Local Agglomeration and Household Mortgage Debt

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Abstract

Using detailed household data, we find that households working in locally agglomerated economies have higher levels of mortgage debt and are more likely to have mortgage debt. Further analyses document that local agglomeration reduces laborers' unemployment risk and increases their promotion probability and wealth. Meanwhile, households with high unemployment risk, low probability of promotion, and low wealth are more likely to get mortgages if they are in more agglomerated economies. These results suggest that the link between local agglomeration and mortgage debt is best explained by the career prospects view. That is, agglomerated economies increase laborers' career potential. Our results hold under instrumental variables analysis and a set of robustness checks. Overall, our findings highlight the importance of local labor market composition in household mortgage debt.

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1. Introduction

Household debts in the economy play a key role in driving economic fluctuations (Mian et al., 2017). Notably, mortgage debt is the largest component of household debts. Understanding the determinants of households' mortgage debt is therefore a question of central economic importance. Although many studies have analyzed the dynamics of mortgage origination in the United States, especially after the 2008–2009 financial crisis, most of them are from the perspective of credit expansion (see Mian and Sufi, 2009; Agarwal et al., 2014; Adelino et al., 2016) or regulatory interventions (Defusco et al., 2019; Chakraborty et al., 2020). There is scarce research taking geographical factors as potential sources of the heterogeneity of household mortgage debt. Given the importance of mortgage debt in driving economic stability and the substantial spatial differences across labor markets in the U.S., the limited research on this link is somewhat surprising. Indeed, households living in locales with dominant industries are exposed to different labor market conditions from those in less agglomerated economies, which possibly affects household mortgage debt.

Local agglomeration, also known as an agglomerated economy, is a group of geographically proximate firms in the same industry. The earliest concept of local agglomeration dates back to Marshall (1890). In his seminal work, *Principles of Economics*, Marshall (1890) made a theoretical analysis of the reasons for the emergence of agglomeration economies, namely, knowledge spillovers, linkages between input suppliers and producers, and labor market interactions.[1] Subsequent theoretical and empirical studies further suggest that agglomerated economies increase corporate productivity, stimulate innovative partnerships, and present opportunities for entrepreneurial activity (Porter, 1998; Almazan et al., 2010; Dougal et al., 2015;

[1] More specifically, spillover effects are related to skill acquisition and technology learning; linkages explicitly mention the benefits of sharing intermediate suppliers; labor market interactions refer to the matching process between workers and job positions.

Engelberg et al., 2018). However, agglomerated economies also come with costs and risks. First, agglomerated economies present fierce competition, which is associated with a lower firm survival rate (Valta, 2012; Dougal et al., 2015). Second, agglomerated economies will exacerbate the negative externalities by contaminating neighbors' performance and subsequently accelerating the bankruptcy process (Benmelech et al., 2018). Notably, although the impact of local agglomeration on corporate activities is well documented in previous literature, its impact on households is largely ignored.

Theoretically, the link between local agglomeration and household mortgage debt is ambiguous. On the one hand, the career prospects view suggests a positive relationship between local agglomeration and mortgage debt. Under the theoretical framework of Marshall (1890), laborers in agglomerated economies benefit from knowledge spillovers and dynamic labor market interactions. These advantages significantly enhance laborers' career prospects. First, knowledge spillover enhances these prospects (Glaeser et al., 1992; Porter, 1998; Duranton and Puga, 2004). The geographical proximity in agglomerated economies facilitates the transmission of knowledge, which facilitates learning among laborers and subsequently increases their skills. Just as Glaeser et al. (1992, p.1127) said, "Intellectual breakthroughs must cross hallways and streets more easily than oceans and continents." As such, agglomerated economies enhance workers' career prospects by equipping them with specialized skills and knowledge, which may lead to a higher probability of promotion. Second, the thick labor market and the dynamic interaction of agglomerated economies reduce the individual–position mismatching costs, further improving laborers' career prospects. Specifically, agglomerated economies present a rich array of employment opportunities to workers. Sufficient positions reduce laborers' unemployment spells, and the dynamic interactions between employees and employers, which reduce the mismatching costs, lessen the unemployment risk (Krugman, 1991). Given higher promotion probability and lower unemployment risk, loan suppliers are more willing to provide mortgages to these borrowers,[2] and laborers are more likely to apply for mortgages due to a higher risk tolerance. Finally, agglomerated economies also benefit employers in terms of productivity and profitability (Davis et al., 2014), which in turn increases laborers' salaries and career prospects.[3] Households with higher wages or wealth are more likely to apply and get approval for mortgages due to lower default concern. Altogether, the career prospects view suggests that local agglomeration increases laborers' career prospects, manifested in lower unemployment risk, larger promotion space, and higher wages. Moreover, these laborers are more likely to apply and get approval for mortgage debt because of their lower probability of default (Mian and Sufi, 2009; Jiang and Lim, 2018). Thus, the career prospects view suggests a positive link between local agglomeration and household mortgage debt.

Alternatively, the layoff risk view suggests that workers in clustered industries are less likely to have mortgage debt. First, firms in agglomerated economies are highly competitive, increasing firms' bankruptcy rate and laborers' layoff risk. In particular, Dougal et al. (2015) argue that firms in locally agglomerated economies compete to grab the market. The fierce competition increases firms' business risks and reduces their survival rate (Valta, 2012). Subsequently, households working in local agglomeration could be exposed to higher layoff risks. Second, the geographical proximity in agglomerated economies aggravates the negative externalities. More precisely, the economies of agglomeration can be detrimental during

[2] For example, Donaldson et al. (2019) document that banks will firstly assess the employment risk of borrowers and then accordingly design the face values of household debts.

[3] The efficient linkage between suppliers and producers, as well as the economies of scale, allows firms to operate productively. For example, studies have shown that firms in urban clusters are more likely to innovate (Glaeser et al., 1992), vertically disintegrate (Holmes, 1999), strategically merge (Almazan et al., 2010), and invest efficiently (Dougal et al., 2015).

downturns, propagating and amplifying the negative effects of financial distress and bankruptcies among firms in the same locality. As an example, Benmelech et al. (2018) find that bankrupt firms impose negative externalities on nonbankrupt neighboring firms, causing contagion from financially distressed companies in agglomerated economies. Third, local agglomeration has been criticized for overspecialization (Granovetter, 1985; Markusen, 1996), which further increases the layoff risk. Specifically, the overspecialization makes firms prone to rather rigid strategies with respect to technological and market potential, finally evolving into a closed system that is vulnerable to downturns (Glaeser et al., 1992). Under this condition, firms' marginal return is stagnant and even decreasing, and laborers face high layoff risk.[4] Thus, with higher layoff risk, households are less likely to apply or get approval for mortgages. As a result, taking the layoff risk into consideration, we expect a negative link between local agglomeration and household mortgage debt.

We use the data provided by the Current Population Survey (CPS) to capture local agglomeration. Following literature (Holmes, 2005; Holmes and Stevens, 2014; Addoum et al., 2022), we define local agglomeration as the labor supply share of an industry in a local labor market scaled by its nationwide labor supply share. Our measure successfully captures the well-known agglomerated economies, including the hotel and motel industry in Las Vegas, the automobile industry in Detroit, the computer industry in Austin, and the aircraft industry in Seattle–Everett. We use the Survey of Income and Program Participation (SIPP) to capture household mortgage debt. We conduct household-level analysis and find empirical results supporting the career prospects view. Specifically, we document that households who work in

[4] Taking Detroit as an example, it used to be one of the most famous clustered industries in the world. However, it filed bankruptcy in 2013, and more than half of the population earning a living in auto-related industries were laid off. The key reason is that Detroit's auto industry had not stepped up its transformation and gradually fell behind other countries' technology.

local agglomeration have a larger amount of mortgage debt, as well as a higher probability of holding mortgage debt. Regarding the economic significance, a one-standard-deviation increase in local agglomeration is associated with a 2% increase in mortgage debt. Given that the average value of household mortgage debt is $41,167, a one-standard-deviation increase in local agglomeration leads to a dollar increase in household mortgage debt of $823. This is economically important and comparable to other studies on household mortgage debt (Barrot et al., 2022). In robustness checks, we show that our results hold when we use alternative measures of local agglomeration, when we control for two important industry-specific local labor market characteristics, and when we exclude the top as well as the bottom 10% of metropolitan statistical areas (MSAs) in the sample based on aggregate labor supply.

One may argue that the potential endogeneity due to omitted variables could bias our results. We address this concern using two approaches. First, we instrument local agglomeration using the United States' granting of Permanent Normal Trade Relations (PNTR) to China in 2001 (Addoum et al., 2022). This event removes the uncertainty of China's most favored nation (MFN) status and increases the import competition from Chinese firms, more importantly leading to significant employment losses for U.S. firms (Autor and Dorn, 2013; Pierce and Schott, 2016). Specifically, we instrument local agglomeration using an indicator for tradable sectors in which production could have been outsourced to Chinese competitors in the post-PNTR period after 2001. Second, by imposing more stringent fixed effects, we use a bunch of alternative specifications to re-examine the link between local agglomeration and mortgage debt. We replace state and year fixed effects with state-by-year fixed effects, metropolitan statistical area (MSA)-by-year fixed effects, and occupation-by-year fixed effects to control for the time-specific sources of variation across states, MSAs, and occupations. The results using both approaches remain the same.

Given the relationship between local agglomeration and mortgage debt, we move on to examine the underlying mechanisms. Before analyzing the specific mechanism, we are interested in whether demand-side or supply-side factors drive our results. We find that both of them contribute. Specifically, both the number of loan applications and the mortgage approval rate significantly increase in local agglomeration. Next, we turn to verify our career prospects view. First, we find that individuals working in agglomerated economies are more likely to get promotions. This result is consistent with our expectation that local agglomeration enhances laborers' career prospects via knowledge spillovers (Marshall, 1890; Porter, 1998; Glaeser, 1999). Second, we find that local agglomeration significantly reduces a household's unemployment weeks. In particular, households working in locally agglomerated economies spend fewer weeks looking for a job. Again, this finding is consistent with our career prospects argument. Namely, the thick labor market of local agglomeration optimizes the employee–position matching process and lowers unemployment spell, reducing unemployment risk. Finally, we find that households in local agglomeration accumulate higher levels of wealth. This finding further supports the theoretical argument that laborers in agglomerations have decent remuneration because of enhanced skills and knowledge. Cross-sectional analyses suggest that households with low probability of promotion, high unemployment risk, and low wealth are more likely to get mortgages if they are in more agglomerated economies compared to those in less agglomerated economies. The cross-sectional analyses suggest that households in local agglomeration are viewed as less exposed to default risk, further supporting our career prospects view. Overall, these results lend support to the intuition that the career prospects channel drives the increase in mortgage debt in agglomerated economies.

Next, we try to rule out alternative explanations for the link between local agglomeration and mortgage debt. First, it is possible that laborers in agglomerated economies are extensively protected by unemployment insurance, subsequently leading to higher approval of mortgage debt (Hsu et al., 2018). To mitigate the impact of unemployment insurance, we add it as an additional control variable and find that our results continue to hold. Second, we examine the impact of house prices on the link between local agglomeration and mortgage debt, as our results might be driven by the rising house prices in agglomerated economies (Mian and Sufi, 2011).[5] To test this alternative explanation, we control for the house price increase in each state-year, finding that our main result is robust. Finally, the increased mortgage debt could be driven by reduced mortgage interest rates in agglomerated economies (Agarwal et al., 2021). More precisely, it is possible that the thriving economy of local agglomeration makes lenders compete for clients and then provide lower mortgage interest rates. If this is true, the channel through which local agglomeration affects mortgage debt is a decrease in mortgage interest rates, rather than the career prospects argument. To dispel this concern, we analyze whether local agglomeration affects mortgage interest rates. As expected, local agglomeration has no perceptible impact on mortgage interest rates. In other words, lower mortgage interest rates do not seem to drive our results.

Finally, we conduct additional analyses. We examine the impact of local agglomeration on mortgage delinquency, other household debts, and total mortgage debt. Also, we analyze the role of education level on the link between local agglomeration and mortgage debt. More

[5] For example, Mian and Sufi (2011) find that households respond to increased house prices by borrowing more debt, most of which is mortgage debt. They subsequently call this result the home equity–based borrowing channel.

precisely, we first find that local agglomeration significantly reduces mortgage delinquency, a result that further supports our career prospects view. Second, we find that local agglomeration increases vehicle debt and marginally decreases credit card debt. In addition, we fail to find that local agglomeration significantly affects business debt and other debts owed to private individuals. Third, we find that local agglomeration increases total mortgage debt, compared with the first mortgage debt we analyzed in our main results. Finally, we examine the role of household heads' education level in the link between local agglomeration and mortgage debt. We document that the impact of local agglomeration significantly increases mortgage debt, especially for those with lower education levels. This result further supports our career prospects argument.

This paper contributes to the mortgage debt literature by providing new evidence on the importance of location-based factors, namely, local agglomeration. Up to now, the focus of this literature has been on person-based factors (Hsu et al., 2018; Jiang and Lim, 2018) and the macroeconomic environment, including the expansion of the credit supply (Mian et al., 2020), house price appreciation (Mian and Sufi, 2011), and bond risk premium (Koijen et al., 2009). In particular, when turning to the person-based factors, studies mainly discuss unemployment risk and individual characteristics. For example, Hsu et al. (2018) find that unemployment insurance helps unemployed households avoid mortgage default. Also, Jiang and Lim (2018) suggest that individuals with higher levels of trust have lower likelihoods of default on household debts. Our paper therefore extends this line of inquiry to place-based factors.

This paper also contributes to the literature of local agglomeration by documenting its impact on household finance. Existing local agglomeration literature predominantly focuses on corporate behavior, while very little of it discusses the impact on households. For example, Kedia and Rajgopal (2009) examine whether the location of a firm's headquarters explains variation in broad-based option grants. Relatedly, Almazan et al. (2010) suggest that firms located within agglomerated economies have more acquisition opportunities. Dougal et al. (2015) find that a firm's investment is highly sensitive to the investments of other firms headquartered nearby. Additionally, Davis et al. (2014) report a positive link between agglomerated economies and total factor productivity. Finally, Engelberg et al. (2018) find that firms in industry clusters have more efficient stock market prices than firms outside clusters. Against the backdrop of prior research seldom analyzing whether location-based factors affect household behaviors, we extend this line of research by documenting a positive relation between agglomeration economies and household mortgage debt. Close to our work, Addoum et al.'s (2022) paper examines the impact of industries' geographic location on household portfolio choice. Our paper therefore furthers their work by showing that the location-based factor, i.e., local agglomeration, affects mortgage debt. To the best of our knowledge, we are the first to link industries' geographic characteristics with household mortgage debt.

2. Data and variables

2.1 Sample construction

To investigate the effect of local agglomeration on household mortgage debt, we start with data provided by the Survey of Income and Program Participation (SIPP) (Chetty et al., 2017; Célerier and Matray, 2019).[6] SIPP is a household-based survey designed as a continuous series of national panels. Each panel generally features a large sample of households that are interviewed multiple times over a four-year period. Particularly, SIPP collects detailed

[6] The main advantages of SIPP relative to other commonly used datasets such as the Survey of Consumer Finances (SCF) and the Panel Study of Income Dynamics (PSID) are its large sample size and detailed information about mortgage debts and covariates.

information about household debts and demographics from 20,000 to 30,000 households over several (8–12) waves within each panel. Each wave includes a "core" survey that collects household sociodemographic data, along with several topical modules that gather specific information on a wide variety of subjects. For instance, the topical module collects information about work disability history, education and training history, and fertility history. We therefore use the core survey data to obtain the information about household demographics and meanwhile use the "Assets and Liabilities" topical module to collect data of household debts. As SIPP began in 1984, we start our sample from 1984. Notably, SIPP has not provided MSA information since its 2004 panel (Taskin and Yaman, 2019). Since local agglomeration is constructed at the MSA level (Addoum et al., 2022), we stop our sample period in 2003.

Given the criticism of SIPP's imputation methodology, we follow Gruber and Yelowizt (1999) and Célerier and Matray (2019) by dropping all observations with imputed wealth information. In addition, we limit our sample to households whose heads are between 24 and 65 years old. This is because individuals are likely to enter the labor market at the age of 24 and to retire at 65 in the U.S. (Poterba et al., 1998; Krebs et al., 2015). Finally, we eliminate all households with negative and zero wealth information, and we merge the SIPP data with the data of local agglomeration by year, MSA, and industry. Our final sample includes 62,040 household-year observations.

2.2 Measuring mortgage debt

As mentioned above, the data of mortgage debt are obtained from the Survey of Income and Program Participation (SIPP) (Chetty et al., 2017; Célerier and Matray, 2019). Particularly, we focus on a household's first mortgage because it is more likely to be driven by housing demand, while second and third mortgage debts are probably driven by investment need.[7] We use two measures to gauge the first mortgage debt. First, we take a logarithmic transformation of the value of mortgage debt (*Log(1+mdebt)*) because Célerier and Matray (2019) argue that wealth and asset variables have highly positive skewness. Second, we use a dummy variable (*Dum_mdebt*) to indicate whether a household has first mortgage debt.

2.3 Measuring local agglomeration

To calculate local agglomeration, we download data from the Current Population Survey (CPS).[8] The CPS is a monthly U.S. household survey conducted jointly by the U.S. Census Bureau and the Bureau of Labor Statistics on over 65,000 households, covering from 1976 to the present. These surveys gather information on education, labor force status, demographics, and other aspects of the U.S. population. Following Addoum et al. (2022), when calculating local agglomeration, we restrict the sample to workers aged between 16 and 64 and laborers who work more than 35 hours per week and 40 weeks per year. In addition, we use sampling weights when aggregating individual labor supply to the industry level. We use metropolitan statistical areas (MSAs) to calibrate the local labor market.

Specifically, we identify the level of local agglomeration by referring to the measure of the location quotient statistic commonly used in prior literature (Hoover, 1936; Holmes, 2005; Holmes and Stevens, 2014). The detailed definition of local agglomeration of industry *j* in local labor market *m* is as follows:

$$local\ agglomeration_{j,m} = \frac{S_{jm}}{S_{jM}}$$

[7] We examine total mortgage debt in further analysis and continue to find a positive impact of local agglomeration.
[8] https://cps.ipums.org/cps/index.shtml

where S_{jm} is industry j's labor supply in local labor market (MSA) m scaled by the total labor supply of all the industries in labor market m. Put differently, S_{jm} is the labor share of industry j in local labor market m. S_{jM} is industry j's labor supply across the whole country M scaled by the total labor supply of all the industries in the U.S. Meanwhile, we define the labor supply as the product of the number of weeks worked last year and the usual hours worked per week last year (Addoum et al., 2022). As such, if the value of the local agglomeration variable is larger than one, that means industry j is highly concentrated in the local labor market.

To show the validity of our measure of local agglomeration, we list the 15 most locally agglomerated industry–location pairs in Appendix 1.[9] Quite a few notable industry–MSA pairs show up on the list. For example, Las Vegas, naturally known for tourism and entertainment, ranks first for its hotel and motel industries, with an agglomeration level of 19.270. In addition, Detroit, known as "Motor City," ranks fifth in the list, having an agglomeration value of 12.299. Meanwhile, Seattle–Everett, commonly known as Boeing's aircraft manufacturing base, shows up on the list with a value of 14.492. In addition, Hollywood, Los Angeles, the heart of the film industry, makes the list because of the theater and motion picture industries, with a value of 7.624. Finally, some other MSAs, including Madison, Houston, Fort Wayne, and Atlanta, rank highly due to their extremely localized industries.

2.4 Control variables

Following previous literature on household debt, we control for four groups of control variables (Hsu et al., 2018; Célerier and Matray, 2019). The first group of controls incorporates household sociodemographic information, including household size and number of children.

[9] Knitting mills industries in Greensboro–Winston Salem have the same value of local agglomeration as hotel industries in Las Vegas because both of them are winsorized. Thus, when designing this table, to keep the original value as much as possible, we chose the 0.5% percentile as the cutoff to winsorize, rather than the 1% we used in the main text.

Specifically, *Size* is the number of individuals in a household, and *Num_kid* is the number of kids in a household. The second group of controls is related to household heads' basic information, including marital status, gender, education level, age, and employment status. More precisely, *Married* is a dummy variable equal to one if the household head is married and zero otherwise; *Female* is also an indicator equal to one if the household head is female and zero otherwise; *Education* is a rank variable denoting the education level of household head, with 1 for elementary, 2 for high school, and 3 for college and above; *Age* denotes the age of household heads; and *Unemp* is a dummy variable set to one if a household head is unemployed and zero otherwise. The third group of control variables contains information about household financial condition, including household monthly income and net worth. *Income* is the natural logarithm of the value of monthly household income. *Net worth* is the household wealth, including home equity, vehicle equity, and liquid wealth, minus total unsecured debt.

The last group of control variables is state-level related variables, including population and GDP growth. Specifically, *Log (1+pop)* is the natural logarithm of the population in the state in which a household worked. *GDP growth* is the annual GDP growth rate in the state. Moreover, following Célerier and Matray (2019), we adjust all the value-related variables (nominal prices) using the CPI in 2000. Finally, to mitigate the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles. Appendix 2 lists the detailed definitions of all the variables used in this study.

2.5 Descriptive statistics

Table 1 reports descriptive statistics for the key variables used in our analysis. In our sample, *Log (1+mdebt)* averages 5.230. We also find that the raw value of first mortgage debt averages $41,166, which is comparable and slightly lower than the $53,685 shown in Chetty et al.

(2017). The lower value is reasonable because we focus on first mortgage debt, while Chetty et al. (2017) report total mortgage debt, and we adjust the value by using CPI in 2000, while Chetty et al. (2017) do not make an adjustment. In addition, *Dum_mdebt* has a mean value of 0.472, indicating that almost half of the households in our sample have mortgage debt. As for our key independent variable, we find that the mean value of *Local agglomeration* is 1.767, which is close to the average value of 1.50 found by Addoum et al. (2022), although in a different period of analysis.

Regarding our control variables, we show that on average, households have about three persons, including one kid. In addition, 57.9% of household heads are married, and 37.9% of household heads are female. As for the age, the household heads in our sample have an average (median) age of 41 (40), which is younger than the age documented by Chetty et al. (2017) and Célerier and Matray (2019). The reason could be that we restrict our sample to households with heads younger than 65. Meanwhile, during our sample period, about 2.8% of household heads are unemployed. Meanwhile, the average monthly logarithmic income of households is 8.038, with an average monthly income of $4,258, and the mean of household net worth is $81,491, which are comparable to the values found in Chetty et al. (2017) and Addoum et al. (2022). Finally, the state-related variables show that the average state population is about 10.5 million and the annual GDP growth averages about 6.1%, with a median value of 5.7%.

3. Empirical analysis

3.1 Baseline specification

To empirically examine the effect of local agglomeration on mortgage debt, we conduct the household-level analysis by using the following pooled multivariate regression model:

$$Mortgage\ debt_{ijmt} = \alpha_0 + \alpha_1 Local\ agglomeration_{jmt} + \alpha_2 Size_{ijmt} + \ \alpha_3 Num\_kid_{ijmt} + \alpha_4 Married_{ijmt} + \alpha_5 Female_{ijmt} + \alpha_6 Education_{ijmt} + \alpha_7 Age_{ijmt} + \alpha_8 Unemp_{ijmt} + \alpha_9 Income_{ijmt} + \alpha_{10} Net\ worth_{ijmt} + \alpha_{11} Log(1 + pop)_{st} + \alpha_{12} GDP\ growth_{st} + \theta_s + \varphi_t + \varepsilon_{ijmt} \quad (1)$$

where $Mortgage\ debt_{ijmt}$ is the mortgage debt of household *i*, working in industry *j* and residing in MSA *m* in year *t*, which is proxied by *Log(1+mdebt)* or *Dum_mdebt*. The key independent variable is $Local\ agglomeration_{jmt}$, which is defined in section 2.3. Control variables include household-level and state-level variables, the definitions of which have been discussed in section 2.4. α_1 is the coefficient we are interested in, which measures the effect of agglomerated economies on household mortgage debt. Following Addoum et al. (2022), we control for state fixed effect θ_s and year fixed effect φ_t in the model.

3.2 Main results

Table 2 presents the results of estimating Equation (1). In column (1), the dependent variable is the natural logarithm of first mortgage debt (*Log(1+mdebt)*), while in column (2), the dependent variable is an indicator variable (*Dum_mdebt*) denoting whether a household has mortgage debt. Robust t-statistics are reported in parentheses, and standard errors are clustered at the household level. We find that for both of the measures of mortgage debt, the coefficients on local agglomeration are positive and statistically significant at the 1% level, suggesting that households working in locally agglomerated economies are more likely to have mortgage debt. This result is consistent with the career prospects view, in which we argue that laborers in locally agglomerated economies have better career potential and higher income by benefiting from the knowledge spillover and labor market interactions of local agglomeration. In terms of economic significance, in column (1), a one-standard-deviation increase in local agglomeration is associated with a 2% increase in mortgage debt. Given that the mean value of mortgage debt is

$41,167 in our sample, this increase represents an $823 increase in mortgage debt. This is comparable to the economic significance shown by Barrot et al. (2022), who examine the impact of import competition on household debts, with economic significance values of 2% and $950, respectively. Column (2) of Table 2 shows that a one-standard-deviation increase in local agglomeration is associated with a 1% increase in the probability of having mortgage debt, a 2% increase relative to the mean of *Dum_mdebt*.

With regard to control variables, we find that households with more family members have lower levels of mortgage debt and are less likely to have mortgage debt. In contrast, households with more kids have more mortgage debt and are more likely to have mortgage debt.[10] This is consistent with the results reported by Ling and Mcgill (1998), who also report a positive impact of number of children on household debt. In addition, households with female heads are less likely to have mortgage debt (Mian and Sufi, 2011). The possible explanation could be that, compared with males, females earn less and are more risk-averse. Moreover, we find that mortgage debt is positively associated with household heads' education level and age. This is in line with our expectation because households that are well educated and older are more likely to be able to afford mortgages. Notably, unemployment is negatively associated with mortgage debt, and household income/net worth is positively related to mortgage debt. These results initially support our argument that employment conditions in labor markets are a key driver of mortgage debt. Overall, the results in Table 2 suggest that local agglomeration significantly increases household mortgage debt, both its level and the probability of having it.

3.3 Alternative specifications

[10] This result means that the negative link between household size and mortgage debt is mainly driven by adult members.

To mitigate the concern that our results are sensitive to heterogeneity across households and local labor markets, and to validate the stability of our baseline results, we examine how the local agglomeration effect varies when imposing different and more stringent fixed effects than those in our baseline specification.[11]

As our first test of alternative specifications, we replace the state and year fixed effects in our baseline regressions with state-by-year fixed effects, reported in columns (1) and (2) of Panel A of Table 3. The objective of this alternative specification is to control for the time-specific sources of variation across states. The results show that we continue to find a positive coefficient of local agglomeration on mortgage debt when we use state-by-year fixed effects. Next, in columns (3) and (4), we instead control for MSA-by-year fixed effects in the regression. The underlying argument is that, even within the same state, there could be substantial heterogeneity in city characteristics that affects household decisions on mortgage debt. As an example, within the state of New York, the house prices in Syracuse are significantly lower than in New York City. Consequently, laborers in Syracuse may be more likely than New Yorkers to have and be able to afford mortgages. After imposing the MSA-by-year fixed effects, we find that the coefficients of local agglomeration still load positively. Collectively, this evidence indicates that the heterogeneity of local demographic and economic conditions, such as employment growth (e.g., Glaeser et al., 1992; Glaeser et al., 1995), is less likely to drive our baseline result.

Finally, it is possible that the heterogeneity of different sectors drives our results. Residents working in high-tech and financial industries are relatively more skillful and have higher wages than workers in other industries, subsequently affecting their decisions on mortgages. So, in the last two columns, we use the occupation-by-year fixed effects to account

[11] Given that we will control for more stringent fixed effects, i.e., state-by-year fixed effects, which absorb the state-related heterogeneities well, and for better comparison, we drop the two state-related variables.

for the time-varying differences across occupation groups. With the occupation-by-year fixed effects, we continue to report a positive and significant effect of local agglomeration on mortgage debt. Overall, the stability of our results in alternative specifications with different sets of fixed effects dispels the concern that the heterogeneous characteristics of different states are spuriously responsible for our core evidence. More precisely, the impact of local agglomeration cannot be explained by latent omitted factors that vary over time within states and MSAs. Even within the industry sectors that households work in, we document that exposure to agglomerated economies is materially important for mortgage debt.

3.4 Robustness checks

In Panel B of Table 3, we further explore the sensitivity of our core evidence by conducting a number of robustness checks. First, we examine whether our findings are driven by a few extremely large metropolitan statistical areas. Additionally, it is possible that a few firms in small labor markets could upwardly bias our local agglomeration measure in these small labor markets. To mitigate these concerns, we exclude extremely small and large local labor markets from our samples and rerun our baseline regressions. Specifically, we exclude the top as well as the bottom 10% of MSAs based on aggregate labor supply. To demonstrate, the largest MSAs in our sample period include Washington DC/MD/VA, Los Angeles–Long Beach CA, New York NY, Chicago–Gary–Lake IL, and Detroit MI; the smallest MSAs include Jamestown NY, Kalamazoo–Battle Creek MI, and Houma–Bayou Cane–Thibodaux LA. After excluding these MSAs, in columns (1) and (2), we find that our earlier evidence is robust.

Second, it is possible that our measure of local agglomeration actually proxies for other industry-level labor market characteristics that vary across geographies but are not related to the career prospects channel we document. For example, workers may feel safer if their employers are in an industry with less intense competition. Also, laborers are more likely to hold positive views on their career prospects if their firms are in industries that are innovation-intensive. Therefore, to control for the impact of these industry-related factors, we add two more control variables, local industry concentration and innovation. To construct local industry concentration, we refer to the measure of the Herfindahl–Hirschman Index (HHI). Exactly, local industry concentration is defined as $Industry\ concentration_{js} = \sum_i S_{ijs}^2$. S_{ijs} is the book equity share of firm *i* in industry *j* in state *s* (Addoum et al., 2022). Thus, a low value of *Industry concentration* implies that the local market of industry *j* is shared by many competing firms, while a high value indicates that a few firms dominate the market. Next, to measure the local *Industry innovation*, we calculate the ratio of aggregate R&D expenditures to aggregate total assets within each industry–state pair. We then add these two variables into our main specification.[12] The results in columns (3) and (4) show that the impact of local agglomeration on household mortgage debt remains positive and significant after we control for the confounding effect caused by industry characteristics. However, the coefficient of local industry concentration is not significant, whereas local industry innovation significantly increases mortgage debt.

Finally, in columns (5) and (6), we replace our key independent variable by using the natural logarithm value. The log transformation well reduces the skewness of *local agglomeration* and mitigates the effect of outliers. We find that the impact of locally agglomerated economies on household mortgage debt remains large and statistically significant after we use the alternative *local agglomeration* measure. Overall, we conclude that our baseline

[12] Here, we only control for the year fixed effect because these two variables are calculated based on the state-industry level. If we add the state fixed effect, it will absorb the explanation power of these two variables.

result is robust to including industry-specific local labor market characteristics as additional controls, as well as an alternative measure of local agglomeration.[13]

3.5 Instrumental variable analysis

So far, we have documented a robust positive impact of local agglomeration on mortgage debt. In this section, we re-examine the link between local agglomeration and mortgage debt in an instrumental variable framework. In particular, following Addoum et al. (2022), we instrument local agglomeration by using the industry-level exposure to the United States' granting of Permanent Normal Trade Relations (PNTR) to China in 2001. U.S. Permanent Normal Trade Relations (PNTR) reduce China's uncertainty in a favorable trade partnership with the U.S. Such reduction in uncertainty largely boosts the imports from Chinese firms to the U.S., subsequently posing a threat to U.S. firms and reducing the labor supply of U.S. firms. As background, China joined the World Trade Organization (WTO) in December 2001. Before joining the WTO, China had enjoyed most-favored-nation (MFN) status as a trading partner of the United States since 1980, which means that China-made goods have a lower tariff rate when exported to the United States. However, China's most-favored-nation status is updated every year and is often lobbied against by American manufacturers (Pierce and Schott, 2016). In other words, China's MFN status is subject to political uncertainty.

As the United States' biggest trading partner, when China joined the WTO, it removed its uncertainty associated with favorable tariffs, leading to a significant increase in Chinese firms' investment and import competition to U.S. firms (Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016; Bloom, Draca, and Van Reenen, 2016). As indicated by Pierce and Schott (2016), U.S. industries exposed to increased Chinese competition experience significant employment

[13] We also find that our baseline results are robust to estimation using nonlinear logit and tobit estimators and are robust if we adjust standard errors by two-way clustering in the household and time dimensions.

losses. Hence, the Permanent Normal Trade Relations (PNTR) are an ideal instrumental variable, simultaneously satisfying the criteria of relevance and exclusion restriction. Specifically, PNTR significantly affects the labor supply of U.S. trade firms yet is not directly related to mortgage debt. Generally, the PNTR has a relatively large impact on the trade industry and less impact on other industries, so we implement our instrumental analysis by including a tradable sector indicator. More precisely, we use the interaction term of the tradable sector indicator with post-PNTR as our instrumental variable. As for the classification of the tradable sector, we include the following 10 broad sectors by referring to prior literature (see, for instance, Mian and Sufi, 2014): agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; wholesale trade; retail trade; finance, insurance, and real estate; services; and public administration.

In Table 4, we show the results of the instrumental variable analysis. In columns (1)-(3), we show the results of full sample, and in columns (4)-(6) we report the results in the 5-year event window to mitigate the concern of unbalanced pre- versus post-period observations. Specifically, column (1) and (4) report the results of first-stage regression, and columns (2) & (5) and (3) & (6) show the second-stage results of *Log(1+mdebt)* and *Dum_mdebt*, respectively. In the first-stage regression, the variable of interest is the trade sector indicator interacted with the post-PNTR period, namely, *Trade_sector*Post_PNTR*. We also include the trade sector indicator (*Trade_sector*) in the regression and exclude the term of *Post_PNTR* for the concern of multicollinearity with year dummies. As expected, in both of the samples, the coefficients of *Trade_sector*Post_PNTR* load negatively at the 1% level. That means, since China joined the WTO in 2001, Chinese firms pose a great threat to local U.S. firms, therefore negatively affecting agglomerative patterns in America. In addition, the Kleibergen-Paap Wald F-statistic are 846.584 and 207.935, respectively, which are significantly larger than the critical value, rejecting the null hypothesis of a weak instrument. As for the second-stage regressions, we continue to find a positive and statistically significant coefficient of our key independent variable. In sum, our IV analysis validates our baseline regression and suggests that local agglomeration has a positive effect on household mortgage debt.

4. Mechanism tests

We document a positive and robust effect of local agglomeration on mortgage debt. In this section, we first examine whether the demand-side or supply-side factors drive the increased mortgage debt. Subsequently, we examine the underlying mechanisms behind the link. We argue that the channel could be enhanced career prospects. To validate this argument, we start with the test to see if local agglomeration increases promotion probability. Next, we examine the impact of local agglomeration on unemployment risk. Finally, we examine whether agglomerated economies increase household wealth.

4.1 Demand-side versus supply-side

Given the career prospects view, both demand- and supply-side factors could lead to increased mortgage debt. On the one hand, enhanced career prospects make laborers in agglomerated economies are more likely to apply for mortgages because they are more likely to be able to afford them. On the other hand, loan suppliers are more willing to approve mortgages for borrowers with enhanced career prospects. This is because these borrowers may have lower unemployment risk and earn higher wages, leading to a lower probability of default. To demonstrate the demand- and supply-side arguments, we use data from the HMDA database. As approval data are available from 1990, the sample period for the HMDA analysis is from 1990 to 2003. Following Barrot et al. (2022), we aggregate data to the MSA level and conduct our analysis at the MSA and year levels. Specifically, we use the number of mortgage applications to proxy the demand-side factor and the mortgage approval rate to measure the supply-side driver. In addition, we aggregate the value of local agglomeration into the MSA-year level.

Table 5 presents the results. In column (1), we find a positive and significant link between agglomerated economies and the number of loan applications. This finding implies that borrowers in more agglomerated economies apply for more mortgage loans than those in less agglomerated economies. Next, column (2) shows that the approval rate also significantly increases with agglomerated economies. This indicates that loan officers are more likely to approve loan applications from MSAs with more agglomerated economies. Overall, the results in Table 5 support the idea that both demand- and supply-side factors drive the increased mortgage debt. In the next subsection, we examine the specific mechanisms of the career prospects channel.

4.2 Career prospects channel: Promotion probability

First, we examine if local agglomeration significantly increases a laborer's promotion probability. Workers in agglomerated economies benefit from learning spillovers (Marshall, 1890; Glaeser et al., 1992), leading to higher skills and knowledge and subsequently higher promotion probability. In other words, agglomerated labor markets increase the prospects of promotions and provide career-enhancing job opportunities for workers. Thus, we expect that local agglomeration is positively associated with career promotion probability and the impact of local agglomeration on mortgage debt is concentrated within households that previously had a smaller career advancement space.

The results are reported in Panel A of Table 6. *Promotion* is an indicator variable equal to one if the occupation of the labor head is executive, administrative, or managerial. Column (1) shows that local agglomeration is positively related to the probability of promotion. This is consistent with the findings of Addoum et al. (2022), who argue that local agglomeration increases the human capital of laborers. Next, to further support the career prospects view, we examine if local agglomeration significantly increases laborers' mortgage debt even for those with lower predicted promotion probability. To do so, we firstly use the predicted value by running the specification in column (1), i.e., *Promotion_hat*, to proxy the probability of promotion. A large value of *Promotion_hat* indicates that a laborer is more likely to get promoted based on the household characteristics and the economic conditions in the state. Then, we interact local agglomeration with the predicted value of promotion.[14] The negative and significant coefficient of the interaction term in column (2) indicates that local agglomeration significantly increases the mortgage debt of laborers that previously had less space for promotion. This promotion effect could be driven by the thicker labor market and broad job opportunities provided by agglomerated economies (Glaeser et al., 1992). Relatedly, the results shown in column (3), using the probability of having mortgage debt, report consistent results with those shown in column (2). Until now, these results suggest that local agglomeration increases the career prospects of laborers working in agglomerated economies and the impact of local agglomeration on mortgage debt is more pronounced for laborers that were previously thought to be less likely to get promoted.

4.3 Career prospects channel: Unemployment risk

As a further test of the career prospects channel, we next examine if laborers working in local agglomeration have lower unemployment risk. Agglomerated economies provide abundant employment opportunities for workers. Such a broad labor market improves employee–position matching and reduces unemployment spells, thereby reducing the risk of unemployment

[14] Considering that promotion hat is predicted by the household characteristics in column (1), in columns (2) and (3), we do not add the single term of *Promotion hat* for the concern of multicollinearity.

(Krugman, 1991). In particular, we first examine the impact of local agglomeration on household heads' unemployment weeks. Then, we interact local agglomeration with the industry median of unemployment weeks, with the expectation that laborers working in industries with high unemployment risk are more likely to get mortgages if they are in more agglomerated economies. This is because the thick labor market of local agglomeration hedges unemployment risk.

We show the results in Panel B of Table 6. In column (1), we find that local agglomeration enters negatively and significantly with household unemployment risk, manifested in fewer weeks looking for a job. Next, in columns (2) and (3), we interact *Median_unempwks* with local agglomeration to examine the role of local agglomeration on the link between unemployment risk and mortgage debt. In particular, the *Median_unempwks* is the median unemployment weeks of each industry. We argue that unemployment spell varies across industries, so we use the median value of unemployment risk in each industry to proxy the unemployment risk. Exactly, we find the coefficient *of Median_unempwks* is negative, while the coefficient of *Local agglomeration* Median_unempwks* is positive. This result indicates that local agglomeration provides a good hedge to households working in industries with long unemployment spells. This is because local agglomeration improves the employee–position matching, thereby increasing laborers' career prospects and mitigating the negative impact of the industry unemployment spell. Put differently, households in local agglomeration are less exposed to downside employment risk. Collectively, our finding is consistent with our argument that local agglomeration decreases household unemployment risk and employment conditions are an important factor to predict household mortgage debt (Hsu et al., 2018).

4.4 Career prospects channel: Wealth effect

Our final channel test examines the impact of local agglomeration on household wealth. We expect that laborers and firms in agglomerated economies benefit from economies of scale and knowledge spillovers (Porter, 1998; Glaeser et al., 1992) that lead to higher income and wealth. Such a wealth effect therefore increases the level of household mortgage, as well as the probability of having mortgage debt.

Panel C of Table 6 reports the results. We use the logarithm value of the sum of net equity of vehicle, house, and liquid wealth to proxy a household's total wealth. As expected, in column (1), we find that local agglomeration significantly increases household wealth. In the next step, we examine if local agglomeration mitigates the negative link between low wealth and mortgage debt. Put differently, despite having low levels of wealth, households in more agglomerated economies are more likely to have mortgage debt compared with those in less agglomerated locales. In particular, we interact local agglomeration with a dummy variable indicating if a household's wealth is above the median. The results reported in columns (2) and (3) show that local agglomeration significantly increases mortgage debt, and the impact is more pronounced for households that previously accumulated less wealth. The reason may be that local agglomeration improves laborers' career prospects, manifested in higher promotion probability and lower unemployment risk, therefore making less wealthy households more likely to have mortgages. Overall, the results of the wealth effect further support the career prospects view of local agglomeration.

5. Alternative explanation

We admit that our analysis is subject to endogeneity, especially due to omitted variables. For example, households choose to live in agglomerated economies based on latent factors, which may be correlated with household mortgage debt decisions (see Mian and Sufi, 2011; Hsu et al., 2018; Addoum et al., 2022). In this section, we consider several potential confounding factors.

5.1 Unemployment insurance

We start by considering the impact of unemployment insurance on the link between local agglomeration and mortgage debt. It is possible that laborers in agglomerated economies are well provided with unemployment insurance, mitigating both borrowers' and lenders' concerns about mortgage default and subsequently increasing mortgage debt (Hsu et al., 2018). If this is true, the observed increase in mortgage debt is not driven by local agglomeration but instead by higher unemployment insurance. To evaluate this possibility, we add unemployment insurance as an additional control variable.

The result is reported in Panel A of Table 7. Following Agrawal and Matsa (2013) and Hsu et al. (2018), we use the product of the maximum number of weeks and the maximum weekly benefit amount to measure the generosity of unemployment insurance (UI) benefits.[15] In our sample, the mean of annual benefits provided by UI is $6,419, and that of annual household income is about $47,712, indicating that unemployment insurance provides protection to the unemployed. We subsequently use the log amount of annual benefit generosity to proxy unemployment insurance. We find that our earlier evidence is robust at the 1% level to the inclusion of UI as an additional control variable. Meanwhile, we find a positive link between UI and mortgage debt, although the coefficients are not significant. Overall, the results in Panel A of Table 7 rule out the possibility that unemployment insurance in agglomerated economies drives our results.

5.2 House prices

[15] Data on the maximum number of weeks and the maximum weekly benefit amount are collected and provided by Chetty (2008).

In this section, we consider another important latent factor that may codetermine households' location and mortgage choices. Previous studies find that house prices are a key driver of household mortgage debt (Mian and Sufi, 2011). For example, Mian and Sufi (2011) find that households increase their mortgage debt by extracting the home equity caused by increased house prices. As such, it is possible that laborers choose to live in agglomerated economies for the consideration of house prices.

To address this concern, we control for the impact of house prices.[16] Specifically, we control for house price growth (*Hprice growth*), which is defined as the annual house price growth in states. The results are reported in Panel B of Table 7. We continue to observe a significant effect of local agglomeration on mortgage debt after we control for the impact of house prices. In addition, we find a positive link between house prices and mortgage debt. In particular, in column (2), we find that higher house prices significantly increase the probability of having mortgage debt. Overall, we find that controlling for house price appreciation does not absorb the effect of local agglomeration on mortgage debt. This finding excludes the alternative interpretation that our main results are driven by house price appreciation in agglomerated economies.

5.3 Mortgage interest rate

Finally, it is possible that the increased mortgage debt is due to lower mortgage interest rates in agglomeration economies. The thriving economy in local agglomeration could promote the development of the financial industry and makes lenders compete for clients. So, loan suppliers would lower the interest rates in mortgage contracts to attract borrowers. To mitigate this concern, we examine the impact of local agglomeration on mortgage interest rates. The

[16] To mitigate the concern of house prices, we also limit our sample period to 1984 to 1999 because house prices in the U.S. were stable before 1999 (Barrot et al., 2022). We continue to find significant and positive impact of local agglomeration when using this subsample analysis.

result is shown in Panel C of Table 7. We find no significant relation between local agglomeration and mortgage interest rates. This result suggests that the increase in mortgage debt in agglomeration economies is unlikely to be driven by lower mortgage interest rates. In other words, this finding mitigates our concern that increased mortgage debt is because of the attractiveness of loan contracts.

6. Further analyses

In this section, we conduct four further analyses. First, we examine the impact of local agglomeration on mortgage delinquency. The enhanced career prospects originating from local agglomeration are further supported if we observe a reduction in mortgage delinquency. More precisely, local agglomeration increases laborers' career prospects, subsequently increasing mortgage affordability and reducing default probability. We follow Hsu et al. (2018) and use the Adult Well-Being topical module in SIPP to examine the link between local agglomeration and mortgage delinquency. The results are reported in Panel A of Table 8.[17] We find that local agglomeration is negatively associated with delinquency, and the link is significant at the 1% level. This finding therefore further supports our career prospects view. That is, households in agglomeration economies have better career prospects and have lower default risk.

Second, we examine the effect of local agglomeration on other household debts, including vehicle debt, credit card debt, business debt, and private debt (Célerier and Matray, 2019; Barrot et al., 2022). The data of other household debts is obtained from SIPP, and the results are reported in Panel B of Table 8. In the first two columns, we analyze the impact of local agglomeration on total non-housing debt, which is the sum of vehicle debt, credit card debt, business debt, and private debt. In particular, *Log (1+tdebt)* is the natural logarithm value of total

[17] This topical module did not provide the data of household net worth, so we cannot add it as a control variable.

non-housing debts, and *Dum_tdebt* is a dummy variable equal to one if the household has any non-housing debt and zero otherwise. We find the impact of local agglomeration on total non-housing debts is not significant. Next, in columns (3) and (4), we find that local agglomeration greatly increases household vehicle debts. These results further support our previous argument that local agglomeration increases households' career prospects, subsequently leading to higher vehicle debt. However, in column (5), we find that credit card debt is lower for households in agglomerated economies, while the impact of local agglomeration on the probability of having credit card debt is not significant. Finally, the results shown in columns (7) to (10) show that there is no discernable or perceptible relationship between agglomerated economies and business debt or debt owed to private persons.

Third, in the main specification, we focus on first mortgage debt for the concern that the employment conditions are particularly important for borrowers to get mortgage debt. As a robustness check and further test, in this section, we examine the effect of local agglomeration on total mortgage debt. We obtain total mortgage debt data from SIPP and present the results in Panel C of Table 8. These results are consistent with our main finding. Explicitly, we find that agglomerated economies significantly increase total mortgage debt.

Finally, as further evidence of the career prospects view, we examine if local agglomeration affects a household's mortgage debt, especially for those with lower education levels, and we also examine the impact of household heads' age. In the first two columns of Panel D of Table 8, we conduct the subsample analysis by separating the full sample. The first column reports the result of household heads without a college diploma, and the second column reports the result of household heads with a college education. The dependent variable is the logarithm value of first mortgage debt. We find that the impact of agglomerated economies is only significant for households with low levels of education. The coefficient difference between these two groups is significant at the 1% level. Finally, in the last two columns, we examine the impact of household age on the link between local agglomeration and mortgage debt. We find that local agglomeration significantly increases household mortgage debt, which is particularly pronounced for younger households. This may be because the first mortgage debt of young households is more likely to be affected by labor market conditions. In contrast, older households accumulate more wealth, making their first mortgages less sensitive to employment conditions. Thus, given this sensitivity, this result further supports our argument that career prospects are potential determinants of household mortgage debt.

7. Conclusion

In this paper, we analyze the role of local agglomeration in household mortgage debt. By using the household survey, we document a strong positive relationship between local agglomeration and household mortgage debt, both the mortgage level and the probability of having mortgage debt. We further show that this pattern is economically significant and robust under an instrumental variable framework by using different model specifications and having alternative measures. In addition, our channel tests support the career prospects view: local agglomeration increases laborers' career prospects by increasing the probability of promotion, reducing unemployment risk, and increasing household wealth.

In a nutshell, our results validate the theoretical argument of agglomerated economies. That is, local agglomeration promotes interaction among employees and between employees and employers, manifested in knowledge spillover and a better employee–position matching process (Porter, 1998; Glaeser et al., 1992; Duranton and Puga, 2004). Such dynamic interactions increase laborers' career prospects, subsequently increasing the affordability and availability to them of mortgage debt. Our study contributes to the literature on mortgage debt. In particular, our findings improve our understanding of the determinants of mortgage debt, which has been proved to have significant consequences for the real economy. Our study also adds new evidence to studies of local agglomeration by extending its impact to household debts.

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Appendix 1. Top 15 Local Agglomeration Economies

This table lists the 15 most locally agglomerated MSA-industry pairs in our sample, based on our local agglomeration measure described in Section 2. To keep the original value as much as possible, the local agglomeration in this table is winsorized at the 0.5% and 99.5% percentiles.

Rank	MSA	Industry	Local Agglomeration
1	Las Vegas, NV	Hotels and motels	19.270
2	Greensboro-Winston Salem, NC	Knitting mills	19.270
3	Seattle–Everett, WA	Aircraft and parts	14.492
4	Madison, WI	Administration of environmental quality and housing programs	13.357
5	Detroit, MI	Motor vehicles and motor vehicle equipment	12.299
6	Austin, TX	Computers and related equipment	11.775
7	Houston-Brazoria,TX	Water transportation	10.592
8	Fort Wayne, IN	Motor vehicles and motor vehicle equipment	10.536
9	Los Angeles–Long Beach, CA	Theaters and motion pictures	7.624
10	Atlanta, GA	Air transportation	6.833
11	Dayton-Springfield, OH	Motor vehicles and motor vehicle equipment	6.214
12	Detroit, MI	Metal forgings and stampings	5.746
13	Washington, DC/MD/VA	Membership organizations, n.e.c.	5.297
14	New York, NY	Bus service and urban transit	5.288
15	Los Angeles–Long Beach, CA	Apparel and accessories, except knit	5.274

Appendix 2. Variable definitions

Variable	Definitions
Key independent variable	
Local agglomeration	The labor supply share of an industry in the local labor market scaled by the industry's labor supply share across the country
Key dependent variables	
Log(1+mdebt)	Natural logarithm value of household first mortgage debt
Dum_mdebt	A dummy variable, equal to one if a household has first mortgage debt and zero otherwise
Control variables	
Size	The number of individuals in a household
Num_kid	The number of kids in a household
Married	A dummy variable, equal to one if the household head is married and zero otherwise
Female	A dummy equal to one if the household head is female and zero otherwise
Education	A rank variable denoting the household head's education level, with 1 for elementary, 2 for high school, and 3 for college and above
Age	The household head's age
Unemp	A dummy variable set to one if the household head is unemployed and zero otherwise
Income	Natural logarithm of the value of monthly household income
Networth (in thousands)	Household wealth, which is the sum of home equity, vehicle equity, and liquid wealth minus total unsecured debt
Log (1+pop)	Natural logarithm of population in the state in which a household works
GDP growth	The annual GDP growth rate in the state
Industry concentration	Refer to the definition of the Herfindahl–Hirschman index (HHI): $\sum s_{ijs}^2$, where s_{jis} is the book equity share of firm i in industry j in state s
Industry innovation	The aggregate R&D expenses of all firms headquartered in a local labor market within an industry, scaled by the total assets of all firms in the local labor market
UI	The product of the maximum number of weeks and the maximum weekly benefit amount (Agrawal and Matsa, 2013; Hsu et al., 2018)
Hprice growth	The annual growth rate of house prices in each state
Other variables	
Delinquency	An indicated variable, equal to one if the mortgage debt is defaulted and zero otherwise
Mortgage interest rate	The interest rate on first mortgage debt

Table 1. Summary statistics

Table 1 reports descriptive statistics of the main variables used in our analysis. The sample comprises 62,040 household-year observations over the period 1984–2003. Variable definitions are provided in Appendix B.

	N	Mean	Std. Dev.	P25	Median	p75
Log(1+mdebt)	62040	5.230	5.568	0	0	11.201
Dum_mdebt	62040	0.472	0.499	0	0	1
Local agglomeration	62040	1.767	2.193	0.784	1.142	1.775
Size	62040	3.022	1.473	2	3	4
Num_kid	62040	1.044	1.193	0	1	2
Married	62040	0.579	0.494	0	1	1
Female	62040	0.379	0.485	0	0	1
Education	62040	2.555	0.627	2	3	3
Age	62040	41.101	10.265	33	40	49
Unemp	62040	0.028	0.164	0	0	0
Income	62040	8.038	0.856	7.504	8.136	8.658
Networth (in thousands)	62040	81.491	155.090	1.502	17.412	92.092
Log (1+pop)	62040	16.168	0.802	15.596	16.250	16.754
GDP growth	62040	0.061	0.031	0.039	0.057	0.083

Table 2. Local agglomeration and mortgage debt

Table 2 reports the regression results of the effect of local agglomeration on household mortgage debt. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* in column (1) is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* in column (2) is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+mdebt)	*Dum_mdebt*
	(1)	(2)
Local agglomeration	0.0387***	0.0039***
	(3.55)	(3.90)
Size	-0.2147***	-0.0168***
	(-7.17)	(-6.17)
Num_kid	0.7495***	0.0634***
	(21.49)	(20.07)
Married	1.8440***	0.1619***
	(28.07)	(27.44)
Female	-0.2253***	-0.0188***
	(-3.80)	(-3.53)
Education	0.8333***	0.0685***
	(19.66)	(17.71)
Age	0.0325***	0.0039***
	(12.64)	(16.48)
Unemp	-0.3981***	-0.0399***
	(-3.32)	(-3.66)
Income	1.7163***	0.1454***
	(46.96)	(44.44)
Net worth	0.0035***	0.0003***
	(14.96)	(15.03)
Log (1+pop)	-0.2421**	-0.0195*
	(-2.06)	(-1.78)
GDP growth	1.7648	0.1966*
	(1.51)	(1.87)
Constant	-9.6778***	-0.8597***
	(-5.06)	(-4.85)
State FE	YES	YES
Year FE	YES	YES
Observations	62040	62040
Adj. R-squared	0.1922	0.1855

Table 3 Panel A. Alternative specification

This table tests the robustness of the baseline results by using alternative specifications. Definitions of variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively. The number of observations is not consistent because some of them are automatically dropped in regression running because of singletons.

	Log(1+mdebt)	*Dum_mdebt*	*Log(1+mdebt)*	*Dum_mdebt*	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)	(4)	(5)	(6)
Local agglomeration	0.0386***	0.0038***	0.0309***	0.0028***	0.0331***	0.0035***
	(3.51)	(3.80)	(2.67)	(2.63)	(2.81)	(3.29)
Size	-0.2132***	-0.0167***	-0.2094***	-0.0163***	-0.1827***	-0.0145***
	(-7.09)	(-6.11)	(-6.95)	(-5.94)	(-5.83)	(-5.12)
Num_kid	0.7471***	0.0633***	0.7384***	0.0623***	0.7108***	0.0603***
	(21.33)	(19.95)	(21.01)	(19.60)	(19.46)	(18.23)
Married	1.8399***	0.1614***	1.8435***	0.1613***	1.8129***	0.1594***
	(27.90)	(27.25)	(27.93)	(27.24)	(26.48)	(25.98)
Female	-0.2205***	-0.0185***	-0.2183***	-0.0182***	-0.0260	-0.0011
	(-3.71)	(-3.46)	(-3.67)	(-3.41)	(-0.36)	(-0.17)
Education	0.8335***	0.0685***	0.8363***	0.0688***	0.6011***	0.0492***
	(19.59)	(17.65)	(19.53)	(17.63)	(12.11)	(10.86)
Age	0.0324***	0.0038***	0.0317***	0.0038***	0.0336***	0.0039***
	(12.56)	(16.36)	(12.26)	(16.04)	(12.33)	(15.97)
Unemp	-0.4067***	-0.0406***	-0.3757***	-0.0379***	-0.3274**	-0.0347***
	(-3.37)	(-3.70)	(-3.08)	(-3.43)	(-2.56)	(-2.98)
Income	1.7120***	0.1450***	1.7201***	0.1461***	1.4948***	0.1259***
	(46.65)	(44.14)	(46.45)	(44.10)	(37.43)	(35.16)
Net worth	0.0035***	0.0003***	0.0037***	0.0003***	0.0033***	0.0003***
	(15.10)	(15.24)	(16.02)	(16.22)	(13.73)	(13.93)
Log (1+pop)			-0.2943***	-0.0263***	-0.2728***	-0.0277***
			(-3.58)	(-3.59)	(-8.16)	(-9.27)
GDP growth			6.7991**	0.6241**	3.6358***	0.2721***
			(2.07)	(2.12)	(3.15)	(2.61)
Constant	-13.4506***	-1.1586***	-9.1646***	-0.7793***	-7.0519***	-0.5360***
	(-45.43)	(-43.61)	(-6.69)	(-6.37)	(-10.93)	(-9.28)
State FE	No	No	No	No	No	No
Year FE	No	No	No	No	No	No
*State*Year FE*	YES	YES	No	No	No	No
*MSA*Year FE*	No	No	YES	YES	No	No
*Occup*Year FE*	No	No	No	No	YES	YES
Observations	62024	62024	62025	62025	60819	60819
Adj. R-squared	0.1938	0.1873	0.1965	0.1914	0.1994	0.1932

Table 3 Panel B. Robustness check

This table reports the results of a robustness check. In columns (1)–(2), we exclude the top as well as the bottom 10% of the MSAs sample based on aggregate labor supply. In columns (3)–(4), we consider two important industry-specific local labor market characteristics as additional regression controls: local industry concentration and local industry innovation, the definitions of which are shown in Section 3. In columns (5)–(6), we use *Ln (1+local agglomeration)* as an alternative measure to proxy local agglomeration. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+mdebt)	*Dum_mdebt*	*Log(1+mdebt)*	*Dum_mdebt*	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(1)	(2)	(5)	(6)
Local agglomeration	0.0267*	0.0028**	0.0432**	0.0048**		
	(1.87)	(2.14)	(2.00)	(2.46)		
Ln(1+local agglomeration)					0.1374***	0.0134***
					(2.71)	(2.92)
Size	-0.1613***	-0.0125**	-0.1865***	-0.0143**	-0.2151***	-0.0168***
	(-2.85)	(-2.40)	(-2.71)	(-2.31)	(-7.18)	(-6.19)
Num_kid	0.6313***	0.0539***	0.7828***	0.0657***	0.7503***	0.0635***
	(9.77)	(9.04)	(9.81)	(9.17)	(21.51)	(20.10)
Married	1.8188***	0.1633***	1.7343***	0.1511***	1.8448***	0.1620***
	(15.31)	(15.10)	(11.34)	(11.07)	(28.08)	(27.45)
Female	-0.1318	-0.0102	-0.3652***	-0.0328***	-0.2290***	-0.0192***
	(-1.24)	(-1.06)	(-2.63)	(-2.64)	(-3.86)	(-3.60)
Education	0.8835***	0.0741***	0.8332***	0.0676***	0.8319***	0.0683***
	(11.55)	(10.53)	(8.40)	(7.51)	(19.63)	(17.67)
Age	0.0370***	0.0043***	0.0368***	0.0043***	0.0326***	0.0039***
	(7.91)	(9.90)	(6.13)	(7.96)	(12.66)	(16.51)
Unemp	-0.3502*	-0.0361*	-0.5461**	-0.0558**	-0.3974***	-0.0398***
	(-1.67)	(-1.87)	(-2.07)	(-2.34)	(-3.32)	(-3.66)
Income	1.8275***	0.1576***	1.5728***	0.1302***	1.7172***	0.1455***
	(27.06)	(25.76)	(19.24)	(17.92)	(46.98)	(44.46)
Net worth	0.0019***	0.0002***	0.0029***	0.0003***	0.0035***	0.0003***
	(3.93)	(3.92)	(5.90)	(5.87)	(14.95)	(15.02)
Log (1+pop)	-0.1981	-0.0158	-0.4574***	-0.0452***	-0.2387**	-0.0191*
	(-0.98)	(-0.85)	(-5.70)	(-6.36)	(-2.03)	(-1.75)
GDP growth	0.8777	0.1107	0.1835	-0.0092	1.7375	0.1938*
	(0.46)	(0.64)	(0.07)	(-0.04)	(1.49)	(1.84)
Industry concentration			-0.0335	-0.0191		
			(-0.06)	(-0.37)		
Industry innovation			2.2266***	0.1817**		
			(2.75)	(2.54)		
Constant	-11.4012***	-1.0250***	-5.1255***	-0.3222**	-9.7868***	-0.8705***
	(-3.53)	(-3.42)	(-3.38)	(-2.40)	(-5.11)	(-4.91)
State FE	YES	YES	NO	NO	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	18424	18424	11663	11663	62040	62040
Adj. R-squared	0.1752	0.1699	0.1946	0.1876	0.1921	0.1853

Table 4. Instrumental variable analysis

This table reports IV regression estimates. *Local agglomeration* is described in Section 2 and is instrumented by increased competition for tradable sectors following the United States' granting Permanent Normal Trade Relations (PNTR) to China. Tradable sectors include the following 10 broad sectors: agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; wholesale trade; retail trade; finance, insurance, and real estate; services; and public administration. Definitions of other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Full sample			5-year window sample		
	First stage	Second stage		First stage	Second stage	
	Local aggl.	*Log(1+mdebt)*	*Dum_mdebt*	*Local aggl.*	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)	(4)	(5)	(6)
*Trade_sector*Post_PNTR*	-0.3647***			-0.5212***		
	(-3.35)			(-2.90)		
Trade_sector	1.8597***			2.0258***		
	(38.34)			(13.47)		
Local agglomeration		0.1873***	0.0179***		0.1353*	0.0129*
		(5.19)	(5.50)		(1.70)	(1.81)
Size	-0.0395***	-0.2091***	-0.0163***	-0.0361	-0.3384***	-0.0263***
	(-3.14)	(-6.96)	(-5.96)	(-1.61)	(-4.70)	(-4.10)
Num_kid	0.0425***	0.7411***	0.0627***	0.0224	0.5983***	0.0472***
	(2.94)	(21.17)	(19.76)	(0.90)	(7.56)	(6.71)
Married	0.0153	1.8381***	0.1613***	0.0008	1.4598***	0.1263***
	(0.64)	(27.92)	(27.27)	(0.02)	(12.19)	(11.90)
Female	-0.0849***	-0.1855***	-0.0150***	-0.0719**	-0.0407	0.0001
	(-4.16)	(-3.09)	(-2.78)	(-2.41)	(-0.41)	(0.01)
Education	0.0209	0.8471***	0.0698***	0.0410*	0.5431***	0.0444***
	(1.22)	(19.90)	(17.95)	(1.65)	(7.52)	(6.81)
Age	0.0021**	0.0320***	0.0038***	-0.0002	0.0296***	0.0033***
	(2.10)	(12.42)	(16.23)	(-0.13)	(6.28)	(7.77)
Unemp	0.0105	-0.3959***	-0.0397***	0.0482	-0.2685	-0.0293
	(0.22)	(-3.30)	(-3.64)	(0.63)	(-1.29)	(-1.58)
Income	0.0644***	1.6993***	0.1438***	0.0529**	1.7716***	0.1478***
	(4.70)	(46.09)	(43.56)	(2.34)	(24.38)	(23.05)
Net worth	0.0000	0.0034***	0.0003***	0.0001	0.0026***	0.0002***
	(0.67)	(14.89)	(14.95)	(0.94)	(8.47)	(8.57)
Log (1+pop)	0.1449***	-0.2625**	-0.0214*	-1.0964	-11.1879**	-0.9499**
	(3.29)	(-2.23)	(-1.96)	(-0.71)	(-2.34)	(-2.22)
GDP growth	-1.1462**	1.9459*	0.2137**	-0.9040	5.6569**	0.4779**
	(-2.31)	(1.66)	(2.03)	(-1.01)	(2.30)	(2.19)
State FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	62040	62040	62040	19382	19382	19382
Adj.R-squared	0.1554	0.1708	0.1622	0.1501	0.1477	0.1387
Kleibergen-Paap rk Wald F-statistic: 846.584 (full sample) and 207.935 (5-year window sample)						

Table 5. Demand-side versus supply-side

This table examines whether demand-side or supply-side factors drive our results. We use the HMDA dataset to conduct the analyses. As approval information is available from 1990, our sample period for HMDA analyses is from 1990 to 2003. Following Barrot et al. (2022), we aggregate data at the MSA level and conduct analyses at the MSA and year levels. In columns (1) and (2), dependent variables are the natural logarithm of number of applications and approval rate, respectively. The key independent variable is the sum of local agglomeration at the MSA-year level. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log (application)	*Approval rate*
	(1)	(2)
Local agglomeration	0.0103***	0.0001**
	(5.30)	(2.44)
Log (1+pop)	1.5945	0.1845***
	(1.54)	(4.58)
GDP growth	-0.7514	0.1666
	(-1.02)	(1.53)
Constant	-15.1179	-2.1493***
	(-0.92)	(-3.34)
State FE	YES	YES
Year FE	YES	YES
Observations	662	662
Adj. R-squared	0.4964	0.6874

Table 6 Panel A: Career potential channel: Promotion probability

This table examines the career potential channel by focusing on promotion probability. Specifically, in column (1), we first examine the impact of local agglomeration on promotion probability. *Promotion* is an indicator variable equal to one if the occupation of the labor head is executive, administrative, or managerial. *Promotion_hat* is the predicted promotion probability, based on a series of household characteristics. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Promotion	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)
Local agglomeration	0.0017**	0.0708***	0.0086***
	(2.24)	(3.57)	(4.66)
Local agglomeration Promotion_hat*		-0.2049*	-0.0299***
		(-1.83)	(-2.96)
Size	-0.0205***	-0.2224***	-0.0179***
	(-10.00)	(-7.36)	(-6.52)
Num_kid	0.0237***	0.7583***	0.0647***
	(9.87)	(21.54)	(20.30)
Married	0.0006	1.8429***	0.1617***
	(0.13)	(28.06)	(27.42)
Female	-0.0022	-0.2282***	-0.0192***
	(-0.50)	(-3.85)	(-3.60)
Education	0.0773***	0.8619***	0.0727***
	(30.31)	(19.13)	(17.71)
Age	0.0004**	0.0326***	0.0039***
	(2.11)	(12.66)	(16.51)
Unemp	-0.0061	-0.3999***	-0.0402***
	(-0.87)	(-3.33)	(-3.69)
Income	0.0695***	1.7405***	0.1489***
	(26.08)	(44.92)	(42.89)
Net worth	0.0002***	0.0035***	0.0003***
	(9.87)	(15.10)	(15.34)
Log (1+pop)	0.0117	-0.2381**	-0.0189*
	(1.52)	(-2.02)	(-1.73)
GDP growth	0.0707	1.8049	0.2022*
	(0.84)	(1.55)	(1.93)
Constant	-0.7817***	-10.0018***	-0.9071***
	(-6.21)	(-5.20)	(-5.09)
State FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	62040	62036	62036
Adj. R-squared	0.0637	0.1922	0.1856

Table 6 Panel B. Career potential channel: Unemployment risk

This table examines the career potential channel by focusing on unemployment risk. Specifically, in column (1), we first examine the impact of local agglomeration on unemployment weeks. *Median_unempwks* is the industry median of unemployment weeks. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Unemployment weeks	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)
Local agglomeration	-0.0031**	0.0434***	0.0046***
	(-2.32)	(3.51)	(4.00)
*Local agglomeration *Median_unempwks*		0.9136***	0.0777***
		(5.87)	(5.92)
Median_unempwks		-3.5425***	-0.3018***
		(-3.33)	(-3.26)
Size	-0.0071*	-0.1230***	-0.0093***
	(-1.71)	(-3.72)	(-3.06)
Num_kid	-0.0140***	0.9104***	0.0792***
	(-2.80)	(23.42)	(22.29)
Married	-0.0192*	2.2073***	0.1951***
	(-1.68)	(27.86)	(27.25)
Female	-0.1008***	-0.2078***	-0.0182***
	(-8.75)	(-2.82)	(-2.72)
Education	-0.0000	1.0655***	0.0870***
	(-0.00)	(20.33)	(18.08)
Age	0.0015***	0.0337***	0.0041***
	(3.35)	(10.93)	(14.55)
Income	-0.1598***	1.7539***	0.1514***
	(-16.51)	(40.26)	(38.43)
Net worth	0.0000	0.0067***	0.0006***
	(0.06)	(19.83)	(19.63)
Log (1+pop)	0.0031	-0.1456	-0.0115
	(0.21)	(-1.19)	(-1.02)
GDP growth	-0.6302**	2.4236	0.2910*
	(-2.44)	(1.48)	(1.96)
Constant	1.4254***	-12.2558***	-1.1006***
	(5.88)	(-6.19)	(-6.00)
State FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	32707	32707	32707
Adj. R-squared	0.1328	0.2407	0.2335

Table 6 Panel C. Career potential channel: Wealth effect

This table examines the career potential channel by focusing on the wealth effect. Specifically, in column (1), we first examine the impact of local agglomeration on household wealth. *Wealth* is the natural logarithm value of the sum of net equity of vehicle, house, and liquid wealth. *Large wealth* is an indicator variable equal to one if household wealth is above the median and zero otherwise. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Wealth	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)
Local agglomeration	0.0132***	0.1428***	0.0136***
	(3.42)	(9.73)	(10.11)
*Local agglomeration*Large wealth*		-0.1903***	-0.0177***
		(-9.51)	(-9.69)
Large wealth		3.4912***	0.3230***
		(51.73)	(53.07)
Size	0.0472***	-0.2606***	-0.0210***
	(3.66)	(-8.96)	(-7.97)
Num_kid	-0.0221	0.7649***	0.0648***
	(-1.47)	(22.69)	(21.27)
Married	0.6719***	1.5615***	0.1356***
	(25.27)	(24.48)	(23.70)
Female	-0.1765***	-0.2118***	-0.0176***
	(-7.22)	(-3.72)	(-3.45)
Education	0.6367***	0.7288***	0.0586***
	(27.75)	(17.92)	(15.82)
Age	0.0337***	0.0039	0.0012***
	(29.57)	(1.56)	(5.39)
Unemp	-0.3061***	-0.4012***	-0.0405***
	(-4.29)	(-3.52)	(-3.91)
Income	1.1278***	1.3673***	0.1131***
	(56.57)	(38.19)	(35.31)
Net worth	0.0052***	-0.0000	-0.0000
	(59.72)	(-0.20)	(-0.93)
Log (1+pop)	0.0149	-0.2173*	-0.0171
	(0.42)	(-1.79)	(-1.52)
GDP growth	0.0623	1.2559	0.1499
	(0.12)	(1.10)	(1.46)
Constant	-3.6538***	-6.9689***	-0.6104***
	(-6.14)	(-3.52)	(-3.34)
State FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	60429	60429	60429
Adj. R-squared	0.4379	0.2501	0.2462

Table 7 Panel A. Alternative explanation: UI

This table controls for the impact of unemployment insurance (UI). *UI* is identified as the product of the maximum number of weeks and the maximum weekly benefit amount (Agrawal and Matsa, 2013; Hsu et al., 2018). *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+mdebt)	*Dum_mdebt*
	(1)	(2)
Local agglomeration	0.0378***	0.0039***
	(3.25)	(3.61)
Size	-0.1902***	-0.0148***
	(-5.91)	(-5.03)
Num_kid	0.7956***	0.0681***
	(21.10)	(19.83)
Married	1.9120***	0.1678***
	(25.80)	(25.10)
Female	-0.2328***	-0.0204***
	(-3.42)	(-3.31)
Education	0.8863***	0.0726***
	(18.45)	(16.50)
Age	0.0307***	0.0038***
	(10.66)	(14.39)
Unemp	-0.4278***	-0.0416***
	(-3.09)	(-3.28)
Income	1.7704***	0.1508***
	(43.20)	(40.91)
Net worth	0.0042***	0.0004***
	(14.06)	(14.25)
Log (1+pop)	-0.3546	-0.0366
	(-0.81)	(-0.91)
GDP growth	2.4189*	0.2379**
	(1.85)	(2.01)
UI	0.5288	0.0351
	(1.22)	(0.89)
Constant	-12.9480	-0.9368
	(-1.54)	(-1.21)
State FE	YES	YES
Year FE	YES	YES
Observations	48467	48467
Adj. R-squared	0.1999	0.1923

Table 7 Panel B. Alternative explanation: House prices

This table controls for the impact of house prices. *Hprice growth* is the annual growth rate of house prices in states. *Local agglomeration* is described in Section 2. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+mdebt)	*Dum_mdebt*
	(1)	(2)
Local agglomeration	0.0377***	0.0038***
	(3.23)	(3.60)
Size	-0.1897***	-0.0147***
	(-5.90)	(-5.00)
Num_kid	0.7951***	0.0680***
	(21.09)	(19.82)
Married	1.9111***	0.1677***
	(25.79)	(25.08)
Female	-0.2323***	-0.0203***
	(-3.41)	(-3.30)
Education	0.8862***	0.0726***
	(18.45)	(16.50)
Age	0.0306***	0.0038***
	(10.64)	(14.36)
Unemp	-0.4256***	-0.0413***
	(-3.08)	(-3.26)
Income	1.7700***	0.1508***
	(43.19)	(40.89)
Net worth	0.0042***	0.0004***
	(14.08)	(14.27)
Log (1+pop)	-0.3959	-0.0419
	(-0.91)	(-1.04)
GDP growth	1.7279	0.1491
	(1.27)	(1.21)
UI	0.7132	0.0588
	(1.55)	(1.41)
Hprice growth	1.0203	0.1311*
	(1.30)	(1.83)
Constant	-13.8819	-1.0568
	(-1.64)	(-1.36)
State FE	YES	YES
Year FE	YES	YES
Observations	48467	48467
Adj. R-squared	0.2000	0.1924

Table 7 Panel C. Alternative explanation: Mortgage interest rate

This table examines the impact of local agglomeration on the mortgage interest rate. *Mortgage interest rate* is the interest rate on first mortgage debt. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Mortgage interest rate
	(2)
Local agglomeration	-0.0056
	(-1.07)
Size	0.1340***
	(7.54)
Num_kid	-0.3980***
	(-20.06)
Married	-0.1396***
	(-4.26)
Female	0.0060
	(0.23)
Education	-0.0957***
	(-4.23)
Age	0.0050***
	(3.75)
Unemp	0.0353
	(0.46)
Income	-0.1103***
	(-5.38)
Log (1+pop)	-0.0009***
	(-14.76)
GDP growth	-0.0435
	(-0.54)
Net worth	1.2465**
	(2.11)
Constant	9.5913***
	(7.39)
State FE	YES
Year FE	YES
Observations	31999
Adj. R-squared	0.2110

Table 8 Panel A. Further analysis: Delinquency

This table examines the impact of local agglomeration on mortgage delinquency. *Delinquency* is an indicator variable equal to one if the mortgage debt is defaulted and zero otherwise. *Local agglomeration* is described in Section 2. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Delinquency
	(1)
Local agglomeration	-0.0010***
	(-5.01)
Size	0.0102***
	(5.59)
Num_kid	0.0009
	(0.70)
Married	-0.0256***
	(-6.92)
Female	0.0118***
	(3.89)
Education	-0.0123***
	(-4.56)
Age	-0.0009***
	(-8.33)
Unemp	0.0877***
	(6.32)
Income	-0.0474***
	(-18.12)
Log (1+pop)	-0.1585***
	(-3.08)
GDP growth	0.0143
	(0.14)
Constant	3.0444***
	(3.64)
State FE	YES
Year FE	YES
Observations	28234
Adj. R-squared	0.0530

Table 8 Panel B. Further analysis: Other household debts

This table examines the impact of local agglomeration on other non-housing debts. *Tdebt* is the sum of vehicle debt (*vdebt*), credit card debt (*cdebt*), debt owed to private persons (*odebt*), and business debt (*bdebt*). Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log (1+tdebt)	*Dum_tdebt*	*Log (1+vdebt)*	*Dum_vdebt*	*Log (1+cdebt)*	*Dum_cdebt*	*Log (1+odebt)*	*Dum_odebt*	*Log (1+bdebt)*	*Dum_bdebt*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Local aggl.	-0.0086	-0.0007	0.0188**	0.0021**	-0.0159**	-0.0014	-0.0032	-0.0001	-0.0040	-0.0004
	(-1.11)	(-0.88)	(2.09)	(2.12)	(-2.06)	(-1.47)	(-0.64)	(-0.19)	(-1.23)	(-1.38)
Size	0.3944***	0.0337***	0.4002***	0.0460***	0.2838***	0.0306***	0.2412***	0.0302***	0.0393***	0.0034***
	(18.12)	(14.28)	(16.23)	(16.70)	(13.35)	(11.47)	(15.79)	(15.35)	(4.65)	(4.76)
Num_kid	-0.2807***	-0.0235***	-0.3240***	-0.0373***	-0.1914***	-0.0222***	-0.1470***	-0.0159***	-0.0234**	-0.0019**
	(-11.20)	(-8.70)	(-11.32)	(-11.69)	(-7.78)	(-7.20)	(-8.20)	(-6.82)	(-2.12)	(-2.16)
Married	1.1024***	0.1077***	0.9742***	0.1128***	0.7916***	0.0971***	0.1001***	0.0151***	0.1640***	0.0136***
	(23.79)	(21.88)	(19.33)	(20.10)	(17.48)	(17.37)	(3.25)	(3.85)	(7.05)	(7.57)
Female	0.5289***	0.0479***	0.3560***	0.0364***	0.4064***	0.0508***	0.1471***	0.0195***	0.1492***	0.0116***
	(12.53)	(10.71)	(7.90)	(7.28)	(9.86)	(10.05)	(5.52)	(5.75)	(6.58)	(6.63)
Education	0.7531***	0.0765***	0.3187***	0.0359***	0.7377***	0.0868***	0.2746***	0.0314***	0.0418***	0.0037***
	(23.66)	(21.89)	(9.63)	(9.71)	(24.66)	(23.03)	(14.46)	(12.57)	(3.31)	(3.70)
Age	-0.0177***	-0.0013***	-0.0293***	-0.0031***	0.0021	0.0000	-0.0147***	-0.0017***	-0.0039***	-0.0003***
	(-9.48)	(-6.43)	(-14.71)	(-14.01)	(1.13)	(0.04)	(-12.34)	(-11.42)	(-4.83)	(-4.19)
Unemp	0.0042	-0.0038	-0.0582	-0.0101	-0.0969	-0.0228*	0.2127***	0.0290***	0.0097	0.0003
	(0.04)	(-0.34)	(-0.60)	(-0.90)	(-1.02)	(-1.89)	(2.94)	(3.02)	(0.27)	(0.12)
Income	1.2816***	0.1096***	1.3305***	0.1329***	1.0644***	0.1164***	-0.0633***	-0.0124***	0.0409***	0.0036***
	(44.16)	(34.76)	(46.00)	(40.95)	(38.92)	(33.98)	(-3.41)	(-5.20)	(2.88)	(3.25)
Net worth	-0.0037***	-0.0004***	-0.0038***	-0.0004***	-0.0038***	-0.0004***	-0.0016***	-0.0002***	0.0011***	0.0001***
	(-21.77)	(-22.07)	(-25.53)	(-23.73)	(-26.08)	(-23.64)	(-21.04)	(-20.40)	(8.62)	(8.66)
Log (1+pop)	-0.2089***	-0.0274***	-0.1790*	-0.0202*	-0.1735**	-0.0324***	0.0040	0.0036	-0.0404**	-0.0033
	(-2.73)	(-3.20)	(-1.87)	(-1.84)	(-2.24)	(-3.17)	(0.09)	(0.62)	(-2.18)	(-1.54)
GDP growth	0.3071	0.0143	1.5762	0.1426	-0.5399	0.0115	-0.0677	-0.0333	0.8926**	0.0475
	(0.35)	(0.15)	(1.63)	(1.32)	(-0.63)	(0.11)	(-0.11)	(-0.40)	(2.23)	(1.45)
Constant	-2.9969**	0.0501	-5.0366***	-0.4248**	-3.8064***	-0.1147	0.8882	0.1061	0.2143	0.0147
	(-2.40)	(0.36)	(-3.23)	(-2.38)	(-3.01)	(-0.69)	(1.25)	(1.12)	(0.71)	(0.42)
State FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	62040	62040	62040	62040	62040	62040	62040	62040	61633	61633
Adj. R-squared	0.1288	0.1014	0.1089	0.1191	0.0911	0.0783	0.0400	0.0436	0.0299	0.0264

Table 8 Panel C. Further analysis: Total mortgage debt

This table examines the impact of local agglomeration on total mortgage debt. *Log(1+tmdebt)* is the natural logarithm value of household total mortgage debt, while *Dum_tmdebt* is a dummy variable indicating if a household has any mortgage debt. *Local agglomeration* is described in Section 2. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log (1+tmdebt)	*Dum_tmdebt*
	(1)	(2)
Local agglomeration	0.0290***	0.0031***
	(2.73)	(3.12)
Size	-0.1902***	-0.0147***
	(-6.31)	(-5.38)
Num_kid	0.8197***	0.0690***
	(23.61)	(21.95)
Married	2.1025***	0.1851***
	(31.70)	(31.06)
Female	-0.2180***	-0.0183***
	(-3.68)	(-3.45)
Education	0.9231***	0.0750***
	(21.42)	(19.03)
Age	0.0398***	0.0045***
	(15.22)	(19.04)
Unemp	-0.3051**	-0.0320***
	(-2.54)	(-2.92)
Income	2.0210***	0.1705***
	(55.37)	(52.14)
Net worth	0.0033***	0.0003***
	(13.94)	(13.83)
Log (1+pop)	-0.1181	-0.0084
	(-1.01)	(-0.78)
GDP growth	1.1972	0.1378
	(1.05)	(1.34)
Constant	-14.2831***	-1.2475***
	(-7.51)	(-7.07)
State FE	YES	YES
Year FE	YES	YES
Observations	62040	62040
Adj. R-squared	0.2366	0.2242

Table 8 Panel D. Further analysis: Education and age

This table examines if a household head's education level and age affect the link between local agglomeration and mortgage debt. *Non_College* indicates the sample of household heads without college diploma, and *College* indicates the sample of household heads with an education level equal to or above college. *Log(1+mdebt)* is the natural logarithm value of household first mortgage debt, while *Dum_mdebt* is a dummy variable indicating if a household has first mortgage debt. *Local agglomeration* is described in Section 2. Definitions of all the other variables are reported in Appendix B. Robust t-statistics clustered at the household level are reported in parentheses beneath each estimate. *, **, and *** refer to significance at the 10%, 5%, and 1% levels, respectively.

	Log(1+mdebt)			
	Non_College	*College*	*Log(1+mdebt)*	*Dum_mdebt*
	(1)	(2)	(3)	(4)
Local agglomeration	0.0685***	0.0182	0.1448***	0.0129***
	(4.27)	(1.22)	(3.30)	(3.21)
*Local agglomeration*Age*	-0.1589***	-0.2871***	-0.0026**	-0.0002**
	(-3.65)	(-6.97)	(-2.45)	(-2.25)
Size	0.5875***	0.8735***	-0.2142***	-0.0168***
	(11.42)	(18.20)	(-7.15)	(-6.16)
Num_kid	1.4078***	2.0981***	0.7484***	0.0634***
	(14.19)	(24.02)	(21.46)	(20.04)
Married	-0.2748***	-0.1675**	1.8447***	0.1619***
	(-2.94)	(-2.20)	(28.09)	(27.45)
Female	0.0140***	0.0386***	-0.2254***	-0.0188***
	(3.66)	(11.17)	(-3.80)	(-3.53)
Age	-0.2988*	-0.5003***	0.8318***	0.0683***
	(-1.90)	(-2.73)	(19.63)	(17.67)
Unemp	1.7433***	1.7169***	0.0369***	0.0042***
	(30.55)	(36.47)	(11.65)	(14.60)
Income	0.0074***	0.0028***	-0.3972***	-0.0398***
	(12.44)	(11.01)	(-3.31)	(-3.66)
Net worth	-0.2732	-0.1749	1.7161***	0.1454***
	(-1.54)	(-1.15)	(46.96)	(44.44)
Log (1+pop)	1.4299	2.0614	0.0035***	0.0003***
	(0.77)	(1.38)	(14.95)	(15.03)
GDP growth	0.0685***	0.0182	-0.2414**	-0.0194*
	(4.27)	(1.22)	(-2.05)	(-1.78)
Education			1.7564	0.1959*
			(1.51)	(1.86)
Constant	-6.9749**	-8.5442***	-9.8656***	-0.8757***
	(-2.41)	(-3.46)	(-5.15)	(-4.93)
State FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	23076	38964	62040	62040
Adj. R-squared	0.1646	0.1817	0.1923	0.1855