimate α_D, controlling for the impact of $log(U_{D,nt})$ with market-time fixed effects. Because the unobserved quality $\delta_{D,nmt}$ of a bank's deposit may be correlated with its interest rate (e.g. a bank may pay a low rate if its ATM network is particularly desirable), we use a two-stage least squares approach with an instrument $z_{D,nmt}$.

3.1.1 Aggregate Demand Elasticity

Having identified the price disutility parameter, α_D, we now present a tractable method to estimate the other term $\frac{\partial \log(U_{D,nt})}{\partial R_{D,nmt}}$ in the bank's demand curve. Because $U_{D,nt}$ varies at the market-time level and not across banks, we estimate it based on how market-level quantities are impacted by market-level shocks.

First, we define

$$\psi_{D,nt} = \log(\sum_m \exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})) \quad (15)$$

to represent the desirability of a "composite good" provided by all banks operating in the market.

We derive in equation (A18) of appendix A.2.1 the following log-linear expression for the quantity $\overline{Q}_{D,nt}$ of deposits in market n at time t

$$log(\overline{Q}_{D,nt}) = \beta_{D,o}\psi_{D,nt} + \log\left[\overline{F}_{D,nt}\int_{-\infty}^{\infty}\frac{\exp(\beta_{D,o}u)}{1+\exp(u)}du\right]. \tag{16}$$

From this equation, we can estimate how $\log\overline{Q}_{D,nt}$ changes with the value of $\psi_{D,nt}$ to learn the value of $\beta_{D,o}$. The parameter $\beta_{D,o}$ quantifies the sensitivity of total deposit quantities to changes in the overall desirability of deposits.

After estimating the demand parameters (α_D, β_D) in equation (13), we can observe all terms in equation (15) that defines $\psi_{D,nt}$ except the market-time specific mean of $\delta_{D,nmt}$ (which is conflated with $log(U_{D,nt})$ in the fixed effect in equation (15)). We therefore decompose $\psi_{D,nt}$ into an unobservable component $\psi^u_{D,nt} = \frac{1}{N_{nt}}\sum_m \delta_{D,nmt}$ and an observable component $\psi^o_{D,nt} = \psi_{D,nt} - \psi^u_{D,nt}$. Equation (A25) in Appendix A.2.3 provides an explicit expression for $\psi^o_{D,nt}$ in terms of observable data.

We use an instrumental variable approach to estimate parameter $\beta_{D,o}$. We need an instrumental variable $z_{D,nt}$ that impacts $\psi^o_{D,nt}$ and is uncorrelated with the unobserved component, $\log\overline{F}_{D,nt} + \beta_{D,o}\psi^u_{D,nt}$. With such an instrument, we estimate $\beta_{D,o}$ using two-stage least squares with time fixed effects added. After estimating $\beta_{D,o}$, we have all necessary parameter estimates that determine quantities as shown by equation A11 in Appendix A.2.3.

3.2 Instruments and Data

Estimating our demand systems requires information on deposits, mortgages, loans, and bank characteristics. In addition, we construct an instrumental variable from property damage data. We first introduce the data we use and then explain how our instrument is constructed. Summary statistics for the demand-side variables are reported in Table 1.

Deposits. Branch-level deposit volumes are obtained from the FDIC, which covers the universe of US bank branches at an annual frequency from June 2001 to June 2017. We exclude branches that consolidate deposits in another location, do not accept deposits, or are owned by foreign banks. We define each county-year as a deposit market and sum branch-level deposits at the bank-county-year level. Our sample is from 2001 to 2017. Table 1 reports the summary statistics.

Branch-level deposit rates are obtained from RateWatch, which collects weekly branch-level deposit rates by product. Data coverage varies by product, especially in the earlier years. To maximize the sample size, we focus on the most commonly available savings account type, which

Table 1: Summary Statistics (Market-Bank-Year Level)

This table reports summary statistics of bank deposits, mortgages, and loans at the market-bank-year level. Rates are reported in basis points and volumes are in millions. For a given variable, #Obs refers to the total number of observations. The sample period is from 2001 to 2017.

	# Obs	Mean	25th Pct.	50th Pct.	75th Pct.	Std. Dev.
Log Deposit Market Share	74007	−2.67	−3.45	−2.33	−1.50	1.69
Deposit Volume	74007	188.47	23.05	47.82	103.16	2287.78
Deposit Rate	45894	58.04	10.00	20.00	80.00	77.98
Log Mortgage Market Share	38957	−4.12	−5.32	−3.73	−2.56	2.08
Mortgage Volume	38957	23.67	1.23	3.79	11.62	209.53
Mortgage Rate	11735	457.62	332.50	450.55	570.00	126.41
Log Loan Market Share	25943	−5.06	−6.62	−4.95	−3.45	2.09
Loan Volume	25989	977.24	40.25	132.00	553.78	3218.81
Loan Spread	25943	183.52	101.38	171.43	250.00	120.46

is the 10K money market account. We compute the average rate at the bank-county-year level from June 2001 to June 2017 (if there is more than one branch), which we match with the total bank-county-year level deposit volume from the FDIC.

The branch-level identifier in RateWatch (accountnumber) is matched to the branch-level identifier in the FDIC data (uninumbr) using the mapping file developed by Bord (2017).[5]

Mortgages. We use data on mortgage originations made available under the Home Mortgage Disclosure Act (HMDA). The data available to us is at the annual frequency and includes information on the lender, loan size, location of the property, loan type, and loan purpose. Any depository institution with a home office or branch in a Central Business Statistical Area (CBSA) is required to report data under HMDA if it has made or refinanced a home purchase loan and has assets above $30 million. As explained by Cortés and Strahan (2017), the bulk of residential mortgage lending activity is likely to be reported under this criterion.[6] We define each county-year as a mortgage market and sum mortgage loan volumes at the bank-county-year level. Our sample is from 2001 to 2017.

County-level mortgage rates are obtained from RateWatch, which collects weekly branch-level mortgages rates by product. Data coverage varies by product, especially in the earlier years. To maximize the sample size, we focus on the most commonly available mortgage loan product, which is the 15-year fixed rate mortgage. We compute the average mortgage rate at the bank-county-year

[5] Special thanks to Vitaly Bord for sharing the mapping file with us.

[6] Any non-depository institution with at least 10% of its loan portfolio composed of home purchase loans must also report HMDA data if its asset size is above $ million. These institutions are not included in our sample given our focus on deposit-taking commercial banks.

level from 2001 to 2017 to match with the reporting of the mortgage volume data from HMDA.

We first merge bank-level identifiers in HMDA to the FDIC bank-level identifiers using the mapping file developed by Bob Avery.[7] Then, the branch-level identifier in the FDIC data (uninumbr) is merged with the branch-level identifier in RateWatch (accountnumber) using the mapping file developed by Bord (2017).

Loans. We use data on syndicated loans from the Thomson Reuters Dealscan database. We select all loans originated by US banks and sum loan volumes at the bank-state-year level, where the location of the borrower is given in Dealscan. We define loan markets at the state-year level instead of the county-year level because firm borrowers tend to be less geographically confined than individual depositors. Similarly, we compute average loan spreads and total loan quantities at the bank-state-year level. Our sample is from 2001 to 2017.

We build on the mapping file used in Chakraborty et al. (2018) to hand-match lenders in Dealscan to Call Report bank identifiers (RSSD).[8]

Bank Characteristics. We use the Call Reports to obtain bank-level characteristics as control variables. Specifically, we calculate the ratio of insured deposits as insured deposits over total liabilities and the ratio of loan loss provision as loan loss provisions over total loans. We average 4 quarterly observations to obtain bank-year level data from 2001 to 2017.

Property losses from natural disasters. We use the Spatial Hazard Events and Losses Database for the United States (SHELDUS) to obtain data on property losses from natural disasters. This dataset records the location, time, and damage brought about by natural disasters in the US. We include all reported disasters in the database and calculate the total property losses for each county-year from 2001 to 2017 for our instrument.

Instruments. We first explain our instrument, $z_{D,nmt}$, for estimating our demand systems. We face the endogeneity problem that banks' choices of interest rates for deposits, mortgages, and loans may be correlated with unobservables that affect demand for the bank's products. With an instrument that impacts interest rates but that is uncorrelated with unobservable demand shifters, we can estimate the price disutility parameter of our demand systems, exploiting the linearity of equation (13). Following Cortés and Strahan (2017), we construct the instrument based on property losses from natural disasters and banks' branch networks. As Cortés and Strahan (2017) show, natural disasters increase the demand for loans in the area where they occur, which means

[7] The version we used is available here https://sites.google.com/site/neilbhutta/data.

[8] Special thanks to Indraneel Chakraborty, Itay Goldstein, and Andrew MacKinlay for sharing the mapping file with us.

that banks present in the area reallocate funds from their branches elsewhere through their internal capital markets. Hence, property losses to bank m's branches in regions n' constitute a supply shock to bank m's branches in county n, which allows us to trace out the demand curves. Appendix D formalizes this argument.

Formally, our natural disaster instrument $z_{D,nmt}$ measures for bank m's branches in county n and year t the property losses from natural disasters accrued to the bank's branches in all other counties n':

$$z_{D,nmt} \quad = \quad \frac{1}{N_{mt}} \log \left(\sum_{n' \neq n} damage_{n't} \cdot \frac{N^B_{n'mt}}{\sum_{m'} N^B_{n'm't}} \right),$$

where N_{mt} is the number of counties in which bank m has branches, and $damage_{n't}$ is the property loss in county n'. Following Cortés and Strahan (2017), we scale $damage_{n't}$ by the fraction of branches belonging to bank m in county n' and take logs after summing the scaled damage losses. The former adjustment captures the portion of the demand shock in county n' absorbed by branches of bank m, while the latter ensures that the largest shocks (e.g. Hurricane Katrina) do not drive the overall result. The instrument for mortgages follows that of deposits. For commercial loans, we use the same instrument constructed at the bank-state-year level instead of the bank-county-year level, where the state is determined by the location of the borrower's headquarters.

One concern for our identification could be that the effect of disasters spills over to affect local demand in unaffected counties. To this end, notice that our exclusion restriction does not require the absence of spillover effects altogether. It only requires that any potential influence of natural disasters on unobserved deposit characteristics in unaffected areas is not correlated with banks' branch networks. We include the log property damage to each county in all specifications to help account for any direct effects of disaster losses on demand. Another concern could be that loan losses from the disaster itself directly influence interest rates. To this end, we also include banks' loan loss provision as control variable in all specifications. Finally, for the deposit demand system, we control for the lagged ratio of insured deposits and limit the sample to observations with above-median natural disaster exposure because of the stickiness of deposit volumes.[9]

Next, to estimate the sensitivity of total deposit quantities to changes in the overall desirability

[9] The stock of deposit volumes is extremely sticky so it is difficult to differentiate the response in deposit volumes to small disaster shocks from small fluctuations in deposit volumes that occur at the same time. This results in noisy estimates if observations with small disaster exposures are used. The underlying assumption is that bank branches exposed to above-median disasters are representative of the full sample in terms of their deposit demand elasticity. We note that the same issue applies much less to mortgage and loan markets because the data for the issuance of mortgages and of loans are much more persistent than the stock of deposits.

of deposits as in equation (A18), we average our market-bank-time level instrument, $z_{D,mnt}$, at the market-year level to construct

$$z_{D,nt} = \frac{1}{N_{nt}} \sum_{m} z_{D,nmt}.$$

This instrument captures how exposed a region is to indirect rate changes coming through internal capital markets. The identifying assumption is that the indirect shocks through banks' internal capital markets are uncorrelated with the log-size of each market, $\log F_{D,nt}$, and with the average unobservable quality, $\psi^u_{D,nt}$. The corresponding instrument for mortgages is constructed in the same way.

3.3 Estimation Results

Table 2 reports the first-stage and second-stage results for estimating the price disutility parameter α for deposits, mortgages, and loans.

The price disutility parameters reported in the first row of panel (b) of Table 2 are positive for deposits and negative for mortgages and loans. Intuitively, deposit rates are paid by the bank so that raising deposit rate increases a bank's market share. In contrast, mortgage, and loan rates are paid by borrowers, so a bank can improve its market share by offering lower mortgage and loan rates. Quantitatively, the coefficients imply that when a bank raises its deposit rate in one county by 10 basis points, its share of total deposits will increase by 15.1%. When the same bank lowers its mortgage and loan rates in one market by 10 basis points, its mortgage and loan shares increase by 53.4% and 31.0%, respectively. The price disutility of deposits is smaller in magnitude than that for mortgages and loans, consistent with depositors being less attentive to interest rates than firm and mortgage borrowers.

Regarding the outside option, we estimate the sensitivity of market-level quantities $\overline{Q}_{P,nt}$ to the market-level desirability parameter $\psi^o_{P,nt}$ as in equation (A18) for deposits and mortgages. We include the average age, average income, the share of residents with a college degree, log population, growth of house prices, and log local property damage due to natural disasters.

Panel (b) in Table 3 reports the sensitivity of market-level quantities $\overline{Q}_{P,nt}$ to the market-level desirability parameter $\psi^o_{P,nt}$ to be 0.04 for deposits and 0.06 for mortgages. Hence, as we show in equation (A33), the increase in deposit quantity when all banks in a county raise their deposit rates

Table 2: Demand System Estimates

This table reports the two-stage least squares results for estimating price disutility of deposit, mortgage, and loan demand systems:

$$R_{D,nmt} = a_{D,nt} + \gamma_D z_{D,nmt} + X_{D,nmt}\gamma_D + e_{D,nmt},$$
$$\log Q_{D,nmt} = \chi_{nt} + \alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \varepsilon_{D,nmt}.$$

These regressions are run at the market-bank-year level. Loan loss provision is the ratio of loan loss provision over total loans, lag insured deposit ratio is the ratio of insured deposits over total liabilities lagged by 1 year, and log property damage is the direct property loss from natural disasters at the county level. For the deposit, mortgage and loan rates, 0.01 means 1%. The sample period is from 2001 to 2017. We report standard errors clustered by bank in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel (a): First Stage Panel Regression			
	(1)	(2)	(3)
	Deposit Rate	Mortgage Rate	Loan Rate
IV	1.69***	12.17***	3.19***
	(0.26)	(2.90)	(0.57)
Loan Loss Provision	0.01***	−0.02	0.01*
	(0.00)	(0.01)	(0.01)
Lag Insured Deposit Ratio	0.00***		
	(0.00)		
Log Property Damage	−0.00***	−0.00**	
	(0.00)	(0.00)	
R^2	0.87	0.91	0.29
Adj. R^2	0.80	0.85	0.27
Num. of Obs.	105551	75470	23393
Market-Year F.E.	Y	Y	Y

Panel (b): 2SLS Panel Regression			
	(1)	(2)	(3)
	Deposit Market Share	Mortgage Market Share	Loan Market Share
Rate (with IV)	151.32***	−533.93***	−310.13***
	(49.07)	(167.24)	(89.13)
Loan Loss Provision	−1.41	−14.53	5.03
	(1.26)	(9.98)	(3.22)
Lag Insured Deposit Ratio	−1.97***		
	(0.18)		
Log Property Damage	1.26***	0.81***	
	(0.02)	(0.07)	
Num. of Obs.	105551	75470	23393
Market-Year F.E.	Y	Y	Y

Table 3: Outside Option Estimates (Deposits and Mortgages)

This table reports two-stage least squares results for estimating the sensitivity of market-level quantities to the aggregate observed desirability parameter ψ^o_{nt}:

$$\psi^o_{D,nt} = \rho_{D,t} + \theta_D z_{D,nt} + \chi_{D,nt}\theta_D + \varepsilon^o_{D,nt},$$
$$\log \overline{Q}_{D,nt} = \alpha_{D,t} + \beta_{D,o}\psi^o_{D,nt} + \chi_{D,nt}\rho_D + \eta_{D,nt}.$$

The regression is run at the market-year level. We include market-year level controls, including average age and income of the population, fraction of residents college degree, log population, annual house price growth, and log property loss due to natural disaster. For the deposit and mortgage rates, 0.01 means 1%. The sample period is 2001–2017. We report standard errors clustered by county in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel (a): First Stage

	(1)	(2)
	Deposit $\psi^o_{D,nt}$	Mortgage $\psi^o_{M,nt}$
IV	0.03^{***}	-1.03^{***}
	(0.01)	(0.21)
R^2	0.98	0.89
Adj. R^2	0.98	0.89
Within Adj. R^2	0.98	0.69
Num. of Obs.	21628	22447
Controls	Y	Y
Year F.E.	Y	Y

Panel (b): 2SLS

	(1)	(2)
	Deposit Quantity	Mortgage Quantity
ψ^o (with IV)	0.04	0.06^{*}
	(0.19)	(0.03)
Num. of Obs.	21628	22447
Controls	Y	Y
Year F.E.	Y	Y

by 10 basis points is given by

$$\frac{\partial \log \overline{Q}_{D,nt}}{\partial R_{D,nt}} = \frac{\partial \log \overline{Q}_{D,nt}}{\partial \psi^o_{D,nt}} \frac{\partial \psi^o_{D,nt}}{\partial R_{D,nt}} = 0.04 \times 15.1\% = 0.6\%.$$

Similarly, when all banks in a county lower their mortgage rates by 10 basis points, the mortgage quantity increases by $0.06 \times 53.4\% = 3.2\%$. While our estimate of $\beta_{D,0}$ is statistically imprecise, we show in our counterfactual analysis that increasing the estimate by a standard deviation of .19 has a modest impact on how much reserve injections crowd out lending.

For loans, our estimate of the quantity of firms choosing the outside option uses the fact that we can observe both firms that do and do not borrow. We count the number of firms in the Dealscan database that did not borrow in a given year and state and the divide the number by four, which reflects the average loan maturity. We then multiply this number of firms times the average size of a loan in its market. The average loan size is linearly projected from the existing loans in that year with state fixed effect to account for state-level heterogeneity in the size of loans. The underlying assumption is that potential borrowers would have on average obtained a loan of the same size as the existing ones in the market that year.

We report the outside option size for firms at the state-year level in the Online Appendix Table OA1. In 2007, for example, the outside option size is equivalent to a β_o of 0.35. This means that when all banks in a state lower their loan rates by 10 basis points, the loan quantity increases by $0.35 \times 31.0\% = 10.9\%$. Notice that the demand elasticity of loans is higher than that of mortgages because although their price disutility parameters are of similar magnitudes, the outside option of loans responds much more to changes in observed desirability than in the case of mortgages. One reason could be that borrowers in the syndicated loan market have more flexibility to borrow from other sources such as the bond market. Although our focus is on bank lending to firms, our framework could be extended to account for a potential substitution from loans to bonds with public firm-level data on bond financing. Deposits have a low sensitivity along both dimensions, which leads to a highly inelastic deposit demand curve.

Because our result that the reserves created by QE crowd out loans relies on our estimate of the elasticity of loan demand, we present an alternative estimation approach in Online Appendix B. This approach to estimating firms' demand for loans exploits the fact that firms tend to borrow persistently from the same bank multiple times, even though they have the option of borrowing from a new bank. Because of this persistence, we can identify firms' elasticity of credit demand by observing how much they decrease their total borrowing when there is a negative credit supply shock to a bank from which they have already borrowed. We find similar results to our benchmark estimates, as we discuss in Online Appendix B.

4 Cost Function

This section specifies and estimates the bank's cost function for producing deposits, mortgages, and loans. Quantifying the cost function is challenging because banks choose all their balance sheet components simultaneously. We propose a specification of how banks' costs depend on their balance sheet components that can be feasibly estimated using multiple instrumental variables. In our novel estimation method, we first perform a reduced form analysis of how banks' marginal costs and balance sheet quantities respond to exogenous shocks. Next, we estimate the bank's cost function by choosing its parameters to replicate these reduced form results. This estimated cost function tells us how a bank's marginal costs are impacted when the supply of reserves in the banking system changes.

We first set up the cost function in Section 4.1 and then explain how we estimate it in Section

4.2. Section 4.3 describes the data and instruments we use and Section 4.4 reports our estimation results.

4.1 Cost Function Specification

Let $\vec{Q} = (Q_{D,mt}, Q_{L^*,mt}, Q_{S,mt})'$ denote the vector of bank m's total deposit, lending, and security quantities at time t.[10] Here, $Q_{L^*,mt} = Q_{L,mt} + Q_{M,mt}$ is the sum of a bank's per-branch corporate loan and mortgage holdings. We specify the bank's cost function with the quadratic expression

$$C(\Theta_{mt}) = \vec{Q}'H\vec{Q} + \sum_{n^*} Q_{L^*,n^*mt}\varepsilon^{L^*}_{n^*mt} + \sum_{n} Q_{D,nmt}\varepsilon^{D}_{nmt} + Q_{S,mt}\varepsilon^{S}_{mt}. \tag{17}$$

Here, n^* is a variable that indexes all lending markets, either mortgage or corporate loan, allowing for more compact notation. H is a symmetric matrix that is the Hessian of our cost function

$$H = \begin{pmatrix} H_{DD} & H_{DL^*} & H_{DS} \\ H_{DL^*} & H_{L^*L^*} & H_{L^*S} \\ H_{DS} & H_{L^*S} & H_{SS} \end{pmatrix}. \tag{18}$$

The cost function depends linearly on each bank-market-level quantity and quadratically on the bank-level quantities. This quadratic specification yields the following linear expressions for a bank's cost of changing its deposit, lending, and security quantities

$$\frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}} = H_{DD}Q_{D,mt} + H_{DL^*}Q_{L*,mt} + H_{DS}Q_{S,mt} + \varepsilon^{D}_{nmt}, \tag{19}$$

$$\frac{\partial C(\Theta_{mt})}{\partial Q_{L^*,n^*mt}} = H_{DL^*}Q_{D,mt} + H_{L^*L^*}Q_{L*,mt} + H_{L^*S}Q_{S,mt} + \varepsilon^{L^*}_{n^*mt}, \tag{20}$$

$$\frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}} = H_{DS}Q_{D,mt} + H_{L^*S}Q_{L*,mt} + H_{SS}Q_{S,mt} + \varepsilon^{S}_{mt}. \tag{21}$$

Our specification allows for flexible interactions between a bank's costs of borrowing, lending, and holding securities. In particular, a bank's holding of securities affects its marginal cost of lending and deposit-taking. An injection of reserves can therefore cause banks to adjust their loan and deposit quantities. The magnitudes of H_{L^*S} and H_{DS} play a particularly crucial role for determining the impact of reserve injections. As shown in equations (6) to (8), the response of our model to external shocks such as an increase in reserve supply depends only on the second derivatives of the bank's cost function reflected in the matrix H.

[10] We normalize these variables by divided by the number of branches where a bank has deposits. This normalization increases the power of our estimates by reducing the weight on a few very large banks.

Our key simplifying assumption is that mortgages and corporate loan quantities can be aggregated into a single term $Q_{L*,mt} = Q_{M,mt} + Q_{L,mt}$ that appears in the bank's cost function. This follows the simple model of Bernanke and Blinder (1988) that summarizes a bank's balance sheet by the 3 main categories of liquid securities, illiquid loans, and deposit liabilities. Within this framework, we are able to capture the key feature of banks that they provide deposits and loans together. A negative cross partial $\frac{\partial C^2(\Theta_{mt})}{\partial Q_{D,mt} \partial Q_{L^*,mt}} = H_{DL^*}$ would explain why it is optimal for banks to jointly provide deposits and loans rather than for each to be provided by a separate firm, which is a key stylized fact about banks. Pragmatically, this reduction of the bank's balance sheet to 3 quantities rather than 4 also makes our model simple enough to estimate using 3 distinct sources of exogenous variations as we explain below.

4.2 Estimation Strategy

To estimate the bank's cost function Hessian H, we first infer each bank's marginal costs of providing deposits, mortgages, and loans using our estimated demand systems. We use the first-order conditions for a bank's profit-maximizing choices of interest rates, equations (2) to (4). We provide an explicit expression for the bank's marginal costs in equations (A34) -(A36) in appendix A.3. Finally, we can use equation (5) to infer a bank's marginal cost of holding securities directly from observed interest rates because the securities market is competitive.

We then observe how a bank's marginal costs and balance sheet quantities respond to an instrument z^i_{mt}. Such an instrument is necessary because a bank's chosen quantities are likely to be correlated with the cost shocks ε that it faces. For example, a bank will likely choose to provide more deposits if it becomes cheaper for the bank to do so. Looking at the covariance between a bank's marginal cost changes and quantity changes will therefore reflect how a bank responds to cost shocks and not allow us to identify the Hessian H. Instead, if we see how marginal costs and quantities respond to an instrument z^i_{mt} that is uncorrelated with unobserved cost shocks, we can use this information to consistently estimate H.

We regress all of the bank's observed marginal costs and bank-level quantities on this instrument. For $A \in \{D, L^*, S\}$ let MC^A_{mt} be bank m's marginal cost of adding additional units of A to its balance sheet. The impact of our instrument on the bank's marginal cost is given by the linear regression

$$MC^A_{mt} = \theta^{i,A}_t + \kappa^{i,A} z^i_{mt} + u^A_{mt}. \tag{22}$$

We include the fixed effect $\theta^{i,A}_t$ to capture time-series variation in banks' costs that is not directly caused by decisions they make. The impact of the instrument on quantities is given by

$$Q_{A,mt} = \alpha_t^{i,A} + \gamma^{i,A} z_{mt}^i + \varepsilon_{mt}^A. \tag{23}$$

Our identifying assumption is that z_{mt}^i is uncorrelated with u_{mt}^A and ε_{mt}^A. From these regressions, we obtain estimates $\gamma^{i,D}$, $\gamma^{i,L*}$, and $\gamma^{i,S}$ of how deposit, loan, and security quantities respond to a one unit increase in the instrument. We obtain similar estimates $\kappa^{i,D}$ and $\kappa^{i,L*}$ of how a bank's deposit and loan marginal costs respond to the instrument. We must have that $\kappa^{i,S} = 0$ because all banks have the same marginal cost of holding reserves in a perfectly competitive reserve market.

Given these regressions, our instrument z_{mt}^i imposes the following equations that the cost function Hessian H must satisfy

$$0 = H_{SD}\gamma^{i,D} + H_{SL^*}\gamma^{i,L*} + H_{SS}\gamma^{i,S} \tag{24}$$

$$\kappa^{i,L*} = H_{L^*D}\gamma^{i,D} + H_{L^*L^*}\gamma^{i,L*} + H_{L^*S}\gamma^{i,S} \tag{25}$$

$$\kappa^{i,D} = H_{DD}\gamma^{i,D} + H_{DL^*}\gamma^{i,L^*} + H_{DS}\gamma^{i,S}. \tag{26}$$

A one unit increase in the instrument z_{mt}^i causes a $\gamma^{i,D}$ increase in deposits, $\gamma^{i,L*}$ increase in loans, and a $\gamma^{i,S}$ increase in security quantities. These changes in the bank's balance sheet quantities cause a change $\kappa^{i,L*}$ in the marginal cost of loans, $\kappa^{i,D}$ change in the marginal cost of deposits, and 0 change in the marginal cost of holding securities. As a result, we have three linear equations that provide information about what the cost function Hessian H must be. In Section 4.3, we present two distinct instruments z_{mt}^i $(i = 1, 2)$ that yields six equations. In addition, we also present a separate high-frequency identification approach to estimating the coefficient H_{SS}.

Once we have H_{SS} estimated, we use equation (24) for both instruments to solve for the two unknowns H_{SD} and H_{SL^*} with two equations. Note that the Hessian's symmetry solves a crucial identification challenge for analyzing the reserve supply channel of QE. We are able to identify H_{SD} and H_{SL^*} from equation (24) because we can infer how the marginal cost of holding reserves responds to changes in deposit and loan quantities. The Hessian's symmetry allows us to conclude that H_{SD} and H_{SL^*} also are respectively equal to the impact of a change in the quantity of reserves on deposit and loan marginal costs. As a result, we are able to learn about the impact of QE's injection of reserves on deposit and loan markets without exogenous variation in reserve supply.

To estimate the remaining parameters $H_{L^*L^*}, H_{L^*D}, H_{DD}$, we first we solve equation (25) from our two instruments for the parameters $H_{L^*L^*}, H_{L^*D}$ with two equations and two unknowns. Finally, from equation (26), we have two equations show how the two instruments impact the marginal cost of deposit holdings. There is only one unknown H_{DD} and two equations corresponding to the two instruments so we solve for H_{DD} by minimizing the sum of the squared errors in these two equations.[11]

4.3 Data and Instruments

Marginal Costs As explained in section 4.2, we infer the marginal costs for mortgages, deposits, and loans using our demand system estimates in section 3.3. We then average these estimated marginal costs to the bank-year level.

Deposits, Loans, Mortgages, and Securities We obtain bank-level quantities from Call Reports, which allows us to keep track of the volume of deposits, loans, mortgages, and securities that are actually retained on bank balance sheets. We measure mortgages with the Call Reports' residential loan variable, and commercial loans make up the remainder of loans from Call Reports. We further include bank-level securities from Call Reports, which is the sum of cash, reserves, Fed funds, repos, Treasury securities, and agency securities. Finally, we normalize all bank-level volume variables by the number of branches where each bank has deposits. This normalization prevents our estimates from being driven by a few banks with a very large amount deposits and loans.

Instruments We use two instrumental variables, z^1_{mt}, z^2_{mt} to identify the cost function parameters. These shocks need to be at the bank-level and must be independent of banks' cost shocks in the cross-section. In addition, we separately use exogenous daily variation in the total supply of reserves to identify the parameter H_{SS}.

Our first instrument is simply the natural disaster losses that a bank's branches are directly exposed to. Unlike in the instrument for demand systems, we are no longer in need of a branch-level supply shock. Rather, disaster losses to an area increase the need to rebuild and repair local infrastructure and housing, which directly comprise a bank-level demand shock for bank lending. These disaster losses are also plausibly unrelated to shocks to banks' marginal costs in the cross-section. Hence, we construct the instrument by adding up the disaster losses that each bank is exposed to through its branches. Specifically, for bank m at time t, we have

$$z^1_{mt} = \frac{1}{N_{mt}} \log\left(\sum_n damage_{nt} \cdot \frac{N^B_{nmt}}{\sum_{n'} N^B_{n'mt}}\right),$$

[11] This lack of an exact solution is because both the impact of deposit quantities on loan costs and the impact of loan quantities on deposit costs tell us about H_{DL^*}. Our use of two instruments therefore results in an overidentifying restriction for this parameter. Our choice to make H_{DD} the parameter that does not exactly solve an equation is because deposit demand is the least elastic, so the value of H_{DD} matters the least for our counterfactual of interest.

where $\sum_n damage_{nt} \cdot \frac{N^B_{nmt}}{\sum_{n'} N^B\_n'mt}$ is the sum of disaster losses accrued to branches of bank m in county n, and N_{mt} is the number of counties in which bank m has branches. We mathematically show in appendix D that for a firm that sells a good in several markets, a demand shock in one market can be used to estimate the firm's marginal cost curve.

Our second instrument is a Bartik deposit instrument. Following Bartik (1991), we construct our instrument based on the average growth rates of deposits in markets where banks have branches. Intuitively, we make use of the fact that counties experience different rates of deposit growth and that banks operate branches in different counties to construct our Bartik deposit instrument. The identifying assumption is that the deposit growth rates in different counties that a bank is exposed to arise from county-level economic conditions rather than shocks to the bank's cost of supplying deposits, mortgages, and loans. Specifically, for bank m in year t, we have

$$z^2_{mt} \quad = \quad \frac{1}{N_{mt}} \left(\sum_n \frac{\overline{Q}_{D,nt} - \overline{Q}_{D,nt-1}}{\overline{Q}_{D,nt-1}} \right),$$

where $\frac{\overline{Q}_{D,nt} - \overline{Q}_{D,nt-1}}{\overline{Q}_{D,nt-1}}$ is the deposit market growth rate in county n and N_{mt} is the number of counties in which the bank has branches.

While the Bartik instrument should primarily serve as a shock to deposit demand, and the natural disaster instrument primarily as a shock to loan demand, we do not require either to affect deposit or loan demand alone. The exclusion restriction holds even if the instruments affect the demand more than one bank balance sheet component as long. We only assume that each instrument is uncorrelated with the ε marginal cost shocks. The only additional requirement for identifying our parameters is that the two instruments are not perfectly collinear, which we show is satisfied in the data.

Finally, we use daily shocks to the Treasury General Account (TGA) to estimate the effect of reserve supply shocks on the marginal cost of securities. The TGA contains cash balances that the U.S. Treasury holds at the Federal Reserve. Since reserves are held either through the TGA or the banking system, a positive shock to the TGA balance corresponds to an equivalent negative shock to the reserves available for the banking system for a given total reserve supply. As also noted by Correa et al. (2020) and Bräuning (2017), these daily changes in the TGA balance are a result of the Treasury's day-to-day business operations that are arguably unrelated to QE and market conditions. Following Bräuning (2017), we include indicator variables for the start and end days of each month and quarter because these periods coincide with both Treasury payment days, which would affect the TGA balance, and changes in banks' regulatory reporting days, which would affect banks' marginal costs. We further control for changes in the volume of the Reverse Repo (RRP) Facility, ΔRRP_t , which is effectively the uptake of reserves by money market funds, as well as the weekly change in total reserves ΔTSY_w.[12] We use these variables to predict changes in the spread between the interest rate on excess reserves (IOER) and the federal funds rate (FFR), $ReserveSpread_t$. This spread measures how much higher of a yield is available to banks that can hold reserves than to other non-bank investors. Specifically, we estimate

$$\Delta ReserveSpread_t = \alpha + \beta \Delta TGA_t + \gamma \Delta RRP_t + \theta \Delta TSY_w + \text{Fixed Effects} + \epsilon_t, \tag{27}$$

where Fixed Effects include indicator variables that equal to one the first and last days of each month and quarter. The coefficient β tells us how a shock to the total reserve supply impacts the IOER-FFR spread.

4.4 Estimation Results

Table 4 reports the coefficients from regressing marginal costs and bank-level quantities on each of the two instruments, i.e., $(\kappa^{i,D}, \kappa^{i,L^*}, \gamma^{i,D}, \gamma^{i,L^*}, \gamma^{i,S})$. Since these parameters are instrument-specific, we report the parameter values corresponding to the bank-level natural disaster shock in Panel (a) and the parameter values corresponding to the bank-level Bartik deposit shock in Panel (b). We report additional summary statistics about the marginal costs using in estimation in web appendix E.

According to Panel (a), banks with branches in areas with larger natural disaster losses increase the volume of deposits, loans, and securities on their balance sheets. At the same time, mortgage and loans become more costly to provide while deposits become less costly to provide for these banks. Taken together, we infer that the increase in volumes is consistent with an increase in loan and mortgage demand following natural disasters. From Panel (b), banks experiencing a positive Bartik deposit shock also increase their deposits, loans, and securities. Deposit costs become less negative, implying that deposits become more costly to provide. At the same time, the costs of lending to firms and issuing mortgage loans declines as deposits become more abundant. Hence, the increase in balance sheet size in this case is aligned with a positive deposit demand shock, as expected from the Bartik deposit instrument.

Table 5 reports the results from the TGA regression. We obtain a point estimate of -7.88, which implies that a 1 trillion dollar increase in the TGA balance is associated with a 7.88 bps movement in the reserve spread. If these reserves were injected and the reserve market allowed to clear holding other quantities fixed, they would be allocated proportionately across the bank

[12] Total reserves are only available the weekly level.

Table 4: Cost Function Regression Estimates

This table reports the sensitivity of bank-level costs and quantities to losses from natural disasters and a Bartik deposit shock as in equations (22) and (23). Sheldus Instrument refers to property losses due to natural disasters as explained in Section 4.3. Bartik Deposit Instrument refers to a Bartik-style instrument of deposit growth as explained in Section 4.3. Rates are in basis points and quantities are in millions. The sample period is from 2001 to 2017. We report standard errors clustered by bank in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Deposit Cost	Mtg/Loan Cost	Deposit Vol	Mtg/Loan Vol	Security Vol
Panel (a): Results using Natural Disaster Instrument					
	(1)	(2)	(3)	(4)	(5)
Sheldus Instrument	−3.17***	2.46***	28.31***	26.37***	18.97**
	(0.33)	(0.92)	(8.11)	(6.25)	(8.12)
Loan Loss Provision	−6.04*	1.91	6.98	527.36***	1.51
	(3.34)	(1.34)	(7.79)	(202.27)	(2.40)
R^2	0.58	0.82	0.00	0.01	0.00
Adj. R^2	0.58	0.82	0.00	0.01	0.00
Num. of Obs.	53651	12733	118942	119236	118923
Panel (b): Results using Bartik Deposit Shock					
	Deposit Cost	Mtg/Loan Cost	Deposit Vol	Mtg/Loan Vol	Security Vol
	(1)	(2)	(3)	(4)	(5)
Bartik Instrument	31.31***	−24.60*	1048.26**	474.34***	1084.52**
	(8.13)	(14.85)	(417.94)	(136.09)	(508.92)
Loan Loss Provision	−4.76	−7.81**	7.19	153.96	−48.37
	(3.35)	(3.47)	(48.79)	(93.89)	(48.10)
R^2	0.43	0.82	0.00	0.01	0.00
Adj. R^2	0.43	0.82	0.00	0.00	0.00
Num. of Obs.	50091	12093	62352	62458	62346

branches in our sample. If we allocate these reserve assets equally to the 65,569 bank branches that exist in 2007 (the year before our counterfactual exercise), we get 0.51 bps change in the reserve spread per 1 million dollar increase in each branch's security holdings. This implies $H_{SS} = 0.51$.

Based on these coefficient estimates, we solve for the cost function's Hessian H and present the results in Table 6. First, notice that all diagonal terms are positive, which means that increased quantities of deposits, loans, or securities respectively increase the marginal cost of providing additional deposits, loans, or securities. Regarding the off-diagonal terms, the marginal costs of loans and securities decrease when deposit quantities increase. In other words, there are cost synergies between banks' deposit-taking and lending that support the joint provision of deposits and loans

Table 5: TGA Regression Estimates

This table reports the results from the TGA regression (27). Rates are in basis points and quantities are in trillions. The sample period is from 2001 to 2017. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Change in TGA Balance	-7.88^{***}
	(1.82)
Change in RRP	0.03^{***}
	(0.00)
Change in Fed Sum	0.00
	(0.00)
R^2	0.46
Adj. R^2	0.46
Num. of Obs.	1770

by the same institution. However, the marginal cost of lending is increasing in securities holdings. This implies that injecting additional reserves that banks must hold makes it not cheaper but more costly to provide corporate loans and mortgages. This increase in the marginal cost of lending is a crucial reason why we find that reserve injections crowd out lending in our counterfactual.

The coefficients imply that a $100 million increase in reserves for each bank branch would increase the marginal cost for mortgages and corporate loans by $100 \times 0.39 =$39 bps. At the same time, the marginal cost of deposits decreases by $100 \times 0.70 = 70$ bps. To put these numbers in context, if $1 trillion in reserves were injected and equally distributed across bank branches in 2007, each bank branch would receive $15.25 million in reserves, which would increase the marginal costs of mortgages and corporate loans by 5.9 bps. Of course, this change in marginal costs does not describe the equilibrium impact of a reserve injection, since banks can adjust their deposit and loan quantities in response. The equilibrium effect of a reserve injection therefore depends on both the supply and demand sides of our model. To quantify the equilibrium impact of reserve injections in the banking system, we present a counterfactual analysis using both our estimated cost function and demand systems in the next section.

Table 6: Implied Hessian

This table reports the implied Hessian matrix H based on the cost function estimates. Please refer to Section 4 for a detailed description of the estimation. The Hessian matrix reports the impact of an extra $1 million dollars per branch of a balance sheet quantity on the number of basis points by which a bank's marginal cost changes.

	$\frac{\partial C}{\partial Q_D}$	$\frac{\partial C}{\partial Q_{L*}}$	$\frac{\partial C}{\partial Q_S}$
Q_D	1.06	-0.66	-0.70
Q_{L*}	-0.66	0.53	0.39
Q_S	-0.70	0.39	0.51

5 Counterfactual Exercise

We use our estimated model to compute the effect of an increase in the supply of central bank reserves, as was caused by the Federal Reserve's QE Programs. These reserves are safe, liquid assets that must only be held by banks, so this increased supply forces banks to hold a larger portfolio of safe assets. While QE is an exchange between Treasuries and reserves, commercial banks only hold a very small proportion of Treasuries on bank balance sheets. Thus, the reserve injection comprises a net increase in banks' liquid asset holdings in our counterfactual.

The impact of this increased reserve supply has two main effects. First, an increase in reserve holdings changes banks' marginal cost of providing deposits, mortgages, and loans. This change in marginal cost is quantified by our estimated cost function in equation (17). Second, because of these cost changes, banks change the interest rates they choose to for deposits, loans, and mortgages. Given our estimated demand systems, we can compute how the equilibrium quantities of deposits, loans, and mortgages respond to these changes in the rates that banks choose. As a result, our model tells us how an increase in the supply of central bank reserves passes through to changes in both interest rates and quantities of deposits, mortgages, and loans provided by the banking system.

We note that our results focus on the effect of reserve injection on the banking system, which is an integral part of QE. Our results complement other transmission channels of QE that have been analyzed in the literature.[13] These transmission channels primarily depend on the effect of asset purchases, while our work is novel in that we zoom in on the effect of reserves that the central bank uses to finance asset purchases.

[13] For example, Gagnon et al. (2010); Krishnamurthy and Vissing-Jorgensen (2011); Christensen and Krogstrup (2019); Rodnyansky and Darmouni (2017); Chakraborty et al. (2020), as discussed in our literature review.

5.1 Computational Strategy

To compute our counterfactual, we need to determine each bank's holdings of reserves as well as the quantity and interest rate each bank charges for loans, deposits, and mortgages in each market after an injection in reserves. Formally, we need to compute an equilibrium set of interest rates and quantities that solve the bank's first order conditions in equations (2)-(5) with an increased supply of reserves. This is an over 38,000-dimensional problem, since we need to solve for interest rates for mortgages, deposits, and loans at every branch of every bank. Nevertheless, we can reduce the dimensionality considerably, and the model is tractable to solve. We define a function in equation (OA37) of the Appendix that maps the set of bank-level deposit, mortgage, and loan quantities to itself whose fixed point yields the equilibrium of our model.

We posit an increase R in the interest paid on securities above the yield earned in the data. We then compute the quantity of reserves the central bank must add to the financial system to attain this interest rate increase. Let $Q^i_{D,mt}, Q^i_{M,mt}, Q^i_{L,mt}$, and $Q^i_{S,mt}$, where i stands for initial, be the bank level quantities of deposits, mortgages, loans, and securities observed in the data. First, we start with a hypothesized vector of bank-level quantities $Q_{D,mt}, Q_{M,mt}, Q_{L,mt}$. Second, for each bank, we compute a security quantity $Q_{S,mt}$ so that the bank's marginal cost of holding securities is consistent with the rise R in the yield on securities. Third, given the vector of bank-level quantities $Q_{D,mt}, Q_{M,mt}, Q_{L,mt}$, $Q_{S,mt}$, we use our estimated cost function to compute a bank's marginal cost of holding deposits, mortgages, loans, and securities. Fourth, we compute the optimal interest rates banks choose that are jointly consistent with all of their marginal costs. Fifth, given the rates chosen in each market, we compute the bank-market-level quantities demanded by depositors/borrowers. Finally, we sum up the bank-market level quantities from the previous step and compute the difference from the hypothesized bank-level quantities $Q_{D,mt}, Q_{M,mt}, Q_{L,mt}$. The market is in equilibrium when this difference is 0. Please refer to Appendix F for further details.

5.2 Counterfactual Results: The Reserve Supply Channel of QE

We conduct a year-by-year counterfactual with the amount of reserves supplied by QE in each year from 2008 to 2017. On average, this amounted to a reserve supply increase of \$1.74 trillion per year. We note that the number of banks present in each year varies, as shown in Online Appendix G. This variation arises mostly due to the improving sample coverage of the mortgage volume data from HMDA. These changes in data coverage should not affect our results if the banks in our sample are representative of those in the true population.

The average changes in interest rates and quantities that resulted are shown in Table 7. From the table, we observe that the interest rate paid on reserves increases by an average of 11.5 bps.

Table 7: Counterfactual Results: QE

This table reports the results of our counterfactual analysis that injects the actual amount of reserves QE supplied for each year from 2008 to 2017. We compute the effects on rates and quantities, and report the average across years.

Average Change in Rates (in Basis Points)				Average Change in Quantities (in Trn Dollars)			
Deposits	Mortgages	Loans	Securities	Deposits	Mortgages	Loans	Securities
15.71	8.59	8.20	11.51	0.0750	-0.0078	-0.1339	1.7440

The increase in reserve yields are passed through to the interest rates on deposits, mortgages, and loans by 15.7 bps, 8.6 bps, and 8.2 bps, respectively. In terms of quantities, bank loans extended to firms respond the most with an average decline of $133.9 billion. Mortgage and deposit volumes respond by less with an average annual drop of $7.8 billion and an annual increase of $75.0 billion, respectively. These results imply each dollar of reserves crowds out 8.125 cents of total lending and crowds in 4.3 cents of deposits.[14]

We next zoom in on lending to firms, where the impact of the reserve injection is largest. In Figure 4 we show the volume of reserves that were in the banking system each year and our estimated impact on bank loan quantities. The volume of reserves injected from QE increased from 2008 to 2014 and remained at elevated levels until 2017. The reduction in firm loans extended follows a very similar trend, reaching a maximum annual volume of $215.5 billion in 2017. Figure 3 compares what banks' syndicated loan issuance would have been without the injection of reserves to what it was in the data. In the data, historically low issuance levels in the 2008 crisis were followed by a rapid recovery to all-time highs. This increase in lending would have been even greater without the injection of reserves, where lending quantities would have been 14.1% higher in 2015, 12.3% higher in 2016, and 13.2% higher in 2017.

The model-implied reserve spread is quite similar to the observed spread between IOER and the FFR in the data. The IOER is a risk-free yield available only to banks, which is strictly above the FFR at which other market participants can lend overnight to banks. We plot both time series in Figure 5. Adding the same volume of reserves as were injected through QE leads to an 11.5 bps average increase in the model-implied reserve spread from 2008 to 2017. This is extremely close to the average spread between the IOER and the FFR during the same period, 11.9 bps.[15] Changes in

[14] In a sensitivity analysis, we re-ran our counterfactual adding one standard deviation, 0.19, to the coefficient $\beta_{D,0}$ that determines how aggregate deposit quantities respond to deposit rates. With this change, the total quantity of lending crowded out falls modestly to $104 billion from $141.7 billion. This modest change is despite a large change in deposit quantities, which increase by $312.6 billion. Hence, our result that reserve injections crowd out lending remains robust.

[15] We calculate the IOER-FFR as the median spread in December of each year because of year-end volatility in the

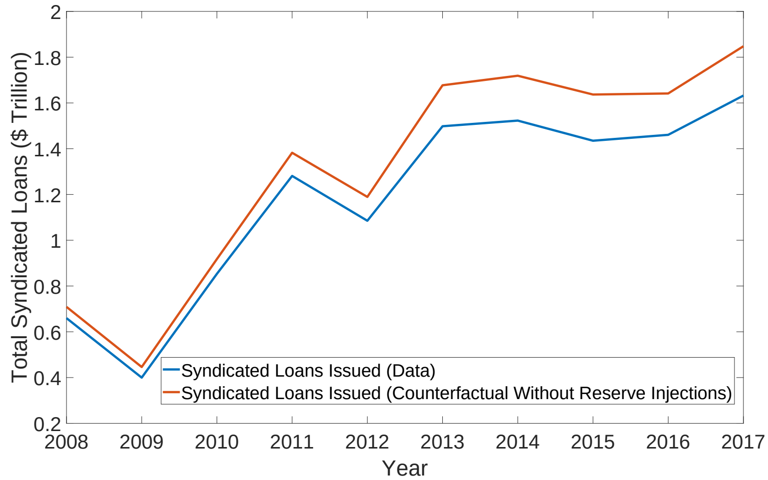


Figure 3: Observed and Counterfactual Lending Quantities

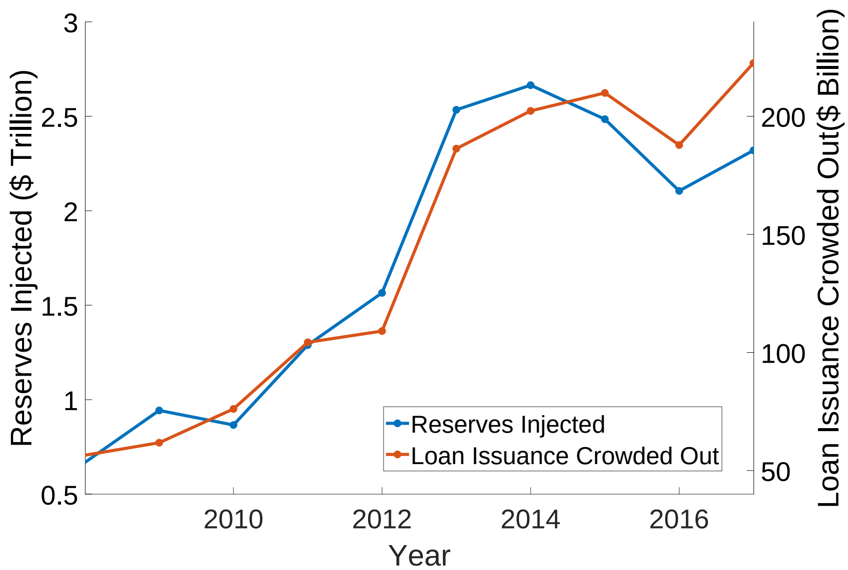


Figure 4: Reserve Supply and Reduction in Corporate Loan Issuance

our reserve spread also appear to move in tandem with changes in the IOER-FFR spread over time, with a correlation between the two series of 0.50. The close mapping between the model and data here is not mechanical or assumed in our estimation. Our model is identified from the response of banks to plausibly exogenous shocks, without using any data directly from the implementation of QE. The results suggest that the positive IOER-FFR spread observed after 2008 may not have occurred without QE.

In summary, our main finding is that reserves crowd out bank lending to firms and that mort-

federal funds market. We omit 2008 since bank credit risk could have impacted the FFR that year.

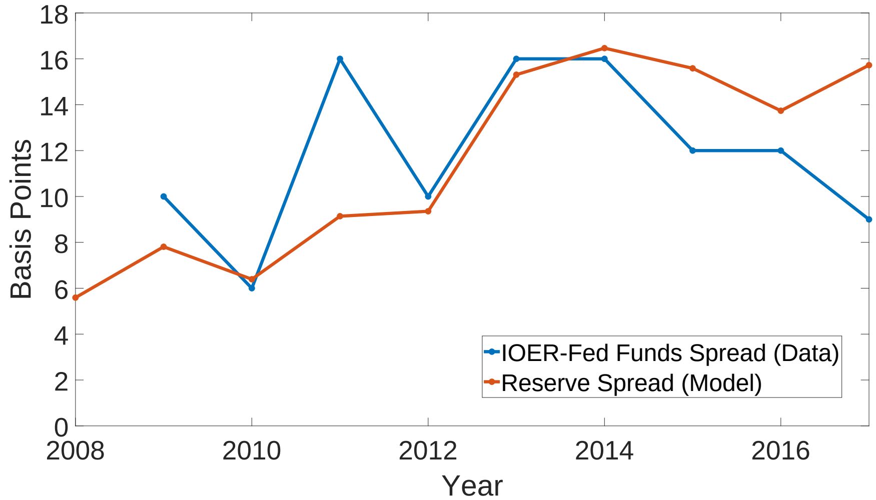


Figure 5: IOER-Fed Funds Spread and Model-Implied Reserve Spread

gage and deposit quantities respond by less. A larger reserve supply reduces lending because holding reserves raises the cost of providing loans, as our cost function estimates in Table 6 show. While loan, mortgage, and deposit rates increase by similar amounts, lending to firms is crowded out the most because the aggregate elasticity of loan demand is higher than of mortgage or deposit demand, as discussed in Section 3.3. On net, central bank reserves take up balance sheet space to crowd out bank lending capacity to the real economy. Therefore, our findings suggest that the increase in reserve supply following QE may bring about a counterproductive effect on the banking system.

Consistent with reserves taking up bank balance sheet space, we show in an additional counterfactual that reserve holdings and lending increase more at banks with less constrained balance sheets. This result echoes Kandrac and Schlusche (2021), who find that both reserve holdings and lending increased more at banks that were exempt from an increase in FDIC deposit insurance fees for non-deposit funded assets compared to non-exempt banks. In Online Appendix H, we simulate a similar counterfactual and find similar results. This is because the increased cost of non-deposit financing makes it more expensive both for reserves and loans to be on a bank's balance sheet, pushing both quantities in the same direction. Our main counterfactual considers a different scenario, where we exogenously inject reserves in the banking system keeping the form of banks' cost function fixed, which is why we find that a larger reserve supply contracts rather than expands aggregate bank lending.

6 Conclusion

There has been a large expansion in the amount of central bank reserves outstanding following multiple rounds of QE. This paper develops and estimates a structural model of the U.S. banking system to analyze the effect of an increase in central bank reserve supply on bank lending and deposit taking. Our framework has two key factors that determine the impact of reserve injections on the banking system. The first one is the demand elasticity banks face in their respective deposit and loan markets. The second one is how banks' cost of capital depends on their balance sheet composition, where the effect of reserve holdings on the cost of capital is of particular importance.

One main challenge in estimating our model is that reserve supply increases are endogenous. In particular, reserve supply increased due to QE, which was implemented in response to the 2008 financial crisis and the Covid-19 pandemic. To avoid confounding by the direct effect of these crises, we estimate our structural model using cross-sectional variation unrelated to QE.

In our estimated model, the increase in reserve supply from 2008 to 2017 reduces firm loans extended by an average of $133.9 billion, which amounts to 8.1 cents in bank lending crowded out per dollar of reserves injected. The impact on mortgage lending and deposit taking is more attenuated. Our model-generated reserve spread closely follows the observed IOER-FFR spread in the data. Importantly, the reduction in bank lending to firms following reserve increases may counteract the stimulative impacts of QE's asset purchases. This counterproductive effect of the reserve supply channel we document is important to consider when thinking about the design of unconventional monetary policy and bank regulation going forward.

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Appendix

A Additional Proofs and Derivations

A.1 Derivation of Equations (6)-(8) in Section 2

Taking the derivatives on the left-hand side of equations (2) to (4) yields

$$
\begin{aligned}
\frac{\partial Q_{D,nmt}}{\partial R_{D,nmt}}(R_t^{D,m} - R_{D,nmt}) - Q_{D,nmt} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}} \frac{\partial Q_{D,nmt}}{\partial R_{D,nmt}}, && \text{(A1)} \\
\frac{\partial Q_{M,nmt}}{\partial R_{M,nmt}}(R_{M,nmt} - R_t^{M,m}) + Q_{M,nmt} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{M,nmt}} \frac{\partial Q_{M,nmt}}{\partial R_{M,nmt}}, && \text{(A2)} \\
\frac{\partial Q_{L,nmt}}{\partial R_{L,nmt}}(R_{L,nmt} - R_t^{L,m}) + Q_{L,nmt} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{L,nmt}} \frac{\partial Q_{L,nmt}}{\partial R_{L,nmt}}, && \text{(A3)} \\
R_{S,t} - R_t^{S,m} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}}. && \text{(A4)}
\end{aligned}
$$

Dividing equations (A1)-(A3) respectively by $\frac{\partial Q_{D,nmt}}{\partial R_{D,nmt}}$, $\frac{\partial Q_{M,nmt}}{\partial R_{M,nmt}}$, and $\frac{\partial Q_{L,nmt}}{\partial R_{L,nmt}}$ yields

$$
\begin{aligned}
R_t^{D,m} - R_{D,nmt} - \frac{Q_{D,nmt}}{\partial Q_{D,nmt}/\partial R_{D,nmt}} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}}, && \text{(A5)} \\
R_{M,nmt} - R_t^{M,m} + \frac{Q_{M,nmt}}{\partial Q_{M,nmt}/\partial R_{M,nmt}} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{M,nmt}}, && \text{(A6)} \\
R_{L,nmt} - R_t^{L,m} + \frac{Q_{L,nmt}}{\partial Q_{L,nmt}/\partial R_{L,nmt}} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{L,nmt}}, && \text{(A7)} \\
R_{S,t} - R_t^{S,m} &= \frac{\partial C(\Theta_{mt})}{\partial Q_{S,mt}}. && \text{(A8)}
\end{aligned}
$$

If we take the left-hand side of equations (A5) - (A7) as a function respectively of the quantities $Q_{D,nmt}, Q_{M,nmt}$ and $Q_{L,nmt}$, we can implicitly differentiate this system of equations to see how the bank responds to an exogenous increase in its security holdings $Q_{S,mt}$. If we differentiate this system with respect to $Q_{S,mt}$, we obtain equations (6)- (8) in the main text.

A.2 Detailed Derivations for Section 3

A.2.1 Characterization of Demand System

Equation (12) gives the probability $P_{D,nmt|\delta_{D,jn0t}}$ that agent j chooses bank m conditional on its realized value of $\delta_{D,jn0t}$. Integrating $P_{D,nmt|\delta_{D,jn0t}}$ over the measure $\mu(\delta_{D,jn0t})$ yields the quantity chosen from bank m

$$\overline{F}_{D,nt}\int_{-\infty}^{\infty}\frac{\exp(\alpha_D R_{D,nmt}+X_{D,nmt}\beta_D+\delta_{D,nmt})\exp(\beta_{D,o}\delta_{D,jn0t})}{\exp(\delta_{D,jn0t})+\sum_{m'>0}\exp(\alpha_D R_{D,nm't}+X_{D,nm't}\beta_D+\delta_{D,nm't})}d\delta_{D,jn0t}. \tag{A9}$$

If we define

$$U_{D,nt}=\overline{F}_{D,nt}\int_{-\infty}^{\infty}\frac{\exp(\beta_{D,o}\delta_{D,jn0t})}{\exp(\delta_{D,jn0t})+\sum_{m'>0}\exp(\alpha_D R_{D,nm't}+X_{D,nm't}\beta_D+\delta_{D,nm't})}d\delta_{D,jn0t} \tag{A10}$$

then the quantity $Q_{D,nmt}$ chosen from bank m in market n at time t is

$$Q_{D,nmt}=U_{D,nt}\exp(\alpha_D R_{D,nmt}+X_{D,nmt}\beta_D+\delta_{D,nmt}). \tag{A11}$$

Taking the log of equation (A11) yields equation (13) that we use to estimate α_D and β_D.[16]

A.2.2 Estimating the Aggregate Elasticity of Demand

Next, we characterize the aggregate elasticity of deposit demand relative to the outside option. This is necessary because unlike in a standard logit demand system, we do not observe the quantity chosen of the outside good. If we sum equation (A9) over all banks m in a market, we get that the total deposit quantity $\overline{Q}_{D,nt}$ equals

$$\overline{Q}_{D,nt}=\int_{-\infty}^{\infty}\frac{\overline{F}_{D,nt}\exp(\beta_{D,o}\delta_{D,jn0t})\sum_{m>0}\exp(\alpha_D R_{D,nmt}+X_{D,nmt}\beta_D+\delta_{D,nmt})}{\exp(\delta_{D,jn0t})+\sum_{m'>0}\exp(\alpha_D R_{D,nm't}+X_{D,nm't}\beta_D+\delta_{D,nm't})}d\delta_{D,jn0t}. \tag{A13}$$

[16] Note that for our loan market following a standard logit demand system, we have $\delta_{L,jn0t}=0$ for all j and the outside good quantity $Q_{L,n0t}$ is observed. If there is a total funding need $\overline{F}_{L,nt}$ (which is observable since we see $Q_{L,n0t}$) for loans in market n at time t, we get the related expression for the quantity chosen from bank k

$$Q_{L,nmt}=\overline{F}_{L,nt}\frac{\exp(\alpha_L R_{L,nmt}+X_{L,nmt}\beta_L+\delta_{L,nmt})}{1+\sum_{m'>0}\exp(\alpha_L R_{L,nm't}+X_{L,nm't}\beta_L+\delta_{L,nm't})}. \tag{A12}$$

This also yields a log-linear expression of the form in equation A11 that allows us to estimate α_L and β_L by two stage least squares. We can then solve for each market for the values of $\delta_{L,nmt}$ that uniquely rationalize our quantity data $Q_{L,nmt}$.

If we define

$$\psi_{D,nt} = \log(\sum_m \exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})) \tag{A14}$$

to represent the desirability of a "composite good" provided by all banks operating in the market, the total quantity of deposits equals

$$\overline{Q}_{D,nt} = \overline{F}_{D,nt} \int_{-\infty}^{\infty} \frac{\exp(\beta_{D,o}\delta_{D,jn0t})\exp(\psi_{D,nt})}{\exp(\delta_{D,jn0t}) + \exp(\psi_{D,nt})} d\delta_{D,jn0t}. \tag{A15}$$

After the change of variables $u = \delta_{D,jn0t} - \psi_{D,nt}$ in the integral, equation (A15) becomes[17]

$$\overline{Q}_{D,nt} = \overline{F}_{D,nt} \int_{-\infty}^{\infty} \frac{\exp(\beta_{D,o}[u + \psi_{D,nt}])\exp(\psi_{D,nt})}{\exp(u + \psi_{D,nt}) + \exp(\psi_{D,nt})} du \tag{A16}$$

$$= \overline{F}_{D,nt} \exp(\beta_{D,o}\psi_{D,nt}) \int_{-\infty}^{\infty} \frac{\exp(\beta_{D,o}u)}{1 + \exp(u)} du. \tag{A17}$$

Equation A17 implies the following log-linear specification that we use to estimate $\beta_{D,o}$

$$log(\overline{Q}_{D,nt}) = \beta_{D,o}\psi_{D,nt} + \log[\overline{F}_{D,nt} \int_{-\infty}^{\infty} \frac{\exp(\beta_{D,o}u)}{1 + \exp(u)} du]. \tag{A18}$$

In equation (A18), we can write $\psi_{D,nt} = \psi^o_{D,nt} + \psi^u_{D,nt}$, where $\psi^o_{D,nt}$ can be computed from observable data based on equation (A25) once $a\alpha_D$ and β_D are estimated. With an instrument for $\psi^o_{D,nt}$, we can then estimate $\beta_{D,o}$ by two-stage least squares. The identifying assumption is that the unobservable $\beta_{D,o}\psi^u_{D,nt} + \log)\overline{F}_{D,nt})$ is uncorrelated with the instrument. After $\beta_{D,o}$ is estimated, the only term in equation (A18) that changes when banks' change their interest rates is the observable term $\psi^o_{D,nt}$. Equation (A18) therefore determines how aggregate quantities respond to rate changes, and equation (A11) pins down the distribution of deposits between banks. We therefore have a completely specified demand system once α_D, β_D, and $\beta_{D,o}$ are estimated.

[17]Note that the change of variable $v = exp(u)$ implies that $\int_{-\infty}^{\infty} \frac{\exp(\beta_{D,o}u)}{1+\exp(u)} du = \int_0^{\infty} \frac{v^{\beta_{D,o}}}{v(1+v)} dv < \int_0^{\infty} v^{(\beta_{D,o}-2)} dv$ is finite for any $0 < \beta_{D,o} < 1$. All of our estimates in the paper lie in this range, so our demand system is well specified.

A.2.3 Explicit Expression for $\psi^o_{D,nt}$

We use equation (A11) to write an individual bank's deposit quantity as

$$Q_{D,nmt} = \int_{-\infty}^{\infty} \frac{\overline{F}_{D,nt} \exp(\beta_{D,o}\delta_{D,jn0t}) \exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\exp(\delta_{D,jn0t}) + \sum_{m'>0} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} d\delta_{D,jn0t}. \quad \text{(A19)}$$

The total quantity of deposits in a market is, summing over $m > 0$,

$$\overline{Q}_{D,nt} = \int_{-\infty}^{\infty} \frac{\overline{F}_{D,nt} \exp(\beta_{D,o}\delta_{D,jn0t}) \sum_{m>0} \exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\exp(\delta_{D,jn0t}) + \sum_{m'>0} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} d\delta_{D,jn0t}. \text{(A20)}$$

Taking the ratio of the expressions in equations (A19)-(A20) yields

$$\frac{Q_{D,nmt}}{\overline{Q}_{D,nt}} = \frac{\exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\sum_{m'} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} \quad \text{(A21)}$$

$$\log Q_{D,nmt} = \log \overline{Q}_{D,nt} + \log \frac{\exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\sum_{m'} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} \quad \text{(A22)}$$

$$= \log \overline{Q}_{D,nt} + \alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt} - \psi^o_{D,nt} - \psi^u_{D,nt}. \quad \text{(A23)}$$

Averaging the expression in equation (A23) across the N_{nt} different banks m in market n at time t yields

$$\frac{1}{N_{nt}} \sum_m \log(Q_{D,nmt}) = log(\overline{Q}_{D,nt}) + \frac{1}{N_{nt}} \sum_m (\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D) - \psi^o_{D,nt}, \quad \text{(A24)}$$

since the market-specific mean of $\delta_{D,nmt}$ is $\psi^u_{D,nt}$. This yields the expression we use to compute $\psi^o_{D,nt}$ directly from data

$$\psi^o_{D,nt} = \frac{1}{N_{nt}} \sum_m (\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D) - \frac{1}{N_{nt}} \sum_m \log(Q_{D,nmt}/\overline{Q}_{D,nt}). \quad \text{(A25)}$$

We also have from the original definition $\psi^o_{D,nt} = \psi_{D,nt} - \psi^u_{D,nt}$ that

$$\frac{\partial \psi^o_{D,nt}}{\partial R_{D,nmt}} = \frac{\partial \psi_{D,nt}}{\partial R_{D,nmt}} = \alpha_D \frac{\exp(\alpha_D R_{D,nmt} + X_{D,nmt}\beta_D + \delta_{D,nmt})}{\sum_{m'>0} \exp(\alpha_D R_{D,nm't} + X_{D,nm't}\beta_D + \delta_{D,nm't})} = \alpha_D \frac{Q_{D,nmt}}{\overline{Q}_{D,nt}}. \text{(A26)}$$

A.2.4 Derivation of Individual Bank and Market-Level Demand Curves

Taking the derivative of the expression in equation (A23) for $\log Q_{D,nmt}$ yields

$$\begin{aligned}\frac{\partial \log Q_{D,nmt}}{\partial R_{D,nmt}} &= \alpha_D + \frac{\partial \log \overline{Q}_{D,nt}}{\partial R_{D,nmt}} - \frac{\partial \psi^o_{D,nt}}{\partial R_{D,nmt}} && \text{(A27)}\\ &= \alpha_D + \left(\frac{\partial \log \overline{Q}_{D,nt}}{\partial \psi^o_{D,nt}} - 1\right)\frac{\partial \psi^o_{D,nt}}{\partial R_{D,nmt}} && \text{(A28)}\\ &= \alpha_D + \alpha_D\left(\frac{\partial \log \overline{Q}_{D,nt}}{\partial \psi^o_{D,nt}} - 1\right)\frac{Q_{D,nmt}}{\overline{Q}_{D,nt}} && \text{(A29)}\\ &= \alpha_D + \alpha_D(\beta_{D,o} - 1)\frac{Q_{D,nmt}}{\overline{Q}_{D,nt}}. && \text{(A30)}\end{aligned}$$

In equation (A30), we apply our log-linear expression in equation (A18) which yields $\beta_{D,o} = \frac{\partial \log \overline{Q}_{D,nt}}{\partial \psi^o_{D,nt}}$. We similarly have that if another bank $m' \neq m$ changes its interest rate, the quantity $Q_{D,nmt}$ changes as

$$\frac{\partial \log Q_{D,nmt}}{\partial R_{D,nm't}} = \frac{\partial \log \overline{Q}_{D,nt}}{\partial R_{D,nm't}} - \frac{\partial \psi^o_{D,nt}}{\partial R_{D,nm't}} = \alpha_D(\beta_{D,o} - 1)\frac{Q_{D,nm't}}{\overline{Q}_{D,nt}}. \tag{A31}$$

The log-linear expression in equation (A18) allows us to derive an expression for the impact of an individual bank's rates on market-level quantities:

$$\frac{\partial \log \overline{Q}_{D,nt}}{\partial R_{D,nmt}} = \beta_{D,o}\frac{\partial \psi^o_{D,nt}}{\partial R_{D,nmt}} = \frac{Q_{D,nmt}}{\overline{Q}_{D,nt}}\alpha_D\beta_{D,o}. \tag{A32}$$

In equation (A32) we use the expression for $\frac{\partial \psi^o_{D,nt}}{\partial R_{D,nmt}}$ in equation (A26). Summing equation (A32) across all banks in the market n at time t gives an expression for how total quantities respond when all banks raise their rates:

$$\frac{\partial \log \overline{Q}_{D,nt}}{\partial R_{D,nt}} = \alpha_D\beta_{D,o}. \tag{A33}$$

A.3 Cost Function Estimation

This appendix provides additional details of how we estimate the cost function for banks to have deposits, mortgages, corporate loans, and securities on its balance sheet. We first infer a bank's marginal costs of holding deposits, mortgages, and loans from the following expressions.

$$-\frac{Q_{D,nmt}}{\partial Q_{D,nmt}/\partial R_{D,nmt}} - R_{D,nmt} = -R_t^{D,m} + \frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}} \quad \text{(A34)}$$

$$-\frac{Q_{M,nmt}}{\partial Q_{M,nmt}/\partial R_{M,nmt}} - R_{M,nmt} = -R_t^{M,m} - \frac{\partial C(\Theta_{mt})}{\partial Q_{M,nmt}}, \quad \text{(A35)}$$

$$-\frac{Q_{L,nmt}}{\partial Q_{L,nmt}/\partial R_{L,nmt}} - R_{L,nmt} = -R_t^{L,m} - \frac{\partial C(\Theta_{mt})}{\partial Q_{L,nmt}}. \quad \text{(A36)}$$

The left-hand side of equations (A34) to (A36) depend only on observed interest rates and markups so we can infer the marginal costs $\frac{\partial C(\Theta_{mt})}{\partial Q_{D,nmt}}$, $\frac{\partial C(\Theta_{mt})}{\partial Q_{M,nmt}}$, and $\frac{\partial C(\Theta_{mt})}{\partial Q_{L,nmt}}$ up to the value of unknown constants $R_t^{D,m}, R_t^{M,m}, R_t^{L,m}$. These constants are market-wide discount rates reflecting the riskiness of cash flows from deposits, mortgages, and loans, so they do not depend on the composition Θ_{mt} of the bank's balance sheet. Hence, we can replace the marginal costs on the left-hand sides of equations (19) to (20) with their observable counterparts from equations (A34) to (A36). The right-hand sides would change only in their intercept since the discount rates $R_t^{D,m}, R_t^{M,m}, R_t^{L,m}$ does not depend on the composition of the bank's balance sheet. The bank-level marginal cost estimates we use are then averages of our bank-market level estimates

$$\frac{1}{N_{D,nt}}\left(\sum_n -\frac{Q_{D,nmt}}{\partial Q_{D,nmt}/\partial R_{D,nmt}} - R_{D,nmt}\right) = MC_{D,mt} \quad \text{(A37)}$$

$$\frac{1}{N_{M,nt}+N_{L,nt}}\left[\left(\sum_n -\frac{Q_{M,nmt}}{\partial Q_{M,nmt}/\partial R_{M,nmt}} - R_{M,nmt}\right) + \sum_n\left(-\frac{Q_{L,nmt}}{\partial Q_{L,nmt}/\partial R_{L,nmt}} - R_{L,nmt}\right)\right] = MC_{L*,mt}. \quad \text{(A38)}$$

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Online Appendix for

The Reserve Supply Channel of Unconventional Monetary Policy

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This document contains additional theoretical and empirical results. It contains

- (A) Corporate loan outside option details
- (B) Extension: loan demand with relationships
- (C) Extension: loan demand by borrower ratings
- (D) Estimating demand and cost curves for firms in multiple markets
- (E) Summary statistics: bank marginal costs and markups
- (F) Computation details for counterfactuals
- (G) Summary statistics: number of banks by year
- (H) Counterfactual: non-deposit funding costs

A Loan outside option

Table OA1: Outside Option estimates (Loans)

This table reports the outside option size for corporate loans in trillions of dollars. The implied β_o gives the value of $\beta_{L,o}$ that would after a Taylor expansion yield the same elasticity of demand for small changes, using equation (OA3) below.

Year	Size of Outside Option	Implied $\beta_{L,o}$
2001	0.75	0.42
2002	0.79	0.46
2003	0.85	0.50
2004	0.75	0.37
2005	0.76	0.34
2006	0.83	0.33
2007	1.00	0.35
2008	1.61	0.66
2009	1.90	0.78
2010	1.56	0.59
2011	1.18	0.39
2012	1.30	0.46
2013	1.15	0.35
2014	1.23	0.37
2015	1.51	0.42
2016	1.58	0.43
2017	1.55	0.39

The estimate of the implied β_o can be inferred from knowing the overall market size $\overline{F}_{L,nt}$, which is possible once the outside option is observed. The total quantity of deposits and total market size in a logit demand system are related by

$$\overline{Q}_{L,nt} = \overline{F}_{L,nt} \frac{\exp(\psi_{L,nt})}{1 + \exp(\psi_{L,nt})}. \tag{OA1}$$

Equation (OA1) can be used to solve for $\psi_{D,nt}$ from observed data on $\overline{Q}_{D,nt}$ and $\overline{F}_{D,nt}$. Moreover, in this logit model,

$$\frac{\partial \log(\overline{Q}_{L,nt})}{\partial \psi_{L,nt}} = 1 - \frac{\exp(\psi_{L,nt})}{1 + \exp(\psi_{L,nt})} = \frac{1}{1 + \exp(\psi_{L,nt})} \tag{OA2}$$

while our modified log-linear model implies $\frac{\partial \log(\overline{Q}_{L,nt})}{\partial \psi_{L,nt}} = \beta_{L,o}$.

Our approximation is therefore

$$\beta_{L,o} = \frac{1}{1 + \exp(\psi_{L,nt})}. \tag{OA3}$$

B Extension: loan demand with relationships

This appendix presents a modification of our demand system that allows us to estimate the aggregate elasticity of corporate loan demand without using an observed outside good quantity. We do so by exploiting data on firm-bank relationships in the DealScan dataset. In the main text, we relied on a proxy for the number of firms in the market that did not borrow from a bank to infer the overall elasticity of loan demand. In contrast, we were able to estimate this aggregate elasticity of demand directly from the data for mortgages and deposits. The model presented here allows us to perform a similar estimation exercise for corporate loans by using the network structure of bank-firm relationships for additional information. This makes up for the small number of state-level corporate loan markets that prevents us from applying the approach we used for deposits and mortgages with county-level markets.

Our modified model is identical to the demand system in the main text except that firms get extra utility k from borrowing from a bank they previously borrowed from. At time t, firm i in market n has the choice to borrow from banks indexed by m. We assume each firm i wants to borrow the same amount $F_{L,nt}$ as all other firms in the market. Firm i gets utility

$$u_{L,inmt} = \alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt} + \epsilon_{i,nmt} \tag{OA4}$$

from choosing to borrow from bank m and selects its bank to maximize utility. Here, $kl_{i,mt}$ is the new term that describes the utility from prior relationships: if this firm borrowed from this bank in the past, then, $l_{i,mt} = 1$; otherwise $l_{i,mt} = 0$. We expect $k > 0$ so that firms prefer to borrow from banks with prior relationships. The variables $\epsilon_{i,nmt}$ follow the type one extreme value distribution and are i.i.d. across firms. Firms also have an outside option yielding utility for firm i of

$$u_{L,in0t} \quad = \quad \delta_{L,in0t} + \varepsilon_{in0t}. \tag{OA5}$$

from not borrowing. The additional variable $\delta_{L,in0t}$ is i.i.d. across firms i and has a measure given by the density $f(\delta_{L,in0t}) = \exp(\beta_{L,o}\delta_{L,in0t})$.

Conditional on the realized $\delta_{F,in0t}$, the probability firm i borrows from bank m is

$$\frac{\exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt})}{\exp(\delta_{F,in0t}) + \sum_{m'} \exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't} + kl_{i,m't})}, \tag{OA6}$$

and the expected amount a firm borrows from a bank is, integrating over $\delta_{F,in0t}$,

$$Q_{L,i,nmt} = \int_{-\infty}^{\infty} \frac{F_{L,nt} \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt}) \exp(\beta_{D,o}\delta_{L,in0t})}{\exp(\delta_{L,in0t}) + \sum_{m'} \exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't} + kl_{i,m't})} d\delta_{L,in0t}. \quad \text{(OA7)}$$

The crucial feature of this modified demand system is that if firms prefer to borrow from the same banks they have previously, a firm's total borrowing quantity is more sensitive to the rates charged by its relationship banks than the rates charged by other banks. That is, if $k > 0$, $\frac{\partial Q_{L,i,nmt}}{\partial R_{L,nmt}}$ is larger if $l_{i,m't} = 1$ than if $l_{i,m't} = 0$. Once we have estimated k, we can infer the aggregate elasticity of loan demand by observing how a shock to a bank's rates impacts the borrowing quantities of its relationship firms relative to the borrowing quantities of other firms.

B.1 Estimating the price disutility parameter α_L from new borrowers

We first consider the borrowing decisions of those firms which have no previous banking relationships. If there is a large number N of such firms, then (by the law of large numbers) the amount borrowed from bank m by firms with no previous borrowing relationships is

$$Q_{nmt}^{new} = N \int_{-\infty}^{\infty} \frac{F_{L,nt} \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt}) \exp(\beta_{D,o}\delta_{F,in0t})}{\exp(\delta_{L,in0t}) + \sum_{m'} \exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't})} d\delta_{L,in0t}. \quad \text{(OA8)}$$

Taking the log of equation (OA8) yields

$$\log(Q_{nmt}^{new}) - \log(Q_{nm't}^{new}) = \alpha_L(R_{L,nmt} + R_{L,nm't}) + (X_{L,nmt} - X_{L,nm't})\beta_L + (\delta_{L,nmt} - \delta_{L,nm't}). \quad \text{(OA9)}$$

This log-linear expression allows us to estimate the demand parameters of our model exactly in the same manner as in our baseline setting, which is a standard logit demand system. The only difference is that here we use the quantities of borrowing by the subset of firms with no previous relationships. Because the latent demand term $\delta_{L,nmt}$ may be correlated with the lending rate, we use the two-stage least squares specification (with the same instrument following Cortés and Strahan (2017) as in the main text)

$$\begin{aligned} \log(Q_{nmt}^{new}) &= \zeta_{L,nt} + \alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + (\delta_{L,nmt} - E_{L,nt}\delta_{L,nmt}) \\ R_{L,nmt} &= \gamma_{L,nt} + \gamma_L z_{L,nmt} + X_{L,nmt}\gamma_D + e_{L,nmt}. \end{aligned}$$

This provides us with a consistent estimate of α_L and β_L. Table OA2 reports the result from this regression. The price disutility parameter $\alpha_l = -244.51$ is somewhat smaller in magnitude than our main text estimate $\alpha_L = -310.13$.

Table OA2: Demand System Estimates

This table reports the two-stage least squares results for estimating price disutility parameter α_L of our loan demand system. These regressions are run at the market-bank-year level, with a control for loan loss provision as in the main text. The sample period is from 2001 to 2017. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:
	Loan Market Share
Rate (with IV)	-244.51^{***}
	(81.43)
Loan Loss Provision	7.21^{**}
	(3.60)
Num. of Obs.	13,364

B.2 Estimating the relationship stickiness parameter k

Having estimated α_L and β_L, we next infer how much firms value borrowing from a bank with which they have a past relationship. We do so by comparing the distribution of borrowing by new firms to the borrowing of firms that have past relationships. Because the unobserved latent demand δ shows up in the borrowing choices of both types of firms, we can use data on the borrowing decisions of new firms to control for unobserved heterogeneity in δ.

It is useful to classify firms by their "relationship vector" l, which equals 1 for every bank m the firm has previously borrowed from and equals 0 otherwise. For such a firm with relationship vector l, its probability of borrowing from a bank with which it already has a relationship conditional on borrowing at all is

$$\frac{\sum_{m\in l}\exp(\alpha_L R_{L,nmt}+X_{L,nmt}\beta_L+\delta_{L,nmt}+k)}{\sum_{m'}\exp(\alpha_L R_{L,nm't}+X_{L,nm't}\beta_L+\delta_{L,nm't}+k1_{m'\in l})}=\frac{\sum_{m\in l}\exp(\log\sum_n Q^{new}_{nm't}+k)}{\sum_{m'}\exp(\log\sum_n Q^{new}_{nm't}+k1_{m'\in l})}. \tag{OA10}$$

Here, $\sum_n Q^{new}_{nm't}$ is the aggregate quantity of lending from bank m' to only new firms with no previous relationships. This equation follows from equation (OA6).

The ratio in equation (OA10) can be compared to the observed data $P_{lt|borrow}$, the fraction of observed borrowing by firms with relationship vector l that is from banks the firms have previous relationships with. Choosing the parameter k to make $P_{lt|borrow}-\frac{\sum_{m\in l}\exp(\log\sum_n Q^{new}_{nm't}+k)}{\sum_{m'}\exp(\log\sum_n Q^{new}_{nm't}+k1_{m'\in l})}$ as close as possible to 0 provides an estimate of k. We use this to construct a moment condition that aggregates across all possible relationship vectors, weighted by their total loan quantities $Q_{l,rel}$:

$$\sum_l Q_{l,rel}\left[P_{lt|borrow} - \frac{\sum_{m\in l}\exp(\log\sum_n Q^{new}_{nm't} + k)}{\sum_{m'}\exp(\log\sum_n Q^{new}_{nm't} + k1_{m'\in l})}\right] = 0. \tag{OA11}$$

Solving equation (OA11) yields our estimate of k. Our solution is $k = 2.268$, which means that holding other characteristics constant, firms are $\exp(k) = 9.66$ times more likely to borrow from banks with past relationships relative to the decisions of new borrowers.

B.3 Estimating the aggregate elasticity of loan demand

To estimate the aggregate elasticity of loan demand, we need to observe how the quantity that a firm borrows is impacted by shocks to the supply of credit. For a firm with relationship vector l, the probability that it borrows from a bank instead of choosing the outside option is

$$\int_{-\infty}^{\infty}\frac{\sum_m \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt})\exp(\beta_{D,o}\delta_{L,in0t})}{\exp(\delta_{L,in0t}) + \sum_{m'}\exp(\alpha_L R_{L,nm't} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt})}d\delta_{L,in0t} \tag{OA12}$$

$$= \int_{-\infty}^{\infty}\frac{\exp(\psi^{i,nt})\exp(\beta_{D,o}\delta_{L,in0t})}{\exp(\delta_{L,in0t}) + \exp(\psi^{i,nt})}d\delta_{L,in0t}, \tag{OA13}$$

where $\psi^{i,nt} = \log(\sum_{m'}\exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't} + kl_{i,m't}))$. As in the main text, we can use a change of variables $u = \delta_{D,jn0t} - \psi^{i,nt}$ in the integral in equation (OA13) to get

$$\exp(\beta_{L,o}\psi^{i,nt})\int_{-\infty}^{\infty}\frac{\exp(\beta_{L,o}u)}{\exp(u)+1}du. \tag{OA14}$$

If k were equal to 0, then $\psi^{i,nt}$ would not depend on the firm i and would be identical to $\psi_{D,nt}$ in the main text. As for $\psi_{D,nt}$ in the main text, every term in $\psi^{i,nt}$ except for the mean of $\delta_{L,nm't}$ is identifiable given the parameters already estimated, so we define

$$\psi^u_{i,nt} = \psi^u_{nt} = \frac{1}{N_{nt}}\sum_m \delta_{L,nmt}. \tag{OA15}$$

$$\psi^o_{i,nt} = \log\left(\sum_m \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} - \psi^u_{i,nt} + kl_{i,mt})\right). \tag{OA16}$$

Here, $\psi^o_{i,nt}$ is observable, ψ^u_{nt} is not observable, and $\psi^o_{i,nt} + \psi^u_{nt} = \psi_{i,nt}$. The expected quantity

$\sum_{i \in l} Q_{i,t}$ borrowed by a firm with relationship vector l is

$$\log(\sum_{i \in l} Q_{i,t}) = \log(F_{L,nt}) + \log(\int_{-\infty}^{\infty} \frac{\exp(\beta_{L,o} u)}{\exp(u)+1} du) + \beta_{L,o}(\psi^o_{i,nt} + \psi^u_{nt}).$$

We can estimate $\beta_{L,o}$ with a firm level instrument $z_{i,nt}$ by

$$\log(\sum_{i \in l} Q_{i,t}) = \log(F_{L,nt}) + \beta(\psi^o_{i,nt} + \psi^u_{nt}) + \epsilon_{int} \quad \text{(OA17)}$$

$$\psi^o_{i,nt} = \kappa_o + \lambda_o z_{i,nt} + \eta_{int}. \quad \text{(OA18)}$$

To construct our instrument, we take for each firm the average amount of log natural disaster damage done in regions where its relationship banks have branches.

The above expressions depend on knowing observed value of $\psi^o_{i,nt}$, which were first initially inferred from looking at the quantity of borrowing from new firms. While $\psi^o_{i,nt}$, can be inferred from observed data, this step has to be done jointly with the estimate of $\beta_{L,o}$.

The fraction of observed borrowing that goes to bank m is

$$\frac{\sum_i Q_{L,i,nmt}}{\sum_m \sum_i Q_{L,i,nmt}} = \frac{\sum_i \frac{\exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt})}{\sum_{m'} \exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't} + kl_{i,mt})} \exp(\beta_{L,o}(\psi^o_{i,nt} + \psi^u_{i,nt}))}{\sum_i \sum_m \frac{\exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} + kl_{i,mt})}{\sum_{m'} \exp(\alpha_L R_{L,nm't} + X_{L,nm't}\beta_L + \delta_{L,nm't} + kl_{i,mt})} \exp(\beta_{L,o}(\psi^o_{i,nt} + \psi^u_{i,nt}))}. \quad \text{(OA19)}$$

This expression depends on the unobserved variable $\beta_{L,o}$ that we aim to estimate. For a postulated value of $\beta_{L,o}$, we solve this system of equations given by equation (OA19) for the values of $\delta_{L,nmt}$. There is one fewer equation than unknown, so we solve for the $\delta_{L,nmt}$ up to the value of their unknown mean. We then use these values to construct the variable $\psi^o_{i,nt}$ (which does not depend on the mean of the $\delta_{L,nmt}$'s) and run the two-stage least square regressions (OA17) and (OA18) above to get a new estimate of $\beta_{L,o}$. We iterate this procedure until $\beta_{L,o}$ reaches a fixed point.

The result is reported in Table OA3. We find $\beta_{L,o} = 0.41$. Compared to Table 4 in the main text, this estimate is similar to the implied value of 0.35 as in the year of 2007, which is the first input for our counterfactual analysis.

Finally, we use our parameters to compute the implied aggregate elasticity of loan demand. For this, we need an expression for how the quantity of total loans varies when every bank raises its loan rates by the same amount. We will denote the total quantity borrowed by Q and a change in every bank's rate a derivative with respect to R.

Table OA3: Outside Option Estimates

This table reports the two-stage least squares results for estimating the outside option parameter $\beta_{L,o}$ in the loan market. The sample period is from 2001 to 2017.

$\beta_{L,o}$	0.41***
	(0.01)
Num. of Obs.	38,851

Equation (OA17) implies that the total quantity of borrowing is

$$Q = \sum_{l} N_l F_{L,nt} \exp(\beta_{L,o}(\psi^o_{i,nt} + \psi^u_{nt})). \tag{OA20}$$

Note that

$$\frac{\partial \psi^o_{i,nt}}{\partial R} = \frac{\left(\alpha_L \sum_m \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} - \psi^u_{i,nt} + kl_{i,mt})\right)}{\left(\sum_m \exp(\alpha_L R_{L,nmt} + X_{L,nmt}\beta_L + \delta_{L,nmt} - \psi^u_{i,nt} + kl_{i,mt})\right)} = \alpha_L \tag{OA21}$$

is the same for all firms i. The derivative of the borrowing quantity in equation (OA20) with respect to an equal increase in the rates of every bank is

$$\frac{dQ}{dR} = \sum_{l} [N_l F_{L,nt} \exp(\beta_{L,o}(\psi^o_{i,nt} + \psi^u_{nt}))]\beta_{L,o} \frac{\partial \psi^o_{i,nt}}{\partial R} = Q\beta_{L,o}\alpha_L \tag{OA22}$$

It follows that $\frac{d \log Q}{dR} = \alpha_L \beta_{L,o}$ just like in the demand systems in the main text. Plugging in our estimates $\alpha_L = -244.51, \beta_{L,o} = .41$, we get that a 10 basis point increase in all bank rates leads to a decline in total loan quantities of $.41 \times 24.45\% = 10.0\%$. This is close to the main text estimate of $0.35 \times 31.0\% = 10.9\%$ using our main text estimate of $\alpha_L = -310$ and the year 2007 outside option estimate of 0.35 on which we based our first benchmark counterfactual.

C Extension: loan demand by borrower ratings

This appendix presents another modification of our demand system that explores the heterogeneity across different loans. We obtain ratings data for borrowing firms from Compustat. We classify firms with an investment-grade rating as high-rating and the remaining ones as low-rating, which includes unrated firms. We then estimate the demand system separately for these two types of loans, assuming that these two markets are fully segmented. Other than splitting the market, our demand system specification and instrument are identical to the main text.

Table OA4: Loan Demand System Estimates with Rating

This table reports the two-stage least squares results for estimating the price disutility parameters of our loan demand systems, with the market split between high-rating and low-rating loans. The sample period is from 2001 to 2017. We report standard errors clustered by bank in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	High Rating	Low Rating
Rate (with IV)	-442.47^{**}	-265.69^{***}
	(221.64)	(88.09)
Loan Loss Provision	5.35	5.51
	(3.79)	(3.75)
Num. of Obs.	13727	18749

Table (OA4) reports the coefficient estimates. Compared to the rate disutility parameter of -310.13 in the baseline specification in the main text, high rating loans have a rate disutility parameter of -442.47, and low rating loans have a rate disutility parameter of -265.69. This implies that the market for high rating loans is more rate-elastic than the market for low rating loans, which possibly reflects the fact that high rating loans are more homogeneous and thus more substitutable.

Following the same procedure we outlined in the main text, we take a stance on the loan markets' outside options. In this case, we compute the outside option separately for firms with high and low ratings, which allows us to construct the loan markets' mark-ups and marginal costs. In the main text, we reported that a 10 basis point change in loan rates would result in a 10.9 % change in loan quantities in the year 2007. Here, using our separate outside option quantities for each group, we compute that there would be a 4.9% change in high rated loan quantities and 12.5% change in low rated loan quantities. Weighted by the relative size of the two loan groups, this leads to an overall quantity change of 9.3%, close to the overall demand elasticity we found in the main text for corporate loans.

Using our loan marginal cost estimates, we repeat our cost function estimation in Table (4). Table (OA5) reports the new results. These cost function estimates imply the following Hessian matrix, which is very similar to the baseline Hessian matrix in the main text.

$$H = \begin{pmatrix} 1.07 & -0.68 & -0.70 \\ -0.68 & 0.55 & 0.39 \\ -0.70 & 0.39 & 0.51 \end{pmatrix}.$$

Table OA5: Cost Function Regression Estimates with Loan Rating Extensions

This table reports the sensitivity of bank-level costs and quantities to losses from natural disasters and a Bartik deposit shock. Sheldus Instrument refers to property losses due to natural disasters as explained in Section 4.3. Bartik Deposit Instrument refers to a Bartik-style instrument of deposit growth as explained in Section 4.3. Rates are in basis points and quantities are in millions. The sample period is from 2001 to 2017. We report standard errors clustered by bank in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel (a): Results using Natural Disaster Instrument					
	Deposit Cost	Mtg/Loan Cost	Deposit Vol	Mtg/Loan Vol	Security Vol
	(1)	(2)	(3)	(4)	(5)
Sheldus Instrument	−3.17***	2.66***	28.31***	26.37***	18.97**
	(0.33)	(0.90)	(8.11)	(6.25)	(8.12)
Loan Loss Provision	−6.04*	1.79	6.98	527.36***	1.51
	(3.34)	(1.45)	(7.79)	(202.27)	(2.40)
R^2	0.58	0.82	0.00	0.01	0.00
Adj. R^2	0.58	0.82	0.00	0.01	0.00
Num. of Obs.	53651	12620	118942	119236	118923
Panel (b): Results using Bartik Deposit Shock					
	Deposit Cost	Mtg/Loan Cost	Deposit Vol	Mtg/Loan Vol	Security Vol
	(1)	(2)	(3)	(4)	(5)
Bartik Instrument	31.31***	−29.90**	1048.26**	474.34***	1084.52**
	(8.13)	(14.82)	(417.94)	(136.09)	(508.92)
Loan Loss Provision	−4.76	−7.83**	7.19	153.96	−48.37
	(3.35)	(3.44)	(48.79)	(93.89)	(48.10)
R^2	0.43	0.82	0.00	0.01	0.00
Adj. R^2	0.43	0.82	0.00	0.00	0.00
Num. of Obs.	50091	12006	62352	62458	62346

D Estimating demand and cost curves for firms in multiple markets

This appendix analyzes the decisions of a firm that sells goods in multiple markets. The key result is that a demand shock in one market can be used both to identify the demand curves the firm faces in other markets as well as to identify the firm's marginal cost curve of production. A firm sets price P_n for the goods it sells in market n, facing demand curve $D_n(P_n, \lambda_n)$. The parameter λ_n is an exogenous shock that shifts demand for the good only in market n. There is a total of N markets. The firm faces a cost $C(\sum_n D_n(P_n, \lambda_n)) + \sum_n \epsilon_n D_n(P_n, \lambda_n)$ of production. The firm maximizes its profits

$$\sum_n P_n D_n(P_n, \lambda_n) - C(\sum_n D_n(P_n, \lambda_n)) - \sum_n \epsilon_n D_n(P_n, \lambda_n) \tag{OA23}$$

yielding first-order condition for P_n

$$D_n(P_n, \lambda_n) + P_n[\frac{\partial(D_n)(P_n, \lambda_n)}{\partial P_n}] - (C'(\sum_n D_n(P_n, \lambda_n)) + \epsilon_n)(D_n)'(P_n, \lambda_n) = 0 \quad \text{(OA24)}$$

$$\frac{D_n(P_n, \lambda_n)}{\frac{\partial(D_n)(P_n,\lambda_n)}{\partial P_n}} + P_n - C'(\sum_n D_n(P_n, \lambda_n)) + \epsilon_n = 0 \quad \text{(OA25)}$$

When this system of equations has a unique solution, it implicitly defines a function $P(\lambda)$, mapping the vector of the λ_n demand shocks to a vector of prices, with price $P_n(\lambda)$ in market n. For j not equal to n, we have that

$$\frac{d}{d\lambda_j}[D_n(P_n, \lambda_n)] = \frac{\partial D_n(P_n, \lambda_n)}{\partial P_n} \frac{\partial P_n}{\partial \lambda_j} \quad \text{(OA26)}$$

$$\frac{\frac{d}{d\lambda_j}[D_n(P_n, \lambda_n)]}{\frac{\partial P_n}{\partial \lambda_j}} = \frac{\partial D_n(P_n, \lambda_n)}{\partial P_n} \quad \text{(OA27)}$$

It follows that if we divide the response of quantities in market n to the demand shock λ_j by the response of prices in market n to the demand shock λ_j, we get the slope $\frac{\partial D_n(P_i,\lambda_i)}{\partial P_n}$ of the demand curve. This implies that a two-stage least squares regression estimating the impact of P_n on D_n using the demand shock λ_j as an instrument identifies the slope of the demand curve in market n. This is the approach we take when using a natural disaster instrument to estimate our demand system.

Having estimated the demand curves D_i faced by the firm, we identify the average MC of the firm's marginal costs across markets by

$$MC = C'(\sum_n D_n(P_n, \lambda_n)) + \frac{1}{N} \sum_n \epsilon_n \quad \text{(OA28)}$$

The response of this marginal cost to a shock to any given λ_j is

$$\frac{dMC}{d\lambda_j} = C''(\sum_n D_n(P_n, \lambda_n)) \frac{d[\sum_n D_n(P_n(\lambda), \lambda_n)]}{d\lambda_j} \quad \text{(OA29)}$$

It follows that if we regress the marginal cost MC on the demand shock λ_j and then regress the total quantity $\sum_n D_n(P_n(\lambda), \lambda_j)$ on the demand shock λ_j, the ratio of these regression coefficients identifies the slope $C''()$ of the firm's marginal cost curve. This shows how in a setting where firms are active in multiple markets, we can use a demand shock in a given market to identify both the demand curve the firm faces in other markets as well as the firm's marginal cost curve.

E Bank marginal costs and markups

This section presents evidence on banks' marginal costs of providing deposits, mortgages, and corporate loans. The marginal cost is the sum of two terms: the observed interest rate the bank offers and the markup it charges. Using our estimated demand systems, we infer a bank's markups and marginal costs from equations (A34)-(A36) together with the expression in equation (A30) for the curvature $\frac{\partial \log Q_{D,nmt}}{\partial R_{D,nmt}}$ of a bank's demand curve.

We present summary statistics on deposit, mortgage, and corporate loan markups in table OA6. Mortgage markups average 20 basis points with a standard deviation of 1.9 basis points. Loan markups average 33 basis points with a standard deviation of 1.6 basis points. As we show in table OA7, mortgage and loan marginal costs are predicted almost perfectly by knowing the interest rate a bank charges in a given market, with an R-squared of .9997 for mortgages and .9998 for corporate loans. In contrast, the average 86 basis point markup for deposits is smaller than the standard deviation of 105 basis points, and deposit rates only predict deposit marginal costs with an R-squared of .3548.

Table OA6: Marginal Cost Summary Statistics

This table reports summary statistics about deposit, mortgage, and corporate loan markups implied by our demand system. For deposits and mortgages, each observation is one bank in one county during one year. For corporate loans, each observation is one bank in one state during one year.

	Deposit Markup	Mortgage Markup	Loan Markup
Average (bps)	86	20	33
Standard Deviation (bps)	105	1.9	1.6

While observed interest rates almost entirely explain mortgage and loan marginal costs, we show that cross-sectional dispersion in the amount of market power each bank has matters as well for deposits. In our logit-style demand systems, market power is determined entirely by the share of deposits each bank has in a market. The larger a bank's market share, the more it acts effectively as a monopolist, and the larger the markup it charges.[18] If we run an OLS regression of deposit markups on a bank's market share in a given county-year, the R-squared is .239. If instead we run this regression separately county-year by county-year, allowing the slope and intercept to be county-year specific, we find an average R-square of .9923 and a minimum value of .9331 across all markets. While it is also possible to accurately predict loan and mortgage markups using market shares, this explains almost

[18] This relationship between market share and the size of markups holds as well for mortgages and loans, but the dispersion in markups is so small that it has little effect on our marginal cost estimates.

Table OA7: Marginal Cost Summary Statistics: Regressions

This table reports the results of regressing a bank's marginal costs on its chosen interest rates. The regression is at the bank-county-year level for deposits and mortgages and the bank-state-year level for corporate loans. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Deposit	Mortgage	Loan
(Intercept)	0.01^{***}	-0.00^{***}	-0.00^{***}
	(0.00)	(0.00)	(0.00)
Rate	1.03^{***}	1.00^{***}	1.00^{***}
	(0.00)	(0.00)	(0.00)
R^2	0.35	1.00	1.00
Num. of Obs.	219542	64411	22165

none of the variation in mortgage and loan marginal costs since the standard deviation of markups is so small for these markets.

F Computation details for counterfactuals

This section derives the system of equations we use for counterfactual simulations with our model. We compute a fixed point in the space of bank-level quantity variables. First, we hypothesize a sequence of quantities of deposits, mortgages, and corporate loans for each bank. Second, taking as given the yield on securities, we solve for the bank-level security quantities that are consistent with this yield. Third, we use these bank-level quantities and the Hessian of our bank's cost function to compute changes in each bank's marginal costs. Fourth, we now can solve separately for each market in which banks operate for the equilibrium rates and quantities that are consistent with these marginal costs. Finally, we sum up these market-level quantities to obtain bank-level quantities. The model is at equilibrium when these final quantities are equal to the hypothesized quantities we started with. Because our problem is high-dimensional, we require an analytic expression for the Jacobian of this fixed point operator we describe below.

Let B be the number of banks and V be the space of 3B dimensional vectors representing each bank's deposit, loan, and mortgage quantities. We want to compute how these quantities change when the central bank raises the supply of reserves so that security yields increase by R. We define a function $f_R : V \to V$ that equals 0 after the economy equilibrates in response to this increased reserve supply.

Step 1: Computing security quantities First, we define a function $f_1^{*,R}$ from bank level deposit, mortgage, and loan quantities to an associated security quantity consistent with the rate rise R. Any quantity variable with an o above (for "original") refers to the quantity we observe in the data before our counterfactual. For each bank m, this function is given by (where B_m is the number of branches of the bank)

$$R = \frac{1}{B_m}\begin{pmatrix} \frac{\partial^2 C}{\partial Q_D \partial Q_S} & \frac{\partial^2 C}{\partial Q_M \partial Q_S} & \frac{\partial^2 C}{\partial Q_L \partial Q_S} & \frac{\partial^2 C}{\partial Q_S \partial Q_S} \end{pmatrix} * \begin{pmatrix} Q_{D,m} - Q^o_{D,m} \\ Q_{M,m} - Q^o_{M,m} \\ Q_{L,m} - Q^o_{L,m} \\ Q_{S,m} - Q^o_{S,m} \end{pmatrix} \tag{OA30}$$

This implies

$$Q_{S,m} = Q^o_{S,m} + \frac{B_m}{\frac{\partial^2 C}{\partial Q_S \partial Q_S}}(R - \frac{1}{B_m}\begin{pmatrix} \frac{\partial^2 C}{\partial Q_D \partial Q_S} & \frac{\partial^2 C}{\partial Q_M \partial Q_S} & \frac{\partial^2 C}{\partial Q_L \partial Q_S} \end{pmatrix} * \begin{pmatrix} Q_{D,m} - Q^o_{D,m} \\ Q_{M,m} - Q^o_{M,m} \\ Q_{L,m} - Q^o_{L,m} \end{pmatrix}). \tag{OA31}$$

The Jacobian of this function is $\frac{-1}{\frac{\partial^2 C}{\partial Q_S \partial Q_S}}\begin{pmatrix} \frac{\partial^2 C}{\partial Q_D \partial Q_S} & \frac{\partial^2 C}{\partial Q_M \partial Q_S} & \frac{\partial^2 C}{\partial Q_L \partial Q_S} \end{pmatrix}$ for the effect of bank i's quantities on bank i's security quantity and 0 for the effect of any other bank j on bank i's quantities. Let f_1^R be given by ($id : V \to V$, $f_1^{*,R}$), which maps each bank's 3 given quantities to themselves together with this implied security quantity.

Step 2: Computing marginal costs

Next, we define a map f_2 from each bank's quantities $Q_{D,m}, Q_{M,m}, Q_{L,m}, Q_{S,m}$ to the change in its marginal costs from those before the counterfactual. This change in marginal costs is given by

$$\begin{pmatrix} MC_{D,m} - MC^o_{D,m} \\ MC_{M,m} - MC^o_{M,m} \\ MC_{L,m} - MC^o_{L,m} \end{pmatrix} = \frac{1}{B_i}\begin{pmatrix} \frac{\partial^2 C}{\partial Q_D \partial Q_D} & \frac{\partial^2 C}{\partial Q_M \partial Q_D} & \frac{\partial^2 C}{\partial Q_L \partial Q_D} & \frac{\partial^2 C}{\partial Q_S \partial Q_D} \\ \frac{\partial^2 C}{\partial Q_D \partial Q_D} & \frac{\partial^2 C}{\partial Q_M \partial Q_M} & \frac{\partial^2 C}{\partial Q_L \partial Q_M} & \frac{\partial^2 C}{\partial Q_S \partial Q_M} \\ \frac{\partial^2 C}{\partial Q_D \partial Q_L} & \frac{\partial^2 C}{\partial Q_M \partial Q_L} & \frac{\partial^2 C}{\partial Q_L \partial Q_L} & \frac{\partial^2 C}{\partial Q_S \partial Q_L} \end{pmatrix} * \begin{pmatrix} Q_{D,m} - Q^o_{D,m} \\ Q_{M,m} - Q^o_{M,m} \\ Q_{L,m} - Q^o_{L,m} \\ Q_{S,m} - Q^o_{S,m} \end{pmatrix}. \tag{OA32}$$

The Jacobian of f_2 is $\frac{1}{B_i}\begin{pmatrix} \frac{\partial^2 C}{\partial Q_D \partial Q_D} & \frac{\partial^2 C}{\partial Q_M \partial Q_D} & \frac{\partial^2 C}{\partial Q_L \partial Q_D} & \frac{\partial^2 C}{\partial Q_S \partial Q_D} \\ \frac{\partial^2 C}{\partial Q_D \partial Q_D} & \frac{\partial^2 C}{\partial Q_M \partial Q_M} & \frac{\partial^2 C}{\partial Q_L \partial Q_M} & \frac{\partial^2 C}{\partial Q_S \partial Q_M} \\ \frac{\partial^2 C}{\partial Q_D \partial Q_L} & \frac{\partial^2 C}{\partial Q_M \partial Q_L} & \frac{\partial^2 C}{\partial Q_L \partial Q_L} & \frac{\partial^2 C}{\partial Q_S \partial Q_L} \end{pmatrix}$ from a bank's own quantities to its marginal cost changes and 0 for all other terms in the Jacobian matrix.

Note that while marginal costs vary across bank branches, the only term in the bank's cost function that changes with the composition of the bank's balance sheet is the Hessian, which depends only on bank level quantities. As a result, the difference $MC_{D,m} - MC^o_{D,m}$ is the same for all deposit markets for bank m, and the same result holds for mortgages and loans.

Step 3: Computing market-level interest rates In each market, given the marginal cost changes of each bank in the market, we now compute the change in the bank's chosen interest rates that are consistent with the marginal cost changes. This step has the benefit that it can be computed separately market by market, drastically reducing the computational burden. However, we do not have a closed-form expression for how marginal costs map to chosen interest rates. That said, we do have a closed-form expression for the inverse function which maps interest rates to implied marginal costs.

That is, we consider a mapping g from each bank's change in interest rates Δr_{nmt} to implied marginal costs that solve that all solve equation (OA53) (for deposits or mortgages) or (OA55) (for loans). This system of equations must be solved numerically, but it is tractable since it can be solved separately market by market. In market n, equations (OA53), (OA55) define a function g from a vector of rate changes for each bank in the market to an expression for that bank's change in marginal cost from that implied in the data. By solving g to equal our vector of marginal cost changes, we are computing the function $f_3 = g^{-1}$ that maps marginal cost changes to interest rates. This is precisely the object we need to solve our model. The Jacobian of $f_3 = g^{-1}$ is the inverse of the Jacobian of g, which is given by equation (OA56) for deposit and mortgage markets and (OA57) for loan markets.

Step 4: Computing new Bank-level quantities Finally, we define a function f_4 that maps the interest rates all banks choose to bank-level quantities implied by the demand side of the model.

The total quantity of deposits on a bank's balance sheet is, summing equation (OA45) across markets,

$$Q_{D,mt} = \sum_n Q_{D,nmt} = \sum_n \overline{Q}^i_{D,nt} \frac{(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't})))^{\beta_o - 1}}{(\sum_{m'} \exp(\delta^i_{nm't}))^{\beta_o}} \exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt})).$$

For our loan demand system, we have

$$Q_{L,mt} = \sum_n \overline{F}_{L,nt} \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt})}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \qquad \text{(OA33)}$$

This defines a function f_4 from the rate changes we computed above back to a list of bank-level deposit, mortgage, and loan quantities. The Jacobian of this function is given by

$$\begin{aligned}
&\frac{\partial}{\partial \Delta r_{nm^*t}} D_{mt} \qquad \text{(OA34)}\\
= \quad & (\beta_o - 1)\alpha \overline{Q}^i_{D,nt} \frac{\left(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))\right)^{\beta_o - 2}}{(\sum_{m'} \exp(\delta^i_{nm't}))^{\beta_o}} \exp(\delta^i_{nm^*t} + \alpha(\Delta r_{nm^*t})) \exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))\\
+ \quad & 1_{\{m=m^*\}} \alpha \overline{Q}^i_{D,nt} \frac{\left(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))\right)^{\beta_o - 1}}{(\sum_{m'} \exp(\delta^i_{nm't}))^{\beta_o}} \exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))
\end{aligned}$$

for deposits and mortgages. For loans, the relevant terms of the Jacobian are given by

$$\frac{\partial}{\partial \Delta r_{nm^*t}} L_{mt} = \alpha \overline{F}_{L,nt}\left[- \frac{\exp(\delta^i_{nm*t} + \alpha(\Delta r_{nm*t})) \exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{(1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't})))^2} \right. \qquad \text{(OA35)}$$

$$\left. + \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}\right] \qquad \text{(OA36)}$$

Finally,

$$f_R = f^R_1 \circ f_2 \circ f_3 \circ f_4 \qquad \text{(OA37)}$$

maps V to V, and a fixed point of f_R yields a counterfactual equilibrium of the economy. The Jacobian of this function is (by the expression for the Jacobian of composed functions) $J(f^R_1) \times J(f_2) \times J(f_3) \times J(f_4)$, where $J(.)$ denotes the Jacobian of each individual function. We provided closed form expressions for all of these Jacobians except f_3, which was a function defined by solving a system of equations (that must be computed numerically). However, f_3 is given by the inverse of our function g that does have a closed form Jacobian, which can be used to give the Jacobian of f_3 at its computed numerical solution. We compute our counterfactual by solving the equation $f_R(v) - v = 0$ numerically, using our analytic expression for its Jacobian to speed computation. The remainder of this appendix provides additional calculations for formulas referenced in the description of the function f_R we use to solve for an equilibrium.

F.1 Demand Systems under Log-linear Functional Form

Each bank m has deposits $Q_{D,nmt}$ in region n at time t. The total quantity of deposits in the region is $\overline{Q}_{D,nt} = \sum_m Q_{D,nmt}$. Let δ_{nmt} denote the desirability of its deposit:

$$\delta_{nmt} = \alpha_D R_{D,nmt} + X_{nmt}\beta_D + \delta_{D,nmt} \qquad \text{(OA38)}$$

and deposits $Q_{D,nmt}$ can be expressed as

$$Q_{D,nmt} = \overline{Q}_{D,nt} \frac{\exp(\delta_{nmt})}{\sum_{m'} \exp(\delta_{nm't})}. \tag{OA39}$$

Let $\overline{Q}^i_{D,nt}$ and $\delta^{o,i}_{nt}$ denote the actual value in the data (i for initial). Assuming that we are analyzing a counterfactual where the only change in the desirability of a deposit is its interest rate, we have

$$\delta_{nmt} = \delta^i_{nmt} + \alpha_D(r_{nmt} - r^i_{nmt}), \tag{OA40}$$

We apply equation (A18) to note that

$$\frac{\partial \log \overline{Q}_{D,nt}}{\partial \delta^o_{D,nt}} = \beta_o \tag{OA41}$$

which implies that

$$\overline{Q}_{D,nt} = \overline{Q}^i_{D,nt} \exp(\beta_o(\delta^o_{D,nt} - \delta^{o,i}_{nt})) \tag{OA42}$$

$$= \overline{Q}^i_{D,nt} \exp(\beta_o(\log \sum_{m'} \exp(\delta_{nm't}) - \log \sum_{m'} \exp(\delta^i_{nm't}))). \tag{OA43}$$

This yields the explicit expression for quantities

$$Q_{D,nmt} = \overline{Q}_{D,nt} \frac{\exp(\delta_{nmt})}{\sum_{m'} \exp(\delta_{nm't})} = \overline{Q}^i_{D,nt} \frac{(\sum_{m'} \exp(\delta_{nm't}))^{\beta_o - 1}}{(\sum_{m'} \exp(\delta^i_{nm't}))^{\beta_o}} \exp(\delta_{nmt}). \tag{OA44}$$

Note that the value of this expression is unchanged if we add a constant to all δ and δ^i variables in region n at time t. We also have the difference between the δ of any two goods in the same market is the difference in their log quantities sold. It follows that we can simply use $\delta^i_{nmt} = \log(Q^i_{D,nmt})$ to compute the expression, since $\delta^i_{nmt} - \log(Q^i_{D,nmt})$ is the constant across all goods in each market.

Under our maintained assumption that only prices and not product qualities change in counterfactuals, we can write $\delta_{nmt} = \delta^i_{nmt} + \alpha(\Delta r_{nmt})$ where $\Delta r_{nmt} = R_{D,nmt} - R^i_{D,nmt}$ is the change in interest rates relative to the pre-counterfactual data. We can therefore write $Q_{D,nmt}$ as

$$Q_{D,nmt} = \overline{Q}^i_{D,nt} \frac{(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't})))^{\beta_o - 1}}{(\sum_{m'} \exp(\delta^i_{nm't}))^{\beta_o}} \exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt})). \tag{OA45}$$

F.2 Logit Demand Systems

For a logit demand system applied in the loan market, we have that

$$Q_{L,nmt} = \overline{F}_{L,nt} \frac{\exp(\delta_{nmt})}{1 + \sum_{m'} \exp(\delta_{nm't})} = \overline{F}_{L,nt} \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt})}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}. \quad \text{(OA46)}$$

Because the outside good is observed for our logit demand system, $\overline{F}_{L,nt}$ is known and this expression can be used to compute quantities. δ^i_{nmt} is known as well too from solving for the unique values that rationalize the initial quantities $Q^i_{L,nmt}$.

F.3 Marginal Cost from Optimality Condition

The optimal pricing-implied marginal cost comes from the first order condition is

$$R_{D,nmt} = R^D_t - \frac{Q_{D,nmt}(R_{D,nmt})}{Q'_{D,nmt}(R_{D,nmt})} - \frac{\partial C(Q_{D,nmt}(R_{D,nmt}), \ldots)}{\partial Q_{D,nmt}}. \quad \text{(OA47)}$$

Because

$$\log(Q_{D,nmt}) = \log(\overline{Q}^i_{D,nt}) + (\beta_o - 1)\log(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))) \quad \text{(OA48)}$$

$$- \beta_o \log(\sum_{m'} \exp(\delta^i_{nm't})) + (\delta^i_{nmt} + \alpha(\Delta r_{nmt})). \quad \text{(OA49)}$$

we have

$$\frac{\partial \log(Q_{D,nmt})}{\partial \Delta r_{nmt}} = \alpha + \alpha(\beta_o - 1)\frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \quad \text{(OA50)}$$

This implies

$$\frac{\partial C}{\partial Q_{D,nmt}} = R^D_t - \left[\frac{\partial \log(Q_{D,nmt})}{\partial r_{nmt}}\right]^{-1} - R_{D,nmt} \quad \text{(OA51)}$$

$$= R^D_t - \left[\alpha + \alpha(\beta_o - 1)\frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}\right]^{-1} - R_{D,nmt} \quad \text{(OA52)}$$

and thus this demand system on its own implies a marginal cost of providing deposits coming from the optimal rate setting first order condition:

$$\frac{\partial C}{\partial Q_{D,nmt}} - \frac{\partial C^i}{\partial Q_{D,nmt}} = \left[\alpha + \frac{\alpha(\beta_o - 1)\exp(\delta^i_{nmt})}{\sum_{m'}\exp(\delta^i_{nm't})}\right]^{-1} - \left[\alpha + \frac{\alpha(\beta_o - 1)\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'}\exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}\right]^{-1} - \Delta r_{nmt} \quad \text{(OA53)}$$

F.4 Marginal Cost from Optimality Condition: Logit

For our pure logit demand system used for loan markets we have

$$\frac{\partial \log(Q_{D,nmt})}{\partial \Delta r_{nmt}} = \alpha - \alpha \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'}\exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}. \quad \text{(OA54)}$$

It follows that

$$\frac{\partial C}{\partial Q_{D,nmt}} - \frac{\partial C^i}{\partial Q_{D,nmt}} = [\alpha - \alpha \frac{\exp(\delta^i_{nmt})}{1 + \sum_{m'}\exp(\delta^i_{nm't})}]^{-1} - [\alpha - \alpha \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'}\exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))}]^{-1} - \Delta r_{nmt}. \quad \text{(OA55)}$$

This defines a function g which maps chosen rate changes to marginal costs. While the inverse of this function is not in closed form, we solve for it numerically. Having done so, we use the inverse function theorem to get its symbolic Jacobian, using the Jacobian expression we derive next.

F.5 Jacobian of marginal cost from optimality condition

For numerical accuracy, the Jacobian of equation (OA53) is needed. The derivative of this marginal cost is only non-zero with respect to other rates in the same region and time. The change of bank m's marginal cost with respect to bank m^*'s rate is give by

$$\begin{aligned}
\frac{\partial}{\partial \Delta r_{nm^*t}} \frac{\partial C}{\partial Q_{D,nmt}} &= \frac{\partial}{\partial r_{nm^*t}} \left(-\left[\alpha + \frac{\alpha(\beta_o - 1)\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right]^{-1} - \Delta r_{nmt} \right) \\
&= -\left[1 + \frac{(\beta_o - 1)\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right]^{-2} \\
&\cdot \quad (\beta_o - 1) \left(\frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))\exp(\delta^i_{nm^*t} + \alpha(\Delta r_{nm^*t}))}{\left(\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))\right)^2} \right. \\
&+ \quad \left. 1_{\{m=m^*\}} \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right) - 1_{\{m=m^*\}} \\
&= -\left[1 + \frac{(\beta_o - 1)\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right]^{-2} (\beta_o - 1) \\
&\cdot \quad \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \left(\frac{\exp(\delta^i_{nm^*t} + \alpha(\Delta r_{nm^*t}))}{\sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} + 1_{\{m=m^*\}} \right) - 1_{\{m=m^*\}}.
\end{aligned} \tag{OA56}$$

The Jacobian for the logit demand system is

$$\begin{aligned}
\frac{\partial}{\partial \Delta r_{nm^*t}} \frac{\partial C}{\partial Q_{D,nmt}} &= \frac{\partial}{\partial r_{nm^*t}} \left(-\left[\alpha - \alpha \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right]^{-1} - \Delta r_{nmt} \right) \\
&= -\left[\alpha - \alpha \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't}))} \right]^{-2} \\
&\cdot \quad \left(\frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))\exp(\delta^i_{nm^*t} + \alpha(\Delta r_{nm^*t}))}{\left(1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't})\right)^2} \right. \\
&+ \quad \left. 1_{\{m=m^*\}} \frac{\exp(\delta^i_{nmt} + \alpha(\Delta r_{nmt}))}{1 + \sum_{m'} \exp(\delta^i_{nm't} + \alpha(\Delta r_{nm't})} \right) - 1_{\{m=m^*\}}.
\end{aligned} \tag{OA57}$$

G Number of banks by Year

We report in table OA8 the number of banks that are included in our counterfactual analysis each year. For a bank to be included, it must have at least one branch with deposits in the FDIC database, Call Reports data at the bank level, and either mortgage lending in HMDA or corporate lending in Dealscan that year. We find a broad upward time trend from 2397 banks initially to 3614 at the end. The main driver of this trend is an increase in the number of banks we are able to identify in the HMDA database. Note that we are able to run our counterfactual even for banks that are missing RateWatch interest rate data, since the model is able to solve for the change in a bank's equilibrium interest rate without knowing the initial level.

We note that the sample size does not mechanically bias our results. Our results would not be significantly effected by changes in the size of the banking industry for two reasons as long as our sample is representative. First, in our cross-sectional instrumental variable regressions, we are able to obtain consistent estimates from any sufficiently large representative sample, since we only use information about differences between observations and not on aggregate sizes. Second, the one place where we do use the aggregate size in our estimation is when we scale our TGA shock estimates to infer the parameter H_{33}. If we had too small or too large of a sample, our scaling makes sure that the aggregate impact of a reserve injection on reserve yields would be the same.

Table OA8: Number of Banks by Year in the Counterfactual

This table reports the number of banks that are present in the counterfactual each year.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Number of Banks	2397	2527	2655	2788	2903	3042	3132	3304	3514	3600	3614

H Counterfactual: non-deposit funding costs

This section presents a counterfactual that raises a bank's cost of non-deposit financing following Kandrac and Schlusche (2021). We specifically analyze a policy counterfactual where the fees for FDIC deposit insurance were adjusted. After the policy change, some banks were charged for their non-deposit debt financing and not only their deposits, effectively raising the cost of their non-deposit financing. As in Kandrac and Schlusche (2021), our counterfactual compares the outcomes of treated banks to a control group who were exempt from deposit insurance fees. We find results consistent with Kandrac and Schlusche (2021) that treated banks lowered both their lending and their holdings of bank reserves relative to control banks.

We first impose that non-deposit debt financing is given a 10 basis point increase in its cost.[19] Second, based on summary statistics in the Call Reports from 2001 to 2017, we find that the average bank has assets of 667 million, equity of 60 million, and deposits of 412 million. Based on this, we have that 74.4% of non-deposit financing is coming from sources other than the equity market. We assume that this fraction of non-deposit financing stays fixed and treat it as a 7.44 basis point increase in the cost of all non-deposit financing. Holding a bank's quantities fixed, this implies that holding reserves, loans, and mortgages has a 7.44 basis point increase in its marginal cost. We randomly select 29.1% of the banking system to receive this treatment, consistent with the summary statistics in Kandrac and Schlusche (2021) and perform our counterfactual in 2010, the year of the policy change.

[19]While the exact number for this insurance fee is complex, 10 basis points is consistent with the ranges presented in https://www.fdic.gov/deposit/insurance/assessments/proposed.html for FDIC assessment rates.

Finally, we hold the equilibrium yield on reserves fixed and allow aggregate reserve quantities to clear that market at this existing yield.

We report our findings in table OA9. Like Kandrac and Schlusche (2021), we find that treated banks have a reduction in their reserves and lending relative to control banks. This is because the treatment simultaneously raises their costs of reserve and loan holdings. Because the market for reserves is perfectly elastic, we find that reserve quantities are the most responsive to the shock. Mortgage and loan quantities are also highly elastic at the level of an individual bank, so these quantities respond in the tens of billions as well. We note that our qualitative result that loans and reserves move in the same direction remains robust to altering the input parameters of the counterfactual.

Table OA9: Outside Option estimates (Loans)

This table reports the impact of a change in the cost of non-deposit financing for a randomly selected 29.1% sample of treated banks. Treated banks have a 7.44 basis point increase in the marginal cost of holding mortgages, corporate loans, and reserves, while control banks have no exogenous change to their cost function. Quantity changes are reported in billions of dollars.

Group	Deposits	Mortgages	Loans	Reserves
Treated	-9.72	-25.60	-36.75	-266.97
Control	14.14	20.56	0.18	-2.03
Difference	-23.85	-46.17	-36.92	-264.94