Regional Banks, Aggregate Effects

Quinn Maingi*

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Abstract

I develop and estimate a quantitative spatial model featuring banks' spatial lending networks to study the real effects of bank funding shocks. I apply the model to the 2023 regional bank panic. I show that, during the panic, deposits were reallocated towards regional banks with better marginal lending opportunities, which offered higher deposit rates. This reallocation substantially mitigated the otherwise negative aggregate output effects of the remaining, panic-related deposit flows. This positive reallocation effect is primarily driven by inflows into banks with good lending opportunities, suggesting that fundamental forces, rather than panic-driven idiosyncratic runs, are behind the positive reallocation effect.

Keywords: banks; regional lending markets; regional banking crisis

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*First version, November 2023. Department of Finance and Business Economics, USC Marshall School of Business. Email: qmaingi@marshall.usc.edu. I am deeply grateful to my advisers Holger Mueller, Alexi Savov, Philipp Schnabl, Simone Lenzu, and Daniel Waldinger for their invaluable guidance, advice, and support. I also thank Viral Acharya, Costas Arkolakis, Sabrina Howell, Erica Jiang, Anil Kashyap, Benny Kleinman, Ezra Oberfield, Maureen O'Hara, Thomas Philippon, Tomek Piskorski, Manju Puri, Adriano Rampini, Rob Richmond, Martin Rotemberg, Anthony Saunders, Johannes Stroebel, Sharon Traiberman, Olivier Wang, and seminar participants at Boston College, Chicago Booth, Columbia, Cornell, Duke, Georgia Tech, Imperial College, London Business School, Michigan State, Notre Dame, the OFR, Ohio State, U Maryland, UBC, UIUC, USC, the West Coast Spatial Workshop, and Yale for their helpful comments and suggestions.

1 Introduction

On March 10th, 2023, Silicon Valley Bank (SVB) failed after experiencing a bank run. Two days later, Signature Bank was shut down by regulators due to large deposit withdrawals in the wake of the SVB failure. These two events mark the beginning of what many observers refer to as the "2023 regional bank panic." Much of the academic and policy debate surrounding this bank panic has focused on two salient features: i) large net deposit flows out of the banking system (into money market funds and other assets), and ii) a "flight to safety" of deposits from midsize ("regional") banks into large national banks.[1] In this paper, I focus on a third, important but understudied, feature of the 2023 regional bank panic: the reallocation of deposits *within* the regional banking sector. I argue that this deposit reallocation was large, and is of first-order significance for understanding the aggregate real effects of the panic. Crucially, I show that deposits flowed out of regional banks with poor lending opportunities into regional banks with good lending opportunities. When I quantify the effect of this (positive) deposit reallocation on aggregate real output, I find that it substantially mitigates the otherwise negative impact of all of the other deposit flows during the panic.

To study the real effects of deposit flows within the economy, I incorporate spatial banking networks into a quantitative Ricardian model of inter-regional trade as developed by Eaton and Kortum (2002). To my knowledge, this is the first paper to integrate regional bank lending networks into a quantitative spatial general equilibrium model with production. My model exactly replicates observed lending patterns between individual banks and regions and incorporates bank-level lending frictions that depend on banks' deposit holdings. This key feature allows the model to produce realistic region-level lending and output responses to bank-level deposit shocks and is crucial for modeling firm substitution across banks in general equilibrium. Using the full general equilibrium structure of the model, I quantify the effect of deposit reallocation during the 2023 regional bank panic on output and find that its overall impact is positive, mitigating the adverse effects on output from all of the remaining deposit flows combined. To understand why the effect of deposit reallocation is positive, I derive a model-based, partial equilibrium bank-specific measure of marginal lending opportunities based on regional aggregates and banks' spatial lending footprints. Using this measure, I find that deposit inflows during the panic were concentrated at banks with good marginal lending opportunities, and these banks offered notably higher deposit rates, consistent with depositors reallocating towards banks offering higher yields.[2]

[1] See, e.g., Caglio et al. (2023); Saphir and Burns (2023).

[2] Why did depositors suddenly become more rate-sensitive? In Online Appendix B.4, I microfound their rate-shopping behavior in a simple model where the sudden fear of bank failure makes previously sticky

To provide more detail, my model extends the production and consumption framework developed in Eaton and Kortum (2002) by incorporating the role of banks in lending to firms for use in production. In my model, firms use labor and bank loans to produce goods, which can be traded across regions. Each region features both small and large firms, differentiated by the nature of the lending markets on which they borrow. Large firms access a national lending market that is perfectly insensitive to distance, whereas small firms' borrowing opportunities depend heavily on their geographic location. Banks can lend across multiple regions, but lending incurs a firm-specific cost. This cost depends on firm size and, for small firms, on distance. Banks set markups under monopolistic competition to maximize joint profits across all lending opportunities. Banks' lending cost distributions depend on financial frictions at the bank level, which in turn depend on their deposit holdings. Accordingly, any shock to a bank's deposit base impacts all regions in which the bank lends. The extent of this impact depends on the bank's importance as a lender in the region and the ability of firms to borrow from other banks in general equilibrium. The model has a unique equilibrium. Moreover, given observed data and parameter values, there exists a unique set of fundamentals which rationalize the observed data as an equilibrium of the model. This feature guarantees that, for any parameter values, the model can replicate observed small-firm lending patterns from banks to counties, which exhibit significant variation across banks and hold particular importance for small and midsize banks (Petersen and Rajan 1994; Berger and Udell 1995; Brevoort and Hannan 2006; Agarwal and Hauswald 2010; Nguyen 2019).

Given the novelty of the lending forces I embed into my model, I need to estimate several key, structural parameters that govern the strength of these forces. Importantly, the model's ability to exactly rationalize observed data for any given set of parameters implies that the parameters are not identified by simple correlations nor by OLS regressions. Thus, I employ an instrumental variables approach to identify the key parameters. Specifically, and in line with my empirical setting, which focuses on small and midsize banks during the 2023 regional bank panic, I explore instruments derived from deposit shocks to small and midsize banks. Inspired by Gilje et al. (2016), I leverage fracking well openings as shocks to local banks' deposit bases. Banks with pre-existing branches in counties where fracking wells are discovered experience substantial deposit inflows following the well openings, driven by local wage increases and payments to mineral rights holders. By tracing these shocks across space through banks' internal branch networks ("internal capital markets"), I can identify lending

depositors willing to leave their banking relationships. Once "unstuck," they become more sensitive to other, salient features of deposit accounts, such as deposit rates. Banks with better lending opportunities have stronger incentives to attract new depositors, thus offering higher deposit rates, consistent with the patterns observed in the data. While some of the causes of why depositors got "unstuck" may be specific to the 2023 regional bank panic, the broad forces described herein are likely to be more general, and may generate similar (positive) deposit reallocations also in other settings.

and output responses in distant regions, which pin down the novel structural parameters in my model. This approach has the advantage that I can identify all of the parameters in one, internally consistent natural experiment with transparent estimation equations and exclusion restrictions. To ensure the robustness of the estimates obtained through this method, and to demonstrate their external validity, I show that the estimated model can also replicate key findings from other work in the literature when implementing their respective set(s) of bank-specific credit supply shocks in my model.[3] As further validation, I show that estimated model generates a key object—ex-ante, partial equilibrium marginal lending opportunities—that predicts banks' actual, observed lending responses to the 2023 regional bank panic.

Having estimated the structural parameters and validated the model, I feed the model with observed deposit flows to quantify their aggregate impacts. Starting from a "pre-panic" (December 2022) baseline economy, I shock each bank's deposit holdings to replicate the actual observed deposit flows that occurred during the subsequent 6 months. I then compute the model's equilibrium based on the new deposit allocations and determine the resulting change in aggregate real output (relative to the baseline economy) within the model. I first show that a *counterfactual*, *proportional* version of the deposit panic, where all regional banks (including those with good lending opportunities) see substantial deposit outflows, would have generated a large contraction in real output of 1.85%. However, feeding the model with the *actual, bank-specific* deposit flows—which includes the reallocation of deposits from regional banks with poor lending opportunities to those with good lending opportunities—generates only a modest contraction in real output of 0.2%.[4]

What is driving the positive real output effect of the deposit reallocation during the regional bank panic? Is it because banks that experienced deposit outflows, such as SVB, had particularly poor lending opportunities, in which case (almost) any reallocation away from those banks would have been positive ("outflow effect")?[5] Or is it because banks

[3]In particular, I show that the estimated model can replicate moments from Chen et al. 2017. This exercise involves using parameters estimated from a positive shock to small banks during normal times to predict the consequences of negative shocks to large banks during financial crises, making it particularly informative about external validity.

[4]I show in Section 5.1 that this qualitative result - deposits were reallocated from regional banks with poor lending opportunities to those with good lending opportunities - holds for other measures of marginal lending opportunities taken from the literature. Further, I show in Online Appendix B.1 that my quantitative findings also hold for an extended model that endogenizes banks' entire balance sheets, including non-loan assets, wholesale funding, and interbank lending markets.

[5]Consider the case of SVB. According to my model, SVB's marginal lending opportunity ranks at the 13th percentile among banks, signifying considerably worse lending opportunities than the average. This aligns well with the narrative that SVB's management was providing to investors on the issue of excessive deposit growth, in conjunction with lending not keeping pace, indicating poor marginal lending opportunities. In SVB's annual 10-K report dated March 2022, senior management explicitly states: "*Rapid deposit growth has exceeded the pace of our loan growth, and as a result, a significant amount of excess deposits not used to*

that experienced deposit inflows had above-average lending opportunities ("inflow effect")? Disentangling the two effects is important. If the overall reallocation effect was mostly driven by the outflow effect, that is, by the *specific* set of banks that were "shocked" during the panic, then one might question whether the economic forces identified in this paper—deposits flowing towards banks with good lending opportunities, which attract new depositors by offering higher yields—have broad relevance also for other, potential crisis episodes. Yet, I find that more than half of the overall reallocation effect can be attributed to the inflow effect. Focusing on this effect—which captures general economic forces, rather than specificities of the banks that failed during the 2023 regional bank panic—I find that the reallocation of deposits towards banks with good lending opportunities *offsets about 60%* of the otherwise negative effects of deposit flows during the panic, including net outflows out of the banking system. Altogether, these results highlight the *aggregate* importance of the *cross-sectional* allocation of deposits within the banking sector.

Contribution to the Literature. First and foremost, this paper contributes to the literature on the connection between bank funding shocks and the real economy.[6] One strand of this literature focuses on the interplay between deposits and lending, as well as the effects of other shocks to the liability side of banks' balance sheets, but does not focus on spatial variation of these shocks (see, e.g., Kashyap et al. 1993; Bernanke and Gertler 1995; Kashyap and Stein 2000; Kashyap et al. 2002; Brunnermeier and Sannikov 2014; Chodorow-Reich 2014; Hanson et al. 2015; Drechsler et al. 2017, 2022; Wang et al. 2022; Abadi et al. 2023). Another strand of this literature, which is particularly relevant to my paper, relies heavily on spatial variation. For instance, various papers exploit spatial variation in exposure to common shocks (e.g., Peek and Rosengren 2000; Chen et al. 2017; Huber 2018; Benmelech et al. 2019; Bord et al. 2021; Mian and Sufi 2022) policy shocks (e.g., Jayaratne and Strahan 1996; Berger and Roman 2017), or location-specific shocks (e.g., Gilje et al. 2016; Gilje 2019; Johnston-Ross et al. 2021). Despite the abundant reduced-form evidence that spatial frictions matter for banks, especially for small and midsize banks, there is limited structural work directly studying spatially segmented credit markets (see Cox et al. 2023 for an exception). I contribute to this literature by nesting banks' regional lending networks into a quantitative spatial general equilibrium model with production. Further, I show that the interplay between bank funding and aggregate output depends on the cross-sectional allocation of funding within the banking sector, rather than aggregate funding conditions alone.

fund loan growth have contributed to the growth of investment balances."

[6] For a comprehensive review of this literature, see Berger et al. (2020).

Second, my paper relates to the modern literature on quantitative spatial economics (e.g., Eaton and Kortum 2002; Allen and Arkolakis 2014; Ahlfeldt et al. 2015; Redding 2016; Redding and Rossi-Hansberg 2017; Monte et al. 2018; Caliendo et al. 2018), and in particular, to a recent strand of this literature that embeds firm or production networks into quantitative spatial models (e.g., Arkolakis et al. 2023; Giroud et al. 2024; Oberfield et al. 2024a). One particularly related strand of literature is the recent literature that works to embed banks and banking networks into quantitative spatial models (e.g., Alekseev and D'Amico 2024; Oberfield et al. 2024b). My paper contributes to this literature in two ways. First, I develop and estimate a novel quantitative model that nests banks' spatial lending networks into a general equilibrium model with production, which allows me to study the regional and aggregate implications of bank-level funding shocks. Second, my findings on deposit reallocations during the 2023 regional bank panic complement the motives documented in Oberfield et al. 2024b, by showing that loan-deposit imbalances can have large aggregate effects, in addition to their effects on banks' spatial sorting.

Finally, my paper is related to the burgeoning literature on the 2023 regional bank panic. Most of this literature focuses on the direct incidence of the panic, showing that uninsured depositors and bank balance sheets are important for understanding panic-related deposit withdrawals and bank failures (e.g., Chang et al. 2023; Drechsler et al. 2024; Haddad et al. 2023; Jiang et al. 2024; Meiselman et al. 2023).[7] Going beyond direct incidence, Caglio et al. (2023) show that large banks witnessed deposit inflows as part of a "flight to safety," while Choi et al. (2023) document panic-induced contagion in equity prices. My paper contributes to this literature by showing that the panic coincided with a substantial bank-level deposit reallocation *within* the regional banking sector, as well as showing that this reallocation is of first-order importance for quantifying the aggregate (real) effects of the panic.

The rest of this paper is organized as follows. Section 2 provides a description of deposit flows during the 2023 regional bank panic and key empirical facts that motivate my theoretical model. Section 3 presents the model. Section 4 discusses the estimation of the model and validates the estimated model vis-à-vis other, historical shocks. Section 5 uses the estimated model to study the 2023 regional bank panic. Section 6 concludes the paper.

[7] Another strand of the literature related to the 2023 regional banking panic relates to policy lessons on financial stability, government interventions, interest rate risk, and deposit insurance (e.g., Acharya et al. 2023b,a; Dávila and Goldstein 2023; Granja 2023; Jiang et al. 2023; Khetan et al. 2023; Metrick and Schmelzing 2023; McPhail et al. 2023).

2 Motivating Facts and Data

Before I describe my theoretical model, I provide a descriptive overview of deposit flows during the 2023 regional bank panic. Given these flows, I review some key stylized facts from the literature that are particularly relevant for my theoretical model and discuss how I account for these facts in my modeling choices.

2.1 Bank Data Sources

The key data source for this paper comes from the Community Reinvestment Act (CRA) small business lending data. These data require all banks with at least one billion dollars in (inflation-adjusted) assets to report new lending activity to small firms each year in each county, based on the borrowing firms' physical locations. The data include all loans banks make to firms below a loan size threshold of one million dollars, and are commonly used in academia and policy circles to measure local small firm lending activity by banks (e.g. Williams 2014; Chen et al. 2017). The data cover two types of loans. First, they include all commercial and industrial (C&I) loans. Second, the data include loans secured by nonfarm, nonresidential properties. These loans are typically classified as commercial real estate (CRE) loans (see, e.g., Federal Reserve Board 2022), representing 63% of all CRE loans on banks' balance sheets as of December 2022.[8]

I augment the CRA data with additional bank-level data and information on banks' branch locations. I obtain balance sheets and income statements from banks' call reports. Bank balance sheet data provide me with measures of banks' assets, insured and uninsured deposits, and lending activity to both small and large firms. For consistency with the CRA data, I measure lending to firms as the sum of C&I lending and loans secured by nonfarm, nonresidential properties. Income statement data allow me to derive a measure of banks' deposit rates. Finally, I use the FDIC's summary of deposits report and banking structure data, garnered through a FOIA request, to measure banks' physical branch locations.

2.2 Regional Bank Panic

My main measure of deposit flows comes from banks' call reports. To make sure that I capture all "panic-induced" deposit flows, which occurred between early March and early

[8]The CRA data also include separate measures of lending to farms and for agricultural production. This represents a tiny fraction of lending reported in the data, so, for simplicity, I exclude these loans. C&I loans represent about 40% of loans to small firms in the December 2022 call reports, and loans secured by nonfarm, nonresidential properties represent approximately 60% of loans.

May of 2023 (Federal Reserve Board 2023), I use 6-month deposit flows from December 2022 to June 2023 to construct my measures of deposit reallocation.

Table 1 provides a breakdown of deposit flows from December 2022 to June 2023 by bank size group.[9] In column 1, the table shows the change in aggregate deposits for each bank size group during this period. As can be seen, net deposit outflows were heavily concentrated in regional banks. Column 2 shows that these outflows were driven by a system-wide flight from uninsured deposits, which, again, was much stronger at regional banks. During the 6-month window surrounding the panic, the banking system experienced a decrease of approximately 1.08 trillion dollars in total uninsured deposits, equal to about 6% of total bank deposits. It is likely that uninsured depositors were reacting to the panic as a flight from perceived bank-level failure risk, as uninsured depositors are, in aggregate, notably more sensitive to this risk (e.g., Iyer and Puri 2012; Egan et al. 2017). Such fears were stoked by the SVB failure, where uninsured depositors at SVB were unsure if they would receive access to their funds, while depositors at other banks were unsure about the safety of their own funds (e.g., Schroeder 2023; White 2023).

While the magnitude of the aggregate deposit outflow during the panic is striking, it masks crucial heterogeneity. In particular, column 3 shows that banks also experienced significant *inflows* into insured deposits during this period, amounting to 547 billion dollars. As shown in Table 1, all bank size groups saw an increase in insured deposit volume, indicating that the heavy focus of the panic on regional banks was mainly driven by the concentration of outflows from uninsured deposits.[10] These "new," insured deposits largely went to different banks than the outflows from uninsured deposits. Columns 4 and 5 provide a simple measure of this cross-bank reallocation. As column 4 shows, banks which saw deposit outflows during this period saw a total outflow of 1.03 trillion dollars. Similarly, as column 5 shows, banks which saw deposit inflows during this period saw a total inflow of 501 billion dollars. Crucially, the majority of this deposit reallocation happened *between* regional banks, rather than from regional to large banks.[11]

[9] I use the term "community bank" or "small bank" to refer to any bank with less than five billion dollars in assets, and "regional bank" or "midsize bank" to refer to banks with more than five billion but less than one trillion dollars in assets. In practice, this leaves six "large banks" or "national banks" (JP Morgan Chase, Bank of America, Citibank, Wells Fargo, Goldman Sachs, Morgan Stanley) as the remaining category. In the structural model presented in Section 3, rather than relying on this discrete set of types I use for summary statistics, I use data on actual spatial lending patterns to pin down how "regional" each bank is.

[10] Dollars that were uninsured deposits at one bank showing up as insured deposits at other banks is consistent with FDIC insurance rules. Specifically, FDIC insurance limits are not just per person, but also per bank. Thus, depositors can spread their funds across multiple banks to insure a greater volume of their deposits, and ensure rapid access to portions of their funds in the event of a bank failure.

[11] With perfectly efficient interbank lending markets, deposit reallocations across banks would not directly impact lending activity, since banks which receive net inflows would lend to banks which experience net outflows, until marginal lending opportunities equalize across the banking system. However, it is well

Large *outflows* from uninsured deposits coinciding with large *inflows* into insured deposits is unprecedented in recent history, making the 2023 regional bank panic a good experiment to study the effects of deposit reallocation. Figure 1 shows quarter-on-quarter *changes* in the aggregate stock of insured and uninsured deposits over the last five years. Prior to Q1 2023, the two series move closely in tandem, with a correlation coefficient of 63%. Notably, this tight relationship between insured and uninsured deposit growth continues during the 2022 monetary tightening cycle from March 2022 to December 2022. However, the two series diverge sharply during the 2023 regional bank panic, particularly during Q1 2023, and, to a lesser extent, in Q2 2023, making the panic a unique episode in recent history.

2.3 Critical Facts About Small and Midsize Banks

Given the central role of deposit reallocation *within* the regional banking sector during the panic, I review critical descriptive facts from the literature about small and midsize banks to motivate certain features of my theoretical model.

Small and Midsize Banks are Disproportionately Important to Firms. Banks constitute an important source of credit for firms (e.g., James 1987; Bernanke and Gertler 1995; Gande and Saunders 2012). In December 2022, firm lending represented roughly four trillion dollars of loans, which is about 17% of total bank assets and 35% of total bank loans. Yet, small and midsize banks play an outsize role in this lending market. Table 2 provides summary statistics showing banks' lending specialization to firms. In particular, the average midsize bank lends disproportionately to firms: 28% of its assets and 45% of its loans are loans to firms. This specialization is even stronger when it comes to lending to small firms. More than half of the average community bank's loans to firms go to small firms, compared to 17% for midsize banks and 9% for large banks. This difference is usually explained through smaller banks' comparative advantage in the ability to harness "soft information" through relationships with local business owners, allowing loan officers to overcome information asymmetries due to the opaque nature of small businesses (e.g., Petersen and Rajan 1994; Berger and Udell 1995). Given this specialization, lending to small firms and CRE lending were two of the markets that popular commentators were most worried about during the 2023 regional bank panic. For example, on May 23, 2023, CNN

documented that bank-specific liability shocks have large effects on lending activity (e.g., Khwaja and Mian 2008; Chava and Purnanandam 2011; Schnabl 2012), indicating imperfect reallocation in the interbank market. Documented frictions in the interbank market include counterparty risk (Iyer and Peydro 2011), run risk (Iyer et al. 2014), or lack of access to wholesale funding by small and midsize banks (Kashyap and Stein 1995). In Online Appendix B.1, I model these interbank market frictions as convex lending costs, and show that in equilibrium, this implies that (marginal) lending behavior is not necessarily equalized across banks.

Business released an article titled "Jamie Dimon warns of a commercial real estate downturn" (Goodkind 2023):

> The regional banking crisis is having a knock-on effect on commercial real estate lending, Dimon warned at his company's shareholder meeting on Monday. ... Lending to commercial real estate developers and managers largely comes from small and mid-sized banks, where the pressure on liquidity has been most severe. About 80% of all bank loans for commercial properties come from regional banks...

Similarly, on March 18th, 2023, the Wall Street Journal released an article titled "Local banks could leave gaps that are hard to fill," writing about fears in the small-business lending market (Lahart and Demos 2023):

> So if deposits shift from a local bank to a big one ... a small business can't simply borrow from it. The big bank would have to conduct its own review of its creditworthiness, without soft information such as the owner's reputation in the community.
>
> ...the U.S. might yet escape a recession. But for some businesses, and in some parts of the country, it could sure feel like one.

Small Firm Lending is Highly Distance Sensitive. Given the importance of lending relationships in lending to small firms, it is perhaps unsurprising that lending to small firms is very distance sensitive (e.g., Petersen and Rajan 2002; Degryse and Ongena 2005; Brevoort and Hannan 2006; Agarwal and Hauswald 2010; Nguyen 2019). To illustrate these distance frictions, I merge the CRA lending data with the bank branch location data and compute the distance between each US county and the nearest bank branch.[12] Notably, most banks do not lend to most counties, so the bank-to-county matrix is relatively sparse. To obtain a nonparametric measure of distance frictions that accounts for these zeros, while also controlling for local credit demand, I collapse all counties into distance buckets based on their distance to the nearest branch and compute market shares within those buckets.

Figure 2 plots the average market share for each bank size group from 2015 to 2019 against the distance buckets. Lending tends to rapidly decay with distance for all three bank size groups, and the effect is particularly strong for smaller banks. This is highly suggestive of spatially segmented credit markets, where the set of banks in a given market is limited

[12] Specifically, I calculate the haversine distance between each bank branch and each US county's centroid, and then take the minimum of those as the bank-to-county distance. I count all banks with a branch within a county in the same, 'local' bucket.

by physical distance. Figure 2 also illustrates the importance of small and midsize banks within their local communities. Specifically, in counties where small and midsize banks have branches, they tend to be significantly more important than large banks, even if the large banks have local branches as well.[13] This supports the popular concern surrounding the reallocation of deposits from small and midsize banks to large banks for local communities, namely, that the local communities may suffer as a result.

2.4 Implications and Modeling Choices

These descriptive facts motivate important features of my theoretical model. First, the strength of the within-regional bank reallocation means that my model must be able to compare lending opportunities across different regional banks. This necessitates a model that can match actual, bank-specific lending footprints, rather than a simpler model with representative regional and national banks. Second, given the focus of the panic on small and midsize banks, I focus on lending to firms as a particularly important market in which they specialize. However, given national banks' specialization in lending to large firms, I model segmented large and small firm credit markets to allow for the mitigating channel that deposit flows to large banks could increase lending to large firms.[14] Finally, the existence of spatial frictions in these markets motivates the use of a quantitative spatial modeling framework. While a simple way of modeling such frictions would be through local, spatially perfectly segmented credit markets, it is well documented that banks optimize loans over their entire set of opportunities (e.g., Cortés and Strahan 2017). Thus, my model includes banks' entire spatial lending networks and joint profit maximization across all lending opportunities.

3 A Quantitative Spatial Model of Lending to Firms

I develop a quantitative spatial general equilibrium model to study the impact of banking shocks on real economic output. My model starts from an Eaton and Kortum (2002) style model of inter-regional trade, which I expand on by incorporating bank loans as a factor of production. Banks provide loans to small and large firms in each region, where firms are differentiated by the nature of the lending markets on which they borrow. Large firms access a national lending market that is perfectly insensitive to distance, whereas small firms' borrowing opportunities depend heavily on their geographic location. Each bank can

[13] See Cole et al. (2004) and Berger et al. (2005) for differences in business models that can explain this difference.

[14] See Chodorow-Reich et al. (2022) for a detailed breakdown of differences between small firm and large firm credit markets.

lend to firms across space, but lending incurs a bank-firm specific cost, which depends on firm size and, for small firms, distance. Banks set markups under monopolistic competition to maximize joint profits across all lending opportunities. Banks' cost distributions are region-specific for small firms, but are constant across the entire economy for large firms. Further, banks' lending cost distributions depend on their financial constraints, which are determined by bank-level deposit holdings and other, non-deposit lending capacity. Thus, any shock to a bank's deposit base impacts all regions in which the bank lends, where the extent of this impact depends on the bank's importance as a lender in the region and firms' ability to substitute to other banks in general equilibrium.

3.1 Primitives

The economy consists of N regions ("locations" or "counties"), indexed by $i, n \in \mathcal{N}$ which interact through goods trade and bank lending. Each location contains a unit mass of small firms and large firms, represented by $s, t \in \mathcal{S} \coloneqq \{sm, lg\}$. I refer to the set of firms that are size s and in location i as market is. Within a market is, I index firms by $\nu \in [0, 1]$, which gives each firm a unique identifier, $is\nu$. Counties differ exogenously in their physical location, the productivity distributions of their small and large firms, and their populations. There are J banks, indexed by $j, k \in \mathcal{J}$. Each bank can lend to large firms in any region, but small firms in a subset of regions. Denote the set of markets to which bank j can lend by $\mathcal{L}_j \subseteq \mathcal{N} \times \mathcal{S}$. Denote the set of banks that lend to market is by $\mathscr{L}_{is} \subseteq \mathcal{J}$.

3.2 Consumers

There is a mass $\bar{L}$ of workers (also, "consumers") in the economy indexed by $\eta \in \mathcal{H}$. Worker η works in market ns with total employment equal to population l_{ns}. Worker η is endowed with one unit of labor which she supplies inelastically for a wage of w_{ns} and an equity share in each bank e_{ns}. Consumer η spends all of her income on consumption goods, and receives a static payoff from consumption of:

$$u_{\eta ns} = C_\eta, \tag{1}$$

where the consumption index C_η is a CES aggregator of a unit mass of consumption varieties denoted by $\omega \in [0, 1]$:

$$C_\eta = \left(\int_0^1 c_\eta(\omega)^{\frac{\sigma-1}{\sigma}} \, d\omega \right)^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

Standard CES results imply that the model admits a price index:

$$P_n = \left(\int_0^1 p_n(\omega)^{1-\sigma} \, d\omega \right)^{\frac{1}{1-\sigma}}, \tag{3}$$

where $p_n(\omega)$ is the cost for a consumer living in location n to source idiosyncratic good ω. Thus, consumer η's realized utility is equal to her real income, denoted by $I_{ns} = \frac{w_{ns} + e_{ns}\pi}{P_n}$, where $e_{ns}\pi$ captures income from banks' dividends.[15]

3.3 Firms

3.3.1 Production

For each consumption variety $\omega \in [0,1]$, firm $is\nu$ produces its component using a Cobb-Douglas production technology:

$$y_{is\nu}(\omega) = A_{is} z_{is}(\omega) \, l_{is\nu}(\omega)^{1-\alpha} \, k_{is\nu}(\omega)^{\alpha}, \tag{4}$$

with idiosyncratic productivity $z_{is}(\omega)$, average productivity A_{is}, labor $l_{is\upsilon}(\omega)$, and bank loans $k_{is\upsilon}(\omega)$.[16] The key parameter α governs firms' output responses to credit supply shocks. Each firm can take a loan from any bank, and bank j offers loans to firm $is\nu$ at an interest rate of $r_{isj\nu}$. In equilibrium, firm υ borrows from the bank which offers it the lowest interest rate, denoted $r_{is\nu}$, and takes the wage w_{is} as given. For each variety of ω, total output by firms in market is of the good is a CES aggregate of all firms' output:

$$y_{is}(\omega) = \left(\int_0^1 \left(y_{is\nu}(\omega) \right)^{\frac{\eta-1}{\eta}} d\nu \right)^{\frac{\eta}{\eta-1}}. \tag{5}$$

For each variety ω, standard CES and Cobb-Douglas production results imply that the cost-minimizing bundle of inputs to produce one unit of the final good is:[17]

$$mc_{is}(\omega) = \frac{w_{is}^{1-\alpha} r_{is}^{\alpha}}{A_{is} z_{is}(\omega)}, \tag{6}$$

[15] For simplicity, I assume that bank equity shares are proportional to wages, ensuring that banks' dividends are nondistortionary. Consistent with this assumption, the correlation between regional payroll share and regional dividend share was 94% in 2019, as measured using the Quarterly Census of Employment and Wages and the IRS's Statistics on Income report.

[16] It is straightforward to relax the Cobb-Douglas production technology assumption to a CES production technology, which allows for the elasticity of substitution between bank loans and labor is one. However, when I test this restriction empirically, I obtain a value for the elasticity of substitution that is neither economically nor statistically significantly different from one.

[17] As is the case with several formulas in this section, the cost to produce one unit of the cost-minimizing bundle technically contains a scale coefficient, which I ignore for expositional simplicity. Such coefficients have no practical impact on the model, since they are simply absorbed into scale normalizations I make when I invert the model.

where the interest cost index, r_{is}, is given by:

$$r_{is} = \left(\int_0^1 {r_{is\nu}}^{\alpha(1-\eta)} d\nu \right)^{\frac{1}{\alpha(1-\eta)}}.$$

3.3.2 Trade

All goods are tradable, but trade is costly. Each variety is sourced from its minimal cost producer, implying that the idiosyncratic component of productivity leads to market-level specialization in production. I make the conventional assumption that goods trade is subject to bilateral "iceberg" trade costs such that $\tau_{ni} \geq 1$ units must be shipped from location i in order for one unit to arrive in location n. Given this technology, we can write the deterministic part of the price of goods shipped from firms in market is to consumers in region n as:

$$p_{nis} = \tau_{ni} \frac{w_{is}^{1-\alpha} r_{is}^{\alpha}}{A_{is}}. \tag{7}$$

Next, I move to characterize trade shares. For simplicity, I assume that idiosyncratic productivity $z_{is}(\omega)$ follows a Fréchet distribution with shape parameter $\Phi > 1$, i.e.:

$$\mathbb{P}\left(\bigcap_{n \in \mathcal{N}} \bigcap_{s \in \mathcal{S}} \{Z_{ns} \leq t_{ns}\} \right) = exp\left\{ - \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{S}} t_{ns}^{-\Phi} \right\}. \tag{8}$$

Intuitively, the shape parameter Φ governs the degree of dispersion in idiosyncratic productivity, and thus the response of trade flows to changes in the deterministic component of prices. For higher values of Φ, the productivity distribution is more compressed, leading to more elastic demand. Standard results on Fréchet distributed productivity imply that region n's import share from firms in market is follows:

$$\frac{q_{nis}}{q_n} = \left(\frac{p_{nis}}{P_n} \right)^{-\Phi}. \tag{9}$$

Further, the local price index follows:

$$P_n^{-\Phi} = \sum_i \sum_s p_{nis}^{-\Phi}. \tag{10}$$

Finally, I move to characterize equilibrium wages in each region. Since goods are tradable, wages depends not only on local conditions, but also on goods demand from consumers in all regions of the economy. This leads to a standard equilibrium condition in spatial models, derived from imposing total expenditure by workers at firms in market is must equal their total income:

$$l_{ns}w_{ns} = \sum_i \sum_t \left(\frac{p_{ins}}{P_i}\right)^{-\Phi} l_{it}w_{it}. \tag{11}$$

3.4 Banks

Each bank is able to lend to firms across the economy, but lending is costly.[18] Denote the per-dollar cost for bank j to lend to firm $is\nu$ by $c_{isj\nu}$. Banks set a net markup over marginal costs to each firm to maximize profits π_j. For simplicity, I assume monopolistic competition and focus on the equilibrium where banks charge one markup in each market. We can write the bank's problem as $\max_{\{\mu_{ij}\}_{i\in\mathcal{N}},\mu_j} \pi_j$, where π_j follows:

$$\begin{aligned}\pi_j = &\sum_{i\in\mathcal{N}} \int_0^1 \mathbf{1}_{i,sm\in\mathcal{L}_j} \mathbf{1}_{j \text{ lends to } i,sm,\nu} \left(\mu_{ij} c_{i,sm,j\nu} k_{i,sm,\nu}\right) d\nu \\ &+ \sum_{i\in\mathcal{N}} \int_0^1 \mathbf{1}_{j \text{ lends to } i,lg,\nu} \left(\mu_j c_{i,lg,j\nu} k_{i,lg,\nu}\right) d\nu,\end{aligned} \tag{12}$$

where μ_{nj} is bank j's net markup for small firms in region n, μ_j is bank j's net markup for large firms, $\mathbf{1}_{j \text{ lends to } is\nu}$ is an indicator function that captures firm $is\nu$'s choice of bank, and $k_{is\nu}$ is the amount that firm $is\nu$ borrows.[19] Note that firms' production technology implies that both substitution between banks and borrowing volumes depend negatively on markups, i.e., all else equal, banks that charge higher markups will have fewer borrowers, and each borrower will borrow less.

The formulation of bank profits in equation (12) allows me to nest both the extensive and intensive margins of banks' spatial lending networks into the production framework described in Section 3.3. On the extensive margin, banks cannot lend to small firms in all regions, as captured by the indicator function $\mathbf{1}_{i,sm\in\mathcal{L}_j}$. On the intensive margin, banks' lending cost structures can embed significant lending advantages to nearby small firms. Empirically, both the extensive and intensive margins are highly sensitive to distance to the nearest branch, implying that banks' physical branch networks play an important role in determining their lending opportunities. Next, I provide a flexible, transparent, and highly tractable parameterization of banks' cost structures that allows me to exactly match both

[18] One possible microfoundation for why lending is costly is monitoring, consistent with the stylized fact shown in Section 2.3 that small-firm lending is highly distance sensitive. When I take the model to the data, the costliness of lending will be used to rationalize equilibrium lending volumes, ensuring that the model matches the sensitivity of lending to distance.

[19] In this baseline model, I abstract away from banks' choices on the liability sides of their balance sheets. In Online Appendix B.1, I provide an extended version of the model, where I endogenize banks' liability structures using standard tools from the literature (see, e.g., Egan et al., 2017; Wang et al., 2022), and then show that, for the set of counterfactuals I consider in Section 5, the extended model generates formally isomorphic predictions to my baseline model.

margins of banks' observed spatial lending footprints.

Parameterizing Banks' Cost Structures. Assume that $c_{isj\nu}$ is a Fréchet distributed random variable with scale parameter $\bar{c}_{isj}$ and shape parameter $\epsilon_s > 1$. The scale parameter $\bar{c}_{isj}$ indexes average lending costs by bank j to firms in market is. I assume $\bar{c}_{i,lg,j} = \bar{c}_{j,lg}\ \forall\ i \in \mathcal{N}$, i.e., banks' lending cost distributions for large firms are independent of the region where the firm is located. The shape parameter ϵ_s controls dispersion in lending productivity between banks; for larger values of ϵ_s, lending costs are more compressed, which induces more elastic firm substitution in general equilibrium in response to changes in interest rates.

Banks face lending frictions which depend on bank-level lending capacity ℓ_j. For simplicity, I account for these frictions directly in lending costs. Specifically, I assume:

$$ln\bar{c}_{isj} = -\theta ln\ell_j + ln\tilde{w} + ln\tilde{c}_{isj}, \tag{13}$$

In this formulation, bank-level increases in lending capacity impact all regions where the bank lends, not just the region where deposits are gathered. The key parameter θ measures the importance of financial constraints in banks' lending costs. I measure lending capacity as $\ell_j = d_j + \tilde{\ell}_j$, where d_j is bank deposits and $\tilde{\ell}_j$ is additional, non-deposit lending capacity.[20] Note that $\tilde{c}_{isj}$ is one of the key fundamentals in this paper; it captures regional specialization of different banks for nonfinancial reasons, such as having a local or nearby branch. Within a bank, this specialization determines which regions are relatively important for the bank's complete set of lending opportunities. Finally, as is common in spatial models, my model only pins down real variables, and not the nominal level of prices. To this end, the average nominal wage $\tilde{w} := \frac{\sum_n \sum_s w_{ns} l_{ns}}{\sum_n \sum_s l_{ns}}$ acts as a nondistortionary aggregate normalization that ties nominal interest rates to the price level of the economy.

Solution to the Bank's Problem. Imposing the production structure described in Section 3.3 allows me to characterize credit demand by firms as a function of banks' chosen markups, which in turn allows me to solve the bank's problem. Imposing that firms choose to borrow from the cheapest bank, combined with standard Fréchet results, gives the form of banks' market shares s_{nsj} and realized average interest rates r_{nsj} as a function of banks'

[20] An alternative specification of my model involves making lending frictions depend only on deposits, i.e., ignoring non-deposit lending capacity. For the majority of banks, this makes very little difference. However, there is a small group of outlier banks which take almost no deposits. For this group, only accounting for deposits induces the model to predict very large lending effects from small deposit changes. Accounting for non-deposit lending capacity in this manner smooths these outlier banks' lending responses.

markups:

$$s_{nsj} \equiv \mathbb{P}\left\{ns\nu \text{ borrows from} j\right\} = \frac{\left(\left(1+\mu_{nsj}\right)\tilde{c}_{nsj}\ell_j^{-\theta}\right)^{-\epsilon_s}}{\sum_{k\in\mathscr{L}_{ns}}\left(\left(1+\mu_{nsj}\right)\tilde{c}_{nsk}\ell_k^{-\theta}\right)^{-\epsilon_s}}, \tag{14}$$

and

$$r_{nsj} = r_{ns} = \tilde{w}\left(\sum_{k\in\mathscr{L}_{ns}}\left(\left(1+\mu_{nsk}\right)\tilde{c}_{nsk}\ell_k^{-\theta}\right)^{-\epsilon_s}\right)^{-\frac{1}{\epsilon_s}}. \tag{15}$$

Next, I move to solve the bank's problem. Plugging in the form of credit demand into equation (12) and solving the first-order condition gives a net markup of:

$$\mu_{njs} = \frac{1}{\epsilon_s}. \tag{16}$$

Similar to my assumption on iceberg trade costs, for simplicity, I assume that costs are paid in units of the output good and that banks redistribute profits to equity holders through a dividend denoted by π_j, which implies the value for the aggregate dividend of $\pi = \sum_j \pi_j$.

Marginal Lending Opportunities Finally, I am ready to characterize banks' marginal lending opportunities, given an additional dollar of deposits. Plugging equations (14), (15), and (16) into equation (12), imposing Cobb-Douglas production, and taking the partial derivative with respect to lending capacity gives (with some manipulation):

$$\frac{\partial \pi_j}{\partial \ell_j} = \sum_{ns\in\mathcal{L}_j} \theta\frac{\alpha}{1-\alpha}\tilde{w}^{-\epsilon_s}\left(\frac{\epsilon_s}{\epsilon_s+1}\right)^{\epsilon_s+1} w_{ns}l_{ns}r_{ns}^{\epsilon_s}\tilde{c}_{nsj}^{-\epsilon_s}\ell_j^{\theta\epsilon_s-1}. \tag{17}$$

The form of marginal lending opportunities nests a rich set of forces. There are three main forces that contribute to bank-level heterogeneity in marginal lending opportunities. First, each bank can only lend to a subset of markets, which generates bank-level heterogeneity through the extensive margin of banks' spatial lending networks. Second, all else equal, lending to regions with higher output, as measured by $w_{ns}l_{ns}$, will lead a bank to have better marginal lending opportunities. Equations (7) and (11) show that two important fundamentals which affect this are regional average TFP, A_{ns}, and proximity to high demand locations, as reflected in trade costs τ_{ni}. Third, bank-region specific lending ability $\tilde{c}_{nj}^{-\epsilon_s}\ell_j^{\theta\epsilon_s-1}$ relative to local interest rates $r_{ns}^{\epsilon_s}$ is also important. Banks that are 'good' at lending to a region with higher equilibrium rates r_{ns} will have better lending opportunities, as they can take advantage of the relatively high marginal product of bank loans better than their competitors. Finally, the form of marginal lending opportunities embeds both direct competition between banks and indirect cross-bank spillovers. First, local interest rates capture direct competition between banks. Second, lending also affects the level and

spatial distribution of output through goods trade, allowing for general equilibrium spillovers that affect regional output, depending on banks' overlap in the goods trade network.

Additionally, the marginal lending opportunities illustrate the critical difference between studying deposit reallocations and isolated, bank-specific deposit shocks. As a simple example, suppose banks j and k have identical lending footprints and marginal lending opportunities in all regions. If bank j loses one dollar of deposits in isolation, it cuts lending to all regions where it lends, decreasing output and inducing general equilibrium responses by firms and other banks. Yet, if we take one dollar from bank j and give it to bank k, bank k's increase in lending exactly offsets bank j's, leading to no real effect of the reallocation. Thus, the aggregate effects of a deposit reallocation depend heavily on the degree of overlap between banks which see inflows and outflows, as well as the relative quality of each banks' lending opportunities in each of those regions.

3.5 Equilibrium

Define the following endogenous objects: market level wages $\boldsymbol{w} := \{w_{ns}\}_{\{n,s\}\in\mathcal{N}\times\mathcal{S}}$, market level realized average interest rates $\boldsymbol{r} := \{r_{ns}\}_{\{n,s\}\in\mathcal{N}\times\mathcal{S}}$, bank-county-level small firm borrowing volumes $\boldsymbol{k}_{sm} := \{k_{n,j,sm}\}_{\{n,j\}\in\mathcal{N}\times\mathcal{J}}$, bank-level national firm lending $\boldsymbol{K} := \{\sum_{n\in\mathcal{N}} k_{n,j,lg}\}_{j\in\mathcal{J}}$, county-level national firm borrowing $\boldsymbol{k}_{lg} := \{k_{n,lg}\}_{n\in\mathcal{N}}$, the deterministic component of market-to-county prices $\boldsymbol{p} := \{p_{nis}\}_{\{n,i,s\}\in\mathcal{N}\times\mathcal{N}\times\mathcal{S}}$, bank-market level markups $\boldsymbol{\mu} := \{\mu_{nsj}\}_{\{n,s,j\}\in\mathcal{N}\times\mathcal{S}\times\mathcal{J}}$, and regional price indices $\boldsymbol{P} := \{P_n\}_{n\in\mathcal{N}}$. Define the following exogenous fundamentals: market level employment $\boldsymbol{l} := \{l_{ns}\}_{n\in\mathcal{N}:s\in\mathcal{S}}$, market level average productivity $\boldsymbol{A} := \{A_{ns}\}_{\{n,s\}\in\mathcal{N}\times\mathcal{S}}$, county-to-county trade costs $\boldsymbol{\tau} := \{\tau_{ni}\}_{\{n,i\}\in\mathcal{N}\times\mathcal{N}}$, bank-to-market non-financial lending costs $\tilde{\boldsymbol{c}} := \{\tilde{c}_{nsj}\}_{\{n,s,j\}\in\mathcal{N}\times\mathcal{S}\times\mathcal{J}}$, banks' sets of lending markets $\boldsymbol{\mathcal{L}} := \{\mathcal{L}_j\}_{j\in\mathcal{J}}$ and bank-level deposits and non-deposit lending capacity $\boldsymbol{\ell} := \left\{d_j, \tilde{\ell}_j\right\}_{j\in\mathcal{J}}$.

I am ready to characterize equilibria in my model. Equilibrium wages, prices, markups, and rates, $\{\boldsymbol{w}, \boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}\}$, are jointly pinned down by equations (7), (10), (11), (15), and (16). Given values of these endogenous quantities, I can solve for all other endogenous objects in closed form.

Proposition 1. *The model has a unique equilibrium. Precisely, taking as given parameter values* $\{\alpha, \epsilon_{sm}, \epsilon_{lg}, \theta, \Phi\}$ *and fundamentals* $\{\boldsymbol{l}, \boldsymbol{A}, \boldsymbol{\tau}, \tilde{\boldsymbol{c}}, \boldsymbol{\ell}, \boldsymbol{L}\}$*, there exists a unique (up to a scale normalization) equilibrium vector* $\{\boldsymbol{w}, \boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}\}$ *which solves equations (7), (10), (11), (15), and (16)*

Proof. See Online Appendix B. □

The proof proceeds by collapsing down the equilibrium conditions into a nonlinear system of 3N equations with 3N unknowns. I then apply results from Allen et al. (2020) to show that there is a unique solution to this system of equations.

3.6 Model Inversion

Finally, I describe the process of recovering model fundamentals, given observed data. Critically for my application, this process guarantees that, regardless of my estimated parameter values, the recovered fundamentals lead the model to exactly match observed bank lending footprints and, thus, accurately measure bank-specific marginal lending opportunities.

Proposition 2. *Taking as given parameter values* $\{\alpha, \epsilon_{sm}, \epsilon_{lg}, \theta, \Phi\}$ *and observed data* $\{\boldsymbol{w}, \boldsymbol{k}_{sm}, \boldsymbol{K}, \boldsymbol{\tau}, \boldsymbol{l}, \boldsymbol{\ell}, \boldsymbol{\mathcal{L}}\}$*, there exists a unique (up to a scale normalization) set of fundamentals* $\{\boldsymbol{A}, \tilde{\boldsymbol{c}}\}$ *and unobserved endogenous objects* $\{\boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}, \boldsymbol{k}_{lg}\}$ *that rationalize the observed data as an equilibrium of the model.*

Proof. See Online Appendix B. □

As part of the proof, I provide a step-by-step guide on how to invert the model, given observed data. The proof proceeds by showing that each step of this process is unique.

3.7 Model Extensions

The model presented in this section focuses on banks' provision of credit to small firms, and abstracts away from banks' decisions on the rest of their balance sheet. This is, of course, a significant simplification of the problem solved by banks, and abstracts from how banks' lending choices interact with the formation of the rest of their balance sheet. In Online Appendix B.1, I extend the model to endogenize banks' entire balance sheets, including endogenous deposit rates and quantities, access to wholesale funding markets and inter-bank lending markets, and an additional outside investment to use to park excess cash, using standard techniques in the literature (see, e.g. Wang et al. 2022). This model extension allows for a rich set of forces to impact the equilibrium outcomes of shocks to the banking sector, and leads to strong general equilibrium interactions between aggregate funding conditions, banks' spatial lending networks, and the spatial allocation of production in the economy.

However, I show that, for the results presented in Section 5 of this paper, this extended model is isomorphic to my baseline model.[21] This is because of two critical features which

[21] In addition, the structural equations presented in Section 4.2 which are used for estimation are unchanged in the extended model, implying that estimation results would not differ for the extended model.

my baseline model captures. First, the baseline model can implement any liability structure shocks, including shocks to non-deposit liabilities such as inter-bank borrowing volumes. While the baseline model treats these as exogenous shocks, this extension shows that it is straightforward to generate these shocks endogenously, as well as uniquely invert observed shocks from the data. Second, the model can match the predictions of having additional assets to invest in because the market power mechanism in the model implies that the optimal marginal propensity to lend by banks to firms is less than one.[22] In other words, the baseline model generates the buffer-stock feature of bank balance sheets, where bank lending does not move one-to-one with bank deposit inflows and outflows, and the magnitude of buffering behavior is pinned down by the structural parameters. All together, while the extended model can consider a broader set of shocks than the baseline model presented in this section, I intentionally leave the baseline model simpler to ensure that the critical underlying forces behind my results are clear.

4 Model Estimation

The model requires estimates of four novel parameters, $\{\theta, \epsilon_{sm}, \epsilon_{lg}, \alpha\}$. However, Proposition 2 implies that estimation via simple OLS regressions is not identified, since any regression coefficient can be rationalized by any set of parameter values. This implies that the model requires an instrument to identify the parameters. In this section, I provide a set of four linear structural equations from the model that jointly pin down my parameters. I then describe how I measure critical quantities employing data as well as a single instrument that can estimate all of these parameters jointly. Finally, I use the model to replicate findings from the literature on the 2008 financial crisis, showing that the model can predict the regional lending and output responses to heterogeneous, bank-specific shocks.

4.1 Data and Measurement

The model requires a number of datasets for measuring key model objects. Below, I provide a description of the various data sources I use to measure these in the estimation procedure.

Bank Data. The model requires measurement of bank balance sheet variables, lending footprints, and locations. For my baseline model, I consider banks which report the CRA lending data described in Section 2. I use the CRA lending data to measure small-firm lending for each county in the US. Call report data provide bank-level data on deposit volumes, small-

[22] Given the parameter estimates in Section 4, the model predicts that, for a (proportional) one dollar deposit inflow into the set of banks I consider, aggregate lending to firms would increase by 16.5 cents.

and large-business lending volume, and total assets. I measure baseline non-deposit lending capacity as non-deposit liabilities plus bank equity.

Regional Data. The critical regional dataset for my analysis comes from the Statistics on US Businesses (SUSB) report from the US Census. This report provides me with county-level employment, wages, and total receipts as a measure of output for establishments of small and large firms separately. Splitting employment by firm size, rather than by establishment size, is critical for my purposes, because financing decisions are made at the firm level (Stein 1997). I use the conventional definition that any firm with less than 500 employees is a small firm, and any firm with 500 or more employees is a large firm (SBA 2023). I supplement the SUSB data with an additional measure of county-level aggregates from the Quarterly Census of Employment and Wages. Finally, I use TIGER/Line Shapefiles to measure distance between regions to calibrate trade costs, setting them equal to $\tau_{ni} = dist_{ni}^{\psi}$, where $\psi = \frac{1.23}{\Phi}$ is set to match the empirical relationship between inter-regional trade and distance reported in Monte et al. (2018).

Instrument Construction. To construct an instrument, I collect fracking well discovery dates from Gilje (2019). I collect banks' deposit footprints from Summary of Deposits data released by the FDIC.

4.2 Structural Equations

In this section, I provide a set of structural equations that pin down the main structural parameters of the model. I also describe the estimation procedure. I focus my estimation on the novel parameters in my model $(\theta, \epsilon_{lg}, \epsilon_{sm}, \alpha)$ and calibrate $\Phi = 5$ consistent with the range of trade elasticities estimated in the literature (see, e.g., Caliendo and Parro 2015).

Bank-Specific Lending. First, I consider bank-specific lending moments. Manipulating equations (14) and (15) gives the pair of structural equations:

$$lnk_j = \theta\epsilon_{lg}\ell_j + \delta - \epsilon_{lg}\tilde{c}_{j,lg}, \tag{18}$$

and

$$lnk_{nj} = \theta\epsilon_{sm}\ell_j + \delta_n - \epsilon_{sm}\tilde{c}_{n,sm,j}, \tag{19}$$

where k_{nj} is total lending by bank j to small firms in region n, k_j is total lending by bank j to large firms, and the δ terms capture market-level credit demand, competition with other banks, and aggregate scale constants which drop out in the normalization of the

model. For these equations, non-financial cost advantages $\{\tilde{c}_j, \tilde{c}_{nj}\}$ are the structural error terms. To match equation (19) to equation (18), I weight the corresponding regression by within-bank lending shares. These two equations capture bank-specific lending responses to lending capacity shocks.

Regional Aggregates. Next, I consider region-specific structural equations. Given the structure of my model, I focus on the equilibrium conditions for small firms. First, I consider the effect of lending capacity shocks on local small firm credit. Taking a first-order approximation of equation (15), plugging in equation (14), and combining with Cobb-Douglass production gives:

$$\Delta ln k_{n,sm} = \theta \sum_j s_{n,sm,j} \Delta ln \ell_j + \frac{\alpha}{1-\alpha} \Delta ln \left(w_{n,sm} l_{n,sm} \right) + \sum_j s_{n,sm,j} \Delta \tilde{c}_{nj}. \tag{20}$$

For this equation, the weighted average non-financial cost advantage $\sum_j s_{nj} \Delta \tilde{c}_{nj}$ serves as the structural error term.

Similarly, plugging equation (7) into (11), imposing Cobb-Douglas production, and differencing the equation gives an equation for the change in the value of output from small firms in location n:

$$\Delta ln y_{n,sm} p_{n,sm} = \frac{\Phi \alpha}{1+\Phi} \Delta ln k_{n,sm} + \frac{1}{1+\Phi} \Delta ln \left(\sum_i \sum_t \left(\frac{\tau_{ni}}{P_i} \right)^{-\Phi} l_{it} w_{it} \right) + \frac{\Phi}{1+\Phi} \Delta ln A_{n,sm}, \tag{21}$$

where $\frac{1}{1+\Phi} \Delta ln \left(\sum_i \sum_t \left(\frac{\tau_{ni}}{P_i} \right)^{-\Phi} l_{it} w_{it} \right)$ is a "market access" term (Donaldson and Hornbeck 2016) that captures goods demand and competition from other producers, and where the change in the deterministic component of regional productivity, $\frac{\Phi}{1+\Phi} ln A_{ns}$, serves as the structural error term for the equation.[23] I weight equations (20) and (21) by county employment to deal with the extreme heterogeneity in county sizes.

4.3 Instrument Description

Equations (18) through (21) jointly pin down the key structural parameters of the model. Direct estimation via OLS is likely to be contaminated in multiple ways. First, efficient banks, with lower nonfinancial lending costs, are likely to take action to grow their deposit

[23] In my model, the market access term, $\frac{1}{1+\Phi} \Delta ln \left(\sum_i \sum_t \left(\frac{\tau_{ni}}{P_i} \right)^{-\Phi} l_{it} w_{it} \right)$, is fully captured by output responses of local large firms. Thus, to implement this in the regressions, I simply include large firm output responses as a control variable in my regressions. This has the added benefit of relaxing the model's precise demand functional form for a weaker symmetry assumption between small and large firms.

bases and thus their lending capacity. For example, they could raise deposit interest rates, expand their branch networks, or anticipate future deposit inflows to set expansion plans. This motivates the use of an instrument for which bank strategic decisions are unlikely to impact exposure (to the instrument). Second, regions that grow due to TFP shocks increase their credit demand in general equilibrium, generating an additional econometric endogeneity problem for regional aggregates.

In line with my empirical setting, which focuses on small and midsize banks during the 2023 regional bank panic, I explore instruments derived from deposit shocks to small and midsize banks. Inspired by Gilje et al. (2016), I leverage fracking well openings as shocks to local banks' deposit bases.[24] Intuitively, banks with pre-existing branches in counties where fracking wells are discovered experience substantial deposit inflows following well openings, driven by local wage increases and payments to mineral rights holders. This approach has the advantage that I can identify all of the parameters in one, internally consistent natural experiment. A critical facet of the fracking boom is that it relied largely on *unanticipated* technological breakthroughs. The first fracking well discovery in the sample was in 2003, so I lag banks' deposit footprints to 2002 to deal with strategic investment concerns by banks. Further, while fracking does increase regional TFP in the regions where wells were discovered, by exploiting banks' internal capital markets, I can study region-level lending and output responses in distant counties where there was no opening of a fracking well. Specifically, I exclude counties where fracking wells opened from the sample when I estimate equations (20) and (21).

Figure 3 demonstrates the "first stage" relevance of these instruments by showing that there are significant county-level deposit inflows into fracking counties following the discoveries of fracking wells. The figure shows the event study graph corresponding to the stacked difference-in-differences regression specification

$$lnDep_{iyt} = \delta_{iy} + \delta_{yt} + \gamma Discovery_{iy} * post_{yt} + \epsilon_{iyt} \tag{22}$$

for county i, discovery year y, and year t, with (interacted) fixed effects δ_{iy} and δ_{yt}, and difference-in-differences coefficient γ.

Given this result, I use difference-in-differences variation in deposit inflows resulting from banks' 2002 deposit shares in counties where a fracking well was eventually discovered as an instrument in equations (18) and (19). To aggregate this up to the region level for equations (20) and (21), I use 5-year average small-firm lending shares from 1998 to 2002 to

[24]The SUSB data are released with a three-year lag, and only contain a subset of the variables outside of the quinquennial economic census. This necessitates the use of historical shocks, such as the fracking boom, as opposed to recent shocks, including the 2023 regional bank panic, to estimate the model.

construct a weighted average of the bank-specific exposure measures. I provide more detail in Online Appendix C.

4.4 Structural Parameters

Table 3 presents the estimates of the structural parameters of the model with GMM standard errors. The estimated value of $\theta = 1.14$ indicates moderately strong financial constraints in banks' lending costs. The elasticity of substitution for small firms, $\epsilon_{sm} = 2.06$, indicates that it is very difficult for small firms to substitute across banks, consistent with a large empirical literature on relationship lending (e.g., Petersen and Rajan 1994; Khwaja and Mian 2008; Chodorow-Reich 2014). For large firms, the estimated elasticity of $\epsilon_{lg} = 2.87$ indicates substantially more substitution across banks by large firms, and is roughly consistent with benchmark values in the literature (see, e.g., Kleinman et al. 2023). Finally, the estimated output elasticity of $\alpha = .58$ indicates an important role for bank loans in individual firms' output, and is consistent with large, local amplification effects of credit supply shocks (e.g., Huber 2018; Mian et al. 2023).

4.5 Validation

To validate my estimated model, and provide evidence of external validity for the parameter estimates, I now use the estimated model to predict the effects of historical, bank-specific shocks and compare them to actual results in the literature. In particular, I focus on Chen et al. (2017) (CHS), since they document a relatively clean set of bank-specific lending shocks and trace out the regional lending and output impacts of these shocks. CHS document that the Big 4 banks (JP Morgan, Bank of America, Wells Fargo, Citibank) decreased their small-firm lending activity across all regions during the 2008 financial crisis due to bank-level strategic objectives and underperformance of the small-firm lending business line. Subsequently, markets that relied heavily on the Big 4 saw their aggregate lending decline, which was followed by decreases in regional aggregate payrolls. The CHS shock is a particularly valuable test for the model and external validity, because it uses parameters estimated from a positive shock to small banks during normal times to predict equilibrium outcomes resulting from a negative shock to large banks during a financial crisis. To implement the CHS shock in my model, I compute a baseline 2007 economy, shock nonfinancial lending ($\tilde{c}_{ijs}$) ability for the Big 4 banks, and replicate regressions from CHS in the model-generated data. I provide more detail in Online Appendix C.2

I test the ability of the model to replicate two key moments from CHS. First, I replicate county-level lending responses to bank-specific shocks. For this test, the model-implied

regression coefficient is -19.6%, which is similar to the point estimate of -21.7 from CHS and well within the 95% confidence interval of $[-32.74\%, -10.60\%]$. Second, I test the model's ability to replicate county-level output responses. Running the regression in my model, I obtain an output elasticity to credit supply shocks of 0.34, which is slightly smaller than the corresponding point estimate from results in CHS of 0.41, but well within a 95% confidence interval of $[.20, .62]$. These results show the generality of the modeling framework developed in Section 3, and show that, despite its simplicity, it is still well suited to studying the real effect of negative shocks, even during financial crises.

5 The 2023 Regional Banking Panic

My estimated model allows me to study the real consequences of deposit flows during the 2023 regional bank panic. I set my baseline economy to December 2022. First, I document that actual changes in lending and deposit flows during this period are strongly related to measures of banks' lending opportunities obtained from my estimated model. Next, I feed my baseline economy with deposit shocks, starting with a *counterfactual*, *proportional* deposit outflow, and sequentially building up to capture all *actual*, *bank-specific* deposit flows. Importantly, I assess the real effects of deposit reallocation during the panic—from banks with poor lending opportunities to those with good lending opportunities. Finally, I decompose the (positive) effect of this reallocation into an "outflow effect" (deposits flowing out of banks with poor lending opportunities) and an "inflow effect" (deposits flowing into banks with above-average lending opportunities). I provide additional detail on measurement of the deposit shocks and the baseline economy in Online Appendix A.

5.1 Deposit Flows, Lending, and Lending Opportunities

Before imposing the full general equilibrium structure of my model, I use the regional bank panic to study the association between actual deposit flows, actual changes in lending, and marginal lending opportunities implied by my model. First, to provide additional validation for my model, I show that ex-ante marginal lending opportunities, measured using the structure of my model, predict lending responses to deposit flows during the regional bank panic. Having validated these marginal lending opportunities, I show that these same lending opportunities predict deposit flows during the panic as well. Finally, I show that my main results on deposit flows and rates are robust to an additional marginal investment opportunity measure, derived from production function estimation results in Egan et al. (2022).

Additional Model Validation. A critical, testable prediction of my estimated model is that—given the same deposit inflow—banks with good marginal lending opportunities will tend to increase lending by more than banks with poor marginal lending opportunities. The regional bank panic provides a set of bank-specific in deposit flows to test this prediction. Using call report data, I measure 6 month realized changes in lending and deposits at the bank level from December 2022 to June 2023 for each bank in my sample. I then use cross-bank variation to test the model predictions. First, consider regional banks that saw deposit inflows during the panic. In aggregate, these banks increased their lending to firms by 23 cents per dollar of deposit inflows. However, regional banks that saw deposit inflows *and* had above-median ex-ante marginal lending opportunities increased their lending by 46 cents per dollar of deposit inflows, compared to only 15 cents for regional banks with below-median ex-ante marginal lending opportunities. As a regression-based version of this test, I estimate the following regression equation using OLS:

$$y_j = \alpha + \beta MLO_{j,Dec22} + \gamma X_j + \epsilon_j, \tag{23}$$

where y_j is the outcome of interest (percent change in lending to firms) and $MLO_{j,Dec22}$ is the model-implied bank-specific measure of marginal lending opportunities in the baseline economy (December 2022), with controls X_j for bank size (indicator for regional bank, national bank, and log assets) and realized, bank-level deposit flows. Table 4 provides the results. As with the aggregate lending result above, better ex-ante marginal lending opportunities are associated with a relative increase in lending, with or without the additional control variables.

Deposit Flows and Lending Opportunities. Given the evidence presented above to validate the model-implied marginal lending opportunities, I seek to understand whether observed deposit flows during the panic also reflected banks' marginal lending opportunities. Using my model, I measure the quality of each bank's marginal lending opportunities in the baseline economy using equation (17). In the data, I measure each banks' deposit rate in December 2022 and 6-month realized deposit changes for each bank in my sample from December 2022 to June 2023. Motivated by Section 2.2, I separate out deposit flows into realized changes in uninsured deposits, which tended to be outflows during this period, and insured deposits, which tended to be inflows during this period. To examine the association between marginal lending opportunities and either deposit flows or deposit rates, I estimate regression equation (23) using OLS, with outcome variables for insured deposit flows, uninsured deposit flows, and deposit rates as of December 2022, and with controls for bank size (indicator for regional bank, national bank, and log assets); for the deposit flows

regressions, I also include book tier 1 leverage and unrealized losses on held-for-sale securities as measures of security portfolio stress, as well as the percent change in the other insurance category of deposits.

Panel A of Table 5 provides the results. Column 1 shows that banks with better lending opportunities saw larger inflows into their insured deposits, and column 2 shows that these banks also saw smaller outflows from their uninsured deposits. These effects are economically large: a bank earning one additional percentage point of income off a marginal dollar in deposits saw an additional insured deposit inflow of 2.91 percent. Finally, column 3 presents the results from regressing banks' deposit rates in the data on the model-implied measure of marginal lending opportunities. This relationship is also strong and positive, consistent with simple forces of bank profit maximization: all else equal, we would expect banks with better lending opportunities to offer higher deposit rates so as to attract additional funding.

Robustness. To show that these results are not unique to my model, nor driven by my focus on lending to firms, I turn to the literature to construct an alternative measure of marginal investment opportunities. Specifically, I turn to Egan et al. (2022), who use IO-style production function estimation techniques to estimate bank-specific return curves as a function of their total assets. The authors assume that banks allocate their assets a_j to investment opportunities to generate total interest income inc_j with a production function $inc_j = f_j(a_j; \Theta)$, where Θ is a set of estimated parameters.[25] Differentiating the production function with respect to total assets provides a measure of banks' investment opportunities. While this measure is not directly informative about real effects, it is based on the same underlying forces, derived from a different source of variation (accounting data rather than regional data), and is a comprehensive measure of banks' investment opportunities.

Panel B of Table 5 presents the results from regression equation (23), replacing my model-implied measure of banks' marginal lending opportunities with the measure implied by Egan et al. (2022). Similar to my model-implied measure, banks with better investment opportunities saw larger inflows into insured deposits and smaller outflows from uninsured deposits, and they offer notably higher deposit rates.

5.2 Aggregate Effects

My model allows me to quantify the aggregate real effects of the deposit flows surrounding the 2023 regional bank panic. Starting from my baseline economy, I feed into the model 6-month bank-level deposit changes from December 2022 to June 2023, compute the new

[25] In particular, Egan et al. (2022) assume that f_j is an isoelastic production function with bank-specific lending productivity A_j, controlling for various measures of noninterest cost and risk.

equilibrium, and calculate the corresponding change in aggregate real output. Leveraging the model's ability to accept as "inputs" any (observed or counterfactual) deposit flows, I sequentially move from a purely aggregate, proportional deposit outflow to the actual, observed bank-specific deposit flows during the panic. By successively adding heterogeneity to the deposit shock, I am able to study the underlying forces that drive the aggregate effect. Importantly, by construction, each (counterfactual) deposit shock leads to the same *aggregate* deposit outflow, so differences in aggregate real effects between the deposit shocks are solely driven by variation in the shocks *across* banks. In Table 6, I provide a summary of the different deposit shocks, and also the aggregate real effects.[26]

I start with a simple, proportional deposit outflow, where all banks in my model experience a 3% deposit outflow to match the observed aggregate deposit outflow experienced by banks over this period ("shock 1"). This provides a simple benchmark for comparison to other results. I find that this (counterfactual) proportional outflow generates a 1.56% contraction in aggregate real output, consistent with an important role of aggregate bank funding conditions for lending and the real economy. Next, I account for heterogeneity across bank size groups. Specifically, I allow for banks in each size group to experience a different deposit outflow ("shock 2"), holding aggregate outflows constant. This shock has regional banks experiencing much larger negative deposit flows than either community banks or national banks. Shock 2 induces a contraction in aggregate real output of 1.85%, consistent with popular concerns that shocks to regional banks could be particularly deleterious for the real economy.[27] Finally, I feed into my model the actual, observed bank-specific deposit flows ("shock 3"). Importantly, shock 3 now includes the large-scale reallocation of deposits within the regional banking sector. Compared to the previous shock(s), the effect on output is markedly different, as aggregate real output now contracts by only 0.2%.[28]

[26]The by-size group effects in Table 6 do not exactly match the summary statistics from Table 1 for community banks. This is because the CRA data exclude tiny community banks with less than $1 billion in assets.

[27]Counterfactual deposit shocks 1 and 2 should be viewed as a benchmark for my reallocation results, rather than a comprehensive analysis of *all* of the potential negative effects of the 2023 region banking panic. On one hand, there are channels beyond deposit financing and lending to firms that can lead bank panics to have negative effects (see, e.g., Baron et al. 2021). On the other hand, aggregate trends during this period could have influenced the magnitude of the aggregate deposit outflow, such as monetary policy tightening (e.g., Drechsler et al. 2017). Finally, the counterfactual intentionally shuts off certain mitigation forces, such as the ability of shocked banks to partially substitute to the wholesale funding market, which could again significantly mitigate a version of the panic where all regional banks saw proportional outflows. The extensions to the model presented in Appendix B.1 show how the modeling framework can capture these forces, when the primary goal of the analysis is to quantify an aggregate shock to the banking system.

[28]In principle, one could separate out the deposit reallocations within community and national banks from the reallocation within regional banks. Specifically, one could implement a version of shock 3 where community and national banks are assigned their actual, bank-specific deposit flows while all regional banks experience a proportional deposit outflow of 5.39%, as in shock 2. When implementing this shock in my model, I find that real output contracts by 1.79%, which is very close to the 1.85% contraction from shock

Understanding the Positive Reallocation Effect. Next, I seek to understand the stark difference between the "popular" view of the 2023 regional bank panic (shock 2 above) and the full effect of the panic taking into account the actual, realized deposit flows, including the within-regional bank reallocation (shock 3). One decomposition that is particularly informative is separating between deposit outflows and inflows. One one hand, banks that experienced outflows during the panic, such as SVB, may have had *particularly* poor lending opportunities, in which case (almost) any reallocation away from those banks would have been positive ("outflow effect"). On the other hand, banks that experienced large deposit inflows may have had particularly good lending opportunities ("inflow effect"). If the overall effect of the deposit reallocation was mainly driven by the outflow effect, that is, by the *specific* set of banks that were "shocked" during the 2023 regional bank panic, then my results might be less informative for future crises. By contrast, if the overall effect was driven by the inflow effect, this might point to more fundamental economic forces—deposits flowing towards banks with good marginal lending opportunities, which are able to attract new depositors by offering higher yields—and thus, my results would have implications that go well beyond this specific panic episode.

I first quantify the outflow effect. This exercise requires a bank-specific measure of gross outflows rather than net outflows, which could be affected by the inflow effect. Motivated by the evidence in Section 2.2, I use bank-specific uninsured deposit flows as my measure of outflows. Specifically, I compare the outflows from banks that *actually* experienced the outflows (such as SVB) with a counterfactual, proportional outflow across all banks, holding total outflow volume constant for each bank size group. In other words, I am asking what the effect on output would have been if all banks within a given size group (including those with good lending opportunities) had experienced the same proportional outflow, as opposed to the actual, bank-specific outflows observed in the data. By construction, both shocks represent a deposit outflow, and thus decrease output in my model. However, I find that the actual, bank-specific outflows decrease output by 0.8 percentage points *less* than the proportional outflow does. Hence, part of the gap between the "popular" view on the regional bank panic and the actual, bank-specific deposit flows is driven by the shocked banks, such as SVB, having poor lending opportunities.

Next, I quantify the inflow effect. Given my choice of bank-specific outflows from uninsured deposits, mechanically, the relevant set of inflows to consider is bank-specific flows into insured deposits. I compute the counterfactual, proportional inflow across all banks using the same method as above. I find that the actual, bank-specific inflows increase output by 1.11

2. Thus, what matters for aggregate output is the reallocation within *regional* banks, not the reallocation within community and national banks.

percentage points *more* than a proportional inflow across all banks would have.[29] This effect is larger than the outflow effect, pointing to an important role for fundamental economic forces, rather than the specific set of shocked banks, in the realized deposit reallocation. Finally, comparing the inflow effect with the aggregate effect from shock 2 implies that the reallocation of deposits towards banks with good lending opportunities offsets about 60% of the otherwise negative effects of deposit flows during the panic.

Rationalizing the Positive Inflow Effect. In Online Appendix B.4, I provide a simple model of depositor behavior and bank rate setting which rationalizes the positive inflow effect. The key mechanism is sticky depositors. In general, depositors are sticky because of their pre-existing relationships, inattention, fixed costs to open deposit accounts, or other, similar forces. Thus, in normal times, depositors exhibit limited responses to changes in other banks' deposit rates. However, when a shock to the existing relationship—e.g., driven by concerns about bank failure—"unsticks" depositors, they become more sensitive to fundamental characteristics of deposit accounts, including the offered deposit rate. Thus, "unstuck" depositors become effectively more price elastic than average depositors, which leads them to gravitate towards banks which offer higher deposit rates. All else equal, banks with better marginal lending opportunities will offer higher rates on their deposits, leading to an overall positive reallocation. Notably, this rationalization is based on general economic forces, rather than being specific to the 2023 regional bank panic. Beyond my setting, banks' marginal lending opportunities may differ for reasons not limited to regional lending footprints, and consumers may become unstuck for reasons other than those emphasized here. Given this explanation, other events that lead consumers to become unstuck would lead them to re-allocate their savings toward banks with better lending opportunities in a similar fashion as described here, to the extent that these better lending opportunities are reflected in higher deposit rates.

Can the magnitude of the inflow effect presented in Table 5 be explained by a plausibly sized shock to price sensitivity? To benchmark this, consider a simple logit demand framework for deposits, where bank j's deposit volume follows $lnD_j = lnD_0 + \alpha\left(r_j - r_0\right) + \left(\xi_j - \xi_0\right)$,for offered deposit rate r_j, "quality" ξ_j (e.g. service quality, branch networks, failure risk), and "bank 0" is the outside option (e.g., money market funds).[30] If there is a shock to

[29] Adding up the outflow and inflow effects yields 0.8 + 1.11 = 1.91, which is slightly larger than the 1.65 percentage point difference between shocks 2 and 3 above. In my model, shocks are not exactly additive separable, because banks influence each others' lending opportunities through lending competition and the spatial footprint of production.

[30] For additional details on a logit deposit demand setup, see Online Appendix B.1

both α and ξ, we get:

$$\Delta lnD_j = \Delta lnD_0 - \Delta\alpha * r_0 - \Delta\xi_0 + \Delta\alpha * r_j + \Delta\xi_j. \tag{24}$$

Equation (24) is a regression equation where the intercept is $\Delta lnD_0 - \Delta\alpha * r_0 - \Delta\xi_0$, the key variable of interest is r_j, and the structural error is $\Delta\xi_j$. Direct estimation of this regression could be subject to econometric endogeneity concerns, where ex-ante low rate banks like SVB saw large deposit outflows due to failure risk shocks. However, the Wald estimator (Wald 1940) can be used to convert the regression results from panel A in Table 5 to an IV coefficient on the change in (logit) deposit price sensitivity, giving an upper bound of how much deposit price sensitivities would have to increase to generate this reallocation.[31] The resulting implied change in price coefficient is 45. Comparing this to a baseline deposit price sensitivity estimates from Wang et al. 2022, which gives a mean price coefficient of 96.8, implies that price sensitivities going up by 47% could generate this result. This simple calculation shows that even moderate increases in price sensitivity can generate a positive inflow effect of similar magnitude to what is observed during this panic.

Spatial Tilt of Deposit Flows. Finally, I consider the spatial tilt of realized deposit flows. It is well documented that bank depositors have heavily spatially sensitive demand functions, suggesting that competition heavily influences within-county deposit reallocations (see, e.g., Dick 2008; Ho and Ishii 2011).[32] Thus, isolating the within-county reallocation can inform the importance of general, competitive forces to the positive reallocation effect. Motivated by this, I construct an alternative version of the deposit shocks that match the aggregate intensity and spatial distribution of deposit outflows, but ignore bank identities and lending networks. I use the bank branch-level deposit data from the Summary of Deposits report to construct county-level deposit shocks, which I then pass to the model as county-level funding shocks. Specifically, I set $c'_{n,sm,j} = c_{n,sm,j}\left(\frac{\Delta d_n}{\ell_n} + 1\right)^{-\theta}$ for county-level lending capacity ℓ_n

[31] Estimating this with the insured deposit price flows mitigates concerns that the deposit flow estimates in Table 5 are driven by shocks to failure risk, as insured deposit flows tend not to be sensitive to this risk (Egan et al. 2017). On the other hand, this exercise should be interpreted as a rough upper bound, both because the estimates in panel B imply a substantially smaller change in price sensitivity of depositors, and also because banks with better model-implied ex-ante marginal lending opportunities also tended to increase their deposit rates over the panic window, which could have also attracted depositors, depending on the timing of the rate increases.

[32] Formally, deposit reallocations can by decomposed into a within-county reallocation $\sum_i \left|\sum_j \Delta d_{ij}\right| - \left|\sum_i \sum_j \Delta d_{ij}\right|$ and across-county reallocation $\sum_i \sum_j |\Delta d_{ij}| - \sum_i \left|\sum_j \Delta d_{ij}\right|$. Slightly more than half (55%) of the observed deposit reallocation is a within-county reallocation. Notably, due to banks' flexibility in how they assign deposits to branches, and particularly online deposits, this decomposition is likely to understate the degree to which the observed reallocation is within-county. For the model presented in Section 3, this is not an issue, given the underlying assumption of efficient internal capital markets.

with realized deposit flows Δd_n for all n, j.[33] This results in a contraction of -1.85%, which is essentially identical to the aggregate contraction reported in Table 6 for shock 2. This shows that the positive reallocation effect is not driven by spatial reallocation of deposits, but rather reallocation of deposits within a county to banks with better marginal lending opportunities.

6 Conclusion

I develop and estimate a quantitative spatial general equilibrium model which nests banks' spatial lending networks into a framework with production and consumption. The model features a rich underlying geography of lending and production, which allows it to generate realistic bank-to-county output responses and substitution by firms between banks in general equilibrium. Despite all this richness, the model remains highly tractable and admits a transparent estimation strategy. To my knowledge, this is the first paper to nest banks' spatial lending footprints into a quantitative spatial model with production.

In my main application, I use my estimated model to study the 2023 regional bank panic. In the data, I show that the panic coincided with a massive reallocation of deposits *within* the regional banking sector. Using a model-implied measure of banks' marginal lending opportunities, I show that this reallocation involved deposits flowing from regional banks with relatively poor lending opportunities to banks with relatively good lending opportunities (which, in the data, offered higher deposit rates). Consistent with this positive reallocation effect, I find that feeding actual, bank-specific deposit flows of regional banks into my model substantially *increases* real output, softening the otherwise negative effects of aggregate deposit outflows and other deposit flows during the panic episode. This central finding of my paper highlights the important role of the *cross-sectional* allocation of deposits (in addition to aggregate deposit volume) for aggregate, real outcomes.

While my application focuses mainly on the real implications of the cross-sectional allocation (and reallocation) of deposits within the banking system, my modeling framework is much more general. One illustration of this generality is a validation exercise in which I show that the model can match the output effects of historical, bank-specific strategic decisions. Beyond that, the model could be used to study policy affecting banks' funding capacities, such as the Troubled Asset Relief Program, both for ex-ante experimentation and ex-post evaluation. Finally, simple extensions of the model could account for endogenous

[33] To ensure that my results are most directly comparable to Shock 2 from Table 6, I hold the aggregate shock to national lending markets constant. However, if I construct alternative versions of shock 2 and this shock where there is no direct effect in the national market, my results are extremely similar. I provide more detail on measurement in Online Appendix A.

balance sheet formation, various other lending markets, or bank non-bank competition, allowing for additional richness in model outputs. Altogether, I believe the modeling framework I develop in this paper has broad applicability to evaluating and quantifying the special role played by banks in the real economy.

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Figure 1: Aggregate Changes in Insured and Uninsured Deposits

This figure shows quarter-over-quarter changes in total insured and uninsured deposits from Q2 2018 to Q2 2023. The dotted line marks the start of the 2023 regional bank panic.



Figure 2: Small Firm Lending and Distance

This figure shows the average log market share in the county-level, small-firm lending market for community, regional, and national banks based on distance from the nearest branch to the business. Averages are taken from 2015 to 2019. Distance is calculated as the haversine distance between the nearest bank branch and the county-level centroid. All banks with a branch inside the focal county are grouped into "local" bucket.

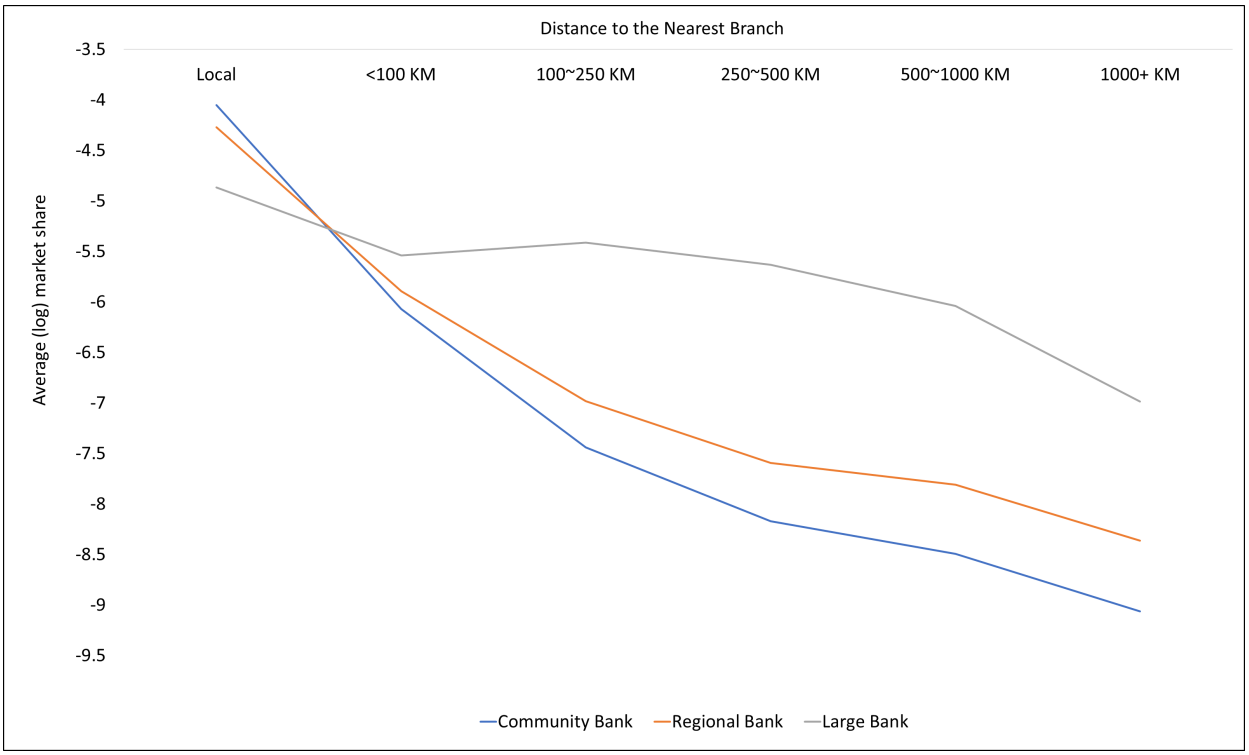


Figure 3: Fracking Well Discoveries and Deposit Inflows

This figure shows the event-study graph corresponding to the stacked difference-in-differences regression specification in equation (22). Error bars represent 95% confidence intervals. Standard errors are double clustered at the year and county level.

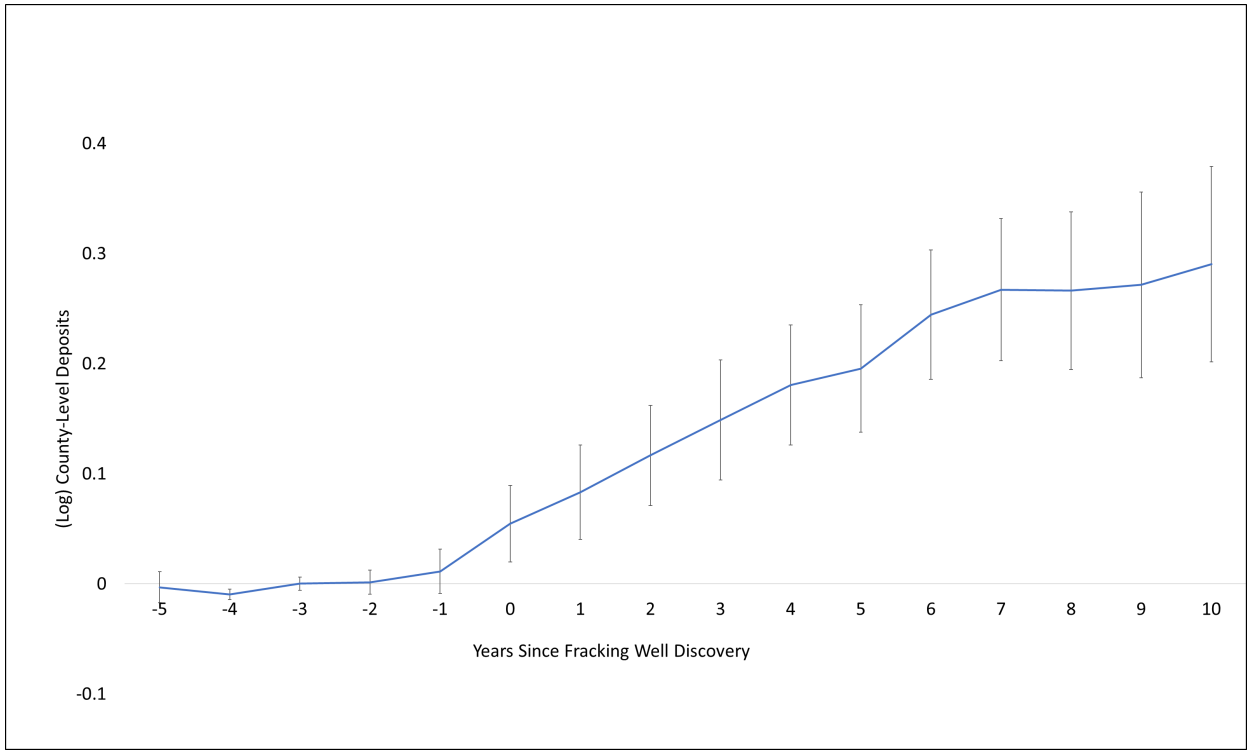


Table 1: Deposit Flows by Bank Size Group

This table provides summary statistics on deposit flows during the 2023 regional bank panic by bank size group. Deposit flows are measured in billions of dollars. Columns 1 through 3 provide net deposit flows (inflows minus outflows). Columns 4 and 5 provide measures of gross inflows and outflows. Gross inflows are calculated as the total inflow of deposits to banks which experienced a net inflow of deposits; gross outflows are calculated as the total outflow of deposits from banks which experienced a net outflow of deposits.

	(1)	(2)	(3)	(4)	(5)
Bank Size	All	Uninsured	Insured	Gross Outflow	Gross Inflow
Community Banks	-8	-56	+47	-76	+68
Regional Banks	-436	-700	+264	-814	+379
National Banks	-84	-320	+236	-138	+54
Total	-528	-1076	+547	-1028	+500

Table 2: Descriptive Statistics

This table provides summary statistics on bank lending to firms by bank size group. Variables are measured as of December 2022.

	N	Mean	StDev	P10	P90
Panel A: Community banks					
Firm loans to assets	4483	23.0%	14.9%	5.4%	43.6%
Firm loans to total loans	4483	38.7%	21.3%	12.9%	65.9%
Small firm loans to total firm loans	4369	55.7%	28.1%	20.7%	100%
Panel B: Regional Banks					
Firm loans to assets	266	28.7%	15.4%	2.3%	46.1%
Firm loans to total loans	266	43.7%	21.0%	10.3%	67.5%
Small firm loans to total firm loans	254	16.9%	16.4%	3.0%	30.3%
Panel C: National Banks					
Firm loans to assets	6	8.2%	4.7%	3.5%	15.3%
Firm loans to total loans	6	20.9%	8.8%	11.0%	33.3%
Small firm loans to total firm loans	6	9.0%	5.6%	1.2%	15.8%

Table 3: Structural Parameter Estimates

This table provides estimates of the structural parameters along with GMM standard errors. θ governs the importance of banks' financial frictions for lending costs. ϵ governs the elasticity of substitution by firms of size $s \in \{sm, lg\}$ between banks. α governs the elasticity of output responses to credit supply shocks. The parameters and estimation procedure are described in Sections 3-4.

Parameter	Estimate	Standard Error
θ	1.14	0.24
ϵ_{sm}	2.06	0.59
ϵ_{lg}	2.87	0.30
α	0.58	0.15

Table 4: Marginal Lending Opportunities and Lending

This table presents the results from regressing percent changes in total loans to firms from from December 2022 to June 2023 on marginal lending opportunities measured in December 2022. Marginal lending opportunities are measured following Equation (17). Only the main coefficients of interest are shown. In both regressions, the sample is restricted to banks included in the baseline model. Robust standard errors are shown in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel A: Model		
	(1) % Change Loans	(2) % Change Loans
Marginal Lending Opportunity	0.62*** (0.19)	0.49** (0.19)
Additional Controls	No	Yes
R^2	2.3%	4.6%
Observations	570	570

Table 5: Marginal Lending Opportunities and Deposit Flows

This table presents the results from regressing deposit flows from December 2022 to June 2023 and deposit rates in December 2022 on marginal lending opportunities measured in December 2022. Panel A uses the model-implied measure of marginal lending opportunities as described in equation (17). Panel B measures marginal lending opportunities using production function estimation results from Egan et al. (2022). Only the main coefficients of interest are shown. In both regressions, the sample is restricted to banks included in the baseline model. Robust standard errors are shown in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

Panel A: Model			
	(1) % Change Insured Deposits	(2) % Change Uninsured Deposits	(3) Deposit Rate
Marginal Lending Opportunity	2.91*** (0.38)	2.18** (0.88)	.064*** (0.019)
Additional Controls	Yes	Yes	Yes
R^2	36.4%	29.0%	4.1%
Observations	570	570	557
Panel B: Egan et al. (2022)			
	(1) % Change Insured Deposits	(2) % Change Uninsured Deposits	(3) Deposit Rate
Marginal Lending Opportunity	4.10*** (1.01)	5.89*** (2.06)	0.37*** (0.041)
Additional Controls	Yes	Yes	Yes
R^2	36.5%	30.4%	30.2%
Observations	558	558	558

Table 6: Aggregate Effects of Bank Deposit Shocks

This table presents the impact of shocks to banks' deposit bases on aggregate real output. Each row corresponds to a different shock in the model. By construction, all shocks generate the same aggregate deposit outflow, so differences in aggregate real effects between the deposit shocks are solely due to variation in the shocks across banks. Columns 1 through 3 show deposit flows associated with a shock, separately for community banks (column 1), regional banks (column 2), and national banks (column 3). For example, shock 2 involves decreasing all regional banks' deposits by 5.39%. "Actual" signifies a deposit shock where banks in the corresponding size category experience their actual, bank-specific deposit flow from the data. Column 4 provides the model-based change in aggregate real output resulting from the corresponding deposit shock.

	(1) Community Banks	(2) Regional Banks	(3) National Banks	(4) Change in Output
Shock 1	-2.98%	-2.98%	-2.98%	**-1.56%**
Shock 2	+1.12%	-5.39%	-0.85%	**-1.85%**
Shock 3	Actual	Actual	Actual	**-0.2%**

Regional Banks, Aggregate Effects

Online Appendix

A Measurement Appendix

A.1 Baseline Economy

To measure bank data, I use a combination of contemporaneous balance sheet data and recent lending data. First, I measure bank balance sheet variables using the call reports as of December 2022. This provides me with contemporaneous stocks of deposits, non-deposit lending capacity, lending to large firms, lending to small firms, and total assets. Second, I use CRA data from 2015 to 2019 to measure within-bank county-level lending shares for small firm lending.[34] Finally, motivated by concerns that CRA data can capture credit card activity rather than new lending (Bord et al. 2021), I drop four regional banks which focus heavily on credit card-based lending.[35]

To measure county-level real activity, I turn to a combination of the SUSB report and the Quarterly Census of Employment and Wages. I measure 2019 employment and wages for each US county for small firms and large firms using the SUSB data. To update these data to 2022, I use the Quarterly Census of Employment and Wages to calculate a 3-year county-level growth rate in payrolls, which I then apply to both small and large firms.

A.2 Bank Variables

The call report requires banks with over one billion dollars in assets to report quarterly estimates of their total deposits, as well as their balances of uninsured deposits. To validate this measure, and provide estimates of uninsured deposit volumes for small, community banks in the descriptive statistics, I construct a second estimate using other reported variables. This alternative estimate consists of all deposit balances held in accounts with balances exceeding \$250K (the FDIC deposit insurance limit), minus the insured balance held in accounts that have a balance exceeding \$250K. The alternative measure is 99% correlated with the bank-supplied measure, supporting both measures. I then construct insured deposits as total bank deposits minus uninsured deposits.

Bank-specific deposit flows require a number of data adjustments for implementation in my model. First, because my model does not include all banks—due to the exclusion of credit card banks and small, community banks—size-group deposit flows in my model do not

[34] When 2022 were not available as-of the end of 2023, as in the case of CRA and SUSB data, I use the most recent available data, excluding 2020 and 2021 due to the transient, distortionary effects of the COVID-19 pandemic on real outcomes and the Paycheck Protection Program on the lending market for small firms.

[35] I drop Capital One, American Express, Discover, and Synchrony. Notably, these four banks saw large net deposit inflows during the 2023 regional bank panic, and have high model-implied marginal lending opportunities. Thus, including these credit card banks makes the real effect of the within-regional bank reallocation to be *even more positive*.

match sector-wide averages. To address this issue, I use a simple, proportional adjustment across banks to ensure that the aggregate deposit outflow is consistent across all shocks, and that size-specific deposit outflows are also consistent across the relevant shocks (shocks 2 to 3). For my regressions, I winsorize bank deposit flows and other flow variables at the 99th percentile, to deal with a handful of extreme outliers likely associated with reporting irregularities.

Second, a handful of banks in my sample acquired other banks in non-government assisted mergers between December 2022 and June 2023. These mergers are likely pre-planned, as they require years of regulator approvals, and thus are exceedingly unlikely to be related to the 2023 regional bank panic. For simplicity, I exclude these banks from my regression samples in Section 5.1, but must make adjustments for implementing deposit shocks in the model. For simplicity, I assume that the acquired bank would have experienced deposit flows based on its size group and insured deposit share. The vast majority of acquired banks were quite small relative to their acquirers, so this adjustment does not have material consequences for my results.

However, I also require adjustments to account for bank failures, which *are* related to the 2023 regional bank panic. For my model-implied results, I assume that the acquirer would have experienced deposit flows based on its size group and insured deposit share, and use the residual change in deposits to pin down the failed banks' deposit flows. This method correctly imputes large deposit outflows for the three large, failed banks during this period, with an average outflow of minus 75%. Admittedly, this excludes part of the deposit reallocation during the 2023 regional bank panic, as acquirers did see notable increases in their deposit bases due to the failed banks' remaining deposit bases on the date of the acquisition. However, if I implement the full acquisitions in my model, and have failed banks stop lending entirely, I find an *even stronger* positive effect of the within-regional bank deposit reallocation on real output. This is because the failed banks, like SVB, tended to have poor (model-implied) lending opportunities relative to their acquirers. Given the focus of this paper on deposit flows, rather than on the full costs of bank failures, I adjust out these failure-related acquisitions to be conservative.

For measuring bank-county-level deposit flows, the Summary of Deposits data are only available annually, so I require an additional adjustment to match deposit flows from the Call Report data. First, I assign bank-level December 2022 deposits and lending capacity to counties proportionally based on bank-county level June 2022 deposits from the 2022 Summary of Deposits report. I then measure county-level deposit changes as changes in county-aggregate deposits between this imputed December 2022 number and observed June 2023 number, adjusted proportionally to match the aggregate deposit outflow from Shock 2.

For the exercise reported in the paper, I restrict my baseline lending capacity measurement and deposit flow measurement to banks that report the CRA data; however, this exclusion does not have a material effect on the model-implied results. Note that this shock does not require any merger adjustments, as changes in ownership of a bank branch do not mechanically affect county-level deposits independently from the regional bank panic.

B Theory Appendix

In this appendix, I first provide an alternative quantitative version of the model which endogenizes banks' entire balance sheets, using standard tools from the literature. Then, I provide proofs of Propositions 1 and 2. Finally, I describe a simple theory model of depositor bank choice, with a primary friction of sticky depositor behavior, which can rationalize the results observed in Section 5

B.1 Comparison to a Model with Endogenous Liabilities and Other Assets

In this section, I provide an extension to my baseline model presented in Section 3 which endogenizes deposit flows and banks' liability structures, and then show that, for the set of counterfactual I consider in Section 5, the model generates an isomorphic set of equilibrium conditions.

Quantitative Depositor Choice Model. For this extension, I derive deposit supply functions $D_j(r_j)$ using standard discrete choice techniques applied to the deposit market, as in Egan et al., 2017; Wang et al., 2022.[36] Suppose that there is a national mass of savers D, each of whom choose a bank ($j = 1, ..., J$) or the outside option ($j = 0$) based on maximizing their own utility. Denote utility for choosing bank j by consumer i follows:

$$u_{ij} = \alpha r_j \tilde{w}^{-1} + \xi_j + \epsilon_{ij}, \tag{A.1}$$

[36]Note that the particular choice of microfoundation isn't critical for the results I derive in this section. The proofs are extremely similar when banks are gross substitutes, each bank faces a twice differentiable residual deposit supply function $D_j(r_j; \xi_j)$ with $0 < \frac{\partial D_j}{\partial r_j} < \infty$, $\frac{\partial^2 D_j}{\partial r_j^2} D_j < 0$, $\lim_{\xi_j \to -\infty} D_j = 0$, and $\lim_{\xi_j \to \infty} D_j = \bar{D} \in \mathbb{R}$, and each bank faces a twice differentiable wholesale funding cost function $\Phi_j(w_j; \phi_j)$ with $0 < \frac{\partial \Phi_j}{\partial w_j} < \infty$, $\frac{\partial^2 \Phi_j}{\partial w_j^2} > 0$, $\lim_{\Phi_j \to -\infty} \Phi_j = 0$, and $\lim_{\xi_j \to \infty} \Phi_j = \infty$. A corollary is that my isomorphism result extends trivially to segmented wholesale or deposit markets, such as product type, spatial segmentation, or debt and equity.

where r_j is the deposit rate offered by bank j, ξ_j captures the average non-pecuniary utility characteristics of bank j (e.g. branch network, failure risk, service quality), and ϵ_{ij} is an iid type I extreme value distributed random variable.[37] Each depositor i chooses a bank $j^*(i)$ based on $j^*(i) = \arg\max_j u_{ij}$, which generates standard logit demand deposit market shares:

$$s_j := \frac{D_j(r_j)}{D} = \frac{\exp\{\alpha r_j \tilde{w}^{-1} + \xi_j\}}{\sum_{k=0}^{J} \exp\{\alpha r_k \tilde{w}^{-1} + \xi_k\}} \tag{A.2}$$

Bank Balance Sheet Structure Before fully describing the banks' problem, I describe the additional choices banks face on their balance sheet. First, suppose that banks can borrow on a generic, "bond" market for wholesale funding, where bank j chooses how much to borrow, $\hat{\ell}_j$, facing total cost function $\Phi_j\left(\hat{\ell}_j\right) = \frac{1}{2}\tilde{w}\phi_j\hat{\ell}_j^2$, for cost parameters $\{\phi_j\}_{j\in\mathcal{J}}$. Second, bank j chooses how much lending capacity to borrow from each other bank $k = 1...J \neq j$, $\tilde{\ell}_{jk}$, taking as given the interest rate r_{jk}. Each bank k sets rates r_{jk},taking as given banks' demand functions and the cost to lend to bank j, $\Lambda_{jk}\left(\tilde{\ell}_{jk}\right) = \frac{1}{2}\tilde{w}\lambda_j\zeta_k\ell_{.k}^{-\gamma}\tilde{\ell}_{jk}^2$,for cost parameters $\{\lambda_j, \zeta_k\}_{j,k\in\mathcal{J}^2}$,and where money lent out on the interbank market is excluded from lending capacity.[38] The additional parameter $\gamma \in [0, 1)$ allows for banks' lending capacity to affect their lending on the interbank market, adding another possible GE propagation force to the model. Finally, each bank invests excess assets in a security which returns a rate r_a.[39] Finally, assume that bank j faces non financial marginal cost $c_j\tilde{w}$ per dollar of deposit funding.

[37] As in the body of the paper, deposit rates rates are scaled by national average wages ($\tilde{w}$) to tie nominal interest rates to the price level of the economy.

[38] The assumption of upward sloping marginal costs to borrow on wholesale markets is standard in the literature (see, e.g. Wang et al. 2022), and is also critical to match the empirical results in my estimation and also my results on marginal lending opportunities in Section V.

[39] For this illustrative exercise, I normalize r_a to zero. Intuitively, this corresponds to a bank that is maximizing excess returns over a competitive rate of return, which is consistent with standard modeling in the literature. It is straightforward to add a non-zero exogenous rate of return, or even to endogenize the return based on claims on aggregate profits.

Bank's problem and Solution The bank's profit maximization problem can now be written as:

$$\max_{\{\mu_{ij}\}_{i\in\mathcal{N}},\mu_j,r_j,\hat{l}_j,\{r_{jk}\}_{k\in\mathcal{J}\setminus\{j\}},\{\tilde{\ell}_{jk}\}_{k\in\mathcal{J}\setminus\{j\}}} \Bigg\{ \sum_{i\in\mathcal{N}}\int_0^1 \mathbf{1}_{i,sm\in\mathcal{L}_j}\mathbf{1}_{j \text{ lends to } i,sm,\nu}\left(\mu_{ij}c_{i,sm,j\nu}\left(\ell_j\right)k_{i,sm,\nu}\right)d\nu$$
$$\sum_{i\in\mathcal{N}}\int_0^1 \mathbf{1}_{j \text{ lends to } i,lg,\nu}\left(\mu_j c_{i,lg,j\nu}\left(\ell_j\right)k_{i,lg,\nu}\right)d\nu$$
$$- D_j\left(r_j\right)\left(r_j + c_j\tilde{w}\right) - \Phi_j\left(\hat{\ell}_j\right) - \sum_{k\neq j}\left(r_{jk}\tilde{\ell}_{jk} + \Lambda_{kj}\left(\tilde{\ell}_{kj},\ell_j\right) - r_{kj}\tilde{\ell}_{kj}\right)\Bigg\}$$
$$s.t.$$
$$\tilde{\ell}_{jk} \geq 0 \quad \forall k$$
$$\ell_j = D_j\left(r_j\right) + \hat{\ell}_j + \sum_{k\in\mathcal{J}\setminus\{j\}}\left(\tilde{\ell}_{jk}\right) \tag{A.3}$$

Taking first-order conditions and manipulating gives a set of equilibrium conditions to the problem:

$$\mu_j = \frac{1}{\epsilon_{lg}} \tag{A.4}$$

$$\mu_{ij} = \frac{1}{\epsilon_{sm}} \tag{A.5}$$

$$r_j = MLO_j + MIB_j - \frac{\tilde{w}}{\alpha\left(1-s_j\right)} - c_j\tilde{w} \tag{A.6}$$

$$\hat{\ell}_j = \frac{MLO_j + MIB_j}{\tilde{w}\phi_j} \tag{A.7}$$

$$\tilde{\ell}_{jk} = \frac{MLO_j + MIB_j}{\tilde{w}\lambda_j}\frac{\ell_k^\gamma}{\zeta_k} \tag{A.8}$$

$$r_{jk} = MLO_j + MIB_j \tag{A.9}$$

where $MLO_j \coloneqq \sum_{ns\in\mathcal{L}_j}\theta\frac{\alpha}{1-\alpha}\tilde{w}^{-\epsilon_s}\left(\frac{\epsilon_s}{\epsilon_s+1}\right)^{\epsilon_s+1}w_{ns}l_{ns}r_{ns}^{\epsilon_s}\tilde{c}_{nsj}^{-\epsilon_s}\ell_j^{\theta\epsilon_s-1}$is the bank-level marginal lending opportunity as presented in the paper and $MIB_j = \frac{\gamma}{2\tilde{w}}\frac{\ell_j^{\gamma-1}}{\zeta_j}\sum_{k\neq j}\frac{MLO_k^2}{\lambda_k}$ are the additional marginal interbank profits.

Relation to the model from Section 3. The model described above nests the model described in Section III, and allows for direct study of an enriched set of shocks, compared to my baseline.[40] However, it turns out that the resulting model is isomorphic to the model I describe in Section III for the set of shocks I consider in Section V.[41] Specifically, consider a set of counterfactual equilibrium outcomes $\left\{d'_j, \hat{\ell}'_j, \tilde{\ell}_{jk}\right\}_{\forall j,k}$that one wants to implement with the fully enriched model.

Claim. Consider a set of counterfactual deposit stocks, wholesale borrowing, and aggregate interbank borrowing volumes, $\left\{d'_j, \hat{\ell}'_j, \sum_{k\neq j}\tilde{\ell}'_{jk}\right\}_{\forall j}$. $\exists!\left\{\xi'_j, \phi'_j, \lambda'_j\right\}_{j\in J}$ that generate the specified bank liability structures as a counterfactual equilibrium of the extended model. Further, the remaining equilibrium objects, $\{\boldsymbol{w}, \boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}\}$, of the extended model are identical (up to scale) to the equilibrium vector generated by the baseline model presented in the paper.

Proof. Define $\delta'_j \coloneqq \alpha r'_j + \xi'_j$, $\tilde{\phi}_j \coloneqq \frac{MLO'_j + MIB_j}{\phi'_j \tilde{w}'}$, and $\tilde{\lambda}_j = \frac{MLO'_j + MIB_j}{\tilde{w}'\lambda'_j}\sum_{k\neq j}\frac{\left(\ell^{\gamma}_k\right)'}{\zeta_k}$. We can set $\tilde{\phi}'_j = \tilde{\ell}'_j$ and $\tilde{\lambda}_j = \sum_{k\neq j}\tilde{\ell}'_{jk}$; Standard logit demand results imply that there is a unique inversion from d'_j to δ'_j. Thus, given δ'_j, $\tilde{\phi}'_j$, and $\tilde{\lambda}_j$, ℓ'_j is pinned down. Given ℓ'_j, the remaining equilibrium conditions of the model are given by equations (7), (10), (11), (15), and (16). By Proposition 1, there is a unique (up to scale) equilibrium vector $\{\boldsymbol{w}, \boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}\}$that satisfies all the equations. Further, the equations are identical to the equilibrium conditions from the baseline model, implying that the equilibrium outcomes $\{\boldsymbol{w}, \boldsymbol{p}, \boldsymbol{P}, \boldsymbol{\mu}, \boldsymbol{r}\}$ are identical (up to scale). Then, given $\{\boldsymbol{w}, \boldsymbol{r}\}$, $\{MLO_j, MIB_j\}_{j\in J}$ are pinned down, which uniquely pins down ϕ'_j and λ'_j. Finally, given $\{\delta_j\}_{j=1}^{J}$, $\{s_j\}_{j=1}^{J}$ is fully pinned down, meaning r'_j is fully pinned down, uniquely pinning down ξ'_j . □

B.2 Unique Equilibrium

In this section, I provide the proof of Proposition 1. First, I collapse down the equilibrium conditions into a pair of joint equilibrium conditions, and then prove that the pair of equations has a unique (up to scale) solution.

Combining Equilibrium Conditions. First, I collapse down the equilibrium conditions enumerated in Section 3.5 into a pair of equilibrium conditions which consist of a nonlinear

[40] For example, an interested researcher could directly estimate the effect of policy interventions on the cost of wholesale funding, and then implement these shocks directly through shocks to the $\{\phi_j\}_{j\in J}$parameters

[41] Formally, for aggregate real output effects to be identical to those reported in paper, an additional assumption that all funding costs, including deposit interest payments, wholesale funding costs, and nonfinancial marginal costs are redistributed to consumers in a proportional dividend is necessary, as I assume for lending profits in the baseline model.

system of 3N equations with 3N unknowns. First, define:

$$\tilde{r}_{ns} = \frac{\epsilon_s + 1}{\epsilon_s} \left(\sum_{k \in \mathscr{L}_{ns}} \left(\tilde{c}_{nsk} \ell_k^{-\theta} \right)^{-\epsilon_s} \right)^{-\frac{1}{\epsilon_s}}. \tag{A.10}$$

Then, plugging equations (A.10), (7), (15), and (16) into equation (10) gives, with some manipulation:

$$P_n^{-\Phi} \tilde{w}^{\Phi\alpha} = \sum_i \sum_s A_{is}^{\Phi} \tau_{ni}^{-\Phi} \tilde{r}_{is}^{-\alpha\Phi} w_{is}^{-\Phi(1-\alpha)}. \tag{A.11}$$

Similarly, plugging equations (A.10), (7), (15), and (16) into equation (11) gives, with some manipulation:

$$w_{ns}^{1+\Phi(1-\alpha)} = \sum_i \sum_t A_{ns}^{\Phi} \tau_{in}^{-\Phi} \tilde{r}_{ns}^{-\alpha\Phi} l_{ns}^{-1} l_{it} \tilde{w}^{-\Phi\alpha} P_i^{\Phi} w_{it}. \tag{A.12}$$

Note that the scale coefficients $A_{is}^{\Phi} \tau_{ni}^{-\Phi} \tilde{r}_{is}^{-\alpha\Phi}$ and $A_{ns}^{\Phi} \tau_{in}^{-\Phi} \tilde{r}_{ns}^{-\alpha\Phi} l_{ns}^{-1} l_{it}$ can be expressed in closed form as a function of exogenous fundamentals. I am now ready to move on to prove that the (scaled) solution to equations (A.11) and (A.12)

Uniqueness Result.

Claim 1. Taking as given fundamentals and parameters, there exists a unique (up to scale) solution to equations (A.11) and (A.12).

Proof. For simplicity, I substitute $\tilde{P}_n \coloneqq P_n^{-\Phi} \tilde{w}^{\Phi\alpha}$ and $\tilde{w}_{ns} \coloneqq w_{ns}^{1+\Phi(1-\alpha)}$ into equations (A.11) and (A.12):

$$\tilde{P}_n = \sum_i \sum_s A_{is}^{\Phi} \tau_{ni}^{-\Phi} \tilde{r}_{is}^{-\alpha\Phi} \tilde{w}_{is}^{-\frac{\Phi(1-\alpha)}{1+\Phi(1-\alpha)}}, \tag{A.13}$$

and

$$\tilde{w}_{ns} = \sum_i \sum_t A_{ns}^{\Phi} \tau_{in}^{-\Phi} \tilde{r}_{ns}^{-\alpha\Phi} l_{ns}^{-1} l_{it} \tilde{P}_i^{-1} w_{it}^{\frac{1}{1+\Phi(1-\alpha)}}. \tag{A.14}$$

The system of equations (A.13) and (A.14) is of the type studied in Allen et al. 2020. Thus, applying their Theorem 1, part ii.b, if the spectral radius of the elasticity matrix $A \coloneqq \begin{bmatrix} 0 & \frac{\Phi(1-\alpha)}{1+\Phi(1-\alpha)} \\ 1 & \frac{1}{1+\Phi(1-\alpha)} \end{bmatrix}$ is equal to one, the system has a unique solution. It is straightforward to show that the eigenvalues of the matrix A are 1 and $-\frac{\Phi(1-\alpha)}{1+\Phi(1-\alpha)} \in (-1, 0)$. □

B.3 Unique Inversion

In this section, I provide a proof of Proposition 2. The proof proceeds constructively, by providing a step-by-step guide to inverting the model, proving uniqueness of the step as

necessary.

Step 1: Recover k_{ns} and r_{ns}. First, I show how the model pins down realized average interest rates in each region and borrowing volumes by large firms. Imposing Cobb-Douglas production for small firms in region n gives the equation:

$$r_{ns} = \frac{\alpha}{1-\alpha}\frac{w_{ns}l_{ns}}{k_{ns}}. \tag{A.15}$$

Equation (A.15) is sufficient to pin down realized average interest rates for local small firms, since I directly observe w_{ns}, l_{ns}, and k_{ns}. Next, I move to pin down $r_{n,lg}$ and $k_{n,lg}$. By assumption, I observe total borrowing by large firms, $\sum_n k_{n,lg}$. Second, by the structural assumptions I make about the capital market, I know $r_{n,lg} = r_{lg}$ for all regions. Manipulating equation A.15 and summing over regions gives the condition:

$$r_{lg} = \frac{\sum_n \frac{\alpha}{1-\alpha} w_{n,lg}l_{n,lg}}{\sum_n k_{n,lg}}. \tag{A.16}$$

Then, re-imposing equation (A.15) pins down local borrowing volumes for large firms as well. Finally, the model requires a scale normalization that pins down the units of k_{ns}, relative to l_{ns}. I choose a normalization such that the model matches realized average interest rates on C&I and CRE bank loans, as reported on the call report.

Step 2: Recover A_{ns}. Having recovered local borrowing volumes and interest rates, I move to recover regional average TFP, A_{ns}.

Claim 2. Taking as given observed data, parameters, and recovered endogenous objects, there exists a unique (up to scale) set of regional average productivity scale parameters which lets equation (11) for all regions, firm size groups.

Proof. To this end, define the function $\mathcal{D}_{ns}\left(\{A_{it}\}_{i,t}\right)$, which embeds equation (11) :

$$\mathcal{D}_{ns}\left(\{A_{it}\}_{i,t}\right) = l_{ns}w_{ns} - \sum_i \sum_t \left(\frac{p_{ins}\left(A_{is}\right)}{P_i\left(\{A_{it}\}_{i,t}\right)}\right)^{-\Phi} l_{it}w_{it}. \tag{A.17}$$

If equation (A.17) characterizes an excess demand system with the gross substitution property, then there exists a unique (up to scale) set of productivities which solves the equation. This requires four properties: (i) $\mathcal{D}_{ns}$ is continuous, (ii) $\mathcal{D}_{ns}$ is homogeneous of degree zero, (iii) $\sum_{n,s} \mathcal{D}_{ns} = 0$, and (iv) $\mathcal{D}_{ns}$ exhibits gross substitution in wages. It is

straightforward to show properties (i) and (ii) hold. For property (iii), note that:

$$\sum_{n,s} \mathcal{D}_{ns}\left(\{A_{it}\}_{i,t}\right) = \sum_{n,s} l_{ns} w_{ns} - \sum_{n,s}\sum_{i,t}\left(\frac{p_{ins}\left(A_{is}\right)}{P_i\left(\{A_{it}\}_{i,t}\right)}\right)^{-\Phi} l_{it} w_{it}$$

$$= \sum_{n,s} l_{ns} w_{ns} - \sum_{i,t}\sum_{n,s}\left(\frac{p_{ins}\left(A_{ns}\right)}{P_i\left(\{A_{it}\}_{i,t}\right)}\right)^{-\Phi} l_{it} w_{it}$$

$$\sum_{n,s} l_{ns} w_{ns} - \sum_{i,t} l_{it} w_{it} = 0.$$

Finally for gross substitution, note that:

$$\frac{\partial \mathcal{D}_{ns}}{\partial A_{it}} = \underbrace{-\Phi}_{<0} \sum_{i,t} \underbrace{p_{ins}\left(A_{ns}\right)^{\Phi} P_i\left(\{A_{it}\}_{i,t}\right)^{\Phi-1} l_{it} w_{it}}_{>0} \underbrace{\frac{\partial P_i}{\partial A_{it}}}_{<0} > 0,$$

which implies, by property (ii), $\frac{\partial \mathcal{D}_{ns}}{\partial A_{ns}} < 0$, completing the proof. □

Step 3: Recover $\tilde{c}_{njs}$. Finally, I show how the model recovers nonfinancial lending costs. Imposing equations (13), (14), (15), and (16) gives, with some manipulation:

$$\tilde{c}_{nsj} = s_{nsj}^{-\frac{1}{\epsilon_s}} \ell_j^{\theta} r_{ns} \tilde{w}^{-1} \frac{\epsilon_s}{\epsilon_s + 1}.$$

B.4 Microfounded Depositor Choice Model

In this section, I sketch a simple model of banks' rate-setting behavior and sticky depositors' bank choice to microfound the results presented in Section 5

Primitives and Depositors' Choices. Suppose there is a continuum of depositors indexed by $i \in [0, d]$, and each depositor has one dollar of available funds. For simplicity, assume there are two banks, $j \in \{1, 2\}$.[42] In the baseline equilibrium, each depositor is currently banking with bank $j\,(i)$, which is her optimal decision. Denote the set of depositors by $\mathcal{D}$, and the set of depositors who initially bank with bank j as $\mathcal{D}_j$. Depositor i is "sticky," so while she receives utility of $u_i\,(j)$ from her pre-existing bank, she only receives utility of $u_i\,(j') - \kappa_i$ with $\kappa_i \geq 0$ if she switches to bank $j' \neq j$. Assume that $u_i\,(j) = \alpha r_j$, where r_j is the rate bank j offers to depositors and α is a parameter controlling rate sensitivity

[42] It is straightforward to extend this model to account for smooth substitution between $N \geq 2$ banks by adding idiosyncratic tastes over banks beyond stickiness. However, this leads the resulting expressions to depend on integrating over $N + 1$ (conditional) densities, rather than a simple univariate density. Thus, for simplicity, I illustrate the force in the two-bank case.

of utility. For simplicity, assume that κ_i can be represented by a continuously differentiable density represented by $f_\kappa()$.

Consumer i will switch banks if and only if she receives more utility by switching than staying, i.e., $\alpha(r_{j'} - r_j) > \kappa_i$. Given these conditions, we can write bank j's total deposits, dep_j, as:

$$dep_j = \int_{\mathcal{D}_j} \mathbf{1}_{\alpha(r_{j'} - r_j) \leq \kappa_i} di + \int_{\mathcal{D}/\mathcal{D}_j} \mathbf{1}_{\alpha(r_j - r_{j'}) > \kappa_i} di. \tag{A.18}$$

We can transform the integral across depositors described in equation (A.18) to a Riemann integral:

$$dep_j = \int_0^\infty \left(p_{j,\kappa} \mathbf{1}\left\{ \Delta r_j \geq -\frac{\kappa}{\alpha} \right\} + (1 - p_{j,\kappa}) \mathbf{1}\left\{ \Delta r_j > \frac{\kappa}{\alpha} \right\} \right) f_\kappa(\kappa) \, d\kappa, \tag{A.19}$$

where $p_{j,\kappa}$ is the fraction of consumers with $\kappa_i = \kappa$ who initially have an account with bank j and $\Delta r_j \coloneqq r_j - r_{j'}$. Intuitively, the first term in this integral, $p_{j,\kappa} \mathbf{1}\left\{ \Delta r_j \geq -\frac{\kappa}{\alpha} \right\}$, captures the behavior of depositors who are stuck with bank j, while the second term, $(1 - p_{j,\kappa}) \mathbf{1}\left\{ \Delta r_j > \frac{\kappa}{\alpha} \right\}$, captures the behavior of depositors who are stuck with bank $j' \neq j$. The wedge between the two behaviors is the different sign on κ; intuitively, stickiness helps bank j retain its own depositors but also makes it harder to attract depositors of bank j'.

Bank Rate Setting. I now provide a simple rationalization for why banks offer different deposit rates in equilibrium. Banks set deposit rates to maximize profits. Suppose that bank j earns a twice differentiable return of $g_j(dep_j)$ from deposits, where $g_j' > 0$ and $g_j'' \leq 0$. Profits follow $\pi_j = g_j(dep_j) - dep_j r_j$. Given (A.19), bank j's profit-maximizing first-order condition is $r_j = g_j' - \frac{1}{\frac{\partial ln dep_j}{\partial r_j}}$. Without loss of generality, assume that $r_1 \geq r_2$, i.e., bank 1 offers the (weakly) higher deposit rate. Consistent with my empirical results, assume that $g_1' \geq g_2'$.[43]

Shocks to Depositor Stickiness. Suppose there is a news story, which leads depositors to worry about their pre-existing banking relationship, leading them to become less sticky. Model this story as a proportional shock to depositors' switching costs, i.e. $\kappa_i' = (1 - \varphi)\kappa_i$,

[43] A sufficient condition for this is that bank 1's deposit base is (weakly) less "sticky" than bank 2's, as captured by the inverse semi-elasticity of deposit supply. In the long run, this may hold in general, since deposits will tend to flow to the bank with higher rates, and deposit flows select for less-sticky depositors.

where $\varphi \in [0,1]$ controls how strong the 'unsticking' is. We have:

$$\frac{\partial dep_1}{\partial \varphi} = \underbrace{\frac{\partial}{\partial \varphi} \int_0^\infty p_{1,\kappa} \mathbf{1}\left\{\Delta r_1 \geq -\frac{(1-\varphi)\,\kappa}{\alpha}\right\} f_\kappa(\kappa)\, d\kappa}_{=0}$$
$$+ \underbrace{\frac{\partial}{\partial \varphi} \int_0^\infty (1-p_{1,\kappa})\, \mathbf{1}\left\{\Delta r_1 > \frac{(1-\varphi)\,\kappa}{\alpha}\right\} f_\kappa(\kappa)\, d\kappa}_{\geq 0}.$$

Intuitively, the first term is zero, because bank 1's ex-ante rate is higher than bank 2's, i.e. $\Delta r_1 > 0$ and $-\frac{(1-\varphi)\kappa}{\alpha} < 0 \ \forall \varphi \in (0,1)$. The second term is (weakly) positive, because 'unstuck' consumers will always substitute to bank 1, since bank 1 offers a higher deposit rate. Thus, by the fundamental theorem of calculus, moving from no unsticking ($\varphi = 0$) to any unsticking event ($\varphi > 0$) will lead consumers to substitute away from bank 2 to bank 1, holding all else equal. Notably, this substitution happens *without* bank 1 changing its offered deposit rate, i.e. the unsticking event makes depositors effectively more rate sensitive.

C Estimation Appendix

C.1 Model Estimation

C.1.1 Bank-Specific Lending Responses

First, I describe the estimation of equations (18) and (19). Given the nature of my instrument, I set up a stacked difference-in-differences regression specification, and use difference-in-differences variation in exposure to fracking shocks. My full regression specifications can be written as:

$$lnk_{jty} = \beta_{natl} \ell_{jty} + \delta_{jy} + \delta_{ty} + \epsilon_{jty}, \tag{A.20}$$

and

$$lnk_{njty} = \beta_{lcl} \ell_{jty} + \delta_{njy} + \delta_{nty} + \epsilon_{njty}, \tag{A.21}$$

where j indexes banks, n indexes regions, t indexes years, y indexes fracking well discovery years, and the δ terms are fixed effects which absorb credit demand and set up the proper difference-in-differences variation in the independent variable. The CRA lending data limit me to including five years of pre-shock data for each fracking cohort. Motivated by Figure 3, which shows that it takes seven years for fracking well discoveries to have their full impact on local deposit bases, I include observations for up to seven years after well discoveries. As

stated in the paper, I weight equation (19) by within-bank county-level lending shares, i.e., $\frac{k_{njty}}{\sum_i k_{ijty}}$. Finally, to instrument for lending capacity ℓ_{jty}, I use 2002 deposit shares in counties where fracking wells were eventually discovered in year y, interacted with a "post" indicator variable (i.e. $t \geq y$). Table A.1 presents the results from estimating equations (A.20) and (A.21) with a 2SLS estimator.

C.1.2 Regional Aggregates

I estimate equations (20) and (21) directly as a long-difference specification between 2007 and 2017. This is motivated by data requirements. First, well discoveries occur between 2003 and 2009, implying that a short post period could miss part of the impact of the later well discoveries. Second, SUSB output data are only available with the quinquennial economic census, starting in 2007. To instrument for $\sum_j s_{n,sm,j}\Delta ln\ell_j$ and $\Delta lnk_{n,sm}$, I construct a county-level average of bank-level 2002 fracking county deposit shares, weighted by county-bank level 1998-2002 small firm lending market shares. I exclude counties where fracking wells were discovered from the estimation equations. I weight the regressions by 2007 county employment. Table A.2 presents the results from estimating equations (20) and (21) with a 2SLS estimator.

C.1.3 Structural Parameters and Standard Errors

The coefficients in tables A.1 and A.2 can be mapped directly to structural parameters. Imposing equations (18), (19), (20), and (21) implies that $\hat{\theta} = 1.14$, $\hat{\alpha} = \frac{1+\Phi}{\Phi}0.48 = 0.58$, $\hat{\epsilon}_{sm} = \frac{2.35}{\hat{\theta}} = 2.06$, and $\hat{\epsilon}_{lg} = \frac{3.27}{\hat{\theta}} = 2.87$. To calculate standard errors, I use a sandwich estimator, $\hat{\Omega} = \left(G'\hat{S}^{-1}G\right)^{-1}$, for gradient of moments to parameters G and estimated sample variance matrix $\hat{S}$. The sample variance matrix is a diagonal matrix of the regression coefficients' squared standard errors. The standard errors for the structural parameters are the square root of the diagonal elements of $\hat{\Omega}$.

Table A.1: Bank-Specific Estimation Equations

This table presents the results from estimation equations (A.20) and (A.21) using a 2SLS estimator. Column 1 corresponds to equation (A.20); column 2 corresponds to equation (A.21). The endogenous variable is ℓ_{jty}. The instrument is the bank's 2002 deposit share in counties where fracking wells were eventually discovered, interacted with a post indicator. Only the main coefficients of interest are shown. Robust standard errors are shown in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
ℓ_{jty}	3.27***	2.35***
	(0.19)	(0.54)
Fixed Effects	Yes	Yes
First Stage F Stat	540	51
Observations	377,213	3,040,408

Table A.2: Regional Estimation Equations

This table presents the results from estimation equations (20) and (21) using a 2SLS estimator. Column 1 corresponds to equation (20); column 2 corresponds to equation (21). The instrument is banks' 2002 deposit shares in counties where fracking wells were eventually discovered, weighted to the county-level by 1998 through 2002 small firm lending market shares. Only the main coefficients of interest are shown. Robust standard errors are shown in parentheses. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
$\sum_j s_{n,sm,j} \Delta ln \ell_j$	1.14***	
	(0.24)	
$\Delta ln k_{n,sm}$		0.48***
		(0.12)
Fixed Effects	Yes	Yes
First Stage F Stat	29	22
Observations	2860	2860

C.2 Validation Exercise

In this subsection, I describe how I replicate the Chen et al. 2017 (CHS) shock in my model. I implement the shock as a proportional shock to nonfinancial lending ability for the Big 4 banks. Specifically, I set $\tilde{c}'_{ijs} = \kappa_j \tilde{c}_{ijs}$, where $\kappa_j = 1$ for all banks except the Big 4 and $\kappa_j = \kappa > 1$ for the Big 4 banks. To replicate the 24.28% decline in bank-county level lending reported in Table 2, column 6, I set $\kappa = 1.118$. Then, I compute a counterfactual equilibrium of my model, stack the data sets to create a panel dataset, and run regressions in the model-generated data that correspond to regressions from CHS. I use the ex-ante small firm lending share of the Big 4 banks as my exposure measure.

I replicate two results from CHS in my model. The first result that I replicate is the county-level lending result, reported in Table 3, column 1. CHS reports a point estimate of -21.67% with a standard error of 5.648%, which I use to calculate the 95 percent confidence interval reported in the paper. I run the corresponding regression in my model-generated data, and get a point estimate of -19.6%. Next, I seek to understand county-level output responses to the credit supply shock, which is based on results in Table 6. To construct the CHS output effect, I sum up the coefficients on change in the employment to population ratio (column 5, panel B) and the wage effect (column 7, panel B) , giving a total change in aggregate payrolls of $0.31 + 0.10 = 0.41$ with a standard error of 0.11.[44] In my model, this measure is directly proportional to nominal output. I run a 2SLS regression in my model, where the outcome variable is nominal regional output, the endogenous variable is small firm credit supply, and the instrument is exposure to the Big 4 banks, and get a point estimate of 0.34 in the second stage regression.

[44] To construct the confidence interval, for simplicity, I assume that the estimation covariance between the coefficients is zero.