Credit Growth and the Financial Crisis: A New Narrative*

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Abstract

A broadly accepted view contends that the 2007-2009 crisis in the U.S. was caused by an expansion in mortgage credit to subprime borrowers during the 2001-2006 boom, leading to the ensuing spike in defaults and foreclosures. Using a large administrative panel of credit report data, we show that credit growth between 2001 and 2006 was concentrated in the prime segment. The rise in mortgage defaults during the crisis was concentrated in the middle and at the top of the credit score distribution, and mostly attributable to real estate investors who at the height of the crisis accounted for over 50% of all foreclosures for these borrowers. Our findings suggest an alternative narrative that challenges the large role of subprime credit for the crisis.

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1 Introduction

Understanding the causes of the 2007-2009 financial crisis is one of the key questions in modern economics and it is critical to designing policies and regulations to prevent similar episodes in the future. The rise in mortgage delinquencies and foreclosures in the United States starting in late 2006 is viewed by most as the precipitating factor, with the expansion of subprime credit during the 2001-2006 housing boom as the leading cause for the subsequent spike in defaults, which caused the collapse of the housing market and the subsequent 2007-2009 recession.[1]

This paper studies the evolution of household borrowing and defaults between 1999 and 2013 using a large, nationally representative administrative panel of anonymous credit reports. Our analysis suggests an alternative narrative that challenges the view that an expansion of mortgage credit to subprime borrowers played a leading role in the mortgage crisis. We show that credit growth between 2001 and 2007 was concentrated among prime borrowers, and that borrowing by individuals with low credit score was virtually constant over this period. Additionally, mortgage balance growth was positively related to individual income growth. We also find that the rise in defaults during the crisis was concentrated in the middle of the credit score distribution. While subprime borrowers have higher default rates than those with higher credit scores, during the 2007-2009 crisis the fraction of mortgage delinquencies attributable to the lowest quartile of the credit score distribution dropped from 40% to 30%, and the fraction of foreclosures from 70% to 35%.

The sharp rise in defaults for borrowers in the middle and at the top of the credit score distribution is puzzling, as these borrowers historically exhibit very low default rates on any type of debt and very low foreclosure rates. To gain insight into what may have driven defaults by borrowers with good credit histories, we explore the role of real estate investors. There are four main reasons that may lead real estate investors to display higher default rates than other borrowers with similar credit scores. First, mortgages for non owner-occupied properties must meet stricter credit standards to qualify for GSE insurance and are usually charged an additional premium. This makes it more likely for investors to contract non-standard mortgages with shorter maturity or variable rates, which are intrinsically more risky.[2] Second, if investors are motivated by the prospect of capital gains,[3] they are more likely to default if the value of the mortgage is higher than the value of the property, especially in states in which foreclosure is non recourse.[4] Third, only the primary

[1] See Mian and Sufi (2009)), Mian and Sufi (2010), Mian and Sufi (2011), Mian, Rao, and Sufi (2013) and Mian, Sufi, and Trebbi (2015)). More recently, Adelino, Schoar, and Severino (2015) and Foote, Loewenstein, and Willen (2016) have made the case that the growth in mortgage balances was concentrated in the middle of the income distribution.

[2] 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 even for standard borrowers.

[3] Case, Shiller, and Thompson (2012) show using survey evidence that long-term home price expectations reached abnormally high levels relative to rental rates during the housing boom. Foote, Gerardi, and Willen (2012) and Adelino, Schoar, and Severino (2015) also emphasize the role of overoptimistic house price expectations.

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

residence is protected in personal bankruptcy. Thus, financially distressed borrowers whose primary residence satisfies the homestead exemption could potentially file for Chapter 7 bankruptcy and discharge unsecured debt to avoid missing payments on the mortgage, or file Chapter 13 bankruptcy to stay foreclosure procedures and possibly restructure their mortgage.[5] Finally, the financial and psychological costs of default for resident owners are typically quite substantial, including moving and storage costs, longer commute times and so on. Real estate investors are not subject to these costs.

We identify investors as borrowers who hold two or more first mortgages, following Haughwout et al. (2011). We find that real estate investors indeed played a critical role in the rise in mortgage debt for the middle and the top of the credit score distribution. Investment activity surged dramatically starting in 2004, especially for prime borrowers. The share of mortgage balances of real estate investors rose from 21% to 33% between 2004 and 2007 for quartiles 2-4 of the credit score distribution. Most importantly, we find that the rise in mortgage defaults is mostly accounted by real estate investors. The fraction of investors with new mortgage defaults grew by a factor of 4 or more for the top three quartiles of the credit score distribution between 2005 and 2008, while it grew by half of that amount from a much smaller base for non-investors. This striking result provides guidance to policy makers interested in understanding the cause of the housing crisis and designing interventions to mitigate and prevent future such episodes.[6]

We also explore the broader macroeconomic implications of our findings, linking them to the literature that emphasizes the role of the collateral channel in the transmission of financial shocks to real economic activity. There is a large theoretical literature on the role of collateral constraints in causing or amplifying swings in economic performance, following the pioneering work of Kiyotaki and Moore (1997), which proliferated in response to the financial crisis.[7] After the 2007-2009 recession, a large empirical literature also developed. The empirical literature exploits geographical variation to relate mortgage debt growth to the severity of the recession at a regional level, linking the size of the credit boom and the depth of the recession in different geographical areas.[8] We also examine the behavior of debt and defaults at the zip code level. Because we have access to individual data as well, 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 outcomes. Following Mian and Sufi (2009), we rank zip codes

[5] Li (2009) describes in detail the protections from foreclosures that are afforded by bankruptcy filing. Albanesi and Nosal (2018) 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 is 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) and Robinson and Todd (2010) 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 (2017).

[8] Some examples include Mian and Sufi (2011), Mian, Sufi, and Trebbi (2015), Mian, Rao, and Sufi (2013), Mian and Sufi (2010), Midrigan and Philippon (2011), Kehoe, Pastorino, and Midrigan (2016), Keys et al. (2014).

by the initial fraction of subprime borrowers. Based on our data, zip codes with the largest share of subprime borrowers exhibit stronger growth in per capita mortgage balances over the 2001-2006 boom, confirming previous findings. However, in all zip codes *prime* borrowers are responsible for most of the credit growth. We also show that in all zip codes it was the prime borrowers that were driving the rise in defaults during the crisis.

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 drop or unemployment rate) attribute this correlation to the tightening of collateral constraints during the crisis, resulting from mortgage defaults by high risk borrowers with high marginal propensity to consume. Our findings are not consistent with this causal mechanism. We therefore explore additional factors that may explain this correlation. We show that zip codes with higher fraction of subprime borrowers are younger, have lower levels of educational attainment and have a disproportionately large minority share of the population. It is well known that younger, less educated, minority workers suffer larger and more persistent employment loss during recessions (see Mincer (1991) and Shimer (1998)). We also show that zip codes with a large fraction of subprime borrowers exhibit more income inequality. This observation can shed some light on the relation between the rise in mortgage debt and income growth. Using zip code level data, Mian and Sufi (2009) emphasize that the growth in mortgage debt was driven by an increase in the supply of credit, since it was not associated with a rise in household incomes over this period, whereas we find a positive relation between income growth and mortgage debt growth in individual data. We show that within zip codes, mortgage debt growth was driven by prime borrowers, who also typically have higher income. The growth in income inequality and especially top incomes during the 2001-2006 boom (see for example Saez (2018)) and the fact that zip codes with large subprime populations display higher inequality may explain the disparity between zip code and individual level behavior.

Finally, we examine real estate investor activity and find that it is very similar across zip codes. However, in zip codes with a large subprime population, investors exhibit a larger growth in mortgage balances and a more pronounced rise in foreclosures. These areas are also disproportionately urban and exhibit higher home price peaks during the boom and more pronounced drops during the crisis. The urban nature of these areas may have jointly contributed to the rise in home prices and the intensity of investor activity, resulting from gentrification (see Guerrieri, Hartley, and Hurst (2013)). Taken together, our findings suggest that using geographically aggregated data does not provide a good approximation of the distribution of debt across different types of borrowers. Moreover, the positive correlation between credit growth during the boom and the depth of the recession may be due to other geographical characteristics, such as the prevalence of young, unskilled and minority workers who are particularly business cycle sensitive.

Our findings are consistent with those in Adelino, Schoar, and Severino (2015) and Adelino, Schoar, and Severino (2017), who show that the growth in mortgage balances during the boom

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 2001-2007 boom and the stark rise in defaults and foreclosures for these households is primarily driven by real estate investors.[9] Our results are also consistent with Foote, Loewenstein, and Willen (2016), who find that the geographical relation in 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 contribution relative to these papers is to explain why previous research had identified subprime borrowers as primarily responsible for both the rise in mortgage debt in 2001-2006 and the subsequent rise in defaults. Mian and Sufi (2009) and Mian and Sufi (2015) identify subprime individuals based on their credit score in 1996 and 1997, respectively. We show that, since low credit score individuals are disproportionally young, this approach confounds an expansion of borrowing by low credit score borrowers with the life cycle demand for credit of borrowers who were young at the start of the boom. To avoid this pitfall, our approach estimates future growth in mortgage balances and mortgage delinquencies based on borrowers' recent lagged credit scores. This is closer to industry practices and 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. This approach is motivated by our analysis of the relationship between credit scores and income using payroll data for 2009. We show that the cross sectional variation of credit scores is mostly explained by variation in labor income, conditional on age, and that the life cycle growth in credit scores is tightly related to the life cycle growth in income.

Our analysis also reconciles the pattern of borrowing at the individual level and at the zip code level, showing that though mortgage balances grow more in areas with a larger fraction of subprime borrowers, within those areas, debt growth is driven by high credit score borrowers. Both at the individual level and at the zip code level, over 80% of the differences in the growth in mortgage balances between the top and the bottom of the initial credit score distribution is due to age. The fact that zip codes with high fraction of subprime borrowers are associated with low income levels and growth during the boom may be due to demographics, specifically the high fraction of young, low education and minority borrowers.

We are also the first to provide comprehensive evidence on the growth of real estate investment activity during the 2001-2006 boom and to isolate the unique role of investors in the 2007-2009 mortgage crisis.[10] The rise in investor activity can reconcile the fact that though the number of mortgage originations rose during the boom, the fraction of the U.S. population with a mortgage

[9] Ferreira and Gyourko (2015) also find that default activity by prime borrowers intensifies during the crisis, however, their definition of prime/subprime borrowers is based on lender characteristics, not on the individual characteristics of the borrower.

[10] Bhutta (2015) examines the contribution of real estate investors to the growth of mortgage balances during the boom but does not document their default behavior and does not differentiate by credit score. Haughwout et al. (2011) focus on investment activity in the sand states and the role mortgage fraud, specifically, the tendency to misreport the use of their properties, in allowing investors to acquire high leverage.

did not vary substantially over the same period. In 2001-2003, the surge in originations was mainly driven by refinancing activity (see Bhutta and Keys (2016a) and Chen, Michaux, and Roussanov (2013)), whereas based on our analysis, investment activity mostly contributed to the ongoing but slower pace of originations growth starting in 2004. Albanesi (2018) provides a comprehensive empirical analysis of the behavior of real estate investors between 2001 and 2012 and explore the factors behind their higher default rates. She shows that all investors, irrespective of their income, display substantially higher leverage than non-investors and are more likely to default strategically rather than as a result of financial distress. Additionally, she finds that investor activity surged especially in high density metropolitan areas that experience strong positive trends in population growth and that investor foreclosure rates during the crisis were positively related to the magnitude of house price fluctuations.

A question left open by our analysis is why real estate investor activity surged in 2004. Mian and Sufi (2009) emphasize that the growth in mortgage debt was driven by an increase in the supply of credit, since it was not associated with a rise in household incomes over this period. However, we show that there is a positive relation between income and mortgage balance growth at the individual level. Justiniano, Primiceri, and Tambalotti (2017) show that starting in June 2003, mortgage rates failed to rise according to their historical relationship with Treasury yields, leading to significantly and persistently easier mortgage credit conditions, and that delinquency rates started to rise for loans originated after mid 2003, exactly when mortgage credit became relatively cheaper. On the other hand, Adelino, Schoar, and Severino (2015) and Adelino, Schoar, and Severino (2017) argue that the growth in mortgage balances among prime borrowers was fueled by overly optimistic expectations about the growth in house prices. Cox and Ludvigson (2018) examines the relative contribution of credit supply conditions and house price expectations on housing price dynamics and find that credit supply indicators seem to be the most important drivers of house prices. Albanesi (2019) shows that expectations of house price growth can reduce equilibrium mortgage rates, as it reduces the cost of default for lenders, and at the same time increase the demand of investor mortgages with higher default rates.

The rest of the paper is organized as follows. Section 2 describes our data and examines the behavior of debt and defaults by recent credit score. Section 3 discusses the relation between our findings and the prior literature on credit growth and default behavior by credit score. Section 4 discusses the role of real estate investors. Section 5 presents the zip code level analysis and Section 6 concludes.

2 Distribution of Debt and Defaults

Our analysis is based on 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

1999Q1 and ends in 2013Q3. We use a 1% sample for the individual analysis, which includes information for approximately 2.5 million individuals in each quarter. We use the full 5% sample for the zip code level analysis. The data contains over 600 variables, 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 financial information, the data contains individual descriptors such as age, ZIP code and credit score. For 2009, we also have access to payroll data for a subset of approximately 11,000 borrowers.[11]

We are interested in classifying borrowers by their default risk at the time of borrowing. The most common proxy for individual default risk is the credit score, an ordinal ranking of borrowers by their predicted default risk widely used by the financial industry. For most unsecured debt, lenders typically check a prospective borrower's credit score at the time of application, sometimes supplemented by a recent information on 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 loan terms, 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 scores. 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. 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 length of the credit history, which explains 15-20% of the variation, followed by new accounts and types of credit used (10-5%) and new "hard" inquiries, that is those resulting from a borrower initiated credit application.[12] We have access to the Equifax Risk Score, which is a proprietary measure designed to capture the likelihood of a consumer becoming 90+

[11]The data is described in detail by the Center for Microeconomic Data at the Federal Reserve Bank of New York. The main reference is The data is described in detail in Lee and van der Klaauw (2010). A technical note with a description of the dataset is available here: `https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/Technical_Notes_HHDC.pdf`. The data dictionary is available at `https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/data_dictionary_HHDC.pdf`. We provide more detail on the variables used in our analysis in Appendix A.

[12]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 Reporting Reform 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 and any information that is not proven to be predictive of future credit performance. Soft inquiries include consumer-initiated inquiries, such as requests to view one's own credit report, promotional inquiries made by lenders in order to make pre-approved credit offers, or administrative inquiries made by lenders to review open accounts. Requests that are marked as coming from employers are also not counted.

days delinquent within the subsequent 24 months. The measure has a numerical range of 280 to 850, where higher scores indicate lower default risk. It can be accessed by lenders together with the borrower's credit report.

Since credit scores are proprietary models, it is useful to relate credit scores to other observables that economic theory would suggest are critical for default risk. Ability to afford loan payments is a key determinant of default risk in most default models (see for example Chatterjee et al. (2007)), so it is useful to explore the relation between income and credit scores. To do so, we use payroll information from a large income verification firm, linked to the Equifax credit files, which is available for 2009. The income data is available for a nationally representative subsample of over 11,000 individuals in the credit panel. We construct a total labor income measure using information on pay rate and pay frequency. Appendix A 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.

We examine the cross-sectional relationship between credit score and income by regressing the credit score on income, income square, age, age square, and interactions between age, income and state fixed effects. The details of the specification are described in Appendix D. We consider contemporaneous as well as 8 and 4 quarter lagged credit scores. The results are very similar for all these measures, and we focus on the relation between between the 8 quarter lagged credit score and 2009 income since credit scores target default risk in the subsequent 8 quarters. Figure 1 displays the in-sample predicted relation between the 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. The intercept of the relation increases with age while the slope declines with age, suggesting that for older borrowers variation in credit scores are less dependent on 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 income conditional on age supports the notion that it is a good indicator of default risk.

2.1 Estimation Strategy

We now present our approach to characterizing the distribution of debt growth and defaults during the boom and defaults during the crisis based on credit scores at the time of borrowing. We adopt a lender's perspective, and relate future credit growth at various horizons to a recent lagged credit score. 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, including mortgages, such requests are processed in a matter of days, the credit score in the

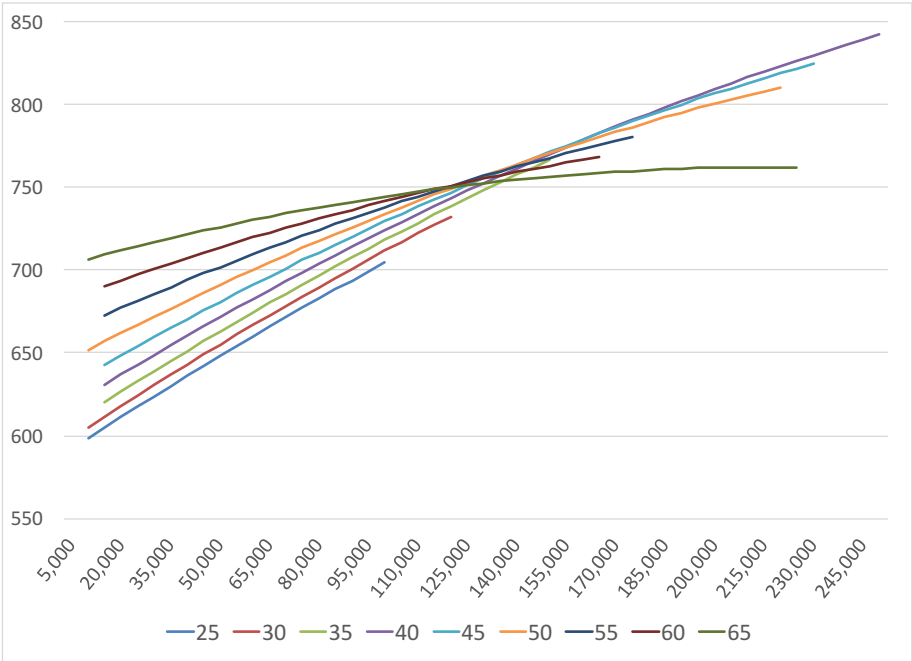


Figure 1: In sample estimated relation between 8Q lagged Equifax Risk Score by age and 2009 total annual labor income, for age specific 1st-99th percentiles of income range. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

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. For these reasons, we also include the change in the credit score as an explanatory variable. For mortgages, lenders typically also verify a borrower'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. As we have shown, income and recent credit score are positively related, conditional on age.

Our baseline specification for studying mortgage balances is:

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

where i denotes an 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 in quarters. We will consider mortgage balances to examine the distribution of debt and 90 days or more delinquent mortgage balances

to describe the distribution of defaults. 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 quarter effects, age effects and their interaction with the 1 quarter lagged credit score quartile. The interaction between quarter effects and the one quarter lagged credit score captures the heterogeneity in borrowing behavior that we seek to identify. Additionally, the interaction between age and quarter and the one quarter lagged score are meant to introduce flexibility to the profiles of mortgage balance growth with respect to the starting score for borrowers of different age. For example, we know that younger borrowers tend to experience steeper growth in their debt balances for standard lifecycle motives.

Our estimates show that during the boom credit growth was highest for borrowers in the middle and top quartiles of the one quarter lagged credit score distribution, at all horizons. We find that past changes in the credit score also have a sizable effect on subsequent balance growth. We also find strong age effects 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 discuss our findings in detail. We complement our regression based evidence with an analysis of extensive margins, such as mortgage originations, first mortgages and foreclosures by recent credit scores. We find there is virtually no growth in the fraction with first mortgages and a slight decline in the fraction with new mortgage originations for borrowers in the first quartile of the credit score distribution. Additionally, consistent with Adelino, Schoar, and Severino (2015), we find that the distribution of credit scores at origination changes little during the boom. Further, we show that the rise in mortgage delinquencies and foreclosures is greatest for borrowers in middle of the credit score distribution.

2.2 Debt

This section presents our regression results for mortgage balances. 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 1 reports the fixed effects estimates, and figure 2 presents the age adjusted interactions between the time effects and each quartile of the 1 quarter lagged credit score distribution.[13]

The credit score quartile fixed effects show a non-monotone pattern, with quartile 2 and 3 estimates of the average eight 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 coefficients on the change in the credit score distribution are \$50 for the 4 quarter lag and \$51 for the 6 quarter lag, and highly significant. To understand the economic impact of

[13] In Appendix B, we report additional results and some robustness analysis.

these estimates, it is useful to consider how common credit events may affect the credit score over 4 or 6 quarters. Based on commonly used credit score simulators,[14] a borrower with credit score of 610 (in quartile 1) with a $15,000 balance on revolving trades and no mortgages can increase their credit score by 30 points over a one year period by paying down 5% of her balance every month for 12 months, while paying their bills on time over the same period may raise their credit score by only 5 points. The simulated changes in credit score corresponding to these events have smaller effects for borrowers in quartile 2, and negligible effects for borrowers in quartiles 3 and 4, based on the same simulators. By contrast, missing a payment reduces the credit score by at least 35 points instantly, irrespective of initial score. Based on these simulations, common positive credit event inducing a 5-30 point increase in the credit score over a 4-6 quarter period could change the predicted eight quarter ahead change in balances by $250-1,530 for low credit score borrowers, while a missed payment could reduce the predicted change in balances by $1,750-1,785 for all borrowers. These magnitudes are sizable, especially for borrowers in quartile 1, for whom the changes are approximately equal to half of their eight quarter ahead predicted change in balances.[15]

Table 1: Mortgage Balance Growth

Dependent Variable: 8Q Ahead Mortgage Balance Change					
1Q Lagged Credit Score Quartile Effects				Credit Score Change	
1	2	3	4	4Q	6Q
221	7,540	7,451	3,297		
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 without credit score change, and with 4Q (second row) and 6Q (third row) past credit score 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 2 presents the estimated age adjusted time effects for each quartile of the 1 quarter lagged credit score distribution.[16] Based on our estimates, quartile 1 borrowers experience a steady

[14]Most credit monitoring services offered by credit card companies and the credit bureaus provide credit score simulators, which customers can use to assess the effects on their score of different actions, such as paying off debt, missing payments, placing an inquiry, opening a mortgage and so on. Most of these services are provided for a fee. A popular free service is `https://www.creditkarma.com`.

[15]Changes in credit score may 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 in order to secure better terms. Since our regressions are not causal, the sizable estimated coefficients on the changes in credit score reflect the strong positive association between improvement in credit scores and credit access.

[16]Specifically, we use the estimated age effects, presented in figure 3, to remove differences in the age distribution

$5,000 eight quarter ahead change in balances throughout the credit boom. The change in balances for quartile 4 is about twice the change for quartile 1 between 2001 and late 2003, when it starts to rapidly decline. Quartiles 2-3 show a very similar increase in balances throughout the sample period. Their 8 quarter ahead change in balances rises from $10,000 in 2001 to a peak of approximately $17,000 at the end of 2005. Starting at the end of 2005, all quartiles experience a sharp decline in the eight quarter ahead growth in mortgage balances, which bottoms out to approximately zero in 2009Q1 for quartile 2-4. For quartile 1, the growth in balances continues to decline until 2009Q4, when it reaches a minimum of -$8,000. 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. Part of the decline in mortgage balances for quartile 1 may also be driven by charge offs by borrowers who had higher credit scores during the boom and drop into quartile 1 during and after the housing crisis as a consequence of mortgage defaults.[17] Figure 19 in Appendix B 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.

The findings are very similar using the 4 quarter ahead and 12 ahead change in mortgage balances. Table 10 in Appendix B summarizes the implied cumulated mortgage debt balance change for 2002-2006 and 2007-2010 by sub period using the 4, 8 and 12 quarter ahead mortgage balance change regressions.

Given the strong positive relation between income and credit scores, our findings suggest that mortgage balance growth is positively related to income levels as well as to income growth, which is proxied in our regression by the change in the credit score. This finding goes counter the negative relation between income growth and debt growth found in zip code level data by Mian and Sufi (2009). We will further discuss the relation between debt and income growth in our data in Section 3.2.

Figure 3 presents the estimated age effects, obtained from the interaction with the quartile fixed effects. The estimates imply that the cumulated growth in mortgage debt balances between age 20 and age 30, which corresponds to peak growth over the life cycle is approximately $35,000.[18] However, the interactions between the quartile and age effects suggest that only borrowers in quartiles 2-4 experience a life cycle growth in mortgage balances, and the size of this growth is increasing with the credit score quartile.

across quartiles of the credit score distribution. Additionally, the quartile fixed effects are used to adjust the level of the raw quartile time effects.

[17] This is consistent with the behavior of delinquent balances, described in Section 2.3.1.

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

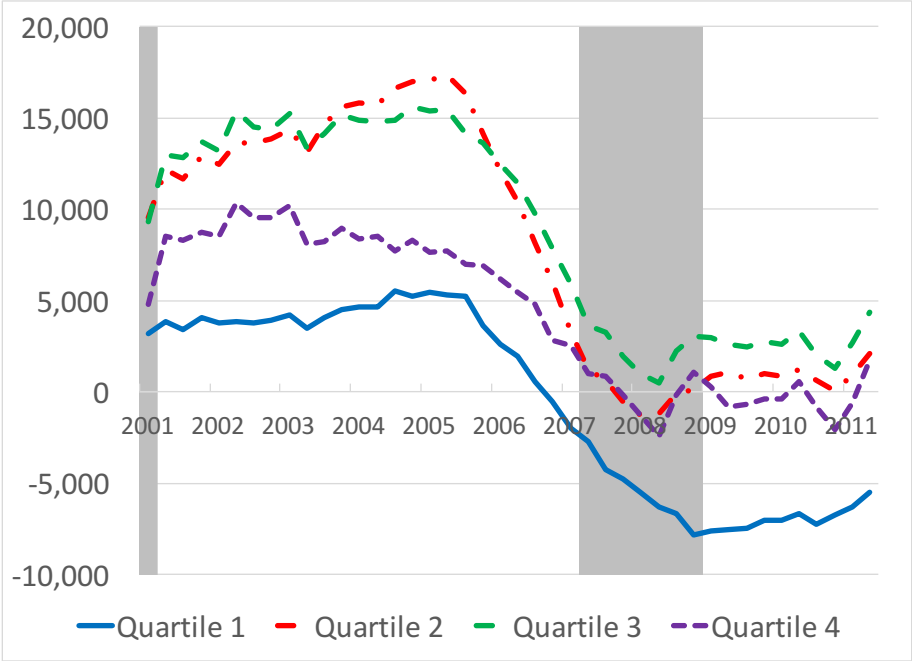


Figure 2: Estimated age adjusted time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions obtained from the time×credit score quartile interactions. Dependent variable is the 8Q ahead change in per capita mortgage balances in USD. Sample period 2001Q1-2011Q4. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

2.2.1 Homeownership and Originations

To corroborate the regression analysis on mortgage balances, we also examine 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 4 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. Both statistics are virtually constant for quartile 1 during the boom. The fraction 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[19] or real estate

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

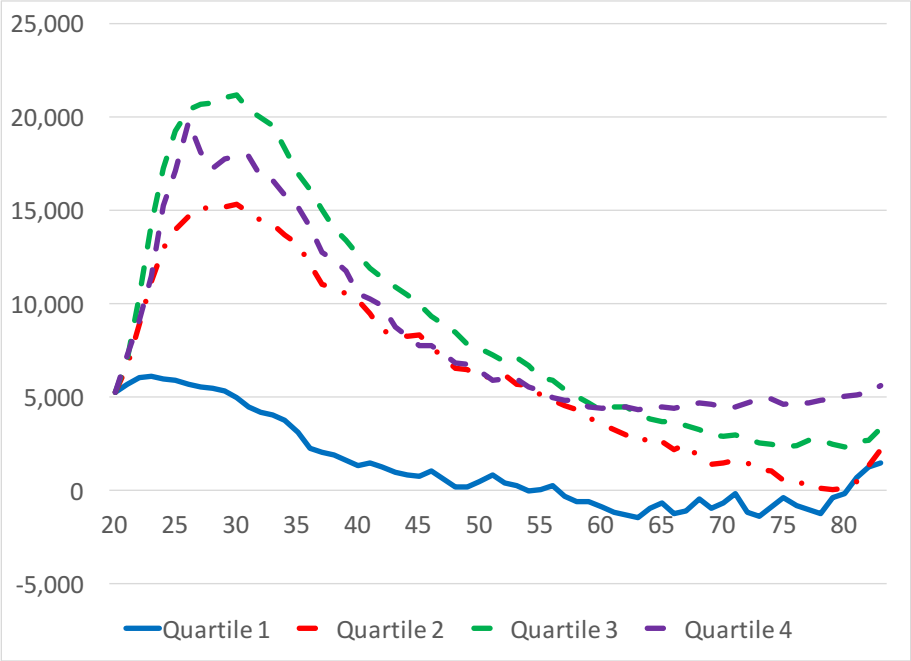


Figure 3: Estimated age effects from balance change regressions obtained from age×credit score quartile interactions. Dependent variable is the 8Q ahead change in per capita mortgage balances in USD, omitted category is age 20. Sample period 2001Q3-2011Q4. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

investing, as we document in Section 4 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. For quartile 1, the fraction of borrowers with new originations declines between 2001 and 2006, reaching 8% in 2006, and then stabilizes between 2006Q1 and 2007Q1. It then declines to close to zero by the end of 2009.

Figure 5 presents the distribution of credit scores at origination for each quarter of our sample period. The fraction of new mortgage originations for 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 quartile 2, from 23% in 2003Q4 to a peak of 30% in 2006Q4, after which they 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 reflecting refinancing activity, but rises during the crisis from 20% in 2006Q4 to 31% in 2011Q2 and then stabilizes. This rise reflects the tightening of lending standards during the crises.[20]

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

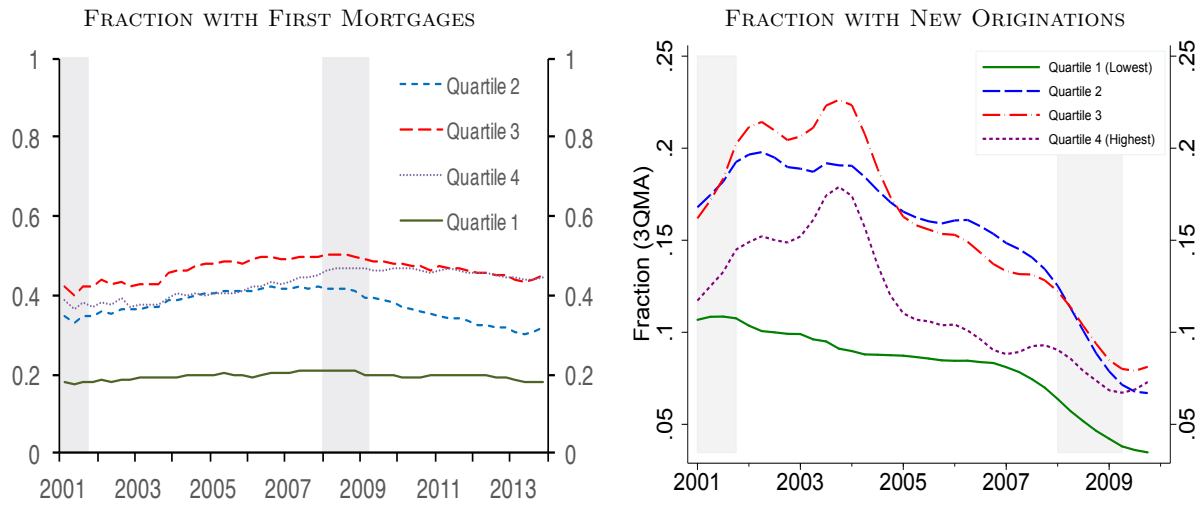


Figure 4: Fraction with first mortgages and fraction with new mortgage originations by 8Q lagged Equifax Risk Score quartile . Quartile cutoffs: 615, 720, 791, 840. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

2.3 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.

2.3.1 Delinquent Balances

We follow the same regression specification described in Section 2.2 for the 8 quarter ahead change in 90+ days delinquent mortgage balances. The estimated quartile fixed effects are presented in Table 2. The average 8 quarter ahead change in delinquent balances falls with the 1 quarter 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 non negligible, especially for low credit score borrowers. For example, a 30 point increase in the credit score over a 4-6 quarter period corresponds to an increase average delinquent balances of approximately $1,000. The fact that a past increase in the credit credit score corresponds to an increase in predicted delinquent mortgage balances is due to the fact that such an increase is associated in an increase in mortgage balances over the same horizon, as shown in Table 1.

Figure 6 presents the age adjusted 8 quarter ahead change in 90 days or more delinquent mortgage balances by 1 quarter lagged credit score. The growth in delinquent balances is very close to zero between 2001 and the end of 2004 for quartiles 1-3, and hovers around -$1,000 for quartile 4. There is a very large rise in the 8 quarter ahead change in delinquent balances for all quartiles starting in late 2004, but the growth in delinquent balances is considerably larger for

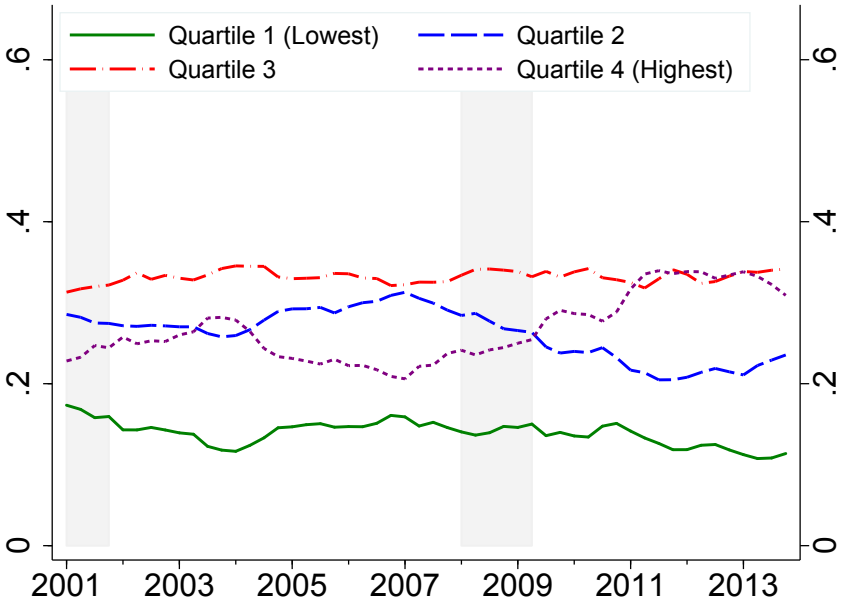


Figure 5: Individuals with a new mortgage origination. Fraction in each quartile of the 4Q lagged Equifax Risk Score distribution. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

quartiles 2-4. For quartiles 2 and 4, the growth in delinquent balances peaks at the start of 2007, when it reaches $5,500 and $4,200, respectively. For quartile 3, the peak occurs in early 2008, at $3,000. Quartile 1 exhibits the smaller growth in delinquent balances during the crisis. The peak in delinquent balance growth for these borrowers occurs at the end of 2006, with a growth of approximately $2,000. The growth in delinquent balances declines for all borrowers during the 2007-09 recession and for about a year after. For quartiles 2-4, it goes back to pre crisis values by 2011, whereas it hovers around -$6,000 in 2009 and 2010 for quartile 1. This pattern is driven by the large decline in mortgage balances for borrowers in the first quartile, discussed in Section 2.2, and may in part be driven by charge offs. We find similar results for the change in delinquent balances at 4 and 12 quarter ahead horizon.[21]

2.3.2 Delinquencies and Foreclosures

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 7 presents the distribution of new mortgage delinquencies. The fraction of borrowers with a new 90+ days mortgage delinquency in the last 4 quarters (left panel) is highest for borrowers in

[21] Appendix B.2 reports additional results for delinquent balances, including the estimated age effects.

Table 2: Delinquent Mortgage Balance Growth

Dependent Variable: 8Q Ahead 90+ Days Delinquent Mortgage Balance Change (USD)					
1Q lagged CS Quartile Effects				ΔCS_{-1}	
1	2	3	4	4Q	6Q
-3378	-435	-254	-1367		
371	91	-3	41	26	
781	287	162	166		27

Estimated 1Q lagged Equifax Risk Score quartile effects and coefficients for 4Q, 6Q past change from 1Q lagged Riskscore in balance change regressions. 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.

quartile 1 in 2001-2004. During this period, it drops from 1.8% to 1%, and by 2004Q1, the fraction with a new mortgage delinquency in quartile 1 is very similar to the fraction for quartile 2. The delinquency rate starts rising for both quartile 1 and 2 in 2005Q2, though the rise for quartile 2 is much bigger than 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. The fraction with new delinquencies hovers around 0.3% for quartile 3 and 0.15% for quartile 4 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 8 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.

In summary, using a lender's approach based on recent credit scores, we find that credit growth during the boom is concentrated in the middle and the top of the credit score distribution and that the rise in defaults during the crisis is concentrated in the middle of the credit score distribution. The share of new mortgage delinquencies and foreclosures to low credit score borrowers drops

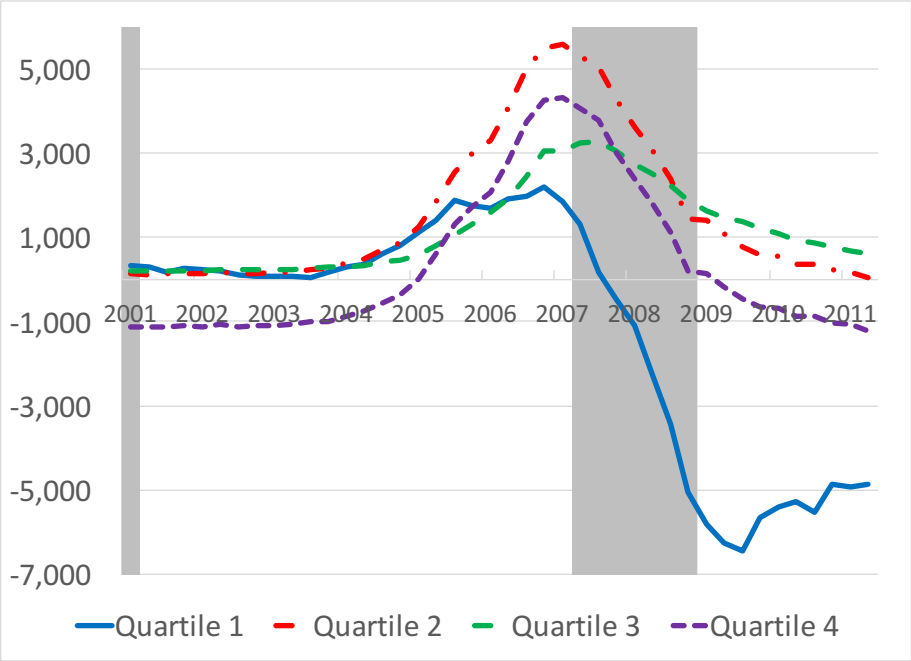


Figure 6: Estimated age adjusted time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

considerably during the crisis, challenging the notion the increase debt and defaults by low credit score borrowers was the main determinant of the housing crisis.

3 Relation to Existing Literature

Most of the existing literature has focussed on the role of subprime borrowers both in fueling the growth in mortgage balances during the 2001-2006 boom and in the subsequent foreclosure crisis. We now illustrate why our results differ from other analyses of the distribution of debt and defaults based on credit scores. The original narrative on the role of subprime borrowers is exemplified by the seminal work of Mian and Sufi (2009). With zip code level data, they rank zip codes in selected Metropolitan Statistical Areas (MSAs) by the fraction of residents with Equifax Risk Score below 660 in 1996 and show that zip codes with a larger fraction of subprime borrowers exhibit stronger credit growth during the credit boom. Mian and Sufi (2015) refine this analysis with individual level data. They rank individuals by their 1997 Vantage Score and show that borrowers in the first quartile of the 1997 credit score distribution show a larger growth in mortgage balances during the boom. We will show that these findings are a consequence of the fact that low credit score individuals are disproportionately young and zip codes with a high share of subprime borrowers

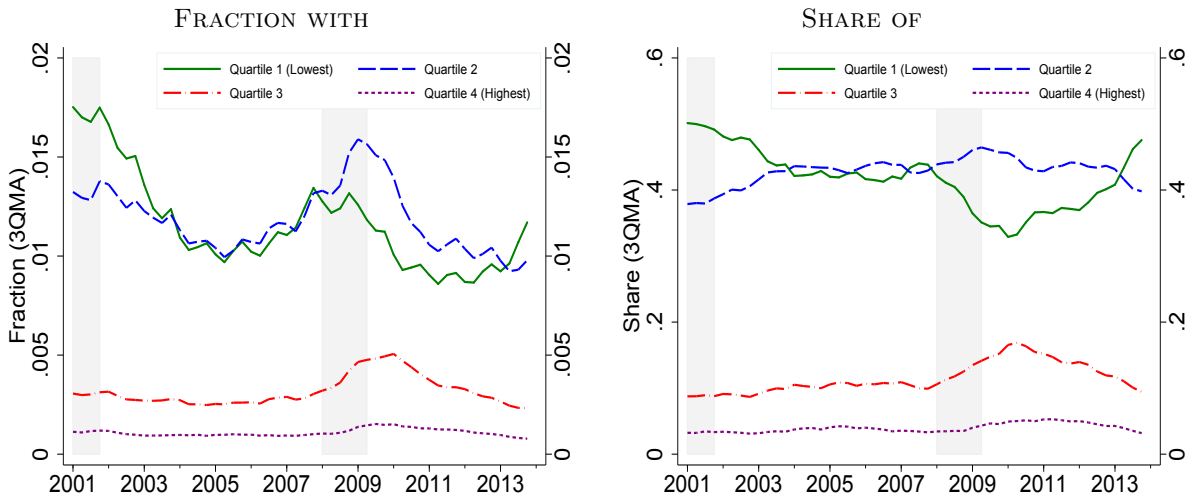


Figure 7: New 90 days+ delinquencies by credit score quartile, 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

have a younger population. The 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 borrowers who were young just before the start of the 2001-2006 boom.

We replicate the results in Mian and Sufi (2015) and Mian and Sufi (2009) by ranking individuals and zip codes by their credit score at the earliest available date in our sample. For individuals, we consider quartiles of the Equifax Risk Score distribution in 1999, while for the zip code level analysis, we rank zip codes by the fraction of individuals with Equifax Risk Score lower than 660 in 2001.[22] Figure 9 displays the growth of per capita mortgage debt balances relative to 2001Q3, which is the 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.[23] 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. 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.[24] All statistics are computed for the population of 20-85 year old individuals.

For the individual data, the net growth in per capita mortgage balances between 2001Q3 and

[22] We use 2001 rather than 1999 as an initial year to avoid problems relating to missing credit scores for certain zip codes in 1999. The findings using the 1999 ranking are virtually identical.

[23] The cut-off for the individual ranking are 615 for quartile 1, 710 for quartile 2, 778 for quartile 3, 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.

[24] Section 5 presents more detailed summary statistics at the zip code level.

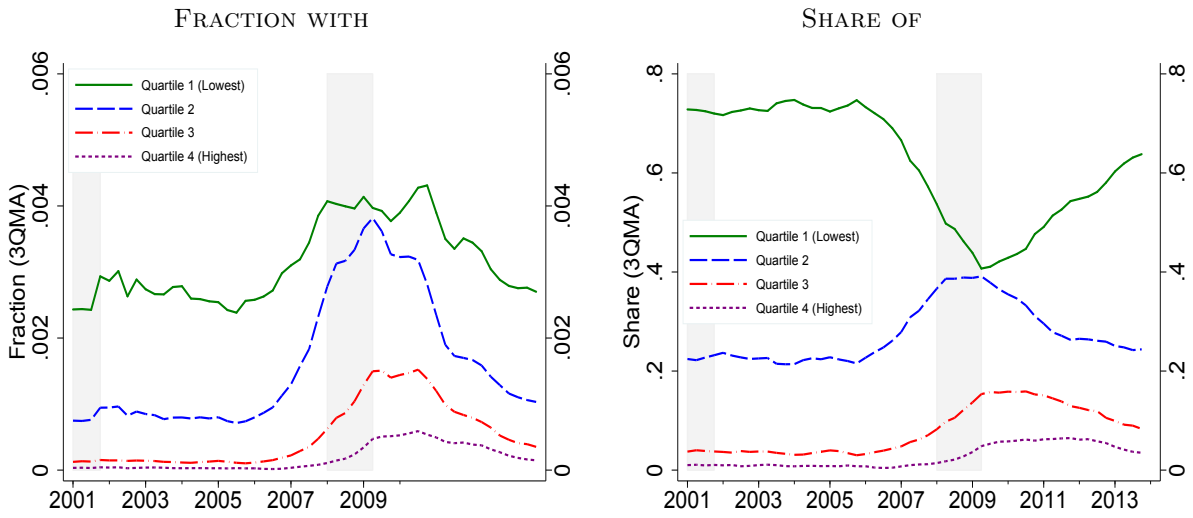
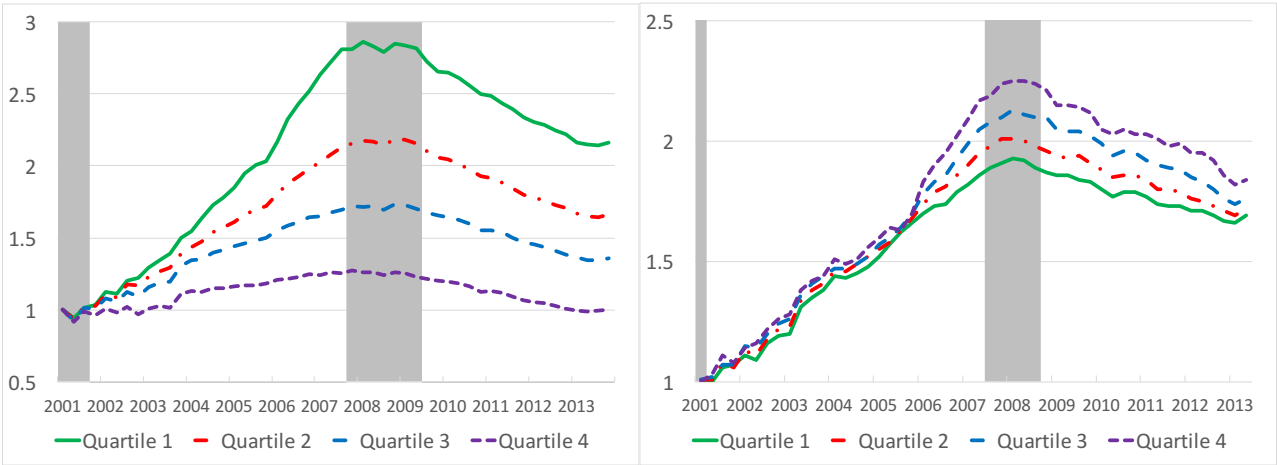


Figure 8: New foreclosures by credit score quartile, 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.



(a) Individuals: Ranked by 1999 Equifax Risk Score

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

Figure 9: 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.

2007Q4 by initial credit score is 146% for quartile 1, 121% for quartile 2, 74% for quartile 3, and 20% for quartile 4. The expansion of mortgage balances continues well into and past the 2007-2009 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 share subprime 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 for borrowers with low initial credit score and zip codes with a large initial fraction of subprime borrowers.[25]

Another basic tenet of the commonly accepted view of the financial crisis is that the growth in credit extended to subprime borrowers during the boom led to a rise in mortgage delinquencies and foreclosures for those borrowers during the crisis. We examine this premise in figure 22 in Appendix C, which displays the per capita foreclosure rate, specifically the difference in this variable relative to the 2001Q3 value. For individuals, the foreclosure rate is virtually constant at close to zero until the end of 2006, after which it rises substantially to a peak of approximately 0.25% in 2009Q3 for borrowers in quartiles 1 and 2 for the 1999 credit score distribution, and of 0.2% for borrowers in quartile 3. At the zip code level, the foreclosure rate is also constant during the boom and rises to a peak of approximately 0.5% in 2010. The rise is virtually identical for zip codes in quartiles 1-3 of the 2001 fraction of subprime, and slightly lower for zip codes in quartile 4, which have the highest fraction of subprime borrowers.

We now explain the discrepancy between the results on the distribution of debt and defaults based on initial and recent credit score rankings, focussing on the link between age, debt and credit scores. This analysis illustrates the problems associated to using initial credit scores and rationalizes the use of recent credit scores.

3.1 Quantifying Life Cycle Effects

We begin by showing that low credit score individuals are disproportionately young. Table 3 reports the median age by quartile of the credit score distribution, which varies from 39 for quartile 1 to 58 for quartile 4. Figure 23 in Appendix C displays the entire age distribution by credit score quartile. Quartile 1 has the highest share of borrowers between the age of 25 and 40, and the mass shifts right for higher credit score quartiles. For quartile 4, most of the mass is concentrated on borrowers older than 60. 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 10, which plots the current over the 2001 credit score ratio over the sample period by 1999 credit score quartile.

[25] The growth in mortgage balances mostly involves intensive margins. Albanesi, De Giorgi, and Nosal (2017) show that for mortgage originations and the fraction of borrowers with first mortgages, the growth is limited only to individuals with 1999 credit scores in quartiles 2-4, and occurs only in the period between 2001Q3 and 2004Q3. At the zip code level, the 2001-2006 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 the zip codes with the largest fraction of subprime borrowers.

For individuals in quartile 1, the credit score 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.

Table 3: Median Age by Credit Score Quartile

Quartile 1	Quartile 2	Quartile 3	Quartile 4
39	44	48	58

Source: Authors' calculation based on Experian Data.

To more precisely assess the relation between age and the credit score, we estimate age effects for the Equifax Risk Score in a specification that includes time effects and state fixed effects.[26] Figure 24 in Appendix C 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. It is important to note that US law prevents age from being used directly in credit scoring models, however, length of the credit history is one of the most important factors in credit score variation, and the estimated age effects capture this property.

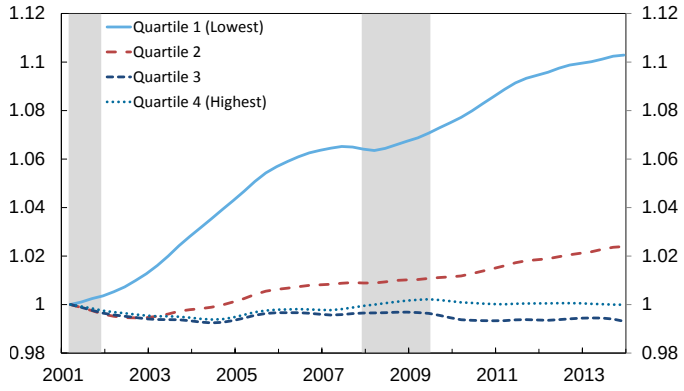


Figure 10: Current credit score as ratio to 2001, by Equifax Risk Score quartile in 1999, 3Q moving average. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

To further illustrate the role of the life cycle in mortgage borrowing by initial credit score, we

[26] U.S. legislation prevents credit scoring agencies to use location as a factor in their models, even if location may affect default behavior. However, we include state effects due to the sizable cross state variation in important regulations regarding foreclosure, bankruptcy, wage garnishment and other factors that could affect the incidence of financial distress and the resulting credit score distribution.

construct two counterfactuals. The first counterfactual eliminates differences in the age distribution across quartiles, while the second removes life cycle effects on the growth in mortgage balances.

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. We consider the following age bins: $1 = [20, 35)$, $2 = [35, 45)$, $3 = [45, 55)$, $4 = [55, 64)$ and $5 = [65, 85]$. Further, let $\overline{m}_t^{j_{1999}}$ be per capita mortgage balances of borrowers in quartile $j = 1, 2, 3, 4$ of the 1999 credit score distribution in quarter t and $m_t^{i_{1999},j_{1999}}$ be per capita mortgage balances for borrowers in age bin i and Equifax Risk Score quartile $j = 1, 2, 3, 4$ in 1999 at quarter t. Then:

$$\overline{m}_t^{j_{1999}} = \sum_i \pi^{i_{1999},j_{1999}} \times m_t^{i_{1999},j_{1999}}. \tag{2}$$

Counterfactual 1: Age Distribution We first calculate a counterfactual designed to isolate the role of differences in the age distribution of across the 1999 credit score quartiles. To do so, we impose the quartile 4 age distribution on quartiles 1-3. That is, for each $j = 1, 2, 3$, we compute:

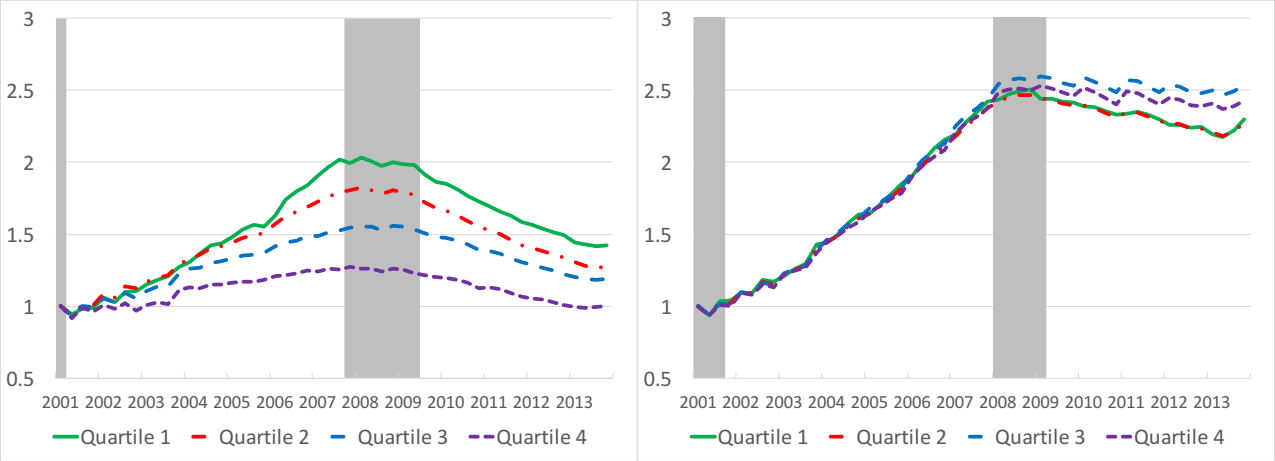
$$\tilde{m}_t^{j_{1999}} = \sum_i \pi^{i_{1999},4_{1999}} \times m_t^{i_{1999},j_{1999}}. \tag{3}$$

Panel (a) in figure 11 plots the resulting counterfactual growth in per capita mortgage balances relative to 2001. Compared to the actual growth rate of mortgage balances displayed in figure 9, mortgage balance growth is much weaker for the counterfactual series than for the actual for quartiles 1-3. However, even in the counterfactual, mortgage balance growth is inversely related to the initial quartile of the credit score distribution, consistent with Mian and Sufi (2015). 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.

Counterfactual 2: Life Cycle Effects The second counterfactual is designed to isolate the impact of life cycle factors for borrowers in different quartiles of the 1999 Equifax Risk Score distribution. We remove life cycle effects by maintaining borrowers at their age in 1999. This is achieved by attributing to borrowers in age bin i and credit score quartile j in 1999 the debt balances of individuals in age bin i and credit score quartile j in each subsequent quarter t. That is:

$$\hat{m}_t^{j_{1999}} = \sum_i \pi^{i_{1999},j_{1999}} \times m_t^{i_t,j_t}. \tag{4}$$

Panel (b) in figure 11 displays the resulting counterfactual mortgage balance growth relative to 2001. Based on this counterfactual, there is virtually no difference in mortgage balance growth across quartiles, which is consistent with differences in life cycle effects accounting for most of the difference in borrowing across 1999 credit score quartiles. The counterfactual removes life



(a) Counterfactual 1

(b) Counterfactual 2

Figure 11: Per capita real mortgage balances, ratio to 2001. Deflated by CPI-U. Counterfactual 1 attributes to all quartiles the age distribution of quartile 4. Counterfactual 2: Attributes to borrowers in a given age bin in 1999 the mortgage balances of borrowers in that age bin in the current quarter. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

cycle effects but captures time effects in mortgage borrowing by age. The strong growth in the counterfactual balances for all quartiles suggests that there was a generalized growth in mortgage borrowing for all age groups. This may be driven by an increase in the supply of credit or by the rise in housing values, which necessarily increases the size of the typical mortgage. Taken together, these results suggest that life cycle effects in borrowing are very strong and sizably affect mortgage debt growth especially for individuals at the bottom of the 1999 credit distribution.

3.2 Relation Between Income Growth, Credit Scores and Debt

We also examine credit score growth between 1999 and 2009 in relation to income levels and debt levels in 2009 for borrowers in the bottom quartile of the credit score distribution in 1999, using our labor income data linked to Equifax. Table 4 summarizes these results. The columns correspond to quartiles of the 2009 credit score distribution 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 debt balances are increasing in the 2009 credit score, even if these borrowers begin in the bottom quartile of the credit score distribution in 1999.

Table 4 clearly shows that the differences in credit growth between 2001 and 2009 are positively related to life cycle growth in income and credit scores. Moreover, in Appendix D.2, we show that debt growth for young borrowers at the start of the boom occurs primarily for individuals who have high income by 2009, and the growth in income is associated in a growth in credit score. This evidence speaks directly to the relation between income and debt during the credit boom. Using

Table 4: 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.

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 to high risk (low income) borrowers. While we also find this pattern for zip code level data (see Section 5), we show that this negative relation does not hold for *individual* data. For robustness, Appendix D.3 reports estimates of the relation between the growth in total debt balances and total income using the PSID over the 1999-2007 period. The PSID analysis confirms the positive relation between income growth and growth in debt balances in 2001-2006 at the individual level.

The positive relation between income growth and debt growth during the credit boom casts doubt on the notion that there was an increase in the supply of credit to high risk borrowers. Instead, it is more likely that the rise in house prices caused an increase in mortgage balances. This is also confirmed by our finding that the fraction of borrowers with mortgages did not rise for any quartile of the credit score distribution, as discussed in Section 2.2.1.

4 Real Estate Investors

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 individuals with good credit histories experienced such abnormally high default rate during the crisis. In this section, we document the rise in real estate investors and we show the increase in defaults for prime borrowers is primarily driven by these borrowers.[27]

Mortgages for investment properties are particularly interesting as they may be more prone to

[27] In Albanesi, De Giorgi, and Nosal (2017), 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 and only for prime borrowers, however, there is no evidence that default rates are higher on these loans. 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. Indeed, Foote, Gerardi, and Willen (2008) argue that negative equity is a necessary but not sufficient condition for mortgage default, and show that negative income shocks may be the ultimate trigger for defaults.

default than those for owner occupied housing. First, mortgages for investment properties must meet stricter credit standards and are usually charged an additional premium to qualify for GSE insurance.[28] This makes it more likely that investors will contract non-standard mortgages with shorter maturity or variable rates, which are intrinsically more risky.[29] Second, if investors are motivated by the prospect of capital gains, they are more likely to be more leveraged and to default under negative equity, especially in states in which foreclosure is non-recourse. Third, only the primary residence is protected in personal bankruptcy. Thus, a financially distressed borrower could potentially file for bankruptcy to stay foreclosure procedures and possibly restructure their mortgage. Finally, the financial and psychological costs of default for resident owners are typically quite substantial, including moving and storage costs, longer commute times and so on. Real estate investors are not subject to these costs.

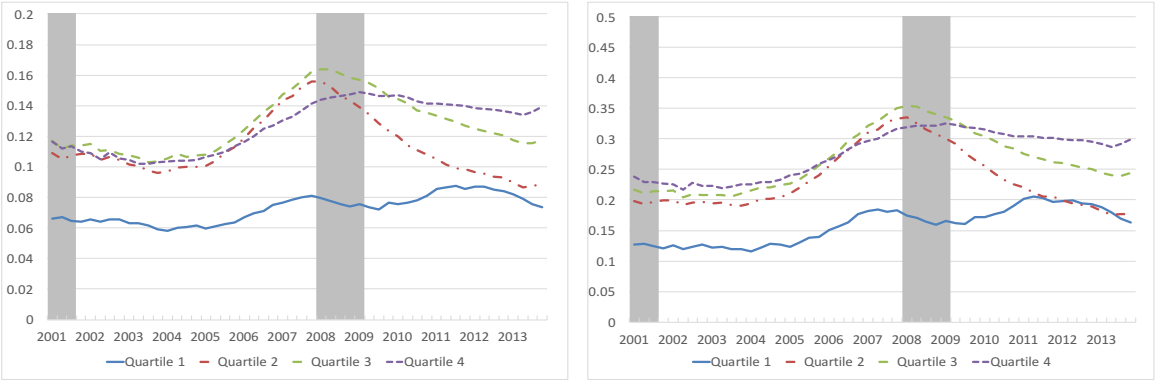
We follow Haughwout et al. (2011) and define investors as borrowers who hold 2 or more first mortgages. Figure 12 presents the fraction of mortgage borrowers with only 1 and with 2 or more first mortgages (left panel) and the share of total balances for investors and non-investors (right panel). The fraction of investors is very stable between 2001Q3 and 2004Q3 for all credit score quartiles, and increases by quartile. The fraction of investors starts increasing rapidly in 2004Q4 and peaks in 2007Q4. Most notably, quartiles 2-4 experience a 50% 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. By contrast, the fraction of investors for quartile 1 is about half of the fraction for higher quartiles, and rises only modestly during the boom.[30] The investor share of mortgage balances (right panel) follows a very similar path, but it is larger than the investor share, as mortgage balances are substantially larger for investors. At the beginning of the sample, the share of mortgage balances held by investors is stable. The average over this period is about 12% for quartile 1, and varies between 20 and 23% for quartile 2-4. The investor share of balances rises by just under 50% for quartile 1 by the end of 2007, while it increases by approximately 65% for those in quartile 2 and 3, starting in 2004, and by 35% for borrowers in quartile 4. During and after the recession the investor share of mortgage balances drops, reaching pre-boom levels for quartile 2 and 3, and stabilizing at the peak level for quartiles 1 and 4.

Investor activity sizably intensifies at the end of 2004. While identifying the cause of this rise is

[28] See `http://www.freddiemac.com/singlefamily/pdf/ex19.pdf` for a classification and quantification of the additional fees charged by the GSEs for mortgages with special attributes, such as investment properties.

[29] 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.

[30] Ferreira and Gyourko (2015) find that the fraction of investors is very similar for prime and subprime borrowers. However, their definition of investors includes only businesses and borrowers with a tax address different from their mortgage address. Chinco and Mayer (2014) also identify real estate investors using the difference between property address and tax address.



(a) Investors as a Fraction of Total

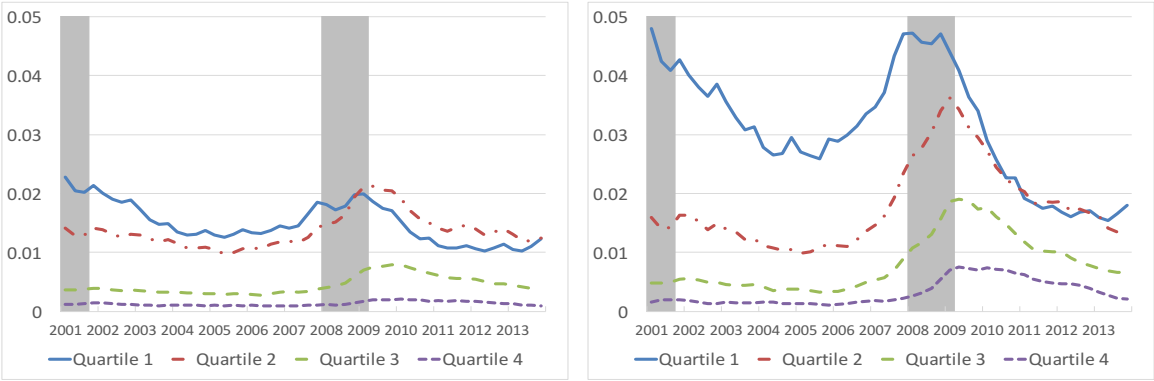
(b) Investor Share of Mortgage Balances

Figure 12: Fraction of borrowers with 2 or more first mortgages (left panel) and share of first mortgage balances of these borrowers (right panel) among all borrowers with at least 1 first mortgage, by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

beyond the scope of this paper, the timing of the rise in investor activity coincides with the decline in the spread for Alt-A and other unconventional mortgages discussed in Justiniano, Primiceri, and Tambalotti (2017). Investors would typically opt to contract such mortgages, which are issued by lenders that rely on private label securitization, since GSE sponsored mortgages for investment properties typically feature very restrictive conditions, such as high loan to value ratios and interest rates, in order to compensate for investors' higher default risk, as discussed above.

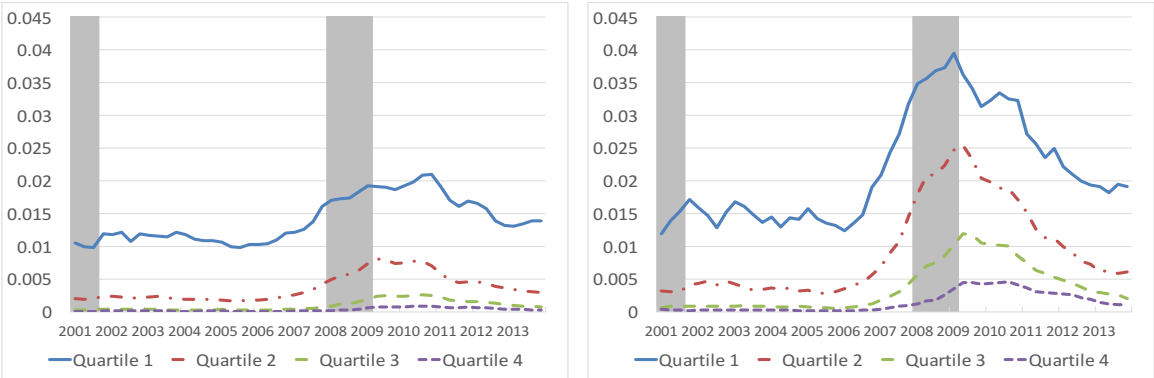
Figure 13 and 14 report the fraction of borrowers with mortgage delinquencies and foreclosures, respectively, by number of first mortgages. Figure 13 reports the fraction of borrowers with a 90+ day mortgage delinquency by number of first mortgages. Between 2002 and 2006, delinquency rates are similar 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 between 2007 and 2009 for quartiles 1-3 of the credit score distribution, and rises very modestly for borrowers in quartile 4, returning close to pre-crisis levels rises by 2012. Strikingly, the fraction with new delinquencies rises much more for investors than for non-investors over the same period. It roughly doubles for quartile 1, and exhibits a more than 5 fold increase for higher quartiles.

Figure 14 presents the fraction of borrowers with new foreclosures in the last 4 quarters. Similar to delinquencies, during the 2002-2006 housing boom the foreclosure rate is very similar for investors and non-investors for all quartiles. However, during the crisis, the foreclosure rate diverges, with investors experiencing much higher foreclosure rates than non-investors, especially for higher credit score quartiles. For investors, foreclosure increases by a factor of 4 for the lowest quartile, and by more than a factor of 10 for quartiles 2-4. For non-investors, the foreclosure rate roughly doubles in quartile 1-2, and rises very modestly for quartiles 3-4.



(a) Non-investors (b) Investors

Figure 13: Fraction with new 90+ days mortgage delinquency in the last 4 quarters for borrowers with 2 or more (Investors, right panel) and only 1 (Non-investors, left panel) first mortgages by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.



(a) Non-investors (b) Investors

Figure 14: Foreclosure rates for borrowers with 2 or more (Investors, right panel) and only 1 (Non-investors, left 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 defaults accounted for by investors rises during the crisis. Figure 15 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, to 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, so that at the height of the crisis, investors accounted for 43% of all foreclosures. 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. Albanesi (2018) shows that investors have much higher leverage compared to non-investors, both in terms of first mortgage balances, and in terms of second mortgage balances and home equity lines of credit. Additionally, she shows that combining all forms of real estate loans, the monthly payment to income ratio for investors is well above 50% whereas it is typically below 25% for non-investors, which may account for their higher default rates.

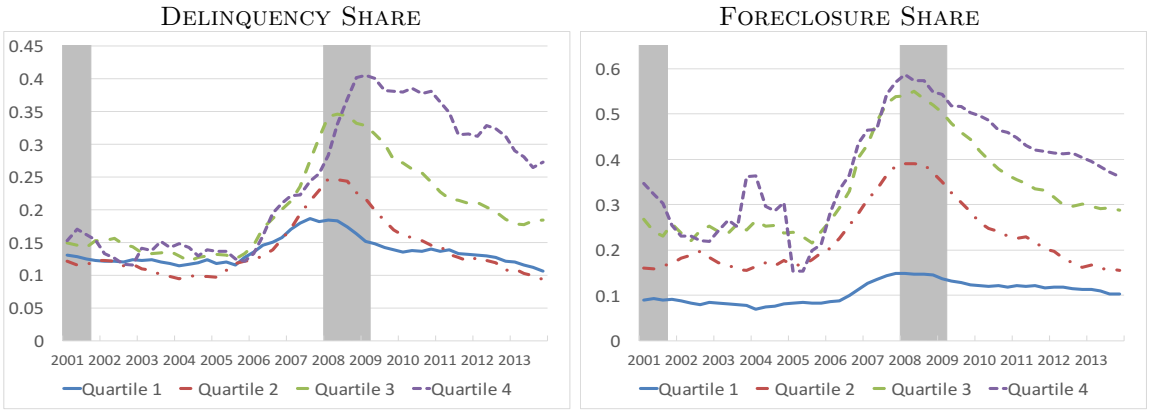


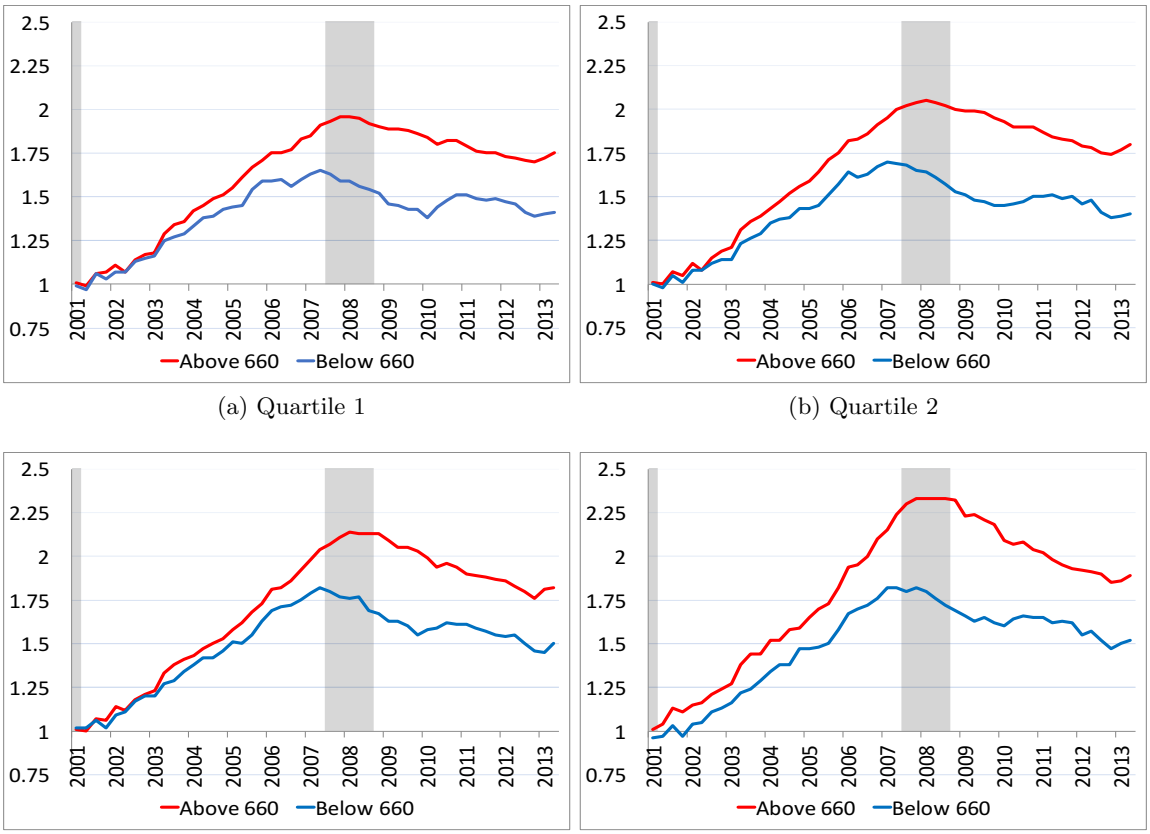
Figure 15: Investor share of 90+ days delinquencies (left panel) and foreclosures (right panel) by quartile of the 8Q lagged Equifax Risk Score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

5 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 9, 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. In this section, we explore this finding

and link it to additional demographic characteristics that could explain both the stronger growth in mortgage balances during the 2001-2006 boom and performance during the 2007-2009 crisis.

Figure 16 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 3, 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.



(a) Quartile 1

(b) Quartile 2

(c) Quartile 3

(d) Quartile 4

Figure 16: Zip code level per capita mortgage debt growth for prime (Equifax risk Score above 660) and subprime (Equifax risk Score below 660) borrowers by quartile of share of subprime in 2001. Based on 8Q lagged individual credit scores. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 5 reports the age distribution by fraction of subprime borrowers. Not surprisingly, based on our results with individual data, the fraction of borrowers younger than 35 increases with the

share of subprime borrowers, ranging from 22% for quartile 1 to 29.3% for quartile 4.

Table 5: 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. We then use this counterfactual to calculate 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 6. We find that for zip codes in quartiles 2 and 3, 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 mortgage balance growth during the 2001-2006 credit boom.

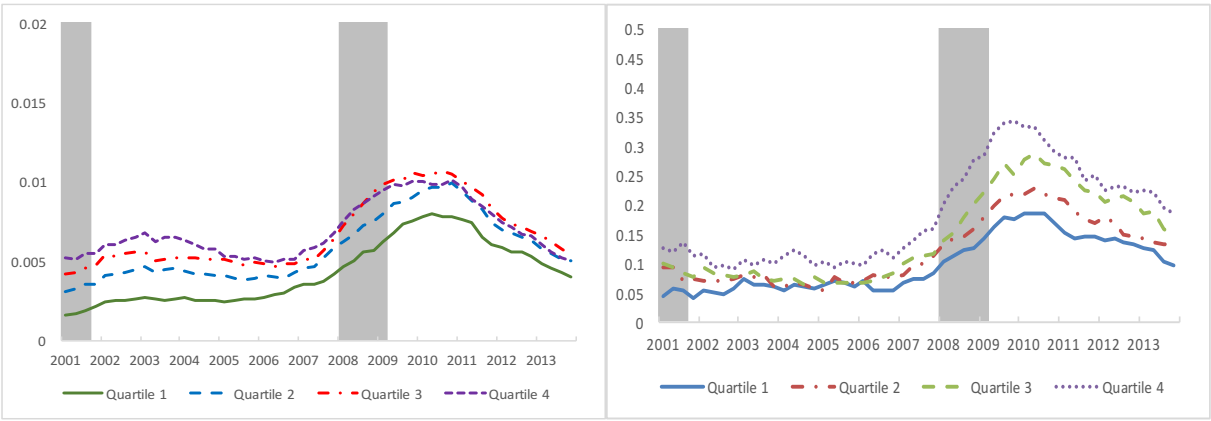
Table 6: Contribution of Age Distribution to Mortgage Balance Growth

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.

5.1 Defaults

We now examine the behavior of defaults by zip code. Figure 17 presents the new foreclosure rate and the prime share of new foreclosures by quartile of fraction of subprime borrowers in 2001. Not surprisingly, zip codes with higher fraction of subprime borrowers exhibit higher foreclosure rate throughout the sample period, thought the variation is modest and the biggest difference is between quartile 1 and the upper quartiles. 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. Turning to the share of new foreclosures for *prime* borrowers, it is clear that prime borrowers contribute more to the growth in foreclosures during crisis in all zip codes. The share of prime borrowers' foreclosures rises approximately by 10-25 percentage points between 2006Q2 and 2009Q4.[31]



(a) Fraction with new foreclosures

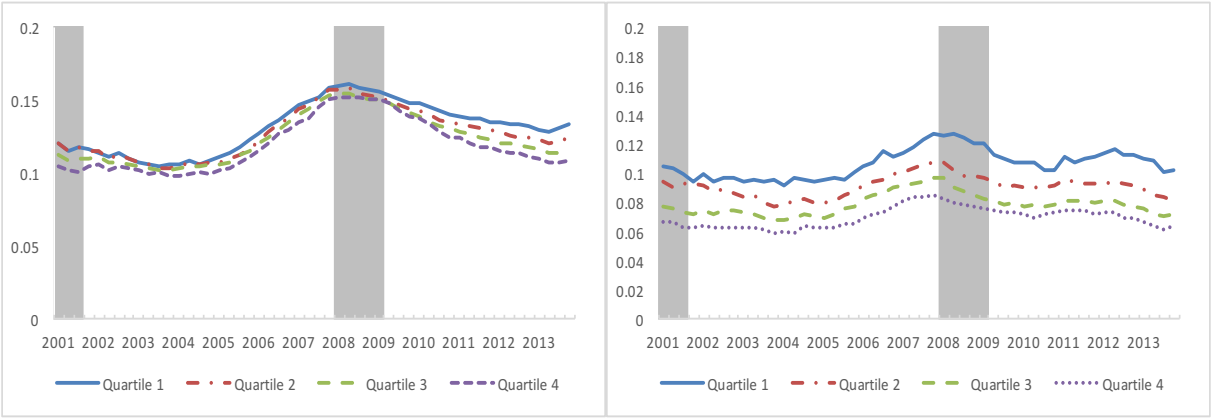
(b) Prime share of foreclosures

Figure 17: Fraction with new foreclosures (a) and share of new foreclosures for prime borrowers (b), based on 8Q lagged individual credit score. 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 foreclosures is 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 have a higher propensity to default. Though other zip code level characteristics may contribute to this pattern, as we discuss in Section 5.2, here we focus on the role of investors, based on our findings using individual data. Figure 18 presents the fraction of investors at the zip code level for prime and subprime 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 7, equal to 12-13%. It then

[31] Mortgage delinquencies follow a similar pattern and are discussed in detail in Albanesi, De Giorgi, and Nosal (2017).

drops during and after the recession, though still remaining above pre-boom levels by the end of 2013. On the other hand, the share of investors among subprime borrowers is decreasing in the share of subprime borrowers. 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 very modest for subprime borrowers, and 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.



(a) Prime Borrowers (b) Subprime Borrowers

Figure 18: Fraction with 2 or more first mortgages for prime and subprime borrowers, by quartile of the share of subprime borrowers in 2001. Subprime/prime based on 8Q lagged credit score. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Given the large rise in the share of defaults to prime borrowers and the link between investor activity and defaults seen in the individual data, we provide more detail on investor activity for prime borrowers in Table 7. The distribution of investors across the number of first mortgages is very similar across zip codes, with 79-80% of investors holding 2 first mortgages, 13-14% holding 3 and 7-8% holding 4 or more. However, the growth in mortgage balances for investors during the boom varies geographically, and is significantly higher in quartiles with a large fraction of subprime borrowers. 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. Turning to defaults, we see that foreclosure rates are sizably 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 in quartiles 3-4 is approximately double the rise in quartiles 1-2, though the difference in investor and non-investor foreclosure rates is largest in zip codes with high fraction of subprime borrowers.[32]

[32]This pattern in investor borrowing and default behavior may explain why despite large regional variation in predictable default risk, GSE mortgage rates for otherwise identical loans do not vary spatially, while the private market does set interest rates that vary with local risk, as shown in Hurst et al. (2016). GSE mortgages are mostly

Table 7: Investor Activity for 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	88%	90%	103%	109%
crisis rise in foreclosure rate				
1 first mortgage	0.008	0.012	0.016	0.017
2+ first mortgages	0.029	0.037	0.057	0.070

Selected zip code level indicators of investor activity by quartile of the fraction of subprime borrowers in 2001. All indicators for prime borrowers, defined as those with credit scores above 660. The crisis rise in the foreclosure rate is the difference in the 2002Q1-2005Q4 average foreclosure rate and the crisis peak. The crisis peak varies by group, with 2007Q4 the most common date. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Summarizing, though the fraction of investors with prime credit score is very similar across quartiles, in those with high share of subprime borrowers, 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 dynamics of house prices. As reported in Table 8, 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 borrowers, ranging from 21% in quartile 1 to 36% in quartile 4. This suggests that stronger growth in prime investors' mortgage balances is associated with a more pronounced house price boom and bust and a more severe rise in foreclosures.

5.2 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 with Saiz (2010) house price elasticities, and the severity of the 2007-2009 recession.[33] These studies attribute this

available for owner occupied properties and default rates among borrowers with only one first mortgage are low in all zip codes. By contrast, default rates on private market products would reflect the geographical variation in investor activity, and corresponding default propensity.

[33]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. Mian, Rao, and Sufi (2013) exploit geographic variation in house price declines over the period 2006-2009 and household balance sheets in

correlation to the tightening of collateral constraints during the crisis, driven by mortgage defaults and the resulting decline in housing values.[34] Since this causal mechanism is not consistent with our findings, we explore additional economic indicators at the zip code level to shed light on this correlation.

Table 8 reports several economic indicators by quartile of the fraction of subprime borrowers in 2001. Many 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 share in the population. It is well known that younger, less educated, minority workers suffer larger employment losses during recessions (see Mincer (1991) and Shimer (1998)). Indeed, zip codes with large subprime population have higher unemployment rates both during the boom and during the crisis. The average unemployment rate for 2001-2007 was 4.94% in quartile 1 and 5.72% in quartile 4. In 2007-2010, the average unemployment rate rose to 6.93% in quartile 1 and 7.81% in quartile 4.

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. However, as we show in Section 3.2, *individual* debt growth is positively related to *individual* income growth. This discrepancy in the relation between income and debt growth at the individual level and at the zip code level may be driven by the fact that zip codes with a large subprime population 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. Since top incomes were growing at a much faster rate than bottom incomes during the sample period (see for example Saez (2018)), the positive relation between income growth and debt growth in individual data need not be matched in aggregate data. Additionally, 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. As shown in the individual level analysis, it was the prime borrowers experiencing the largest growth in mortgage balances: but aggregation would mask this fact at the zip code level.

2006, to estimate the elasticity of consumption expenditures to changes in the housing share of household net worth, and find a positive and sizable elasticity. Kaplan, Mitman, and Violante (2016) refine this analysis and find that, once the direct effect of the fall in local house prices has been controlled for, household balance sheets do not have an effect on durable consumption.

[34] However, Ferreira and Gyourko (2011) show that local income is the only potential demand shifter found that also had an economically and statistically significant change around the time that local housing booms began. Liebersohn (2017) also shows that the share of growing industries drives the size of housing demand shocks, the magnitude of the housing price increase and household consumption variation between 2000-2006.

Zip codes with high fraction of subprime borrowers experience higher house price growth in 2001-2007, as previously noted. This may be related to 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.[35] 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[36], 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, as we show in Appendix E. 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 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 report 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 a good approximation 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 demographics or population density.

6 Conclusion

Our analysis suggests a new narrative on the 2001-2006 housing boom and the 2007-2009 mortgage crisis. We find 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. Additionally, we show that the growth in defaults is mostly accounted for by real estate investors, whose numbers surged starting in early 2004, especially among high credit score borrowers. The disproportionate role of investors in the foreclosure crisis are consistent with the findings in Ospina and Uhlig (2016), who show that most of the losses for non-agency residential mortgage backed securities, which would

[35] See Guerrieri, Hartley, and Hurst (2013). However, the more sizable housing boom in some zip codes with large subprime population may have masked negative employment growth over this period, as shown by Hurst et al. (2016), and increased income and reduced unemployment rates in those areas above what would have been consistent with their industry and demographic composition.

[36] 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. Chinco and Mayer (2014) show that in Phoenix, Las Vegas and Miami out of town second home buyers may have contributed to an inflation in housing values.

Table 8: 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%
Per-capita Income 2001-2007	\$41,045	\$30,442	\$25,692	\$21,019
Per-capita Income 2007-2010	\$46,341	\$33,224	\$27,491	\$21,898
Per-capita Income Growth 2001-2007	25%	16%	10%	4%
Per-capita Income 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
Pop per sq mile	1214	1380	1386	2322
In sand states	11%	13%	16%	16%

Selected zip code level indicators by quartile of the fraction of subprime borrowers in 2001. Per-capita income and HPI (housing price index) expressed in 2012 USD, adjusted by CPI-U. UR (unemployment rate) is the U3 official rate. Saiz elasticity is from Saiz (2010). Sand states are Arizona, California, Colorado, Florida, and Nevada. Source: Authors' calculations based on FRBNY CCP/Equifax Data, IPUMS and IRS data.

have been used for investor mortgages, were concentrated among a small set of securities issued after 2004. We also show that there is a positive relation between income growth and mortgage balances at the individual level during the 2001-2006 boom.

In addition, we document that prime borrowers experience a larger rise in mortgage balances than subprime borrowers in all zip codes, though zip codes with a large fraction of subprime

borrowers do experience stronger mortgage credit growth during the boom. We show that these zip codes are predominantly urban and that they exhibit the most dramatic house price fluctuations between 2001 and 2010. Zip codes with a large share of subprime borrowers also have a large share of young, unskilled and minority residents who may be particularly sensitive to business cycles. Importantly, our findings suggest investors played a central role in the mortgage crisis. Albanesi (2018) provides a very detailed empirical analysis of real estate investors, while Albanesi (2019) examines the impact of these borrowers on housing markets and their response to shocks and different policy interventions in a quantitative model.

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A Data

A.1 Individual Income Data for 2009

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, also known as Worknumber 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 9: 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.

A.2 Zip Code Level Data

Demographic and Economic Indicators We obtain zip code level demographic and economic indicators for the 2000 and 2000 Census from Ruggles et al. (2019). Per-capita income corresponds to Total Personal Income (INCTOT). Educational attainment measured with HIGHGRADE.

IRS Income Data We use zip-code level data on Adjusted Gross Income published by the IRS to construct our measure of inequality. Starting in 2006, the IRS splits the income returns into 7 brackets: (i) under $10,000, (ii) $10,000 under $25,000, (iii) $25,000 under $50,000, (iv) $50,000 under $75,000, (v) $75,000 under $100,000, (vi) $100,000 under $200,000 and (vii) $200,000 or more. For each of the income brackets, the IRS provides the number of returns, the number of joint returns, and total AGI. To compute our measure of inequality, we first calculate the average per-return AGI for the over $200,000 bracket and the per-return AGI for the pooled brackets (i)-(vi). We make an adjustment for joint returns by counting joint returns as two returns to get the per-filer AGI. Our inequality measure is the ratio of the over-$200,000 per-filer income to the under-$200,000 per-filer income for each year. The data is available for download at the following link: `https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi`.

B Balance Change Regressions: Additional Results

B.1 Mortgage Balances

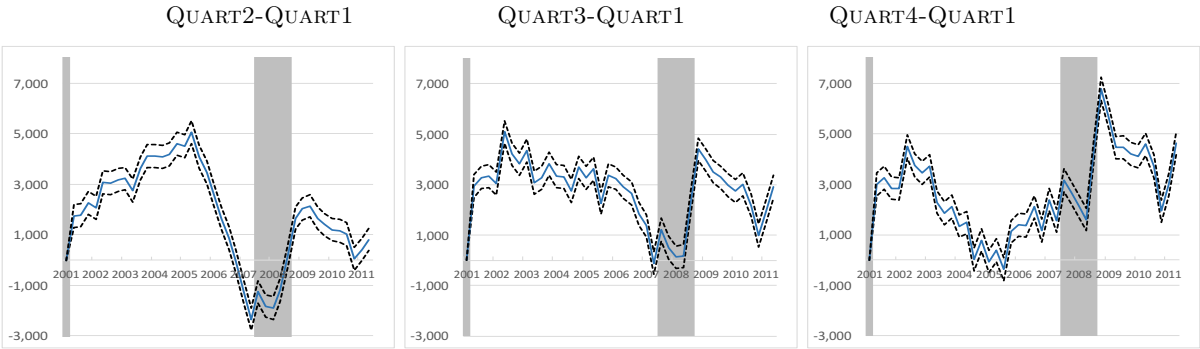


Figure 19: Estimated time effects by 1Q lagged Equifax Risk Score quartile from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita mortgage balances in USD. Dashed lines denote 5% confidence intervals. Sample period 2001Q3-2011Q4. Number of obs. (baseline) 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

Table 10 presents the estimated cumulative change in mortgage balances for different time periods in our sample based on the balance change regressions. These are derived from the 8 quarter ahead change specification, discussed in detail in Section 2.2, as well as for the 4 quarter ahead and 12 quarter ahead change. The variation across quartiles for the 4 and 12 quarter ahead change is consistent with the findings for the 8 quarter ahead change.

B.2 Delinquent balances

We report additional results for the estimates for delinquent balances described in Section 2.3.1. Figure 20 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 21 reports the estimated age effects. The age effects for dellinquent balances largely reflect the age pattern of total debt balances.

Table 10: Mortgage Balances: Summary Regression Results

	Average 4 Quarter Ahead Change in Mortgage Balances			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2002-03	-206	1,998	2,329	1,269
2003-04	235	3,622	4,355	3,182
2004-05	173	3,173	3,150	1,702
2005-06	936	5,316	4,996	2,209
2006-07	798	4,937	3,854	1,115
2007-08	-1,700	1,732	2,505	818
2008-09	-4,690	-2,691	-1,724	-2,355
2009-10	-6,463	-3,075	-1,964	-2,369
2010-11	-5,538	-2,670	-1,269	-1,591
2011-12	-5,189	-3,020	-2,281	-2,921
2002-2006	1,138	14,108	14,831	8,361
2007-2010	-12,853	-4,035	-1,183	-3,905
	Average 8 Quarter Ahead Change in Mortgage Balances			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2002-04	1,202	7,760	9,663	6,745
2004-06	2,449	10,696	10,657	6,351
2006-08	1,175	8,397	8,896	4,260
2008-10	-7,459	-4,732	-2,192	-2,864
2010-12	-9,053	-3,413	-1,276	-2,515
2002-2006	5,304	27,419	30,604	20,248
2007-2010	-9,689	3,835	9,500	2,002
	Average 12 Quarter Ahead Change in Mortgage Balances			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4
2002-05	2,073	9,390	10,605	7,132
2005-08	3,256	12,123	11,470	5,417
2008-11	-10,039	-9,680	-7,010	-6,390
2002-2006	5,589	22,032	23,454	15,411
2007-2010	-3,583	8,870	12,561	2,476

Cumulative change in mortgage balances at various horizons in USD. Based on 1 quarter lagged credit score quartile fixed effects and time effect from balance change regressions. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

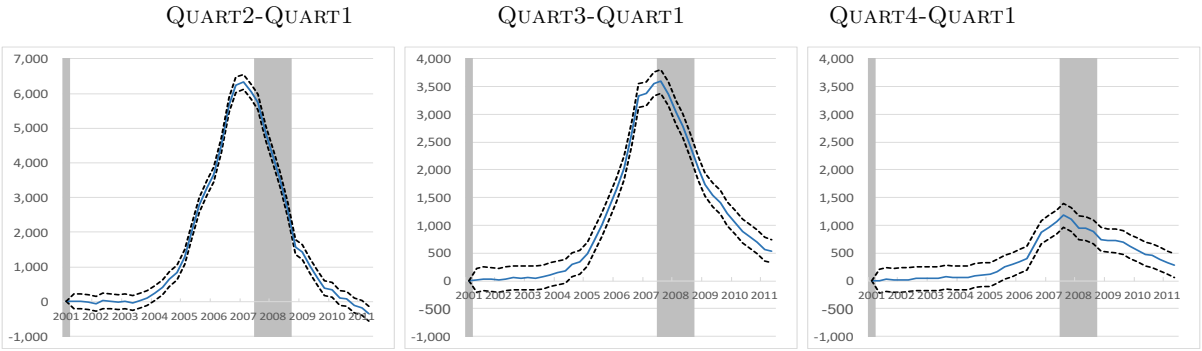


Figure 20: Difference in estimated time effects by 1Q lagged Equifax Risk Score quartile relative to quartile 1. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Dashed lines denote 5% confidence intervals. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

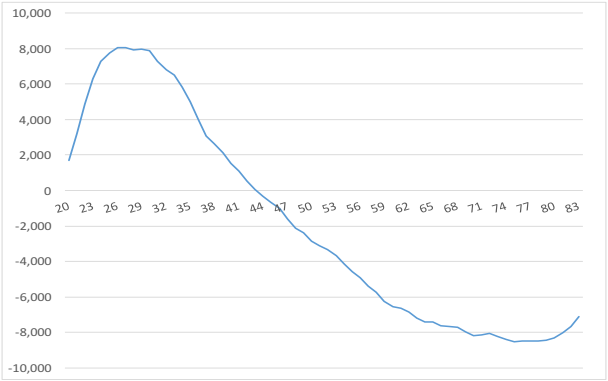
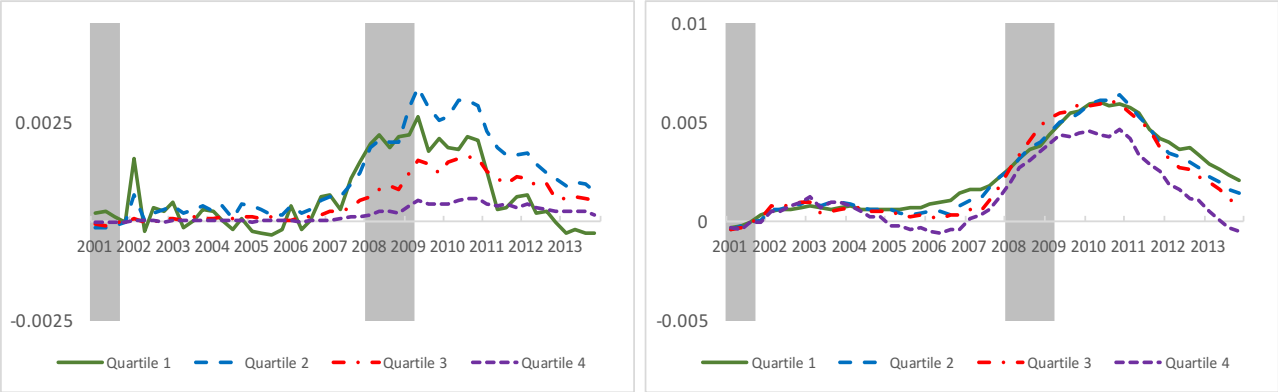


Figure 21: Estimated age effects from balance change regressions. Baseline specification. Dependent variable is the 8Q ahead change in per capita 90+ days delinquent debt balances in USD. Sample period 2001Q3-2011Q4. Number of obs. 64,588,488. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

C Initial Credit Score Ranking



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

Figure 22: Per capita foreclosure rate, difference from 2001Q3. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

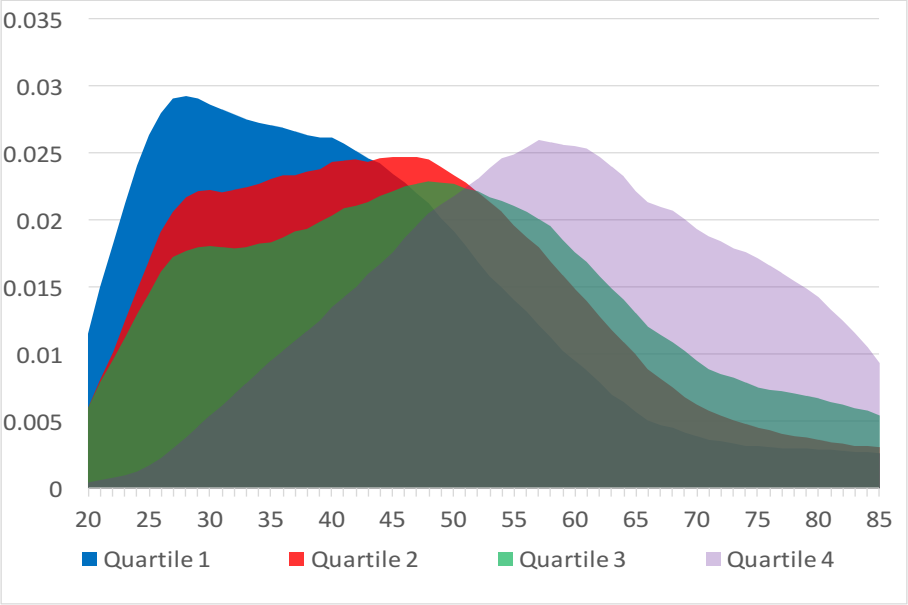


Figure 23: Age distribution by credit score quartile. Source: Authors' calculation based on Experian Data.

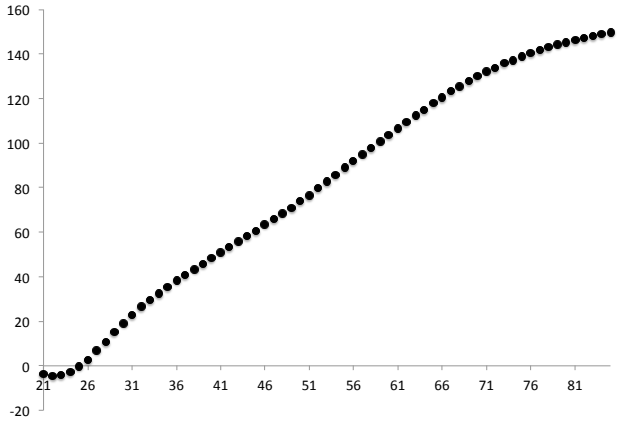


Figure 24: Estimated age effects for the Equifax Risk Score. Source: Authors' calculation based on Federal Reserve Bank of New York's Consumer Credit Panel/Equifax Data.

D Credit Scores, Income and Debt

This section documents the life cycle relation between income, credit scores and debt. 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.

D.1 Cross-sectional Evidence

We regress the 8 quarter lagged credit score on income, income square, age, age square, and interactions between age, income and state fixed effects.[37] Specifically, we estimated the following:

$$CS^i_{2009-h} = \alpha + \beta_1 y^i_{2009} + \beta_2 \left(y^i_{2009}\right)^2 + \gamma_1 \text{age}^i_{2009} + \gamma_2 \left(\text{age}^i_{2009}\right)^2 + \text{interactions} + \varepsilon^i_{2009} \quad (5)$$

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.

D.2 Life Cycle Evidence

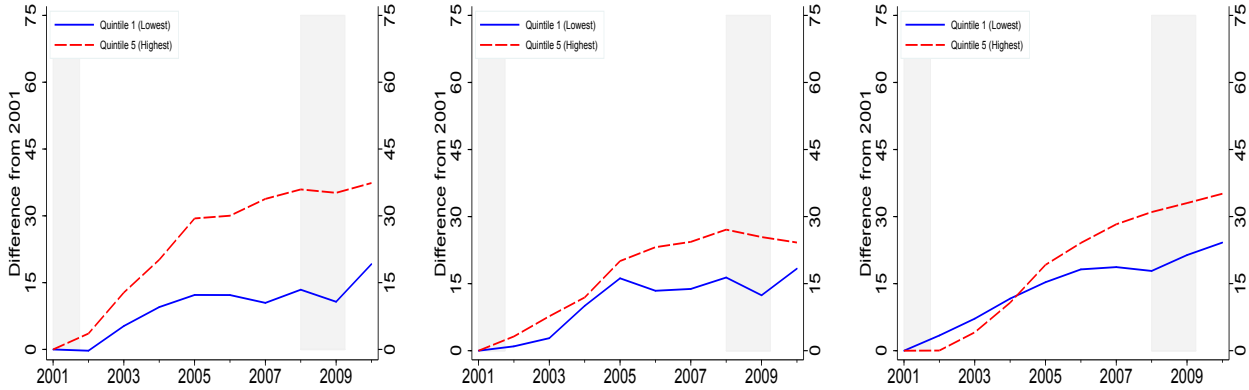
The availability of labor income data for a subsample of borrowers in 2009 and their full credit profile enables us to assess the lifecycle relation between income, credit score and debt.

We relate the evolution of credit scores from 1999 to 2009 to total labor income in 2009 by age in 1999. We find that young borrowers in 1999 with high income in 2009 exhibit the largest growth in credit scores between 1999 and 2009. The results are displayed in figure 25. 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. 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. The growth in credit scores is monotonically increasing in 2009 income quintile. We report only quintile 1 and 5 for clarity. The same qualitative patterns hold for 35-44 year olds in 1999 and 45-54 year olds in 1999, however, the magnitude of the increase in credit scores is smaller, as these groups start with higher initial credit scores.

D.3 PSID Evidence on Income and Debt

To assess the generality of the relation between income, age and debt described in Section 3.2, 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 structure of the PSID, we can directly assess the relation between income and debt growth at the individual data. While debt is poorly measured in

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



(a) 25-34 yo (b) 35-44 yo (c) 45-54 yo

Figure 25: Equifax Risk Score by age in 1999 in relation to borrowers' 2009 Worknumber total annual labor income quantile. Difference with 2001. Source: Authors' calculations based on FRBNY CCP/Equifax Data.

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
$log(\text{income}_{1999})$			0.001	-0.270
1999 age $\times$ $log(\text{income}_{1999})$				0.006*

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

E Zip Code Level Evidence

E.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 12 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) 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.

Table 12: 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.

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 13. 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 borrowers and leverage.

Table 13: 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.