Long Shadow of the U.S. Mortgage Expansion: Evidence from Local Labour Markets

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5 April 2023

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April 5, 2023

Abstract

We construct U.S. county-level credit supply shocks by interacting the mortgage growth of multi-market lenders with a county's initial exposure to those lenders. The credit shocks did not impact the local labour markets during the credit boom but had a negative effect during the Great Recession. While local unemployment rates recovered post-Recession, wage growth remained depressed. Further, a long-run increase in older firms' employment share suggests a credit-induced reduction in business dynamism and labour demand. A mechanism through occasionally binding financial constraints tied to house prices can qualitatively explain these asymmetric effects of credit shocks in booms and busts.

Keywords: mortgage lending, credit supply shocks, local labour markets
JEL Codes: E24, E32, E44, G01, G20

*A previous single-authored version of this paper formed part of Mengying Wei's doctoral dissertation at the University of British Columbia. We are grateful for comments from James Banks, Paul Beaudry, Michael Devereux, Viktoria Hnatkovska and Henry Siu, and seminar participants at the Canadian Economic Association Annual Conference, and the Macro and Empirical Lunch seminars at the Vancouver School of Economics. This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors. We alone are responsible for all errors and interpretations.

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1 Introduction

Fisher (1933) proposed a debt-deflation mechanism to explain the Great Depression of the 1930s. Ever since then, economists have studied the role of the financial market in driving fluctuations in the real economy. The topic received renewed attention after the 2008 financial crisis that started with the collapse of the U.S. housing market but consequently led to the loss of jobs and depressed wages for millions of workers for many years after the recession. While standard business cycle theory suggests recessions to be temporary downturns due to transitory adverse shocks, the slow recovery of most major economies after the Great Recession prompted researchers to ask whether credit-induced boom-bust cycles have permanent scarring effects.[1] The problem of identifying the long-run impact of credit shocks lies at the heart of this question.

The current paper fills a gap in the literature on the long-run impact of credit shocks on labour market outcomes. In particular, we study the long-term U.S. labour market consequences of the mortgage credit boom that began after the Dotcom recession of 2001. While existing works have studied either the short-run effects of credit shocks (see García (2020)) or the long-run impact of labour market shocks (see Yagan (2019)), we are the first to study the long-run effect of credit shocks on the performance of the real economy, covering periods of the pre-recession boom, the recessionary downturn and the post-recession recovery.

Our focus on the expansionary credit shock of the early 2000s stands in contrast to the predominant literature studying the contractionary credit shock during the Great Recession. We chose to study the impact of the expansionary shock because the contraction was arguably not an exogenous event. The relaxation in banking regulation, the rise in private-label securitization, and the growth in subprime mortgages have all contributed to the acceleration of mortgage expansion and sown the seeds for the subsequent collapse (see Justiniano, Primiceri and Tambalotti (2019)). While several papers have documented a strong correlation between household debt accumulation and the severity of the subsequent economic downturn (see, for example, Jordà, Schularick and Taylor (2015) and Mian and Sufi (2022)), few have made the direct causal link between credit expansion and the real economy over long horizons like this present work.[2]

The main difficulty in identifying the long-run causal impact of credit supply shocks on the

[1] Ball (2009), Summers (2014) and Fernald et al. (2017) have studied the persistent economic stagnation, especially the anaemic labour market performance, in the post-Great Recession U.S. The long-run adverse impact on labour productivity and technological investment has been studied by Haltmaier (2012) and Reifschneider, Wascher and Wilcox (2015), among others. Cross-country analyses by Cerra and Saxena (2008), Reinhart and Rogoff (2009), and others have also documented long-term losses in output and productivity after financial crises.

[2] Di Maggio and Kermani (2017) study the impacts of the federal preemption of national banks from anti-predatory lending laws on local mortgage and labour markets during the mortgage boom and bust periods. Gilchrist, Siemer and Zakrajšek (2018) identify the expansionary and contractionary mortgage supply shocks separately and study their respective impacts in the short-run over the boom and bust periods. Our work differs from these existing papers in that we study the impact of a single expansionary shock throughout the boom, bust and recovery periods.

real economy is that numerous credit-independent channels (viz., technological and demographic changes, trade shocks, etc.) can affect the long-run trend of economic outcomes. Therefore, studying national trends has little hope of yielding causal estimates of the effect of a credit shock, particularly over long horizons. To overcome this challenge, we construct U.S. county-level credit supply shocks that are not correlated with local labour market trends. We achieve this by exploiting spatial variation in the initial exposure of U.S. counties to lending institutions operating in multiple counties. In effect, we construct a Bartik (1991)-style instrument by interacting the heterogeneous lending strategies of multi-market lenders during the mortgage boom period of 2002 through 2006 with their pre-expansion market share in each county.

The identifying assumption for the exogeneity of our county-level credit supply shock is that initial market shares of lenders are uncorrelated with any county-level characteristic that we do not control for (see Goldsmith-Pinkham, Sorkin and Swift (2020)). We show that conditional on a set of county-level economic characteristics, there is no correlation between our credit shock measure and the pre-trends in local labour market performance, either in the long run between 1994 and 2003 or in the short run during the Dotcom recession.

We use the county-level credit supply shock to measure its long-run impact on local labour markets. We find the shock had no long-run effect on unemployment rates but hurt wage growth in local labour markets between 2003 and 2017. To the best of our knowledge, we are the first to show hysteresis in wage growth in response to the credit expansion of the early 2000s. We also show that the long-run decline in wage growth in high credit shock counties happened across all industries and all education classes of workers. In particular, the effect of credit shocks was not limited to the construction, real estate and financial sectors, which were primarily impacted during the Great Recession.

We decompose the long-run effect of the credit shock into effects in three sub-periods: expansion (2003-2006), recession (2006-2010) and recovery (2010-2017). We find a strong negative impact of the shock on all local labour market outcomes during the recession but no statistically significant impact during the credit boom period.[3] During the post-recession period, we find that local unemployment rates recovered faster in areas with more expansionary credit shocks, contributing to the long-run null effect of the credit shock on local unemployment rates. In contrast, wage growth did not recover, leading to the overall negative impact of the credit shock on local wage growth between 2003 and 2017.

In search of an explanation for the credit-driven long-run decline in wage growth, we find evidence of reduced business dynamism in areas with larger credit shocks. Counties with more

[3]The asymmetric effects of credit shocks on labour markets between periods of expansion and contraction are consistent with recent studies on the relationship between household consumption and house-price fluctuations. For instance, Guerrieri and Iacoviello (2017) find that house price appreciation has a negligible effect on household consumption, while price depreciation has a sizeable negative impact on household consumption.

expansionary credit supply shocks experienced a reallocation of employment from younger to older firms over the long term, suggesting a credit-induced persistent decline in labour demand since the Great Recession.

Credit shocks can influence the labour market through various channels, e.g., credit constraints can hurt R&D investment, which is crucial for long-run productivity and wage growth (see Duval, Hong and Timmer (2020)). While our paper is silent about the exact mechanism through which credit shocks led to wage hysteresis in the U.S., our findings nevertheless have implications for the relative importance of scarring and cleansing effects of recessions. Recessions are typically viewed as periods of cleansing when the least productive firms die, thereby increasing productivity and possibly wages. However, even the more productive firms might die or not grow as much if their credit constraints are binding during a recession. This can depress productivity during a recession (see evidence in Siemer (2019)) and scar future long-run productivity by driving out the potentially better-performing businesses in their nascent stages. Our empirical finding of a credit-induced long-run reduction in wage growth and business dynamism is thus complementary to the theoretical works in Barlevy (2003), Ouyang (2009) and Osotimehin and Pappadà (2017), which have highlighted how the scarring effect of credit market frictions can potentially dominate the cleansing effect of recessions. The hysteresis in wage growth and business dynamism caused by easy credit supply more than a decade ago highlights the importance of policy measures to protect young firms from the negative impacts of credit-induced boom-bust cycles.

We rationalize our empirical findings through a framework where credit supply shocks not only affect the labour market via their impact on the housing market but do so asymmetrically along the business cycle — no effect during a boom but a negative impact in a recession. In our model, fluctuations in the household borrowing constraint affect the collateral value of housing, which, in turn, impacts firms' production and labour demand through changes in the working capital constraint. A relaxation in the household's borrowing constraint (i.e., a positive credit supply shock) has no effect if the working capital constraint is already slack. However, a tightening of the borrowing constraint (i.e., a negative credit supply shock) can trigger a binding working capital constraint, leading to a labour reallocation from the impatient, constrained firms (akin to the young firms in the data) to the patient, unconstrained ones (similar to the old firms in the data). Furthermore, in our model, such a labour reallocation can potentially lead to a loss in labour productivity and wages when production technology exhibits decreasing returns to scale. While our proposed mechanism is simple and is by no means the only possible channel through which credit shocks can impact the labour market, the model can still explain a fifth of the wage decline during the Great Recession under reasonable parameterization.

The rest of the paper is organized as follows. Section 2 discusses the empirical strategy. Section 3 describes the data sources and summary statistics of the key variables used in the analysis.

Section 4 presents the empirical results, with robustness and validity checks presented in Section 5. Section 6 uses a simple model to rationalize the empirical findings. Finally, Section 7 concludes.

2 Empirical Strategy

Our goal is to estimate the causal effect of credit supply shocks on the labour market performance of U.S. counties. A key challenge in this exercise is to find an exogenous source of variation in credit supply that is uncorrelated with the long-run trend of the local labour markets. A simple OLS estimate of the effect of credit fluctuations on local labour market outcomes would not only be biased if the underlying performance of these local economies drove the credit shocks, but even the direction of the bias would be ambiguous. While credit supply growth through subprime mortgage lending would suggest a downward bias for the true impact of credit shocks, higher demand for credit in counties with better economic performance could lead to an upward bias.[4] In what follows, we construct a plausibly exogenous credit supply shock and estimate the effect of the shock on the labour market outcomes of U.S. counties.

2.1 Identifying the Credit Supply Shock

Fluctuation in the amount of credit issued is an equilibrium object, determined simultaneously by credit demand and supply. To identify the supply channel separately at the level of U.S. counties, we rely on the differential lending strategies of depository and non-depository lending institutions operating in multiple counties. We measure the growth in national credit supply Δc_j for each lender j to be its average annual mortgage origination between 2002 and 2006 relative to the level in the base year of 2000. To eliminate the finite sample bias when constructing the credit supply shock for county i, we leaving out the mortgage origination of lender j in county i, that is, calculate Δc_j using data for all counties in which lender j operates except county i. The local credit supply shock ξ_i in county i is then constructed as the interaction between the national growth of mortgage credit for individual lenders, Δc_j and the lenders' initial shares in the local market s_{ij}, summed over a selected set of lenders J:

[4] Mian and Sufi (2009) show that credit and income growth have been negatively correlated at the zip-code level in metropolitan areas, indicating excess lending to subprime borrowers (see Demyanyk and Hemert (2011)). Others also find evidence for an increase in credit supply through the channels of relaxing financial regulations (see Dell'Ariccia, Igan and Laeven (2012), Favara and Imbs (2015) and Di Maggio and Kermani (2017)) and private-label securitization along with its associated agency problem (see Keys et al. (2010), Purnanandam (2011), Nadauld and Sherlund (2013), and Griffin and Maturana (2016)). On the other hand, several empirical studies have rejected the reallocation of mortgages to low-income groups (see Adelino, Schoar and Severino (2016) and Foote, Loewenstein and Willen (2021)) and instead argued that higher credit demand from prime borrowers contributed to the mortgage expansion of the early 2000s (see Albanesi, DeGiorgi and Nosal (2022)).

$$\xi_i = \sum_{j\in J} s_{ij} \underbrace{\ln\left(\frac{\frac{1}{5}\sum_{t=2002}^{2006} c_{j,t}}{c_{j,2000}}\right)}_{=\Delta c_j} = \sum_{j\in J} s_{ij}\Delta c_j \tag{1}$$

The intuition behind this identification strategy is that markets with access to lenders with more lenient lending criteria are more likely to observe faster credit growth or, equivalently, a larger positive credit supply shock. This technique of identifying regional shocks by interacting aggregate or national-level changes of a specific entity (like industry or occupation) with the initial share of that entity in each region is due to Bartik (1991). Most existing works on the Great Recession that employ this shift-share technique to identify the credit supply shock have used it to either measure the contractionary shock during the recession (see García (2020)), or studied the growth of small business loans instead of mortgage growth (see Greenstone, Mas and Nguyen (2020)), or studied the lending strategy of one specific large lender like the Lehman Brothers (see Chodorow-Reich (2014)) and Wachovia (see Mondragon (2020)). To the best of our knowledge, we share the construction of local mortgage credit supply shocks for the credit boom period using the shift-share technique for multi-market lenders with only Gilchrist, Siemer and Zakrajšek (2018). However, we also differ from Gilchrist, Siemer and Zakrajšek (2018) in that we study the long-run impact of the expansionary supply shock, while they study the short-run impact of the expansionary shock during the boom period and the effect of a separate contractionary credit shock during the recession.

Identifying Assumption. Goldsmith-Pinkham, Sorkin and Swift (2020) point out that using the Bartik (1991) instrument is equivalent to using $\{s_{ij}\}_{j\in J}$ as the vector of instruments and $\{\Delta c_j\}_{j\in J}$ as a weighting matrix. Intuitively, since aggregate credit growth Δc_j is common to all counties, the identifying variation comes from the local shares of lender j across the counties. In other words, the identification assumption requires that each lender $j \in J$ does not locate its branches across counties based on correctly predicting the future local labour market trends; that is, county-level labour market trends should be uncorrelated with the county shares of each lender.[5] Thus, our identification strategy does not require us to specify the source of the difference in mortgage supplies across lenders since the exogeneity condition is imposed on the lender's initial market share instead of the change in the lender's national credit supply.

Threats to Identification. To ensure that initial local market shares of lenders are uncorrelated with local labour market trends, they should at least operate in multiple markets. A lender that

[5] This identifying assumption is sufficient but not necessary. Adão, Kolesár and Morales (2019) and Borusyak, Hull and Jaravel (2022) point out that even if the initial share s_{ij} is correlated with local economic growth across counties, the instrument remains valid as long as the national growth Δc_j is exogenous to the average local economic trends that it is exposed to. We focus on the sufficient identifying assumption of exogeneity of the shares s_{ij}.

only operates in one county would likely have its credit supply highly correlated with the county's labour market trend. However, due to historical regulations, banking markets have been highly geographically segmented in the U.S. (see Rice and Strahan (2010)). For instance, the McFadden Act of 1927 permits states to restrict branching for national banks, and the Bank Holding Company Act of 1956 restricts entry by out-of-state banks and bank holding companies. Despite waves of bank branching deregulation, our calculations, based on the HMDA dataset, show that the median number of counties covered by each lender was only 7 in the year 2000. Such high spatial segmentation of lenders is problematic for our identification strategy.

After the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, the U.S. banking industry experienced a historically high number of mergers and acquisitions. According to Pilloff (2004), 3517 bank mergers were completed between 1994 and 2003. In the literature, the standard approach is to treat the acquiring and acquired lenders as the same entity throughout the period of analysis (see, for example, Bernanke and Lown (1991), and Greenstone, Mas and Nguyen (2020)). However, one main rationale behind mergers and acquisitions is for banks to enter new geographical markets for profit-seeking purposes. This challenges our identifying assumption by making lenders in better-performing counties with growing mortgage demands more likely to be merged. That, in turn, would generate an unwanted positive relationship between bank shares and local economic trends.

Addressing Threats to Identification: Selection of Lenders. To overcome the challenges of high geographic segmentation and high rates of mergers of banks in the U.S., we impose a couple of selection criteria to include lending institutions operating in multiple regions in our sample set J. A selected lender must (i) operate in at least 100 counties and 2 census regions in the year 2000; and (ii) be in continuous operation between 2000 and 2006, the period over which our credit shock measure is constructed. Importantly, we apply these criteria at the reporting lender level instead of the parent company level. Since some lenders are subsidiaries of parent commercial banks or bank holding companies, our focus on lender-level selection ensures that if the identifying assumption holds at the lender level, it will also hold at the parent company level.

We compare the characteristics of selected and non-selected lenders in Section 3.2.1, and show the robustness of our key findings to alternative selection criteria in Section 5.2. It is worth noting that excluding some lenders who satisfy the identifying assumption does not pose a problem. However, with too few lenders, the relevance of the credit shock for local economic outcomes will be affected. Ultimately, a balance has to be struck between the goal to select lenders that do not concentrate their mortgage supply in a few areas driven by local demand and the need to have a sufficiently large number of lenders.

Finally, we perform a 'placebo' test to allay the concern that lenders could target certain local markets based on the correct prediction of county-level economic performance. The findings, discussed in Sections 5.1, show that our constructed credit supply shock is uncorrelated with county-level labour market pre-trends both in the long run between 1994 and 2003 as well as in the short run during the Dotcom recession of the early 2000s.

2.2 Empirical Design

Once the credit supply shock is identified for each county, we can measure its impact on local labour market outcomes after adequately controlling for the initial economic conditions at the county level. We consider changes in the county-level unemployment rate and nominal weekly wage rate as our key labour market outcome variables. The changes in the variables are calculated over the three sub-periods of expansion (2003-2006), recession (2006-2010) and recovery (2010-2017), as well as the entire long-term horizon (2003-2017). Thus, we run cross-sectional regressions of the following form:

$$\Delta^t y_i = \beta^t \xi_i + \gamma^t x_{i,2000} + \delta^t_{s(i)} + \varepsilon^t_i \tag{2}$$

where $\Delta^t y_i$ is the change in outcome y of county i during the time-interval t, ξ_i is the county-level credit supply shock in equation (1), $x_{i,2000}$ is a set of county characteristics measured in the year 2000, and $\delta^t_{s(i)}$ is the state fixed effect during period t for the state s in which county i is situated.

The superscript t in equation (2) highlights that our identifying assumption of the error term in the regression being conditionally orthogonal to the credit shock needs to be satisfied within each period t over which the changes in the outcome variables are measured. It also brings forth the time-varying nature of the state fixed-effect term, e.g., for the sub-period analysis of expansion-recession-recovery, we essentially have three sets of state fixed effects, one for each sub-period.

We control for the following county-level characteristics measured in the year 2000: sub-prime rate (defined as the fraction of the population with a credit score below 660), per capita establishment, employment rate, unemployment rate, log weekly wage, log annual per capita income, log median household income, poverty rate and the employment shares of 23 two-digit industries. The state fixed effects further control for state-level economic trends arising possibly from state policy changes. Adding these controls is crucial because the true effect of the credit supply shock could be attenuated or overestimated depending on how certain economic conditions interact with the magnitude of the shock. For instance, if the credit shock occurred more in regions with a high employment share of a particular industry, not controlling for county-level industry composition would contaminate the true effect of the credit shock. See Charles, Hurst and Notowidigdo (2016) for an example of how manufacturing hubs were particularly hit during the mortgage credit boom-bust cycle.

It is worth noting that equation (2) is the reduced form instrumental variable regression specification without any particular endogenous explanatory variable. We have chosen this as our baseline specification because of two reasons. First, specifying an endogenous explanatory variable restricts the interpretation of the 2SLS estimate to a particular causal channel, e.g., the effect of actual mortgage growth or the effect of the house price increase on the local labour markets. Such mechanisms are typically simultaneous and not mutually exclusive. By focusing on the direct effect of the exogenous credit shock, we can remain agnostic among various causal channels that ultimately lead to fluctuations in the local labour markets. Second, the relationship between the credit supply shock and the local labour market outcome variables is itself of research interest. Our empirical work on this relationship can be viewed as complementary to the theoretical literature that studies how shocks to financial constraints affect the real economy (see, for example, Eggertsson and Krugman (2012), Korinek and Simsek (2016), Guerrieri and Iacoviello (2017), Guerrieri and Lorenzoni (2017), Justiniano, Primiceri and Tambalotti (2019) and Jones, Midrigan and Philippon (2022)). Nevertheless, we have included results from a 2SLS specification using county mortgage growth as the endogenous explanatory variable in Section 5.3.

As an alternative to the specification in (2), following the methodology in Yagan (2019), we also present the effects of the credit shock disaggregated by each year but normalise the effects to be zero in a base year.

3 Data and Summary Statistics

3.1 Data Sources

Our county-level home mortgage data come from an application-level dataset published by the Federal Financial Institutions Examination Council (FFIEC) under the Home Mortgage Disclosure Act (HMDA), covering about 80-90% of all mortgages written during the 2000s (see Avery, Brevoort and Canner (2007) and Dell'Ariccia, Igan and Laeven (2012)). Our baseline results consider mortgages for home purchases, home improvements and refinancing. Appendix C.2 shows robustness results by using only home purchase mortgages to construct the credit shock.[6]

Our baseline house price variable is the Housing Price Index (HPI), constructed by the Federal Housing Finance Agency (FHFA) with a weighted repeated sales methodology on single-house conforming loans taken from the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae). We use the Zillow home price index,

[6]The FFIEC requires mortgage lenders that have offices in metropolitan areas and total assets above a certain threshold to disclose detailed mortgage information every year. These mortgage lenders include both depository and non-depository institutions. The non-depository institutions must report all loans in Metropolitan Statistical Areas (MSAs) with more than five applications.

which covers fewer counties than the HPI, as a robustness check.

Data on economic performance at the county level comes from various sources. Annual unemployment and labour force participation rates are taken from the Local Area Unemployment Statistics (LAUS). Private employment (annual average of monthly measures) and wage data (weekly average of annual payroll per employed worker) are collected from the Quarterly Census of Employment and Wage (QCEW). Establishment data is taken from County Business Pattern (CBP), which shares the same data source as QCEW. Data on the remaining county-level characteristics are sourced as follows: poverty rate, household median income, population and other demographic data from the U.S. Census, income data from the Statistics of Income published by the U.S. Internal Revenue Service, and the subprime population from Equifax New York Federal Reserves. For heterogeneity analyses, we use data from the Quarterly Workforce Indicator (QWI), which covers 95% of private-sector jobs and calculates local labour market characteristics by industry, worker demographics, and employer size and age, based on the linked employer-employee micro-data in the Longitudinal Employer-Household Dynamics (LEHD).

3.2 Summary Statistics

The fastest growth in U.S. mortgage origination happened between 2000 and 2002, mostly driven by the decline in the federal funds rate from 6.5% to 1.7% in response to the Dotcom crash. However, even after the interest rate decline was arrested, the flow of new mortgage origination remained high until 2006. The high mortgage growth between 2003 and 2006 has been largely viewed as supply-driven. Following the literature, we take 2003–2006 as the period of mortgage credit supply expansion. The subsequent periods of credit crunch during the recession (2006-2010) and the recovery period (2010-2017) are more easily identified from the data.

Table 1 presents summary statistics for key housing and labour market variables for all counties in the U.S. (except those in Hawaii and Alaska), separately for the three sub-periods of mortgage expansion, recession and recovery. While mortgage origination almost doubled between 2003 and 2006, it fell sharply by an average of 24% during the next four recessionary years. It declined further by an average of 11% during the next seven years of recovery when house prices started rising again in most counties. As for labour market indicators — local unemployment rate, private employment level, and weekly wage exhibited the usual business cycle patterns across the counties - worsening during the recession and improving during the credit expansion and recovery periods. However, it is instructive to note that unlike the measures of labour quantity, local wage growth did not recover back to its pre-recession speed in the post-recession period. Nominal weekly wage increased 12% on average for the three years between 2003 and 2006, while the corresponding figure is 17% for the seven post-recession years, implying a much slower annual growth in the recovery period. Subsequent analysis in Section 4 will reveal that this long-term scarring effect on wage growth can be attributed causally to the credit supply shocks at the county level.

Table 1: County Summary Statistics

Variables	**Mean**	**Std. Dev.**	**10^{th} Percentile**	**Median**	**90^{th} Percentile**
A. Changes between 2003 and 2006					
Log home mortgage	0.97	0.39	0.53	0.95	1.44
Log house price	0.20	0.13	0.07	0.16	0.40
Unemployment rate	-0.01	0.01	-0.02	-0.01	0.00
Log employment	0.05	0.10	-0.05	0.04	0.15
Log weekly wage	0.12	0.07	0.05	0.11	0.18
B. Changes between 2006 and 2010					
Log home mortgage	-0.24	0.34	-0.62	-0.22	0.12
Log house price[a]	-0.08	0.13	-0.22	-0.06	0.03
Unemployment rate	0.05	0.02	0.02	0.04	0.07
Log employment	-0.06	0.11	-0.18	-0.06	0.05
Log weekly wage[a]	0.07	0.07	0.00	0.06	0.14
C. Changes between 2010 and 2017					
Log home mortgage[b]	-0.11	0.35	-0.45	-0.16	0.30
Log house price	0.11	0.13	-0.03	0.09	0.29
Unemployment rate	-0.05	0.02	-0.08	-0.05	-0.02
Log employment	0.08	0.15	-0.08	0.07	0.23
Log weekly wage	0.17	0.09	0.09	0.17	0.26

Note: Summary statistics for the time differences of the five variables across 3,108 U.S. counties are reported. Home mortgage changes are computed as the difference between the average annual dollar value of mortgage origination during the period and the level of mortgage origination at the start. It does not include mortgages for home improvement and refinancing purposes.
[a] Housing price and weekly wage changes are taken over 2007–2010, as 2007 is the start of the turning point for these variables.
[b] Mortgage change is taken between 2010 and 2015 due to a lack of data beyond 2015.

3.2.1 Lender Characteristics

As argued in Section 2.1, to construct our measure of credit supply shocks, we had to select mortgage lenders with sufficiently wide geographic coverage in the year 2000 and which remained in continuous operation until 2006. Table 2 compares various characteristics of selected and non-selected lenders both for the initial year 2000 (Panel A) as well as the credit expansion period of 2002 through 2006 (Panel B).

In terms of initial geographic spread in 2000, the selected lenders had a median coverage of 333 counties and 32 states as opposed to only 7 counties and 1 state for the non-selected lenders. The selected lenders are also considerably larger on average than their non-selected counterparts in terms of mortgage application and origination volumes. The *Maximum* column for non-selected lenders shows that the right tail of the distribution of non-selected lenders has some institutions which satisfy the threshold for being large and geographically diverse enough to be selected. They were not selected because they did not remain in continuous operation until 2006, mostly due to the pre-2003 wave of merger and acquisition activities.

Table 2: Characteristics of Selected & Non-Selected Lenders

	Non-Selected Lenders			**Selected Lenders**		
Lender Characteristics	**Minimum**	**Median**	**Maximum**	**Minimum**	**Median**	**Maximum**
A. Characteristics in 2000	**No. of lenders** = 7407; **Share**[a] = 64%			**No. of lenders** = 216; **Share**[a] = 36%		
No. of counties	1.00	7.00	3097.00	103.00	333.00	2840.00
No. of states	1.00	1.00	51.00	3.00	32.00	51.00
No. of regions	1.00	1.00	4.00	2.00	4.00	4.00
Application per bank (log $)	1.79	9.14	17.75	9.36	13.14	17.78
Application per bank (log no.)	0.69	4.83	13.25	4.92	8.64	13.01
Origination per bank (log $)[b]	0.00	8.98	17.53	0.00	12.69	17.47
Origination per bank (log no.)[b]	0.00	4.67	12.53	0.00	8.11	12.61
B. Characteristics between 2002 and 2006	**No. of lenders** = 11104; **Share**[a] = 49%			**No. of lenders** = 216; **Share**[a] = 51%		
No. of counties	1.00	10.70	3074.62	5.69	512.92	3045.50
No. of states	1.00	2.00	51.00	1.77	37.00	51.00
No. of regions	1.00	1.00	4.00	1.00	4.00	4.00
Application per bank (log $)	2.30	9.83	19.57	8.89	14.26	19.15
Application per bank (log no.)	0.69	5.11	14.38	3.35	9.36	13.62
Origination per bank (log $)[b]	0.92	9.68	19.37	8.85	13.84	18.80
Origination per bank (log no.)[b]	0.00	4.95	14.18	3.27	8.89	13.25

Note: The selected lenders operated in at least 100 counties and 1 census region in 2000 and remained operating until 2006.
[a] *Share* is defined as the dollar value of mortgage originated by lenders in a specific group (selected or non-selected) relative to the total mortgage origination during the period (in the year 2000 for Panel A, and between 2002 and 2006 for Panel B).
[b] We report statistics for log(1+x) to include zero values of the variables.

Between 2002 and 2006, most lenders experienced a boom in the volume of mortgage applications and an expansion in the geographical spread of operations. The growth was significantly faster for our selected lenders, with their market share in dollar value of mortgage origination increasing from 36% in 2000 to 51% during 2002–2006. However, not all selected lenders were as successful. Some significantly shrunk their mortgage market coverage from more than 100 counties to less than 6 counties. These shrinking lenders contribute to a negative mortgage credit supply shock. This suggests a significant change in the performance of initially large and fast-growing lenders. In fact, we show in Appendix A that among the top 10% largest and fastest growing lenders in the selected sample, about a third ceased mortgage business altogether during the financial crisis. Nevertheless, Table 3 shows that the mortgage market shares of the fastest and slowest growing lenders explain none of the local economic indicators of per capita income, private employment, unemployment rate and weekly wage during the credit boom period.

Table 3: Effect of Lender Market Share on Local Economy: 2003-2006

	Per Capita Income		**Pvt. Employment**		**Unemployment Rate**		**Weekly Wage**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Slow Expanding Lenders	3.14		7.67		0.33		0.63	
	(9.02)		(7.18)		(0.78)		(4.78)	
Fast Expanding Lenders		-3.31		14.15		-2.56		-17.84
		(12.63)		(24.62)		(1.56)		(11.38)
Observations	2916	2916	2906	2906	2911	2911	2901	2901
Adjusted R^2	0.18	0.18	0.21	0.21	0.48	0.48	0.21	0.21

Note: This table reports regression estimates of the effect of lender market share on the local per capita income growth, private employment growth, the change in the unemployment rate and the weekly wage growth between 2003 and 2006. *Slow Expanding Lenders* refers to the 20% slowest expanding lenders, while *Fast Expanding Lenders* refers to the 20% fastest expanding lenders. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the commuting zone level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5.

3.2.2 Credit Supply Shock

The credit supply shock has large variation across counties. The 10^{th} and 90^{th} percentiles of the shock are 0.01 and 0.34, with a median of 0.16 and a standard deviation of 0.12. In Table 4, we show that the credit shocks have not been systematically more severe in economically better or worse-performing regions. In particular, we split counties below and above the median based on the magnitude of the credit shock and find that none of the economic characteristics has a statistically significant difference between the two groups of counties in the year 2000. Nevertheless, we control for all these county characteristics while estimating the effect of the credit shock on the local labour market performance in the next section. We also do not find any noticeable geographic concentration of the shock from Appendix Figure A.1 that plots the county-level map of the shock.

Table 4: County-Level Economic Characteristics in 2000 by Size of Credit Supply Shock

	Below Median Credit Shock (N = 1550)		**Above Median Credit Shock** (N = 1587)	
Variables	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Sub-prime rate[a]	33.52	8.29	32.73	6.37
Establishment per capita	0.02	0.01	0.03	0.01
Employment rate	0.46	0.06	0.49	0.05
Unemployment rate	0.05	0.02	0.04	0.01
Weekly wage (log)	6.15	0.18	6.45	0.26
Annual income per capita (log)	9.72	0.21	10.07	0.30
Median household income (log)	10.40	0.19	10.69	0.23
Poverty rate	0.15	0.06	0.12	0.05

Note: All statistics are weighted by the county population in 2000.
[a] Sub-prime rate is defined as the fraction of the population with a credit score below 660.

4 Results

Having presented the identification of the credit supply shock and a summary of the data, we now discuss the effects of the shock on the performance of local economies using our main empirical specification in equation (2). The unit of observation for the regressions is all U.S. counties except those in Hawaii and Alaska. We winsorize 1% of the most extreme counties based on the outcome variable, which implies that a different set of counties is excluded in each regression. To avoid the results being driven by smaller counties, we weigh the observations by the county population in the 2000 census. We cluster standard errors at the state level to allow for within-state spatial correlations across counties due to state-related institutional differences.

4.1 Effect of Credit Supply Shock on Local Housing Markets

While our goal is to study the impact of the credit shock on local labour markets, we begin by showing the impact of our credit shock on local mortgage growth and house prices. We constructed the credit shock using local exposure of counties to national growth in mortgages of individual lending institutions between 2002 and 2006. Therefore, it is unsurprising that we find the shock to predict an increase in both county-level mortgage growth and house price increase during the credit boom period. In terms of magnitude, one standard deviation larger credit supply shock caused local mortgage growth and house prices to be 4.6 percentage points (pp) and 1.4 pp higher during the expansion period, respectively. These changes are equivalent to a little more than one-tenth of a standard deviation hike in the outcome variables for every standard deviation increase in the credit shock.[7] Interestingly, the same expansionary credit shock can also predict a significant drop in mortgage growth (5.8 pp or 0.17 standard deviation) and house prices (2.5 pp or 0.19 standard deviation) across counties during the Great Recession.

Areas with larger expansionary credit supply shocks experienced larger subsequent housing market contractions. One explanation is that the more lenient lenders became relatively more financially stressed during the recession and had to reduce mortgage supply. Supportive evidence for this mechanism can be found in a few works, ranging from the impact of the bankruptcy event of Lehman Brothers (see Chodorow-Reich (2014)) and Wachovia (see Mondragon (2020)) to mortgage supply contraction by multi-market lenders (see Gilchrist, Siemer and Zakrajšek (2018) and García (2020)). An alternative explanation could be that the higher debt exposure of the households in high credit shock areas made them vulnerable to interest rate fluctuations and adverse economic shocks, which in turn caused credit demand to collapse during the recession. Our paper is silent about which of these two channels of credit demand and supply contributed to the negative

[7] One standard deviation of the shock (=0.12) leads to $0.12\hat{\beta}^t$ percentage point (pp) change or $\frac{0.12\hat{\beta}^t}{s.d.(\Delta^t y)}$ standard deviation change in the growth rate of the outcome variable during period t.

impact of expansionary credit shocks on mortgage growth and house prices during the downturn (see Landvoigt, Piazzesi and Schneider (2015)). Nevertheless, given the robust relationship between credit supply shock and the boom-bust cycle in the housing market, we are confident that the credit shock we constructed indeed captures financial frictions faced by U.S. counties. In the next subsection, we address if these credit-induced financial frictions impacted the real economy, particularly the labour market.

Table 5: Effect of Credit Supply Shock on Mortgage Growth & Alternative Indices of House Price

	Expansion 2003-2006	**Recession 2006-2010**	**Recovery 2010-2017**
	(1)	(2)	(3)
A. Mortgage Growth			
Credit Supply Shock	38.62***	-48.31***	-6.38
	(12.45)	(10.55)	(9.92)
Observations	3041	3039	3038
Adjusted R^2	0.42	0.434	0.34
B. House Price - FHFA Index			
Credit Supply Shock	11.43***	-21.11***	2.92
	(4.20)	(5.07)	(3.89)
Observations	2619	2630	2608
Adjusted R^2	0.69	0.69	0.52
C. House Price - Zillow Index			
Credit Supply Shock	18.79***	-29.36**	3.03
	(6.31)	(11.11)	(7.72)
Observations	947	979	1146
Adjusted R^2	0.74	0.66	0.44

Note: This table reports the effect of credit supply shock on mortgage growth and house price changes for sub-periods between 2003 and 2017. Due to limited data availability, instead of 2017, the end date is 2015 for Panel A and 2016 for Panel C. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for (i) *State Fixed Effects*, (ii) *County Controls*: the fraction of sub-prime population, per capita establishment, employment rate, unemployment rate, weekly wage, annual income per capita, median household income, and the poverty rate in 2000, and (iii) *Industry Controls*: employment share in the year 2000 for each county for 23 two-digit industries: Agriculture, Mining, Utilities, Construction, Manufacturing, Wholesale Trade, Retail Trade, Transportation, Information, Finance, Real Estate, Professional Services, Management, Administrative Services, Education, Healthcare, Entertainment, Accommodation and Food Services, Other Services.

4.2 Effect of Credit Supply Shock on Local Labour Markets

Two key indicators of labour market performance are the unemployment rate and the wage rate. Therefore, we begin by measuring the impact of our constructed credit supply shock on these outcomes at the county level. Table 6 shows the long-run effects of the credit shock, and the disaggregated effects over the three sub-periods of expansion, recession and recovery.

Table 6: Effect of Credit Supply Shock on Unemployment Rate & Weekly Wage Rate

	Long Run 2003-2017	**Expansion 2003-2006**	**Recession 2006-2010**	**Recovery 2010-2017**
	(1)	(2)	(3)	(4)
A. Unemployment Rate				
Credit Supply Shock	-0.19	0.016	1.67***	-1.79***
	(0.42)	(0.28)	(0.49)	(0.60)
Observations	3048	3038	3035	3045
Adjusted R^2	0.43	0.48	0.63	0.70
B. Weekly Wage Rate				
Credit Supply Shock	-7.25***	-0.45	-4.43***	-1.84
	(2.36)	(1.01)	(1.39)	(1.53)
Observations	3017	3022	3022	3024
Adjusted R^2	0.35	0.19	0.19	0.19

Note: This table reports the effect of credit supply shock on the unemployment rate changes (Panel A) and the percentage changes in average nominal weekly wage rate (Panel B) for sub-periods between 2003 and 2017. Observations are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5. We leave out the value of the dependent variable in 2000 from the list of controls.

We find that the credit shock had no significant impact on either measure of local labour market performance during the credit boom period. This suggests no positive spillover from the local mortgage market expansion and the house price increase to the local labour market and also rejects the hypothesis that the credit supply shock was more expansionary in areas with systematically better or worse local labour market trends. Nevertheless, the expansionary credit supply shock of the early 2000s caused county-level unemployment rates to rise and wages to fall significantly during the Great Recession of the late 2000s. One standard deviation higher credit shock between 2002 and 2006 increased the unemployment rate by 0.2 percentage point (pp) or 0.10 standard deviation and decreased the weekly wage growth by 0.5 pp or 0.08 standard deviation between 2006 and 2010. After the recession, while unemployment rates recovered faster in counties with a more expansionary credit shock, growth in weekly wage rates remained depressed. A fall in the recovery period by almost the same magnitude as the rise during the recession left the long-run impact of the credit shock on local unemployment rates close to a net zero. On the other hand, the lack of post-recession recovery contributed to a long-run wage hysteresis in response to the county-level credit supply shocks of the early 2000s. Figure 1 corroborates these findings by showing the year-by-year impact of the credit shock, starting from a null effect in 2003. It clearly shows the difference in the dynamic effects of the credit shock on local unemployment rates and wage rates.

One concern with using nominal wage growth from QCEW is that the regression coefficients can capture price changes instead of real wage growth. Unfortunately, inflation measures at the county level are not available. However, insofar as inflation varies at the state level, the goods inflation effect on nominal wage growth will be eliminated by the time-varying state fixed effect. Even controlling for commuting zone fixed effects leaves the estimate of the effect of the credit shock on wage growth virtually unchanged (see Appendix Table B.1).

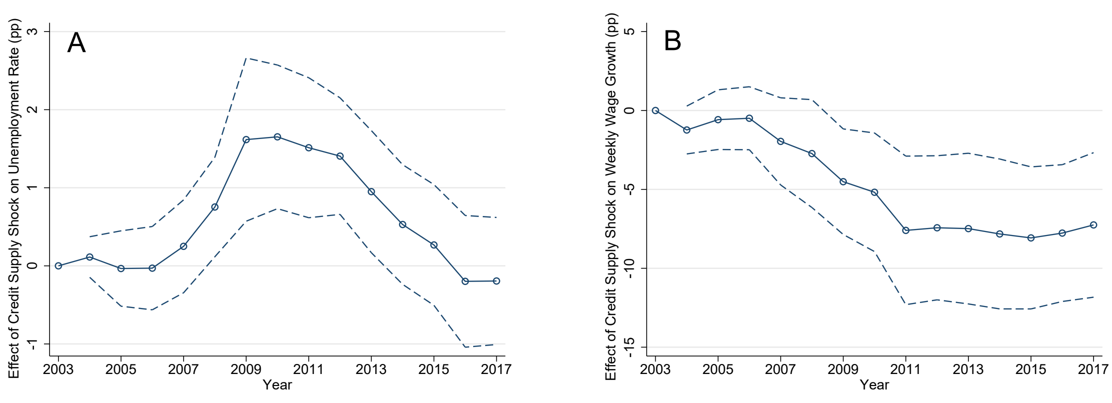

Figure 1: Year-wise Impact of Credit Supply Shock on Unemployment Rate and Weekly Wage Growth

Note: The solid line plots the year-wise impact of the credit supply shock on the unemployment rate (Panel A) and the nominal weekly wage growth (Panel B) after normalizing the effects to be zero in the base year 2003. The dotted lines show the 95% confidence interval of the yearly estimates. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

Estimates of the direct relationship between expansionary credit shocks and wage growth are missing from the literature.[8] The closest relationship to ours is the one in Mian, Rao and Sufi (2013) between wage growth and a decline in housing net worth. Using the land elasticity index in Saiz (2010) as an instrument, which varies at the MSA-level, they find a small but statistically significant decline in payroll growth in response to a reduction in housing value. We find a stronger and prolonged negative effect on wage growth, possibly because we can use the significant county-level variation in wage growth within the same MSA.

[8]In related work, Beraja, Hurst and Ospina (2019) establish a strong relationship between wage growth and employment growth at the state level during the Great Recession, while Gilchrist, Siemer and Zakrajšek (2018) estimate the elasticity of wage to employment changes in response to household credit contraction at both county and commuting zone levels.

Heterogeneity of the Wage Effect by Industry and Education. We estimated the effect of the credit shock on weekly wages by controlling for the initial industry composition of the counties in the year 2000. However, the Great Recession arguably affected some industries more intensely, like finance and real estate. In Appendix Table B.2, we show that the magnitude of the long-run impact of the credit shock between 2003 and 2017 is similar across the following four industry-groups: construction, finance and real estate, manufacturing and the rest of the non-manufacturing industries. This finding of homogeneity of the wage effects suggests high mobility of labour across sectors so that the effect on affected industries spills over to the so-called unaffected sectors over time.

The nominal average wage dynamics in response to a credit shock could also be contaminated by county-level trends in the skill composition of workers. In Appendix Table B.3, we study the long-run effect of the credit shock on quarterly earnings across three different education groups of workers: less than high school, some college, and college graduates and above. Due to data limitations, we can only study the dynamics of earnings across education groups and not wages, which would have purged out the effect of hours worked dynamics. The differences in the magnitudes of the effects of the shock across education groups are not statistically significant.

Distinction between Unemployment and Employment Dynamics. Our finding of declining county-level unemployment rates during the recovery period in response to local credit shocks is consistent with the U.S. state-level unemployment dynamics documented by Blanchard and Katz (1992). This contrasts the unemployment hysteresis often observed in European economies (see, for example, Blanchard and Summers (1986)).

The long-run null effect of the credit shock on local unemployment rates does not, however, rule out the possibility of employment hysteresis in response to the shock. If people exited the labour force at a higher rate in regions with more expansionary credit shocks, it could leave the unemployment rate unchanged in response to the shock while simultaneously decreasing employment. In fact, using longitudinal administrative data, Yagan (2019) finds that even when unemployment rates reverted to their pre-Recession levels, individuals in areas with larger unemployment increases during the Great Recession continued to be less likely to be employed through 2015. While Yagan (2019) measures the Great Recession shock as the difference between the 2007 and 2009 unemployment rates in the local labour markets, ours is a county-level credit supply shock from multi-market lenders. Given the difference in the definitions of the shocks, it is difficult to compare our results to those in Yagan (2019). Nevertheless, one can see from Figure 2, that counties with larger credit shocks had a greater decline in private employment levels since the recession, and recovery was very slow, at least until 2015. While the effect of the credit shock is statistically insignificant for the last two years of 2016 and 2017, the magnitude is still strongly negative.

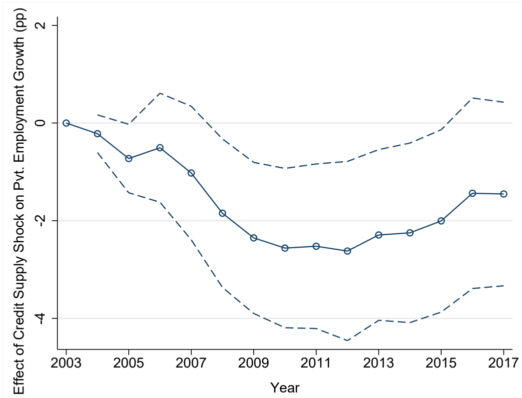

Figure 2: Year-wise Impact of Credit Supply Shock on Private Employment Growth

Note: The solid line plots the year-wise impact of the credit supply shock on changes in county-level log private employment after normalizing the effect to be zero in the base year 2003. The dotted lines show the 95% confidence interval of the yearly estimates. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

While Figure 2 seems broadly consistent with the evidence of employment hysteresis in Yagan (2019), albeit in response to a different shock, the level of private employment can itself vary due to changing population size of counties. It would, therefore, be instructive to study the dynamics of the labour force participation rate or the employment rate, which normalizes employment with the total or working-age population. Unfortunately, reliable yearly data on county-level populations are absent.[9] Therefore, we can only study long-run changes in these rates using reliable population data from consecutive censuses. In Appendix Table B.4, we show that the long-run effect of the credit shock between 2003 and 2017 is zero for both the employment rate and the labour force participation rate. Taking all this evidence into consideration, we conclude that the credit shock negatively impacted labour quantity, both employment and unemployment, during the recession, and the recovery in the unemployment rate was much quicker than in employment.

4.3 Effect of Credit Supply Shock on Local Business Dynamism

Our finding of a persistent decline in wage growth with a nearly complete recovery of labour quantities like unemployment rate and employment rate, in the long run, is consistent with the narrative of credit shocks depressing local labour demand. For instance, in a neoclassical labour market with a long-run inelastic labour supply, a credit-induced inward shift of the labour demand curve can reduce wages without changing equilibrium employment.

One of the indicators of depressed labour demand is a decline in business dynamism. We study the effect of the credit shock on one particular indicator of local business dynamism — the

[9] While yearly estimates of county-level population are available from Census Bureau's State and County Intercensal Datasets, using such projection-based estimates often leads to labour force participation rates of more than or very close to 100%. Therefore, we refrain from using those population estimates.

employment share of old versus young firms. We find that counties with more expansionary credit shocks before the recession experienced a greater increase in the employment share of older firms during the recession and recovery period, that is, between 2006 and 2016. The evidence in Figure 3 is related to the accelerated decline in firm entry after the Great Recession (see Siemer (2016)) and the positive relationship between housing price and firm startup rate at the MSA and state levels (see, for example, Gourio, Messer and Siemer (2016) and Davis and Haltiwanger (2021)). This evidence of the credit shock causing a decline in business dynamism will motivate our model in Section 6, where a key influence for a credit shock would be on changes in labour demand.

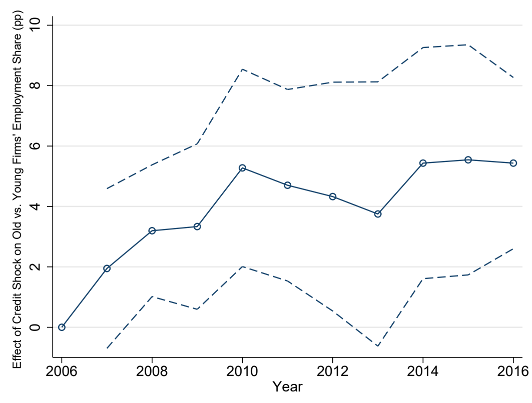

Figure 3: Year-wise Impact of Credit Supply Shock on Employment Share of 'Old' versus 'Young' Firms

Note: The solid line plots the year-wise impact of the credit supply shock on $\log\left(\frac{\text{Old Firm Employment}}{\text{Young Firm Employment}}\right) * 100$, after normalizing the effect to be zero in the base year 2006. 'Old' firms as those with age greater than 5 years, and 'young' firms are of age less than 4 years. The dotted lines show the 95% confidence interval of the yearly estimates. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5.

5 Validity Tests and Robustness Checks

To assess the robustness and validity of our findings, we perform several checks. First, we test the validity of our identifying assumption by checking for any correlation between the credit supply shock and local labour market pre-trends. Second, we show the robustness of our findings to changing the selection criteria for the set of multi-market lenders used to construct the credit shock. Finally, we present results from a 2SLS regression specification using mortgage growth as the endogenous explanatory variable and the credit supply shock as the instrumental variable.

5.1 Credit Supply Shock and Pre-trend in Local Labour Markets

The absence of any correlation between the credit shock and labour market pre-trends is crucial for the validity of our identifying assumption that multi-market lenders could not predict local labour market trends. Reassuringly, Table 7 shows that the credit supply shock is correlated with the county-level unemployment rate and weekly wage rate neither for the decade before 2003 (columns (1) and (2)), nor for the recession that immediately preceded the credit boom (columns(3) and (4)).

One potential concern with the estimated effects of the credit supply shock is that it might simply be picking up trends in national labour market performance instead of estimating the local effects of the shock. This is particularly true because large lenders tend to locate in metropolitan areas, which are arguably more responsive to the aggregate economy. However, the lack of correlation between the credit shock and the local labour market performance during the Dotcom crash suggests that the local effects of the shock that we uncovered between 2003 and 2017 are unlikely to be mere "placebo" effects of aggregate labour market dynamics.

Table 7: 'Placebo Test': Credit Supply Shock and Local Labour Market Pre-trends

	1994-2003		**Dotcom Crash: 2001-2003**	
	Unemployment Rate	**Weekly Wage**	**Unemployment Rate**	**Weekly Wage**
	(1)	(2)	(3)	(4)
Credit Supply Shock	-1.13	2.30	0.37	0.72
	(0.72)	(3.22)	(1.16)	(1.33)
Observations	3047	3028	3021	3021
Adjusted R^2	0.37	0.18	0.09	0.06

Note: Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

5.2 Robustness to Changing Selection of Lenders

Table 8: Robustness to Selection of Lenders: Long-Run Effects of Credit Supply Shock

	Unemployment Rate^a	**Weekly Wage**^{a}	**Old Firm Employment Share**^{b}
	(1)	(2)	(3)
Credit Supply Shock	-0.24	-6.39**	5.54***
	(0.37)	(2.58)	(1.59)
Observations	3048	3017	2502
Adjusted R^2	0.43	0.35	0.16

Note: This table reports regression estimates of credit supply shock on the change in the unemployment rate, the employment rate, the weekly wage rate and the employment share of old firms (age > 5 years) relative to the employment share of young firms (age < 4 years). Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000 in columns (1) and (2).
^{a} Changes in the unemployment rate and weekly wage rate are taken between 2003 and 2017.
^{b} Changes in the old firm employment share relative to young firms' share are taken between 2006 and 2016.

In our benchmark results, we restricted the set of lenders to those operating in at least 100 counties and one census region in the year 2000. One potential issue with that strategy is geographical selection bias, wherein lenders operating at the border of census regions are more likely to be selected. We implement a stricter selection criterion to overcome this concern, requiring lenders to operate in at least 10 states. This restricts the sample to 193 selected lenders. We construct the county-level credit supply shocks with these lenders following the same methodology as before. Table 8 shows the long-run effects of the credit supply shock on the local labour market using this alternative sample of lenders. The coefficients are very close to the benchmark estimates. The sub-period analysis, found in Appendix Table C.1, is consistent with the benchmark results. In Appendix Table C.2, we further show that the main results are also robust to a credit shock constructed using an even shorter list of lenders which operated in at least 200 counties in 2000.

5.3 Two-Stage Least Square Regression: Causal Effect of Mortgage Growth

In our baseline specification, we regressed the outcome variables directly on the credit supply shock to measure the causal impact. Alternatively, one can use credit shock as an instrumental variable (IV) for an intermediate endogenous explanatory variable. A natural candidate for such an endogenous explanatory variable is the growth in mortgage origination. The 2SLS coefficient can be interpreted as the causal effect of mortgage growth on the outcomes if the credit shock cannot affect local labour markets except through the mortgage channel.

Table 9: Effect of Mortgage Growth on Local Labour Markets: OLS and 2SLS Estimates

	Unemployment Rate		**Weekly Wage Rate**	
	OLS	**2SLS**	**OLS**	**2SLS**
Mortgage Growth	0.31**	-0.32	0.56	-24.82**
	(0.12)	(1.15)	(0.79)	(9.88)
Weak-IV-Robust Confidence Interval	-	[-4.01, 1.82]	-	[-63.56, -10.35]
Kleibergen-Paap F-statistic	-	9.60	-	9.20
Observations	3040	3040	3020	3020
Adjusted R^2	0.43	0.41	0.32	0.05

Note: This table reports the OLS and 2SLS estimates of mortgage expansion on changes in the unemployment rate and the weekly wage rate between 2003 and 2017. Mortgage growth in county i is defined as the growth in the average mortgage origination between 2002 and 2006 relative to the level in 2000. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. Anderson-Rubin confidence intervals (robust to a potentially weak instrumental variable) for the estimated causal effects are reported along with the F-statistics for the first-stage regressions. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

Table 9 shows the long-run effect of the mortgage growth between 2002 and 2006 relative to the level in 2000 on the changes in the county-level unemployment rate and wage rate between

2003 and 2017. The sub-period results are available in Appendix Table C.4. The first-stage F-statistic is marginally below 10, suggesting the problem of a weak IV. However, the reported Anderson-Rubin confidence interval, which is robust to a potentially weak IV, indicates that the statistical significance of the effects is unaffected. Appendix Table C.5 shows that using the smaller set of lenders operating in at least 200 counties alleviates the weak-IV problem.

The 2SLS results are qualitatively similar to the direct effect of the credit supply shock on local labour market performance — no long-run effect on unemployment rates but a significant permanent drop in wage growth. The OLS coefficients are biased upwards for both measures of labour market performance. While the positive bias in the wage effect supports the narrative of higher mortgage demand from better-performing regions, the positive bias for the unemployment effect supports the hypothesis of excessive supply of subprime mortgages to worse-performing counties. Therefore, the direction of endogeneity bias remains inconclusive about identifying the credit demand or supply channel as the key mechanism for credit expansion.

6 Mechanism

The empirical section shows that county-level credit supply shocks cannot explain long-run changes in labour quantities but a decline in wage growth in local labour markets that cannot be explained by industry-specific or skill-specific mechanisms. We also found that counties with a larger credit supply shock experienced a long-run decline in business dynamism, as evident from a larger decline in the employment share of young firms. This suggests that the mortgage credit supply shock adversely affected labour demand, possibly by making newer firms credit-constrained. In this section, we propose a stylized model that highlights this credit-induced drop in labour demand. While establishing a possible channel through which shocks in the credit market can be transmitted to the labour market, our model also generates the empirical finding of asymmetric effects of the credit shock along the business cycle — no effect during a boom but a negative impact during a recession. Our framework of financial constraints has parallels with the vast literature on the macroeconomic implications of collateral constraints, for example, Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Jermann and Quadrini (2012).

6.1 Setup

We consider a discrete-time, infinite-horizon economy populated by workers and two types of entrepreneurs: patient and impatient, defined by their high and low discount factors β_H and β_L, respectively. Workers share their discount factor with that of the relatively impatient entrepreneur. For simplicity, we abstract away from any uncertainty. There are two goods in the economy: a fixed stock of durable housing and a numeraire non-durable consumption good produced and consumed every period. Workers earn wages through the supply of labour, the only factor of production. Labour supply is assumed to be inelastic and normalized to one for each worker. Entrepreneurs provide the technology and claim production residuals. To allow for a role of financial friction, we introduce two constraints: a borrowing constraint faced by all agents and a working capital constraint faced only by entrepreneurs. Both of these constraints are tied to the value of housing. The idea is to emulate credit supply shocks by tightening and slackening these constraints. Below we present the optimization problems of the agents and delegate the details of the model setup, including the optimality conditions, the market-clearing conditions, and the steady-state conditions to Appendix D.1.

6.1.1 Workers

Each identical worker maximizes discounted lifetime utility by choosing a path for non-durable consumption, $c_{W,t}$ and a portfolio of bond and housing assets, $b_{W,t+1}$ and $h_{W,t+1}$ respectively, subject to a budget constraint and a borrowing constraint:

$$\begin{aligned} \max_{\{c_{W,s}, h_{W,s+1}, b_{W,s+1}\}_{s=t}^{\infty}} \quad & \sum_{j=0}^{\infty} \beta_L^j u\left(c_{W,t+j}, h_{W,t+j}\right) \text{ subject to} \\ c_{W,t} + p_t h_{W,t+1} + b_{W,t+1} &= w_t + p_t h_{W,t} + (1+r_t) b_{W,t} \\ -b_{W,t+1} &\leq \phi_b p_t h_{W,t+1} \end{aligned}$$

Here, p_t is the house price, and r_t is the interest rate on bonds at time t. The only income source for workers is wage, w_t which they use to fund non-durable consumption, $c_{W,t}$ as well investment in housing assets, $p_t\left(h_{W,t+1} - h_{W,t}\right)$ and bonds, $[b_{W,t+1} - (1+r_t)\, b_{W,t}]$. Workers can borrow up to ϕ_b fraction of the present value of their housing stock in the next period, $p_t h_{W,t+1}$. The parameter ϕ_b thus determines the tightness of the borrowing constraint. Workers are the relatively impatient agents in the economy and, therefore, always borrowing-constrained in the steady state.

6.1.2 Entrepreneurs

Entrepreneurs hire workers to produce consumption goods using a decreasing-returns-to-scale production function, l_t^{γ}, where l_t is the labour input and $\gamma \in (0,1)$. Production scale is subject to a working capital constraint, which requires the wage bill to be paid before production occurs. The wage bill is financed by within-period borrowing without any interest cost. The decreasing return to scale assumption is essential in this framework, as it requires an equal distribution of resources among entrepreneurs at the optimal allocation. Under a constant return to scale assumption, the working capital constraint would not affect labour productivity and wage, as the marginal product of labour would be constant. As in the standard financial friction literature (see, for example, Kiyotaki and Moore (1997) and Iacoviello (2005)), we assume limited enforcement on debt repayment so that entrepreneurs need to use their houses as collateral. They can borrow up to ϕ_h fraction of their current house value, where ϕ_h captures the amount of debt that can be recovered with the housing collateral if a default happens. Then, the optimization problem for each type-$i \in \{L, H\}$ entrepreneur with discount factor β_i is specified as follows:

$$
\begin{aligned}
\max_{\{c_{i,s}, l_{i,s}, h_{i,s+1}, b_{i,s+1}\}_{s=t}^{\infty}} \quad & \sum_{j=0}^{\infty} \beta_i^j u(c_{i,t+j}, h_{i,t+j}) \text{ subject to} \\
c_{i,t} + p_t h_{i,t+1} + b_{i,t+1} &= \pi_{i,t} + p_t h_{i,t} + b_{i,t}(1 + r_t) \\
\pi_{i,t} &= l_{i,t}^{\gamma} - w_t l_{i,t} \\
-b_{i,t+1} &\leq \phi_b p_t h_{i,t+1} \\
w_t l_{i,t} &\leq \phi_h p_t h_{i,t}
\end{aligned}
$$

The borrowing and working capital constraints are not necessarily binding simultaneously for the entrepreneurs. The borrowing constraint always binds in the steady state for the impatient entrepreneur, similar to the workers. However, the patient entrepreneur will be the saver in the economy, with slack borrowing constraints. Whether each type of entrepreneur faces a binding or slack working capital constraint depends on particular parameter values.

6.2 Shock Transmission: From Credit to Labour Market

We now study how borrowing constraint fluctuations, which mimic credit shocks, can affect the labour market through their intermediate effect on the housing market. Since the borrowing constraint always binds in the steady state for the worker and the impatient entrepreneur, a change in borrowing constraint affects their incentive to invest in housing. Consequently, house price is affected. House price fluctuations, in turn, affect the working capital constraint for all entrepreneurs and, in so doing, transmit the shock in the credit market to the labour market, provided the working capital constraint is not too slack initially.

The transmission of a credit shock to the labour market is summarized in Figure 4. For a range of values for ϕ_b and ϕ_h, the figure plots the steady-state wages (left panel) and outputs (right panel). When the working capital constraint is tight, i.e., ϕ_h is low, relaxing the borrowing constraint leads to house price appreciation, which, in turn, relaxes the working capital constraint. Because production technology features decreasing return to scale, labour reallocation from the unconstrained patient firm to the constrained impatient firm improves the marginal product of labour.[10] In other words, in our framework, labour reallocation across firms leads to productivity loss due to firm-side financial constraints (see Khan and Thomas (2013) and Buera and Moll (2015) for recent research linking financial frictions with productivity losses). This positive transmission from housing to the labour market disappears when ϕ_h is sufficiently high. When ϕ_h is high, changes in the borrowing constraint barely affect production because the working capital constraint is slack for both entrepreneurs. This brings forth the asymmetry of the impact of credit shocks on the labour market along the business cycle — the transmission channel is muted when financial constraints are slack during a boom, while it becomes relevant when constraints are binding in a downturn. Introducing two separate constraints allows the credit shock to affect the housing and bonds market separately without necessarily affecting the labour market, and to generate the empirically observed asymmetric effects on the real economy.

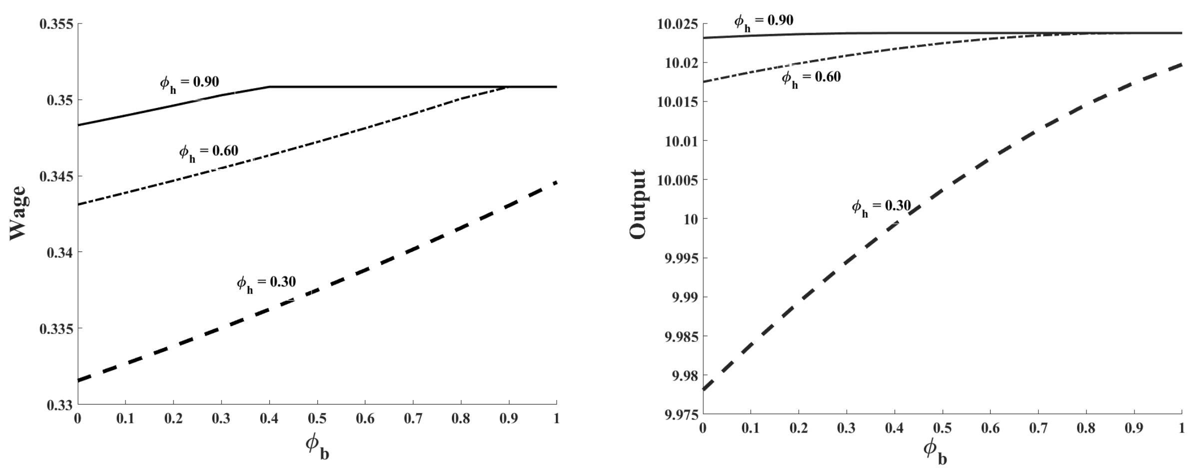

Figure 4: Steady-State Wage and Output for Different Values of ϕ_b and ϕ_h

In Appendix D.2, we match the change in the borrowing constraint to empirically observed changes in the mortgage market and show that, under reasonable parameter calibration, the model can explain about a fifth of the Great Recession wage decline. While this model and the associated quantitative exercise are quite simplistic, they nonetheless shed light on an important mechanism through which financial constraints impact labour market fluctuations.

7 Conclusion

What is the long-run impact of credit shocks on the real economy? This paper answers this question by focusing on the impact of county-level credit supply shocks on the local labour market

[10] Note that the parameter values used in the simulation (see Appendix Table D.1) are set such that the working capital constraint is always slack for the patient entrepreneur.

outcomes. We construct an exogenous mortgage supply shock by interacting the differential credit growth of multi-market lenders at the national level during the credit boom period of the early 2000s with a county's initial exposure to these lenders. We find no long-run effect of these shocks on local unemployment rates, but a significant negative impact on wage growth between 2003 and 2017. Disaggregating the long run into three sub-periods of expansion, recession and recovery, we show that the housing market boom did not have any positive spillover effects into the local labour markets but affected all labour market variables adversely during the recession. This was, however, followed by a complete recovery in unemployment, but a persistently depressed wage growth. While industry-specific or skill-specific mechanisms do not seem to explain the wage hysteresis, counties with larger credit shocks experienced a greater reallocation of employment from young to old firms. This suggests credit shocks have negatively impacted local labour demand by depressing business dynamism.

To rationalize the empirical results, we propose a simple mechanism with two types of financial constraints: a borrowing constraint on the household side and a working capital constraint on the firm side, both tied to the collateral value of housing. A mortgage credit shock, modelled as a change in the household borrowing constraint, affects housing value through its impact on the incentive to hold houses. The change in housing value, in turn, tightens or slackens the working capital constraint for firms and affects labour demand. This model can generate the negative effect of credit shock on wage growth and the empirically observed labour reallocation towards more patient firms, which is our model counterpart of older firms in the data. Moreover, through occasionally binding constraints, the model can also generate the asymmetric effect of credit shock on labour markets along the business cycle, that is, no effect of credit expansion on the local labour market, but a negative effect of a credit contraction. While our proposed mechanism can qualitatively replicate our empirical findings, it is by no means the only possible channel through which credit shocks can affect the labour market. There could be other mechanisms, such as productivity loss for unemployed workers due to human capita decay in the aftermath of a credit-crunch-induced recession, wage drops below the reservation wage for some workers who consequently drop out of the labour force, reduced R&D investment by credit-constrained firms hurting labour productivity, etc. Future research can try to quantify the long-run impacts of credit fluctuations on wage growth through these various mechanisms.

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Appendix

There are four appendices, A through D corresponding to Sections 3 through 6 in the main paper, respectively.

A Appendix to Section 3

A.1 The Largest and Fastest Growing Lenders

Table A.1: Top Decile of Largest Selected Lenders

Lender Name	Mortgage Origination ($)	Status
Washington Mutual Bank	8.5×10^{11}	bankruptcy[a]
Bank of America	5.9×10^{11}	
Wells Fargo Bank	5.3×10^{11}	
World Savings Bank	2.4×10^{11}	acquired[b]
GMAC Mortgage LLC	2.1×10^{11}	bankruptcy
Flagstar Bank	2.0×10^{11}	
First Horizon Home Loan	1.9×10^{11}	
Greenpoint Mortgage Funding	1.9×10^{11}	
SunTrust Mortgage	1.9×10^{11}	
PHH Mortgage Corporation	1.6×10^{11}	

Note: The selected lenders satisfy the restriction for lending in more than 100 counties and 1 census region in 2000 and remained operating during 2000–2006.
[a] The holding company of GMAC Mortgage filed chapter 11 bankruptcy in 2012.
[b] World Savings Bank was acquired by Wells Fargo in 2008 as part of Wachovia Corporation.

Table A.2: Top Decile of Fastest Growing Selected Lenders

Lender Name	Mortgage Growth	Status
Everbank	446%	
Wells Fargo Bank	425%	
Lehman Brothers Bank	398%	bankruptcy
Mortgageit	381%	acquired[a]
TD Banknorth	367%	
WMC Mortgage Company	354%	bankruptcy
Dollar Mortgage Corporation	323%	
USAA Federal Savings Bank	314%	
The Huntington National Bank	309%	
American Home Mortgage Corporation	302%	bankruptcy
Novastar Mortgage Inc.	301%	bankruptcy

Note: Mortgage growth rate is computed as the average annual mortgage origination between 2002 and 2006 relative to the level in 2000. The selected lenders satisfy the restriction for lending in more than 100 counties and 1 census region in 2000 and remained operating during 2000–2006.
[a] Mortgageit was acquired by Deutsche Bank in 2007.

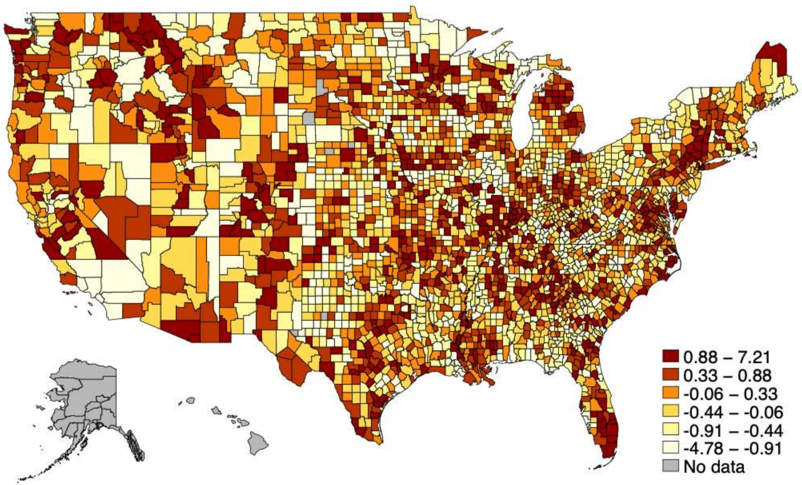

Figure A.1: Credit Supply Shocks across U.S. Counties

Note: The map sorts the U.S. counties into six quantiles based on the residual credit supply shock after controlling for state fixed-effects and the following county characteristics: sub-prime rate, per capita establishment, employment rate, unemployment rate, log weekly wage, log annual per capita income, log median household income, poverty rate and the employment shares of 23 two-digit industries in the year 2000. The shock is normalized by its standard deviation.

B Appendix to Section 4

B.1 Relation between Credit Supply Shock and Weekly Wage Rate

Table B.1: Effect of Credit Supply Shock on Weekly Wage Rate: Controlling for CZ Fixed Effects

	Long Run 2003-2017	**Expansion 2003-2006**	**Recession 2006-2010**	**Recovery 2010-2017**
	(1)	(2)	(3)	(4)
Credit Supply Shock	-8.75**	-1.95	-4.55**	-1.21
	(3.42)	(1.88)	(2.17)	(2.45)
Observations	3017	3022	3022	3024
Adjusted R^2	0.43	0.27	0.21	0.25

Note: This table reports the effect of credit supply shock on changes in weekly wage rate for subperiods between 2003 and 2017. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the commuting zone level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for commuting zone fixed effects and all the county and industry controls listed in the Note to Table 5, except the wage rate in 2000.

Table B.2: Effect of Credit Supply Shock on Weekly Wage Rate by Industry

	Construction	**Finance & Real Estate**	**Manufacturing**	**Other**
	(1)	(2)	(3)	(4)
Credit Supply Shock	-6.11	-9.71**	-3.11	-10.19**
	(3.86)	(4.44)	(4.24)	(4.75)
Observations	2594	2476	2614	3026
Adjusted R^2	0.15	0.08	0.11	0.19

Note: This table reports the effect of credit supply shock on changes in the weekly wage rate in four industry groups between 2003 and 2017. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the commuting zone level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5, except the wage rate in 2000.

Table B.3: Effect of Credit Supply Shock on Quarterly Earnings by Education

	Less than 12 Years	**Between 12 & 15 Years**	**More than 15 Years**
	(1)	(2)	(3)
Credit Supply Shock	-4.98**	-3.26*	-5.90**
	(2.24)	(1.79)	(2.24)
Observations	2938	2944	2868
Adjusted R^2	0.39	0.41	0.33

Note: This table reports the effect of credit supply shock on changes in the weekly wage rate of workers of different educational attainment between 2003 and 2017. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the commuting zone level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5.

B.2 Effect of Credit Shock on Employment & Labour Force Participation

Table B.4: Long-Run Effect of Credit Supply Shock on Employment & Labour Force Participation Rates

Change between	**Employment Rate**		**Labour Force Participation Rate**	
2003 & 2017	**Total**	**Working Age**	**Total**	**Working Age**
	(1)	(2)	(3)	(4)
Credit Supply Shock	0.29	-0.64	0.02	1.44
	(1.37)	(1.24)	(1.33)	(2.00)
Observations	3046	3019	3045	3042
Adjusted R^2	0.15	0.11	0.18	0.17

Note: This table reports the effect of credit supply shock on the changes in employment and labour force participation rates between 2003 and 2017. The *Total* columns use the total county population to calculate the employment and participation rates, while the *Working Age* columns use the working-age population between 16 and 65 years of age. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and the full list of county and industry characteristics listed in Note to Table 5.

C Appendix to Section 5

C.1 Alternative Credit Shock - Changing the Selection of Lenders

Table C.1: Effect of Credit Supply Shock: Lender Presence in At Least 10 States

	Long Run 2003-2017	**Expansion 2003-2006**	**Recession 2006-2010**	**Recovery 2010-2017**
	(1)	(2)	(3)	(4)
A. Unemployment Rate				
Credit Supply Shock	-0.24	0.00	1.76***	-1.92***
	(0.37)	(0.25)	(0.48)	(0.57)
Observations	3048	3038	3035	3045
Adjusted R^2	0.43	0.48	0.64	0.70
B. Weekly Wage				
Credit Supply Shock	-6.39**	-0.82	-4.28***	-0.35
	(2.58)	(1.09)	(1.38)	(1.51)
Observations	3017	3022	3022	3024
Adjusted R^2	0.35	0.19	0.19	0.19

Note: This table reports regression estimates of the effect of credit supply shock on the unemployment rate changes (Panel A) and average monthly private employment changes (Panel B) for various sub-periods between 2003 and 2017. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

Table C.2: Long-Run Effects of Credit Supply Shock: Lender Presence in At Least 200 Counties

	Unemployment Rate[a]	**Weekly Wage Rate**[a]	**Old Firm Employment Share**[b]
	(1)	(2)	(3)
Credit Supply Shock	-0.24	-6.02**	5.93***
	(0.41)	(3.00)	(1.71)
Observations	3048	3017	2502
Adjusted R^2	0.43	0.35	0.16

Note: This table reports regression estimates of the long-run effect of the credit supply shock on the change in the unemployment rate, the employment rate, the weekly wage rate and the employment share of old firms (age > 5 years) relative to the employment share of young firms (age < 4 years). The credit supply shock is measured with lenders that operated in more than 200 counties and one census region in 2000 and remain in operation during 2000–2006. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000 in columns (2) and (3).
[a] Changes in the unemployment rate, employment rate and weekly wage rate are taken between 2003 and 2017.
[b] Changes in the old firm employment share are taken between 2006 and 2016.

C.2 Alternative Credit Shock - Using Only Home Purchase Mortgages

Table C.3: Long-Run Effects of Credit Supply Shock: Home Purchase Mortgage Only

	Unemployment Rate[a]	**Weekly Wage Rate**[a]	**Old Firm Employment Share**[b]
	(1)	(2)	(3)
Credit Supply Shock	-0.22	-6.43**	5.56***
	(0.37)	(2.52)	(1.56)
Observations	3048	3017	2502
Adjusted R^2	0.43	0.35	0.16

Note: This table reports the long-run effect of the credit supply shock (constructed using home purchase mortgage data only, excluding mortgages for home improvement and refinancing) on the change in the unemployment rate, the weekly wage rate and the employment share of old firms (age > 5 years) relative to the employment share of young firms (age < 4 years). The credit supply shock is measured with the baseline set of lenders. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000 in columns (2) and (3).
[a] Changes in the unemployment rate, employment rate and weekly wage rate are taken between 2003 and 2017.
[b] Changes in the old firm employment share are taken between 2006 and 2016.

C.3 2SLS Estimates with Mortgage Growth as Endogenous Regressor

Table C.4: Effect of Mortgage Growth on Local Labour Markets: Lender Presence in At Least 100 Counties

	Expansion 2003-2006		**Recession 2006-2010**		**Recovery 2010-2017**	
	OLS	**2SLS**	**OLS**	**2SLS**	**OLS**	**2SLS**
	(1)	(2)	(3)	(4)	(5)	(6)
A. Unemployment Rate						
Mortgage Growth	0.14**	-0.26	0.16	4.37***	0.00	-4.46**
	(0.06)	(0.77)	(0.14)	(1.67)	(0.17)	(2.18)
Weak-IV-Robust Confidence Interval	-	[-2.31, 1.49]	-	[1.92, 10.94]	-	[-12.99, -1.27]
Kleibergen-Paap F-statistic	-	9.51	-	9.51	-	9.60
Observations	3033	3033	3033	3033	3040	3040
Adjusted R^2	0.45	0.44	0.62	0.36	0.68	0.42
B. Weekly Wage Rate						
Mortgage Growth	0.10	-0.88	-0.09	-12.97**	0.52	-9.16*
	(0.49)	(3.85)	(0.50)	(6.34)	(0.54)	(4.98)
Weak-IV-robust Confidence Interval	-	[-10.17, 8.72]	-	[-37.81, -3.69]	-	[-25.12, 0.10]
Kleibergen-Paap F-statistic	-	9.16	-	9.93	-	10.05
Observations	3021	3021	3019	3019	3021	3021
Adjusted R^2	0.18	0.18	0.21	0.02	0.14	0.06

Note: This table reports regression estimates of mortgage expansion between 2002 and 2006 relative to the level in 2000 on unemployment rate changes and weekly wage growth for various sub-periods between 2003 and 2017, using credit supply shock as the instrumental variable in the even columns. The credit supply shock is measured with the baseline set of lenders. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. Anderson-Rubin confidence intervals (robust to a potentially weak instrumental variable) for the estimated causal effects are reported along with the F-statistics for the first-stage regressions. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

Table C.5: Effect of Mortgage Growth on Local Labour Markets: Lender Presence in At Least 200 Counties

2SLS Estimates **IV: Credit Supply Shock**	**Long Run Effect** **2003-2017** (1)	**Expansion** **2003-2006** (2)	**Recession** **2006-2010** (3)	**Recovery** **2010-2017** (4)
A. Unemployment Rate				
Mortgage Growth	-0.30	-0.21	3.22***	-3.34**
	(0.73)	(0.48)	(1.00)	(1.30)
Weak-IV-robust Confidence Interval	[-2.01, 1.06]	[-1.21, 0.79]	[1.43, 5.72]	[-6.69, -1.13]
Kleibergen-Paap F-statistic	24.81	24.59	24.59	24.81
Observations	3040	3033	3033	3040
Adjusted R^2	0.41	0.44	0.48	0.53
B. Weekly Wage Rate				
Mortgage Growth	-13.56**	0.01	-8.96**	-4.28
	(6.48)	(3.17)	(3.96)	(3.63)
Weak-IV-robust Confidence Interval	[-29.20, -2.01]	[-6.64, 6.66]	[-19.12, -2.21]	[-11.90, 3.35]
Kleibergen-Paap F-statistic	24.12	24.17	25.34	25.50
Observations	3020	3021	3019	3021
Adjusted R^2	0.23	0.18	0.12	0.12

Note: This table reports regression estimates of mortgage expansion on unemployment rate changes and weekly wage growth for various sub-periods between 2003 and 2017, using credit supply shock as the instrumental variable. The credit supply shock is measured with the set of lenders who operate in at least 200 counties as in Table C.2. Regressions are weighted by the county-level population in 2000. Standard errors are clustered at the state level. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels respectively. Anderson-Rubin confidence intervals (robust to a potentially weak instrumental variable) for the estimated causal effects are reported along with the F-statistics for the first-stage regressions. All regressions control for state fixed effects and county and industry characteristics listed in Note to Table 5, except the dependent variable in 2000.

D Appendix to Section 6

D.1 Details of the Model Setup

Workers. The optimality conditions for workers are given as follows:

$$u^W_{c,t} = \beta_L(1 + r_{t+1})u^W_{c,t+1} + \lambda_{W,t} \tag{D.1}$$

$$p_t u^W_{c,t} = \beta_L u^W_{h,t+1} + \beta_L p_{t+1} u^W_{c,t+1} + \phi_b p_t \lambda_{W,t} \tag{D.2}$$

Equation (D.1) is the consumption Euler equation, and equation (D.2) is the trade-off between present consumption and investing in housing. In both equations, the Lagrange multiplier term $\lambda_{W,t}$ represents the shadow value of the borrowing constraint. If the worker is borrowing constrained ($\lambda_{W,t} > 0$), there is a benefit $\phi_b p_t \lambda_{W,t}$ for holding an additional unit of housing, as workers can increase their borrowing by $\phi_b p_t$ amount. Workers are the relatively impatient agents in the economy and, therefore, always borrowing-constrained in the steady state.

Entrepreneurs. The borrowing and working capital constraints are associated with different timings of housing values. At the beginning of period t, the entrepreneur borrows against the current housing stock to hire workers and conduct production. At the end of the period t, production is distributed, and the entrepreneur i makes a saving decision $b_{i,t+1}$ for the next period $t + 1$, subject to the current value of the next period's housing stock $h_{i,t+1}$.

The type-i entrepreneur's optimal choices satisfy the following first-order conditions:

$$u^i_{c,t} = \beta_i(1 + r_{t+1})u^i_{c,t+1} + \lambda_{i,t} \tag{D.3}$$

$$p_t u^i_{c,t} = \beta_i u^i_{h,t+1} + \beta_i p_{t+1} u^i_{c,t+1} + p_t \phi_b \lambda_{i,t} + \beta_i \phi_h p_{t+1} \mu_{i,t+1} \tag{D.4}$$

$$u^i_{c,t}(\gamma l^{\gamma-1}_{i,t} - w_t) = w_t \mu_{i,t} \tag{D.5}$$

$\lambda_{i,t}$ and $\mu_{i,t}$ denote, respectively, the Lagrange multiplier of the borrowing and working capital constraint for the type-i entrepreneur. The consumption Euler equation (D.3) for entrepreneurs is the same as the workers'. Crucially, since all impatient agents will borrow up to the limit and the patient entrepreneur will loan the funds, the steady-state interest rate is determined by the discount factor of the patient entrepreneur, $r = \frac{1}{\beta_H} - 1$. The condition governing the optimal housing stock for entrepreneurs, equation (D.4), features an extra incentive to hold housing compared to the optimal condition for workers. In the presence of a working capital constraint, an additional housing unit allows the impatient entrepreneur to expand production by borrowing an extra amount of $\phi_h p_{t+1}$, which increases the entrepreneur's utility by $\mu_{i,t+1}$. Finally, equation (D.5) represents the optimal choice of labour demand, given the working capital constraint.

Market Clearing. For every pair of the two types of entrepreneurs, we assume there are $\bar{l}$ workers and a housing stock of $\bar{h}$. We are implicitly making a simplifying assumption of an equal number of the two types of entrepreneurs. Since in our closed economy model, bonds are in net-zero supply, the market-clearing conditions for bonds, housing and non-durable goods markets are as follows.

$$\begin{aligned} b_{W,t}\bar{l} + b_{L,t} + b_{H,t} &= 0 \qquad (D.6)\\ h_{W,t}\bar{l} + h_{L,t} + h_{H,t} &= \bar{h} \qquad (D.7)\\ c_{W,t}\bar{l} + c_{L,t} + c_{H,t} &= l_{L,t}^{\gamma} + \left(\bar{l} - l_{L,t}\right)^{\gamma} \qquad (D.8)\end{aligned}$$

Equilibrium. The equilibrium in our model economy without any stochastic shocks is defined by an allocation $\{h_L, h_H, h_W, c_L, c_H, c_W, b_H, b_L, b_W\}$ together with prices $\{w, r, p\}$ that satisfies equations (D.1) through (D.8). The steady-state can be found by solving the optimal housing distribution, and all the steady-state conditions are presented below.

Steady State Conditions. In steady state, the model is described by the follow equations:

$$r = \frac{1}{\beta_H} - 1 \qquad (D.9)$$

$$b_W = -\phi_b p h_W \qquad (D.10)$$

$$b_L = -\phi_b p h_L \qquad (D.11)$$

$$b_H = -(b_L + b_W\bar{l}) \qquad (D.12)$$

$$w = \min\left(\frac{\phi_h p h_L}{l_L}, \gamma l_L^{\gamma-1}\right) = \min\left(\frac{\phi_h p h_H}{l_H}, \gamma l_H^{\gamma-1}\right) \qquad (D.13)$$

$$\bar{l} = l_L + l_H \qquad (D.14)$$

$$\beta_L u_h^W + \phi_b p(1 - \beta_L(1+r))u_c^W = p(1-\beta_L)u_c^W \qquad (D.15)$$

$$\beta_L u_h^L + \beta_L\phi_h p(\gamma l_L^{\gamma-1}/w - 1)u_c^L + \phi_b p(1 - \beta_L(1+r))u_c^L = p(1-\beta_L)u_c^L \qquad (D.16)$$

$$\beta_H u_h^H + \beta_H\phi_h p(\gamma l_H^{\gamma-1}/w - 1)u_c^H = p(1-\beta_H)u_c^H \qquad (D.17)$$

$$h_W\bar{l} + h_L + h_H = \bar{h} \qquad (D.18)$$

$$c_W\bar{l} + c_L + c_H = l_L^{\gamma} + l_H^{\gamma} \qquad (D.19)$$

D.2 Quantitative Analysis

D.2.1 Calibration

We assume a log-linear utility function $u(c_{j,t}, h_{j,t}) = log(c_{j,t}) + \alpha_h log(h_{j,t})$ for each agent $j \in \{W, H, L\}$. The time period is set to an annual frequency, consistent with the empirical section. Parameter values used to simulate the model are presented in Table D.1.

The patient agent's discount factor is set to match an equilibrium interest rate of 2%. Following the literature, the impatient agent's discount factor is set as 0.95 (see Iacoviello (2005) for empirical evidence). Since housing is non-depreciable in our framework, we cannot use the expenditure share on housing to calibrate the utility weight on housing. Instead, we set α_h to the conventional value of 0.10, used in Iacoviello (2005) and Justiniano, Primiceri and Tambalotti (2019). The parameter ϕ_b governs the maximum loan-to-value (LTV) ratio, which we set to 0.8 following the fact that conforming loans that meet Fannie Mae and Freddie Mac underwriting guidelines are limited to a maximum LTV ratio of 80%. Since data on working capital loans are unavailable for either aggregate or regional economies, we cannot get an empirical value for the parameter ϕ_h, which regulates the working capital constraint in our model. Instead, we choose ϕ_h to place the impatient entrepreneur at marginal slackness of the working capital constraint, such that any negative credit shock will make the constraint binding. This choice maximizes the share of the wage decline that can be explained by credit shock through our model mechanism. We set the decreasing returns to scale parameter γ equal to the labour income share in the U.S. economy. Since we observe 10 employees per firm, on average, in county-level data, and our model features 2 entrepreneurs, we set the total labour supply, $\bar{l}$ to be 20. The total housing stock is set so that the mortgage debt payment to income ratio is close to 5.56%, matched with the aggregate moment in 2000.

Table D.1: Calibration of Parameters

Description	**Parameter**	**Value**
High discount factor	β_H	0.98
Low discount factor	β_L	0.95
Weight on housing service	α_h	0.10
Borrowing constraint	ϕ_b	0.80
Working capital constraint	ϕ_h	0.65
Labour Share	γ	0.70
Total housing stock	$\bar{h}$	10
Total labour supply	$\bar{l}$	20

We mimic unexpected credit shocks through two parameter changes in our model: first, an expansionary credit shock through an increase in ϕ_b by 0.15 to match a 40% mortgage growth during 2003–2006, and second, a contractionary credit shock through a decrease in ϕ_b by 0.30 to match a 45% decline from 2006–2010. Note that both shocks are considered exogenous and permanent to all agents. The second shock occurs when the new steady state is reached after the first shock.

The positive credit shock is supported by much empirical evidence documenting the relaxation in lending standards in the early 2000s. However, the credit crunch process is complex and hard to explain with any single mechanism. Endogenizing the process of credit contraction requires a framework with financial intermediaries, which is beyond the scope of this paper. We assume an exogenous tightening of the borrowing constraint to keep our model simple.

D.2.2 Results

Table D.2 compares changes in the model moments with the empirical ones in response to the two credit shocks. During credit expansion, the model over-predicts the house price increase (17% versus 11% in the data), which might be due to the fixed housing supply in the model. In reality, the housing supply clearly responded to increasing housing demand, dampening the price increase. The wage and employment share of the patient and impatient entrepreneurs are held constant in the model in response to the credit expansion shock, while the corresponding data moments also show statistically insignificant changes. We observe the debt payment to income ratio in aggregate data, but not at the county level. Nevertheless, we compare the observed increase of 1.5pp in aggregate debt service to the 2.2pp increase in the model's interest payment to wage ratio.

Table D.2: Quantitative Results

	Δb_W	Δw	Δp	$\Delta l_H/\bar{l}$	$\Delta r b_W/w$
A. Expansion (2003-2006)					
Data	38.6%	-0.5%[a]	11.4%	0.7%[a]	1.5pp[b]
Model	38.5%	0	17.0%	0	2.2pp
B. Contraction (2006-2010)					
Data	-48.3%	-4.4%	-21.1%	-2.2%	-1.0pp[b]
Model	-47.6%	-0.9%	-20.7%	-1.3%	-3.8pp

Note: This table shows the model and data moments in response to credit shocks — panel A for a positive shock, and panel B for a negative shock. The data moments (except for the debt payment to income ratio) are taken from the empirical estimates of the effect of the credit supply shock on the outcome variables, described in Section 4. For the model simulation, a positive credit shock is achieved by increasing ϕ_b by 0.15, and the negative shock by decreasing ϕ_b by 0.30. These values are chosen to match empirical mortgage growth in the respective periods.
[a] Data moment is statistically insignificant.
[b] Data moment for the debt service to income ratio uses aggregate data obtained from the Federal Reserve Board since we do not have data at the county level.

In the recession period, the model's changes in debt and house-price are matched well with empirical moments. However, the model can only predict about 20% (=0.9/4.4) of the wage decline in the data. It also under-predicts the changes in employment share, with a 1.3% decline of the impatient firm's employment share in the model compared to a 2.2% decline in the employment share of young firms in the data. Counterfactually, even if the employment share is perfectly matched with data moment, the model predicts only a 1.3% decrease in wage. This implies that the labour reallocation effect can explain at most 30% of the wage decline in the data, suggesting the relevance of other channels to depress wage growth.