Credit Growth and the Financial Crisis: A New Narrative*

Stefania Albanesi, University of Pittsburgh, NBER and CEPR
Giacomo DeGiorgi, University of Geneva
Jaromir Nosal, Boston College

July 31, 2017

Abstract

A broadly accepted view contends that the 2007-09 financial crisis in the U.S. was caused by an expansion in the supply of credit to subprime borrowers during the 2001-2006 credit boom. The expansion in subprime credit led to the spike in defaults and foreclosures that sparked the crisis. The subsequent severe contraction in credit caused a decline in household consumption that substantially contributed to the ensuing recession. We use a large administrative panel of credit report data to examine the evolution of household debt and defaults between 1999 and 2013. Our findings suggest an alternative narrative that challenges the large role of subprime credit for the crisis. We show that credit growth between 2001 and 2007 was concentrated in the prime segment, and debt to high risk borrowers was virtually constant for all debt categories during this period. The rise in mortgage defaults during the crisis was concentrated in the middle of the credit score distribution, and mostly attributable to real estate investors. We argue that previous analyses confounded life cycle debt demand of borrowers who were young at the start of the boom with an expansion in credit supply over that period. Moreover, A positive correlation between the concentration of subprime borrowers and the severity of the 2007-09 recession found in previous research is driven by the high incidence of young, low education, minority individuals in zip codes with high fraction of subprime.

*We are grateful to Christopher Carroll, Gauti Eggertsson, Nicola Gennaioli, Virgiliu Midrigan, Giuseppe Moscarini, Joe Tracy, Eric Swanson, Paul Willen and and many seminar and conference participants for useful comments and suggestions. We also thank Matt Ploenzke, Harry Wheeler and Richard Svoboda for excellent research assistance. Correspondence to: stefania.albanesi@gmail.com.

1 Introduction

The broadly accepted narrative about the financial crisis is based on the findings in Mian and Sufi (2009) and Mian and Sufi (2016) suggesting that most of the growth in credit during the 2001-2006 boom was concentrated in the subprime segment and most of the new defaults during the 2007-2009 crisis were also concentrated in this segment. The expansion of subprime credit is then viewed as a leading cause for the crisis, having lead to a rise in insolvencies and foreclosures, which causes a contraction of credit supply and a decline in house prices that also otherwise solvent households (see Mian and Sufi (2011), Mian and Sufi (2010), Mian, Sufi, and Trebbi (2011) and Mian, Rao, and Sufi (2013)).

This paper studies the evolution of household borrowing and default between 1999 and 2013, leading up and following the 2007-09 great recession. Our analysis is based on the Federal Reserve Bank of New York Consumer Credit Panel/Equifax data, a large administrative panel of anonymous credit files from the Equifax credit reporting bureau. The data contains information on individual debt holdings, delinquencies, public records and credit scores. We examine the evolution of debt and defaults for variety of debt categories during the credit boom and throughout the financial crisis and its aftermath. Our findings suggest an alternative narrative that challenges the view that the expansion of the supply of credit, especially mortgage loans, to subprime borrowers played a large role in the credit boom in 2001-2007 and the subsequent financial crisis. Specifically, we show that credit growth between 2001 and 2007 is concentrated in the middle and high quartiles of the credit score distribution. Borrowing by individuals with low credit score is virtually constant for all debt categories during the boom. We also find that the the rise in defaults during the financial crisis is concentrated in the middle and upper quartiles of the credit score distribution. While low credit score individuals typically have higher default rates than individuals with higher credit scores, during the financial crisis the fraction of mortgage delinquencies to the lowest quartile of of the credit score distribution drops from 40% to 30%, and the fraction of foreclosures from 70% to 35%.

Mian and Sufi (2009) and Mian and Sufi (2016) identify subprime individuals based on their credit score in 1996 and 1997, respectively. We show that, since low credit score individuals at any time are disproportionally young, this approach confounds an expansion of the supply of credit with the life cycle demand for credit of borrowers who were young at the start of the boom. To avoid this pitfall, our approach is based on ranking individuals by a recent lagged credit score, following industry practices. This prevents joint endogeneity of credit scores with borrowing and delinquency behavior but ensures that the ranking best reflects the borrower's likely ability to repay debt at the time of borrowing. Using payroll data for 2009, we show that the cross sectional dispersion of credit scores is mostly explained by the cross sectional dispersion of labor income, conditional on age. Moreover, the lifecycle pattern of borrowing and credit scores is tightly related to the lifecycle evolution of income.

Our findings confirm and expand those in Adelino, Schoar, and Severino (2015) and Adelino, Schoar, and Severino (2017), who show that the growth in mortgage balances during the boom and the new defaults during the financial crisis are concentrated in the middle of the income distribution. We show that the large contribution of middle and upper credit score and income households to credit growth during the 2001-07 boom applies to *all* debt categories, and is associated to a stark rise in defaults and foreclosures for these households. Our results are also consistent with Foote, Loewenstein, and Willen (2016), who find that the geographical relation of mortgage debt growth and income does not change relative to previous periods during the 2001-2006 credit boom, and there is no relative growth in debt for low income households.

Our finding that borrowers in middle and high quartiles of the credit score distribution disproportionally default during the crisis is puzzling, as these borrowers historically exhibit very low default rates on any type of debt, as well as very low foreclosure rates. To gain insight on what may have driven defaults by borrowers with relatively high credit scores, we explore the role of real estate investors. Using our data, we can identify real estate investors as borrowers who exhibit 2 or more first mortgages, following Haughwout et al. (2011). There are four main reasons that may lead real estate investors to display higher default rates than other borrowers with similar credit scores. First, only mortgages contracted for a borrower's primary residence are eligible for GSE insurance. Thus, real estate investors would need to contract non-standard mortgages, such as Alt-A, Adjustable Rate Mortgages (ARMs), which charge higher interest rates and are intrinsically more risky.[1] Second, if investors are motivated by the prospect of capital gains,[2] they have an incentive to maximize leverage, as this strategy increases the potential gains from holding a property, while the potential losses are limited, especially in states in which foreclosure is non recourse.[3] Third, only the primary residences is protected in personal bankruptcy, via the homestead exemption.[4]

[1] Agarwal et al. (2016) document clear patterns of product steering by mortgage brokers, who directed borrowers eligible for conventional fixed interest rate mortgages to riskier products with higher margins, increasing default risk for standard borrowers.

[2] This is highly likely give the decline in the rent to price ratio for residential housing over this time period, as discussed in Kaplan, Mitman, and Violante (2015).

[3] Ghent and Kudlyak (2011) show that foreclosure rates are 30% higher in non-recourse state during the crisis.

[4] See Li (2009) for an excellent discussion.

Thus, a financially distressed borrower could potentially file for Chapter 7 bankruptcy and discharge unsecured debt using non exempt assets to avoid missing payments on the mortgage for their primary residence.[5] Finally, the financial and psychological costs of default for mortgage borrowers who reside in the home are typically quite substantial, as the resulting relocation would generate moving and storage costs, and possibly cause difficulties for household members in reaching their workplace or their school.

We find that real estate investors play a critical role in the rise in mortgage debt only for the middle and the top of the credit score distribution. The share of mortgage balances of real estate investors rose from 20% to 35% between 2004 and 2007 for quartiles 2 and 3 of the credit score distribution. Most importantly, we find that the rise in mortgage delinquencies is virtually *exclusively* accounted for by real estate investors. The fraction of borrowers with delinquent mortgage balances growth by 30 percentage points between 2005 and 2008 for quartiles 1-3 of the credit score distribution, and by 10 percentage points for borrowers in quartile 4, while it is virtually constant for borrowers with only one first mortgage. This striking result provides guidance to policy makers interested in designing interventions to mitigate the crisis and legislation to prevent future such episodes.[6]

We also explore the broader macroeconomic implications of our findings, linking them to the theoretical literature that emphasizes the role of the collateral channel in the transmission of financial shocks to real economic activity, and more directly, to the sizable empirical literature that uses geographical variation in mortgage borrowing to link mortgage debt growth to the severity of the recession at a regional level. There is a large theoretical literature on the role of collateral constraints in causing or amplifying swings in economic activity, following the pioneering work of Kiyotaki and Moore (1997). This literature proliferated in response to the financial crisis, leading to numerous theoretical and quantitative contributions.[7] Following the 2007-2009 recession, a large empirical literature also developed, linking the size of the credit boom and the depth of the recession in different geographical units.[8]

We examine the behavior of debt and defaults at the zip code level, using the Federal

[5] Albanesi and Nosal (2015) provide empirical evidence on the relation between consumer bankruptcy, delinquency and foreclosure, while Mitman (2016) develops a quantitative model of bankruptcy where default on unsecured debt prioritized over mortgage default.

[6] One implication of our findings is that many renters were displaced as their landlords defaulted on their mortgages, leading to foreclosure of the home. See Bazikyan (2009) for a discussion.

[7] Some recent contributions include Iacoviello (2004), Guerrieri and Lorenzoni (2011), Berger et al. (2015), Corbae and Quintin (2015),Mitman (2016), Justiniano, Primiceri, and Tambalotti (2016), Kaplan, Mitman, and Violante (2015).

[8]Some examples include Mian and Sufi (2011), Mian, Sufi, and Trebbi (2011), Mian, Rao, and Sufi (2013), Mian and Sufi (2010), Midrigan and Philippon (2016), Kehoe, Pastorino, and Midrigan (2016), Keys et al. (2014).

Reserve Bank of New York Equifax Data/Consumer Credit Panel. Because we also have access to individual data, our analysis can provide important insights into the relation between individual and geographically aggregated outcomes, shedding light on the mechanism through which credit growth affects other economic variables.[9]

Following Mian and Sufi (2009), we rank zip codes by the fraction of subprime borrowers in 1999, the first available year in our data.[10] Based on our data, zip codes in the top quartile in the distribution of the fraction of subprime borrowers exhibit larger growth in per capita mortgage balances (but not total debt balances), confirming previous findings. However, in all quartiles *prime* borrowers are responsible for most of the credit growth. The growth in mortgage debt by subprime borrowers during the boom is modest in terms of balances, and even weaker in terms of number of mortgages and originations. We also show that irrespective of the fraction of subprime borrowers, the rise in defaults during the crises is mostly driven by prime borrowers.

Based on our findings with individual level data, we examine the role of the age distribution in different quartiles of the fraction of subprime. The median age declines by quartile of the fraction of subprime, while the proportion of borrowers younger than 35 rises. This is not surprising, given that subprime borrowers are disproportionately young. We conduct counterfactuals to quantify the role of the age distribution, and find that 83% of the difference in credit growth between the 4th and 1st quartile of the fraction of subprime is accounted for by differences in the age structure of borrowers. These findings confirm and amplify our findings at the individual level on the effect of life cycle demand for credit on the observed borrowing behavior during the boom.

The empirical papers that exploit geographical variation to link the size of mortgage debt growth during the credit boom to the depth of the recession (measured in terms of consumption drops or unemployment rate increases) attribute this correlation to the tightening of collateral constraints during the crisis, resulting from mortgage defaults by high risk/low income borrowers. Our findings are not consistent with this causal mechanism. We therefore explore additional characteristics of these geographical areas that may explain this correlation. We show that several indicators that are critical to business cycle sensitivity are systematically related to the fraction of subprime borrowers. Zip codes with higher fraction of subprime borrowers are younger, as previously noted, have lower levels of educational attainment and have a disproportionately large minority and African American share in the

[9] Most existing analyses have access to either geographically aggregated data or individual data, but not both, due to small samples for the individual data.

[10] Subprime borrowers have credit scores below 660, as captured by the Equifax Risk Score. See Section 8 for more detail.

population. It is well known that younger, less educated, minority workers suffer larger and more persistent employment loss during recessions. Zip codes with a large fraction of subprime borrowers also have higher population density and exhibit more income inequality. It follows that the aggregation bias that is generated by the fact that, within zip code, prime borrowers experience larger credit growth than subprime borrowers is accentuated.[11]

Taken together, our findings suggest that using geographically aggregated data does not provide an accurate account of the patterns of borrowing at the individual level. Moreover, the positive correlation between credit growth during the boom and the depth of the recession may be due to other characteristics at the zip code level, such as the prevalence of young, minority or low education workers.

The rest of the paper is organized as follows. Section 2 provides describes the data used in this analysis. Section 3 reports the new evidence on credit growth and default behavior by credit score. Section 4 examines the role of life cycle factors for credit demand and credit scores. Section 5 explores the relation between credit score and income. Section 6 examines the behavior of debt and defaults by recent credit score and Section 7 discusses the role of investors. Section 8 presents the zip code level analysis and Section 9 concludes.

2 Data

We use the Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data (CCP), which is an anonymous longitudinal panel of individuals, comprising a 5% random sample of all individuals who have a credit report with Equifax. Our quarterly sample starts in 1999:Q1 and ends in 2013:Q3. The data is described in detail in Lee and van der Klaauw (2010). In our analysis, we use a 1% sample for the individual analysis. This includes information for approximately 2.5 million individuals in each quarter. We use the 5% sample for the zip code level analysis.

The data contains over 600 variables,[12] allowing us to track all aspects of individuals' financial liabilities, including bankruptcy and foreclosure, mortgage status, detailed delinquencies, various types of debt, with number of accounts and balances. Apart from the

[11] The distribution of the fraction of subprime borrowers is quite stable at the zip code level, and this is also true for other characteristics salient to business cycle sensitivity. Therefore, the timing of the ranking by fraction of subprime does not change zip code level patterns. However, some aggregate trends, such as the historical decline in wages, labor force participation and employment rates for unskilled, young and minority workers, and the rise in income inequality may influence economic outcomes at the zip code level over time.

[12] For data dictionary, go to `http://www.newyorkfed.org/householdcredit/2013-q3/data/pdf/data_dictionary_HHDC.pdf`.

financial information, the data contains individual descriptors such as age, ZIP code and credit score. The variables included in our analysis are described in detail in Appendix A.

3 Credit Growth and Default Behavior

The credit score is a summary indicator intended to predict the risk of default by the borrower and it is widely used by the financial industry. For most unsecured debt, lenders typically verify a perspective borrower's credit score at the time of application and sometimes a short recent sample of their credit history. For larger unsecured debts, lenders also typically require some form of income verification, as they do for secured debts, such as mortgages and auto loans. Still, the credit score is often a key determinant of crucial terms of the borrowing contract, such as the interest rate, the downpayment or the credit limit.

The most widely known credit score is the FICO score, a measure generated by the Fair Isaac Corporation, which has been in existence in its current form since 1989. Each of the three major credit reporting bureaus– Equifax, Experian and TransUnion– also have their own proprietary credit score. Credit scoring models are not public, though they are restricted by the law, mainly the Fair Credit Reporting Act of 1970 and the Consumer Credit Reporting Reform Act of 1996. The legislation mandates that consumers be made aware of the 4 main factors that may affect their credit score adversely. Based on available descriptive materials from FICO and the credit bureaus, these are payment history and outstanding debt, which account for more than 60% of the variation in credit scores, followed by credit history, or the age of existing accounts, which accounts for 15-20% of the variation, followed by new accounts and types of credit used (10-5%) and new "hard" inquiries, that is credit reports inquiries coming from perspective lenders after a borrower initiated credit application.

U.S. law prohibits credit scoring models from considering a borrower's race, color, religion, national origin, sex and marital status, age, address, as well as any receipt of public assistance, or the exercise of any consumer right under the Consumer Credit Protection Act. The credit score cannot be based on information not found in a borrower's credit report, such as salary, occupation, title, employer, date employed or employment history, or interest rates being charged on particular accounts. Finally, any items in the credit report reported as child/family support obligations are not permitted, as well as "soft" inquiries[13] and any

[13] These include "consumer-initiated" inquiries, such as requests to view one's own credit report, "promotional inquiries," requests made by lenders in order to make pre-approved credit offers, or "administrative inquiries," requests made by lenders to review open accounts. Requests that are marked as coming from employers are also not counted.

information that is not proven to be predictive of future credit performance.

We have access to the Equifax Risk Score, which is a proprietary measure designed to capture the likelihood of a consumer becoming 90+ days delinquent within the subsequent 24 months. The measure has a numerical range of 280 to 850, where higher scores indicate lower credit risk. It can be accessed by lenders together with the borrower's credit report. Mian and Sufi (2009) rank MSA zip codes by the fraction of residents with Equifax Risk Score below 660 in 1996, and Mian and Sufi (2016) rank individuals by their 1997 Vantage Score, the credit score produced by the Experian credit bureau. Based on this approach, they show that zip codes and individuals with lower credit scores exhibit stronger credit growth during the credit boom. We will show that this result is a consequence of the fact that low credit score individuals are disproportionately young and zip codes with a high share of subprime borrowers have a younger population. Individuals who are young exhibit subsequent life cycle growth in income, debt and credit scores. Hence, the growth in borrowing by individuals who have low credit score at some initial date does not necessarily reflect an expansion in the supply of credit, but simply the typical life cycle demand for borrowing.

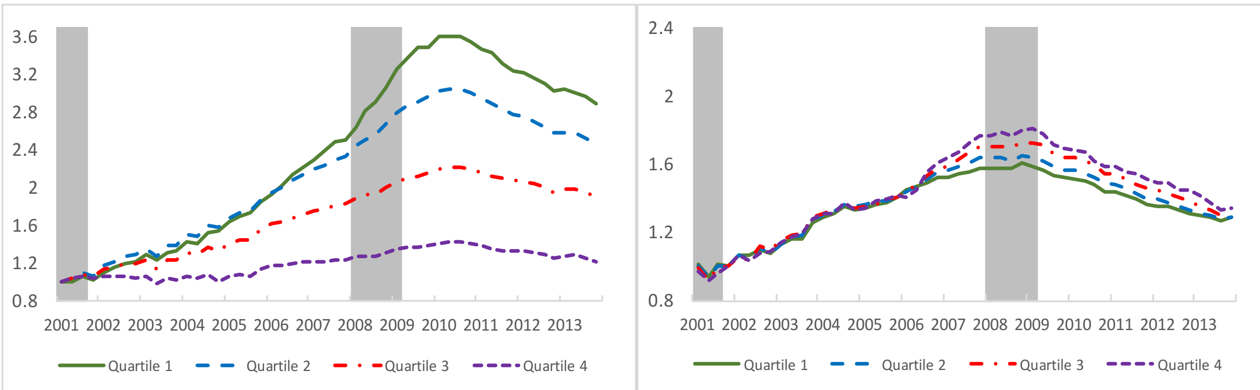
To illustrate the results associated with ranking borrowers by their initial credit score, we consider data at the individual and at the zip code level and, following Mian and Sufi (2016) and Mian and Sufi (2009), we rank them by the earliest available ranking. For individuals, we compute per capita averages by quartiles of the Equifax Risk Score distribution in 1999.

We rank zip codes by the fraction of individuals with Equifax Risk Score lower than 660 in 2001.We use credit scores for 2001 to rank zip codes to avoid small sample problems associated to missing initial credit scores for zip codes with very small population. This cutoff is a standard characterization for subprime individuals, and mirrors the approach in Mian and Sufi (2009). We then calculate a number of per capita variables by quartiles of the distribution over the fraction of subprime in 2001.

Figure 1 displays the growth of per capita mortgage debt balances relative to 2001Q3, which is the first last quarter of the 2001 recession, according to the NBER business cycle dates. The left panel displays the individual data, where borrowers are ranked based on their average credit score in 1999. The first quartile contains the individuals with the lowest credit score.[14] The right panel presents zip code level evidence. Here, quartile 1 corresponds to the zip codes with the *lowest* fraction of subprime borrowers in 2001, where subprime borrowers are identified as having an Equifax Risk Score lower than 660, following Mian and

[14]The cut-off for the individual ranking are 615 for quartile 1, 710 for quartile 2, 778 for quartile 4, and 836 for quartile 4. The cut-off used to identify subprime borrowers with the Equifax Risk Score is 660, therefore, quartile 1 comprises only subprime borrowers, while quartile 2 contains mainly prime individuals and a small subset of subprime.

Sufi (2009). The median fraction of subprime borrowers in 2001 is 19% in quartile 1, 32% in quartile 2, 44% in quartile 3 and 60% in quartile 4.[15] All statistics are computed for the population of 20-85 year old individuals.



(a) Individuals: Ranked by 1999 Equifax Risk Score (b) Zip Codes: Ranked by Fraction of Subprime in 2001

Figure 1: Per capita real mortgage balances, ratio to 2001Q3. Deflated by CPI-U. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

For the individual data, the growth in per capita mortgage balances between 2001Q3 and 2007Q4 is 146% for quartile 1, 121% for quartile 2, 74% for quartile 3, and 20% for quartile 4 of the 1999 credit score distribution. The expansion of mortgage balances continues well into and past the recession, reaching a peak of 255% for quartile 1, 188% for quartile 2, 111% for quartile 3, and 38% for quartile 4 in 2010Q2. The drop in mortgage balances in the aftermath of the crisis is very dramatic for quartiles 1 and 2, approximately one third from the peak, whereas it is considerably smaller for quartiles 3 and 4, approximately 10% and 5% from the peak.

At the zip code level, the growth of per capita mortgage balances by the fraction of subprime borrowers during the expansion is 58% for quartile 1 (lowest fraction), 64% for quartile 2, 70% for quartile 3, and 77% for quartile 4 (highest fraction). For quartile 4, mortgage balances grow by an additional 5 percentage points during the recession, while they are approximately stable for the other quartiles. Between 2009Q2 and the end of the sample, mortgage balances drop from 19% for quartile 1 to 24% for quartile 4. While at the individual level there is much more dispersion across quartiles in mortgage debt growth, both the individual and the zip code level data suggest a stronger growth in mortgage balances

[15] Section 8 presents more detailed summary statistics at the zip code level.

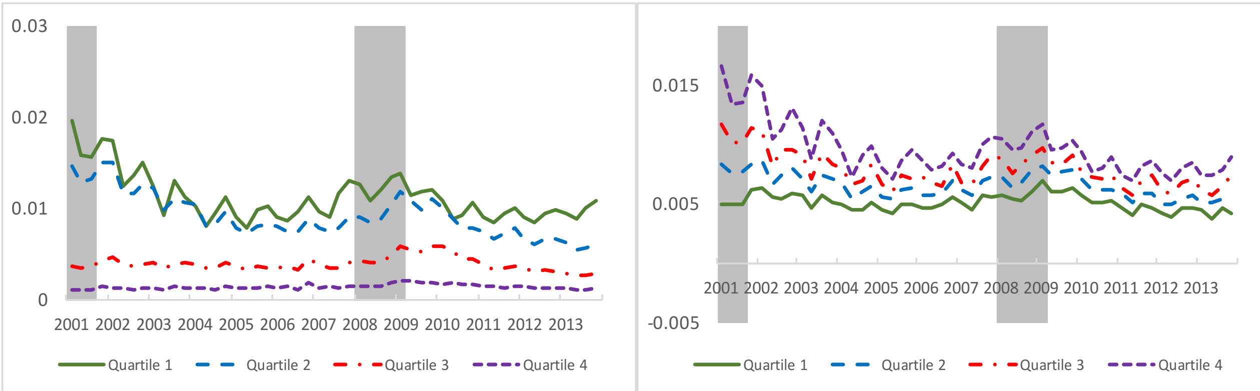
for individuals with low credit score in 1999 and zip codes with a large share of subprime borrowers in 2001.[16]

Another basic tenet of the commonly accepted view of the financial crisis is that the growth in credit extended to subprime individuals during the boom led to a rise in defaults for that segment during the crisis. Specifically, this view emphasizes that the rise in mortgage defaults and foreclosures was concentrated among subprime borrowers. We examine this premise in the next two charts, which present the per capital default rate and foreclosure rate at the individual and at the zip code level, based on the initial credit score and fraction of subprime ranking.

Figure 2 presents the per capita default rate, defined as the fraction of individuals who show a new 90+ delinquency in the last four quarters. For the individual data, the default rate for individuals in quartile 1 and 2 of the 1999 credit score distribution is quite similar and fluctuates between 1% and 2% over the same period. Individuals with credit score below the median experience a sustained reduction in the default rate until 2005 and then an increase of approximately 50% and 25% for quartile 1 and 2, respectively. For quartile 3, the default rate hover at around 0.4% until 2007Q3 when it starts rising, to peak at approximately double its pre-recession value in early 2010. For quartile 4 the default rate is an order magnitude smaller, with very little response to the recession. At the zip code level, there is a notable convergence in defaults rates across quartiles during the boom. Defaults rates start rising in mid-2007 only for quartiles 2-4, with a higher growth for quartile 4.

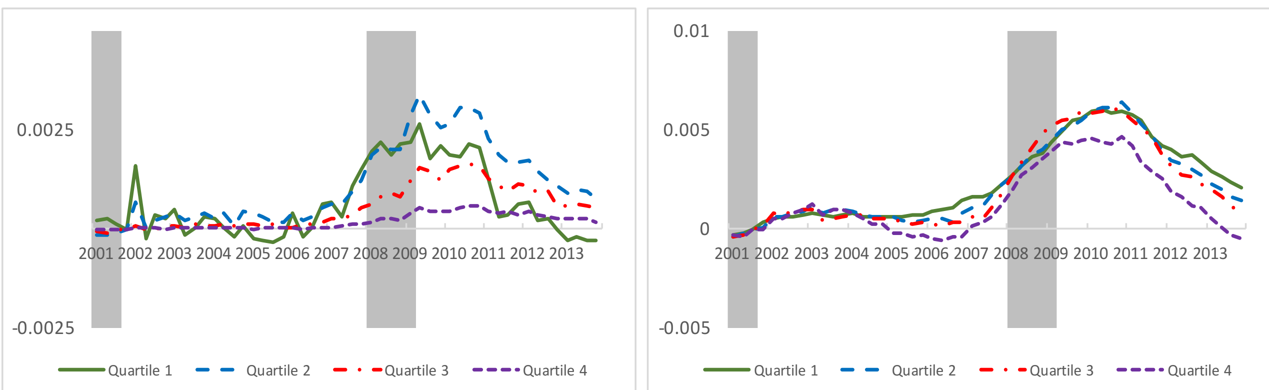
Figure 3 presents the per capita foreclosure rate, specifically the difference in this variable relative to the 2001Q3 value. For individuals (left), the foreclosure rate is virtually constant until the end of 2006. The foreclosure rates during the boom are significantly higher for individuals with low credit scores and modestly higher in zip codes with higher fraction of subprime borrowers, though these differences are very small. However, at the individual level, during the crisis they notably converge, so that the change in the foreclosure rate relative to 2006Q4 is larger for borrowers in quartile 2 than in quartile 1, and also sizable for borrowers in quartile 3. At the zip code level, the growth in the foreclosure rate is virtually identical for quartiles 1-3 and is lower for zip codes in quartile 4, which have the highest share of subprime borrowers.

[16] The growth in mortgage balances mostly involves intensive margins. If we consider mortgage originations, displayed in Appendix B, the growth is limited only to individuals with 1999 credit scores in quartiles 2-4, and occurs only in the period between 2001Q3 and the end of 2004. A similar pattern prevails at the zip code level, where and the growth in originations is negatively related to fraction of subprime borrowers, and there is virtually no growth in the fraction with new mortgage originations in the last year for quartile 4, the zip codes with the largest fraction of subprime borrowers displays the behavior of originations.



(a) Individuals: Ranked by 1999 Equifax Risk Score (b) Zip Codes: Ranked by Fraction of Subprime in 2001

Figure 2: Per capita default rate. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.



(a) Individuals: Ranked by 1999 Equifax Risk Score (b) Zip Codes: Ranked by Fraction of Subprime in 2001

Figure 3: Per capita foreclosure rate, difference from 2001Q3. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

To avoid the influence of the age distribution, in Section 6.1 we take a lenders' perspective and estimate credit growth at various horizons based on a recent lagged credit score. This approach prevents joint endogeneity between credit score and borrowing behavior, and at the same time provides a more accurate description of borrowers credit worthiness as perceived by lenders at the time in which the loans are extended. The use of a recent credit score to rank individuals, in addition to being closer to industry practices, also better reflects the probability of default at the time of borrowing. In the next section, we examine in detail the link between age, debt and credit scores. This analysis illustrates the flaws associated to using initial credit scores to rank individuals and rationalizes the use of recent credit scores by showing that the most important determinant of credit score variation, in addition to age, is income, which is closely related to a borrower's ability to remain current on debt payments.

4 The Role of Age

We now explain why ranking individuals by their credit score 15 years prior, as in Mian and Sufi (2016) and Mian and Sufi (2009) magnifies credit growth for low credit score individuals. Specifically, we will show that low credit score individuals are disproportionately young, and they experience future credit growth, as well as income and credit score growth, due to life cycle factors. As a consequence, their credit score at the time of borrowing is considerably higher than when young. On this basis, we will argue that using a recent lagged credit score provides a better assessment of a borrower's default risk. We will also show that a recent lagged credit score is closely related to income at time of borrowing.

We begin by showing that low credit score individuals are disproportionately young. Figure 5 displays the fraction of borrowers in each 1999 credit score quartile by age. We consider 5 age groups. For the youngest groups, up to age 34, the fraction is the first quartile is 44%, the fraction in the second quartile is 33%, the fraction in the third quartile is 19%, and the fraction in the fourth quartile is 5%. The weight for older age groups increases gradually by quartiles. For 45-54 year olds, the fraction in quartiles 1-4 is approximately 20%. For the oldest age group, 65 and older, the fraction in quartile 1 is 4%, while the fraction in quartile 4 is 44%. This distribution is extremely stable over time, and a similar chart for a later quarter would look virtually identical to the one for 1999 presented here.

Given their relatively young age, and correspondingly short credit history, low credit score individuals in 1999 exhibit credit score growth over time. This is illustrated in figure 5, which plots the current/1999 credit score ratio over the sample period by 1999 credit score quartile. For individuals in the first credit score quartile in 1999, the credit scores grows by more than 10% between 2001 and the end of 2013. The credit score grows by about 2% for individuals in the second quartile, and is essentially flat for quartiles 3 and 4 of the 1999 credit score distribution.

4.1 Age Effects

To more precisely assess the relation between age, credit score and credit growth, we regress the Equifax Risk Score in each quarter on age fixed effects, time effects and state fixed effects.

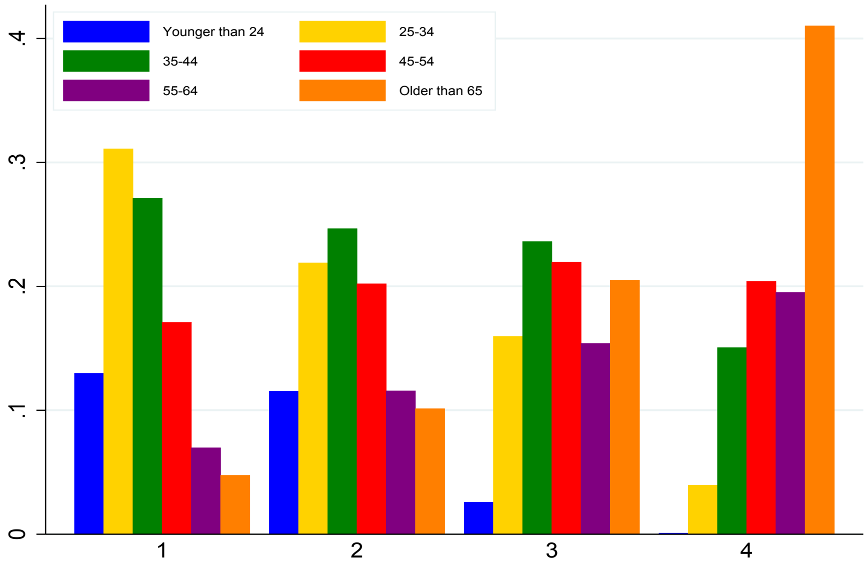


Figure 4: Fraction in each age bin in 1999 by Equifax Risk Score quartile in 1999. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

We include state effects due to the sizable cross state variation in important regulations regarding foreclosure, health insurance and other factors that could affect the incidence of financial distress and the resulting credit score distribution.[17]

Figure 6 plots the estimated age effects between age 20 and 85. The growth in credit score as a function of age is strongest between age 25 and 35, and weakest after age 65. Between the age of 25 and 35, credit score rise by approximately 40 points, and by 60 points between the age 25 and 45. Therefore, an individual in the first quartile of the credit score distribution at age 25 would typically be in the second quartile at 35 and in the third at 45.

We adopt the same approach to evaluate the relation between age and debt balances, regressing them on age fixed effects, time effects and state fixed effects. Figure 7 plots the age effects of this regression for aggregate debt balances, mortgage balances, credit card and auto loans balances. There is a striking life cycle pattern in all these measures. Mortgage balances do not start rising until age 25, then peak just above 25,000$ at age 45. Credit card balances peak at 3,000$ at age 55, whereas auto loans reach a peak of approximately 2,000$ at age 32. Total debt balances reflect the path of mortgage balances.

[17] Recall that U.S. legislation prevents credit scoring agencies to use location as a factor in their models, even if location may affect default behavior.

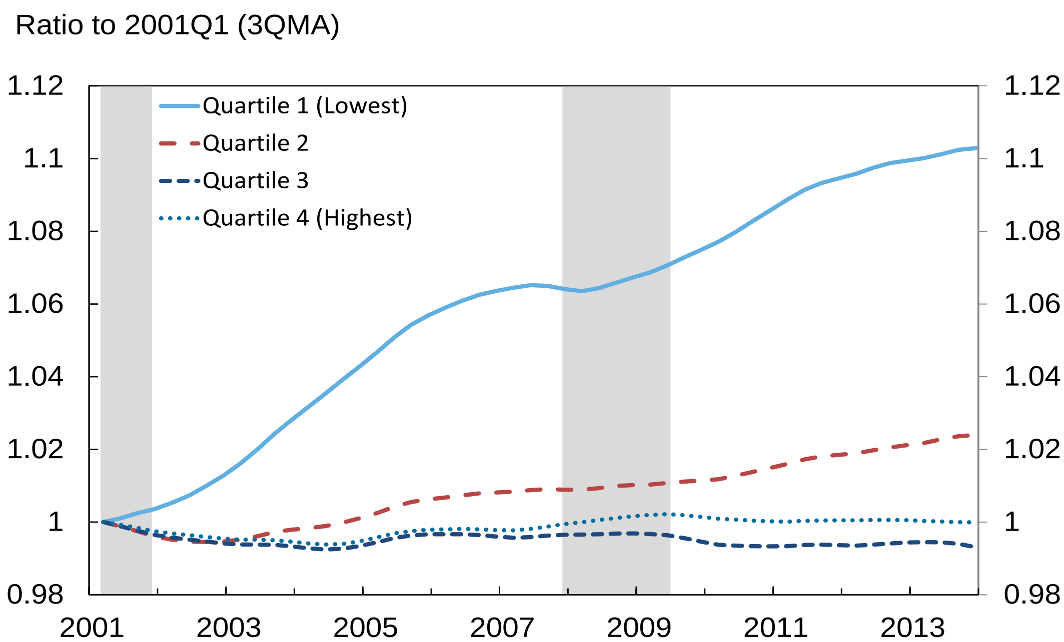


Figure 5: Current credit score as ratio to 1999, by Equifax Risk Score quartile in 1999. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

4.2 Counterfactuals

To further illustrate the role of the life cycle for credit demand, we construct a series of counterfactuals using the individual data. We will consider similar counterfactuals at the zip code level in Section 8.

The objective of these calculations is to remove life cycle effects on credit growth by assigning to borrowers in each 1999 age bin debt balances of borrowers who are in that same age bin in later quarters. For example, a 35-44 year olds in 1999 will be attributed average debt balances of current 35-44 year olds in each quarter.

Specifically, we consider the following age bins: $1 = [20, 34)$, $2 = [35, 44)$, $3 = [45, 54)$, $4 = [55, 64)$ and $5 = [65, 85]$. Let $\pi^{i,j_{1999}}$ be the fraction of individuals in age bin $i = 1, 2, ...$ and Equifax Risk Score quartile $j = 1, 2, 3, 4$ in 1999. Let $\overline{x}_t^{i_s}$ be the average value of a variable x in quarter t for individuals in age bin i in quarter s. We compute $\overline{x}_t^{i_{1999}}$ the per capita value of the variable at t for individuals in age bin i in 1999. This measure forces individuals to continue to behave according to their age in 1999 in all future time periods.

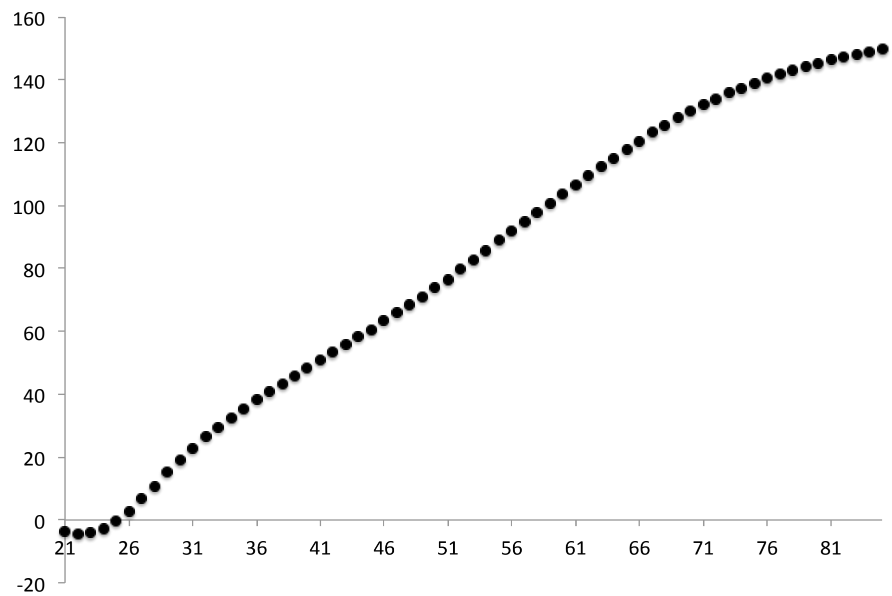


Figure 6: Equifax Risk Score. Estimated age effects. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

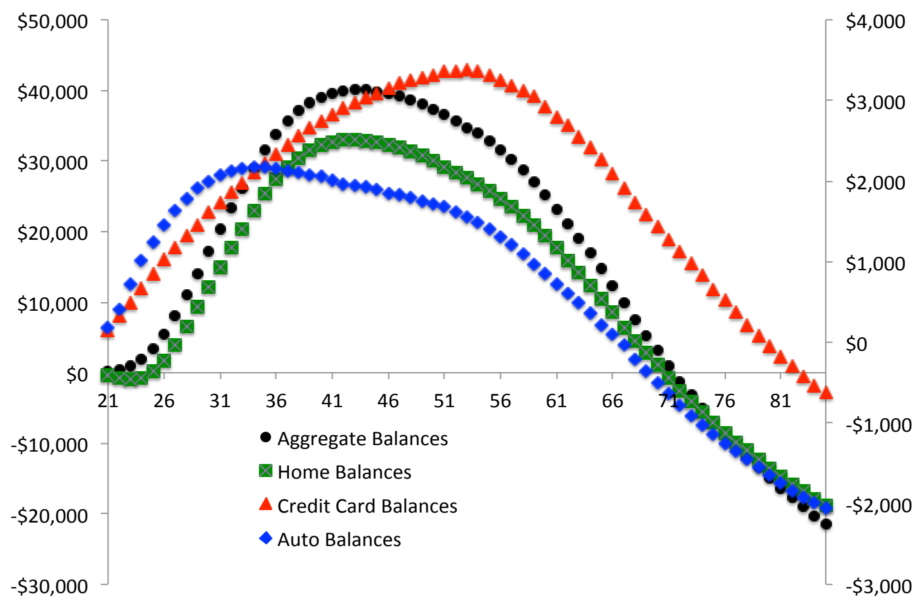


Figure 7: Estimated age effects for total debt balances and mortgage balances (left axis), and credit card and auto loan balances (right axis). Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

Since age is kept constant, this counterfactual eliminates life cycle effects.

The results are displayed in figure 8. We find that 25-34 year olds in 1999 experience more debt growth than current 25-34 year olds, whereas 45-54 and 65+ year olds in 1999 experience lower debt growth than current 45-64. The 35-44 year olds in 1999 experience very similar debt growth to the current 35-44 year olds. The gap between aggregate debt balances for individuals currently in each age group and those in that age group in 1999 measures the component of credit demand due to the life cycle. For example, in 2007Q1, aggregate debt balances for 25-34 year olds in 1999 would have been approximately 25,000$ lower if their age had remained constant. By contrast, for 55-64 year olds in 1999, per capita aggregate debt balances would have been approximately 30,000$ higher in 2007Q1 if they had not aged.

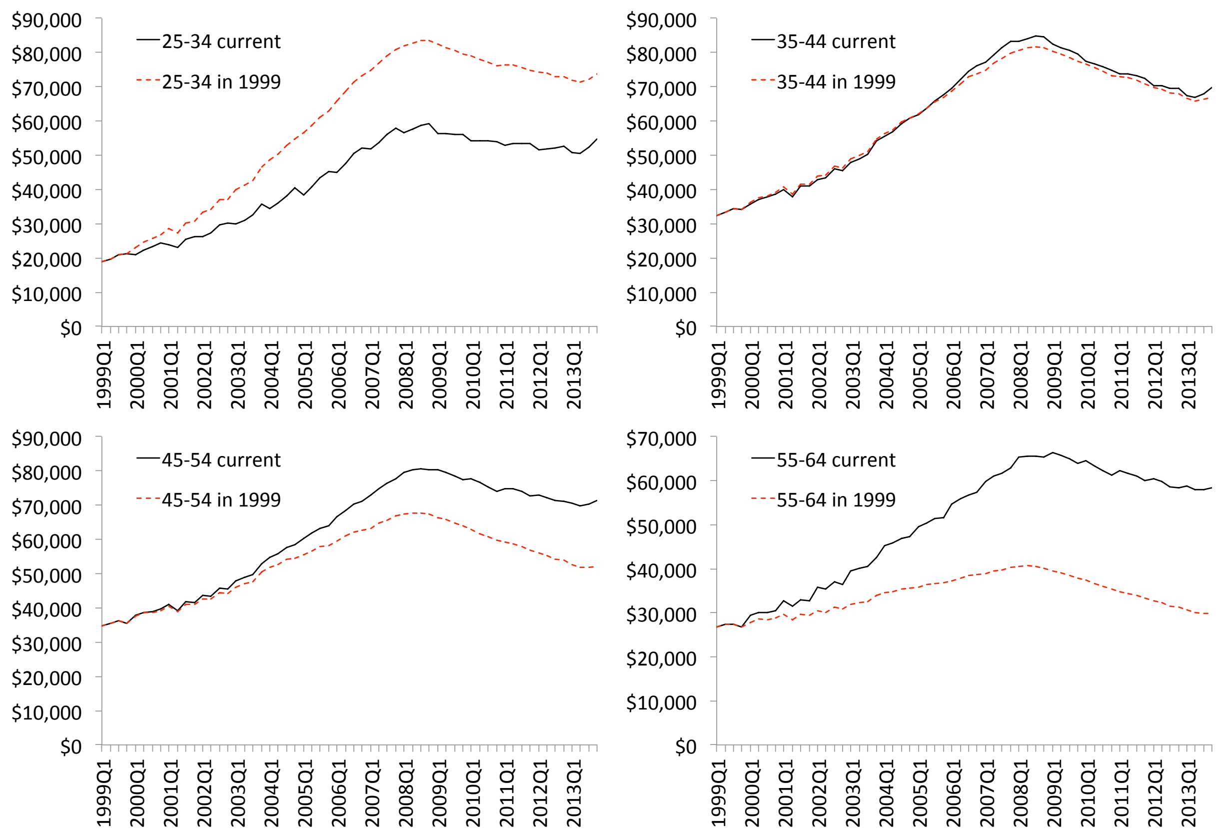


Figure 8: Aggregate debt balances by current age, and by age in 1999. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

To quantify the role of life cycle borrowing by 1999 credit score quartile, we compute the same counterfactual by credit score. Let $x_t^{i_{1999},j_{1999}}$ be the value of a variable x for individuals in age bin i and Equifax Risk Score quartile $j = 1, 2, 3, 4$ in 1999 at quarter t. Then, the value of that variable for quartile $j = 1, 2, 3, 4$ of the 1999 credit score distribution is:

$$x_t^{j_{1999}} = \sum_i \pi^{i_{1999}, j_{1999}} \times x_t^{i_{1999}, j_{1999}}. \tag{1}$$

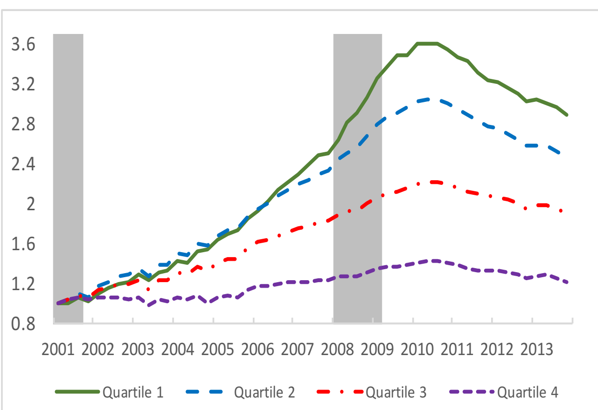
.

The first counterfactual that we consider is designed to isolate the differential role of life cycle borrowing for individuals in different quartiles of the 1999 Equifax Risk Score distribution. To do so, we maintain individuals at their age in 1999, by attributing borrowing in age bin i in 1999 and 1999 credit score quartile j the debt balances of individuals in age bin i_t and credit score quartile j_t in each subsequent quarter t. That is:

$$\hat{x}_t^{j_{1999}} = \sum_i \pi^{i_{1999}, j_{1999}} \times x_t^{i_t, j_t}. \tag{2}$$

This approach maintains borrowers' age constant to the time in which they are classified in a particular initial credit score quartile.

We compare the cumulative growth from 2001Q3 in counterfactual and actual balances by quartile of the 1999 credit score distribution. Figure 9 displays the actual and counterfactual series for mortgage debt balances. The results suggest that there is virtually no difference across quartiles in the counterfactual debt growth, which is consistent with differences in life cycle credit demand accounting for most of the difference in borrowing between the 1999 credit score quartiles.



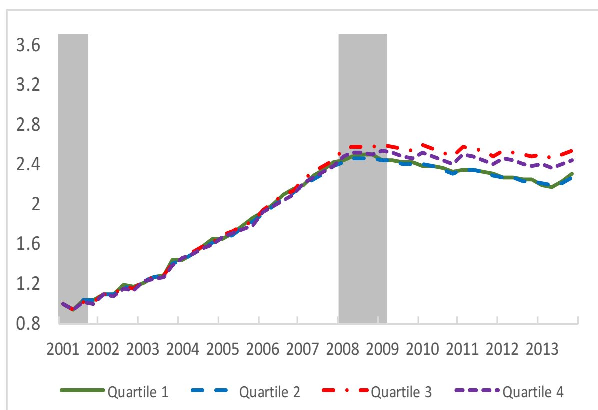


Figure 9: Real mortgage balances by 1999 Equifax Risk Score quartile, actual and counterfactual. Ratio to 2001Q3. Counterfactual assigns to each 1999 age bin, in each quarter, debt balances of those who currently are in that age bin. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

We also compute a counterfactual designed to isolate the role of differences in the age distribution of across 1999 credit score quartiles. To do so, we alternatively set the age distribution in each quartile to be the same as in quartile 1 or 4. That is, for each $j = 1, 2, 3, 4$, we compute:

$$\tilde{x}_t^{j_{1999}} = \sum_i \pi^{i_{1999}, k_{1999}} \times x_t^{i_{1999}, j_{1999}}. \tag{3}$$

Figure 10 plots the actual real growth in mortgage balances against the two counterfactuals for each quartile of the 1999 Equifax Risk Score ranking. The biggest effects can be seen for quartiles 1 and 4, which have the most extreme age distributions. For quartile 1, the growth in real mortgage balances between 2001Q3 and 2007Q4 would have been 100 percentage points lower with the quartile 4 age distribution. By contrast, the growth for quartile 4, would have been 50 percentage points higher with the quartile 1 age distribution. Based on this approach, we can compute the fraction of the difference between quartile 1 to 3 and quartile 4 in cumulative 2001Q3-2007Q4 growth in mortgage balances accounted by the difference in the age distribution relative to quartile 4. This amounts to 26% for quartile 1, 20% for quartile 2 and 14% for quartile 3.

Taken together, these results suggest that life cycle effects in borrowing are very strong and sizably effect debt growth especially for individuals at the extremes of the 1999 credit distribution. They are especially important for individuals in the first quartile of the credit score distribution in 1999, for whom most of the subsequent credit growth is due exclusively to these life cycle considerations.

5 Credit Scores, Income and Debt Over the Life Cycle

This section documents the life cycle relation between income, credit score and borrowing. Based on this analysis, we argue that a recent lagged credit score should be used to assess a borrower's probability of default, as this measure better reflects default risk at the time of borrowing. In addition, we show that the life time evolution of credit score and debt is closely related to the lifetime evolution of income. Since the ability to make timely payments on outstanding debt critically depends on income at the time of borrowing and throughout the life of the loan, the tight relation between a recent credit score and contemporaneous income conditional on age supports the notion that it should be used as an indicator of default risk.

To estimate the relation between credit scores and income, we use payroll information- so called Worknumber data- for 2009 from a large income verification firm, which is linked to the Equifax credit files. The income data is available for a subsample of over 11,000 individuals

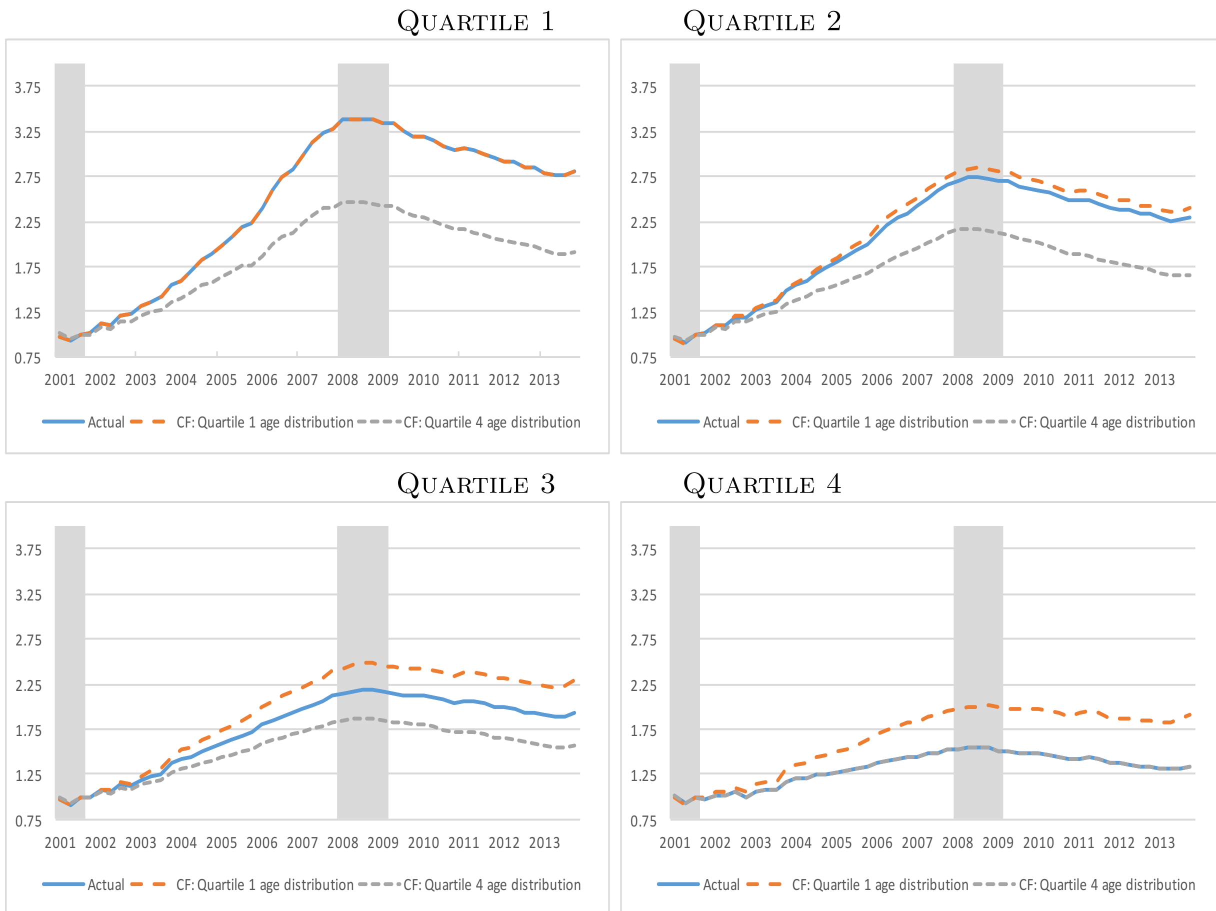


Figure 10: Real mortgage balances by 1999 Equifax Risk Score quartile, actual and counterfactual. Counterfactuals set the age distribution equal to the one for quartile 1 and quartile 4. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

in the credit panel. We construct a total labor income measure using information on pay rate and pay frequency. Appendix C reports detailed information on the construction of this income measure, and shows that the distribution of our income measure is comparable by age and location to that of similar measures obtained from the CPS and the ACS.

5.1 Cross-Sectional Relation

We first examine the cross-sectional relation between credit scores and income, conditional on age. We will show that recent credit scores are strongly positively related to income, given age, and that the slope of the relation between recent credit scores and income declines with age.

To evaluate the relation between income and credit score, we regress the 8 quarter lagged credit score on income, income square, age, age square, and interactions between age, income and state fixed effects.[18] Specifically, we estimated the following:

$$CS^i_{2009-h} = \alpha + \beta_1 y^i_{2009} + \beta_2 \left(y^i_{2009}\right)^2 + \gamma_1 \text{age}^i_{2009} + \gamma_2 \left(\text{age}^i_{2009}\right)^2 + \text{interactions} + \varepsilon^i_{2009} \quad (4)$$

where i denoted individual borrowers, CS^i_{2009-h} = is a borrower's credit score in quarter $2009 - h$, and h denotes the leads/lags in the credit score relative to income, with $h \in \{-8Q, -4Q, 0, 4Q, 8Q\}$. The coefficient α corresponds to the constant and y^i_{2009} is a borrower's total labor income in 2009.

Figure 11 displays the in sample projected relation between the 8 quarter lagged credit score and income for different age levels. The range of income levels varies by age as they do in our sample. Clearly, credit scores are strongly positively related to income given age, and the slope of this relation declines with age. We estimate the same specification for the 4 quarter lagged, current, and 4 quarter and 8 quarter ahead credit score, with very similar results.

5.2 Life-Cycle Relation

The availability of labor income data for a subsample of borrowers in 1999 and their full credit profile enables us to assess the lifecycle relation between income, credit score and debt.

We begin by relating the debt and credit score evolution from 1999 to 2009, by 2009 total labor income and 1999 age. We find that young borrowers in 1999 with high income in 2009 exhibit the largest growth in mortgage and total balances, and credit score between 1999 and 2009. Figure 12 illustrates this pattern for the 25-34 year olds in 1999 that are in our Worknumber Data sample in 2009. The charts clearly show that 25-34 year olds in 1999 who are in the top quintile of the labor income distribution in 2009 exhibit a much stronger growth in credit scores and mortgage balances. For those in the bottom quintile, the credit score rises by only 10 points between 2001 and 2009, while it grows by 40 points for those in the top quintile. Similarly, (real) mortgage balances grow by a factor of 3.3 between 2001 and and the start of the recession for the top quartile, and by a factor of 2.4 for the bottom quintile. The growth in both credit scores and mortgage debt balances is monotonely increasing in 2009 income quintile. We report only quintile 1 and 5 for clarity.

[18] Since the credit score is bounded above, we use a truncated regression approach. Standard errors are clustered at the state level.

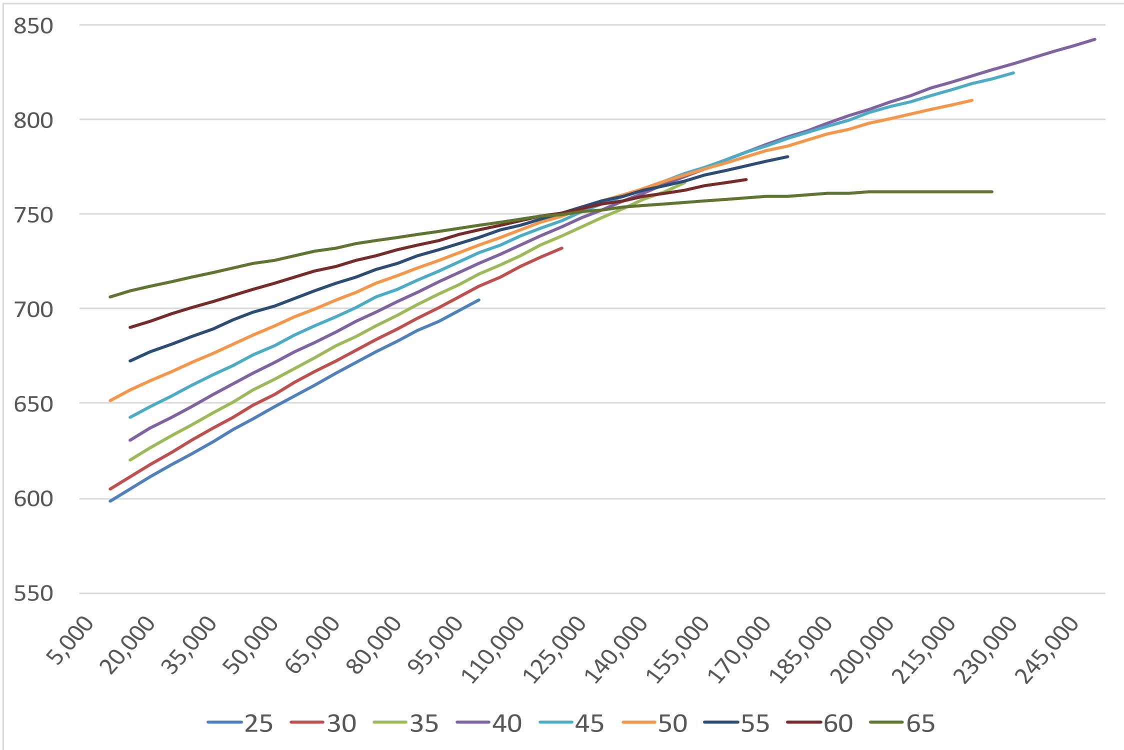


Figure 11: Predicted 8Q lagged Equifax Risk Score by age and 2009 Worknumber total annual labor income, for age specific 1-99 percentile of income range. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figures 13 and 14 present the same variables for 35-44 year olds in 1999 and 45-54 year olds in 1999. The same qualitative patterns apply, however, the magnitude of the increase in both credit score and total debt balances between 2001 and 2009 is much smaller, as credit demand is much smaller for these age groups. Appendix E presents the same charts for total debt balances, which show a very similar pattern.

Our second exercise relates credit score growth between 1999 and 2009 to income levels and debt levels in 2009 for borrowers in the bottom quartile of the credit score distribution in 1999. Table 1 summarizes these results. The columns correspond to the quartiles on the 2009 credit distributions for borrowers (of any age) that were in the first quartile of the credit score distribution in 1999. We report mean income and mean total debt balances. Clearly, 2009 income and total debt balances are increasing in the 2009 credit score, even if all these borrowers begin in the bottom quartile of the credit score distribution in 1999.

To summarize, the differences in credit growth between 2001 and 2009 are positively

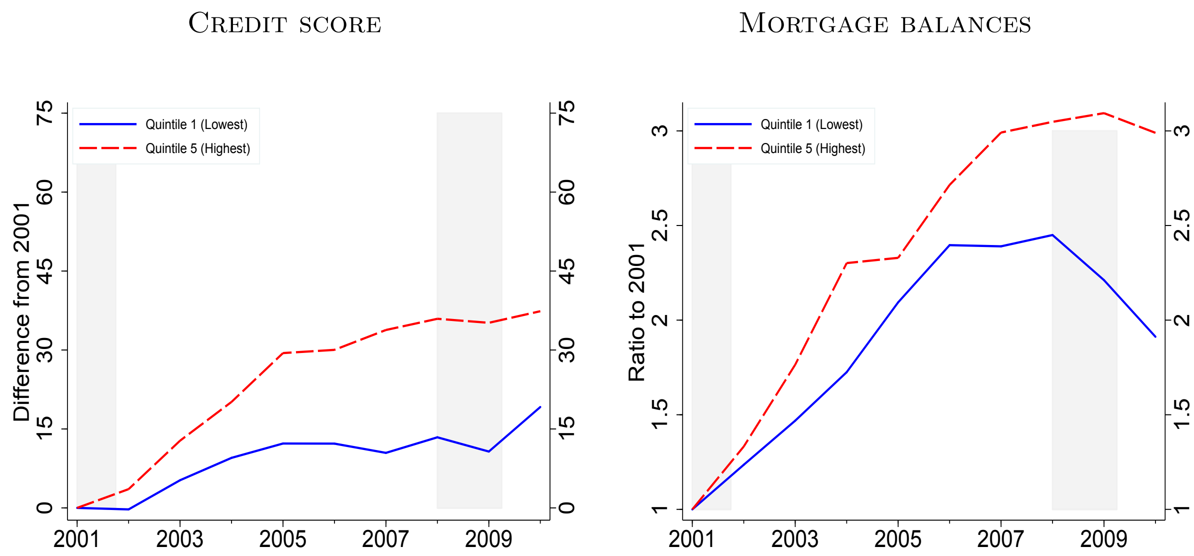


Figure 12: Equifax Risk Score and mortgage balances for 25-34 yo in 1999 by their 2009 Worknumber total annual labor income quantile. Difference with 2001 (credit score) and ratio to 2001 (balances). Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 1: Relation between Credit Score, Income and Debt Balances

2009 credit score	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Debt balances	\$38k	\$74k	\$126k	\$213k
Income	\$39k	\$47k	\$57k	\$62k

Mean income and total debt balances by 2009 Equifax Risk Score quartile for individuals in the first quartile of the 1999 Equifax Risk Score distribution. Worknumber total annual labor income for restricted Worknumber sample. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

related to life cycle growth in income and credit scores. Credit score and debt growth for young/low credit score in 1999 occurs primarily for individuals who have high income in 2009. Older individuals in 1999 exhibit much lower subsequent credit score and debt growth, still positively related to their income in 2009. The strong correlation between recent credit scores and income suggests recent credit scores better indication of default risk. These results are consistent with a lifecycle analysis of the relation between income and borrowing using PSID data, presented in Appendix F.

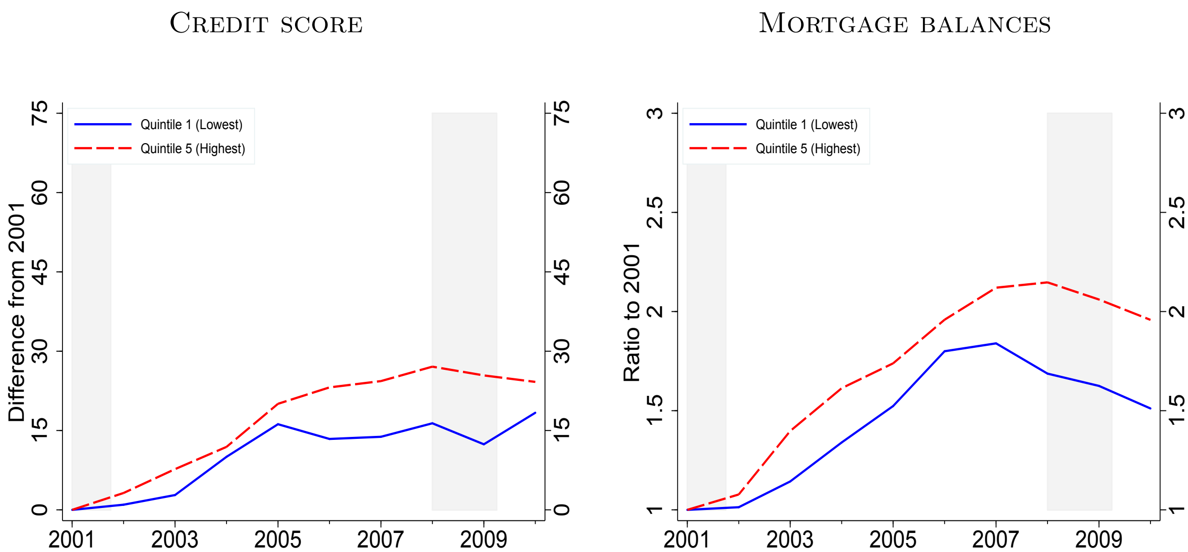


Figure 13: Equifax Risk Score and mortgage balances for 35-44 yo in 1999 by their 2009 Worknumber total annual labor income quantile. Difference with 2001 (credit score) and ratio to 2001 (balances). Source: Authors' calculations based on FRBNY CCP/Equifax Data.

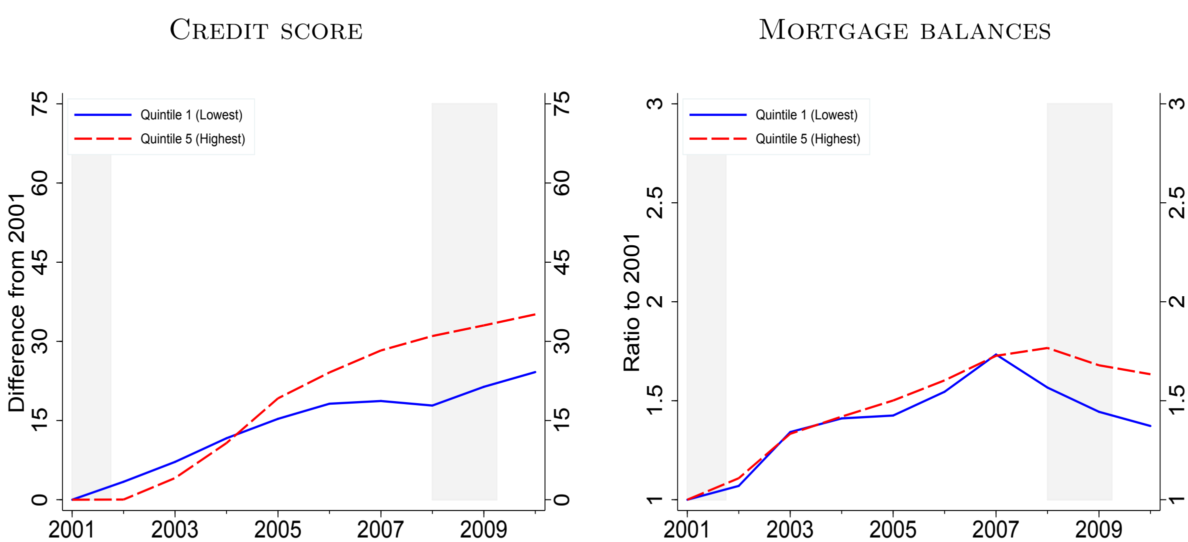


Figure 14: Equifax Risk Score and mortgage balances for 45-54 yo in 1999 by their 2009 Worknumber total annual labor income quantile. Difference with 2001 (credit score) and ratio to 2001 (balances). Source: Authors' calculations based on FRBNY CCP/Equifax Data.

6 Debt and Defaults by Recent Credit Score

We now present our approach to characterize the distribution of debt growth during the boom and defaults during the crisis based on recent credit scores. We adopt a lender's perspective, and relate future credit growth at various horizons to a recent lagged credit score to capture the credit score at the time of borrowing. This strategy is based on the observed patterns of credit extension in the U.S. An increase in debt balances between two time periods, say one year, would arise due to either a new loan or credit line, or to an increase in the maximum balance on an outstanding loan or credit line. In most cases, the borrower would have applied for the loan or the balance increase, leading the lender to check the borrower's credit score. Given that our data is quarterly and for most types of debt such requests are processed in a matter of days, the credit score in the quarter before the increase in debt balances is the best proxy of the one that would be available to the lender at the time of application.

Lenders often may also check some other variables in an applicant's credit history, such as the number of missed payments or credit utilization in the last 1-2 years. These factors would be reflected in changes in the credit score in the corresponding period. Changes in the credit score before the application date may also be motivated by the intention to borrow. For example, individuals intending to finance a car purchase may be motivated to improve their credit score in the period leading up to their purchase or to delay the purchase until their credit score has improved- for example by paying down credit card balances- in order to secure better terms. For these reasons, we also include the change in the credit score as an explanatory variable. For most unsecured debt and auto loans, lenders would not typically verify a borrower's income. For mortgage loans, lenders typically also verify a lender's recent income history. We do not have access to income, therefore, we only use the credit score in the last quarter and the change in the score between the last quarter and some previous dates as our main explanatory variables.

Our baseline specification is:

$$\Delta B^i_{t,t+h} = \sum_{j=1,2,3,4} \alpha(j_{-1}) + \eta \Delta CS^i_{t-1,t-1-k} + \text{ time fe} + \text{ age fe} + \text{ interactions} + \varepsilon^i_t, \tag{5}$$

where i denotes and individual, t denotes a quarter, $\Delta B^i_{t,t+h}$ is the change in balances between quarters t and $t+h$, and $h \in \{4, 8, 12\}$ is the horizon. The explanatory variables are $\alpha(j_{-1})$ which is a fixed effect for the 1 quarter lagged quartile of the credit score distribution and $\Delta CS^i_{t-1,t-1-k}$, which represents the change in credit score between $t-1$ and $t-1-k$, with

$k \in \{4, 6\}$ length of the credit score history considered. The baseline specification includes time $\times$ 1 quarter lagged credit score quartile interactions. In additional specifications, we also include age $\times$ 1 quarter lagged credit score quartile interactions.

Our estimates show that during the boom credit growth was highest for borrowers in the middle and top quartiles of the 1 quarter lagged credit score distribution, at all horizons. We find that past changes in the credit score have virtually no effect on subsequent balance growth. Consistent with our analysis in Section 4, we find strong age effects in in balance growth but *only* for individuals in quartile 2-4 of the 1 quarter lagged credit score distribution. We also find that the growth in delinquent balances during the crisis is concentrated in the middle of the credit score distribution.

In the rest of this section we report our findings. We complement our regression based evidence with an analysis of extensive margins, such as mortgage origination, first mortgages, foreclosures by 8 quarter lagged credit scores. We find there is no growth in the fraction with mortgages or with new mortgage originations for borrowers in the first quartile of the 8 quarter lagged credit score distribution. Additionally, consistent with Adelino, Schoar, and Severino (2015), we find that the distribution of credit score at originations is virtually constant throughout the boom. Further, we show that the rise in mortgage defaults and foreclosures is greatest for borrowers in quartiles 2 and 3 of the 8 quarter lagged credit score distribution.

6.1 Debt Growth

This section presents our regression results for mortgage balances. In Appendix G, we report results for total debt balances, credit card balances and auto loans, as well as some robustness analysis.

Our baseline specification uses the 8 quarter ahead change in mortgage balances as the dependent variable and includes the 4 quarter change in credit score as a regressor. Table 2 reports the fixed effects estimates, and figure 15 presents the interactions between the time effects and each quartile of the 1 quarter lagged credit score distribution. The credit score quartile fixed effects show a non-monotone pattern, with quartile 2 and 3 showing estimates of the average 8 quarter ahead mortgage balance change above \$9,000, approximately three times as large as the value for the first quartile, and approximately double the value for quartile 4. The coefficient on the change in the credit score distribution is \$50 for the 4 quarter lag and \$51 for the 6 quarter lag. These estimates are highly significant, though the economic impact of the past change in credit score on future debt growth seems negligible, both in terms of the size of the effect and for its small impact on the estimated average changes.

Table 2: Mortgage Balance Growth

Dependent Variable: 8Q Ahead Mortgage Balance Change					
1Q lagged CS Quartile Effects				Credit Score Change	
1	2	3	4	4Q	6Q
3,182	9,559	9,291	4,803	50	
4,129	10,164	9,787	5,173		51

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q past change from 1Q lagged score in balance change regressions, in USD. Baseline specification. All estimates significant at 1% level. Sample period 2001Q1-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 15 presents the estimated time effects for each quartile of the 1 quarter lagged credit score distribution, net of the averages presented in Table 2. The estimated time effects suggest little growth for quartile 1 during the boom, for which average 4 quarter ahead growth in balances hovers around \$1,000 between 2001Q3 and 2004Q1 and then peaks at \$3,000 in 2005. Quartiles 2-4 show a very similar increase in balances between 2001Q3 and 2004Q1, averaging approximately \$3,000 in each quarter over that period. Starting in 2004Q1, the growth rate in balances for quartiles 2 and 3 accelerates, reaching a peak of approximately \$7,000 in 2005Q4, while the growth in balances is stable over that period for quartile 4. Starting in 2006Q1, all quartiles experience a sharp decline in the 8 quarter ahead growth in mortgage balances, which bottoms out in 2009Q1 for quartile 2-4 and in 2009Q4 for quartile 1. Figure 36 in Appendix G presents the difference between the time×quartile effect interactions for quartiles 2-4 relative to quartile 1, with 5% confidence intervals. These charts clarify that the difference in time effects across quartiles is sizable and highly significant throughout the sample period.

Summing the time effects to the quartile fixed effects in Table 2, which gives us the total change in balances, suggest that mortgage balance growth was close to zero during the 2007-2009 recession, and returns to positive, though much slower than during boom, in the recovery for quartiles 2-4. For quartile 1 borrowers, however, balance growth is negative during the crisis, ranging between -\$3,000 and -\$6,000 in each quarter, and remains around these values throughout the sample period. This finding is particularly striking, since quartile 1 borrowers experienced very modest mortgage balance growth during the boom, suggesting the the costs in terms of credit contraction were mainly borne by borrowers who reaped little benefit from the previous boom.

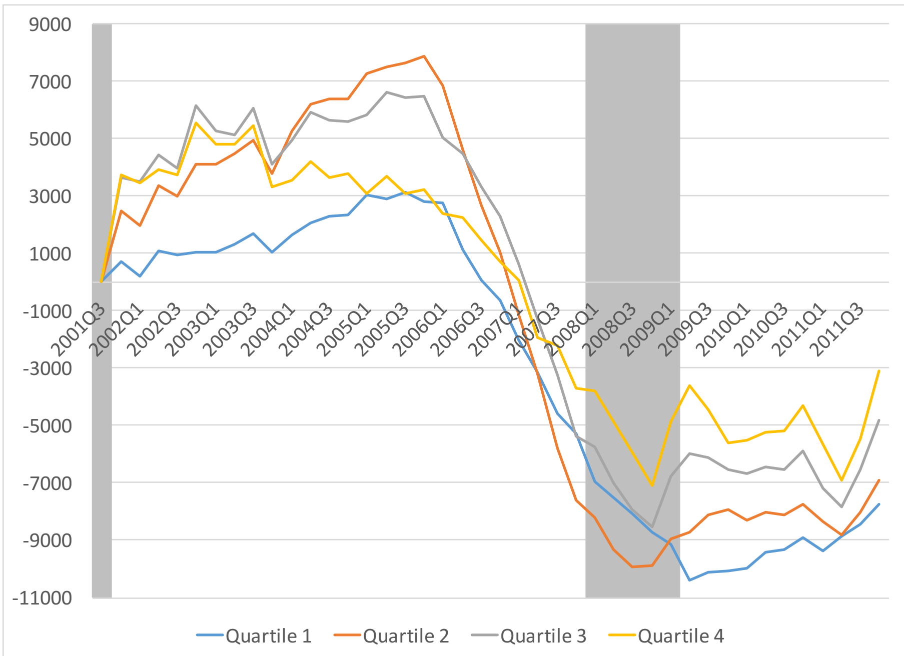


Figure 15: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita mortgage balances in USD. Sample period 2001Q1-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

The findings are very similar using the 4 quarter ahead and 12 ahead change in mortgage balances. Appendix G reports additional robustness results for the change in mortgage balances, as well the estimates for total debt balances, credit card balances and auto loan balances. For all these different types of debt, we find that the growth in balances during the boom is greatest for borrowers in quartiles 2-4, while borrowers in quartile 1 experience the largest drop in the growth in balances during the crisis.

Role of Age Figure 16 presents the estimated age effects for the baseline specification (left panel) and for the version in which the age effects are interacted with the quartile fixed effects (right panel).[19] The common age effect estimated in the left panel is consistent with

[19]The estimated quartile effects and quartile time effects differ very little across these two specifications.

our estimates in Section 4.1, since the cumulated growth in mortgage debt balances between age 20 and age 30, which corresponds to peak growth over the life cycle, based on the 8 quarter ahead change is approximately \$35,000.[20] However, the interactions between the quartile and age effects suggest that only borrowers in quartiles 2-4 of the 1 quarter lagged credit score distribution experience a life cycle growth in mortgage balances, the size of this growth is increasing with the credit score quartile. This result is consistent with our findings in Section 5, where we show that the life cycle growth in mortgage balances is closely related by the life cycle growth in income and credit scores.

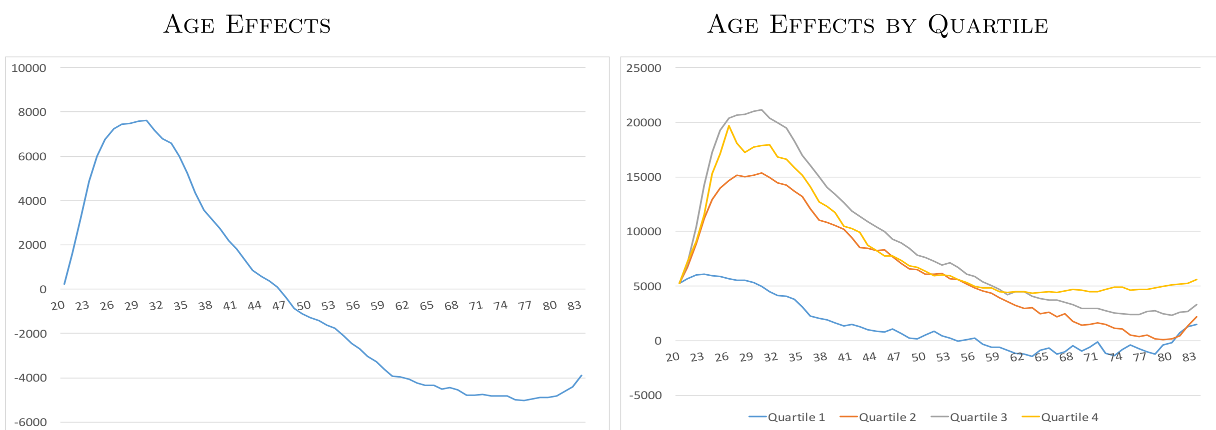


Figure 16: Estimated age effects from balance change regressions. Baseline specification (left) and specification with age×credit score quartile interactions (right). Dependent variable is the 8Q ahead change in per capita mortgage balances in USD. Sample period 2001Q3-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

6.1.1 Homeownership and Originations

To corroborate the regression analysis on mortgage balances, we also examine the borrowing behavior by recent credit score on the extensive margin. Consistent with our baseline regression specification, we rank borrowers by their 8 quarter lagged credit score. Our findings are robust to alternative recent rankings such as 4 quarter lagged credit score.

Figure 17 presents the fraction with first mortgages, which can be taken to correspond to the home ownership rate in these data, and the fraction with new originations by 8 quarter lagged credit score. Both the fraction with first mortgages and the fraction with new mortgage originations are virtually constant for quartile 1 during boom. The fraction

[20]This estimate is obtained by averaging out the quartile fixed effects and adding them to the age effects.

with first mortgages grows by approximately 10 percentage points between 2001Q3 and 2007Q4 for quartiles 2 and 3, and by about 6 percentage points for quartile 4. Quartiles 2-4 experience a boom in new originations between 2001 and 2004Q1. The fraction with new mortgage originations rises from just below 20% in 2001Q1 to 23% and 27% at the peak for quartiles 2 and 3, respectively. For quartile 4, it rises from 12% in 2001 to 22% in 2004Q1. The sizable rise in mortgage originations for prime borrowers early in the boom combined with the modest rise in the fraction of borrowers with first mortgages for that period suggests that most of the originations reflect refinancing activity[21] or real estate investing, as we document in Section 7.1 below. The fraction with new mortgage originations drops thereafter for quartiles 2-4, reaching lows of 6-8% in 2009Q2, when it starts to slowly recover. Quartile 1 only experiences a very modest rise in the fraction of borrowers with new mortgage originations between 2006Q1 and 2007Q2. Moreover, the recovery of originations after the crisis is much slower for borrowers in quartile 1.

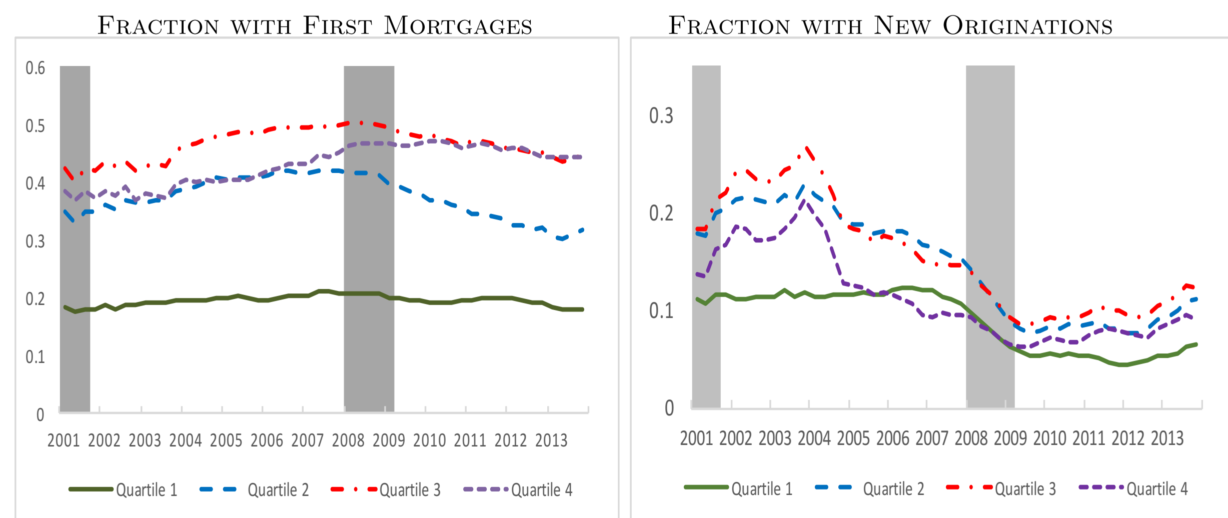


Figure 17: Fraction with first mortgages and fraction with new mortgage originations by 8Q lagged Equifax Risk Score quartile . Quartile cutoffs: 615, 720, 791, 840.
Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 18 presents the distribution of credit scores at originations for each quarter of our sample period. The fraction of new mortgage originations attributable to borrowers in quartiles 1 and 3 of the credit score distribution remains virtually constant throughout the sample period. There is a modest rise in the fraction of originations to borrowers in the

[21] Chen, Michaux, and Roussanov (2013) and Bhutta and Keys (2016) document the rise of refinancing activity during the credit boom and argue that in 2001-2004 it was mainly driven by lower mortgage rates.

second quartile, from 23% in 2003Q4 to a peak of 30% in 2006Q4, after which originations to the second quartile drop to a low of 20% in 2011Q2. The fraction of new originations to borrowers in quartile 4 of the credit score distribution peaks at 28% in 2003Q3 during the boom, but rises during the crisis from 20% in 2006Q4 to 31% in 2011Q2 and then stabilizes. This rises reflects the tightening of lending standards during the crises.[22]

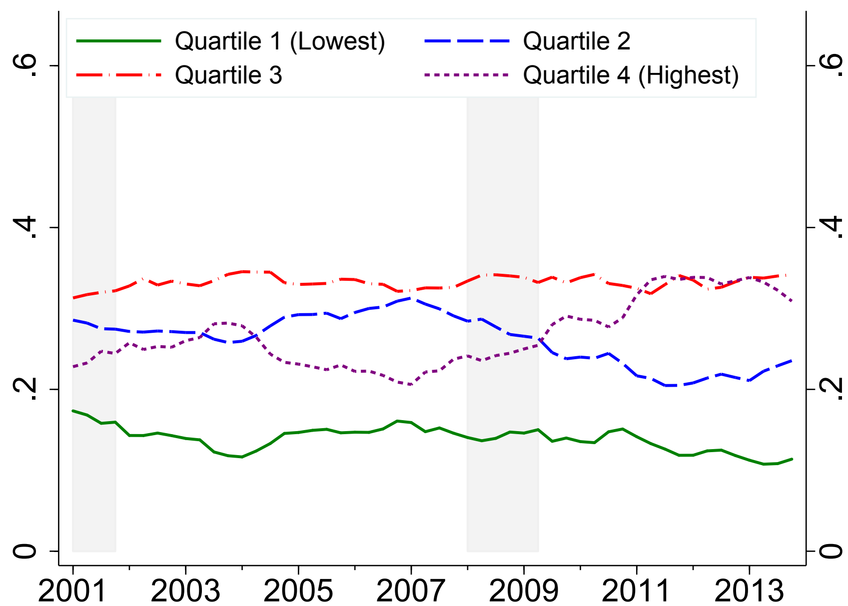


Figure 18: Individuals with a new mortgage origination. Fraction in each quartile of the 4Q lagged Equifax Risk Score distribution. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

6.2 Defaults

We now examine default activity by recent credit score. As for debt growth, we use regression analysis to examine the behavior of delinquent balances over the sample period, and then use a recent credit score ranking to the examine the distribution of mortgage delinquencies and foreclosures.

[22]See Brown et al. (2014) for a discussion.

6.2.1 Delinquent Balances

We follow the same regression specification described in Section 6.1 for the 8 quarter ahead change in 90+ days delinquent mortgage balances. The estimated quartile fixed effects are presented in Table 3. The average 8 quarter ahead change in delinquent balances falls with 1Q lagged credit score, with the estimated effects for quartiles 3-4 about half as large as for quartiles 1-2. As for debt growth, the contribution of past credit score changes to the growth in delinquent balances is negligible.

Table 3: Growth in Delinquent Balances

Dependent Variable: 8Q Ahead Delinquent Balance Change					
1Q lagged CS Quartile Effects				Credit Score Change	
1	2	3	4	4Q	6Q
505	635	227	194	33	
993	856	404	318		34

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q past change from 1Q lagged Risk Score in balance change regressions, in USD. Baseline specification. All estimates significant at 1% level. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 6.2.1 presents the balance change time effects by 1 quarter lagged credit score. There is a very large rise in the 8 quarter ahead change in delinquent balances for quartiles 2-3 starting at the end of the credit boom into the crisis. For quartile 2, the change in delinquent balances is very close to zero until 2004Q4, when it starts rising to a peak of \$5,900 in 2007Q3. For quartile 3, the growth in delinquent balances also started to pick up in 2004Q4, reaching a peak of \$3,900 in 2008Q2. Quartile 4 also experience a modest rise in the growth in delinquent balances to a peak of about \$1,000 in 2008Q2. The growth in delinquent balances declines for all borrowers during the 2007-09 recession and for about a year after. For quartiles 2-4, the growth in delinquent balances goes back to zero by 2011, whereas it hovers around -\$7,000 in 2009 and 2010 for quartile 4. This pattern is driven by the large decline in mortgage balances for borrowers in the first quartile, discussed in Section 6.1. We find similar results for the change in delinquent balances at 4 and 12 quarter ahead horizon.[23]

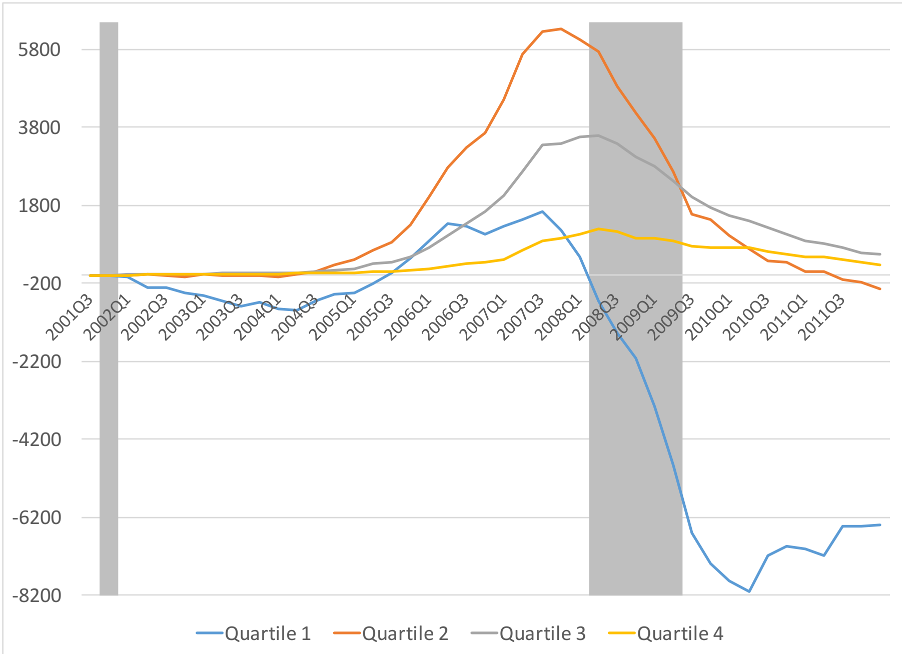


Figure 19: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

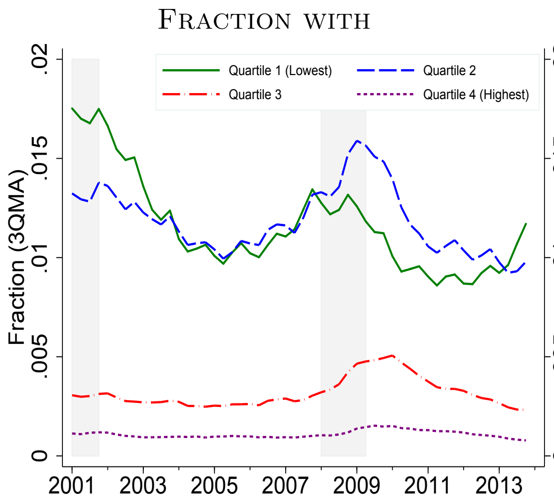
6.2.2 Defaults by Recent Credit Score

We now examine default behavior on the extensive margin by recent credit score, and again we present results by 8 quarter lagged credit score as a baseline. Results are very similar for 4 quarter lagged credit score.

Figure 20 presents the distribution of new mortgage delinquencies. The fraction of borrowers with a new 90+ days mortgage delinquencies in the last 4 quarters (left panel) is highest for borrowers in quartile 1 in 2001-2004, when it drops from 1.8% to 1% for this group. Starting in 2004Q1, the fraction with a new mortgage delinquency is very similar for borrowers in quartile 1 and 2, and starts rising for both groups. The rise for quartile 2 leading up to the crisis is much bigger that for quartile 1, so that the fraction with new delinquencies peaks at 1.3% in 2007Q2 for quartile 1 and at 1.7% in 2009Q1 for quartile 2.

[23]Appendix G.5 reports additional results for delinquent balances, including the estimated age affects.

The fraction with new delinquencies hovers around 0.3% for quartile 3 and 0.15% for quartile for during the boom. During the crisis, it rises to a peak of 0.45% in 2009Q3 for quartile 3, with a very modest rise for quartile 4 over the same period. As a result of the large rise in the fraction of new delinquencies for borrowers in quartile 2 and 3, the quartile 1 share of new delinquencies (right panel) falls by 10 percentage points during the crisis. The share of delinquencies for quartile 2 borrowers rises by 8 percentage points during the crisis and by 11 percentage points for quartile 3.



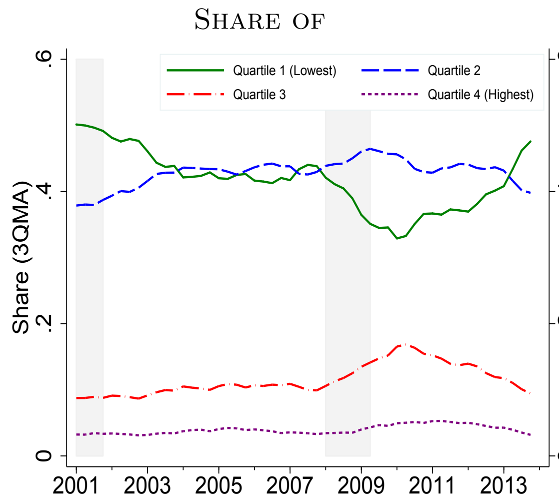


Figure 20: New 90 days+ delinquencies by credit score quartile, 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 21 presents the same statistics for new foreclosures. The quartile 1 and 2 fraction with new foreclosures in the last 4 quarters (left panel) average to 0.26% and to 0.1%, respectively, for the period ending in 2005Q2. For quartile 3 and 4, this fraction is very close to zero until 2006Q3. In mid 2006, new foreclosures start rising for all quartiles, and the rise is particularly pronounced for borrowers in quartile 2 and 3 of the 8 quarter lagged credit score distribution. As a result, the share of new foreclosures (right panel) for quartile 1 borrowers drops from 73% during the boom to a low of 39% in 2009Q1. By contrast, the share of new foreclosures to quartile 2 borrowers rises from 21% during the boom to a peak of 38% in 2009Q1. The share of foreclosures to quartile 3 also rises noticeably from around 4% during the boom, to a peak of 13% in 2009Q2, and the share for quartile 4 also experiences a 5 percentage point rise over the same period.

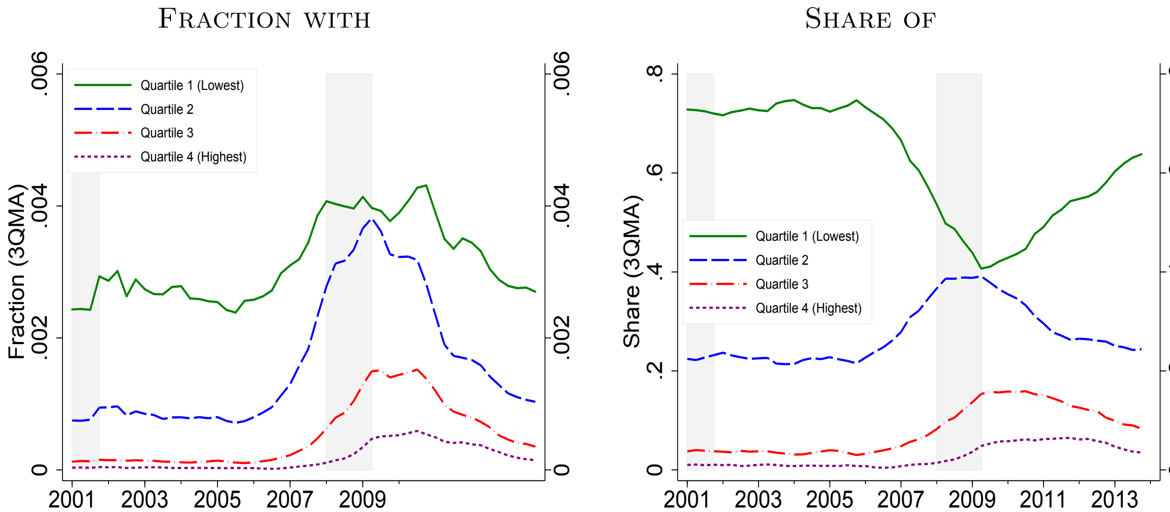


Figure 21: New foreclosures by credit score quartile, 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

6.3 Summary

We conclude this section with a brief summary of our findings. As discussed in Section 4, initial credit score rankings overstate credit growth for low credit scores borrowers. This is true for mortgage balances, but as presented in Appendix G, this observation applies to all debt categories, including total debt balances, credit card and auto loan balances.

Using a lender's approach based on recent credit scores, we find:

- credit growth during boom is concentrated in the middle and the top of the credit score distribution;
- the rise in defaults during the crisis is concentrated in the middle of credit score distribution;
- the share of new mortgage delinquencies and foreclosures to low credit score borrowers drops considerably during the crisis.

7 Explaining Defaults by Prime Borrowers

The findings presented in the previous section are puzzling given the typically very low default rates for high credit score borrowers. It is then natural to ask why did individuals with good credit histories experience defaults during crisis. In this section, we document the rise in real estate investors in the prime segment, and we show the increase in mortgage defaults among prime borrowers is primarily driven by real estate investors. We also consider the rise in non-conforming loans. We focus specifically on jumbo loans, which are not eligible for GSE insurance. We find that jumbo loans rise modestly only for prime borrowers.[24]

7.1 Role of Investors

We follow Haughwout et al. (2011) and define investors as borrowers who hold 2 or more first mortgages. Real estate investors are particularly interesting as they may be to prone to default than mortgage borrowers who reside in the property that secures the mortgage, as we discuss below. Moreover, conventional GSE sponsored mortgages are only available for primary residences, which implies investors are more likely to use alternative products, such as Alt-A mortgages, adjustable rate mortgages and other non-standard mortgages.[25] Additionally, if investors are motivated by the prospect of capital gains,[26] they have an incentive to maximize leverage, as this strategy increases potential gains, while the potential losses are limited, especially in states in which foreclosure is non recourse.

Figure 22 presents the fraction of borrowers with only 1 first mortgage and the fraction with 2 or more, among all first mortgage holders, by 8 quarter lagged credit score quartile. The fraction of investors increases with credit score quartile. Most notably, quartiles 2-4 experience a 14-16 percentage point increase in the fraction of investors between early 2004 and the start of the 2007-09 recession. For quartiles 2-3, the fraction of investors drops to pre boom levels by 2011, but it settles at the 2007 peak for borrowers in quartile 4. The fraction of investors for quartile 1 is about half of the fraction for higher quartiles, and rises only modestly during the boom.

Figure 23 reports the share of mortgage balances for borrowers with only 1 first mortgage and those with 2 or more. The time path of the the share is very similar to the path of the fraction of investors, but the share of investor balances is sizably higher than the fraction

[24] Another possibility is that the 2007-2009 was so severe that it affected relatively high income individuals and led to a rise in mortgage defaults in populations that are not usually affected. We leave this line of work for future research.

[25] Keys et al. (2012) document the sizable increase of Alt-A mortgages, that have low standard for income documentation and would be particularly appropriate for real estate investors who have variable and hard to document income. Further, Foote and Willen (2016) also discuss the role of alternative mortgage products and the fact that their structure may increase the risk of default. However, Elul and Tilson (2015) present evidence of substantial misrepresentation of home purchases as primary residences, for the purpose of qualifying for GSE sponsored mortgages.

[26] Adelino, Schoar, and Severino (2015) argue that this is the only explanation for the high levels of borrowing towards the end of the boom.

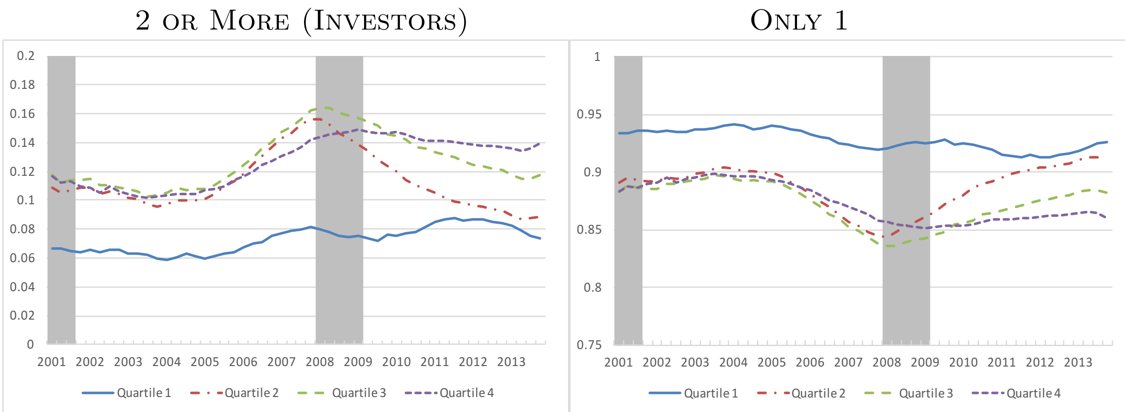


Figure 22: Fraction of borrowers with 2 or more (left panel) and only 1 (right panel) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

of investors, as balances per capita are substantially higher for investors. At the beginning of the sample, the share of mortgage balances held by investors is 15% for quartile 1, 25% for quartile 2-3 and 30% for quartile 4. This share remains mostly stable for quartile 1 borrowers throughout the sample period while it increases by approximately 15 percentage points for those in quartile 2 and 3, starting in 2004. For quartile 4 borrowers, investor mortgage balances grows steadily during the boom peaking at 43% at the start of the 2007-09 recession. During and after the recession the investor share of mortgage balances drops, reaching pre-boom levels for quartile 2, and dropping below those levels for quartiles 2 and 4. Appendix H presents the fraction of investors and the share of balances by specific number of first mortgages (only 2, only 3 and 4+), and shows that both these statistics are increasing with credit score quartile and display the same overall patterns as the combined statistics.[27]

Figure 24 and 25 report the fraction of borrowers with mortgage delinquencies and foreclosures, respectively, by number of first mortgages. Figure 24 reports the fraction of borrowers with a 90+ day mortgage delinquency by number of first mortgages. Between 2002 and 2006, delinquency rates are similar for investors and non investors for borrowers in quartiles 2-4, but more than twice as high for investors relative to non-investors for borrowers in quartile 1. For non investors, the fraction of borrowers with mortgage delinquencies approximately doubles for quartiles 1-3 of the credit score distribution, and rises very modestly for borrowers in quartile 4 from the start of 2007 until the end of 2009, returning close to pre-crisis levels rises by 2012. Strikingly, the fraction with new delinquencies rises much more strongly

[27]Bhutta (2015) also finds that new mortgages to real estate investors grew markedly during the housing boom, but he does not examine the differentiation by credit score.

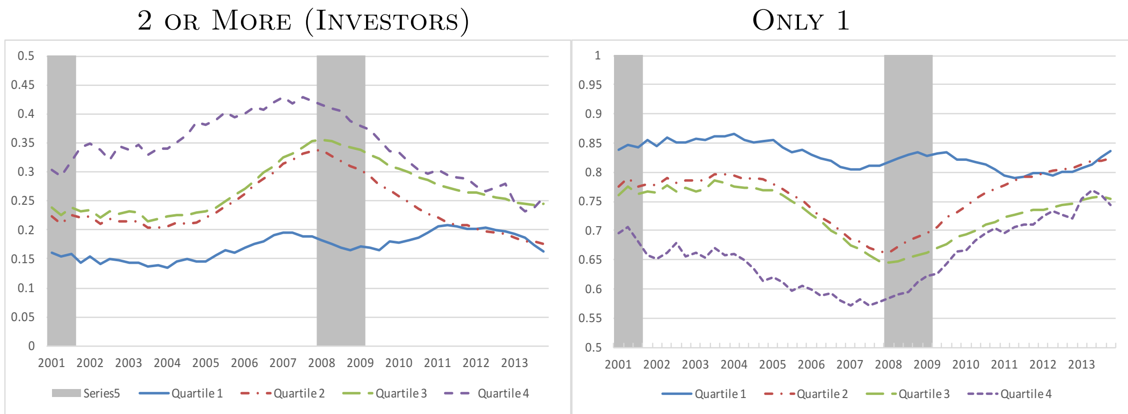


Figure 23: Share of mortgage balances held by borrowers with 2 or more (left panel) and only 1 (right panel) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

for investors than for non-investors over the same period. It roughly doubles for quartile , and exhibits a more than 5 fold increase for higher quartiles.

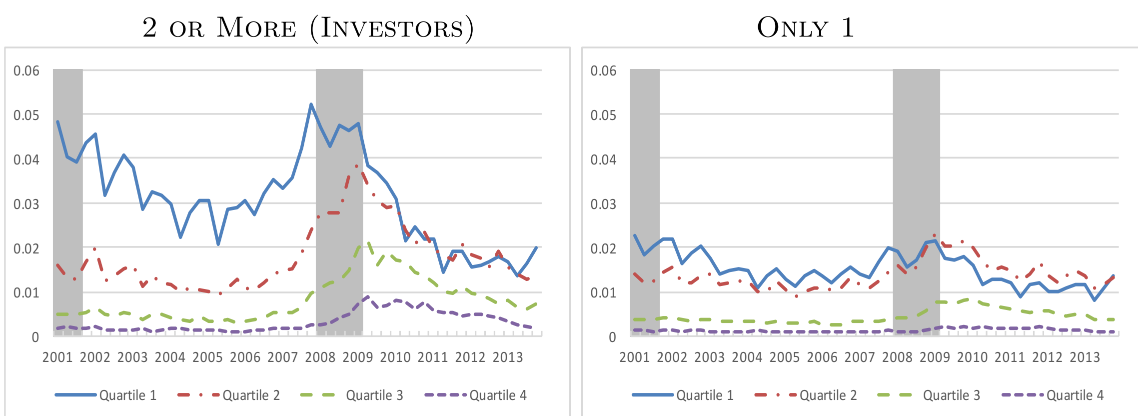


Figure 24: Fraction with new 90+ days mortgage delinquency in the last 4 quarters for borrowers with 2 or more (left panel) and only 1 (right panel) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 25 presents the fraction of borrowers with new foreclosures in the last 4 quarters. Again, during the 2002-2006 housing boom, the foreclosure rate is very similar for investors and non-investors in all quartiles, though slightly higher for investors. During the crisis, however, the foreclosure rate rises more dramatically for investors relative to non-investors. Specifically, the foreclosure rate roughly doubles for non-investors in quartile 1-2, and rises very modestly for quartiles 3-4. For investors, the foreclosure rate rises by a factor of 4 for quartile 1, by a factor of 10 or more by quartiles 2-4. Appendix H reports delinquency and foreclosure rates by specific number of first mortgages by quartile of the 8 quarter lagged credit score distribution, showing that the the rise is delinquency and foreclosure rates during the crisis is monotonically increasing in the number of first mortgages.

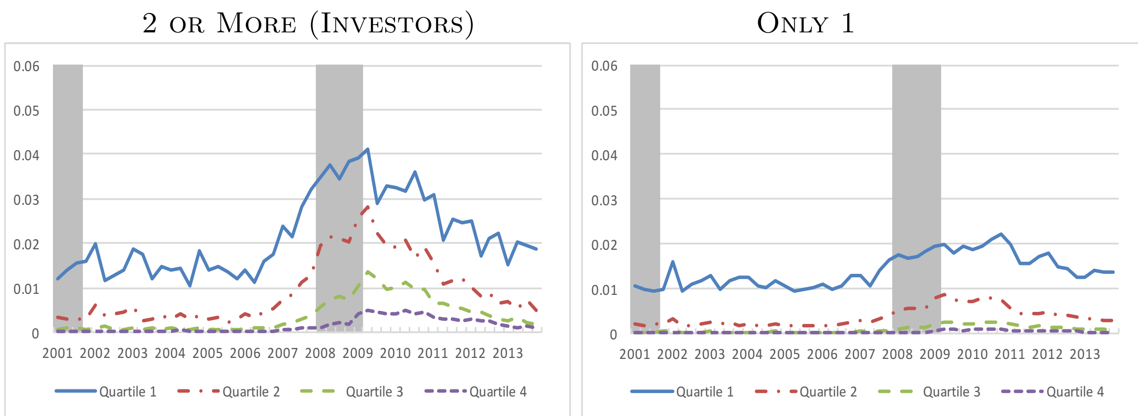


Figure 25: Foreclosure rates for 2 or more (left panel) and only 1 (right panel) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

As a consequence of the greater rise of default rates for investors relative to non-investors, the share of investor defaults rises during the crisis. Figure 26 presents the investor share of 90+ days mortgage delinquencies and foreclosures. The delinquency share of investors is about 10% for all quartiles until mid 2006. This is similar to the share of investors for quartiles 2-4, but about twice the share of investors for quartile 1 over that period. The foreclosure share of investors is about 20% on average during the 2002-2006 boom for quartiles 2-4, which is about twice the fraction of investors for those groups, whereas the investor share of foreclosures for quartile 1 is close to 10%. At the onset of the crisis, there is a sharp rise of the investor share of delinquencies, and especially foreclosures, for borrowers in quartiles 2-4 of the credit score distribution. The share of investor delinquencies rises from 10% to 17% for quartile 1, 20% for quartile 2, to 30% for quartile 3 and to 40% for quartile 4, with the peak for quartiles 1-3 occurring at the start of the 2007-09 recession, and the peak for quartile 4 at the end of the recession. The investor share of delinquencies subsequently declines, reaching pre-crisis levels by 2012 for quartiles 1-2, but remaining much higher relative to pre-recession levels for quartiles 3-4. The pattern is similar but more dramatic for foreclosures. The investor share of foreclosure rises from 20% to approximately 60% for quartiles 3 and 4, to 40% for quartile 2 and only to 15% for quartile 1 between early 2006 and the start of 2008. For quartiles 1-2, the investor share of foreclosures converges back to pre-crisis levels by the end of 2011, while it remains at more than twice the pre-crisis levels for quartiles 3-4.

Delinquency Share Foreclosure Share

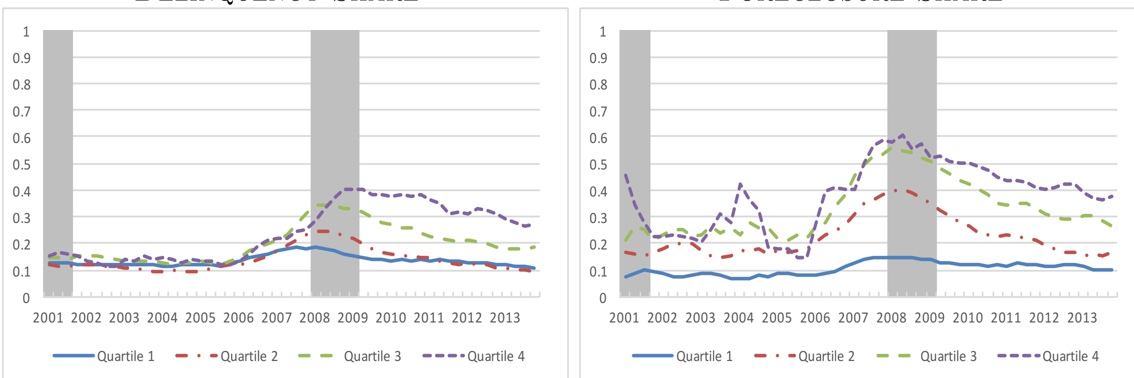


Figure 26: Investor share of 90+ days delinquencies (left panel) and foreclosures (right panel) by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

To more precisely quantify the role of investors in the growth in mortgage balances and defaults, we run a number of counterfactuals presented in Table 4. The top panel considers the growth in mortgage balances in 2001Q3-2006Q4. The first row presents the dollar change in per capita mortgage balances by quartile of the 8 quarter lagged credit score distribution over that period. The second row computes the same change in balances maintaining the distribution of the fraction of first mortgages at the 2001Q3 values, allowing balances per capita by number of first mortgages to take their historical value. Both measures are reported as a fraction of the total change.[28] The growth of mortgage balances per capita for given distribution of number of first mortgages accounts for 77% of the total for quartile 1, 62% of the total for quartiles 2 and 3, and 69% for quartile 4. The third row presents the growth in mortgage balances per capita keeping mortgage balances per capita constant by number of first mortgages, but allowing the distribution of the number of first mortgages to follow its historical path. The change in the distribution of the number of first mortgages accounts for only 13% of the total for quartile 1, 20% for quartiles 2 and 4, 22% for quartile 3. This

[28]Total balances per capita for quartile $i = 1, 2, 34$ is $B_t^i = \sum_j \pi_t^{i,j} B_t^{i,j}$, where j denotes the number of first mortgages (0,1,2,3,4+) and $t = \{\underline{t}, ..., \bar{t}\}$ is the quarter. The variables $\pi_t^{i,j}$, $B_t^{i,j}$ are the corresponding fraction of borrowers and the per capita value of balances for that category of borrowers. In the first counterfactual, we set $\pi_t^{i,j} = \pi_{\underline{t}}^{i,j}$ for all periods, and in the second counterfactuals we set $B_t^{i,j} = B_{\underline{t}}^{i,j}$ for all periods. we then consider the change in these 3 statistics between $\underline{t}$ and $\bar{t}$, and report the ratio of the change in the counterfactual value to the total value. These two statistics need not add up to 1 as interactions are not included. The same counterfactuals are computed for delinquency and foreclosure rates, where we only include two groups (j), borrowers with only 1 first mortgages or borrowers with 2 or more.

pattern confirms that the the rise in the fraction of borrowers with 2 or more first mortgages is more important for borrowers in higher quartiles.

The second and third panel of Table 4 report similar calculations for the change in delinquency and foreclosure rates in 2006Q3-2009Q4. Here, we report the log change in the rates, since the base delinquency and foreclosure rates vary substantially across quartiles.[29] For delinquency rates, the log change for quartiles 2-4 is 2 to 5 times higher than for quartile 1. Maintaining the investor share constant account for 97% of the total change in delinquency rates for quartile 1, 99% for quartile 2, 98% for quartile 3 and 95% for quartile 4. The change maintaining the delinquency rate constant for investors for generates a rise in delinquency rates that is 91% of the total for quartile 1, 82% for quartile 2, 76% for quartile 3 and 63% for quartile 4. These results confirm the large role of rising investor delinquency rates and rising share of investors in the rise of delinquency rate for high credit score borrowers during the crisis.

A similar but more dramatic pattern holds for foreclosures. In this case the log change in foreclosure rates is 0.27 for quartile 1, approximately 2.5 larger for quartile 2, and approximately 5 and 6 times higher for quartiles 3 and 4, respectively. The counterfactuals show that the increase in foreclosure rates for investors account for a much larger fraction of the total rise in foreclosure rates for higher quartiles of the credit score distribution.

Real estate investors are particularly likely to contract non-conventional mortgages that are intrinsically more risky and they are also likely to prefer highly leveraged products, as discussed above. An additional factor that may increase the default rate for investors is that only the primary residence is protected in personal bankruptcy, via the homestead exemption.[30] Thus, a borrower who is experiencing difficulties in making payments could potentially file for Chapter 7 bankruptcy and discharge unsecured debt using non exempt assets, and avoid a mortgage delinquency. Perhaps more importantly, the financial and psychological costs of default for mortgage borrowers who reside in the home are typically quite substantial, including moving and storage costs, increased commuting costs, and so on. Our results suggest that these factors may have been quite prevalent during the housing crisis.

[29]Similar results obtain using the simple difference in delinquency and foreclosure rates. We select the 2006Q3-2009Q4 time period as it comprises the trough and peak of the delinquency and foreclosure rates for all quartiles of the credit score distribution.

[30] See Li (2009) for an excellent discussion.

Table 4: Role of Investors in Mortgage Balance, Delinquency and Foreclosure Growth

	2001Q3-2006Q4 change in mortgage balances[a]			
total (USD)	8,478	27,608	28,538	20,063
with constant distribution of number of first mortgages[c]	0.7684	0.61594	0.61554	0.6909
with constant balances by number of first mortgages[c]	0.13423	0.2013	0.2180	0.1961
	2006Q3-2009Q4 change in delinquency rates[d]			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
total[b]	0.1175	0.3149	0.5426	0.4373
with constant investor share[c]	0.9706	0.9929	0.9758	0.9497
with constant investor rate[c]	0.9113	0.8177	0.7634	0.6261
	2006Q3-2009Q4 change in foreclosure rate[d]			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
total[b]	0.2649	0.6338	1.0622	1.2854
with constant investor share[c]	0.9892	0.9934	0.9742	0.9676
with constant investor rate[c]	0.8854	0.8535	0.76535	0.6595

Contribution of changing fraction of investors and changing behavior of investors by quartiles of the 8Q lagged Equifax Risk Score distribution. Delinquency rate is defined as fraction with new 90+ day delinquency in last 4 quarters. Foreclosure rate is fraction with new foreclosure in last 4 quarters. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

a. Includes all borrowers.
b. Log difference.
c. Ratio to total. Ratios need not add up to 1 as interaction terms are not reported.
d. Includes only borrowers with at least 1 first mortgage.

7.2 Non Conforming Mortgages

We also examine the size of the average mortgage. As house prices were rising during between 2001-2007, some borrowers were taking on increasingly larger mortgages. Some of these mortgages satisfy the criteria of jumbo loans, which do not qualify for GSE insurance and therefore typically display higher rates.

The distribution of jumbo loans by quartile of the credit score distribution in reported in Table 5 between 2001 and 2007.[31] There is a small rise in the fraction of jumbo mortgages, but only for borrowers in the top quartile of the credit score distribution. The rise in the fraction of jumbo loans seems too small to account for the rise in mortgage delinquencies for this group.

Table 5: Fraction of Jumbo Mortgages

quartile	1	2	3	4
2001Q1	0.1%	0.4%	0.7%	1.1%
2003Q1	0.1%	0.5%	1.1%	1.4%
2005Q1	0.1%	0.7%	1.5%	1.7%
2007Q1	0.2%	0.7%	1.5%	1.9%
2009Q1	0.1%	0.3%	0.3%	0.7%

Fraction with non-conforming mortgages by 8Q lagged Equifax Risk Score ranking. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

8 Interpreting Zip Code Level Evidence

Starting with the seminal work of Mian and Sufi (2009), the macroeconomic literature has used geographical variation to link mortgage debt growth to the severity of the housing crisis and of the ensuing 2007-2009 recession. As shown in figure 1, ranking zip codes by the fraction of subprime borrowers in 2001, suggests that mortgage debt growth in 2001-2007 is stronger in zip codes with high fraction of subprime borrowers at the starting date. However, there is no difference in the growth in total debt balances across quartiles of the fraction of subprime borrowers, as shown in figure 49 reported in Appendix I.

[31] In 2008, the Obama Administration increased the thresholds for jumbo loans in the major metropolitan areas that exhibited the largest house price increases.

In this section, we explore the link between the fraction of subprime borrowers at the zip code level and other population characteristics.

Figure 27 presents zip code level mortgage balance growth since 2001Q3 for prime and subprime borrowers by quartile of the fraction of subprime borrowers. It is clear that prime borrowers experience much higher growth in mortgage balances during the boom relative to subprime borrowers, in all zip codes. However, in zip codes with the highest fraction of subprime borrowers, mortgage balances grow more than in other zip codes for *both* prime and subprime borrowers. As we show in Section 4.1, subprime borrowers are disproportionately young and have high demand for credit due to life cycle considerations. Based on this observation, we explore the role of the age distribution at the zip code level.

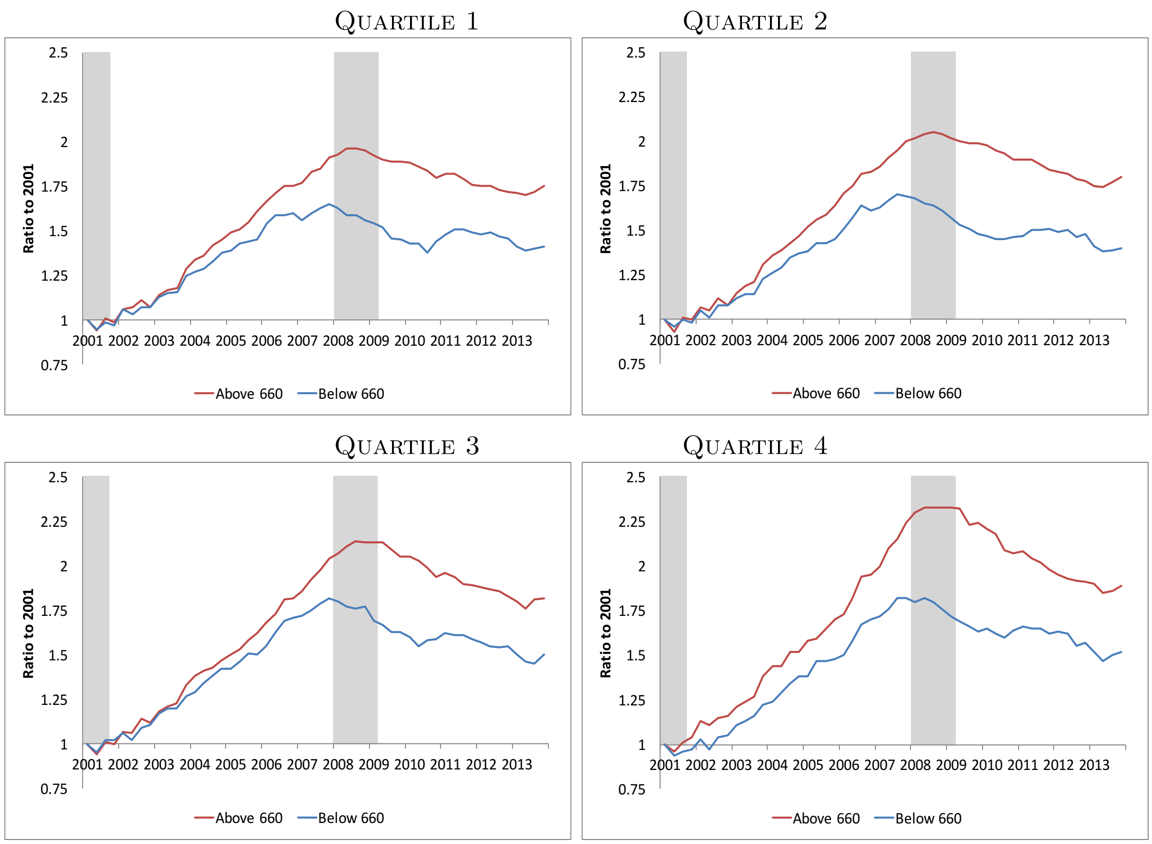


Figure 27: Mortgage debt growth for prime&subprime individuals by quartile of share of subprime in 2001. Based on 8Q lagged individual credit scores. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

8.1 The Role of Age

Table 6 reports the age distribution by fraction of subprime borrowers. Not surprisingly, based on our results with individual data, zip codes in quartile 4 of the fraction of subprime borrowers exhibit a much larger share of borrowers younger than 35.

Table 6: Age Distribution by Fraction of Subprime Borrowers

Fraction in each age bin, 2001Q1-2013Q4						
	20-24	25-34	35-44	45-54	55-64	65-85
Quartile 1	0.063	0.157	0.200	0.218	0.171	0.192
Quartile 2	0.070	0.184	0.200	0.205	0.161	0.181
Quartile 3	0.074	0.201	0.206	0.200	0.152	0.168
Quartile 4	0.081	0.212	0.210	0.199	0.145	0.153

Average age distribution in 2001Q1-2013Q4 by quartile of fraction of subprime in 2001. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

To quantify the role of the age distribution, we construct counterfactual mortgage balance growth with the age distribution set equal to the age distribution for quartile 1 for all quartiles. The difference between the actual and the counterfactual growth in mortgage balances for quartiles 2-4 is displayed in figure 28.

We summarize these counterfactuals by calculating the contribution of the differences in age distribution across quartiles of the fraction of subprime borrowers to the difference in 2001Q1-2007Q4 (trough to peak) mortgage debt growth relative to quartile 1. These results are reported in Table 7. We find that for zip codes in quartiles 2 and 3 of the distribution fraction of subprime borrowers in 2001, respectively 44% and 43% of the additional cumulative growth in mortgage debt balances relative to quartile 1 is accounted for by differences in the age distribution. This statistic is 84% for zip codes in quartile 4. These findings suggest that even at the zip code level, the age structure is an important determinant of borrowing demand, and strongly affects the observed pattern of debt growth during the 2001-2007 credit boom.

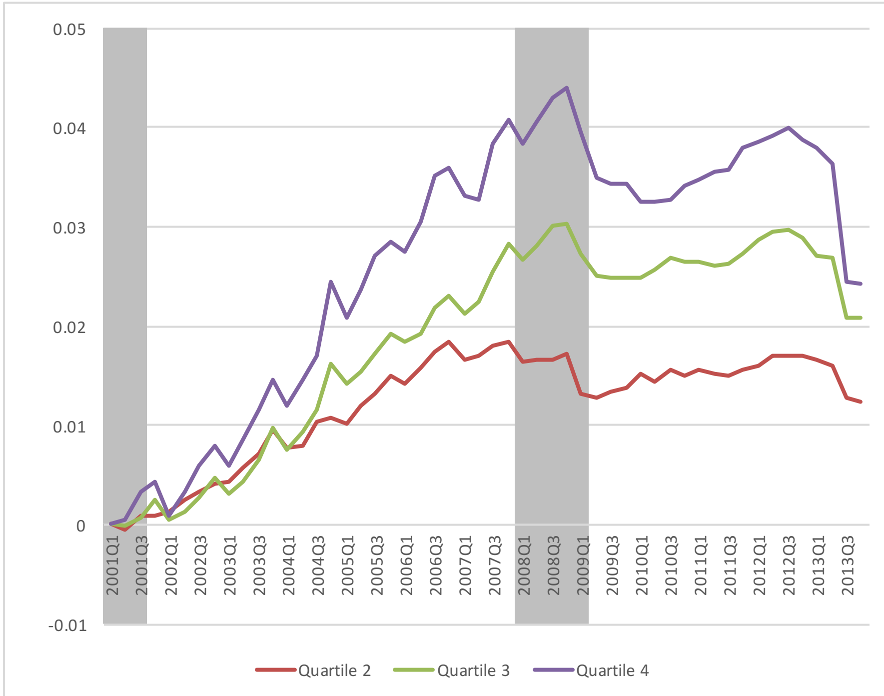


Figure 28: Difference between actual and counterfactual growth in mortgage balances for quartiles 2-4 of fraction of subprime in 2001. Counterfactual sets age distribution equal to quartile 1. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 7: Age Distribution and Mortgage Balance Growth

Mortgage Balances		
Quartile 2	Quartile 3	Quartile 4
0.44	0.43	0.84

Contribution of differences in the age distribution to differences in mortgage balance growth 2001Q1-2007Q4. Counterfactuals computed by attributing to each quartile the age distribution of quartile 1 of the fraction of subprime borrowers in 2001. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

8.2 Defaults

We now examine the behavior of defaults by zip code. Figure 29 presents the 90+ mortgage delinquency rate and the foreclosure rate by quartile of fraction of subprime borrowers in 2001. Not surprisingly, zip codes with higher fraction of subprime borrowers exhibit higher delinquency and foreclosure rates, throughout the sample period, with a 2-3 percentage point difference between adjacent quartiles for most of the sample period. The delinquency rate increases modestly during the housing crisis, mostly for zip codes in quartiles 2-4 of the fraction of subprime borrowers in 2001. Foreclosure rates display a similar pattern across quartiles for the entire sample period, despite modest differences in levels. The increase in the foreclosure rate during the crisis is sizable for all quartiles. Foreclosure rates for quartiles 2-4 converge during the crisis, whereas the rate for quartile 1 remains lower, despite its increase. Figure 30 presents the share of 90+ days delinquencies and foreclosures of *prime* borrowers by quartile of the 2001 distribution of the fraction of subprime borrowers. Clearly, prime borrowers contribute more to the growth in delinquent mortgage balances and foreclosures during crisis in all zip codes. The share of prime borrowers' delinquent mortgage balances rises by approximately 30 percentage points between 2006Q2 and 2009Q4, while the share of prime borrowers' foreclosures rises approximately by 40 percentage points over the same period.

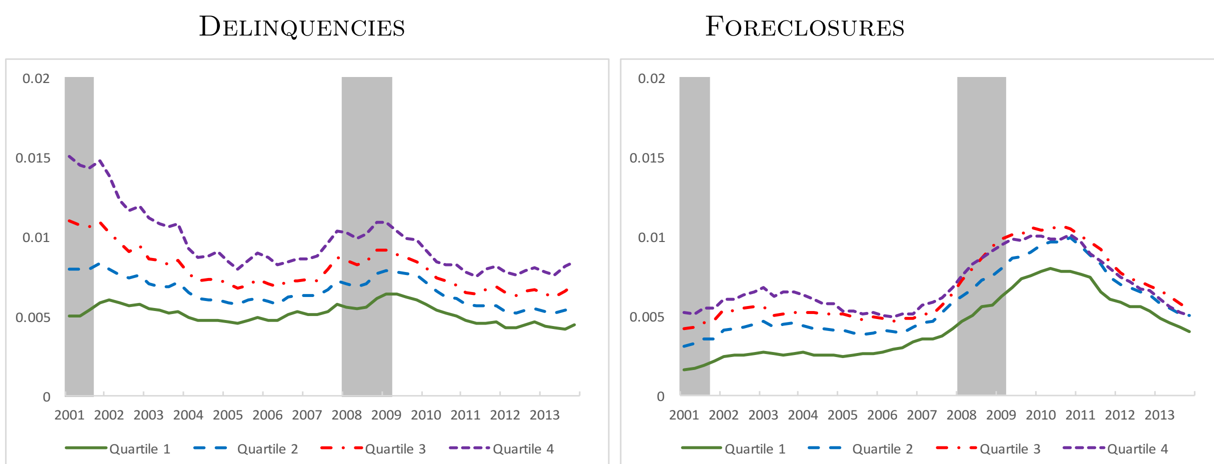


Figure 29: Fraction with 90+ days delinquencies and foreclosures. Zip code level average by quartile of the fraction of subprime share in 2001. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Interestingly, the prime share of mortgage delinquencies and foreclosures are higher in zip codes with *high* fraction of subprime borrowers, despite the fact that prime borrowers account for a smaller fraction of the population. This suggests that prime borrowers in zip codes with high fraction of subprime borrowers are more vulnerable to financial distress. Though other zip code level characteristics may contribute to this pattern, as we discuss in Section 8.3, here we focus on the role of investors, based on our findings using individual data. Figure 31 presents the fraction of investors at the zip code level for prime and subprime

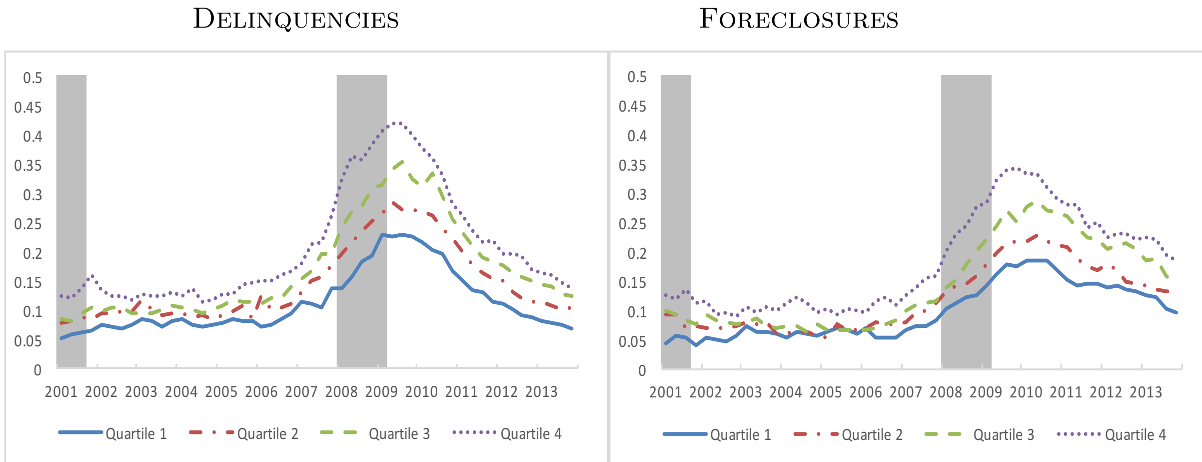


Figure 30: Share of 90+ days delinquencies and foreclosures for prime borrowers, based on 8Q lagged individual credit score. Quartiles of subprime share in 2001. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

borrowers. There is virtually no difference across quartiles in the fraction of investors for prime borrowers. It starts at approximately 10% in 2001, rises by 5 percentage points between 2005Q1 and 2007Q4, with the average for 2005-2007, reported in Table 8 equal to 12-13%. The fraction of investors among prime borrowers drops during and after the recession, although it still remains above pre-boom levels by the end of 2013. For subprime borrowers, the fraction of investors is decreasing in the quartile of the fraction of subprime in 2001. At the beginning of the sample it is 10% for quartile 1, with a 1-3 percentage point difference across quartiles throughout the sample. The 2005Q1-2007Q4 rise in the fraction of investors is more modest for subprime borrowers, also decreasing with the quartile of the subprime distribution in 2001. The 2005-2007 average of the fraction of investors among subprime borrowers is 11% and 10% for quartile 1 and 2, and 8% and 7% for quartiles 3 and 4.

Given the large rise in the share of defaults to prime borrowers and the link between investor activity and foreclosures we established using individual data, we examine more detail on investor activity for prime borrowers in Table 8. The distribution of investors across the number of first mortgages is very similar across quartiles, with 79-80% of investors holding 2 first mortgages, 13-14% holding 3 and 7-8% holding 4 or more. However, the growth in average mortgage balances per capita during the boom varies substantially by quartile, and is significantly higher in quartiles with a large fraction of subprime borrowers, especially for investors. The growth in per capita mortgage balances for investors is around 20 percentage points higher for prime borrowers in quartile 4 relative to quartile 1. The

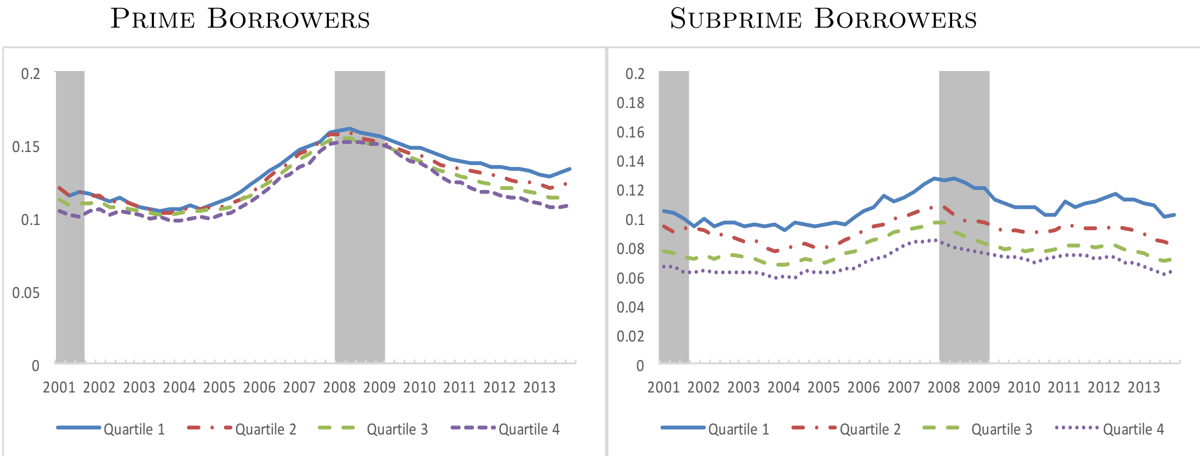


Figure 31: Fraction with 2 or more first mortgages for prime borrowers (left) and subprime borrowers (right), by quartile of fraction of subprime borrowers in 2001. Subprime/prime based on 8Q lagged credit score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

growth in mortgage balances for investors with 4 or more first mortgages is particularly high in quartiles 2-4. Turning to defaults, we see that foreclosure rates are substantially higher for investors relative to non-investors, as we found in the individual data. This difference is increasing in the fraction of subprime borrowers. The rise in the foreclosure rate during the crisis for investors in quartiles 3-4 is nearly double the rise in quartiles 1-2, reaching a high of 15% for investors with 4 or more first mortgages in quartile 4.

Summarizing, though the fraction of investors with prime credit score is very similar across quartiles, in quartiles with high share of subprime, investors exhibit larger increases in mortgage balances during the boom and a more severe increase in foreclosures during the crisis. This difference in behavior for prime investors may be driven by the behavior of real estate values. As reported in Table 9, the average growth house price index in 2001-2007 varies from 29% in quartile 1 to 47% in quartile 4. The total decline in housing values in 2007-2010 is also increasing in the fraction of subprime, ranging from 21% in quartile 1 to 36% in quartile 4. This suggests that investor activity by *prime*borrowers is associated with a more pronounced house price boom and bust and a more severe foreclosure crisis, especially in areas with high fraction of subprime borrowers.

8.3 Zip Code Characteristics

Several studies find a positive relation between the size of the increase in mortgage debt growth or house price debt growth during the 2001-2006 credit boom, often instrumented

Table 8: Investor Activity

	2005-2007 fraction of investors			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
prime borrowers	13%	13%	13%	12%
subprime borrowers	11%	10%	8%	7%
	Prime Borrowers			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2007Q4 fraction of investors with				
2 first mortgages	80%	80%	80%	79%
3 first mortgages	13%	13%	14%	14%
4+ first mortgages	7%	7%	7%	8%
2001Q3-2007Q4 mortgage balance growth				
1 first mortgage	59%	62%	66%	69%
2 first mortgages	86%	85%	97%	104%
3 first mortgages	94%	104%	117%	118%
4+ first mortgages	102%	122%	133%	125%
boom average-peak change in foreclosure rate				
1 first mortgage	0.008	0.012	0.016	0.017
2 first mortgages	0.023	0.027	0.045	0.053
3 first mortgages	0.040	0.063	0.087	0.115
4+ first mortgages	0.076	0.096	0.123	0.151

Selected zip code level indicators for prime borrowers by quartile of the fraction of subprime borrowers in 2001. The boom average for the foreclosure rate corresponds to the 2002Q1-2005Q4 average. The peak of the foreclosure rate varies by group, with 2007Q4 the most common date. Source: Authors' calculations based on FRBNY CCP/Equifax Data, IPUMS, IRS, BLS, ACS data.

with Saiz (2010) house price elasticities, and the severity of the 2007-2009 recession.[32] These studies attribute this correlation to the tightening of collateral constraints during the crisis, driven by mortgage defaults and the resulting decline in housing values, however, this causal mechanism is not consistent with our findings. In this section, we explore additional economic

[32]For example, Mian, Sufi, and Trebbi (2015) find that states with higher foreclosure rates experienced a larger decline in consumption, while Mian and Sufi (2014) use county level data and show that a larger decline in household net worth during the crisis experience a more pronounced decline in non-tradable employment.

indicators at the zip code level to shed light on this correlation.

Table 9 reports several economic indicators by quartile of the fraction of subprime borrowers in 2001. Several indicators that are critical to business cycle sensitivity are systematically related to the fraction of subprime borrowers. Zip codes with higher fraction of subprime borrowers are younger, as previously noted, have lower levels of educational attainment and have a disproportionately large minority and African American share in the population. It is well known that younger, less educated, minority workers suffer larger employment loss during recessions.

Zip codes with a large fraction of subprime borrowers also exhibit lower per capita income levels in both the boom and the recession. In 2001-2007, the average real per capita income was $41,045 in quartile 1 and only $21,019 in quartile 4, whereas in 2007-2010 it was $46,341 for quartile 1 and $21,898 for quartile 4. Consistent with Mian and Sufi (2009), income growth during the boom was lower in zip codes with higher fraction of subprime. Average per capita income grew by 35% between 2001 and 2007 for quartile 1 and only 4% for quartile 4. Zip codes with a large fraction of subprime borrowers also exhibit higher income inequality. We measure this with the ratio of average income for individuals with incomes above $200,000 over average income for the entire population, based on IRS data. Higher inequality implies that the aggregation bias generated by the fact within each zip code prime borrowers experience more credit growth than subprime borrowers is accentuated.

Zip codes with high fraction of subprime borrowers experience higher house price growth in 2001-2007, as previously noted. This may be related to the their higher population density, suggesting the prevalence of urban areas for this group. Gentrification exerted particularly high pressure on housing values in urban areas over this period, and may have encouraged real estate investor activity. The distribution of zip codes with low housing supply elasticity, as captured by the Saiz (2010) index, is fairly even across quartiles. However, 16% of zip codes in quartiles 3 and 4 are in sand states[33], whereas only 11% and 13% of zip codes in quartiles 1 and 2 are in those states.

The distribution of the fraction of subprime borrowers is quite stable at the zip code level, and this is also true for other characteristics salient to business cycle sensitivity.[34] Therefore, the timing of the ranking by fraction of subprime does not change the patterns at the zip code level. However, some aggregate trends, such as the historical decline in wages, labor force participation and employment rates for unskilled, young and minority

[33]These are Arizona, California, Colorado, Florida, and Nevada. These states exhibit the largest swings in housing values during the housing boom and the subsequent foreclosure crisis.

[34] Appendix I reports the time correlation of the zip code ranking by fraction of subprime borrowers.

Table 9: Zip Code Level Indicators

	Demographics			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Median age	50	49	48	46
Associate+ degree (2012)	45%	31%	23%	17%
Percent white	93%	90%	83%	63%
Percent black	1.7%	3.6%	7.6%	24.6%
	Economy			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Average UR 2001-2007	4.94%	5.19%	5.38%	5.72%
Average UR 2007-2010	6.93%	7.30%	7.51%	7.81%
Average PDI 2001-2007	$41,045	$30,442	$25,692	$21,019
Average PDI 2007-2010	$46,341	$33,224	$27,491	$21,898
PDI Growth 2001-2007	25%	16%	10%	4%
PDI Growth 2007-2010	10%	10%	11%	10%
$\frac{\text{Mean Income} \geq \$200K}{\text{Mean Income}}$ (2006-11)	6.4	7.9	9.4	11.8
	Mortgage Markets			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2001 fraction subprime (med)	19%	32%	44%	60%
HPI Growth 2001-2007	29%	37%	42%	47%
HPI Growth 2007-2010	-21%	-30%	-27%	-36%
Low Saiz elasticity	17%	13%	11%	12%
	Geography			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
In sand states	11%	13%	16%	16%
Pop per sq mile	1214	1380	1386	2322
Percent never moved	53%	53%	51%	51%

Selected zip code level indicators by quartile of the fraction of subprime borrowers in 2001. PDI and HPI expressed in 2012 USD, adjusted by CPI-U. Source: Authors' calculations based on FRBNY CCP/Equifax Data, IPUMS, IRS, BLS, ACS data.

workers, and the rise in income inequality may influence economic outcomes at the zip code level over time. One motivation for considering zip code level evidence is the scarcity of information on individual borrowers in credit file data. Geographical aggregation provides access to a number of additional indicators, such as income, housing values and so on. Very often, geographical patterns are interpreted as reflecting individual behavior. For example, differences in debt growth across two zip codes with different fraction of subprime borrowers are assumed to be similar to differences in debt growth across individuals with different credit scores. Our findings suggest that using geographically aggregated data does not provide an accurate account of the patterns of borrowing at the individual level. Moreover, the positive correlation between credit growth during the boom and the depth of the recession may be due to other characteristics at the zip code level, such as the prevalence of young, minority or low education workers.

9 Conclusion

Our analysis suggests a reassessment of role of growth in the supply of subprime credit in the 2001-2006 housing boom and in the 2007-2009 financial crisis. We finds that most of the increase in mortgage debt during the boom and of mortgage delinquencies during the crisis is driven by mid to high credit score borrowers. The growth in defaults is mostly accounted for by real estate investors. Moreover, we show that at the zip code level, prime borrowers experience a larger rise in debt and defaults than subprime borrowers. Zip codes with a large share of subprime borrowers have a young, low education, high minority population that may be particularly sensitive to business cycle shocks. These new findings should inform discussions of the causes and consequences of the 2007-2009 financial crisis and of the appropriate policy responses.

References

Adelino, Manuel, Antoinette Schoar, and Felipe Severino. 2015. "Loan Originations and Defaults in the Mortgage Crisis: The Role of the Middle Class." Working paper 20848, National Bureau of Economic Research.

———. 2017, June. "Dynamics of Housing Debt in the Recent Boom and Great Recession." Working paper 23502, National Bureau of Economic Research.

Agarwal, Sumit, Gene Amromin, Itzhak Ben-David, and Douglas D. Evanoff. 2016, September. "Loan Product Steering in Mortgage Markets." Working paper 22696, National Bureau of Economic Research.

Albanesi, Stefania, and Jaromir Nosal. 2015. "Insolvency After the 2005 Bankruptcy Reform." Cepr discussion papers 10533, C.E.P.R. Discussion Papers.

Bazikyan, Armine. 2009. "Renters: The Innocent Victims of the Foreclosure Mortgage Crisis." *Sw. L. Rev.* 39:339.

Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra. 2015, October. "House Prices and Consumer Spending." Working paper 21667, National Bureau of Economic Research.

Bhutta, Neil. 2015. "The ins and outs of mortgage debt during the housing boom and bust." *Journal of Monetary Economics* 76:284 – 298.

Bhutta, Neil, and Benjamin J Keys. 2016. "Interest rates and equity extraction during the housing boom." *The American Economic Review* 106 (7): 1742–1774.

Brown, Meta, Andrew Haughwout, Donghoon Lee, and Wilbert van der Klaauw. 2014. "The Financial Crisis at the Kitchen Table: Trends in Household Debt and Credit." *Current Issues in Economics and Finance* 19, no. 2.

Chen, Hui, Michael Michaux, and Nikolai Roussanov. 2013, September. "Houses as ATMs? Mortgage Refinancing and Macroeconomic Uncertainty." Working paper 19421, National Bureau of Economic Research.

Corbae, Dean, and Erwan Quintin. 2015. "Leverage and the Foreclosure Crisis." *Journal of Political Economy* 123 (1): 1–65.

Elul, Ronel, and Sebastian G Tilson. 2015. "Owner occupancy fraud and mortgage performance."

Foote, Christopher L, Lara Loewenstein, and Paul S Willen. 2016. "Cross-sectional patterns of mortgage debt during the housing boom: evidence and implications." Technical Report, National Bureau of Economic Research.

Foote, Christopher L, and Paul S Willen. 2016. "subprime mortgage crisis, the." In *Banking Crises*, 324–336. Springer.

Ghent, Andra C, and Marianna Kudlyak. 2011. "Recourse and residential mortgage default: evidence from US states." *Review of Financial Studies*, p. hhr055.

Guerrieri, Veronica, and Guido Lorenzoni. 2011. "Credit crises, precautionary savings, and the liquidity trap." Technical Report, National Bureau of Economic Research.

Haughwout, Andrew, Donghoon Lee, Joseph S Tracy, and Wilbert Van der Klaauw. 2011. "Real estate investors, the leverage cycle, and the housing market crisis."

Iacoviello, Matteo. 2004. "Consumption, house prices, and collateral constraints: a structural econometric analysis." *Journal of Housing Economics* 13 (4): 304–320.

Justiniano, Alejandro, Giorgio E Primiceri, and Andrea Tambalotti. 2016. "Quantitative Modeling of the Financial Crisis A Simple Model of Subprime Borrowers and Credit Growth." *The American Economic Review* 106 (5): 543–547.

Kaplan, Greg, Kurt Mitman, and Gianluca Violante. 2015. "Consumption and house prices in the Great Recession: Model meets evidence." *Manuscript, New York University.*

Kehoe, Patrick, Elena Pastorino, and Virgiliu Midrigan. 2016. "Debt constraints and employment." Technical Report, National Bureau of Economic Research.

Keys, Benjamin J, Tomasz Piskorski, Amit Seru, and Vikrant Vig. 2012. "Mortgage financing in the housing boom and bust." In *Housing and the Financial Crisis*, 143–204. University of Chicago Press.

Keys, Benjamin J, Tomasz Piskorski, Amit Seru, and Vincent Yao. 2014. "Mortgage rates, household balance sheets, and the real economy." Technical Report, National Bureau of Economic Research.

Kiyotaki, Nobuhiro, and John Moore. 1997. "Credit Cycles." *Journal of Political Economy*, no. 2:211–248.

Lee, Donghoon, and Wilbert van der Klaauw. 2010. "An Introduction to the FRBNY Consumer Credit Panel." FRBNY Staff Report 479.

Li, Wenli. 2009. "Residential housing and personal bankruptcy." *Business Review Q* 2:19–29.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household Balance Sheets, Consumption, and the Economic Slump." *The Quarterly Journal of Economics* 128 (4): 1687–1726.

Mian, Atif, and Amir Sufi. 2009. "The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis." *The Quarterly Journal of Economics* 124 (4): 1449–1496.

———. 2010. "The Great Recession: Lessons from Microeconomic Data." *The American Economic Review* 100 (2): 51–56.

———. 2011. "House Prices, Home Equity–Based Borrowing, and the US Household Leverage Crisis." *The American Economic Review* 101 (5): 2132–2156.

———. 2014. "What explains the 2007–2009 drop in employment?" *Econometrica* 82 (6): 2197–2223.

Mian, Atif, Amir Sufi, and Francesco Trebbi. 2011. "Foreclosures, house prices, and the real economy."

———. 2015. "Foreclosures, house prices, and the real economy." *The Journal of Finance* 70 (6): 2587–2634.

Mian, Atif R, and Amir Sufi. 2016. "Household debt and defaults from 2000 to 2010: The credit supply view."

Midrigan, Virgiliu, and Thomas Philippon. 2016. "DP11407 Household Leverage and the Recession."

Mitman, Kurt. 2016. "Macroeconomic effects of bankruptcy and foreclosure policies." *The American Economic Review* 106 (8): 2219–2255.

Saiz, Albert. 2010. "The geographic determinants of housing supply." *The Quarterly Journal of Economics* 125 (3): 1253–1296.

A Consumer Credit Panel Data and Variables

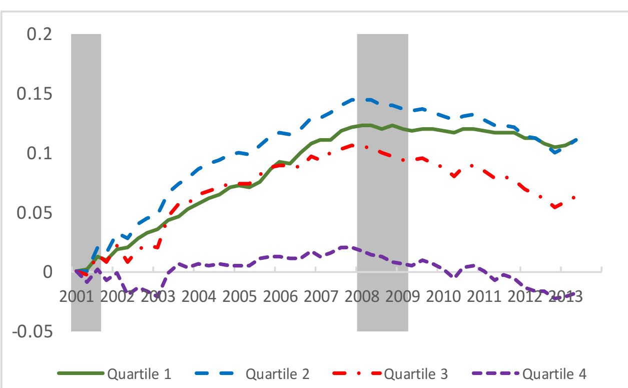
We describe in detail the definitions of delinquency and foreclosure used in the analysis.

90+ Days Delinquent: An individual is delinquent if they have at least one loan in their CCP report in that quarter that is 90+ days past due, severely derogatory, or bankrupt (crtr_attr16, crtr_attr17, or crtr_attr18). Also, at least one of crtr_attr16, crtr_attr17, or crtr_attr18 must be non-missing.

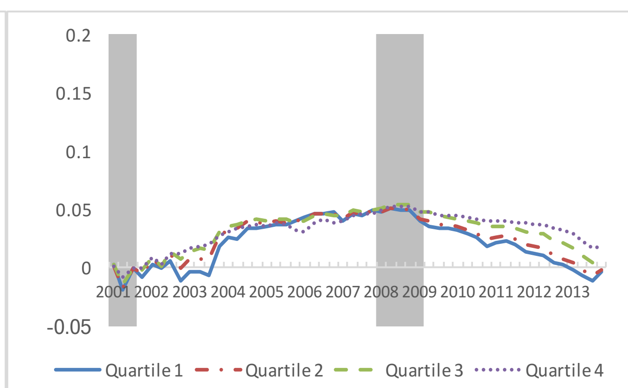
Foreclosure: There are two scenarios in which an individual is marked as being in the state of foreclosure. First, if the individual forecloses on a home (that is, if cma_attr3905 switches from off ("0") to on ("1" or "7")), then that individual is marked as being in a state of foreclosure for seven years after the date of their foreclosure. Second, if the individual enters the dataset for the first time while under foreclosure (which almost exclusively occurs at the dataset's 1999 Q1 truncation), that individual is marked as being in the state of foreclosure until the flag (which is supposed to stay on for seven years after the date of the foreclosure) turns off.

B Initial Credit Score Ranking: Additional Results

Figure 32 displays the fraction with first mortgages by 1999 credit score ranking for individuals (left panel) and by fraction of subprime borrowers in 2001 for zip codes (right panel). Based on the individual level data, the fraction with first mortgages growth by 10-13 percentage points between 2001Q3 and the start of the recession for quartiles 1-3, and only by 2 percentage points for borrowers in quartile 4. At the zip code level, there is little difference in the change in the fraction with first mortgages across zip codes during the boom, though the decline during and after the recession is more pronounced for lower quartiles.



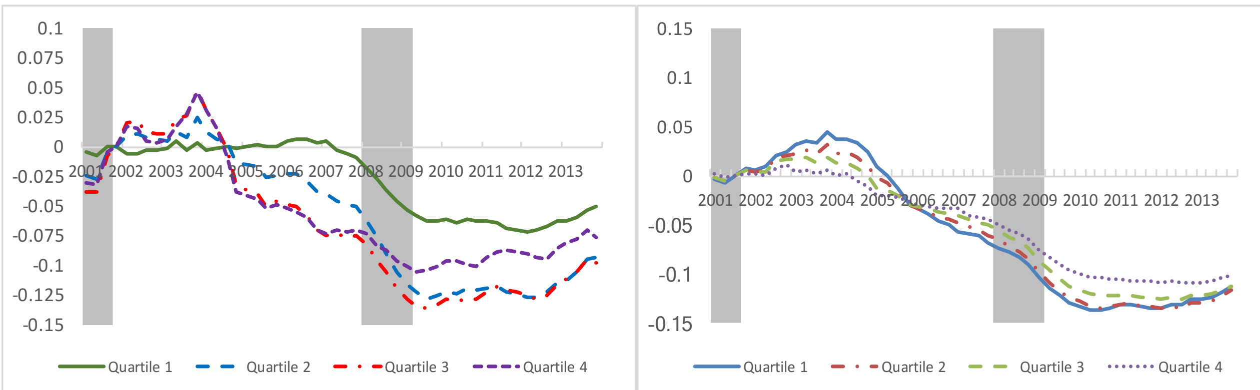
(a) Individuals: Ranked by 1999 Equifax Risk Score



(b) Zip Codes: Ranked by Fraction of Subprime in 2001

Figure 32: Fraction with first mortgages, difference from 2001Q3. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

Figure 33 displays the fraction with new mortgage originations. Even with the 1999 quartile ranking, borrowers in quartile 1 do not exhibit any growth in new mortgage originations during the boom, and most of the growth in new mortgage originations occurs between 2001 and 2004 for borrowers in quartiles 2-4 (left panel). At the zip code level (right panel), zip codes with the lowest fraction of subprime borrowers exhibit stronger growth in mortgage originations between 2001 and 2004, and this fraction declines for all quartiles after 2004.



(a) Individuals: Ranked by 1999 Equifax Risk Score (b) Zip Codes: Ranked by Fraction of Subprime in 2001

Figure 33: Fraction with new mortgage originations in the last 4 quarters, difference from 2001Q3. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

C Income Data

In this section, we describe the supplementary payroll data used for the income imputation procedure. This data is merged with our credit panel data, allowing us to map individuals' incomes for 2009 to their credit files.

The Equifax Workforce Solutions data provided by Equifax is a nationally-representative random sample of individuals containing employment and payroll verification information provided directly from the employers. The information provided for each employee includes the last three years of total income, the date of first hire, tenure, and for the current year status (part time/full time), weekly hours, pay rate and pay frequency.

Income Measure Description There are various income measures provided in the Worknumber dataset. For each year of data available variables are given for the total 12-month base, bonus, overtime, and commission compensation in year t, $t-1$, and $t-2$. This information however is only available for a little over $\frac{1}{3}$ of the sample. The other measure of income, which is widely available across the sample, is rate of pay and pay frequency. We therefore impute total income using a simple *rate* $\times$ *frequency* approach to account for the lack of representation found in the sample regarding the total 12-month income variables. This yields about 11,000 observations for 2009. The sample of records is nationally representative, both in terms of geographical and age distribution.

Comparison with the CPS To gauge the accuracy of the imputed income measure in our data, we performed a simple comparison with the income levels reported in the Consumer Population Survey. We present results based on income quintiles below.

Table 10: Income Distribution Comparison by Quintile

Calculation	Dataset	1	2	3	4	5
Mean	CPS	11058.67	24791.32	36584.61	51872.45	110192.2
	Worknumber	17078.07	26565.46	39589.76	58510.22	117260.1
Median	CPS	12000	25000	36000	50000	85000
	Worknumber	16640	27040	39520	57512	99990

Source: IPUMS, Equifax Worknumber. Worknumber income calculations made using proxied income from pay periods and pay rate. CPS income calculations made using total wage and salary income.

We conduct a similar analysis, comparing the distribution of income and age by state in the Worknumber sample and compare it to the American Community Survey. We also find that the sample is consistent with this survey. These results are available upon request.

D Age Counterfactuals: Regression Approach

As an alternative to the approach in Section 4.2, we also construct regression based age counterfactuals. Specifically, we use the estimated age fixed effects regression to predict the individual path of mortgage balances from 1999 to 2013 using the actual age effects and with the age effects corresponding to the individual's age in 1999 in every subsequent period. This amounts to keeping each individual borrower at the same age that they were in 1999. We then aggregate these individual paths by quartile of the 1999 credit score redistribution, and compute the gross growth rate relative to 2001Q3 for the predicted paths with the constant 1999 age effect and with the actual age effects and calculate the difference. Since the difference in the age distribution across the quartiles is constant over time, the result, displayed in figure 34, gives us a measure of the cumulative impact of differences in the age distribution on mortgage balance growth in the subsequent period by quartile of the 1999 credit score. Borrowers in quartile 1 are relatively young and would experience debt growth in subsequent years, thus the difference between debt growth at constant age and actual projected debt growth is negative. For borrowers in quartile 2, this difference is close to zero until 2007 when it becomes positive, suggesting that they would have borrowed more starting in 2007 if they had remained at their age in 1999, with a peak of 10% at the end of the sample. For quartiles 3-4, the difference is positive and sizable and suggests that if the individuals in these higher quartiles had remained younger, they would have experienced 8-27% higher mortgage balance growth by 2007, and 40-70% higher mortgage balance growth by the end of the sample. Specifically, for quartile 4, for the period between 2001Q3 and 2007Q4, the cumulative growth rate in mortgage balances would have been 27 percentage points higher had age been constant at 1999 values. This implies that 21% of the difference in cumulative mortgage balance growth between quartile 1 and quartile 4 over that period is due to age effects. This is a substantial contribution, though, consistent with the findings in Mian and Sufi (2016), it does not alter the ranking in mortgage balance growth across the quartiles based on the 1999 credit score ranking.

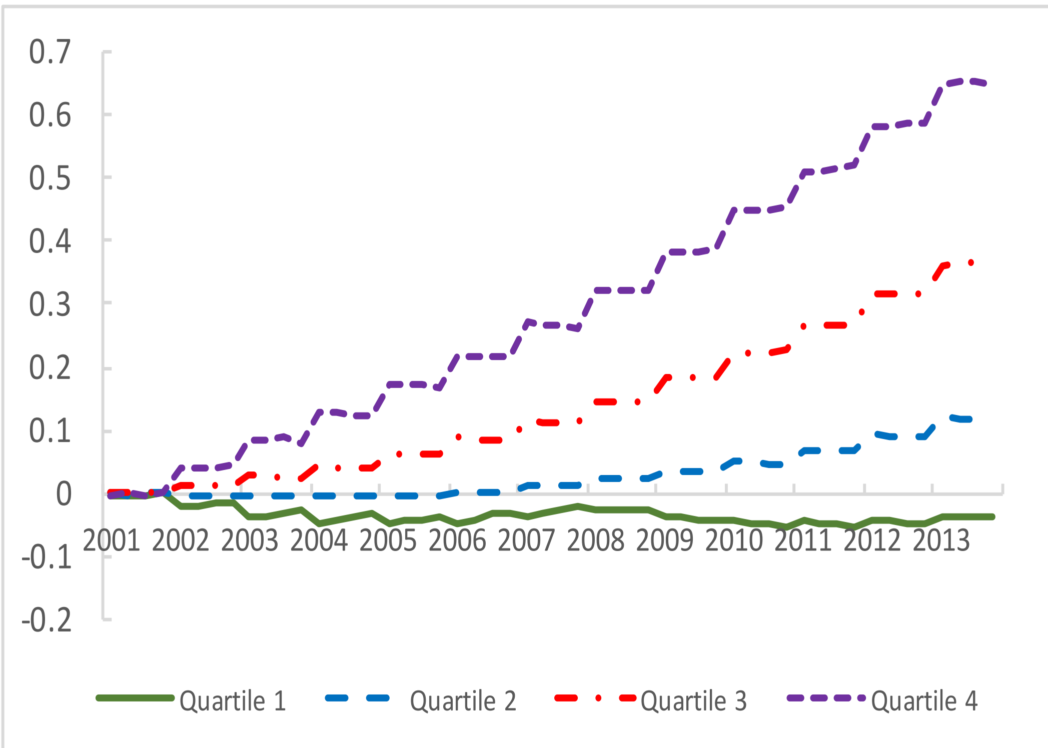


Figure 34: Change in cumulative growth in mortgage balances since 2001Q3 due to age effects, by quartile of the 1999 Equifax Risk Score distribution. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

E Age, Income and Debt Growth

Figure 35 reports the path of total debt balances for 25-34, 35-44 and 45-54 year olds in 1999 based on the income quintile in 2009. As for mortgage debt balances, higher income in 2009 corresponds to higher growth in total debt balances between 2001 and 2007.

25-34 YO 35-44 YO 45-54 YO

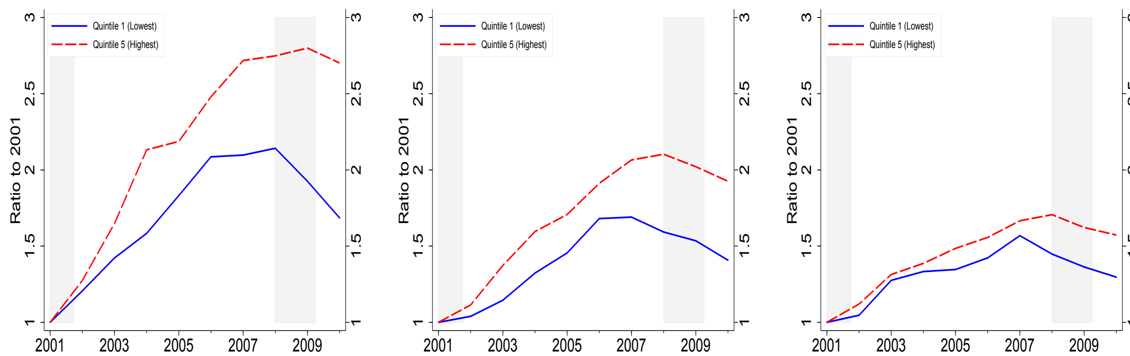


Figure 35: Total debt balances for 25-34, 35-44 and 45-54 year olds in 1999 by their 2009 Worknumber total annual labor income quantile. Ratio to 2001.
Source: Authors' calculations based on FRBNY CCP/Equifax Data.

F PSID Evidence on Income and Debt

To assess the generality of the relation between income, age and debt described in Section 5.1, we use the PSID to estimate the relation between debt growth and income during the boom period. Using zip code level data, Mian and Sufi (2009) show that during the period between 2001 and 2006, the zip codes that exhibited the largest growth in debt were those who experiences the smallest growth in income. They argue that the negative relation between debt growth and income growth at the zip code level over that period is consistent with a growth in the supply of credit, via a relaxation of lending standards. Using the panel stricture of the PSID, we can directly assess the relation between income and debt growth at the individual data. While debt is poorly measured in the PSID relative to the Consumer Credit Panel that we use for our main analysis, we have income at a yearly or bi-yearly frequency.

The estimates for various specifications are displayed in Table 11. The dependent variable is the change in real log total debt between 2007 and 1999, and the baseline specification includes the change in log income over the same period as a dependent variable. The coefficient is positive and highly significant, with a 1 log point change in income corresponding to a 0.066 log point increase in the change in debt over the period. This coefficient implies that 1 10,000$ increase in income from a value of 50,000$ in 1999 is associated with a 1$

increase in debt. The second column includes 1999 age and 1999 age squared. The coefficient on the change in income changes little, and the coefficient on age is negative and significant, consistent with our previous finding on the fact that debt accumulation slows with age, and debt accumulation is strongest for borrowers who are young in 1999. The third column includes a an interaction between 1999 age and the change in income, log income in 1999 and no squared age term. In this case the coefficient on the change in log income is positive but much smaller and not significant, while the coefficient on age is still negative and significant, but smaller in magnitude. The coefficient on log income in 1999 is positive but not significant. The last column also adds an interaction between log income in 1999 and age in 1999. In this case the coefficient on the change in income is positive and larger in magnitude relative to previous specifications, but not significant. The other coefficients are similar, with a larger magnitude of the negative coefficient on age. The interaction between age and log income in 1999 is positive and significant, suggesting that higher initial income is associated with larger growth in debt conditional on age. These results confirm our findings based on the Equifax data, suggesting that income growth and debt growth are positively related over the 2001-2006 boom.

Table 11: Relation Between Debt Growth and Income Growth

Dependent Variable: 2007-1999 change in log total debt (real USD)				
Δlog(income)	0.066**	0.068**	0.21	0.081
1999 age		-0.064***	-0.01***	-0.070**
1999 age sq		0.001***		
1999 age $\times \Delta log$(income)			-0.003	-0.001
log(income$_{1999}$)			0.001	-0.270
1999 age $\times$ log(income$_{1999}$)				0.006*

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ No. obs. 1,395. Source: Authors' calculations based on PSID Data.

G Balance Change Regressions: Additional Results

G.1 Mortgage Balances

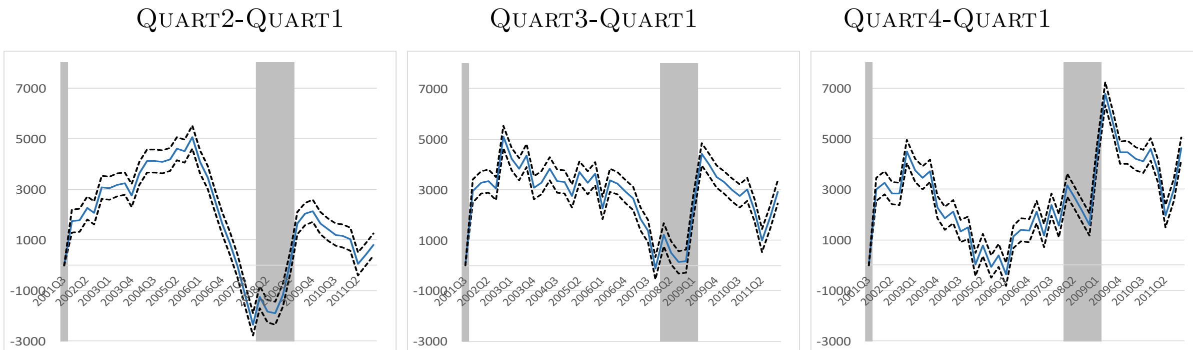


Figure 36: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita mortgage balances in USD. Dashed lines denote 5% confidence intervals. Sample period 2001Q3-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 37 displays some robustness analysis. The left panel plots the estimated age effects for the baseline specification, as well as the specifications that include the past changes in the credit score. The estimated age effects are very similar across specifications, consistent with the notion that changes in past credit scores exert negligible impact on credit growth. The right panel reports the estimated interaction between the 4 quarter past change in the credit score from its 1 quarter lagged value and the time effect, for the specification that includes these two variables. The estimated averages and time effects by credit score quartile are very similar to those in the baseline specification. The effect of the 4 quarter past change in credit score is more sizable during crisis, but still economically negligible.

G.2 Total Debt Balances

In this section, we report the estimates for total debt balances, focussing on the 8 quarter ahead change. As for mortgage balances, we find that the average change in total debt balances over the sample period, reported in Table 12 is highest for quartiles 2 and 3, followed by quartile 4, and much lower for quartile 1 of the 1 quarter lagged credit score distribution. The contribution of past credit score changes to average 8 quarter ahead balance growth is negligible. Figure 38 presentes the estimated time effects by quartile of the 1 quarter lagged credit score distribution. As for mortgage balances, there is little growth in total debt balances for quartile 1 borrowers during the boom. The growth in total debt balances peaks in 2004 for borrowers in quartile 4 and in 2006 for borrowers in quartile 2 and 3. Growth for quartile 4 is limited to the 2004-2006 period. All quartiles experience a very dramatic drop in the change in total debt balances during the crisis, reaching a minimum

Age Effects by Specification $\Delta_{4Q}CS_{-1} \times$ T

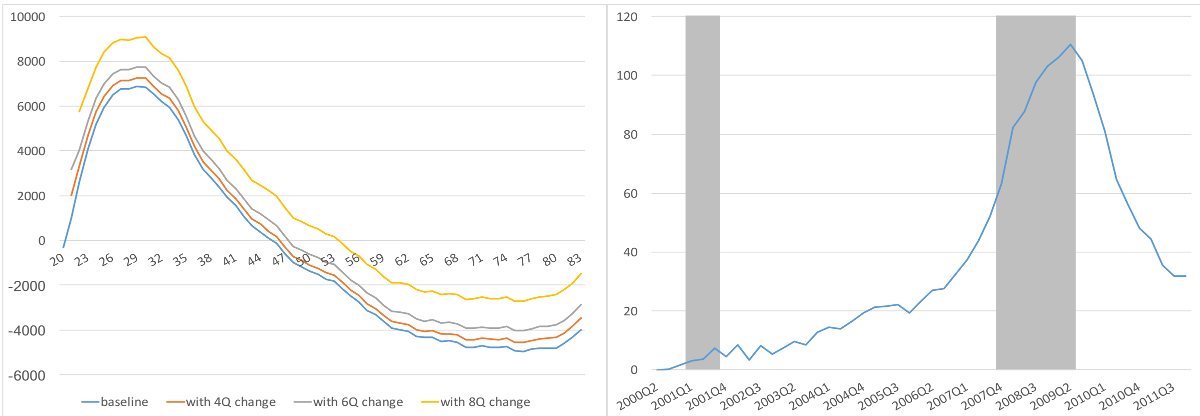


Figure 37: Robustness analysis. Left panel: Estimated age effects from balance change regressions. Baseline specification, plus variant with 4Q, 6Q, 8Q past change from 1Q lagged score. Right panel: Interaction of 4Q past change from 1Q lagged score with time effect. Dependent variable is 8Q ahead change in mortgage balances per capita in USD. Sample period 1999Q2-2012Q4. Number of obs. (baseline) 77,943,776. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

of -10,000-15,000$ for quartiles 2-4 by the start of 2009. The change in total debt balances remains negative until the end of the sample period for all quartiles. Figure 39 reports the difference in the 8 quarter ahead change in balances for quartiles 2-4 of the 1 quarter lagged credit score distribution and quartile 1, with 5% confidence intervals. In all periods the difference between quartiles is sizable and highly significant, as for mortgage balances. We find similar results for the 4 quarter and 12 quarter ahead change in total debt balances.

Table 12: 8 Quarter Ahead Growth in Total Debt Balances

Dependent Variable: 8Q Ahead Total Debt Balance Change (USD)					
1Q lagged CS Quartile Effects				ΔCS_{-1}	
1	2	3	4	4Q	6Q
5,552	15,428	16,056	10,761	83	
6,841	16,131	16,610	11,111		85

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q past change from 1Q lagged score in balance change regressions. Baseline specification. All estimates significant at 1% level. Sample period 2001Q1-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

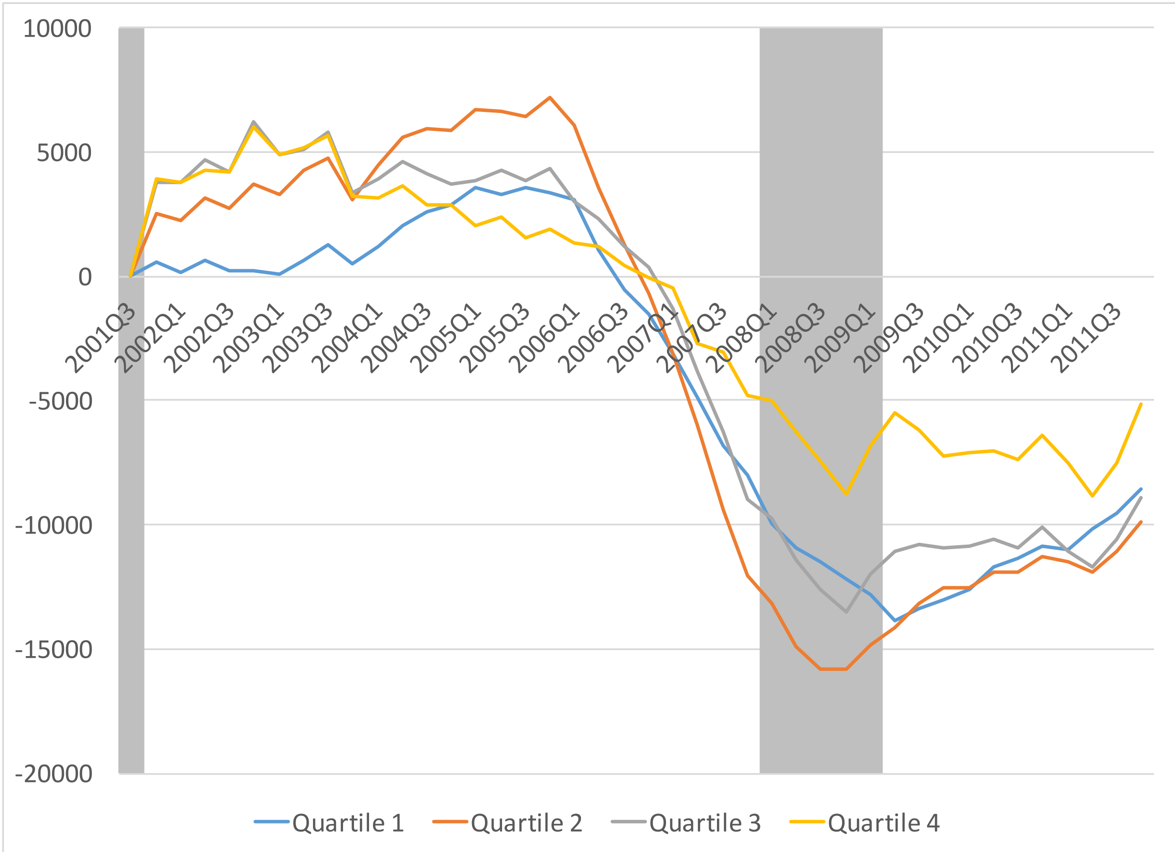


Figure 38: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita total debt balances in USD. Sample period 2001Q1-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 40 reports the estimated age effects for the 8 quarter ahead change in total debt balances. The left panel reports the age effects for the baseline specification, and the right panel the age effects by quartile for the specification that includes the age credit score quartile interactions. As for mortgage balances, there are sizable age effects, but only for borrowers with credit scores in quartile 2-4, with no life cycle growth in total debt balances for young borrowers who remain in quartile 1.

G.3 Credit Card Balances

We perform the analysis described in Section 6.1 for credit card balances. Credit cards are the main source of financing for consumer durable purchases and may be helpful to smooth unanticipated expenses, and therefore, are tightly linked to consumption, especially for lower income households. Table 13 presents the estimated averages for the 8 quarter ahead change in credit card balances by 1 quarter lagged credit score. The average change in credit card

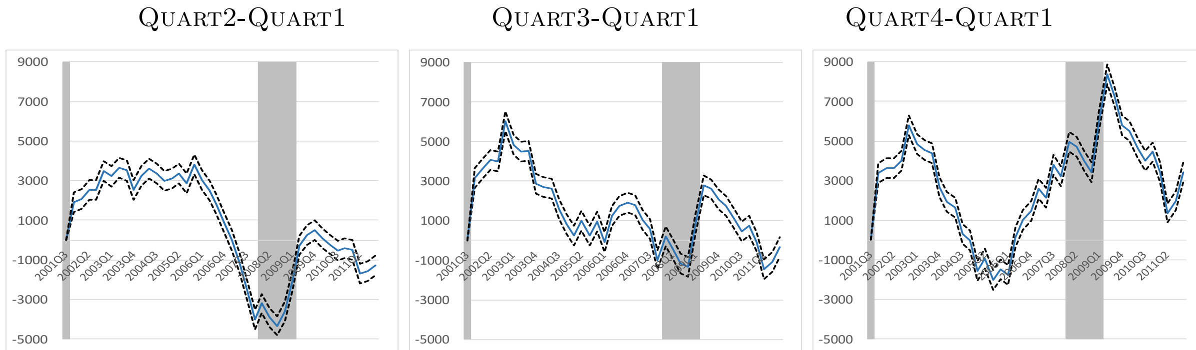


Figure 39: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita total debt balances in USD. Dashed lines denote 5% confidence intervals. Sample period 2001Q3-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

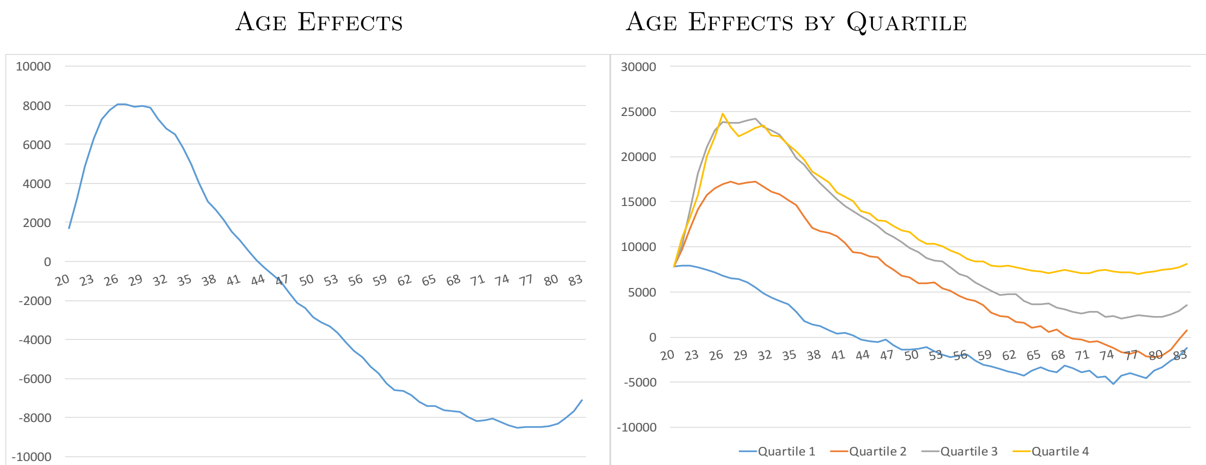


Figure 40: Estimated age effects from balance change regressions. Baseline specification (left) and specification with age × quartile interactions (right). Dependent variable is the 8Q ahead change in per capita total debt total debt. Sample period 2001Q1-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

balances is 3-4 times larger for quartiles 2-4 relative to quartile 1. As for mortgage debt and total balances, the contribution of of past credit score changes to future borrowing is negligible for all the horizons considered.

Figure 41 the estimated time effects by quartile of the 1 quarter lagged credit score distribution (left panel) and the estimated age effects (right panel). The time effects show an interesting countercyclical pattern of credit card balance changes for quartiles 1 and 2, suggesting that lower credit score/lower income borrowers reduce reliance on credit card debt during economic expansions up until 2007. The growth in credit card balance declines

Table 13: Average 8 Quarter Ahead Change in Credit Card Balances

Dependent Variable: 8Q Ahead Credit Card Balance Change (USD)						
1Q lagged CS Quartile Effects				ΔCS_{-1}		
1	2	3	4	4Q	6Q	8Q
586	1,930	2,043	1,797			
898	1,947	1,901	1,628	15		
866	1,814	1,986	1,722		15	
546	1,579	1,909	1,613			15

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q, 8Q past change from 1Q lagged score in balance change regressions. Age effects included. All estimates significant at 1% level. Sample period 1999Q2-2012Q4. Number of obs. (baseline) 77,843,568. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

substantially for quartiles 1-3 during crisis, with only a modest decline for borrowers in quartile 4. Credit card balance growth recovers starting in 2011 for all quartiles. Turning to the age effects, we see credit card balance growth highest at age 20 and decline monotonically with age until age 75 when it bottoms out, consistent with standard notions of the relation between consumption and income at different points in the life cycle. The results are similar for the 4 quarter ahead and 12 quarter ahead change in credit card balances.

G.4 Auto Loan Balances

Turning to auto loan balances, we find that the average 8 quarter ahead change in auto balances, displayed in Table 14, is higher for quartiles 2-4, relative to quartile 1, and once again, the contribution of past credit score changes to future changes in balances is negligible.

Figure 42 presents the estimated time affects by quartile of the 1 quarter lagged credit score distribution (left panel) and the estimated age effects (right panel). We find no growth in auto balances for quartile 1 during boom, and limited growth for higher quartiles between 2001 and 2004. All quartiles exhibit large decline in auto loan balanced during the crisis and a recovery which brings the growth back to zero by the end of the sample. The estimated age effects for the change in auto loan balances start at 1,400$ for age 20 and monotonically decline with age, reaching zero by the early 70s. We obtain similar results when we consider the 4 quarter ahead and 12 quarter ahead change in balances.

Time Effects by Quartile　　　　　　　　　　Age Effects

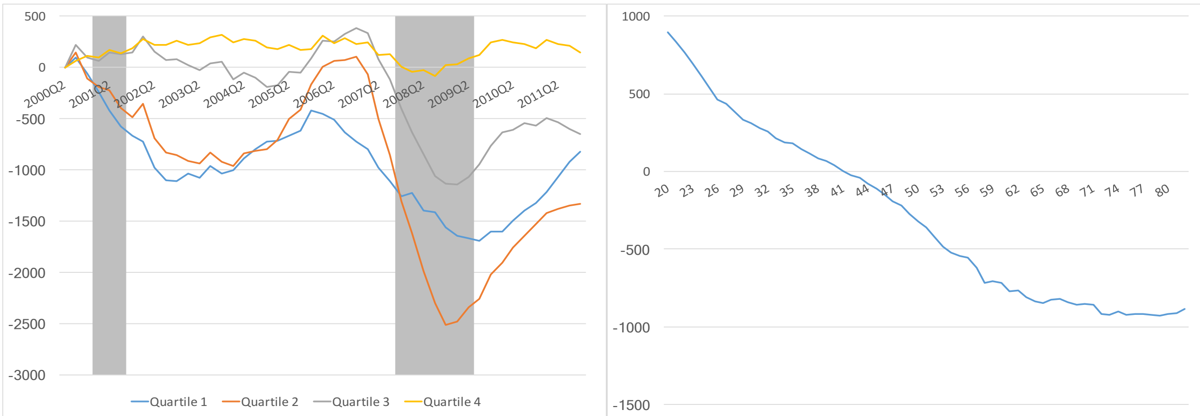


Figure 41: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions (left panel) and age effects (right panel). 4Q credit score change included. Dependent variable is the 8Q ahead change in per capita credit card balances in USD. Sample period 1999Q2-2012Q4. Number of obs. 66,086,120. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 14: Average 8 Quarter Ahead Change in Auto Loan Balances

Dependent Variable: 8Q Ahead Auto Loan Balance Change (USD)						
1Q lagged CS Quartile Effects				ΔCS_{-1}		
1	2	3	4	4Q	6Q	8Q
1,503	1,858	1,620	1,528			
1,449	1,851	1,703	1,585	7		
1,582	2,035	1,879	1,711		7	
1,267	1,832	1,755	1,595			6

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q, 8Q past change from 1Q lagged score in balance change regressions. Age effects included. All estimates significant at 1% level. Sample period 1999Q2-2012Q4. Number of obs. (baseline) 77,943,776. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

G.5 Delinquent balances

We report additional results for the estimates for delinquent balances described in Section 6.2.1. Figure 43 reports the differences in the estimated time effects for quartiles 2-4 relative to quartile 1. As for debt balances, there is a sizable and highly significant difference in time effects across quartiles. Figure 44 reports the estimated age effects.The age effects for

Time Effects by Quartile　　　　Age Effects

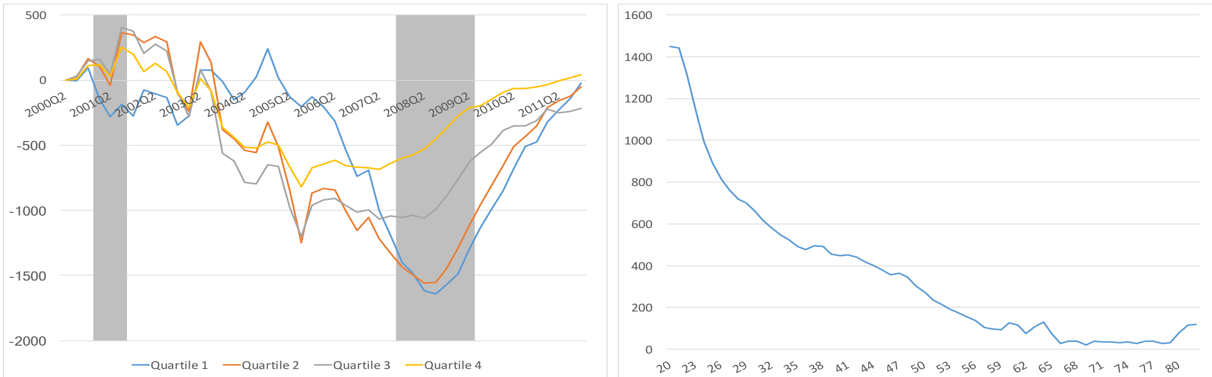


Figure 42: Estimated time effects (left panel) by 1Q lagged Equifax Risk Score quartile and age effects (right panel) from balance change regressions. 4Q credit score change included. Dependent variable is the 8Q ahead change in per capita auto loan balances in USD. Sample period 1999Q2-2012Q4. Number of obs. 69,925,656. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

dellinquent balances largely reflect the age pattern of total debt balances.

Quart2-Quart1　　　　Quart3-Quart1　　　　Quart4-Quart1

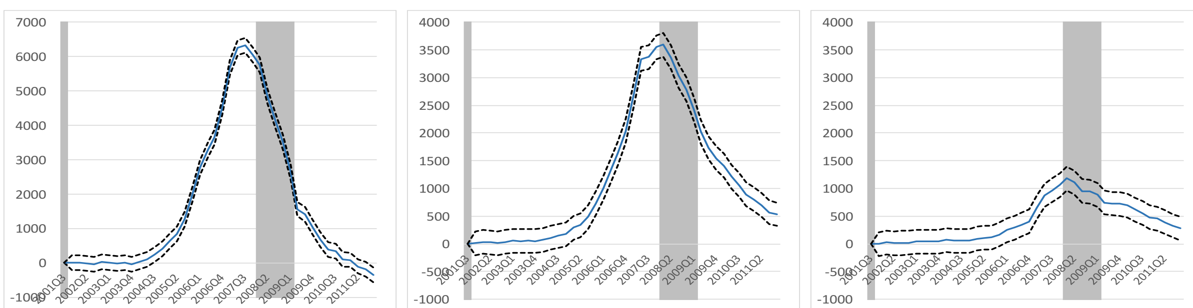


Figure 43: Difference in estimated time effects by 1Q lagged Equifax Risk Score quartile relative to quartile 1. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Dashed lines denote 5% confidence intervals. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

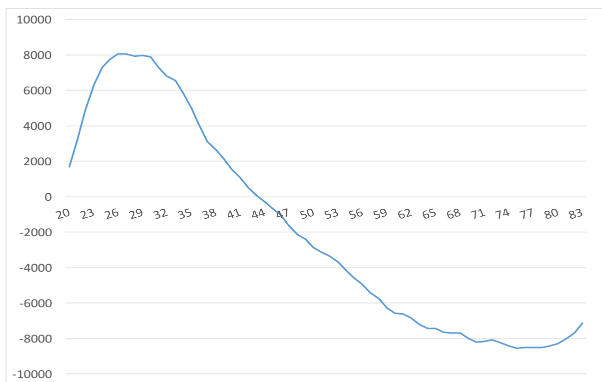


Figure 44: Estimated age effects from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

H Investors

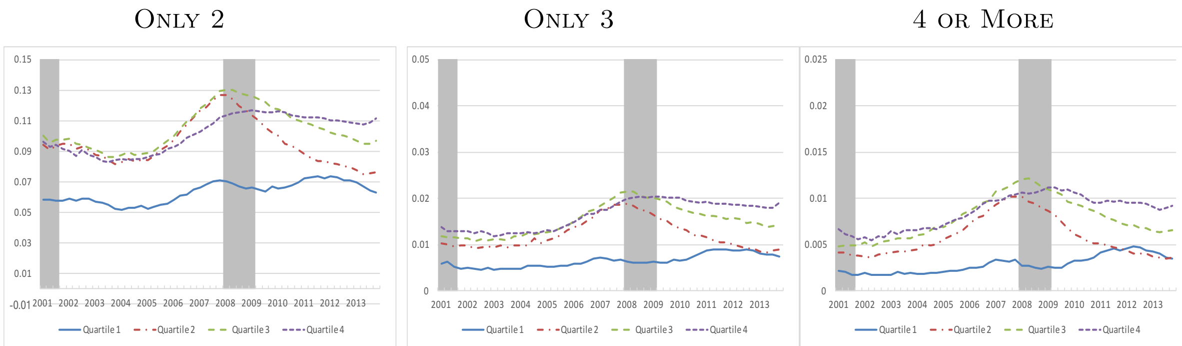


Figure 45: Fraction of borrowers with only 2 (left), only 3 (center) and 4 or more (right) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

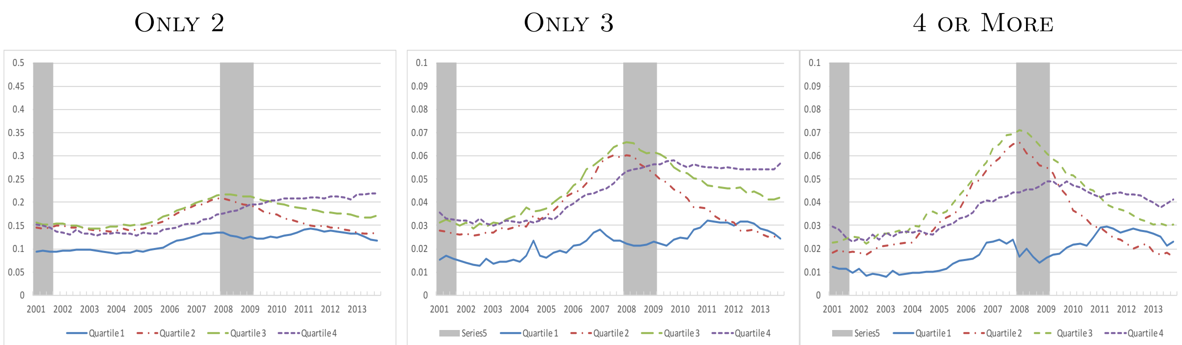


Figure 46: Share of mortgage balances held by borrowers with only 2 (left), only 3 (center) and 4 or more (right) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

I Additional Zip Code Level Evidence

In this section, we report additional results for the zip code level analysis. We start by plotting the gross level of total debt balances per capita as a ratio to 2001Q3 by fraction of subprime borrowers in 2001. While for mortgage balances, zip codes in quartile 4 exhibit faster growth in debt balances, relative to those in lower quartiles, there is virtually no difference across quartiles for total debt balances. While total balance growth is more pronounced for prime borrowers in zip codes with the highest fraction of subprime, there is virtually no difference in debt growth for subprime borrowers across quartiles.

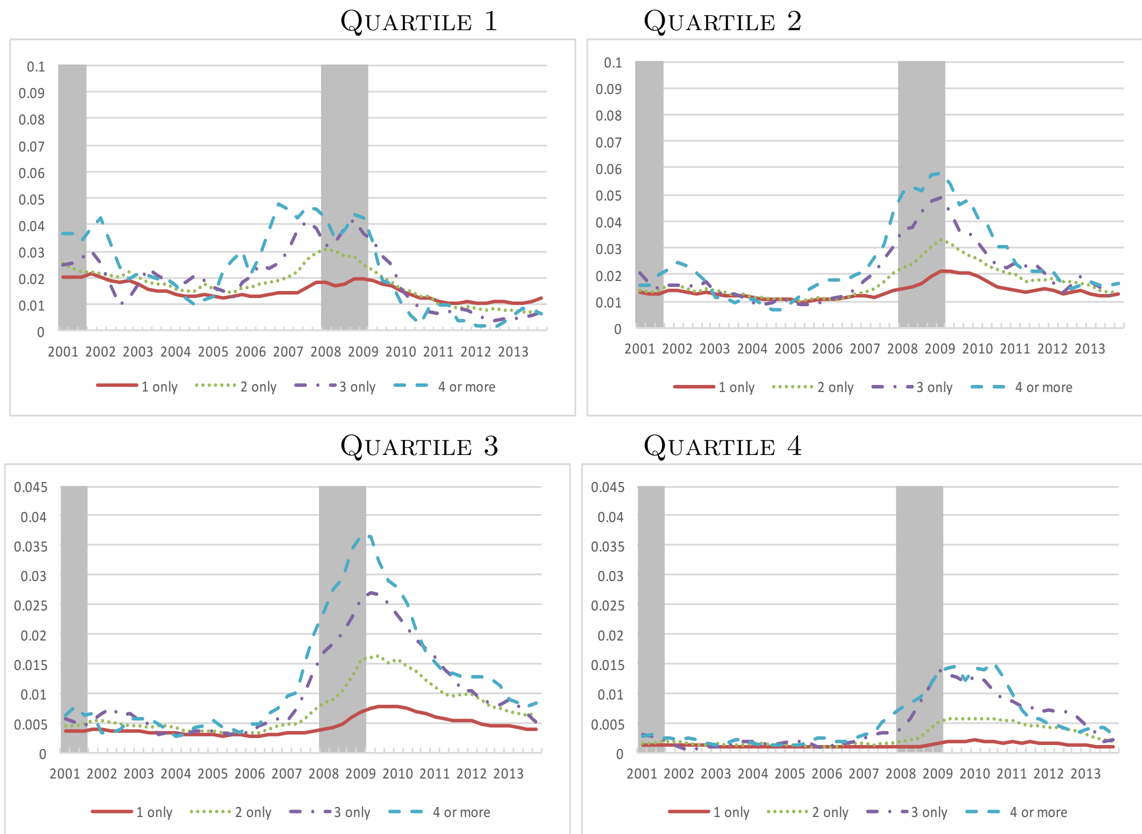


Figure 47: 90+ days mortgage delinquency rates by quartile of 8Q lag Equifax Risk Score quartile by number of first mortgages. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Figure 50 displays debt growth by prime and subprime borrowers at the zip code level by fraction of subprime borrowers in 2001. As for mortgage balances, prime borrowers exhibit higher growth in total debt balances in quartiles.

I.1 Stability and Consistency of Zip Code Rankings

Mian and Sufi (2009) ranks zip codes by the fraction of subprime in 1996. Mian and Sufi (2011) ranks zip codes by initial personal disposable income or initial leverage, which they define as total debt balances per capita over average personal disposable income. Mian and Sufi (2014) rank counties by the decline in household net worth during the crisis, which is instrumented by the Saiz (2010) house prime elasticities to capture the rise in house prices during the boom and the associated rise in leverage. Here, we examine the relation between these measures at the zip code level.

We first consider the stability of each ranking. Table 15 reports the fraction of zip codes that remain in the same quartile of each ranking in the subsequent year. We consider three indicators: the fraction of subprime borrowers, average personal disposable income (PDI)

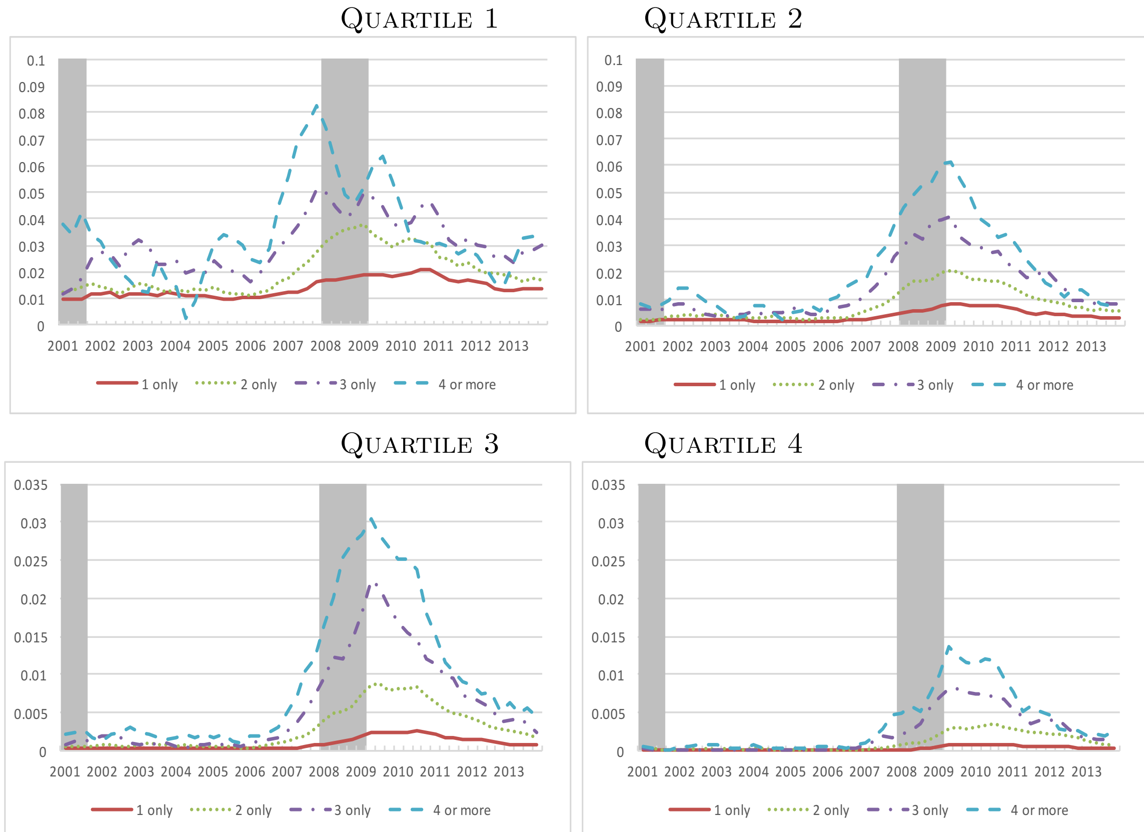


Figure 48: Foreclosure rates by quartile of 8Q lag Equifax Risk Score quartile by number of first mortgages. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

and average leverage, defined as total balances per capita over average personal disposable income. All rankings are very stable, with approximately 70% of all zip codes remaining in the same quartile of the fraction of subprime borrower distribution year to year, over 90% for personal disposable income and 59-75% for leverage. We also examine the correlation between various rankings. The Spearman correlation between fraction of subprime and PDI ranges from -0.46 and -0.58, and decreases over the sample period. The Spearman correlation between fraction of subprime and leverage is negative, ranging between -0.03 at the end of the sample and -0.15 at the height of the credit boom. This is consistent with a greater growth in leverage for zip codes with low fraction of subprime during the boom.

We now concentrate on quartile 4 by fraction of subprime on 2001. We examine their income and leverage ranking throughout the sample period. The results are reported in Table 16. Depending on the sample year, 51-58% of the zip codes in quartile 4 of the fraction of subprime borrowers in 2001 are in the lowest PDI quartile in 2001-2011. Moreover, the fraction of subprime zip codes in higher PDI quartiles declines later in the sample period. The distribution of zip codes with high fraction of subprime borrowers across the leverage distribution is more even, however, in all years more than 50% are in the first 2 quartiles of the leverage distribution, confirming the negative relation between fraction of subprime

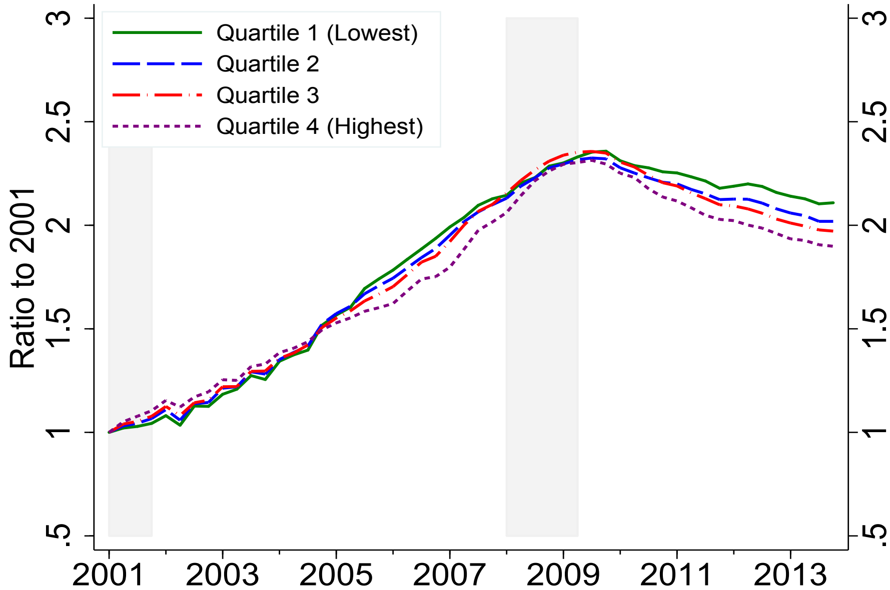


Figure 49: Growth in total balances by share of individuals with Equifax Risk Score below 660 in 1999. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 15: Stability and Correlation of Zip Code Rankings

	Fraction in same quartile			Correlation with % subprime	
	% subprime	PDI	Leverage	PDI	Leverage
2001	0.68	0.88	0.59	-0.46 ***	-0.04 ***
2002	0.71	0.91	0.62	-0.50 ***	-0.05 ***
2003	0.73	0.92	0.66	-0.51 ***	-0.06 ***
2004	0.70	0.90	0.63	-0.53 ***	-0.10 ***
2005	0.71	0.90	0.67	-0.53 ***	-0.15 ***
2006	0.72	0.89	0.67	-0.55 ***	-0.15 ***
2007	0.72	0.87	0.69	-0.58 ***	-0.09 ***
2008	0.72	0.92	0.73	-0.58 ***	-0.11 ***
2009	0.72	0.95	0.74	-0.58 ***	-0.04 ***
2010	0.73	0.95	0.75	-0.58 ***	-0.03 ***
2011	0.72			-0.57 ***	-0.03 ***

Fraction of zip codes in same quartile in subsequent year, by fraction of subprime borrowers, PDI and leverage. Correlation (Spearman ρ) of fraction of subprime borrowers in 2001 and PDI or leverage in each sample year. Leverage is the ratio of total debt balances to PDI. *** denotes significance at the 1% level. Source: Authors' calculations based on FRBNY CCP/Equifax Data, IPUMS, IRS, BLS, ACS data.

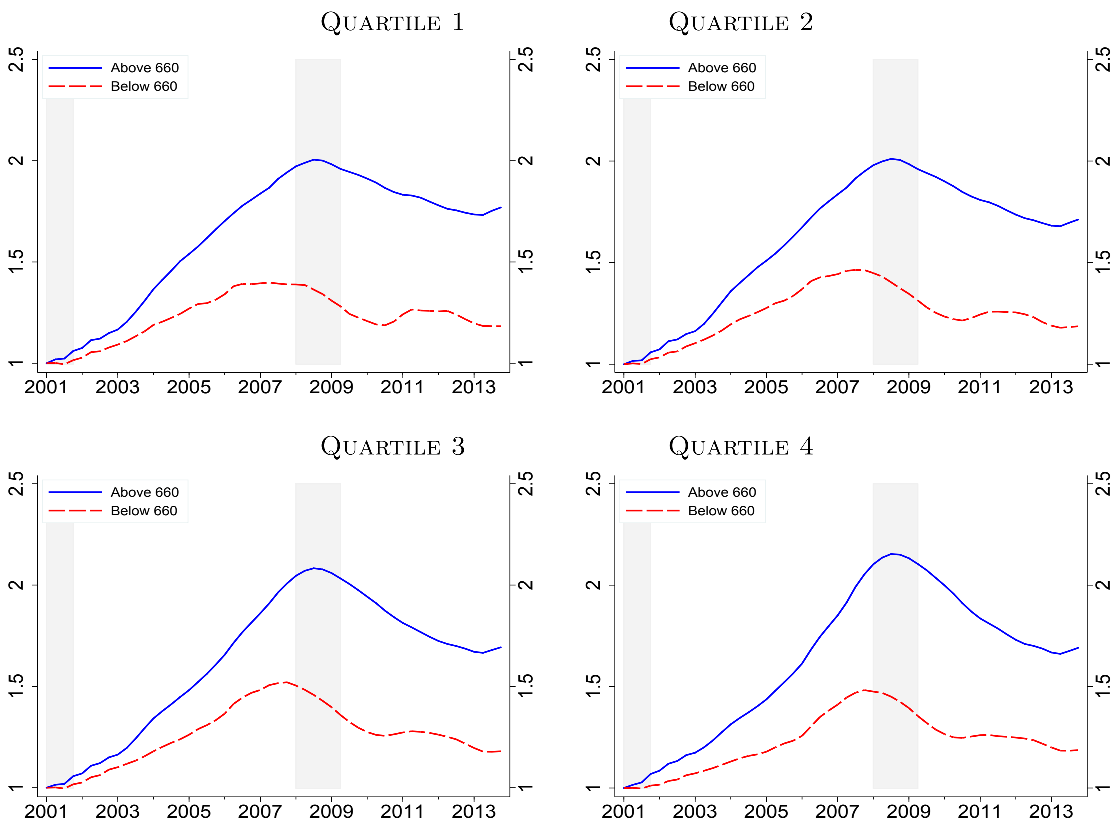


Figure 50: Total debt growth for prime&subprime individuals by quartile of share of subprime in 1999. Based on 8Q lagged individual credit scores. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

borrowers and leverage.

Table 16: Zip Codes in Quartile 4 by % of Subprime Borrowers in 2001

	PDI Quartile				Leverage Quartile			
	1	2	3	4	1	2	3	4
2001	0.51	0.27	0.14	0.07	0.28	0.27	0.23	0.22
2002	0.54	0.27	0.13	0.07	0.29	0.26	0.23	0.21
2003	0.55	0.26	0.13	0.07	0.29	0.27	0.22	0.21
2004	0.57	0.24	0.12	0.07	0.31	0.28	0.21	0.19
2005	0.59	0.23	0.11	0.07	0.35	0.27	0.21	0.17
2006	0.57	0.25	0.12	0.07	0.35	0.28	0.20	0.17
2007	0.58	0.25	0.11	0.06	0.33	0.28	0.20	0.19
2008	0.58	0.26	0.11	0.06	0.34	0.27	0.20	0.19
2009	0.58	0.25	0.11	0.06	0.31	0.26	0.20	0.23
2010	0.58	0.25	0.11	0.06	0.32	0.25	0.20	0.23
2011	0.58	0.26	0.11	0.06	0.31	0.24	0.20	0.24
2002-06 average	0.56	0.25	0.12	0.07	0.32	0.27	0.21	0.19

Fraction of zip codes in quartile 4 of the fraction of subprime borrowers in 2001 in various quartiles of the PDI and leverage distribution in each sample year. Leverage is the ratio of total per capital debt balances to average PDI. Source: Authors' calculations based on FRBNY CCP/Equifax Data, IPUMS, IRS, BLS, ACS data.