Income Inequality and Mortgage Credit Allocation

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Abstract

This paper studies how income inequality at the Metropolitan Statistical Area (MSA) level affect mortgage credit allocation along the income distribution of households *within* MSAs. I find that MSA-level income inequality has heterogeneous effect on household-level mortgage debt accumulation. Two measures of inequality, the ratio of 95th-to-80th percentile (p95/p80) and the ratio of 80th-to-50th percentile (p80/p50) of household income, exhibit significant impact. With respect to credit approval along the income distribution, high p95/p80 inequality works more in favor of low-income households while high p80/p50 inequality benefits high-income households more.

JEL codes: G21, G50, G51, R31, J31

Keywords: mortgage credit, income inequality, real estate, housing prices

1 Introduction

Two parallel surging trends over the past four decades motivate studying income inequality and household debt jointly. One is the well-documented rising trend of income inequality in the United States over the post-1980 period. The other is the build-up of household debt which started in the 1980s and accelerated over the 2000s. One central question is whether widening income gap drives surge in household debt.

In this paper, I study how income inequality at the Metropolitan Statistical Area (MSA) level affect mortgage credit allocation along the income distribution *within* MSAs. I find that MSA-level income inequality has heterogeneous effect on household-level mortgage debt accumulation. Two measures of inequality, the ratio of 95th-to-80th percentile (p95/p80) and the ratio of 80th-to-50th percentile (p80/p50) of household income, exhibit significant impact. Interestingly, these two inequality measures act as opposing forces. Over the 2001-2018 period, going from an MSA at the 10th percentile to an MSA at the 90th

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percentile of the p95/p80 inequality distribution, a low-income household with $30, 000 annual income experiences 2.3 percentage points *higher* probability of loan approval, while a high-income household with $300, 000 annual income has 0.8 percentage points *lower* probability of loan approval. In contrast, consider a rise in MSA-level inequality from the 10th percentile to the 90th percentile of the p80/p50 inequality distribution, a low-income household with $30, 000 annual income faces 3.3 percentage points *lower* probability of loan approval, while a high-income household with $300, 000 annual income has 0.7 percentage points *lower* probability of loan approval. Taken together, with respect to credit approval along the income distribution, high p95/p80 inequality works more in favor of the lower end while high p80/p50 inequality hurts the lower end more.

After observing the aforementioned opposing forces, I then probe for how these forces work jointly. I sort MSAs into inequality categories based on {high, low} combinations of (p95/p80, p80/p50) and do pair-wise comparison between these categories. I find two heterogeneous effects. First, in comparison to the {low p95/p80, high p80/p50} category, the {high p95/p80, high p80/p50} category elevates loan approval probability at the lower end of income distribution and suppresses loan approval probability at the higher end. Second, relative to the {low p95/p80, low p80/p50} category, the {low p95/p80, high p80/p50} category favors loan approval to high-income households and lowers loan approval rate to low-income households.

Related Literature. My paper contributes to the study of income inequality and household debt. One strand of this literature queries for the implications of rising top income share at the *aggregate (national)* level. Kumhof et al. (2015), Rannenberg (2019) and Mian et al. (2020a) build theoretical frameworks to show a rise in income inequality can simultaneously explain a surge in household debt and lower interest rate. The key mechanism at work is that high income households (Top 1% or Top 5%) save disproportionally more out of labor income, lend to the rest of households, and put a downward pressure on interest rate due to the savings glut of the rich. On the empirical side, Mian et al. (2020b) documents an increase in the net household debt position of the bottom 90% of the income distribution, which is consistent with a dramatic rise in the debt-to-income ratio of the bottom 90% from 1983 to 2016 found in Bartscher et al. (2019). After unveiling financial intermediation, Mian et al. (2020b) uncovers Top 10% as the ultimate holder of household debt and proposes that a rise in income inequality can imply for a rise in the saving by top-income which finance an increased net debt position to the rest of households.

Another strand of this literature examines the role of *regional (local)* inequality on household debt. It is not clear how regional inequality affects debt accumulation for households within the region. Some argue that inequality increases household debt at the lower end. Rajan (2011) argues that governments have political interest to incentivize banks to expand housing credit to low-income households whose income growth is lagging behind those at the top. The "Keeping up with the Joneses" hypothesis supported by some empirical studies (e.g., Bertrand and Morse (2016)) states that rising consumption of the rich induces non-rich in their region to consume more. This hypothesis can potentially associate rising inequality with more debt at the bottom if the low-income households use debt to finance their increase in consumption. On the contrary, others argue that inequality tilts credit supply to the higher end of the income distribution. Coibion et al. (2020) finds that low-income households living in low-inequality regions have accumulated more debt relative to their counterpart in high-inequality regions during the 2002-2007 period. My paper brings new evidence on this conflicting matter. By zooming in on inequality along different segments of the income distribution, I find that debt accumulation differs depending on *where* inequality lies on the regional income distribution.

My research also relates to studies on how regional heterogeneity affect household debt accumulation. One stream of this literature examines how heterogeneity across regions drives variation of household debt at the *regional* level. Several studies document differential household refinance response due to regional heterogeneity. Beraja et al. (2019) shows that the snapshot of heterogeneity in home equity prior to QE1 across MSAs underscores the cross-regional variation in refinance activity in response to the mortgage interest rate cut induced by QE1 in 2009. Barrot et al. (2018) finds that households in Commuting Zones (CZs) where labor markets are more adversely impacted due to higher exposure to import competition accumulate more debt to smooth consumption through refinance and home equity extraction. In contrast to these studies who are interested in debt outcome at the regional level, I seek to understand how regional heterogeneity (in income inequality) affects household debt distribution across households *within* regions. While existing studies tend to find that regional heterogeneity is responsible for variation in refinance debt, I seek to identify how it affects home-purchase loans.

2 Data

Mortgage Data. I use mortgage data from the Home Mortgage Disclosure Act (HMDA) database. The HMDA data contains loan application data filed by depository and non-depository institutions that satisfy certain asset threshold, engage in mortgage lending activity in an MSA and have mortgage loan share exceeding 10% of total loan origination. HMDA provides extensive coverage for all mortgage loan originations in the United States. Dell'Ariccia et al. (2012) reports that HMDA's loan coverage ranges from 78% to 96% over the 2000 - 2006 period. I obtain Home Purchase loans from HMDA over the sample period 2001-2018. The main variables at use include loan decision (originated, approved but not accepted and denied by financial institution), applicant total gross annual income, loan amount granted or requested and property location at the Metropolitan Statistical Area (MSA) level. Since the county elements of MSAs evolve over time, my empirical analyses use counties that are common to an MSA over the whole 2001-2018 sample period so that the MSAs are defined consistently over time. I restrict the sample to loan-MSA-year observations that have no missing values for applicant income, loan size and with Loan-to-Income (LTI) ratios between 0.01 and 10.

Income Inequality data. I obtain household income at the 20th, 80th, 95th percentile of an MSA in a given year from Table B19080: Household Income Quintile Upper Limit from the American Community Survey (ACS). I obtain MSA median household income from Table S1901: Income In The Past 12 Months from the ACS. Starting from 2010, the 95th percentile above $\$250,000$ is top-coded to be "$\$250,000+$". I extrapolate the 95th percentiles of MSAs that are top-coded by assuming constant growth at its average annual growth rate over the years prior to reaching the threshold. I confirm that my extrapolation is in line with available estimates for some metro areas made by the Brookings Institute using ACS microdata [1]. Since the ACS data for quintile upper limit and median household income only starts from 2006, I supplement the income data using annual wage income from the Occupational Employment Statistics (OES) data conducted by the U.S. Bureau of Labor Statistics (BLS) over the 2001-2005 period. The OES data contains MSA-level annual wage income at the 10th, 25th, 50th, 75th and 90th percentile. I first extrapolate the 20th, 80th and 95th percentile of annual wage income by assuming linear relationship within neighboring percentiles available from OES for each MSA-year during 2001-2018. For each MSA, I estimate the ACS/OES ratio for the 20th, 50th, 80th and 95th percentile using the average of the corresponding ratios over 2006-2018. I then multiply this estimated ACS/OES ratio to the imputed OES wage income at the 20th, 50th, 80th and 95th percentile to obtain the estimates for ACS household income at the 20th, 50th, 80th and 95th percentile for each MSA-year during 2001-2004.

House Price data. I use Zillow Home Value Index (ZHVI) for house price at MSA-year [2]. ZHVI is a smoothed, seasonally adjusted measure of the typical home value. To be specific, I use ZHVI All Homes, top-tier ZHVI and bottom-tier ZHVI in my sample. ZHVI All Homes is the house price index for the typical home value for all housing types at the MSA-year unit. Top-tier ZHVI is the typical value for homes within the 65th to 95th percentile range of an MSA-year. Bottom-tier ZHVI is the typical value for homes that fall within the 5th to 35th percentile range of an MSA-year.

Other data. I obtain the MSA-level unemployment rate data from the Local Area Employment Statistics data conducted by the BLS. After merging these data together, my final sample contains 78,806,248 home purchase loan applications at 310 MSAs over the period 2001-2018.

3 Empirical Analysis

3.1 MSA income inequality and loan approval

I study the effect of regional income inequality on household mortgage credit allocation with a focus on how inequality interacts with applicant income level to result in differential loan-granting outcomes.

[1] https://www.brookings.edu/research/city-and-metropolitan-income-inequality-data-reveal-ups-and-downs-through-2016/
[2] Data source: https://www.zillow.com/research/data/

I focus on home-purchase mortgage loans. The geographical unit within which I measure income inequality is Metropolitan Statistical Area (MSA). The reason I select MSA as unit of observation is due to its high degree of socioeconomic integration as an economic cluster. Measuring inequality at more disaggregated levels such as counties or zip codes may miss important economic channels through which income inequality affect mortgage credit allocation since a borrower who earns income from an MSA have multiple choices of counties and zip codes for purchasing a house.

Inequality measure. Economies that spin out different *shapes* of income distribution can have disparate socioeconomic underpinning encompassing but not limited to industry and job composition, demographics, spectrum of labor skill and labor force mobility. These underlying features can be potential channels through which regional inequality affect the allocation of mortgage credit to rich and poor borrowers differentially. Depending on where inequality is produced along the income distribution, the differential impact on loan outcomes may also differ. For a concrete illustration of this point, one can imagine two economies: one with rich people's income pulling ahead relative to the median and the other with poor people's income lagging behind the median. If we measure inequality as the ratio of high-to-low income, the two economies would have the same level of income inequality despite operating under different economic fundamentals. Sorting regions based on inequality measure of this kind and probing for how inequality affects household debt tend to mask the heterogeneity in the socioeconomic underpinnings which present the same ratio. If the unaccounted heterogeneity points to diverging implications for loan approval, it would be hard to identify which force is at play when we interpret the result of regressing loan outcome on inequality measured as the ratio high-to-low income in a region. Similar concern applies when one adopts the commonly used Gini index as inequality measure. The fact that different income distribution can yield the same Gini index renders it not an informative measure on where income concentrates along the income distribution.

To suit my purpose on examining how income inequality interacts with income level to affect loan approval, it is important to use a measure that can inform on *where* along the income distribution inequality stems from. My measure of inequality seeks to capture three components of an income distribution: how much the poor are lagging behind the median, how well do middle class do relative to median, and how far apart the top income earners are pulling ahead from the upper middle class. Piecing these components together gives a fuller depiction of inequality that echoes the economic fundamentals of a region. To be specific, I characterize inequality along the income distribution at the MSA-level by three inequality measures: household income percentile ratios *95th/80th percentile* (p95/p80), *80th/50th percentile* (p80/p50) and *50th/20th percentile* (p50/p20). This allows me to examine the heterogeneous interactions between inequality at different segments of income distribution and applicant income level.

Inequality across MSAs. I report summary statistics on household income at the 20th, 50th, 80th and 95th percentile and inequality measures p95/p80, p80/p50 and p50/p20 for 310 MSAs averaged over the period 2001-2018 in Table 1. Figure 1 shows pair-wise scatter plots for the three inequality measures. The three inequality measures are positively correlated, with p50/p20 being the largest and most dispersed. Figure 2 plots the three MSA-level inequality measures on maps of the United States. High inequality MSAs are located along the east and west coast, as well as the southern part. Most mid-west inland MSAs have low inequality. Although the three inequality measures are positively correlated, we do see variation in the degree of inequality depending on which measure is at use.

Table 1: Summary Statistics: MSA Income Percentile and Income Inequality

	Mean	Std.Dev.	Min	p10	p25	p50	p75	p90	Max
Panel A: Income Percentile									
p20 (N = 310)	20.6	4.0	12.0	15.8	18.0	19.9	23.1	25.8	38.1
p50 (N = 310)	48.5	8.6	30.6	39.1	42.6	46.8	53.1	58.8	88.6
p80 (N = 310)	92.3	15.2	65.6	77.3	82.8	89.6	99.5	112.1	178.2
p95 (N = 310)	160.6	32.1	120.5	130.5	140.5	154.7	171.3	200.9	422.7
Panel B: Income Inequality									
p95/p80 (N = 310)	1.734	0.089	1.541	1.642	1.675	1.727	1.775	1.823	2.367
p80/p50 (N = 310)	1.915	0.097	1.675	1.787	1.851	1.911	1.971	2.035	2.225
p50/p20 (N = 310)	2.364	0.149	2.001	2.189	2.266	2.351	2.447	2.556	2.958

Notes: Income is measured in $1000.

Figure 1: MSA-level Income Inequality: $p95/p80$, $p80/p50$ and $p50/p20$

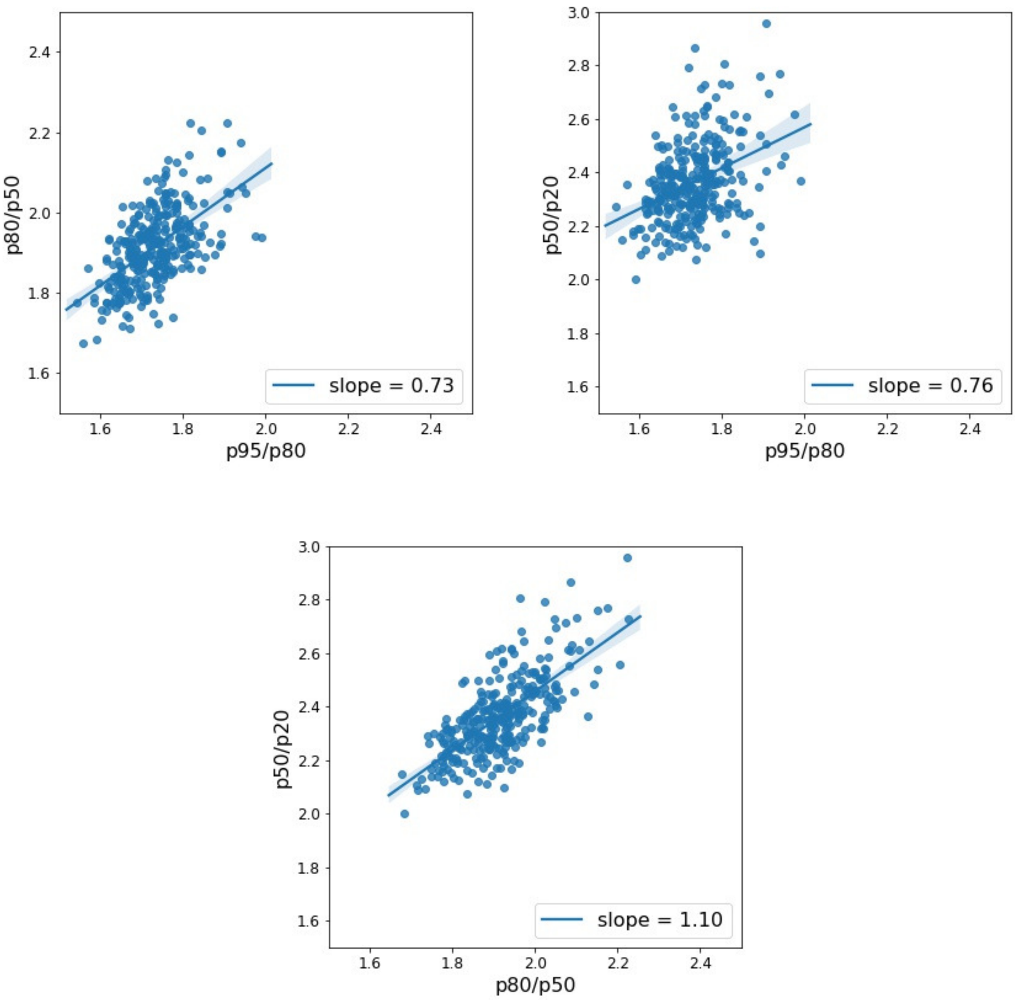
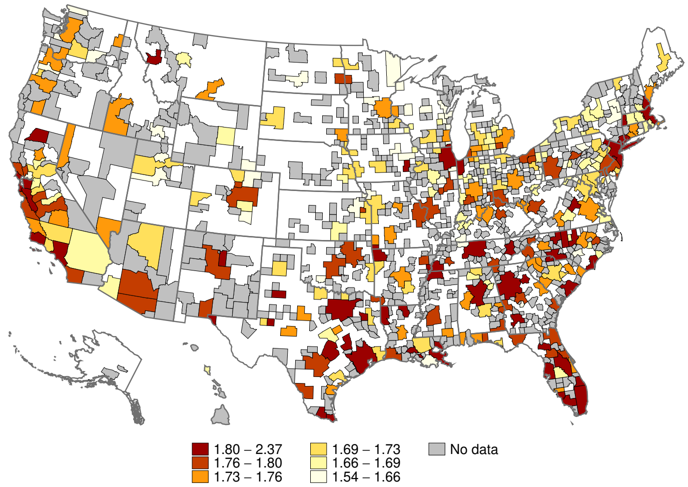
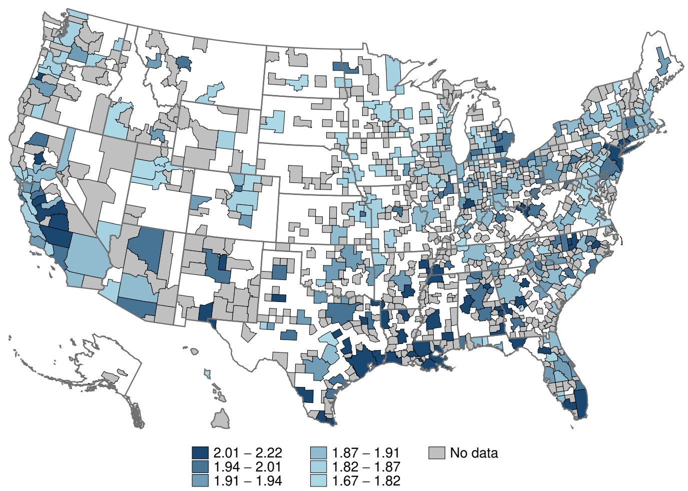


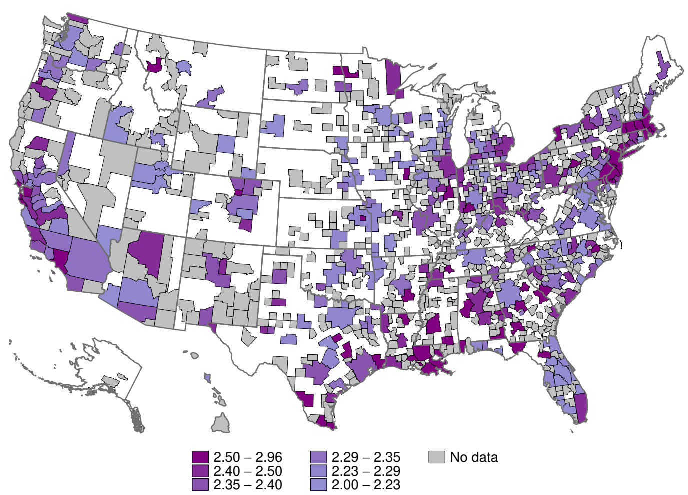
Figure 2: MSA-level Income Inequality: $p95/p80$, $p80/p50$ and $p50/p20$



(a) Average MSA inequality 2001-2018: p95/p80



(b) Average MSA inequality 2001-2018: p80/p50



(c) Average MSA inequality 2001-2018: p50/p20

Balancing of Covariates. A number of observable characteristics of MSAs can affect loan approval and may systematically covary with MSA income inequality. Therefore, the empirical exercises that follow on studying the effect of MSA inequality on loan outcome control for these observables. Table 2 displays summary statistics for the control variables after splitting each inequality measure into four quantiles based on MSA inequality values and reports the difference on each variable between the bottom (lowest) inequality quartile and quartiles 2, 3, 4, respectively. MSAs with p95/p80 at the top quartile has significantly higher median applicant income, average application loan amount and average house price than MSAs in the lowest p95/p80 quartile. Compared to MSAs in the bottom p80/p50 quartile, MSAs in the top quartile for p80/p50 inequality has significantly lower median MSA income and Loan-to-Income (LTI) ratio, but higher unemployment rate.

Table 2: Balancing of Covariates by MSA Income Inequality

	Quartile of Inequality					Group Difference		
	ALL	Q1	Q2	Q3	Q4	Q1-Q2	Q1-Q3	Q1-Q4
Panel A: Inequality p95/p80								
Median income in MSA	48.9	49.5	48.6	48	49.5	0.97	1.5	0.03
	(8.5)	(7.3)	(7.7)	(7.8)	(10.8)	(1.2)	(1.2)	(1.5)
Median applicant income	63.9	57.6	60.3	65.7	72.2	-2.6	-8.0***	-14.5***
	(15.8)	(9.4)	(10.6)	(17.3)	(19.6)	(1.6)	(2.2)	(2.5)
Avg. application loan amount	161.1	138	143.4	167.4	195.8	-5.4	-29.4***	-57.7***
	(66.9)	(44.8)	(44)	(63)	(89.9)	(7.1)	(8.8)	(11.4)
Loan-to-Income	2.259	2.21	2.186	2.301	2.338	0.023	-0.091	-0.128
	(0.334)	(0.342)	(0.337)	(0.302)	(0.335)	(0.055)	(0.052)	(0.054)
Unemployment Rate	6.1	5.8	6.4	6.2	5.9	-0.6**	-0.4*	-0.02
	(1.6)	(1.1)	(2.3)	(1.7)	(1.1)	(0.3)	(0.2)	(0.2)
Avg. House Price	177	152	160	181	215	-7.7	-28.5**	-62.2***
	(99)	(68)	(77)	(86)	(139)	(11.6)	(12.4)	(17.6)
Panel B: Inequality p80/p50								
Median income in MSA	48.9	53.5	51	46.4	44.7	2.4*	7.0***	8.8***
	(8.5)	(7.1)	(8.6)	(6.6)	(8.6)	(1.3)	(1.1)	(1.3)
Median applicant income	63.9	63.1	67	61.8	63.8	-3.9	1.3	-0.7
	(15.8)	(12)	(19.9)	(14.2)	(16)	(2.6)	(2.1)	(2.3)
Avg. application loan amount	161.1	160.4	174	153.3	156.8	-13.6	7.1	3.5
	(66.9)	(51.3)	(80)	(63.2)	(69.5)	(10.8)	(9.2)	(9.8)
Loan-to-Income	2.259	2.334	2.311	2.216	2.174	0.022	0.118**	0.159***
	(0.334)	(0.324)	(0.371)	(0.318)	(0.298)	(0.056)	(0.051)	(0.05)
Unemployment Rate	6.1	5.3	6.6	6.3	6.3	-1.3***	-1.0***	-1.0***
	(1.6)	(1.2)	(2.1)	(1.3)	(1.5)	(0.3)	(0.2)	(0.2)
Avg. House Price	177	185	197	162	164	-11.5	23.4*	21.2
	(99)	(77)	(118)	(98)	(96)	(15.9)	(14.1)	(14.0)
Panel C: Inequality p50/p20								
Median income in MSA	48.9	51.4	49.3	46.9	48	2.0*	4.5***	3.3**
	(8.5)	(7.7)	(7.4)	(6.6)	(11.1)	(1.2)	(1.1)	(1.5)
Median applicant income	63.9	63.3	63.6	61.4	67.4	-0.3	1.8	-4.1
	(15.8)	(11.5)	(17.3)	(12.6)	(20.1)	(2.4)	(1.9)	(2.6)
Avg. application loan amount	161.1	162.5	157.9	150.8	173.3	4.7	11.8	-10.8
	(66.9)	(50.3)	(62.4)	(58.9)	(89.2)	(9.1)	(8.8)	(11.6)
Loan-to-Income	2.259	2.34	2.248	2.191	2.257	0.092	0.148***	0.083
	(0.334)	(0.307)	(0.33)	(0.346)	(0.34)	(0.051)	(0.052)	(0.052)
Unemployment Rate	6.1	5.7	6.1	6.6	6.0	-0.3	-0.8***	-0.3
	(1.6)	(2.0)	(1.6)	(1.6)	(1.1)	(0.3)	(0.3)	(0.3)
Avg. House Price	177	184	170	159	195	13.5	25*	-11.2
	(99)	(73)	(86)	(85)	(138)	(12.8)	(12.7)	(17.7)

Notes: Income and loan amounts are measured in \$1000. Significance levels: *(p<0.1), ** (p<0.05), *** (p<0.01)

Baseline regression. The effect of MSA income inequality on the probability of loan approval can depend on the level of applicant income. Taking advantage of the more detailed depiction of income distribution by the three measures mentioned above, I introduce an additional layer of heterogeneity. That is, the effect of interaction between income inequality and level of income can depend on *where* the inequality arises along the income distribution. Therefore, with the three-part characterization of MSA-level income distribution, I allow for inequality at different segments of income distribution to have heterogenous effects. My baseline empirical specification in Regression 1 formalizes this:

$$
\begin{aligned}
Prob.(LoanApproval)_{i,m,t} = {} & \alpha_m + \lambda_t + \beta log(Income)_{i,m,t} \\
& + \delta_1 p95/p80_{m,t} + \gamma_1 p95/p80_{m,t} \times log(Income)_{i,m,t} \\
& + \delta_2 p80/p50_{m,t} + \gamma_2 p80/p50_{m,t} \times log(Income)_{i,m,t} \\
& + \delta_3 p50/p20_{m,t} + \gamma_3 p50/p20_{m,t} \times log(Income)_{i,m,t} \\
& + X_{i,m,t} + \zeta_{m,t} + \epsilon_{i,m,t} \qquad (1)
\end{aligned}
$$

The dependent variable is the probability of approval of loan i, in MSA m and year t. An application of home-purchase loan is considered to be approved if it is either *originated* or *approved but not accepted by the applicant* . An application is denied if it is *denied by financial institution*. I exclude applications withdrawn by applicant or closed due to incomplete files from my sample. Year fixed effect, λ_t, controls for any aggregate time-trends, while MSA fixed effect, α_m, absorbs any MSA-specific determinants of loan approval rate. I include loan-level control loan-to-income ratio (LTI). I also control for observables on labor market, housing and economic conditions at the MSA-year level, $\zeta_{m,t}$, including median applicant income, median household income, median house price and unemployment rate. Holding constant the level of an applicant's income, the effect of inequality between household at the 95th and 80th percentile, $p95/p80$, on probability of loan approval is $\delta_1 + \gamma_1 log(income)$. Similarly, $\delta_2 + \gamma_2 log(income)$ and $\delta_3 + \gamma_3 log(income)$ captures the effect of inequalities $p80/p50$ and $p50/p20$ on the probability of loan approval respectively.

Applicant income is the first and foremost determinant for mortgage loan issuance. Within a wide applicant income interval, the probability that a borrower obtains approval on mortgage should increase with her income level. Before introducing the effect of MSA inequality, I present the quantitative result of this baseline increasing relationship. In all specifications, I include MSA fixed effect to absorb any unobserved heterogeneity across MSAs and use year fixed effect to account for any time-varying factors that are common to all MSAs and affect mortgage approval. My benchmark specifications (apply to Columns (1) and (2) in Table 3) examine the full sample period from 2001 to 2018. Table 3 column (1) presents the estimate for average elasticity of probability of loan approval with respect to applicant income to be 0.076. That is, a 50 percent rise in applicant income is associated with 3.8 percentage point ($0.5 \times 0.076 = 0.038$) increase in the probability of loan approval.

Column (2) of Table 4 examines whether the elasticity of probability of loan approval with respect to applicant income depends on MSA income inequality. To account in greater detail, this specification allows for inequality at different *segments* of MSA income distribution to exert heterogeneous effect on probability of loan approval. Inequality measures $p95/p80$ and $p80/p50$ stand out signifiant both in terms of their own coefficient and their interactions with applicant income. Interestingly, these two inequality measures act as opposing forces.

To put the estimates into perspective, imagine two households, one lies at the lower end of income distribution and earns \$30K a year and another sits at the higher end of income distribution and has annual income \$300K. I first address the effect of $p95/p80$. Going from 10th to 90th percentile of MSA inequality measure $p95/p80$ ($\Delta(p95/p80) = 1.823 - 1.642 = 0.181$ as in Table 1) implies the low-income household has a 2.3 percentage point *increase* in the probability of loan approval from calculation $0.181 \times 0.374 + \ln(30) \times 0.181 \times (-0.073) = 0.023$. The same increase in $p95/p80$ implies the high-income household has a 0.8 percentage point *decrease* in the probability of loan approval from calculation $0.181 \times 0.374 + \ln(300) \times 0.181 \times (-0.073) = -0.008$. An increase in inequality measure $p95/p80$ has *more positive* effect on the probability of loan approval to *low-income* households than *high-income* households. Next I interpret the estimates on $p80/p50$. Holding all else constant, an increase in MSA inequality $p80/p50$ from 10th to 90th percentile ($\Delta(p80/p50) = 2.035 - 1.787 = 0.248$ as in Table 4) implies the low-income household experience a 3.3 percentage point decline in the probability of loan approval from calculation $0.248 \times (-0.29) + 0.248 \times \ln(30) \times 0.046 = -0.033$. The same increase in $p80/p50$ implies the high-income household experience a 0.7 percentage point drop in the probability of loan approval from calculation $0.248 \times (-0.29) + 0.248 \times \ln(300) \times 0.046 = -0.007$. An increase in inequality measure $p80/p50$ affects the probability of loan approval *more negatively* on low-income households relative to high-income households.

Table 3: Loan Approval, Income Inequality and Applicant Income

	2001:2018		2001:2008		2009:2018	
Prob.(Loan Approval)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Applicant Income)	0.076***	0.096	0.077***	0.191**	0.075***	0.022
	(0.004)	(0.060)	(0.005)	(0.091)	(0.004)	(0.048)
Income Inequality: p95/p80		0.374***		0.531***		0.309***
		(0.113)		(0.169)		(0.070)
Log(Applicant Income) × p95/p80		-0.073***		-0.126***		-0.061***
		(0.026)		(0.037)		(0.016)
Income Inequality: p80/p50		-0.290***		-0.337***		-0.292***
		(0.074)		(0.104)		(0.077)
Log(Applicant Income) × p80/p50		0.046***		0.056**		0.069***
		(0.016)		(0.023)		(0.015)
Income Inequality: p50/p20		0.006		0.066		-0.004
		(0.058)		(0.085)		(0.057)
Log(Applicant Income) × p50/p20		0.010		0.002		0.012
		(0.014)		(0.021)		(0.011)
Loan-to-Income	0.011***	0.011***	0.013***	0.013***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Median Applicant Income)	-0.133***	-0.120***	-0.032	-0.032	-0.071***	-0.052**
	(0.040)	(0.040)	(0.043)	(0.038)	(0.022)	(0.025)
Log(Median MSA Income)	-0.035	-0.159***	-0.202***	-0.341***	-0.034**	-0.077**
	(0.032)	(0.038)	(0.049)	(0.060)	(0.014)	(0.037)
Log(Avg. Application Loan Amount)	0.101***	0.096***	0.131***	0.102***	0.058***	0.050***
	(0.028)	(0.027)	(0.031)	(0.028)	(0.015)	(0.015)
Unemployment Rate	-0.009***	-0.006***	-0.010***	-0.009***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Log(Median House Price)	-0.133***	-0.122***	-0.261***	-0.225***	-0.049***	-0.043***
	(0.016)	(0.014)	(0.024)	(0.021)	(0.014)	(0.013)
Constant	2.349***	2.536***	3.994***	3.760***	1.294***	1.361***
	(0.156)	(0.286)	(0.264)	(0.356)	(0.106)	(0.307)
MSA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Number of Loans	78,806,248	78,806,248	46,664,015	46,664,015	32,142,233	32,142,233
R^2	0.028	0.028	0.027	0.027	0.029	0.029
Number of MSAs	310	310	299	299	309	309

Notes: Income, loan amount and house price are measured in $1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: ** ($p<0.05$), *** ($p<0.01$)

Split-period analysis. The mortgage market has undergone significant structural changes since the Financial Crisis. The collapse of securitization market for Jumbo loans, tighter regulatory compliance requirement imposed by Dodd-Frank Act to contain risk-taking by financial institutions, the post-crisis surge in guarantee fees (g-fees) charged to lenders by the Government Sponsored Enterprises (GSEs) on the mortgage-backed securities (MBS), together with the Fed's usage of unconventional monetary policy to purchase of mortgages guaranteed by the GSEs through the large-scale asset purchase programs all can leave footprint on the allocation of mortgage credit to borrowers with different levels of income. To investigate whether the effect of regional income inequality on loan approval differ under the pre- and post- crisis scheme, I split the baseline regression specification into the 2001-2008 pre-crisis and 2009-2018 post-crisis periods. Columns (4) and (6) in Table 3 report the results. The qualitative effect of inequality measures $p95/p80$ and $p80/p50$ remains the same as in the full sample over the period 2001-2018. Table 4 compares the quantitative effect over the full sample period, pre-crisis and post-crisis period using the same thought experiment of comparing the probability of loan approval of a low-income (30K$) household and a high-income (300K$) household in MSAs with inequality at $10th$ and $90th$ percentile. Noticeably, the negative impact on high-income's loan approval in high $p95/p80$ MSA is smaller going from pre- to post-crisis period (-3.4 VS - 0.7 percentage points). Households in high $p80/p50$ MSAs has elevated relative probability of loan approval comparing to their equal-income counterparts in low $p80/p50$ MSAs (-3.6 VS -1.4 percentage points for low-income, -0.4 VS + 2.5 percentage points for high-income). The qualitative effect in Table 3 is also robust to further splitting the post-crisis scheme into the 2009-2012 bust period and the 2013-2018 recovery period as shown in Table A.2, suggesting this result is not specific to credit boom or credit bust.

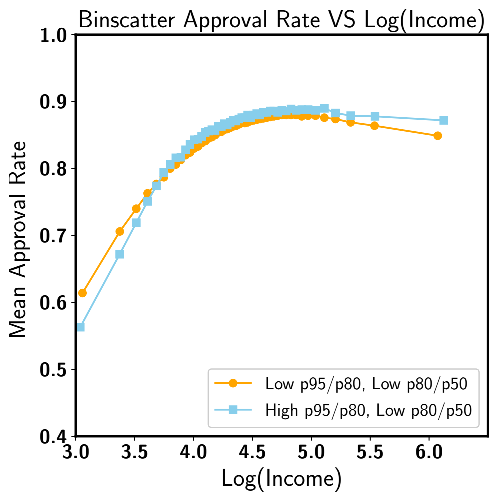
Table 4: Estimated effect of Loan approval from change in MSA inequality

MSA inequality: from 10th to 90th percentile	Δ Prob.(Loan Approval) in percentage points	
	Low Income (30K$)	High Income (300K$)
Panel A: $\Delta(p95/p80) = 0.181$		
Period: 2001 to 2018	$+2.3$	-0.8
Period: 2001 to 2008	$+1.8$	-3.4
Period: 2009 to 2018	$+1.8$	-0.7
Panel B: $\Delta(p80/p50) = 0.248$		
Period: 2001 to 2018	-3.3	-0.7
Period: 2001 to 2008	-3.6	-0.4
Period: 2009 to 2018	-1.4	$+2.5$

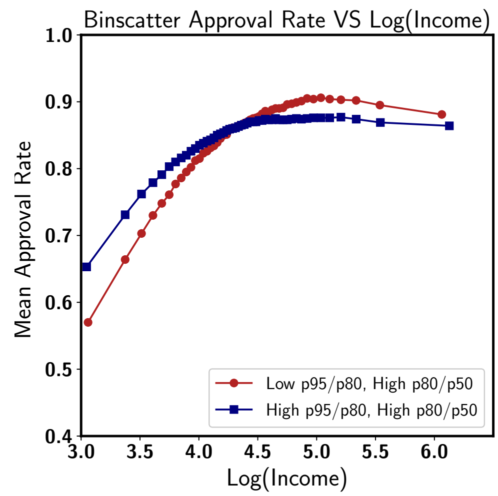
Joint effects of opposing inequality forces. My findings above have revealed inequality measures $p95/p80$ and $p80/p50$ as opposing forces that exert differential impact on the loan approval probability of low- versus high-income households. Next I explore how these two opposing forces work jointly to affect mortgage allocation in MSAs with different combinations in the level of inequality measures $p95/p80$ and $p80/p50$. For each year, I sort MSA inequalities $p95/p80$ and $p80/p50$ into terciles respectively. I group the top one-third inequality values into the "high" category, and the bottom one-third inequality values into the "low" category. Then I obtain four categorical combinations of the two inequality measures: (I) - {low $p95/p80$, low $p80/p50$}, (II) - {low $p95/p80$, high $p80/p50$}, (III) - {high $p95/p80$, low $p80/p50$} and (IV) - {high $p95/p80$, high $p80/p50$}.

Binscatter visualization. To obtain a visual impression, Figure 3 shows a binscatter plot of applicant income and probability of loan approval. I first regress Log(applicant income) and probability of loan approval on a set of controls: Loan-to-Income, median applicant income, median household income, median house price and unemployment rate. I then group the residualized values of Log(applicant income) into 50 equal-sized bins and plot the average of Log(applicant income) in each bin against the corresponding average loan approval rate. In the plot, I use year fixed effect to control for any aggregate time-trends and MSA fixed effect to absorb any MSA-specific determinants of loan approval rate. In each subfigure (Figures 3a to 3f), I plot the binscatter curves from two inequality categories for pair-wise comparison. Figures 3b, 3c and 3e show a "crossing" pattern between plots in the inequality category pair in comparison. One can see from Figure 3b that below an income threshold, the conditional mean approval rate is higher in {high $p95/p80$, high $p80/p50$} MSAs than that in {low $p95/p80$, high $p80/p50$} MSAs. This relationship is flipped when income goes above the threshold. This points toward an interaction effect between the inequality categories at examination and applicant income. Figure 3c shows an opposite relationship in mean approval rates above and below an income threshold for inequality categories {low $p95/p80$, low $p80/p50$} and {low $p95/p80$, high $p80/p50$}. Despite with smaller gaps in between the two crossing curves, Figure 3e suggests a potential interaction effect between categories {low $p95/p80$, high $p80/p50$} and {high $p95/p80$, low $p80/p50$} with applicant income. For robustness check, Figure B.1 shows the binscatter plot with applicant income percentile within an MSA-year on the x-axis and loan approval rate on the y-axis. Both variables are residualized on the same set of controls as in Figure 3 and the plots feature both year fixed effect and MSA fixed effect. Binscatter plots using applicant income percentile yield similar pattern as using Log(applicant income) in all six pairs of inequality categories in comparison.

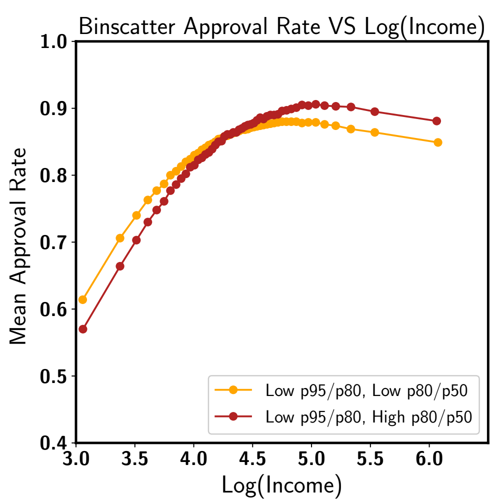
Figure 3: Binscatter with controls: Prob.(Loan Approval) VS Log(Income) by inequality category



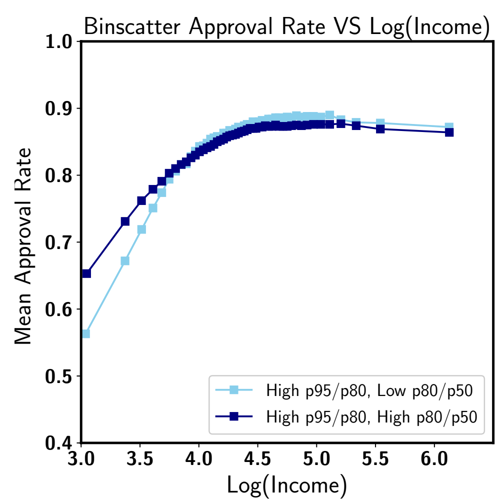
(a) Inequality Category: (I) vs (III)



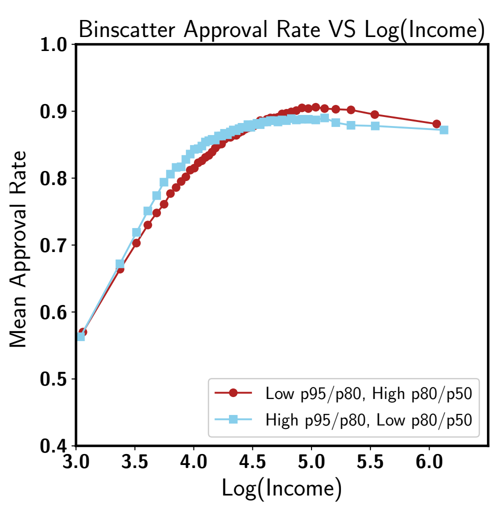
(b) Inequality Category: (II) vs (IV)



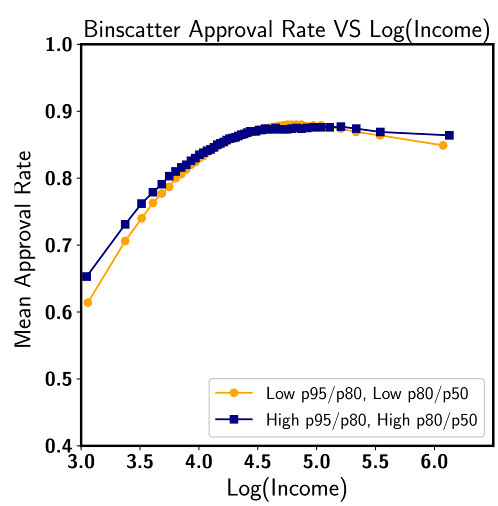
(c) Inequality Category: (I) vs (II)



(d) Inequality Category: (III) vs (IV)



(e) Inequality Category: (II) vs (III)



(f) Inequality Category: (I) vs (IV)

Quantitative result. After observing the potential *differential* impacts on loan approval rate to applicants with different levels of income by several inequality category pairs, I use regressions to quantify these impacts. Table 5 reports pair-wise comparison of the effect of inequality category on loan approval. I include an interaction term between the indicator variable for inequality category and applicant income to allow for the effect of being in an inequality category to depend on the level of applicant income. The generic specification for results in Table 5 is:

$$\begin{aligned} Prob.(LoanApproval)_{i,m,t} = \; & \alpha_m + \lambda_t + \beta log(Income)_{i,m,t} \\ & + \delta InequalityCategory_{i,m,t} \\ & + \gamma InequalityCategory_{i,m,t} \times log(Income)_{i,m,t} \\ & + X_{i,m,t} + \zeta_{m,t} + \epsilon_{i,m,t} \end{aligned} \tag{2}$$

The variable $InequalityCategory_{i,m,t}$ equals to 1 if a loan is in an MSA belonging to the *treatment* category (e.g., {high p95/p80, low p80/p50} in Column (1) of Table 5) and equals to 0 if a loan is in an MSA in the *control* category (e.g., {low p95/p80, low p80/p50} in Column (1) of Table 5). Year fixed effect, λ_t, controls for any aggregate time-trends, while MSA fixed effect, α_m, absorbs any MSA-specific determinants of loan approval rate. I control for loan-to-income ratio (LTI) at the loan-level. $\zeta_{m,t}$ are MSA-year level controls, which include inequality measure $p50/p20$, median applicant income, median household income, median house price and unemployment rate.

Table 5 shows three significant results. Relative to {low p95/p80, high p80/p50}, MSAs in the {high p95/p80, high p80/p50} category favor loan approval for low-income than high-income borrowers. This quantitative result corroborates the visual result shown in Figure 3b. In comparison to {low p95/p80, low p80/p50}, MSAs in the {low p95/p80, high p80/p50} category tilt loan approval toward the high-income group. This echoes the binscatter finding in Figure 3c. When compared to the {low p95/p80, high p80/p50} category, MSAs in the {high p95/p80, low p80/p50} category benefit low-income rather than high-income in loan approval, which is reminiscent of the finding in Figure 3e. The qualitative results for all pair-wise comparisons on the effect of inequality categories still hold after I perform the same analysis using subsamples during the pre-crisis (2001-2008) and the post-crisis (2009-2018) periods (see Appendix Tables B.3 and B.4).

Table 6 illustrates the magnitude of the effect on loan approval of the joint forces of MSA inequality measures $p95/p80$ and $p80/p50$. Again, compare a low-income and a high-income household with annual income \$30K and \$300K, respectively. My estimate in Column (2) of Table 5 suggests that relative to their equal-income counterparts in {low p95/p80, high p80/p50} MSAs, the low-income household in {high p95/p80, high p80/p50} MSAs has a $0.128 + \ln(30) * (-0.027) = 0.036$, i.e., 3.6 percentage points higher probability of loan approval, while the high-income household has a $0.128 + \ln(300) * (-0.027) =$

-0.026, i.e., 2.6 percentage points lower probability of loan approval. In contrast, pair-wise comparison of {low p95/p80, low p80/p50} and {high p95/p80, low p80/p50} MSAs does not yield significant differences (Column (1) of Table 5). Column (3) of Table 5 reports another significant interaction effect. Relative to a household with the same income in {low p95/p80, low p80/p50} MSAs, the low-income household in {low p95/p80, high p80/p50} MSAs has 2.2 percentage points lower probability of loan approval, while the high-income household has 3.3 percentage points higher probability of loan approval. Pair-wise comparison of {high p95/p80, low p80/p50} and {high p95/p80, high p80/p50} MSAs does not yield significant difference (Column (4) of Table 5). Column (5) of Table 5 reports an additional significant effect. A household with $\$30K$ income has 3.7 percentage points higher probability of loan approval in {high p95/p80, low p80/p50} MSAs that in {low p95/p80, high p80/p50} MSAs, while the equivalent estimate for a household with $\$300K$ is -0.5 percentage points. Pair-wise comparison of {low p95/p80, low p80/p50} and {high p95/p80, high p80/p50} MSAs does not yield significant difference (Column (6) of Table 5).

Table 5: Loan Approval, Inequality Combination and Applicant Income

Prob.(Loan Approval): 2001 to 2018	(1)	(2)	(3)	(4)	(5)	(6)
Log(Applicant Income)	0.070***	0.087***	0.071***	0.067***	0.100***	0.065***
	(0.005)	(0.006)	(0.005)	(0.007)	(0.006)	(0.004)
$\mathbb{1}$\{high p95/p80, low p80/p50\}	-0.028				0.098***	
	(0.030)				(0.037)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} ×	0.006				-0.018**	
Log(Applicant Income)	(0.007)				(0.007)	
$\mathbb{1}$\{high p95/p80, high p80/p50\}		0.128***		0.023		0.020
		(0.036)		(0.045)		(0.034)
$\mathbb{1}$\{high p95/p80, high p80/p50\} ×		-0.027***		-0.009		-0.005
Log(Applicant Income)		(0.008)		(0.009)		(0.008)
$\mathbb{1}$\{low p95/p80, high p80/p50\}			-0.104***			
			(0.022)			
$\mathbb{1}$\{low p95/p80, high p80/p50\} ×			0.024***			
Log(Applicant Income)			(0.005)			
$\mathbb{1}$\{low p95/p80, low p80/p50\} (omitted)	0.000		0.000			0.000
	(0.000)		(0.000)			(0.000)
$\mathbb{1}$\{low p95/p80, high p80/p50\} (omitted)		0.000			0.000	
		(0.000)			(0.000)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} (omitted)				0.000		
				(0.000)		
Income Inequality: p50/p20	0.026	0.073**	0.051***	0.039	0.068***	0.042*
	(0.017)	(0.028)	(0.017)	(0.037)	(0.022)	(0.023)
Loan-to-Income	0.011***	0.003	0.012***	0.001	0.017***	0.005*
	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Log(Median Applicant Income)	-0.137***	-0.233***	-0.146***	-0.211**	-0.009	-0.222***
	(0.049)	(0.060)	(0.042)	(0.095)	(0.072)	(0.048)
Log(Median MSA Income)	-0.083**	-0.151	-0.114**	-0.084	-0.046	-0.131**
	(0.037)	(0.103)	(0.046)	(0.091)	(0.066)	(0.054)
Log(Avg. Application Loan Amount)	0.061**	0.159***	0.073***	0.167**	0.029	0.124***
	(0.027)	(0.052)	(0.028)	(0.066)	(0.056)	(0.037)
Unemployment Rate	-0.010***	-0.009***	-0.007***	-0.009**	-0.005*	-0.010***
	(0.002)	(0.003)	(0.001)	(0.004)	(0.002)	(0.002)
Log(Median House Price)	-0.092***	-0.119***	-0.096***	-0.136**	-0.120***	-0.099***
	(0.026)	(0.044)	(0.019)	(0.064)	(0.024)	(0.028)
Constant	2.258***	2.536***	2.322***	2.551***	1.772***	2.560***
	(0.290)	(0.337)	(0.243)	(0.459)	(0.176)	(0.233)
MSA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Number of Loans	17,886,175	18,943,936	18,885,978	17,944,133	6,044,321	30,785,790
R^2	0.027	0.026	0.031	0.024	0.036	0.028

Notes: Income, loan amount and house price are measured in \$1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: *(p<0.1), ** (p<0.05), *** (p<0.01)

Table 6: Estimated effect of Loan approval by change in MSA inequality combination

MSA Inequality Category: (*control*, *treatment*)	Δ Prob.(Loan Approval) in percentage points	
	Low Income ($30*K*)	High Income ($300*K*)
({low p95/p80, low p80/p50}, {high p95/p80, low p80/p50})	No Change	No Change
({low p95/p80, high p80/p50}, {high p95/p80, high p80/p50})	+3.6	−2.6
({low p95/p80, low p80/p50}, {low p95/p80, high p80/p50})	−2.2	+3.3
({high p95/p80, low p80/p50}, {high p95/p80, high p80/p50})	No Change	No Change
({low p95/p80, high p80/p50}, {high p95/p80, low p80/p50})	+3.7	−0.5
({low p95/p80, low p80/p50}, {high p95/p80, high p80/p50})	No Change	No Change

Notes: An MSA belongs to {low p95/p80} in year t if its $p95/p80$ are among the bottom one-third of MSA inequality measure $p95/p80$ in year t. {high p95/p80} denotes the top one-third of MSA inequality measure $p95/p80$ in year t. Same definition applies to {low p80/p50} and {high p80/p50} sorted by MSA inequality measure $p80/p50$ in each year.

4 Potential Channels

4.1 Credit Supply driven by demand-side factors: borrower's income growth and income risk

Regions that differ in degrees of income inequalities measured by ratios of 95th-to-80th, 80th-to-50th and 50th-to-20th percentile of household income, or in different inequality categories sorted by combinations of (95th-to-80th, 80th-to-50th) percentile ratios can operate under different economic fundamentals. In particular, they can differ in industry and occupation composition, demographics, spectrum of labor skill and labor force mobility. If these fundamentals have differential implications for high- and low-income households' income growth and income risk, and banks can use "soft information" on cross-regional variations in fundamentals to infer the implied income processes, we may see differential loan origination along the income distribution to vary with regional inequality.

Inequality and wage structure changes. Widening income inequality can be associated with different changes in wage structure. In the aggregate time series, as earnings inequality measured by the gap between hourly wages of 90th and 10th percentile enters into a widening trend since mid-1970s, salient differences of wage growth at the lower end of income distribution separates wage structure into two distinct eras. Figure 9 in Acemoglu and Autor (2011) shows this divergence. Over the 1974-1988 period, income at the lower-end has been falling steeply relative to the median. During the 1988-2008 period, income at the lower-tail has been rising disproportionally relative to the median. Wage changes above the median are nearly parallel during these two periods. Time-series studies on income distribution have revealed that under seemingly identical rising inequality trends, the income growth for households at the lower end may be differ depending on the underlying economic fundamentals.

Income distribution can differ by occupation and industry composition. David and Dorn (2013) unveils that income growth at the lower tail between 1980 to 2005 is substantially accounted for by rising employment and wages in *low-skill service occupations*. They show that, in the cross-section, Commuting Zones (CZs) initially specialized in routine task-intensive jobs exhibit a more pronounced U-shape polarization of employment and wage along the skill distribution. That is, in regions with higher routine task share, employment growth and wage growth are steeper at both the right tail and the left tail of income distribution, but growth is shallower near the median. One can infer from this result that some regions with more inequality at the top end could have some positive spillover effect that contributes to higher income growth at the lower end.

Aggregate credit flow due to wage structure. Regional inequality may signal on borrowers' income growth outlook that incentivize lenders to infuse more credit to a region and allocate credit differentially along the regional income distribution.

4.2 Credit Supply: borrower income inequality

Regional inequality can directly translate into income inequality of the borrower pool within a region. If lenders are constrained on the total loan amount they can issue, inequality of the applicant pool can operate through lenders' profit-maximization to affect credit distribution.

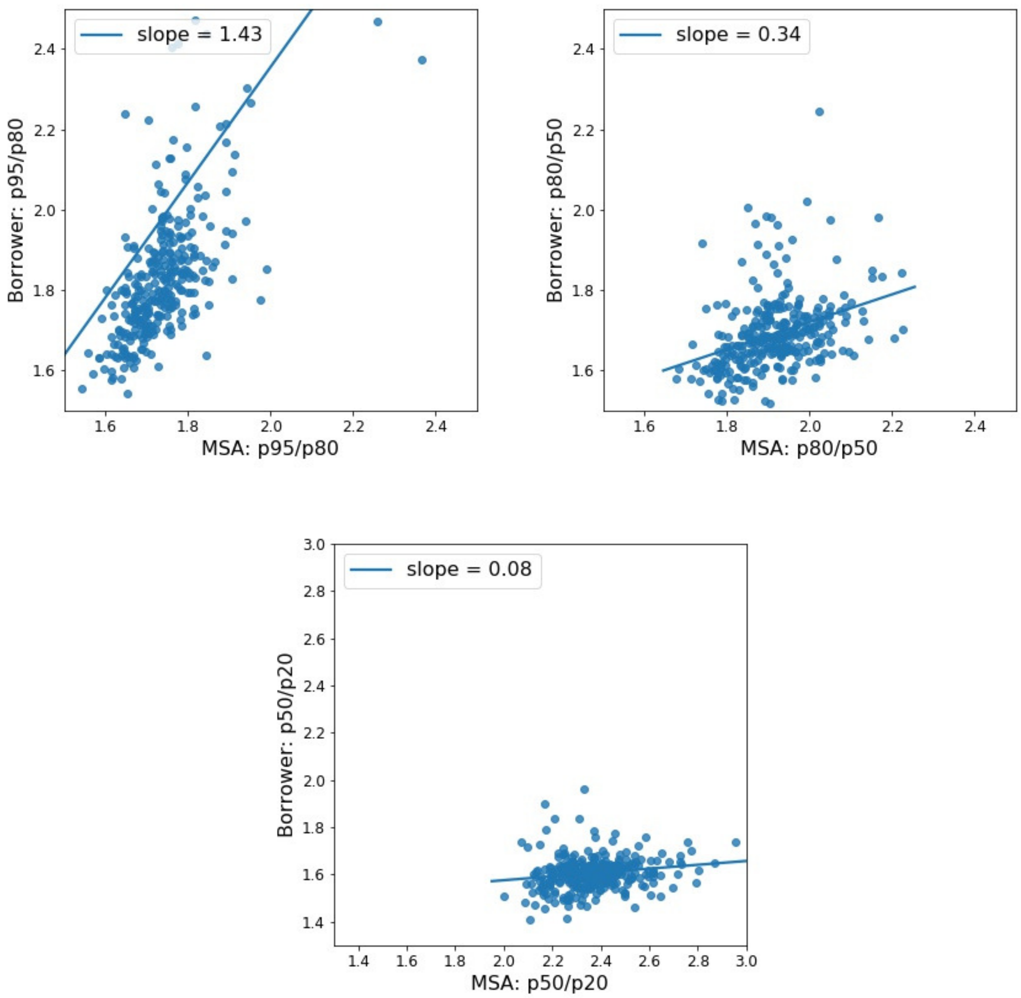
I first examine the relationship between the loan applicant pool and the MSA household pool in terms of income distribution and income inequality. Borrower pool within an MSA is a more affluent draw from the income distribution of MSA household pool, as exemplified in Table 1 and Table 7, where the 20th, 50th, 80th and 95th percentiles of borrower income distribution are all much higher than those of MSA household income distribution. Inequality has diverging patterns as shown in Figure 4. Borrower pool of an MSA features higher p95/p80, but lower p80/p50 and p50/p20, in terms of inequality measures compared to the MSA household pool.

Table 7: Summary Statistics: Applicant Income Percentile and Income Inequality

	Mean	Std.Dev.	Min	p10	p25	p50	p75	p90	Max
Panel A: Applicant Income Percentile									
p20 (N = 310)	39.8	9.7	27.8	30.9	33.9	37.4	42.3	49.3	94.3
p50 (N = 310)	63.9	15.8	43.4	49.7	54.3	60.3	68.1	79.4	144.6
p80 (N = 310)	108.5	29.6	73.1	82.9	90.8	99.7	118.2	141.6	273.1
p95 (N = 310)	215.5	192.2	120.5	143.1	158.7	181.6	220.9	296.8	3223.6
Panel B: Applicant Income Inequality									
p95/p80 (N = 310)	1.974	1.683	1.543	1.65	1.726	1.801	1.896	2.045	28.732
p80/p50 (N = 310)	1.692	0.093	1.518	1.597	1.638	1.681	1.732	1.778	2.244
p50/p20 (N = 310)	1.606	0.069	1.409	1.521	1.566	1.607	1.64	1.68	1.96

Notes: Income is measured in $1000.

Figure 4: MSA Income Inequality VS Applicant Income Inequality



I replace MSA-level inequality by applicant pool inequality to study the interaction between borrower inequality and borrower income in Regression 3. Apart from replacement of inequality, the specification for control variables and fixed effects are the same as Regression 1.

$$
\begin{aligned}
Prob.(LoanApproval)_{i,m,t} = {} & \alpha_m + \lambda_t + \beta log(Income)_{i,m,t} \\
& + \delta_1 ApplicantPool\ p95/p80_{m,t} + \gamma_1 ApplicantPool\ p95/p80_{m,t} \times log(Income)_{i,m,t} \\
& + \delta_2 ApplicantPool\ p80/p50_{m,t} + \gamma_2 ApplicantPool\ p80/p50_{m,t} \times log(Income)_{i,m,t} \\
& + \delta_3 ApplicantPool\ p50/p20_{m,t} + \gamma_3 ApplicantPool\ p50/p20_{m,t} \times log(Income)_{i,m,t} \\
& + X_{i,m,t} + \zeta_{m,t} + \epsilon_{i,m,t} \qquad (3)
\end{aligned}
$$

The results of this regression are presented in Table 8. Over the whole sample period 2001-2018, applicant inequalities p80/p50 and p50/p20 act opposing forces to differentially affect loan approval to high-income and low-income borrowers (Column (2) of Table 8). Nevertheless, unlike results using MSA inequality measures, the result does not hold when I do split-period analysis for the 2001-2008 pre-crisis and 2009-2018 post-crisis regimes. Over the 2001-2008 period, p95/p80 and p50/p20 stand out as opposing forces (Column (4) of Table 8). Over the 2009-2018 period, borrower inequality does not have significant impact on loan approval rate (Column (6) of Table 8). Table 9 presents the estimated change on the probability of loan approval to a low-income (\$30K) and a high-income (\$300K) household in response to a change in borrower inequality measures, p95/p80, p80/p50 and p50/p20, from the 10th to 90th percentile, respectively. The main takeaway is that high p95/p80 borrower inequality tilts loan approval towards low-income while high p50/p20 borrower inequality favors loan approval to high-income. And this result only holds over the 2001-2008 period.

By comparing Table 3 and Table 8, I find that MSA inequality measures has an interaction effect with income on loan approval that is qualitatively persistent for either whole-period or split-period analyses, while borrower inequality measures only interact significantly with income over the 2001-2008 period. Taken together, MSA inequality operates beyond its translation into variation in borrower pool inequality that lenders face at the MSA level.

Table 8: Loan Approval, Applicant Income Inequality and Applicant Income

	2001:2018		2001:2008		2009:2018	
Prob.(Loan Approval)	(1)	(2)	(3)	(4)	(5)	(6)
Log(Applicant Income)	0.076***	-0.082**	0.077***	-0.118***	0.075***	0.064**
	(0.004)	(0.034)	(0.005)	(0.040)	(0.004)	(0.030)
Applicant Income Inequality: p95/p80		0.001		0.408***		0.001**
		(0.001)		(0.070)		(0.000)
Log(Applicant Income) ×		-0.000		-0.105***		-0.000**
Applicant Income Inequality: p95/p80		(0.000)		(0.016)		(0.000)
Applicant Income Inequality: p80/p50		0.444***		0.017		0.072
		(0.081)		(0.127)		(0.102)
Log(Applicant Income) ×		-0.109***		-0.011		-0.022
Applicant Income Inequality: p80/p50		(0.020)		(0.027)		(0.023)
Applicant Income Inequality: p50/p20		-0.857***		-1.135***		-0.133
		(0.121)		(0.144)		(0.113)
Log(Applicant Income) ×		0.215***		0.260***		0.030
Applicant Income Inequality: p50/p20		(0.027)		(0.032)		(0.025)
Loan-to-Income	0.011***	0.011***	0.013***	0.012***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log(Median Applicant Income)	-0.133***	-0.133***	-0.032	-0.009	-0.071***	-0.074***
	(0.040)	(0.036)	(0.043)	(0.038)	(0.022)	(0.026)
Log(Median MSA Income)	-0.035	-0.056*	-0.202***	-0.170***	-0.034**	-0.034**
	(0.032)	(0.031)	(0.049)	(0.041)	(0.014)	(0.015)
Log(Avg. Application Loan Amount)	0.101***	0.094***	0.131***	0.125***	0.058***	0.062***
	(0.028)	(0.025)	(0.031)	(0.028)	(0.015)	(0.016)
Unemployment Rate	-0.009***	-0.009***	-0.010***	-0.009***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
Log(Median House Price)	-0.133***	-0.110***	-0.261***	-0.251***	-0.049***	-0.056***
	(0.016)	(0.016)	(0.024)	(0.027)	(0.014)	(0.014)
Constant	2.349***	2.812***	3.994***	4.651***	1.294***	1.452***
	(0.156)	(0.218)	(0.264)	(0.389)	(0.106)	(0.170)
MSA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Number of Loans	78,806,248	78,806,248	46,664,015	46,664,015	32,142,233	32,142,233
R^2	0.028	0.029	0.027	0.029	0.029	0.029
Number of MSAs	310	310	299	299	309	309

Notes: Income, loan amount and house price are measured in \$1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: ** (p<0.05), *** (p<0.01)

Table 9: Estimated effect of Loan approval from change in Applicant inequality

Applicant inequality: from 10th to 90th percentile	Δ Prob.(Loan Approval) in percentage points	
	Low Income (\$30K)	High Income (\$300K)
Panel A: $\Delta(p95/p80) = 0.395$		
Period: 2001 to 2018	No Change	No Change
Period: 2001 to 2008	$+2.0$	-7.5
Period: 2009 to 2018	$+0.04$	$+0.04$
Panel B: $\Delta(p80/p50) = 0.181$		
Period: 2001 to 2018	$+1.3$	-3.2
Period: 2001 to 2008	No Change	No Change
Period: 2009 to 2018	No Change	No Change
Panel C: $\Delta(p50/p20) = 0.159$		
Period: 2001 to 2018	-2.0	$+5.9$
Period: 2001 to 2008	-4.0	$+5.5$
Period: 2009 to 2018	No Change	No Change

4.3 Credit Supply: the role of GSEs

Institutional details on GSEs. Fannie Mae and Freddie Mac are two large government-sponsored enterprises (GSEs) that buy mortgages from mortgage originators (banks and mortgage companies) and bundle the mortgages into mortgage-backed securities (MBSs) for sale on the secondary market. The mortgages that GSEs can buy are called conforming loans and need to meet the criterion: below certain loan-size (conforming loan limits: one for standard and another for high-cost areas), have credit score above 620 for fixed-rate mortgages and 640 for adjustable-rate mortgages, have Loan-to-value (LTV) below 0.8 or with private mortgage insurance if LTV goes above 0.8, with Debt-to-income (DTI) below 0.36 or 0.45 for borrowers with high credit score and below 0.5 for loans processed with automated processing system. GSEs guarantee the MBS investors against losses from credit risks on the underlying mortgages and charge a guarantee fee (g-fee) to mortgage originator for this guarantee. Banks are required to hold \$1.60 in capital for every \$100 if the MBSs were guaranteed by the GSEs. This is substantially lower than the \$4.00 per \$100 of mortgage assets if banks were to hold the same mortgage on their balance sheet but in absence of GSEs. GSEs are also subject to a low capital requirement of \$0.45 for every \$100 of mortgage face value guaranteed. Established as agencies to enhance flow of credit to low-income borrowers and promote homeownership, GSEs are special due to their "government-sponsored" nature: they carry implicit guarantee of the US Government, have special access to US Treasury financing and enjoy favorable capital requirements. These characteristics make GSEs a convenient vehicle in turning illiquid mortgage assets into liquid MBS that can reach broad-base investors on the secondary market thus lower mortgage interest rates by reducing liquidity premium. Meanwhile, as reviewed in White et al. (2017), this lower mortgage credit cost made available by cheaper funding cost for GSEs due to the government guarantee comes at the expense of underpriced credit risk and makes the mortgage finance sector fragile.

Market power by GSEs. Importantly, as large purchasers of mortgage loans that meet the conforming loan standard and with their MBS guarantees for a large fraction of single-family residential mortgages, GSEs delineate a segmentation in the mortgage market that affect lenders' incentive for loan origination. Over the past two decades, several major structural changes in the mortgage market have altered the relative market power between GSEs and their competitors on mortgage asset purchase and the issuance of MBS. As issuers of mortgage-backed securities to investors, GSEs compete with non-agency issuers of MBS. Fannie Mae reports in their 10-K filing in 2008 (page 40) [3] that the rapid growth of private-labeled MBS from 2003 to 2006 has caused decrease of their market share in the issuance of MBS to investors. With the mortgage and credit market disruption in 2007, the market for private-labeled securities collapsed, yielding their market share to MBSs backed by GSEs. The market share for new single-family MBS of Fannie Mae increased from 24.6% in 2006 to 41.7% in 2008. Ginnie Mae filled in the void in this market as its share surged from 3.6% in 2006 to 37.8% in 2008. The private-label securities never grows back since its collapse in 2007. As of 2017, MBS are mainly issued by GSEs: 39% by Fannie Mae, 33% by Ginnie Mae and 26% by Freddie Mac. From 2003 to 2006, GSEs need to compete with private-labeled MBS issuers. After 2007, GSEs became the dominant issuers of MBS.

The change in market power of GSEs can affect lender's mortgage credit allocation to borrowers of different levels via several channels. One natural channel is that the loans that are purchased by and packaged into MBSs by GSEs must satisfy the conforming loan standard. Issuance of larger loans with non-conforming size (jumbo loans) can be sensitive to the market share of GSE-backed MBSs and private-labeled MBSs. One related evidence is that unconventional monetary policy induces differential response in the conforming and non-conforming loan segments delineated by the presence of GSE. Di Maggio et al. (2020) shows that relative to QE-ineligible jumbo mortgages, the QE-eligible conforming mortgage interest rate fell by an additional 40bp in response to the Fed's unconventional monetary policy via large-scale asset purchase on GSE-guaranteed MBS during QE1.

The presence of GSEs can also affect lender's risk-taking behavior. One well-documented channel involves the distortion of lender's screening incentive with information friction and moral hazard problem introduced by securitization. Exploiting the *ad hoc* credit score cutoff at 620 in the guidelines of GSEs for securitization, Keys et al. (2010) finds that the ease of securitization did adversely affect the screening incentives of subprime lenders. Several studies seek to understand the distributional implications of

[3] https://www.fanniemae.com/resources/file/ir/pdf/quarterly-annual-results/2008/form10k_022609.pdf

GSEs and use general equilibrium models to perform counterfactual analysis on GSE phaseout. Elenev et al. (2016) argues that underpriced government guarantees lead to more and riskier mortgage originations, higher financial sector leverage and loading credit risk to fiscal uncertainty. Phasing out GSEs and crowding in the private sector can reduce fragility of financial sector and improve social welfare mainly by increasing the welfare of depositors and financial intermediaries. A less-noticed risk-taking is induced by the increasing concentration of GSEs as larger holder and guaranteer of single-family mortgage loans. Gupta (2019b) proposes a theory in which concentration of mortgage risk held by large institutions incentivizes them to internalize their influence on house price changes via credit channeling. As house price starts going down, large holders of mortgages may continue to make loans of high-risk in exchange for the benefit of keeping profits that they can make from existing mortgage repayments by keeping house price high. Therefore, concentration can affect both the quantity and quality of mortgage credit.

Additionally, the goal for GSEs to channel credit to low-income households in low-income and high-minority regions as stipulated by their regulators can affect mortgage credit allocation.

4.4 Credit demand: number of loan applications

In contrast to the credit supply channel driven by demand-side factors as mentioned above, here I consider the role of credit demand while holding credit supply factors (total credit and lending standard) constant. Low probability of loan approval may reflect a rising number of loan applications due to an increase in credit demand. Several reasons could allow this credit demand channel to drive my result on cross-region differential loan approval rate to high- and low- income group. One of the reasons could be low-income households in a region within certain inequality category have higher expected income growth than their counterparts in other regions and thus we see more low-income households in that region apply for loans. In this case with a fixed credit supply, we can see lower approval rate to low-income. One can also replace higher expected income growth by higher expected house price growth of low-income to generate increase in credit demand to explain the same empirical result. Barrot et al. (2018) isolates a credit demand channel which drives cross-region variation in household debt accumulation. They show that Commuting Zones (CZs) with larger exposure to import competition induce negative income shock and households take on more mortgage debt mainly through refinancing and home equity loans (HELOCs) to smooth consumption. They see higher denial rates in refinance loans due to demand-driven increase in application numbers. This negative income shock demand channel is unlikely to explain my findings on approval rates of home-purchase loans. The reason is that households that incur negative income shock are unlikely to obtain new loans to finance home-purchase. Their main resource for debt-financing is the extraction of home equity as existing borrowers. In fact, Barrot et al. (2018) reports no difference in the denial rates of home-purchase loans in regions with various exposure to import competition.

On the flip-side of the coin, the fact that in some regions low-income households have higher approval probability relative to their counterparts in other regions could result from a smaller pool of loan application participation. The reasons behind could be some regional factors such as higher house price, demographical composition (e.g.: age structure), mobility and more stringent lending standards deter loan application from certain income group in the first place.

4.5 Feedback through house price and collateral value

One unique feature that distinguishes mortgage loans from other household debt is that it uses physical properties as collateral. In case of default, the lender can seize the house from the borrower. This opens up a channel through which collateral value affects loan approval rate. Regional income inequality can operate through the collateral channel in several ways. First, a rise in inequality can bid up house price, increase the loan-to-income (LTI) ratio for low-income households and lower their approval rate. Alternatively, widening income gap can generate neighborhood segmentation that makes lender perceive low-price properties as inferior collateral to hold in comparison to high-price properties. The adverse effect can be a result that low-price houses are expected to have lower house price growth in regions with high inequality. Or it could due to higher inequality leads to sorting of low-income households into foreclosure-prone neighborhoods. Gupta (2019a) shows that foreclosure raises the probability of default among neighbors. Under the influence of this neighborhood spillover effect, a borrower with given credit risk can face lower loan approval probability if she purchases a house in a more foreclosure-prone neighborhood.

To get a sense on which factor is at play, I examine the relationship between MSA-level house price at each tercile and income inequality measures p95/p80 and p80/p50, respectively. I use Zillow Home Value Index (ZHVI) from Zillow to get house price index for each tercile at the MSA-level. I sort MSA-level inequality measures p95/p80 and p80/p50 into quartiles based on their average value over the 2001-2018 period. I find that inequality measure p95/p80 is positively correlated with house price at all terciles. Noticeably, in comparison to MSAs with p95/p80 in the bottom quartile, MSAs with p95/p80 at the top quartile has about 50% higher top-tercile house price and roughly 30% higher bottom-tercile house price (Panel A of Table 10). Higher house price in high p95/p80 regions did not result in higher loan-to-income (LTI) on average, potentially due to the fact that applicant income is also higher in these regions (Panel A of Table 2).

High inequality p80/p50 is not correlated with the top-tercile and the average MSA-level house price. Interestingly, the bottom-tercile house price in high (top-quartile) p80/p50 MSAs are about 20% lower than low (bottom-quartile) p80/p50 MSAs. This echoes my previous finding that high p80/p50 MSAs have lower loan-to-income (LTI) on average (Panel B of Table 2). Putting into context with my empirical result that high p80/p50 inequality works in favor of loan approval to high-income relative to low-income borrowers, this result suggests that lower house price at the bottom-tier does not improve approval rates to low-income borrowers. Another hint pointing towards the neighborhood clustering effect is the house price dispersion between the top-tercile and the bottom-tercile. Although both high p95/p80 MSAs and high p80/p50 MSAs have higher house price dispersion, the dispersion in high p95/p80 is mainly due to higher price in the top-tier, while the dispersion in high p80/p50 MSAs results from lower price in the bottom-tier. Assembling these evidence makes neighborhood segmentation a plausible channel for explaining the effect of inequality measure p80/p50 on credit distribution.

Table 10: House Price by MSA Income Inequality

	Quartile of Inequality					Group Difference		
	ALL	Q1	Q2	Q3	Q4	Q1-Q2	Q1-Q3	Q1-Q4
Panel A: Inequality p95/p80								
Top-tier House Price	296	240	261	306	377	-20.5	-65.6***	-136.5***
	(172)	(96)	(121)	(152)	(248)	(17.5)	(20.4)	(30.2)
Avg. House Price	177	152	160	181	215	-7.7	-28.5**	-62.2***
	(99)	(68)	(77)	(86)	(139)	(11.6)	(12.4)	(17.6)
Bottom-tier House Price	112	98	101	114	133	-2.5	-16*	-34.5***
	(71)	(52)	(59)	(66)	(95)	(9.0)	(9.5)	(12.3)
Top-to-Bottom House Price	2.868	2.689	2.876	2.89	3.019	-0.187	-0.2*	-0.33**
	(0.701)	(0.645)	(0.78)	(0.666)	(0.681)	(0.115)	(0.105)	(0.107)
Panel B: Inequality p80/p50								
Top-tier House Price	296	295	330	274	285	-35.7	20.6	9.2
	(172)	(130)	(205)	(172)	(171)	(27.5)	(24.4)	(24.4)
Avg. House Price	177	185	197	162	164	-11.5	23.4*	21.2
	(99)	(77)	(118)	(98)	(96)	(15.9)	(14.1)	(14.0)
Bottom-tier House Price	112	124	127	99	97	-2.6	24.6**	26.9***
	(71)	(55)	(85)	(68)	(68)	(11.5)	(9.9)	(10.0)
Top-to-Bottom House Price	2.868	2.485	2.741	2.996	3.253	-0.256***	-0.512***	-0.768***
	(0.701)	(0.51)	(0.439)	(0.653)	(0.881)	(0.076)	(0.094)	(0.115)
Panel C: Inequality p50/p20								
Top-tier House Price	296	301	285	269	329	16.6	32.4	-28
	(172)	(139)	(152)	(153)	(228)	(23.4)	(23.4)	(30.3)
Avg. House Price	177	184	170	159	195	13.5	25*	-11.2
	(99)	(73)	(86)	(85)	(138)	(12.8)	(12.7)	(17.7)
Bottom-tier House Price	112	122	110	97	119	12.1	24.7***	2.9
	(71)	(50)	(66)	(61)	(97)	(9.4)	(8.9)	(12.4)
Top-to-Bottom House Price	2.868	2.52	2.799	3.024	3.13	-0.278***	-0.504***	-0.61***
	(0.701)	(0.42)	(0.588)	(0.731)	(0.842)	(0.082)	(0.095)	(0.107)

Notes: House Price is measured in \$1000. Top-tier House Price is the average home value for houses within 65th to 95th percentile in 310 MSAs over 2001-2018 period. Avg. House Price is the average home value for houses in 310 MSAs over 2001-2018 period. Bottom-tier House Price is the average home value for houses within 5th to 35th percentile in 310 MSAs over 2001-2018 period. Top-to-Bottom House Price is the average of the ratio Top-tier House Price/Bottom-tier House Price in 310 MSAs over 2001-2018 period. Significance levels: *($p<0.1$), ** ($p<0.05$), *** ($p<0.01$)

A Appendix Tables

Table A.1: Balancing of Covariates by MSA Income Inequality

	Quartile of Inequality					Group Difference		
	ALL	Q1	Q2	Q3	Q4	Q1-Q2	Q1-Q3	Q1-Q4
Panel A: Inequality p95/p80								
Avg. applicant income	87.1	74.3	79.9	90.5	103.8	-5.7**	-16.3***	-29.6***
	(25.4)	(12.4)	(15.2)	(27.1)	(31.3)	(2.2)	(3.4)	(3.8)
Panel B: Inequality p80/p50								
Avg. applicant income	87.1	83.1	91.1	84.8	89.5	-8.0**	-1.7	-6.4*
	(25.4)	(18.8)	(30.1)	(22.8)	(28.2)	(4.0)	(3.3)	(3.8)
Panel C: Inequality p50/p20								
Avg. applicant income	87.1	86.3	86.0	83.6	92.6	0.3	2.7	-6.3
	(25.4)	(21.4)	(27.7)	(21.3)	(29.8)	(4.0)	(3.4)	(4.2)

Notes: Income and loan amounts are measured in $1000. Significance levels: *(p<0.1), ** (p<0.05), *** (p<0.01)

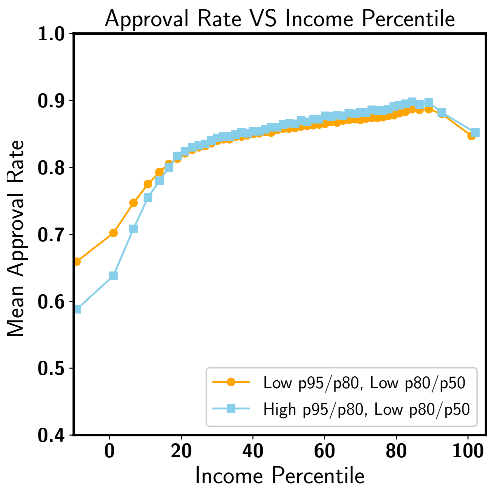
Table A.2: Loan Approval, Income Inequality and Applicant Income

	2009:2012		2013:2018	
Prob.(Loan Approval)	(1)	(2)	(3)	(4)
Log(Applicant Income)	0.076***	-0.044	0.074***	0.056
	(0.004)	(0.046)	(0.004)	(0.050)
Income Inequality: p95/p80		0.250***		0.308***
		(0.071)		(0.082)
Log(Applicant Income) × p95/p80		-0.044***		-0.068***
		(0.015)		(0.017)
Income Inequality: p80/p50		-0.246***		-0.378***
		(0.092)		(0.082)
Log(Applicant Income) × p80/p50		0.049**		0.084***
		(0.020)		(0.017)
Income Inequality: p50/p20		-0.107**		0.072
		(0.054)		(0.065)
Log(Applicant Income) × p50/p20		0.044***		-0.009
		(0.012)		(0.012)
Loan-to-Income	0.006***	0.006***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Log(Median Applicant Income)	-0.055	-0.045	-0.036*	-0.015
	(0.052)	(0.051)	(0.021)	(0.021)
Log(Median MSA Income)	-0.059*	-0.246***	-0.023*	-0.107**
	(0.031)	(0.090)	(0.013)	(0.043)
Log(Avg. Application Loan Amount)	0.139***	0.109**	-0.004	0.003
	(0.052)	(0.050)	(0.022)	(0.020)
Unemployment Rate	0.001	0.002	-0.005***	-0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Log(Median House Price)	-0.126***	-0.091***	-0.034*	-0.021
	(0.034)	(0.033)	(0.019)	(0.019)
Constant	1.764***	2.491***	1.242***	1.287***
	(0.243)	(0.492)	(0.170)	(0.312)
MSA FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Number of Loans	10,602,013	10,602,013	21,540,220	21,540,220
R^2	0.026	0.027	0.028	0.028
Number of MSAs	309	309	309	309

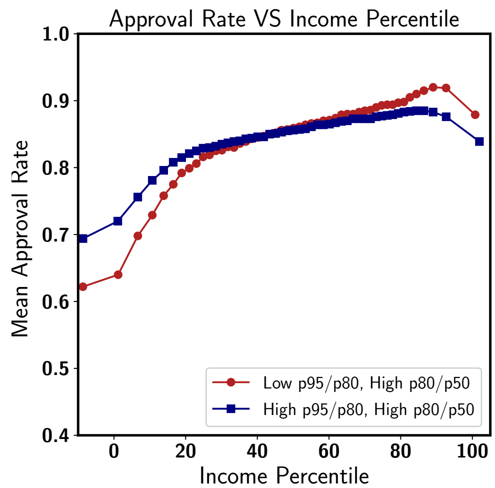
Notes: Income, loan amount and house price are measured in \$1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: ** (p<0.05), *** (p<0.01)

B Appendix Figures

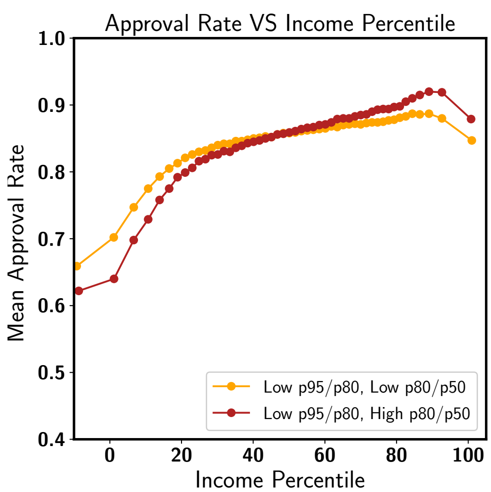
Figure B.1: Binscatter with controls: Prob.(Loan Approval) VS Income Percentile by inequality category



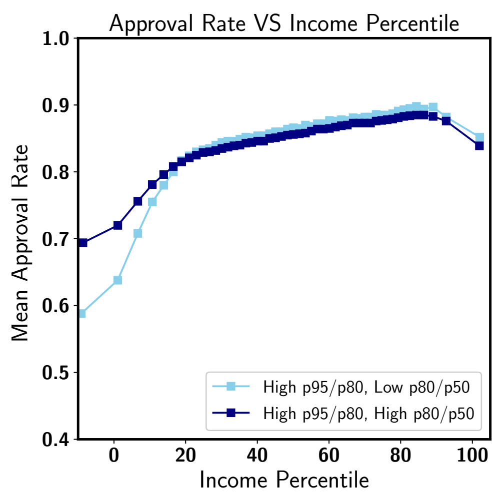
(a) Inequality Category: (I) vs (III)



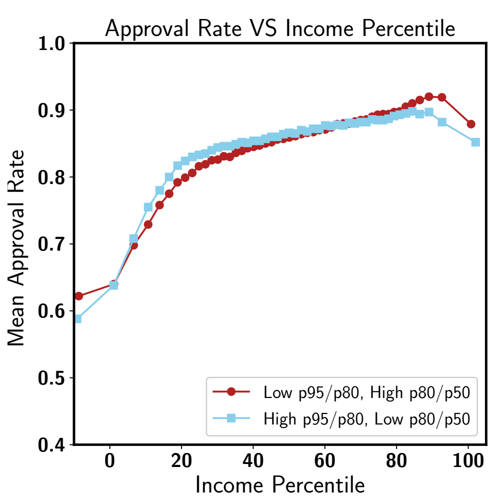
(b) Inequality Category: (II) vs (IV)



(c) Inequality Category: (I) vs (II)



(d) Inequality Category: (III) vs (IV)



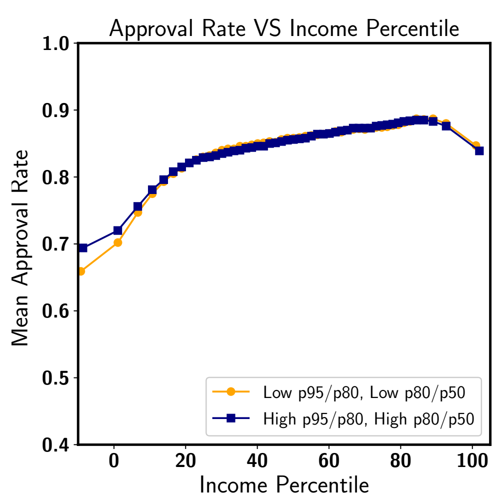


Table B.3: Loan Approval, Inequality Combination and Applicant Income

Prob.(Loan Approval): 2001 to 2008	(1)	(2)	(3)	(4)	(5)	(6)
Log(Applicant Income)	0.067***	0.088***	0.068***	0.067***	0.101***	0.063***
	(0.006)	(0.007)	(0.006)	(0.010)	(0.007)	(0.005)
$\mathbb{1}$\{high p95/p80, low p80/p50\}	-0.038				0.091*	
	(0.041)				(0.051)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} ×	0.008				-0.019*	
Log(Applicant Income)	(0.010)				(0.010)	
$\mathbb{1}$\{high p95/p80, high p80/p50\}		0.106**		0.002		-0.018
		(0.046)		(0.050)		(0.038)
$\mathbb{1}$\{high p95/p80, high p80/p50\} ×		-0.033***		-0.013		-0.007
		(0.010)		(0.012)		(0.009)
$\mathbb{1}$\{low p95/p80, high p80/p50\}			-0.117***			
			(0.030)			
$\mathbb{1}$\{low p95/p80, high p80/p50\} ×			0.027***			
Log(Applicant Income)			(0.007)			
$\mathbb{1}$\{low p95/p80, low p80/p50\} (omitted)	0.000		0.000			0.000
	(0.000)		(0.000)			(0.000)
$\mathbb{1}$\{low p95/p80, high p80/p50\} (omitted)		0.000			0.000	
		(0.000)			(0.000)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} (omitted)				0.000		
				(0.000)		
Income Inequality: p50/p20	0.075**	0.071	0.085***	0.048	0.122*	0.037
	(0.030)	(0.046)	(0.033)	(0.052)	(0.062)	(0.036)
Loan-to-Income	0.012***	0.003	0.013***	0.002	0.019***	0.006**
	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Log(Median Applicant Income)	-0.125**	-0.052	-0.124***	-0.019	0.123	-0.183***
	(0.059)	(0.060)	(0.047)	(0.079)	(0.125)	(0.052)
Log(Median MSA Income)	-0.339***	-0.353***	-0.337***	-0.339***	-0.261*	-0.375***
	(0.075)	(0.082)	(0.080)	(0.103)	(0.142)	(0.064)
Log(Avg. Application Loan Amount)	0.127***	0.102*	0.148***	0.089*	0.141*	0.113***
	(0.044)	(0.052)	(0.047)	(0.051)	(0.083)	(0.042)
Unemployment Rate	-0.011**	-0.018***	-0.011***	-0.015***	-0.013**	-0.011***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)	(0.002)
Log(Median House Price)	-0.179***	-0.238***	-0.183***	-0.251***	-0.300***	-0.167***
	(0.043)	(0.067)	(0.038)	(0.078)	(0.056)	(0.036)
Constant	3.844***	4.381***	3.735***	4.578***	3.557***	4.281***
	(0.366)	(0.449)	(0.324)	(0.424)	(0.748)	(0.265)
MSA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Number of Loans	10,509,707	11,369,187	10,821,780	11,057,114	3,329,717	18,549,177
R^2	0.025	0.025	0.029	0.024	0.034	0.026

Notes: Income, loan amount and house price are measured in $1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: *(p<0.1), ** (p<0.05), *** (p<0.01)

Table B.4: Loan Approval, Inequality Combination and Applicant Income

Prob.(Loan Approval): 2009 to 2018	(1)	(2)	(3)	(4)	(5)	(6)
Log(Applicant Income)	0.073***	0.088***	0.075***	0.067***	0.099***	0.067***
	(0.004)	(0.008)	(0.004)	(0.007)	(0.008)	(0.005)
$\mathbb{1}$\{high p95/p80, low p80/p50\}	-0.034				0.068*	
	(0.027)				(0.036)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} $\times$	0.004				-0.018**	
Log(Applicant Income)	(0.005)				(0.008)	
$\mathbb{1}$\{high p95/p80, high p80/p50\}		0.090**		0.026		0.004
		(0.040)		(0.036)		(0.031)
$\mathbb{1}$\{high p95/p80, high p80/p50\} $\times$		-0.022**		-0.004		0.000
		(0.009)		(0.008)		(0.007)
$\mathbb{1}$\{low p95/p80, high p80/p50\}			-0.097***			
			(0.027)			
$\mathbb{1}$\{low p95/p80, high p80/p50\} $\times$			0.023***			
Log(Applicant Income)			(0.006)			
$\mathbb{1}$\{low p95/p80, low p80/p50\} (omitted)	0.000		0.000			0.000
	(0.000)		(0.000)			(0.000)
$\mathbb{1}$\{low p95/p80, high p80/p50\} (omitted)		0.000			0.000	
		(0.000)			(0.000)	
$\mathbb{1}$\{high p95/p80, low p80/p50\} (omitted)				0.000		
				(0.000)		
Income Inequality: p50/p20	0.028**	0.088***	0.019	0.099***	0.012	0.067***
	(0.014)	(0.017)	(0.017)	(0.016)	(0.013)	(0.017)
Loan-to-Income	0.009***	0.001	0.011***	-0.002	0.013***	0.003
	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.003)
Log(Median Applicant Income)	-0.062**	-0.110*	0.019	-0.126**	-0.004	-0.104***
	(0.027)	(0.061)	(0.041)	(0.050)	(0.062)	(0.040)
Log(Median MSA Income)	-0.066	-0.148***	-0.056	-0.177***	-0.077	-0.109***
	(0.041)	(0.037)	(0.039)	(0.045)	(0.052)	(0.030)
Log(Avg. Application Loan Amount)	0.041*	0.044	0.060**	0.004	0.153***	0.028
	(0.021)	(0.002)	(0.024)	(0.046)	(0.049)	(0.018)
Unemployment Rate	-0.003***	-0.004**	-0.002**	-0.006***	0.001	-0.005***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Log(Median House Price)	-0.019	-0.016	-0.072***	0.017	-0.156***	0.007
	(0.015)	(0.033)	(0.025)	(0.024)	(0.037)	(0.020)
Constant	1.051***	1.307***	1.210***	1.382***	1.787***	1.093***
	(0.181)	(0.244)	(0.199)	(0.199)	(0.312)	(0.187)
MSA FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Number of Loans	7,376,468	7,574,749	8,064,198	6,887,019	2,714,604	12,236,613
R^2	0.025	0.027	0.033	0.024	0.040	0.028

Notes: Income, loan amount and house price are measured in $1000. Robust standard errors clustered at the MSA level in parentheses. Significance levels: *(p<0.1), ** (p<0.05), *** (p<0.01)

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