Bank Health and Local Economic Outcomes

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Abstract

We use a comprehensive data set of home mortgage loan originations from 2001-2018 matched with banks' income and balance sheet statements to analyze how fluctuations in bank health influence local credit supply and county-level economic outcomes. To isolate fluctuations in the supply of credit, our identification strategy exploits the fact that banks originate home mortgage loans across multiple local markets, which allows us to estimate statistical credit supply effects that are then linked to the health of bank balance sheets. We find that a worsening of bank health is associated with a significant reduction in credit supply. Our findings further indicate that a worsening in credit supply during the 2007-10 global financial crisis lead to significant—in both economic and statistical terms—declines in local home prices as well as various measures of county-level economic activity. These credit-induced supply effects also influence broad-based measures of economic activity in the post-GFC period. Importantly, the effect of bank health on the local economy is estimated to be as strong during the post-GFC period as during the GFC. The findings are robust to controlling for the decline in local household demand. Our results further highlight a robust relationship between expansions in bank mortgage lending and expansions in local business lending that are also independent of local demand conditions. These findings imply that bank credit supply spurs local economic activity by causing direct expansions in credit supply to bank-dependent firms.

JEL Classification: E24, E32, E44, G01, G20

Keywords: mortgage lending, local credit supply shocks, home prices, county-level economic performance, HMDA

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1 Introduction

The global financial crisis (GFC) that unfolded from 2007 to 2010 originated in the U.S. housing sector and resulted in about 3.8 million foreclosures over the 2007–10 period, ultimately leading to a loss of approximately eight million American jobs. During this period, policymakers focused intensely on the developments in the financial sector—especially in the banking sector—as a deterioration in the financial health of banks significantly impaired their ability to supply credit to fund private investment and consumption. More recently, an aggressive tightening of monetary policy led to sharp increases in interest rates along with falling values for commercial property. This in turn has significantly impaired the financial position of banks that failed to hedge such risks, again raising concerns regarding the extent to which bank health matters for both lending and economic activity.

There is a large existing literature that studies the importance of both household and bank balance sheets during the GFC. This literature includes studies that attribute the massive decline in private employment during this period almost entirely to a household demand channel—which links a contraction in household spending to declines in home prices (see Mian and Sufi, 2014)—as well as studies that stress the importance of adverse credit supply shocks emanating from the banking sector, which worked primarily by restricting firms' access to credit and hence their employment demand (see Chodorow-Reich, 2014; Huber, 2018).[1]

Although banks were frequently blamed for being too restrictive with credit during the Great Recession and its aftermath, they were also accused of excessive credit creation that contributed importantly to the housing bubble in the years leading to the crisis. This view is echoed in recent research, which shows that there is a strong systematic relationship between credit booms and subsequent economic downturns, with the credit supply channel being the main culprit on the upside as well as the downside of the cycle (see Jordà et al., 2013; Jordà et al., 2016; Mian et al., 2017). In the post-GFC period, concerns have been raised that tighter bank regulation has impeded bank lending and the economic activity of households and firms that rely on bank loans as a primary source of finance.

In this paper, we contribute to the empirical literature on the role of bank health for local economic activity using a comprehensive loan-level data set, which combines detailed U.S. geographic data on home mortgage lending with bank-level regulatory income and balance sheet information. Specifically, we analyze how differences in the financial health of banks affect the local supply of credit at various times, and how the resulting geographic differences in credit supply conditions influence local economic outcomes. To isolate fluctuations in the local supply of credit due to dif-

[1] Within this latter strand of the literature, there is a considerable disagreement regarding the quantitative significance of credit supply shocks for the employment decline during the Great Recession. Duygan-Bump et al. (2015) and Greenstone et al. (2020), for example, present evidence showing that such effects account for less than one-tenth of the employment decline, whereas Siemer (2019) estimates a number on the order of one-sixth to one-fifth. Studies by Chodorow-Reich (2014), Mondragon (2020), García (2020), and Glancy (2021), on the other hand, argue that up to one-third of the total employment employment decline during this period is attributable to adverse credit supply shocks.

ferences in the financial health of banks, we use a novel variant of the influential Khwaja and Mian (2008) identification strategy. In particular, we estimate the component of the standard Khwaja-Mian statistical measure of bank-specific credit supply that is due to observable changes in the quality of bank balance sheets. This procedure allows us to measure shifts in the local supply of home mortgage bank credit due to changes in the quality of bank balance sheets that have been orthogonalized with respect to changes in local demand conditions. Importantly, the richness of the HMDA data allow us to control for credit demand at the granular level of U.S. census tracts rather than at the relatively course level of counties as has been done previously in this literature.

During the 2007–2010 period, these bank balance-sheet induced contractions in lending have stark implications for local economic outcomes. Our estimates imply that a one percent credit-supply induced decline in local bank mortgage lending leads to a 0.42 percent decline in home prices, a 0.08 percent decline in the local employment-to-population ratio, and a 0.15 percent decline in local real GDP per capita. This credit supply shock also implies a 0.09 percent reduction in retail spending and a 0.4 percent decline in the number of motor vehicle registrations (both in per capita terms). In addition, we document that these bank-health induced contractions in credit-supply had an especially adverse effect on employment growth at small and young firms and affected, in particular, employment in the construction and non-tradable sectors. Based on these estimates, a back-of-the-envelope calculation implies that the direct effect of the aggregate loan losses incurred by banks during the GFC can account for a 2.2 percent drop in GDP and a 1.2 percent drop in employment over this period.

During the ensuing 2011–2018 post-GFC period we find that adverse credit supply shocks continued to affect the economy on a fairly broad level. We find that an equivalent-sized one percent contraction in bank mortgage credit leads to a decline in house prices of 0.55 percent, and a decline in the employment-to-population ratio of 0.09 percent. These estimates imply that bank balance sheet losses have equally powerful effects during the post-GFC period as during the GFC itself and therefore validate recent concerns regarding the possible spillover effects of bank health into local economic activity.

For the 2002–2006 period, by contrast, we find that the identified credit supply shocks have no discernible effect on either housing prices, employment, or household spending. This may reflect the limited variation in bank balance sheet losses during a period of rapid home price appreciation. It may also reflect that the credit boom was primarily driven by expansions in private-label mortgage lending that is not directly linked to bank balance sheets.[2]

Finally, we seek to determine the extent to which expansions in bank credit supply increases economic activity through the expansionary effects of house price increases on household net worth or due to direct expansions of credit to firms that then leads to greater local employment. Notably, the local employment response to bank health that we estimate is three times greater than what one can typically explain through the response of local spending to changes in household wealth as

[2] Another possibility is that lending constraints were loosened during this period with banks not restricting lending in response to a deterioration of their balance sheet, a view consistent with the findings of Justiniano et al. (2019).

estimated in recent work by Guren et al. (2021). To assess the relative importance of the household spending and firm-financing channels, we directly control for household motor vehicles registrations, which serves as a proxy for the consumption of tradeable goods. Tradeable goods consumption is uniquely suitable as a control for household spending because there are no local feedback effects that influence the price of such goods. Using a simple, small-open economy model, we show that the ratio of coefficients on bank credit supply that are obtained with versus without controlling for household demand determines the relative strength of the two distinct channels. Our empirical results imply that 50 to 75 percent of the employment effects that we estimate during the GFC period remain after controlling for household spending. In the post-GFC period, the role of the firm-financing channel is arguably even more significant. According to our estimates, 85 to 90 percent of the total employment effects remain after controlling for household demand.

We further show that our credit supply measure leads to significant increases in small business lending and that these estimates remain unchanged after controlling for household spending. This expansion in small business lending may be due to rising collateral values as real estate prices rise. Another possibility is that our granular-level estimates of bank-health induced changes in credit supply capture the overall willingness of banks to lend, and this increased willingness is then reflected in both greater home mortgage and small business loan originations.

The remainder of the paper is organized as follows. In Section 2, we first describe the construction of our data set, which matches HMDA lending by depository institutions with their regulatory income and balance sheet filings; we also document that our data set is representative of the national trends in home mortgage lending, in both the time-series and cross-sectional dimensions. Section 3 discusses the identification strategy used to obtain county-level estimates of credit supply shocks; in this section, we also briefly describe our estimation methodology. Section 4 presents our empirical results, while Section 5 discusses our framework and results that seek to distinguish household net worth and firm lending channels. Section 6 offers a brief conclusion.

2 Data Sources and Methods

Our goal is to construct a measure of bank health that influences local credit conditions through its effect on local credit supply. This requires separating credit demand from credit supply at the local level and estimating the effect of bank health on credit supply. To do so requires loan data that can be traced back to banks, and hence their balance sheets, and is rich enough to provide the necessary local information to estimate credit demand. Our key micro-level data for this analysis is the confidential version of the Home Mortgage data. This data allows us to observe every loan issued by a given mortgage issuer within a narrowly defined region – a census tract. We use this data to estimate issuer-supply effects and geographically distinct (census-tract-level) demand effects using all mortgage issuers, both banks and non-banks. We then use the resulting statistical measures of issuer-specific credit supply to estimate the relationship between credit supply and bank health for the subset of mortgage issuers that are banks. Finally, we construct a weighted average of local bank-health by aggregating across active banks in a local area, using local bank branch deposits as weights. This defines our credit supply measure that may then be used to study the effect of changes in bank health on local economic outcomes. In this section, we provide full details regarding the data sources used in this analysis.

2.1 Home Mortgage Lending

The key micro-level data for our analysis come from the confidential version of the Home Mortgage Disclosure Act (HMDA). The Home Mortgage Disclosure Act requires a vast majority of U.S. financial institutions to maintain, report, and publicly disclose information about home mortgages. Institutions subject to HMDA must meet certain criteria, such as having assets above a specific threshold.[3]

In terms of types of mortgage loans, we limit the HMDA sample to home mortgages for single-family home purchases, as opposed to loans extended for home improvements or refinancing.[4] We also exclude FHA and VA guaranteed loans.

Figure 1 depicts selected indicators in residential mortgage markets during the 2001–2018 period. Panel A, shows the annual growth of aggregate single-family home mortgage loan originations from HMDA against the growth of home prices.[5] Clearly evident is the massive contraction in home mortgage lending that started to materialize in 2006, as home prices began to slide from their lofty peaks. Note that mortgage lending and home prices did not start to increase until 2012, well after the official end of the recession.

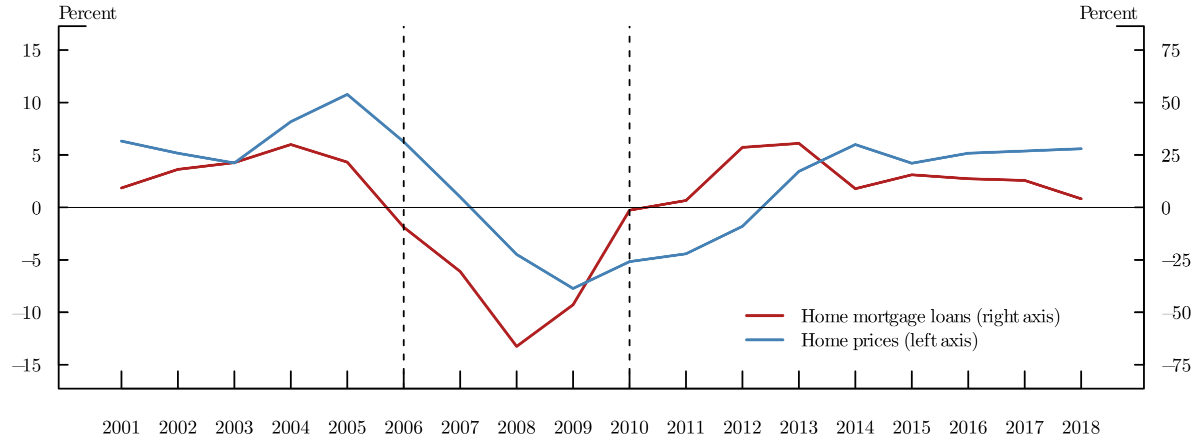
The dynamics of mortgage lending and home prices over the 2001–2018 suggest three distinct phases of a credit cycle: a credit boom that lasted from 2001 to 2006 and was followed by a credit bust that lasted until 2010, and a subsequent normalization phase that started in 2011 and runs through the end of our sample period. These three phases are also reflected in Panel B, which shows the evolution of changes in banks' credit standards on mortgage loans and the corresponding changes in loan demand, as reported in the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). According to this survey, the boom period was characterized by a steady erosion in banks' credit standards, a pattern that was abruptly reversed in late 2006, as more and more banks began to report that they have tightened standards (and terms) on home mortgage loans. During the subsequent bust, credit conditions in residential mortgage markets tightened significantly further, while the demand for mortgages weakened substantially. Credit conditions reportedly started to ease somewhat in late 2012, while the demand for home mortgage credit was about unchanged, on balance, during the subsequent normalization phase of the credit

[3] The Congress originally enacted HMDA in 1975, and with passage of the Dodd-Frank Act in 2011, HMDA rule-making authority was transferred from the Federal Reserve Board to the Consumer Financial Protection Bureau.

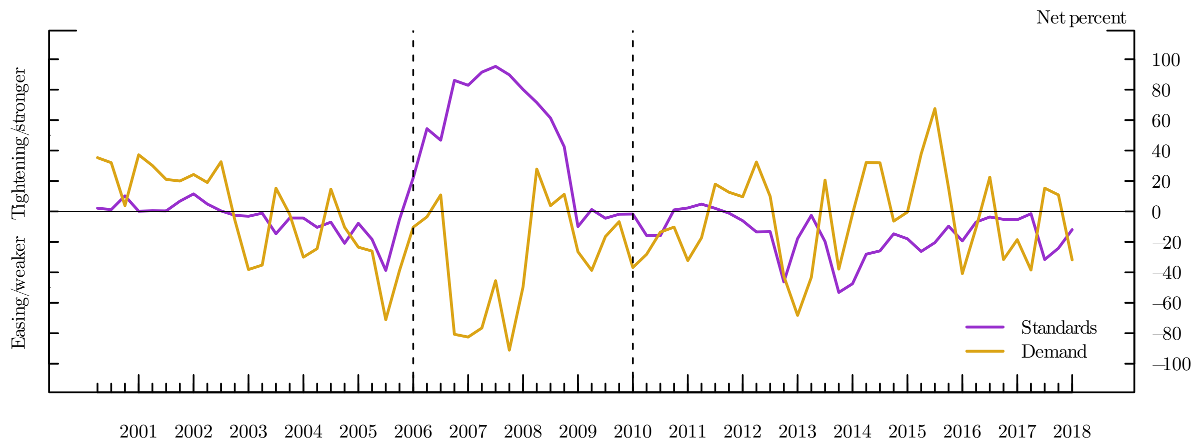
[4] Because we do not observe repayment of mortgage loans, limiting the sample to loans for home purchases means we are capturing newly originated credit in a county, rather than an economically less important refinancing activity. We restrict our sample to single-family home purchases because the HMDA data do not distinguish between home purchases versus improvements or refinancing for multi-family homes.

[5] Throughout this paper we use the house price index (HPI) based on Bogin et al. (2019), the only index that, to our knowledge, is currently available at all geographic levels utilized in this paper.

Figure 1 – Residential Mortgage Markets



A. Home mortgage lending and home prices



B. Changes in credit standards and demand for home mortgage loans

Note: Panel A depicts the annual growth of single-family home mortgage loan originations from HMDA and the Q4/Q4 growth in the FHFA house price index. Panel B shows quarterly changes in bank lending standards on, and demand for, residential real estate loans, as reported in the Senior Loan Officer Opinion Survey on Bank Lending Practices.

cycle.

An important subset of financial institutions subject to HMDA are insured depository institutions, or "banks" for short.[6] The other major actors in the residential mortgage markets, which are also subject to HMDA, are "non-banks," mortgage companies such as Quicken loans, Loan Depot, PennyMac Financial, and United Wholesale Mortgage, which are more loosely supervised. The banks' share of home mortgage loan originations fluctuates in the narrow range around 65 percent during the boom and GFC periods, but has trended down to roughly 50 percent by the end of our

[6]By "bank" we mean a top holder financial institution, such as a bank holding company (BHC) or a savings and loan holding company (SLHC). Example of banks are institutions such as JPMorgan Chase, Bank of America, and Wells Fargo.

Figure 2 – Home Mortgage Lending by Type of Institution

Note: The figure depicts the annual growth of home mortgage loan originations by banks and nonbanks.

sample period, as banks scaled back their presence in the mortgage market, following the imposition of regulations in the wake of the financial crisis. As discussed above, we are primarily interested in the determinants of bank lending as a function of bank health. The non-bank mortgage lending is obviously important from both an aggregate perspective and as an additional source of lending data that allows us to cleanly identify local credit demand. As shown in Figure 2, growth in home mortgage lending at banks and non-banks is highly correlated over our sample period, an indication that these two types of lenders behave in a similar manner over the different sample periods under consideration.

For the subset of mortgage issuer that are banks, we match the HMDA-reported home mortgage loan originations with the income and balance sheet data from the Consolidated Financial Statements for Holding Companies (FR Y-9C), the Reports of Condition and Income (Call Reports), or the Thrift Financial Reports. We restrict our analysis to mortgage loans extended in the 48 contiguous U.S. states. Because our identification strategies exploit variation in banks' lending footprint across U.S. census tracts, we limit our sample to banks that are lending in at least 10 census tracts, on average, per year. We also remove from our sample those census tracts that do not have at least five banks originating home mortgage loans, on average, per year. In general, our matched HMDA sample provides very good coverage for most of the country, including all large population centers, although there exist some—mostly rural—areas for which our coverage of mortgage lending is noticeably sparser.

2.2 Summary of Deposits

We use bank branch level summary of deposits data to construct a local measure of bank market share that's independent from Home Mortgage lending. Unlike home mortgage lending, deposits are much less volatile and are closely tied to the physical footprint of a bank. Bank branches have historically been important to establish and maintain customer relationships and are thus a meaningful measure for the importance of a bank at the local level.

2.3 Local Economic Outcomes

While our primary geographic unit of analysis for home mortgage lending is a U.S. census tract, we examine the effects of a credit-supply induced changes in bank mortgage lending on a wide range of county-level economic outcomes. Our analysis focuses on about 950 counties with, on average, a population of at least 50,0000. The county-level economic indicators we consider in our analysis include: (1) home prices, which are published by the FHFA; (2) data on private employment (aggregate and sectoral) and annual wages from the Business Dynamics Statistics (BDS) database maintained by the U.S. Census Bureau; (3) data on employment by firm size and age from the BDS; (4) data on personal and business bankruptcy from the administrative office of the U.S. Courts/Haver Analytics (5) the number of building permits obtained from the Building Permits Survey collected by the U.S. Census Bureau; (6) personal income data from the Statistics of Income published by the U.S. Internal Revenue Service; (7) retail sales data obtained from Moody's economy.com; (8) the number of new motor vehicle registrations using IHS Markit (formerly R. L. Polk & Company); and (9) small business lending data from the Community and Reinvestment Act (CRA).

Table 1 provides the unweighted means and standard deviations for the various county-level economic indicators during three periods we will focus on in this paper: 2002–2006, 2007–2010, and 2011–2018. Annual growth rates of all relevant variables are computed as log-differences from year $t-1$ to year t. To mitigate the effects of outliers on our results, we winsorize all growth rates (or changes) at the bottom 0.25th percentile and the top 99.75th percentile.

Not surprisingly, all measures of economic activity indicate a severe, and in many instances an abrupt, change in the pace of economic activity between the 2002–2006 economic expansion and the 2007–2010 global financial crisis. For example, home mortgage lending expanded at an average annual rate of almost 11 percent during the 2002-2006 period, but plummeted at 35 percent per year, on average, during the ensuing the period 2007–2010. The swings in home mortgage lending growth were even more extreme for non-banks than for banks during our sample. Following the global financial crisis home mortgage lending growth swung back about 11 percent, similar to pre-GFC levels. However, growth in the 2011–2018 period was largely driven by nonbanks home mortgage lending growth. Consistent with the sharp turnaround in home mortgage lending, the switch in the growth of home prices was also abrupt and severe—after rising at an average annual rate of almost six percent during the boom, home prices fell almost 2.5 percent per year, on average, during the subsequent downturn before recovering at a rate around 2 percent throughout 2011-2018. The concomitant deterioration in labor market conditions was also severe. Whereas the employment-population ratio rose about a third of a percent per year, on average, during the 2002–2007 period, it declined at more than a two percent average annual rate during the global financial crisis, and grew at an about one percent rate in the period 2011–2018. Consistent with

Table 1 – Summary Statistics of Local Economic Outcomes

	Sample Period					
	2002–2006		2007–2010		2011–2018	
Indicator	Mean	SD	Mean	SD	Mean	SD
Home prices	6.07	4.94	−2.54	5.33	2.20	4.15
Mortgages[a, b]	11.16	15.48	−35.11	27.42	11.19	15.98
By banks	10.41	15.49	−33.06	29.59	6.65	20.46
By nonbanks	12.93	25.80	−41.60	38.89	18.00	24.52
Bld. permits[b]	0.99	29.06	−27.02	43.42	5.79	39.90
Employment[b]	0.32	2.56	−2.61	3.17	0.93	2.09
GDP[a]	2.00	3.51	−0.85	4.56	0.94	2.09
Earnings[c]	0.83	2.99	0.58	3.25	0.46	3.46
Income[b]	1.53	2.32	0.66	3.3	1.34	2.34
Rtl. sales[b]	1.65	3.68	−2.36	5.42	1.33	2.69
MV regs.[b]	−1.52	6.72	−10.87	15.33	4.62	7.91
SB loans[b]	1.51	18.76	−15.83	22.21	0.91	14.18
Bankruptcies[b]	−18.62	55.74	19.79	18.98	−9.20	12.45
Business[b]	−13.83	67.85	23.67	60.09	−12.94	58.45
Consumer[b]	−18.49	56.03	19.73	19.01	−9.12	12.59

Note: The sample consists of counties with average population over the 2002–18 period equal or greater than 50,000 people. The entries in the table denote the unweighted means (Mean) and standard deviations (SD) of (100×) the log-difference (from year $t-1$ to year t) of the specified county-level economic indicator over the specified sample period. Home mortgage originations, GDP, earnings, income, small business loan originations, and retail sales are in real terms. Summary statistics are based on winsorized data (see the text for details).
[a] Excludes VA-backed and FHA-backed home mortgage originations.
[b] Per capita.
[c] Per employee.

these patterns, the growth of average wages, real GDP and personal income, retail sales, motor vehicle registrations, and small business loans per capita slowed considerably between the housing boom of the early 2000s and the ensuing financial crisis before rebounding in the 2011-2018 period.

3 Identification and Estimation

In this section, we describe the identification strategy used to estimate the shifts in the local supply of home mortgage credit that may be attributed to changes in bank health. Our approach relies on a statistical decomposition based on Khwaja and Mian (2008), Schnabl (2012), Jiménez et al. (2014), and Greenstone et al. (2020) and exploits the fact that the financial institutions in our sample originate mortgages in different local geographic areas. As a by-product, this approach yields estimates of changes in the census-tract-level demand for credit. Because this methodology is purely statistical in nature however, it is silent on the sources of differences in the supply of credit by banks within these narrowly defined geographic areas.[7] To isolate the portion of the effects of

[7]We restrict our sample to those financial institutions that are actively originating mortgages in at least 3 commuting zones, on average, and those census tracts that have at least 15 mortgage originations per year, on average.

statistical credit supply arising from differences in banks' asset quality and capital positions, we link the statistical supply measure with bank income and balance sheet data. Furthermore, we use the estimated time-varying local credit demand shocks to orthogonalize the supply-side effects based on bank health to obtain a novel measure of bank-health induced changes in local credit supply. We begin by discussing how we construct a bank-specific credit supply shock from the mortgage origination data at the census-tract level. We then discuss how this relates to indices of bank health and how we aggregate this information across census tracts within a county to study the relationship between bank health and county-level economic outcomes.

3.1 Credit Supply Shocks at the Census Tract Level

Let $i = 1, \ldots, I_t$ index banks, $c = 1, \ldots, C_t$ census tracts, and $t = 1, \ldots, T$ time (in years). Then let $L_{i,c,t}$ denote the total dollar amount of home mortgage loan originations by financial institution i in census tract c in year t. We decompose the variation in the growth of home mortgage loan originations between any given years $t-1$ and t, denoted by $\nabla L_{i,c,t}$, into the within-census-tract and between-census-tract components, according to

$$\nabla L_{i,c,t} = \mu_t + S_{i,t} + D_{c,t} + \epsilon_{i,c,t}, \tag{1}$$

where μ_t denotes the aggregate (period-specific) fixed effect, $S_{i,t}$ denotes a (period-specific) financial institution fixed effect, while $D_{c,t}$ denotes a (period-specific) census-tract fixed effect. To allow financial institutions to enter and exit census tracts between any two consecutive years, we compute growth rates as in Davis et al. (1996):

$$\nabla L_{i,c,t} \equiv \frac{L_{i,c,t} - L_{i,c,t-1}}{0.5 \times (L_{i,c,t} + L_{i,c,t-1})}.$$

In this statistical framework, geographic fixed effects capture the variation in lending between census tracts arising from differences in the local demand for credit. Financial institution fixed effects, in contrast, capture variation in lending within census tracts and thus measure differences in the supply of credit across lenders, controlling for differences in their between-census-tract exposures.[8]

A number of recent studies employ a similar type of statistical decomposition as above, using lending data at the bank/county level (see Mondragon, 2020; Greenstone et al., 2020; Flannery and Lin, 2016; García, 2020). Our choice of the more granular aggregation at the lender/census-tract level is motivated by the fact that counties can be very heterogeneous and thus a single fixed effect is unlikely to accurately capture local credit demand considerations. A prime example for this concern is Los Angeles County as shown in Figure 3, the most populous county in the U.S. with about 10 million inhabitants. Los Angeles County includes places such as Bel Air, Silver Lake, the Watts neighborhood, and Lancaster in the Antelope Valley. These localities differ significantly along

Furthermore, we require that lenders remain in our sample for at least 3 years.

[8] Because specification (1) allows for a time-varying intercept μ_t, the effects of aggregate shocks, which are common to all banks and census tracts, are averaged out.

socio-economic, ethnic, geographic and racial dimensions.[9] As a consequence, a county fixed effect is unlikely to accurately capture local credit demand factors. Census tracts, on the other hand, are designed to be much more homogeneous. When census tracts are established, the Census Bureau requests them to contain a population with similar socioeconomic and housing characteristics (if possible). Census tracts average about 4,000 inhabitants, with a minimum population of 1,200 and a maximum population of 8,000. Census tracts may be adjusted—that is, reshaped, split, or merged—every 10 years to ensure that they remain within these parameters. Furthermore, census tract boundaries often follow visible geographical features, such as streets, roads, highways, rivers, or canals.[10] In the case of Los Angeles county, as shown in Figure 3, conducting our analysis at the census tract—as opposed to county level—means that we estimate almost 2,400 census tract fixed effects every year, instead of a single county fixed effect, an approach that is far more likely to accurately capture local credit demand factors.

Letting $N_{i,c,t}$ denote the number of loan originations by bank i in census tract c during year t, the dollar amount of loan originations, $L_{i,c,t}$, can be decomposed as

$$L_{i,c,t} = N_{i,c,t} \times \bar{L}_{i,c,t},$$

where $\bar{L}_{i,c,t} = L_{i,c,t}/N_{i,c,t}$ is the *average* size of a loan by bank i in census tract c during year t.

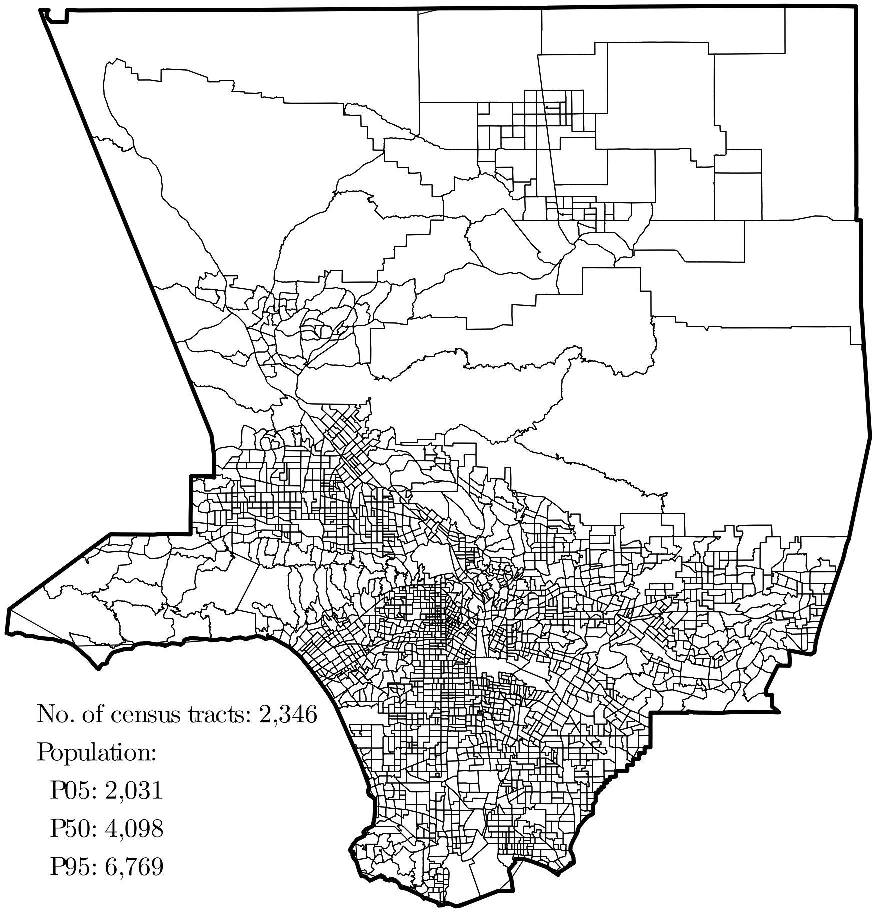
Recent studies that estimate variants of specification (1) use the growth of the dollar amount of loan originations between two adjacent time periods as a dependent variable. Our approach, in contrast, identifies bank-specific shifts in the supply of credit between years $t-1$ and t, the estimates of $S_{i,t}$, $i = 1, \ldots, I_t$, using growth in the *number* of loan originations—that is, lending at the bank's *extensive* margin. The motivation for this choice is provided in Figure 4. The black dots in the figure represent the growth rates of aggregate home mortgage loan originations, while the red and yellow bars represent the corresponding aggregates of the growth in the number of loans and of the average size of the loan, respectively. This decomposition clearly shows that fluctuations in mortgage lending over time are driven primarily by changes in the number of loans extended—that is, by changes at the lenders' extensive margin of lending—rather than by changes in the average size of the loan, the intensive margin. In fact, during the global financial crisis, the collapse in lending is almost entirely due to the reduction in the number of loan originations, since the size of an average home mortgage loan actually increased over the first couple of years. The average size of a home loan also tends to fluctuate with home prices because the average size of a loan is likely to increase in periods during which home prices are rising.

We apply this approach to our HMDA data year-by-year starting in 2001 and ending in 2018.

[9] Median family income in LA county based on the 2019 American Community Survey's 5-year-estimates ranges from about \$250.000 (Census Tract 1415 - Encino) to about \$18.000 (Census Tract 2421 - Watts). The median family income across census tracts in LA county is approximately \$73,000 (Census Tract 5546 - Artesia). On most days, you can easily spend 2 hours driving more than 90 miles from the northern edge of the county to the southern edge, or more than 1.5 hours driving more than 70 miles from the western edge to the eastern edge.

[10] Because the average population of a census tract is about 4,000, census tracts covering a larger geographic area are less densely populated, whereas more densely populated tracts cover a smaller geographical area. For more details on census tracts see https://www2.census.gov/geo/pdfs/reference/GARM/Ch10GARM.pdf.

FIGURE 3 – Census Tracts Within Los Angeles County



NOTE: The figure depicts the census tract boundaries in Los Angeles county based on the 2010 Census.

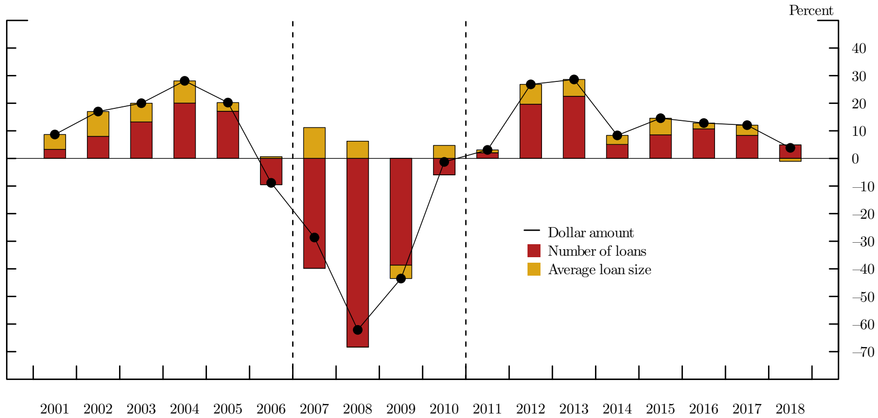
Specifically, using $\nabla N_{i,c,t}$ as a dependent variable, we estimate equation (1) by weighted least squares (WLS), using market shares as weights. These weights—denoted by $\bar{\omega}^b_{i,c,t}$—are given by

$$\bar{\omega}^b_{i,c,t} = \frac{1}{2} \sum_{s=t-1}^{t} \frac{L_{i,c,s}}{\sum_{i \in \mathscr{B}_{c,s}} L_{i,c,s}},$$

where $\mathscr{B}_{c,s}$ denotes a set of mortgage originators that are active lenders in census tract c in year s. Note that for any two consecutive years $t-1$ and t, the estimated fixed effects $\widehat{S}_{i,t}$, $i = 1, \dots, I_t$, only identify relative shifts in the supply of credit across mortgage originators. Similarly, the estimated census tract fixed effects $\widehat{D}_{c,t}$, $c = 1, \dots, C_t$, only identify relative shifts in the demand for credit across census tracts; hence without the loss of generality, we center the estimated mortgage originator and geographic fixed effects to have a mean equal to zero in each period.

As discussed above, our goal is to isolate the component of local credit supply that can be attributed to shifts in bank health. Accordingly, throughout the remainder of our analysis, we

Figure 4 – Decomposition of Home Mortgage Lending



Note: The red bars depict the growth of the number of loan originations (i.e., lending at the extensive margin), while the yellow bars depict the growth in the average loan size (i.e., lending at the intensive margin) for the sample of all financial institutions. The solid circles depict the growth of the dollar amount of loan originations (i.e., the sum of extensive and intensive lending margins).

limit the sample of financial institutions we study to banks.[11] To isolate changes in bank-specific credit supply due to changes in banks' financial health, we estimate the following panel regression at the bank level:

$$\widehat{S}_{i,t} = \beta' \text{BankHealth}_{i,t} + \theta' \text{Controls}_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t}, \tag{2}$$

where $\text{BankHealth}_{i,t}$ denotes a vector of bank health variables that influence the willingness and ability of banks to intermediate credit, conditional on a vector or pre-determined bank-specific control variables, denoted by $\text{Controls}_{i,t-1}$, as well as bank and time fixed effects, η_i and λ_t, respectively. The portion of the statistical credit supply shift $\widehat{S}_{i,t}$ that is attributable to observable changes in banks' financial health is then given by

$$\widetilde{S}_{i,t} = \hat{\beta}' \text{BankHealth}_{i,t}. \tag{3}$$

We consider bank health along two key—though intertwined—dimensions: capital and loan losses. The role of bank capital and loan losses in the credit allocation mechanism is well understood. A well-capitalized bank, or a bank with ready access to additional sources of capital, will be able to accommodate capital losses without reducing its assets and hence its lending. Moreover, if banks actively manage their assets to maintain a target equity-capital-to-assets ratio—because they are

[11] A bank is a depository institution for which we have branch level deposit data from the Summary of Deposits data and financial information from the Call/Thrift reports and Y9C. Analogously to our requirement for HMDA data, we require depository institutions to be active in three commuting zones, on average, and be in the sample for at least three years. We exclude foreign bank holding companies as well as foreign-owned banks. We also exclude large banks with minimal exposure in the mortgage markets: the two largest custodian banks (BONY and State Street), investment banks Goldman Sachs, Morgan Stanley, Metlife, Merrill Lynch, and American Express.

unable to easily raise equity to offset declines in capital—a capital loss will result in a reduction in its assets that is equal to the size of the bank's capital loss scaled up by the inverse of its capital ratio (i.e., leverage ratio). To empirically capture this intuition, the vector $\text{BankHealth}_{i,t}$ in specification (2) consists of the difference of the bank's Tier 1 leverage ratio at the end of year $t-1$ from it's 12 quarter moving average ($\text{Gap-T1LEV}_{i,t-1}$), and the bank's (net) charges on its portfolio of loans during year t, scaled by its stock of outstanding loans at the end of year $t-1$ ($\text{CHGOFF}_{i,t}$).[12]

TABLE 2 – Bank Health and Mortgage Credit Supply Shocks (2000–2018)

	Dependent Variable: $\widehat{S}^E_{i,t}$		
Bank Health Indicator	(1)	(2)	(3)
$\text{CHGOFF}_{i,t}$	-5.855^{***}	.	-5.587^{***}
	(1.433)		(1.407)
$\text{Gap-T1LEV}_{i,t-1}$	.	2.307^{**}	2.053^{**}
		(0.899)	(0.872)
R^2 (within)	0.173	0.169	0.175
No. of banks	399	399	399
Avg. T_i (years)	12	12	12
Observations	4,968	4,968	4,968

Memo:
Std. deviation of CHGOFF = 0.84
Std. deviation of Gap-T1LEV = 1.06

NOTE: The dependent variable in all specifications is $\widehat{S}^E_{i,t}$, the estimated home mortgage credit supply shock at the extensive margin for bank i from year $t-1$ to year t. The entries denote the OLS estimates of the parameters associated with the specified bank health indicator: $\text{CHGOFF}_{i,t}$ = total loan charge-off rate during year t; and $\text{Gap-T1LEV}_{i,t-1}$ = deviation of Tier 1 leverage ratio at the end of year $t-1$ from its trailling twelve-quarter moving average. All specifications include bank and time fixed effects, as well as a set of pre-determined bank-specific control variables (see the text for details). Asymptotic standard errors reported in parentheses are clustered across banks: * $p < .10$; ** $p < .05$; and *** $p < .01$.

The vector $\text{Controls}_{i,t-1}$ consists of the bank's exposure to real estate as measured by the ratio of real estate loans to total loans outstanding ($\text{RELNS/LNS}_{i,t-1}$) and how actively a bank engages in securitization of its home mortgage loan portfolio as captured by an indicator variable ($SEC_{i,t-1}$) that equals 1 if, in a given year, the bank securitized more than 10 percent of its mortgage originations and 0 otherwise.[13] In addition, we control for the extent to which banks engage in lending by including the ratio of total loans to total assets ($[LNS/A]_{i,t-1}$) and for bank

[12] In a somewhat confusing banking parlance, the Tier 1 leverage ratio measures the banking organization's core capital relative to its total assets and is used by regulators worldwide to ensure the capital adequacy of banks and to place constraints on the degree to which a financial company can leverage its capital base. The Tier 1 leverage ratio is calculated by dividing Tier 1 capital by a bank's average total consolidated assets and certain off-balance sheet exposures. We use the difference between the Tier 1 leverage ratio and it's 12 quarter moving average to allow for slow moving changes in this ratio that may reflect regulatory changes but are unrelated to a banks financial condition. The "net" in the charge-off rate refers to losses on real estate loans net of the estimated recoveries.

[13] We compute for each bank the fraction of loans in the confidential HMDA data in the first 9 months of the year that are securitzed.

size measured by the log of (real) total assets ($\ln A$). We also control for the difference in banks' funding models by including the ratio of core deposits to total liabilities ($[CDEP/L]_{i,t-1}$) in the vector $\text{Controls}_{i,t-1}$.

Table 2 reports the estimates of the relationship between statistical credit supply shocks and these two measures of bank health. As shown in column (1), an increase in real estate charge-offs are associated with negative credit supply shocks. Column (2) shows that banks with a higher Tier 1 leverage ratio gap have, on average, more positive credit supply shocks. In other words, an increase in the Tier 1 leverage ratio relative to the 12 quarter trailing moving average is associated with a positive credit supply shock. Column (3) shows that including both charge-offs and the Tier 1 leverage ratio gap leave the coefficients unchanged.

Having estimated the bank-level credit supply effects attributable to variation in banks' financial health—the estimates of $\tilde{S}_{i,t}$—an estimate of a *census-tract-level* shift in credit supply in year t, denoted by $\tilde{S}_{c,t}$, is then calculated as a deposit-share weighted average of bank-specific credit supply shocks in that census tract:

$$\widetilde{S}_{c,t} = \sum_{i \in \bar{\mathscr{B}}_{c,t}} \bar{\omega}^{b}_{i,c,t} \times \widetilde{S}_{i,t}, \tag{4}$$

where $\bar{\omega}^{b}_{i,c,t}$ is the market share of deposits around a given census tract c of bank i in years t and $t-1$.[14] A deterioration in these census-tract-level estimates of banks' financial health reflects, in part, the willingness and ability of banks to supply mortgage credit, but, of course, it could also be driven by a worsening of local economic conditions that at the same time depress the demand for credit. To remove any local demand effects from our census-tract-level measures of bank health, we estimate the following panel regression:

$$\widetilde{S}_{c,t} = \theta_{I} \widehat{D}^{(I)}_{c,t} + \theta_{E} \widehat{D}_{c,t} + \eta_c + \lambda_t + \xi_{c,t} \tag{5}$$

where $\widehat{D}_{c,t}$ and $\widehat{D}^{(I)}_{c,t}$ denote the census-tract-level estimates of the credit-demand effects at the extensive and intensive margins, respectively, estimated using specification (1); η_c is the census tract fixed effect; and λ_t is the time fixed effect. The residuals $\hat{\xi}_{c,t}$ thus capture variation in banks' financial health that can explain variation in credit supply across census tracts, which is orthogonal to the estimated changes in local credit demand, as well as time and census tract fixed effects.[15]

Figure 5 depicts the census-tract-level credit supply shock estimates for the periods 2002–2006, 2007–2010, and 2011-2018 in Los Angeles County.[16] Importantly, in all three periods, there is sub-

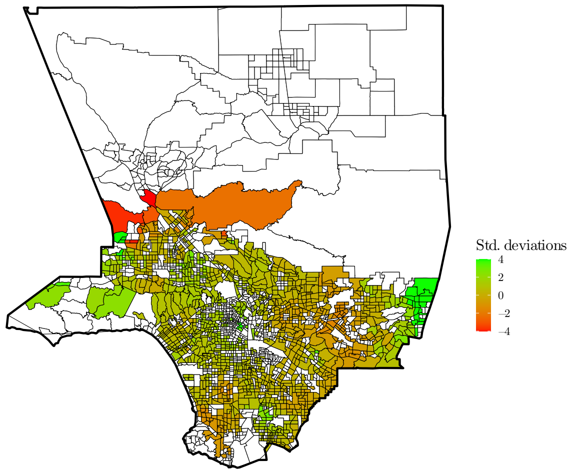
[14]For a given census tract we construct the market share of deposits for a given bank by computing the sum of all deposits for a given bank i of all branches in a 15 miles radius around the mid-point of census tract c relative to the sum of all deposits in the same area. For rural areas we increase the radius to 50 miles. We rely on rural-urban county delineation from the USDA.

[15]To obtain an estimate for the intensive margin census-tract-level credit-demand effect, $\widehat{D}^{(I)}_{c,t}$, we estimate a slightly modified version of equation (1) using the average loan size $\overline{L}_{i,c,t}$, namely

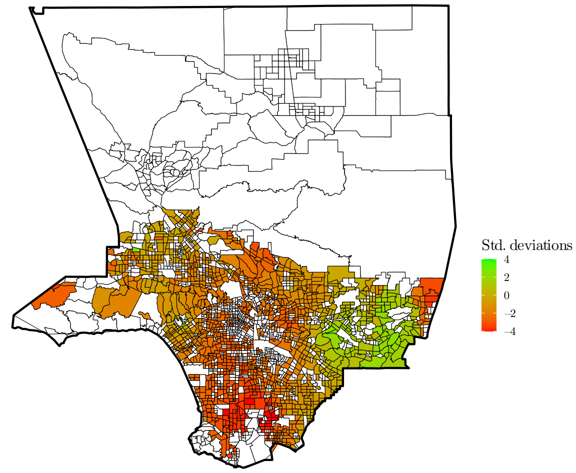
$$\nabla \overline{L}_{i,c,t} = \mu^{(I)}_t + S^{(I)}_{i,t} + D^{(I)}_{c,t} + \epsilon^{(I)}_{i,c,t},$$

[16]White areas correspond to census tracts with insufficient data to estimate credit supply shocks, census tracts

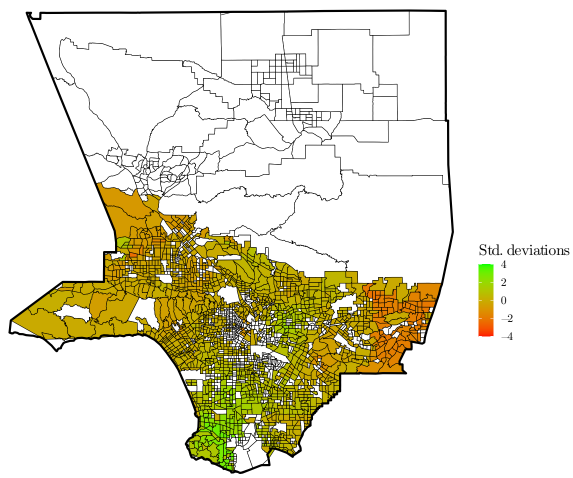
Figure 5 – Credit Supply Shocks in Los Angeles County



A. Period: 2002–2006



B. Period: 2007–2010



C. Period: 2011–2018

Note: The panels of the figure depict the relative variation across census tracts in Los Angeles county in the average estimated credit supply shocks, $\hat{\xi}_{c,t}$, based on banks' financial health during the years 2002–2006 (Panel A), 2007–2010 (Panel B), and 2011–2018 (Panel C). White areas correspond to census tracts with insufficient data to estimate credit supply shocks or census tracts that do no satisfy the aforementioned criteria to be included in our sample.(See the text for details).

stantial heterogeneity in the estimated credit supply shocks across census tracts, which underscores the importance of conducting this analysis at the census tract rather than the county level.

Because we are interested in studying the effects of credit supply shocks on local economic outcomes, we aggregate our estimates of the census-tract-level credit supply shocks to the county level. To do so, we construct the county level credit supply shock, denoted by $Z^{BH}_{k,t}$, as the weighted

that do no satisfy the aforementioned criteria to be included in our sample, or to census tracts whose shock consists of of estimates based on fewer than 3 depository institutions. Because we rely on confidential HMDA data, we are not able to show estimates that are based on fewer than 3 institutions.

average of the census-tract-level credit supply shocks in that county:

$$Z^{BH}_{k,t} = \sum_{c \in \mathscr{C}_k} \bar{\omega}^c_{c,t} \times \hat{\xi}_{c,t}. \tag{6}$$

The weights in the above aggregation—denoted by $\bar{\omega}^c_{c,t}$—are given by the population share of the census tract in that county, i.e.

$$\bar{\omega}^c_{c,t} = \frac{1}{2} \sum_{s=t-1}^{t} \frac{pop_{c,s}}{\sum_{c \in \mathscr{C}_k} pop_{c,s}}, \tag{7}$$

where $\mathscr{C}_k$ denotes the set of census tracts in county k.

Figure 6 provides a visualization of these estimated credit supply shocks across U.S. counties.[17] Specifically, the three heat maps show the geographic variation in our estimated county-level credit supply shocks during the 2002–2006 boom period (Panel A), during the ensuing bust (Panel B), and during the recovery (Panel C). In these maps, the green-shaded counties experienced, in a relative sense, positive credit supply shocks, whereas their red-shaded counterparts experienced negative shocks, relative to other counties.

During the 2002–2006 housing boom (Panel A), parts of the west coast and the south experienced relatively favorable credit conditions. A mere three years later during the Global Financial Crisis (GFC) (Panel B), the situation reverses abruptly: The Sand States of Arizona, California, Florida, and Nevada—the epicenter of the housing downturn—all experienced a severe relative contraction in the supply of home mortgage credit. A similar pullback in the supply of credit is also evident in the coastal areas of Northwest and the Northeast Corridor, regions that during the boom period also experienced escalating home prices, which significantly outpaced income growth.

The years after the GFC (Panel C), unlike the preceding periods, are less extreme along the coasts, on average. Favorable credit supply shocks are concentrated along the mountainous west, rather than along the coasts, likely reflecting the housing boom that these areas experienced as people moved inland from expensive west coast cities in the later part of the sample period.

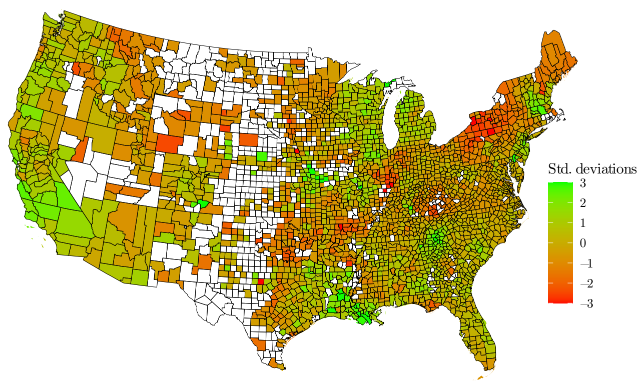
4 Local Economic Outcomes

To examine how our estimated credit supply shocks affect economic outcomes across counties, we estimate the following regression using county-level data:

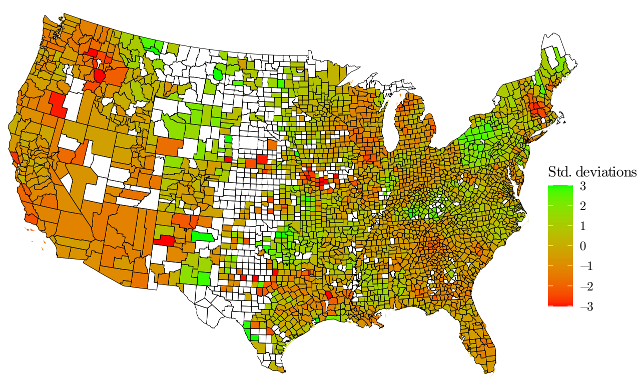
$$\Delta_2 Y_{k,t} = \beta \Delta_2 \overline{M}^B_{k,t} + \gamma' X_{k,t-3} + \delta_t + \epsilon_{k,t}, \tag{8}$$

[17] White areas correspond to counties with insufficient data to estimate credit supply shocks, counties that do no satisfy the aforementioned criteria to be included in our sample, or to counties whose shock consists of estimates based on fewer than 3 depository institutions. Most omitted counties tend to be sparsely populated, have few banks, as well as few mortgage originations, thus dropping out of our sample.

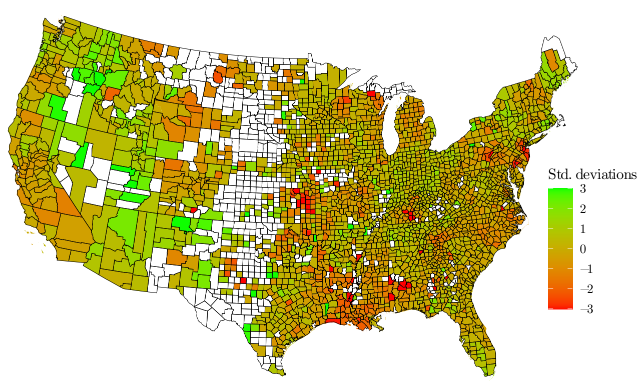
Figure 6 – Credit Supply Shocks Across U.S. Counties



A. Period: 2002–2006



B. Period: 2007–2010



C. Period: 2011–2018

Note: The panels of the figure depict the relative variation across U.S. counties in the average estimated credit supply shocks based on bank health during the years 2002–2006 (Panel A), 2007–2010 (Panel B), and 2011–2018 (Panel C). White areas correspond to counties with insufficient data to estimate credit supply shocks, counties that do no satisfy the aforementioned criteria to be included in our sample, or to counties whose shock consists of estimates based on fewer than 3 depository institutions.(see the text for details).

where $\Delta_2 Y_{k,t}$ denotes the annualized log-difference (or change) in an indicator of economic conditions in county k from year $t-2$ to year t, $\Delta_2 \overline{M}^B_{k,t}$ denotes the growth in bank-issued mortgages over this two year period and δ_t denotes the time fixed effect, which captures aggregate economic shocks.

To isolate the variation in local bank mortgage lending that is attributable to our local credit supply shock, we then instrument $\Delta_2 \overline{M}^B_{k,t}$ using $\overline{Z}^{B,H}_{k,t}$, the corresponding average two-year average credit supply shock in county k. Our instrumental variables approach provides a natural normalization such that the effect of a local credit supply shock results in a 1 percent increase in local bank mortgages. By using $\overline{Z}^{B,H}_{k,t}$ as an instrument rather than a reduced-form variable we also avoid the need to correct standard errors because our supply shock is generated from a regression of local credit supply on measures of bank health.[18]

The use of annual two-year overlapping growth rates allows fluctuations in bank mortgate lending induced by changes in credit supply conditions to filter into local economic outcomes over time (see Nakamura and Steinsson, 2014). The vector of covariates $X_{k,t-3}$ in specification (8) includes variables that control for systematic differences in counties that can potentially affect the relationship between changes in home prices and local economic outcomes. Specifically, these control variables capture county-level heterogeneity in the following dimensions: (1) *Industry composition*: We use the industry-level employment data from the County Business Patterns to calculate the share of county employment in the following four broad economic sectors: construction ($\text{EMP-CST}_{k,t-3}$), tradable goods industries ($\text{EMP-TRD}_{k,t-3}$), nontradable goods industries ($\text{EMP-NTRD}_{k,t-3}$), and other industries ($\text{EMP-OTH}_{k,t-3}$).[19] The inclusion of these variables captures differences in the composition of economic activity across counties: (2) *Racial composition*: To control for differences in racial composition between counties, we use the 2000 Census data to calculate the share of county population that is black ($\text{SHR-BLACK}_{k,2000}$), white ($\text{SHR-WHITE}_{k,2000}$), and other ($\text{SHR-OTH}_{k,2000}$); (3) *Educational attainment*: To control for differences in educational attainment across counties, we use the 2000 Census data to calculate the share of the population that does not have a high school diploma ($\text{SHR-LESS-HS}_{k,2000}$), the share that has a four-year college degree or higher ($\text{SHR-COLLEGE}_{k,2000}$), and the share that has a high school diploma and possibly some college ($\text{SHR-HS}_{k,2000}$); (4) *Poverty rate*: To control for differences in income and wealth across counties, we include the poverty rate ($\text{POVERTY}_{k,t}$) from the Small Area Income and Poverty Estimates program in the vector of control variables $\mathbf{X}_{k,t-3}$; and (5) *Banking concentration*: To control for differences in lenders concentration across counties, we use the full HMDA data set to calculate the Herfindahl-Hirschman Index ($\text{HHI}_{k,t}$) of lender concentration for each county and year.

We consider a large number of county-level regressions as outlined in Equation (8). All regressions are unweighted and include counties with a population larger than 50.000, on average.[20]

[18] In practice, the reduced form OLS results give very similar standard errors to the IV estimates so that the IV procedure primarily acts as as a scaling device.

[19] In constructing these employment shares, we follow the methodology of Mian and Sufi (2014).

[20] In order to make estimates nationally representative researchers at times weight their regressions by population.

Throughout all regression specifications we employ standard errors based on Adão et al. (2019). The key idea underlying their work is that the variation in our instrument occurs at the bank level rather than at the county level. Counties that are similar in the composition of the banking sector thus experience similar variation in the county-level credit supply shock measure. The Adão et al. (2019) standard errors take that explicitly into account.

4.1 County Heterogeneity

We start our analysis by considering a set of housing market and economic outcomes throughout our 2003-2018 sample. Table 3 shows our findings. Panel (A) shows our estimate in a specification with the aforementioned controls but without county fixed effects (all regression include time fixed effects). Our findings are what one would intuitively expect: a negative bank credit supply shock lead to a decline in mortgage lending overall. Our point estimate implies that a one percent reduction in bank mortgage lending causes a 0.641 percent reduction in overall mortgage lending. Although not shown, in the full sample, this decline in overall mortgage lending is due to a combination of a contraction in bank lending combined with a modest expansion in non-bank mortgage lending. While there is a substitution from bank lending to non-bank lending the overall decline in mortgage lending indicates that the effect on banks dominates. Unsurprisingly, the local real estate market is also affected by a negative bank credit supply shock: the house price index as well as building permits per capita both decline. With regards to key macroeconomic outcomes we observe that both GDP growth, employment growth (both in per capita terms) and growth in earnings per employee decline in response to contractionary shocks to bank mortgage credit supply.

Panel (B) shows the same regressions but includes county fixed effects. The inclusion of county fixed effects has minimal effects on the point estimates of the expansion in bank credit supply. This means in turn that unobserved county characteristics are not an important factor in our analysis. Throughout the remainder of the paper we will consider pre-GFC, GFC, and post-GFC periods separately. We do not include county fixed effects in those specifications as some periods cover only a few years and thus, given the short time-series dimension of our panel, don't lend to the inclusion of county-level fixed effects.

4.2 Analysis by Sub-Period

Figure 7 and Figure 8 visually illustrate the correlation between our credit supply shocks and key economic outcome variables across sub-periods in the sample divided into the pre-GFC boom

However, Solon et al. (2015) caution that weighting by population does not necessarily result in a population-average treatment effect. They show that population weighting can potentially yield a coefficient that is farther from the true effect than that of an unweighted regression as least squares regression already weights observations based on their contribution to the overall variance of the regressors. Weighted regressions can also decrease efficiency, especially with skewed weights. Taking those considerations into account, our estimations are unweighted, while limiting our sample to counties with a population of at least 50.000, on average, limits heterogeneity across counties. Our sample corresponds to about 1/3 of all U.S. counties and represents roughly 80% of the U.S. population. Qualitatively, our findings are similar for population weighted regressions. For an excellent guide to working with regional data in macroeconomics see Chodorow-Reich (2020).

TABLE 3 – Bank Health, Mortgage Credit Supply, and Local Economic Outcomes (2003–2018)

	Dependent Variable: $\Delta_2 \ln Y_{k,t}$					
	Total mortgages[a]	Home prices	Bldg. permits[a]	GDP[a]	Employment[a]	Earnings[b]
Regressor	(1)	(2)	(3)	(4)	(5)	(6)
A. *Without county fixed effects*						
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	0.641**	0.455***	0.801***	0.106***	0.054***	0.072**
	(0.037)	(0.045)	(0.074)	(0.019)	(0.008)	(0.014)
No. of counties	951	951	950	935	951	928
Observations	15,174	15,165	15,122	14,918	15,174	14,557
B. *With county fixed effects*						
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	0.642***	0.466***	0.836***	0.103***	0.055***	0.073***
	(0.037)	(0.039)	(0.074)	(0.013)	(0.006)	(0.005)
No. of counties	951	951	950	935	951	928
Observations	15,174	15,165	15,122	14,918	15,174	14,557

NOTE: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference of the specified economic indicator in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated mortgage credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Per capita.
[b] Per employee.

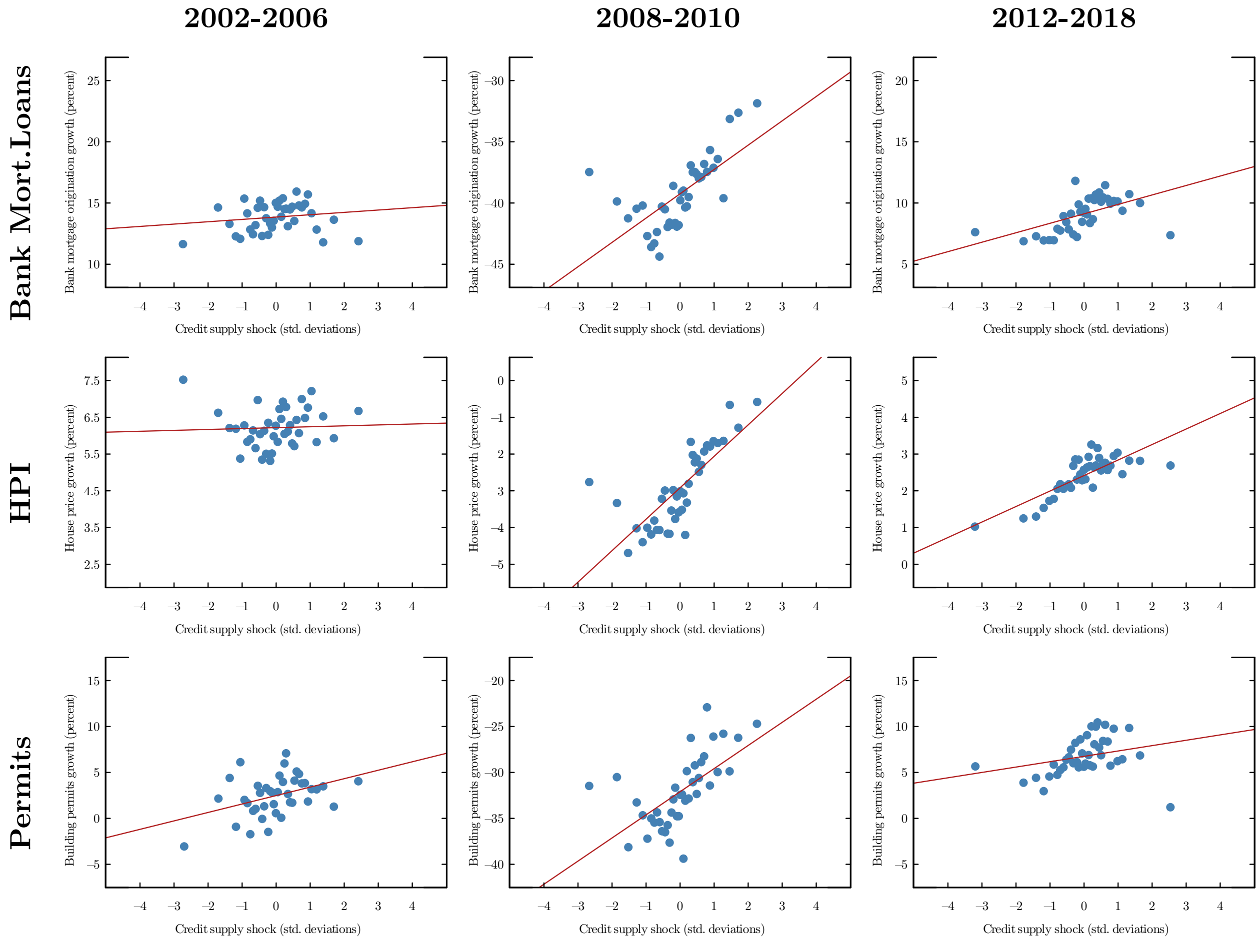
period, the GFC period, and the post-GFC period. It is clear that the periods are quite different. While a key difference is unsurprisingly the average growth rate, it is perhaps more surprising that the boom looks very different from both the GFC and post-GFC period.

Figure 7 plots the relationship between bank credit supply and housing market outcomes. During the GFC and post-GFC periods, we observe a positive relationship between bank credit supply and both home prices and home mortgage lending. In contrast, during the boom, the relationship between bank credit supply and both home prices and bank home mortgage originations is much weaker.

Figure 8 plots the relationship between bank credit supply and employment outcomes using total employment, employment in the construction sector, and employment in the non-tradeable sector. Here differences between the early boom period and the later periods are even more striking. Again, there is no robust pattern linking increases in bank credit supply to increases in employment in any of these categories during the boom. In contrast, we see a strong positive relationship between credit supply and employment growth across all three employment categories during both the GFC and post-GFC periods.

Table 4 and 5 provide a formal econometric analysis of the relationship between bank credit

FIGURE 7 – Credit Supply Shocks and the Housing Market

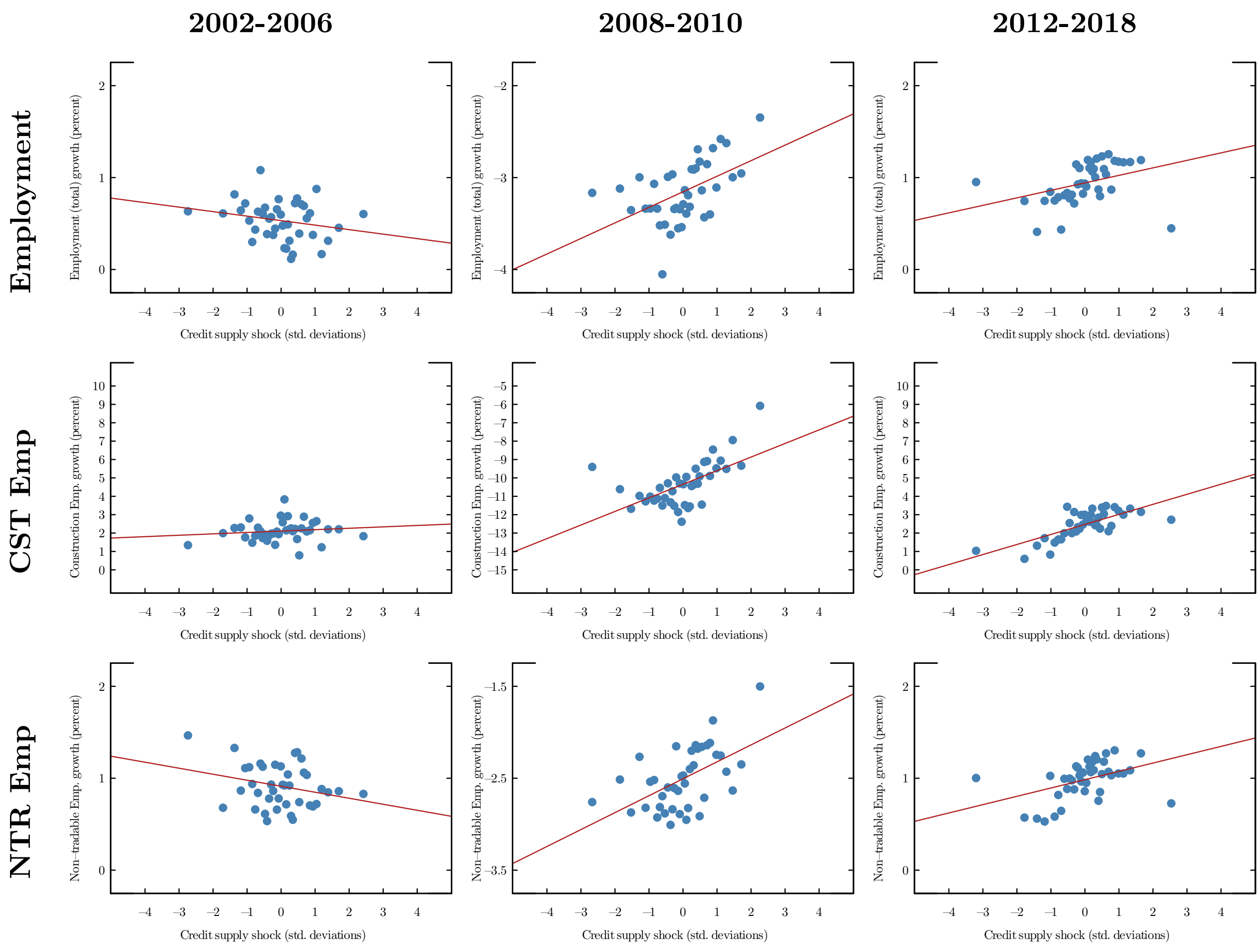


NOTE: Panels depicts bin-scatter plots of the average estimated credit supply shocks, $\hat{\xi}_{c,t}$, during years 2002-2006 (column A), 2008-2010 (column B), and 2012-2018 (column C) periods, against growth in house prices, bank home mortgage loan originations and building permits for counties with a population of at least 50.0000, on average. Each panel bins counties into 100 bins.

supply and local economic outcomes across these three sub periods. Starting with the housing market in Table 4, we find that a negative credit supply shock during the boom implies a reduction in overall mortgage loan growth in a county. This response is estimated with considerable noise however. The effect of bank credit supply shocks on housing prices and permits is positive but not significant. With regards to other county level macroeconomic outcomes, shown in Table 5, bank credit supply shocks appear to have no significant effect during the boom. The main issue here is that bank health has little variation and hence a relatively weak effect on bank mortgage lending during this period. These findings are also consistent with prior research that emphasize the role of private-label (non-bank) mortgages as the driving force for house prices during the boom.

In contrast to the boom period, a credit-supply induced contraction in bank mortgage lending

FIGURE 8 – Credit Supply Shocks and Employment



NOTE: Panels depict a bin-scatter plot of the average estimated credit supply shocks, $\hat{\xi}_{c,t}$, during years 2002-2006 (column A), 2008-2010 (column B), and 2012-2018 (column C) periods, against employment, construction employment and non-tradable employment growth for counties with a population of at least 50.0000, on average. Each panel bins counties into 100 bins.

causes an economically large and statistically significant decline in overall mortgage lending during both the GFC and the post-GFC periods. Similar to the full-sample results, a one percent decline in bank-lending results in a slightly smaller drop in overall mortgage lending. This reduction in bank mortgage lending also leads to a substantial drop in house prices and building activity as measured by building permits. The point estimates imply a somewhat stronger effect of bank mortgage lending during the recovery (0.55) relative to the bust (0.417) but somewhat weaker effect on building permits.

The effect of bank health credit supply shocks on economic activity measures are reported in Table 5. As noted above, the estimated effects of bank health on the housing market and other economic indicators during the boom vary in sign and are statistically insignificant. We

Table 4 – Bank Health, Mortgage Credit Supply, and Local Housing Markets

	Dependent Variable: $\Delta_2 \ln Y_{k,t}$			
	Total mortgages[a]	Nonbank mortgages[a]	Home prices	Bldg. permits[a]
Regressor	(1)	(2)	(3)	(4)
A. *Sample period*: 2003–2006				
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	-1.415	-5.278	0.101	3.528
	(3.737)	(9.728)	(0.916)	(3.248)
No. of counties	949	949	949	948
Observations	3,785	3,785	3,780	3,781
B. *Sample period*: 2007–2010				
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	0.634***	-0.302	0.417***	1.261***
	(0.083)	(0.295)	(0.083)	(0.259)
No. of counties	951	951	951	949
Observations	2,853	2,853	2,853	2,843
C. *Sample period*: 2011–2018				
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	0.795***	0.110	0.555***	0.756***
	(0.107)	(0.266)	(0.094)	(0.268)
No. of counties	949	949	949	949
Observations	6,642	6,642	6,638	6,611

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference of the specified housing market indicator in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated mortgage credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Per capita.

therefore focus on the GFC and post-GFC periods. These results imply that a credit-supply induced contraction in bank mortgage lending leads to significant declines in all economic activity measures during the bust.

While it may be expected that bank health mattered during the GFC, it is worth highlighting that bank health also has economically important effects also during the post-GFC period. The point estimates imply very similar economic magnitudes for the effect of a one percent increase in bank lending on employment and GDP during the GFC and post-GFC period while the effects on income and earnings are larger during the latter period. Retail sales and motor vehicle registrations also respond strongly to the credit-supply shock during both periods.

One way to gauge the strength of these effects is to compare the employment responses reported in Table 5 to the housing price responses reported in Table 4. Recent work by Guren et al. (2021) imply that a 1 percent increase in housing prices causes a 0.055 percent increase in retail employment. They interpret this finding as consistent with a life-cycle model where households increase their consumption in response to exogenous changes in housing wealth. The implied elasticity based on our estimates for total employment is 0.19 during the GFC and 0.17 during the post-GFC period. As shown below, we obtain very similar estimates when confining attention to retail employment rather than total employment (these estimates are 0.16 and 0.18 for the GFC and post-GFC period).[21] Thus, if we interpret our results solely through the lens of a household wealth effect that stimulates local consumption and hence local employment, our implied estimates of the wealth channel would be three times larger than other estimates in the literature. This suggests that alternative channels to a pure household wealth effect may help account for our findings.

4.3 Bank Health and Alternative Measures of Economic Activity

In this section we examine a large range of economic outcomes but limit our analysis to the GFC and post-GFC periods as our bank health credit supply shock has little relevance during the boom period as discussed previously. Our goal is to provide further insight into what might account for the quantitatively large employment responses to bank-health induced changes in mortgage supply.

An obvious concern is the extent to which bank mortgage lending primarily works by stimulating construction employment. Using sectoral data, we show that the employment response is broad-based but cannot be traced to the response of employment in manufacturing and hence tradeable-goods sector. We also show that the employment of bank-dependent firms appear to be more sensitive to credit supply shocks, and that credit supply shocks influence the bankruptcy rates of both firms and households. Finally, we document a sharp increase in bank lending to small firms in response to a bank-health induced increase in home mortgage lending. These estimates suggest independent channels whereby credit supply shocks stimulate local lending and hence employment to local bank-dependent firms, conditional on local household demand. This section lays out these findings. The next section then considers formal ways to examine the strength of the household spending channel vis-a-vis the firm lending channel.

Table 6 shows the effect of bank health on local employment in different sectors; Table 7 considers employment by firm size and firm age; Table 8 examines the effect on small business lending; and Table 9 documents the effect on personal and business bankruptcies.

With regards to sectoral employment, shown in Table 6, we find that credit supply shocks most directly affect employment in construction. Given that our credit supply shocks are identified from home mortgage lending data this is perhaps unsurprising. More importantly, we find that the effect on employment outside the construction sector is large and significant. [22]

[21] Formally, these elasticities are equal to estimated response of employment to housing prices, using our measure of bank credit supply as an instrument. The IV regression delivers precise estimates with standard errors that are similar in magnitude to those reported in the tables.

[22] While the U.S. Census Bureau's Quarterly Workforce Indicators (QWI) data are available at the 4 digit NAICS level at the county level and thus allow for the construction of the industries corresponding to Mian and Sufi (2014), the

Table 5 – Credit Supply Shocks and Local Economic Outcomes

	Dependent Variable: $\Delta_2 \ln Y_{k,t}$					
	GDP[a]	Employment[a]	Income[a]	Earnings[b]	Rtl. sales[a]	MV regs.[a]
Regressor	(1)	(2)	(3)	(4)	(5)	(6)
A. *Sample period*: 2003–2006						
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.117	−0.289	−0.271	−0.167	−0.373	0.304
	(0.267)	(0.500)	(0.416)	(0.202)	(0.613)	(2.856)
No. of counties	933	949	932	914	933	932
Observations	3,721	3,785	3,717	3,530	3,721	2,827
B. *Sample period*: 2007–2010						
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.147***	0.081***	0.099***	0.066***	0.088***	0.412***
	(0.038)	(0.021)	(0.029)	(0.015)	(0.028)	(0.090)
No. of counties	935	951	934	916	935	947
Observations	2,805	2,853	2,802	2,748	2,805	2,841
C. *Sample period*: 2011–2018						
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.112***	0.093***	0.171***	0.124***	0.176***	0.278***
	(0.039)	(0.028)	(0.028)	(0.024)	(0.041)	(0.076)
No. of counties	933	949	932	926	933	945
Observations	6,530	6,642	6,523	6,453	6,530	6,614

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference of the specified economic indicator in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\text{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Per capita.
[b] Per employee.

In addition to construction (NAICS 23), our table reports the findings for Manufacturing (NAICS 31-33), Retail (NAICS 44-45) and Non-tradables which combines Retail with Accomodation and Food services (NAICS 44-45). Manufacturing generally comprises largely tadable goods, whereas accomodation and food services largely contains non-tradable goods. Mian and Sufi (2014) find a significant correlation between the decline in housing net worth and employment only for non-tradable goods, but not for tradable goods. The authors interpret that as evidence that household demand rather than credit frictions are the driver of their findings. Our results indicate that credit supply shocks have economically large and statistically significant effects on employment in the non-tradeable sector but not in the manufacturing sector during both the GFC and post-GFC

"noise infusion process" that the U.S. Census Bureau uses to ensure confidentiality in the data, limits it's usefulness.

Table 6 – Bank Health, Mortgage Credit Supply, and Local Sectoral Employment

	Dependent Variable: $\Delta_2 \ln[E/P]_{k,t}$				
	All Sectors (xCST)	Construction	Manufacturing	Rtl. trade	Nontradable goods[a]
Regressor	(1)	(2)	(3)	(4)	(5)
A. *Sample period*: 2007–2010					
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.080***	0.349***	0.038	0.065***	0.091***
	(0.019)	(0.074)	(0.049)	(0.025)	(0.023)
No. of counties	951	951	951	951	951
Observations	2,853	2,853	2,853	2,853	2,853
B. *Sample period*: 2011–2018					
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.061**	0.678***	0.074	0.100**	0.116***
	(0.028)	(0.093)	(0.064)	(0.042)	(0.032)
No. of counties	949	949	949	949	949
Observations	6,642	6,642	6,642	6,642	6,642

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified sectoral employment-population (E/P) ratio in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\text{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Nontradable goods employment is the sum of retail trade employment (NAICS 44) and Accomodation and Food Services (NAICS 72).

periods. This is consistent with the notion that the tradeable sector is largely immune to local financial conditions. In section 5 we will return to the question as to the extent that our credit supply shock measure stimulates economic activity primarily through a local demand channel linked to housing wealth effects versus a more general mechanism that allows for an expansion conditional on local demand conditions.

Table 7 shows our finding for employment by firm age and size. In general, we expect younger and smaller firms to be more reliant on local bank-lending conditions. During the GFC young firms (firms less than 5 years of age) and startups in particular were impacted more strongly than old firms. While we also find a differential effect on small vs large firms, the difference is only about half the size than the differential effect of young versus old firms. Credit supply also has strong effects on employment at start-ups during the post-GFC period but this comes at the expense of employment at existing young firms during this period.

Our findings with regards to small business lending, shown in Table 8, support the notion that small business lending expands in conjunction with credit-supply induced bank mortgage lending during both the bust and the recovery period. This finding implies that credit-supply induced increases in bank mortgage lending *crowd in* rather than *crowd out* small business lending. These

Table 7 – Bank Health, Mortgage Credit Supply, and Local Employment by Firm Age and Size

	Dependent Variable: $\Delta_2 \ln[E/P]_{k,t}$				
	Startups	Young firms	Old firms	Small firms	Large firms
Regressor	(1)	(2)	(3)	(4)	(5)
A. *Sample period*: 2007–2010					
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.575***	0.222***	0.061***	0.083***	0.057*
	(0.120)	(0.066)	(0.020)	(0.021)	(0.029)
No. of counties	951	951	951	951	951
Observations	2,853	2,853	2,853	2,853	2,853
B. *Sample period*: 2011–2018					
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.449***	−0.229**	0.139***	0.094***	0.082
	(0.121)	(0.098)	(0.033)	(0.024)	(0.053)
No. of counties	949	949	949	949	949
Observations	6,642	6,642	6,642	6,642	6,642

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified firm-type employment-population (E/P) ratio in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\text{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

effects are particularly large during the bust, and for loans under \$1m. The response of small business lending may reflect the fact that expansions in credit supply leads to higher real estate values that raise collateral and facilitates small business lending. It may also reflect the fact that expansionary lending in the mortgage market indicates a broad-based increase in bank lending due to higher risk tolerance at the bank level. Alternatively, the increase in small business lending may be induced by an increase in loan demand as local firms seek to expand in response to an increase in household spending. We directly examine the extent to which increased spending by households may explain the expansion in small business lending in the next section.

Finally, Table 9 examines the relationship between county level bank credit supply shocks and bankruptcies for businesses as well as consumers. The total effect is similar to the effect on consumer bankruptcies for the simple reason that the number of consumer bankruptcies is much larger than the number of business bankruptcies. We find that both consumers and business bankruptcies increase significantly in counties that experience a negative bank credit supply shock. The magnitude of the effect for business bankruptcies is in fact much larger during the post-GFC period while the reverse is true for consumer bankruptcies. In conjunction with the lending data, this suggests that the combination of rising real estate prices and small business credit expansions induced by bank credit supply shocks were particularly effective at staving off business bankruptcies

Table 8 – Bank Health, Mortgage Credit Supply, and Local Small Business Lending

	Dependent Variable: $\Delta_2 \ln[\text{SBL}/P]_{k,t}$	
	Small business loans (All)	Small business loans (< \$1M)
Regressor	(1)	(2)
A. *Sample period*: 2007–2010		
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.798***	0.967***
	(0.189)	(0.254)
No. of counties	951	951
Observations	2,853	2,853
B. *Sample period*: 2011–2018		
$\Delta_2 \ln[\text{BM}/P]_{k,t}$	0.349***	0.509***
	(0.119)	(0.161)
No. of counties	949	949
Observations	6,642	6,642

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified type of per capita small business loan originations (SBL/P) in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\text{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

during the period following the Great Recession.

4.3.1 Macroeconomic Effect

Our results imply quantitatively large effects of shocks to bank health on local employment, particularly in the non-tradeable goods and construction sectors. To gauge the potential macroeconomic effects, we note that loan chargeoffs in the banking sector were on the order of 2.5 percentage points during the GFC. Given the coefficient estimates in Table 2, this implies a fifteen percent reduction in bank credit supply (-5.855*2.5). Our reduced form estimate of the effect of bank health on local employment implies that a 1 percentage point decline in bank health leads to a 0.08 percent decline in local employment per capita and a 0.15 percent decline in GDP per capita. Thus, the increase in bank loan charge offs during the GFC imply a reduction a 1.2 percent reduction in local employment and a 2.2 percent drop in local GDP. These effects can be considered the local-GE estimates and hence do not take into account the aggregate effect on tradeable employment or the feedback effects of declining house prices on the bank balance sheets.

Table 9 – Bank Health, Mortgage Credit Supply, and Local Bankruptcies

	Dependent Variable: $\Delta_2 \ln[\mathrm{BK}/P]_{k,t}$		
	Total bankruptcies	Business bankruptcies	Consumer bankruptcies
Regressor	(1)	(2)	(3)
A. *Sample period*: 2007–2010			
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	-0.907^{***}	-0.953^{***}	-0.939^{***}
	(0.207)	(0.237)	(0.220)
No. of counties	946	946	951
Observations	2,817	2,803	2,853
B. *Sample period*: 2011–2018			
$\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$	-0.562^{***}	-1.416^{***}	-0.547^{***}
	(0.141)	(0.238)	(0.143)
No. of counties	949	949	949
Observations	6,642	6,348	6,642

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified type of per capita bankruptcies (BK/P) in county k from year $t-2$ to year t. The endogenous regressor in all specifications is $\Delta_2 \ln[\mathrm{BM}/P]_{k,t}$, the (annualized) log-difference of per capita home mortgage originations by banks in county k from year $t-2$ to year t, which is instrumented with $\bar{Z}^{BH}_{k,t}$, the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by 2SLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

5 Controlling for Household Demand

Mian and Sufi (2014) emphasize the housing net worth channel as a key factor in explaining the decline in employment during the financial crisis. Our findings above strongly suggest that bank credit supply shocks play an important role for local economic outcomes in both the GFC as well as the post-GFC period. This is consistent with a household net worth channel if household consumption increases in response to housing prices and, through this mechanism, causes expansions in local employment. As discussed above, when interpreted purely through the lens of the housing wealth channel, our estimated employment responses are much larger than can be typically explained by models of household spending however. In addition, the employment effects are concentrated in sectors and firms that are likely to be dependent on local bank credit for their borrowing needs. This suggests considering additional channels that expand available credit to local bank-dependent firms independent of local demand conditions. In this section, we develop a simple economic model to understand the extent to which such forces may be at play. We then use these insights to consider a natural control for household demand in our empirical framework.

5.1 Household Demand vs Firm Credit Supply in a Simple Model

Following much of the literature, we model a local geographic area as a small open economy that produces and consumes both tradeable and non-tradeable goods. We use this model to discuss how one can potentially control for the household demand channel and thereby identify other mechanisms by which expansions in bank credit supply cause increases in economic activity in our regression framework.

The model that we consider is static and allows for the production and consumption of tradeable and nontradeable goods, along with nominal rigidities that give rise to a New Keynesian multiplier. Households in a given location are subject to an expansion in their spending capacity that relaxes the budget constraint. We view this as a simple reduced-form device to capture the increased spending that is engendered by an increase in local mortgage supply and the accompanied increase in housing prices and therefore household wealth. It is straightforward to develop a dynamic model with the same implications for household demand. In particular, the spending shock that we consider is formally equivalent to a change in the long-run borrowing costs that enters the household's log-linearized Euler equation in a dynamic version of our model.

Households choose consumption and labor supply to maximize utility:

$$U(C_{NT}, C_{TR}, N) = log\left(C_{NT}^{\lambda} C_{TR}^{1-\lambda} - \frac{N^{1+\phi}}{1+\phi}\right)$$

subject to the household budget constraint:

$$P_{TR}C_{TR} + P_{NT}C_{NT} = \Pi_{TR} + \Pi_{NT} + WN + T + A$$

where W is the nominal wage, Π denotes profits, T are transfers and A denotes an initial stock of assets. Household optimality implies

$$\frac{P_{NT}C_{NT}}{P_T C_T} = \frac{\lambda}{1-\lambda}$$

The local CPI price index P is defined as the cost of purchasing one unit of the composite consumption good $C_{NT}^{\lambda} C_{TR}^{1-\lambda}$

$$P = c(\lambda) P_{NT}^{\lambda} P_{TR}^{1-\lambda}$$

with

$$c(\lambda) = \frac{1}{\lambda^{\lambda}(1-\lambda)^{1-\lambda}}$$

Because of GHH preferences, there is no wealth effect on labor supply so that the household labor supply is purely a function of the real wage

$$N^{\phi} = \frac{W}{P}.$$

The coefficient ϕ is the inverse of the Frisch labor supply elasticity.

To add nominal price rigidities we assume that there is monopolistic competition in the non-tradeable goods sector, along with Cobb-Douglas preferences over two locally produced goods, one with fixed and one with flexible prices. These goods are combined to produce the non-tradeable bundle Y_{NT}. Let $Y_{NT,1}$ denote output of the fixed-price goods and $Y_{NT,2}$ denote output of the flexible-price goods. Define

$$Y_{NT} = Y_{NT,1}^{\beta} Y_{NT,2}^{1-\beta}.$$

so that β measures the share of fixed-price non-tradeables. Relative demands are

$$\frac{P_{NT,1} Y_{NT,1}}{P_{NT,2} Y_{NT,2}} = \frac{\beta}{1-\beta}$$

and the non-tradeable price index is:

$$P_{NT} = c(\beta) P_{NT,1}^{\beta} P_{NT,2}^{1-\beta}$$

In addition to an expansion in household spending capacity, we allow for the possibility that the increase in mortgages has a direct effect on firms by reducing financial frictions that determine the cost of borrowing to finance labor inputs. This would occur if rising real estate values increase the collateral value of pledgeable assets. It would also occur if there were some form of complementarity between banks issuing mortgages and banks issuing loans to businesses. We again model this in a reduced form way as financial wedges that enter the labor demand equation.

The nontradeable output, and therefore labor input of firms with fixed prices, is demand determined. Flexible price firms in the tradeable and non-tradeable sectors choose labor inputs to maximize profits

$$\begin{aligned} \Pi_{TR} &= P_{TR} Y_{TR} - R_{TR} W N_{TR} \\ \Pi_2 &= P_2 Y_2 - R_{NT} W N_2 \end{aligned}$$

where R_{TR} and R_{NT} denote financial frictions in the tradeable and non-tradeable sectors and production has decreasing returns to scale:

$$\begin{aligned} Y_{TR} &= \theta N_{TR}^{\alpha} \\ Y_{NT,1} &= \theta N_{NT,1}^{\alpha} \\ Y_{NT,2} &= \theta N_{NT,2}^{\alpha} \end{aligned}$$

where θ measures local productivity and $0 < \alpha < 1$. Profit maximization implies

$$\begin{aligned} \alpha P_{TR} N_{TR}^{\alpha-1} &= R_{TR} W \\ \alpha P_{NT,2} N_{NT,2}^{\alpha-1} &= R_{NT} W. \end{aligned}$$

Assuming that costs due to financial frictions are transferred back to the household lump-sum, the goods market equilibrium satisfies

$$P^{\star}C_{TR} + P_{NT}C_{NT} \quad = \quad P^{\star}Y_{TR} + P_{NT}Y_{NT} + A$$

where we use the notation $P_{TR} = P^{\star}$ to denote that tradeable goods prices are exogenous to the region. Non-tradeable goods consumption must equal non-tradeable goods output, $C_{NT} = Y_{NT}$, so that the goods market equilibrium can be expressed as the trade balance:

$$C_{TR} - Y_{TR} = \frac{1}{P^{\star}}A$$

Finally, labor demand sums to labor supply so that

$$N = N_{TR} + N_{NT,1} + N_{NT,2}.$$

Given the specification of price indices and production functions, the equilibrium is determined by the optimality conditions for household and firms, along with the trade balance equation and the equilibrium condition that labor demands sum to labor supply, taking A,R_{TR},R_{NT}, $P^{\star}$ and $P_{NT,1}$ as given. We are then interested in analyzing the implications of a credit supply shock that simultaneously increases A and reduces R_{NT}, the financial friction in the non-tradeable sector. We restrict attention to the non-tradeable sector because such firms are more likely to rely on banks that are local to their geographic area when seeking to finance inputs. Let $\tilde{x}$ denote deviations from steady-state for a given variable X. Starting from a steady-state with $A = 0$, $P^{\star} = \bar{P}$ and $R_{NT} = 1$, we consider the log-linear solution that perturbs A and R_{NT}.

From the household demand conditions we know that the expenditure shares are constant between flexible and fixed price non-tradeable goods, and between tradeable and fixed-price non-tradeable goods so that

$$\tilde{p}_2 + \alpha\tilde{n}_2 = \alpha\tilde{n}_1 = \tilde{c}_t$$

Assuming no financial friction on firms in the tradeable sector we have the following labor demand equations that equate cost shares to revenue shares:

$$\tilde{p}_2 = \tilde{w} + (1-\alpha)\tilde{n}_2 + \tilde{r}_n$$

and given fixed tradeable goods prices:

$$0 = \tilde{w} + (1-\alpha)\tilde{n}_t$$

We also must have the trade balance equation

$$c_t - \alpha\tilde{n}_t = \tilde{a}$$

and the labor supply condition

$$\tilde{n} = (1-\lambda)\tilde{n}_t + \lambda(\beta\tilde{n}_1 + (1-\beta)\tilde{n}_2)$$

Nominal Wage Rigidity

Now suppose nominal wages are perfectly rigid so that $\tilde{w} = 0$. The labor demand equation for employment in the tradeable sector implies that tradeable employment must also be constant so that $\tilde{n}_t = 0$. We then have that consumption of tradeables and therefore employment in the sticky-price non-tradeable sector is fully accounted for by the household spending channel:

$$\tilde{c}_t = \alpha\tilde{n}_1 = \tilde{a}$$

Combining goods and labor demand for flexible price non-tradeables we have

$$\tilde{n}_2 + \tilde{r}_n = \tilde{a}$$

Intuitively, expenditures on flexible price goods must rise in proportion to expenditures on other goods, so by the amount of the injection $\tilde{a}$. The labor demand equation implies that the wage bill inclusive of financial costs must then rise by the same amount. Solving for non-tradeable and total employment we have

$$\begin{aligned} \tilde{n}_n &= \left(\frac{\beta}{\alpha} + 1 - \beta\right)\tilde{a} - (1-\beta)\tilde{r}_n \\ \tilde{n} &= \lambda\left[\left(\frac{\beta}{\alpha} + 1 - \beta\right)\tilde{a} - (1-\beta)\tilde{r}_n\right] \end{aligned}$$

Note if $\beta = 1$, all prices are perfectly rigid, $\alpha\tilde{n}_n = \tilde{a}$ and we have a non-tradeable output multiplier equal to one. Employment must then expand by $\frac{\tilde{a}}{\alpha}$ to meet such demand. With perfectly flexible prices, prices in the flexible price sector will rise with real marginal cost: $\tilde{p} = (1-\alpha)\tilde{n}_2$. As a result, non-tradeable employment must increase by $\tilde{a}$ for non-tradeable expenditures to rise by the same amount.

Now assume that $\tilde{a} = \gamma_a z + \varepsilon_a$ and $\tilde{r}_n = -\gamma_r z - \varepsilon_r$ where γ_a and γ_r measure the elasticity of response of household wealth and firm financial conditions to a credit supply shock z. Our regression framework then estimates

$$\tilde{n}_n = bz + \sigma_a\varepsilon_a + \sigma_b\varepsilon_r$$

where $= \left[\left(\frac{\beta}{\alpha} + 1 - \beta\right)\gamma_a + (1-\beta)\gamma_r\right]$, $\sigma_a = \left(\frac{\beta}{\alpha} + 1 - \beta\right)$, and $\sigma_r = (1-\beta)$. Alternatively, by controlling for tradeable consumption, we estimate

$$\tilde{n}_n = b_c\tilde{c}_t + b_r z + \sigma_b\varepsilon_r$$

where $b_c = \left(\frac{\beta}{\alpha} + 1 - \beta\right)$ and $b_r = (1-\beta)\gamma_r < \beta$. The attenuation in these coefficients as measured by the ratio

$$\frac{b_r}{b} = \frac{(1-\beta)\gamma_r}{\left[\left(\frac{\beta}{\alpha} + 1 - \beta\right)\gamma_a + (1-\beta)\gamma_r\right]} < 1$$

then provides a direct measure of the relative importance of the household finance channel relative to the firm credit supply channel in response to a bank credit supply shock.

Partially flexible wages and fixed tradeable employment.

Now consider the situation where wages in the tradeable sector are perfectly rigid but wages in the non-tradeable sector are partially flexible. With perfectly rigid wages in the tradeable sector we again have that $\tilde{n}_t = 0$ so that

$$c_t = \alpha\tilde{n}_1 = \tilde{a}$$

Partially rigid wages are modeled as

$$\tilde{w} = \kappa(\phi\tilde{n} + \lambda(1-\beta)\tilde{p}_2)$$

where the second term is the local CPI and $0 \leq \kappa \leq 1$ so that nominal wages only partially respond to increased labor supply or a rising CPI.

Labor demand satisfies

$$\tilde{p}_2 = \kappa(\phi\tilde{n} + \lambda(1-\beta)\tilde{p}_2) + (1-\alpha)\tilde{n}_2 + \tilde{r}_n$$

We write this as

$$\tilde{p}_2 = \Omega\left[\kappa\phi\tilde{n} + (1-\alpha)\tilde{n}_2 + \tilde{r}_n\right]$$

where

$$\Omega = \frac{1}{1 - \kappa\lambda(1-\beta)}$$

Now impose the household demand condition

$$\tilde{p}_2 + \alpha\tilde{n}_2 = \tilde{a}$$

to obtain

$$\tilde{a} = \Omega\kappa\phi\tilde{n} + \left[\Omega(1-\alpha) + \alpha\right]\tilde{n}_2 + \Omega\tilde{r}_n$$

Labor supply satisfies

$$\tilde{n} = \lambda\left(\frac{\beta}{\alpha}\tilde{a} + (1-\beta)\tilde{n}_2\right)$$

Solving for $\tilde{n}$ we have

$$\tilde{n} = \left[\frac{\lambda(1-\beta)}{\lambda(1-\beta)\Omega\kappa\phi + \Omega(1-\alpha) + \alpha}\right]\left[\frac{(1-\beta)\alpha + \beta(\Omega(1-\alpha) + \alpha)}{(1-\beta)\alpha}\tilde{a} - \Omega\tilde{r}_n\right]$$

Note, as long as $\tilde{n}_t = 0$, we have that $c_t = \tilde{a}$ and our coefficient estimates from a regression of employment on z with and without controlling for $\tilde{c}_t$ will imply the same formula for attenuation bias.

For simplicity, consider the case where $\alpha = 1$ in which case

$$\tilde{n} = \left[\frac{\lambda(1-\beta)}{\lambda(1-\beta)\Omega\kappa\phi + 1}\right]\left[\frac{1}{(1-\beta)}\tilde{a} - \Omega\tilde{r}_n\right]$$

which we can express as

$$\tilde{n} = \left[\frac{\lambda}{\lambda(1-\beta)\Omega\kappa\phi + 1}\right]\left[\tilde{a} - \Omega(1-\beta)\tilde{r}_n\right]$$

We also have

$$\tilde{n}_n = \left[\frac{1}{\lambda(1-\beta)\Omega\kappa\phi + 1}\right]\left[\tilde{a} - \Omega(1-\beta)\tilde{r}_n\right]$$

The coefficient estimates then imply

$$\frac{b_r}{b} = \frac{\Omega(1-\beta)\gamma_r}{\gamma_a + \Omega(1-\beta)\gamma_r}$$

We can write this as

$$\frac{b_r}{b} = \frac{(1-\beta)\gamma_r}{\left(1-\kappa\lambda(1-\beta)\right)\gamma_a + (1-\beta)\gamma_r}$$

This formula makes clear that increased nominal wage rigidity (lower κ) raises the relative importance of the household spending channel and therefore increases the attenuation that results from controlling for household demand in our regression framework. It also suggests that, to the extent that downward nominal wage rigidity played an important role in the GFC, we might observe greater attenuation during this period relative to the post-GFC period.

5.2 Controlling for Household Demand: Empirics

In this section we include a direct control for household demand at the local level in our regression specifications. Our simple model implies that consumption of tradeable goods fully captures household wealth effects that stimulate local demand, since tradeable goods prices are not influenced by local supply conditions. We therefore consider the growth rate of motor vehicle registrations as an additional control variable in our regression framework. Motor vehicle registrations are a natural way to measure local demand because they are a tradeable good and as such prices are largely the same across counties.[23] Below we report the findings for three key tables, the remainder of our regression specifications with motor vehicle registrations as additional controls can be found in the appendix.

[23] Our framework abstracts from the fact that motor vehicles are durable goods that are infrequently purchased. Recent work by Beraja and Zorzi (2024) that allows for infrequent adjustment and matches the hazard rates of adjustment of the motor vehicle stock implies that the annual marginal propensity to spend on durables is slightly higher than but comparable in magnitude to the marginal propensity to spend on non-durables.

TABLE 10 – Bank Health, Mortgage Credit Supply, and Local Housing Markets Controlling for Local Demand)

	Dependent Variable: $\Delta_2 \ln Y_{k,t}$			
	Total mortgages[a]	Bank mortgages[a]	Home prices	Bldg. permits[a]
Regressor	(1)	(2)	(3)	(4)
A. *Sample period*: 2007–2010				
$\bar{Z}^{BH}_{k,t}$	0.335*	0.684***	0.348***	0.868***
	(0.173)	(0.190)	(0.071)	(0.253)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.727***	0.779***	0.166***	0.929***
	(0.071)	(0.066)	(0.018)	(0.126)
R^2	0.578	0.567	0.435	0.292
No. of counties	947	947	947	945
Observations	2,841	2,841	2,841	2,831
B. *Sample period*: 2011–2018				
$\bar{Z}^{BH}_{k,t}$	0.697***	0.907***	0.529***	0.575*
	(0.171)	(0.139)	(0.074)	(0.322)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.313***	0.313***	0.081***	0.491***
	(0.042)	(0.052)	(0.010)	(0.076)
R^2	0.230	0.171	0.538	0.088
No. of counties	945	945	945	945
Observations	6,614	6,614	6,610	6,583

NOTE: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference of the specified housing market indicator in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.
[a] Per capita.

Table 10 restates the response of key housing market variables to a bank credit supply shock now including an additional control for motor vehicle registrations. Because some of the expansionary effects of the credit supply shock on bank mortgages may be captured by the motor vehicle control, we also report the response of bank mortgage loans in this table. The credit supply shock is again normalized such that without the additional control, the response of bank mortgages is unity. The motor vehicles variable enters positively in all regressions in this table. It also implies significant attenuation of response of bank mortgages to the credit supply shock during the GFC but not the post-GFC period – the response of bank mortgages falls from one to 0.684 during the GFC and from one to 0.907 during the post-GFC period. The housing price response shows even less attenuation. The ratio of response coefficients for housing prices to credit supply shocks with versus without controlling for demand is 0.84 during the GFC and 0.95 during the post-GFC period. Building permits show similar though slightly larger attenuation but the overall message is that the housing market results are robust to controlling for local demand conditions as measured by motor vehicle registrations.

Table 11 – Mortgage Credit Supply Shocks and Local Economic Outcomes (Controlling for Local Demand)

	Dependent Variable: $\Delta_2 \ln Y_{k,t}$				
	GDP[a]	Employment[a]	Income[a]	Earnings[b]	Rtl. sales[a]
Regressor	(1)	(2)	(3)	(4)	(5)
A. *Sample period*: 2007–2010					
$\bar{Z}^{BH}_{k,t}$	0.110***	0.036*	0.061**	0.053***	0.048*
	(0.036)	(0.021)	(0.028)	(0.017)	(0.028)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.083***	0.104***	0.088**	0.064***	0.097*
	(0.015)	(0.009)	(0.010)	(0.008)	(0.010)
R^2	0.158	0.340	0.531	0.291	0.426
No. of counties	931	912	930	912	931
Observations	2,793	2,736	2,790	2,736	2,793
B. *Sample period*: 2011–2018					
$\bar{Z}^{BH}_{k,t}$	0.106***	0.072***	0.148***	0.101***	0.172***
	(0.038)	(0.029)	(0.028)	(0.021)	(0.039)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.056***	0.067***	0.093***	0.066***	0.047***
	(0.013)	(0.012)	(0.017)	(0.010)	(0.008)
R^2	0.035	0.050	0.226	0.231	0.323
No. of counties	929	922	928	922	929
Observations	6,502	6,425	6,495	6,425	6,502

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference of the specified economic indicator in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Per capita.

[b] Per employee.

Table 11 reports the results for the real activity variables when controlling for local demand through motor vehicle registration. Again, motor vehicles enter significantly and have a positive relationship with other activity variables. We again see some attenuation of real activity variables to the credit supply shock with the motor vehicle controls relative to without. These range in magnitude from 0.45 for employment to 0.75 for real GDP during the GFC period. Similar to the findings for the housing variables, the attenuation is much lower during the post-GFC period.

Here the comparable numbers for employment and GDP are 0.78 and 0.95 respectively. These findings suggest that a significant component of the expansionary effects of bank credit supply may be attributed to factors that are not directly linked to wealth effects that influence household spending. This appears to be particularly true during the post-GFC period where controlling for household demand has very little impact on the estimate response coefficients of the real activity variables to the bank credit supply shock.

Table 12 – Bank Health, Mortgage Credit Supply, and Local Small Business Lending Controlling for Local Demand

	Dependent Variable: $\Delta_2 \ln[\text{SBL}/P]_{k,t}$	
	Small business loans (All)	Small business loans (< \$1M)
Regressor	(1)	(2)
A. *Sample period*: 2007–2010		
$\bar{Z}^{BH}_{k,t}$	0.782***	0.980***
	(0.110)	(0.141)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	0.054	−0.021
	(0.039)	(0.056)
R^2	0.547	0.339
No. of counties	947	947
Observations	2,841	2,841
B. *Sample period*: 2011–2018		
$\bar{Z}^{BH}_{k,t}$	0.322**	0.473**
	(0.123)	(0.157)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	0.124***	0.126***
	(0.032)	(0.039)
R^2	0.060	0.067
No. of counties	945	945
Observations	6,614	6,614

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified type of per capita small business loan originations (SBL/P) in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\text{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

Finally, Table 12 reports the response of small business lending to the credit supply shock, controlling for local demand with motor vehicle registrations. Here the estimated response of business lending to the credit supply shock is essentially unchanged whether one does or does not control for household demand. Indeed, in the recession, the MV registration coefficient is essentially zero. In the post-GFC period, the MV registration coefficient is positive and significant but small in economic terms so that again, the response of small business lending is entirely captured by the credit supply shock, with and without controls for local demand. These results provide direct evidence in favor of the hypothesis that bank-health induced expansions in bank credit supply have independent effects on small business financing that is unrelated to household wealth effects that stimulate economic activity and indirectly give rise to an increase in business lending.

6 Conclusion

This paper studied the varying role of bank credit supply shocks during the 2002-18 period. We document that bank health driven credit supply played an insignificant role during the credit boom of the early 2000s. In contrast, however, we find the bank health driven credit supply shocks played an important economic role during the ensuing 2007-2010 financial crisis and, somewhat surprisingly, appear to have a quantitatively similar effect on local economic outcomes during the post-GFC period.

One channel emphasized in the literature is that expansions in mortgage credit lead to increase in house prices, and rising household wealth. These wealth effects then translate into increased demand for non-tradeables and stimulate employment. To capture this mechanism, we use tradeable consumption as measured by motor vehicle registration as an additional control that proxies for increases in household demand. This demand variable accounts for 25-50 percent of the response of various econonomic activity variables during the GFC and even less during the post-GFC period. In addition, local small business lending responds strongly to local bank health but is insensitive to changes in local demand as measured by motor vehicle registrations. These findings imply that credit supply shocks that influence local bank conditions have a direct expansionary effect on the supply of credit to small businesses and provides further evidence that bank credit affects the local economy not only because of household wealth effects but importantly through expansions in credit supply to local firms.

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Bank Health and Local Economic Outcomes

Appendix

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Additional Empirical Results

Table A1 – Bank Health, Mortgage Credit Supply, and Local Sectoral Employment Controlling for Local Demand

	Dependent Variable: $\Delta_2 \ln[E/P]_{k,t}$				
	All Sectors (xCST)	Construction	Manufacturing	Rtl. trade	Nontradable goods[a]
Regressor	(1)	(2)	(3)	(4)	(5)
A. *Sample period*: 2007–2010					
$\bar{Z}^{BH}_{k,t}$	0.043**	0.206**	−0.006	0.022	0.050**
	(0.019)	(0.083)	(0.049)	(0.023)	(0.021)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.087***	0.341***	0.105***	0.105***	0.101***
	(0.009)	(0.033)	(0.025)	(0.009)	(0.008)
R^2	0.257	0.307	0.131	0.238	0.268
No. of counties	947	947	947	947	947
Observations	2,841	2,841	2,841	2,841	2,841
B. *Sample period*: 2011–2018					
$\bar{Z}^{BH}_{k,t}$	0.042	0.618***	0.047	0.089**	0.101***
	(0.029)	(0.073)	(0.066)	(0.041)	(0.031)
$\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$	0.060***	0.199***	0.100***	0.039***	0.047***
	(0.011)	(0.025)	(0.022)	(0.007)	(0.007)
R^2	0.051	0.108	0.025	0.211	0.151
No. of counties	945	945	945	945	945
Observations	6,614	6,614	6,614	6,614	6,614

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified sectoral employment-population (E/P) ratio in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\mathrm{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

[a] Define nontradable goods sector.

Table A2 – Bank Health, Mortgage Credit Supply, and Local Employment by Firm Age and Size
Controlling for Local Demand

	Dependent Variable: $\Delta_2 \ln[E/P]_{k,t}$				
	Startups	Young firms	Old firms	Small firms	Large firms
Regressor	(1)	(2)	(3)	(4)	(5)
A. *Sample period*: 2007–2010					
$\bar{Z}^{BH}_{k,t}$	0.471***	0.140**	0.024	0.042*	0.016
	(0.090)	(0.062)	(0.021)	(0.024)	(0.030)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	0.261***	0.200***	0.083***	0.100***	0.093***
	(0.049)	(0.025)	(0.009)	(0.009)	(0.013)
R^2	0.057	0.106	0.266	0.421	0.115
No. of counties	947	947	947	947	947
Observations	2,841	2,841	2,841	2,841	2,841
B. *Sample period*: 2011–2018					
$\bar{Z}^{BH}_{k,t}$	0.441***	−0.261***	0.119***	0.080***	0.065
	(0.105)	(0.085)	(0.033)	(0.021)	(0.054)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	0.057	0.080***	0.067***	0.050***	0.049***
	(0.052)	(0.026)	(0.011)	(0.006)	(0.016)
R^2	0.008	0.038	0.055	0.102	0.021
No. of counties	945	945	945	945	945
Observations	6,614	6,614	6,614	6,614	6,614

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified firm-type employment-population (E/P) ratio in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\text{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.

Table A3 – Bank Health, Mortgage Credit Supply, and Local Bankruptcies Controlling for Local Demand

	Dependent Variable: $\Delta_2 \ln[\text{BK}/P]_{k,t}$		
	Total bankruptcies	Business bankruptcies	Consumer bankruptcies
Regressor	(1)	(2)	(3)
A. *Sample period*: 2007–2010			
$\bar{Z}^{BH}_{k,t}$	-0.714^{***}	-0.721^{***}	-0.723^{***}
	(0.173)	(0.216)	(0.175)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	-0.512^{***}	-0.733^{***}	-0.504^{***}
	(0.061)	(0.120)	(0.061)
R^2	0.481	0.163	0.468
No. of counties	942	942	947
Observations	2,805	2,791	2,841
B. *Sample period*: 2011–2018			
$\bar{Z}^{BH}_{k,t}$	-0.490^{***}	-1.299^{***}	-0.477^{***}
	(0.149)	(0.275)	(0.149)
$\Delta_2 \ln[\text{MV}/P]_{k,t}$	-0.251^{***}	-0.417^{***}	-0.239^{***}
	(0.041)	(0.093)	(0.041)
R^2	0.374	0.044	0.367
No. of counties	945	945	945
Observations	6,614	6,320	6,614

Note: The dependent variable is $\Delta_2 \ln Y_{k,t}$, the (annualized) log-difference in the specified type of per capita bankruptcies (BK/P) in county k from year $t-2$ to year t. Explanatory variables: $\bar{Z}^{BH}_{k,t}$ = the average of the estimated bank-health credit supply shocks in county k in years $t-1$ and t; $\Delta_2 \ln[\text{MV}/P]_{k,t}$ = the (annualized) log-difference of per capita motor vehicle registration in county k from year $t-2$ to year t, a proxy for the change in local demand conditions. All specifications include time fixed effects and a set of pre-determined control variables (see the text for details) and are estimated by OLS. Asymptotic standard errors reported in parentheses are computed according to Adão et al. (2019): * $p < .10$; ** $p < .05$; and *** $p < .01$.