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The Effects of Mortgage Credit Availability: Evidence from Minimum Credit Score Lending Rules*

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Abstract

Since the housing bust and financial crisis, mortgage lenders have introduced progressively higher minimum thresholds for acceptable credit scores. Using loan-level data, we document the introduction of these thresholds, as well as their effects on the distribution of newly originated mortgages. We then use the timing and nonlinearity of these supply-side changes to credibly identify their short- and medium-run effects on various individual outcomes. Using a large panel of consumer credit data, we show that the credit score thresholds have very large negative effects on borrowing in the short run, and that these effects attenuate over time but remain sizable up to four years later. The effects are particularly concentrated among younger adults and those living in middle-income or moderately black census tracts. In aggregate, we estimate that lenders' use of minimum credit scores reduced the total number of newly originated mortgages by about 2 percent in the years following the financial crisis. We also find that, among individuals who already had mortgages, retaining access to mortgage credit reduced delinquency on both mortgage and non-mortgage debt and increased their propensity to take out auto loans, but had little effect on migration across metropolitan areas.

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1 Introduction

Since the housing bust and subsequent financial crisis, US mortgage lenders have significantly tightened their lending standards. These tight lending conditions have likely contributed to the steep decline in the homeownership rate as well as the slow recovery in residential construction. In addition, tight mortgage credit may pose a problem for housing affordability, as the historically low interest rates over the past few years mean that mortgage-financed owner occupied housing would be less expensive than rental housing for many people. More broadly, there is considerable evidence connecting the availability of household credit to overall consumer demand (Guerrieri and Lorenzoni, 2011; DiMaggio and Kermani, 2015; Mondragon, 2016).

While the evidence that mortgage credit conditions have tightened is fairly strong, it is difficult to quantify the magnitude of the tightening or to disentangle the effects of tight mortgage supply from low mortgage demand. Factors that prevent households from qualifying for a mortgage—such as low credit scores, high debt balances, and a lack of liquid assets—also reduce demand for owner-occupied housing. For example, the decline in mortgage originations to less credit-worthy borrowers over the past few years (see Bhutta (2015)) likely reflects more stringent lender standards, but it also likely reflects relatively weak labor market conditions among such borrowers, as well as reluctance by more financially vulnerable households to assume housing market risk following a period of extreme volatility.

In this paper, we address this identification challenge by focusing on lenders' requirements that borrowers must meet a sharply defined minimum credit score threshold in order to qualify for a loan. In some cases, these thresholds may be imposed to allow the lenders to securitize the mortgages through government programs that specify minimum credit scores. In other cases, they may simply reflect a rule-of-thumb about which mortgages are too risky to underwrite. Importantly for our work, lenders' use of these minimum credit scores has varied over time in response to concerns that are likely unrelated to changes in demand from marginal borrowers.

Focusing on the most recent time period, we show that lenders progressively tightened their standards in the years following the financial crisis of 2008. Much of this tightening occurred for loans guaranteed by the Federal Housing Administration (FHA), which dominated lending to borrowers with low credit scores during this time period. In particular, we document the effects of several large lenders imposing minimum credit scores of 620 on FHA loans in the first quarter of 2009, and then raising this threshold to 640 (on some loans) in the second half of 2010. In the data, these minimum score thresholds manifest as discontinuities in the distribution of credit scores on newly originated mortgages, with substantially fewer loans made to borrowers with credit scores just below the thresholds.[1] We use the size of these discontinuities as a measure of how important the thresholds are during each period.

Our empirical analysis is based on a difference-in-differences approach in which we compare borrowers above and below the credit thresholds in periods where the thresholds were more and less important in lenders' underwriting decisions. More specifically, we calculate a single measure of credit availability that captures the effects of the changes in the thresholds on borrowers with different credit scores. Crucially, the nonlinear relationship between our credit availability measure and borrowers' credit scores allows us to separately identify its effect while still controlling for variation in mortgage demand that is also correlated with borrowers' credit scores. Equally important, we are able to control for this difference in mortgage demand between high and low score borrowers even as it varies over time. In other words, our approach lets us separate out mortgage demand from mortgage supply even as both are simultaneously changing during our sample period.

We calculate our credit availability measure for individuals in the FRBNY Consumer Credit Panel (CCP) and estimate its impact on various outcomes.[2] Starting with mortgage attainment, we find that for borrowers with scores below the relevant thresholds, the tightening that occurred between 2008 and 2011 reduced their probability of obtaining a mortgage in the subsequent quarter by 0.5 percentage points, compared to an average probability of taking out a mortgage of just under 1 percent. When we look over longer horizons of up to 16 quarters, the effects shrink in magnitude relative to the average probabilities but remain very large, indicating that credit availability (or the lack thereof) has persistent consequences for individual borrowing behavior.

In aggregate, we estimate that lenders' use of minimum credit scores reduced the total number of newly originated mortgages by about 2 percent, with much larger effects among prospective borrowers with scores near the thresholds. Furthermore, we show that the effects of this tightening are largest in areas with moderate income, which feature a combination of relatively low credit scores and relatively high housing demand. Similarly, we find that the effects are largest for borrowers aged 34-45 and for borrowers living in census tracts with moderate shares of black residents.[3]

[1] We plot this distribution for several different years in figure 1.

[2] The Equifax Risk Score included in the CCP is distinct from the FICO scores typically used by mortgage lenders. We spend considerable effort addressing this challenge in our analysis.

[3] Working with data from the Home Mortgage Disclosure Act (HMDA) that contains information on the race of individual borrowers, Bhutta and Ringo (2016) find that tight credit conditions have had a disproportionate effect on credit access for minorities.

The fact that our approach produces any substantial estimates of the effect of these thresholds on mortgage attainment results establishes two non-trivial facts about the credit scores in consumer credit data. First, these scores are in fact a meaningful measure of access to mortgage credit, even though, as we discuss below, they are not the actual credit score used for mortgage underwriting. Second, these scores are sufficiently stable that a single observation taken at the end of the quarter does reflect the individual's ability to borrow over the following three months. Establishing these facts is particularly important given the wide range of studies that use these scores as a measure of individuals' access to credit.

Our study of the effects of these credit score thresholds on mortgage attainment falls within a larger literature that has tried to identify the effects of mortgage credit availability on homeownership. Early work in this literature includes Barakova et al. (2003) and Rosenthal (2002) who constructed measures of mortgage credit access from responses to the Federal Reserve's Survey of Consumer Finances (SCF). More recently, Barakova et al. (2014) constructed a measure of mortgage credit access from the National Longitudinal Survey of Youth and Acolin et al. (2016) use more recent waves of the SCF. Among the few papers that have explicitly considered the effect of credit score, Chomsisengphet and Elul (2006) use credit scores merged with mortgage data to shed light on the effect of personal bankruptcy exemptions on secured lending. We conduct our analysis on a far larger data set with many more observable outcomes and also, crucially, while controlling for the variation in demand that is correlated with access to credit. However, like other studies based on consumer credit data, we are unable to see income or assets and therefore unable to account for the impact of those factors on individuals' ability to borrow.

We also examine the implications of mortgage credit availability for other outcomes. First, we find that credit availability has relatively little effect on mortgage or other loan delinquency among new mortgage borrowers, but that it dramatically lowers delinquency of both types among individuals who already had a mortgage, suggesting that the ability to refinance a mortgage is an important financial cushion. While Keys et al. (2014) show that lower *costs* of mortgage credit, in the form of ARM rate resets, lead to fewer mortgage defaults and lower delinquent card balances, we are not aware of previous work showing that increased *access* to mortgage credit reduces borrowers' delinquency rates. In contrast, Skiba and Tobacman (2015) show that increased access to payday lending leads to higher bankruptcy rates, but the settings of our respective analyses are quite different.

Next, we study the impact of credit availability on moving and migration behavior, finding mixed effects depending on the horizon and whether an individual already had a mortgage. Perhaps most notably, our results on cross-metropolitan migration suggest that lacking access to new mortgage credit did not "lock in" prior borrowers to their current city. This part of our paper contributes to the discussion of whether fall-out from the housing crisis might have hampered the economic recovery by preventing workers from relocating to stronger labor markets. Previous research has asked whether underwater homeowners were locked into their homes because they were unable to pay off their mortgages by selling their homes (Schulhofer-Wohl, 2011; Ferreira et al., 2011; Farber, 2012). Our approach allows us to answer a slightly different question, which is whether low-score homeowners who could no longer qualify for a new mortgage would remain in their home rather than relocate to a new area where they would be forced to rent. We find that this is not the case. Current homeowners without access to mortgage credit are as likely to move as homeowners with access to credit.

In our final set of results, we show that mortgage credit availability seems to affect auto borrowing, positively in the case of individuals who were prior mortgage borrowers—again pointing to the importance of refinancing—and negatively in the case of prior non-borrowers, perhaps because of substitution from houses to cars when mortgages are not available. This last result contrasts somewhat with the conclusions of Gropp et al. (2014), who document a reduction of consumer debt for renters in areas with larger house price declines and interpret this finding as a response to cutbacks in the provision of mortgage credit in those areas. Our finding relies on a different and potentially sharper identification of credit constraints.

More broadly, our paper is related to a growing literature that has used a variety of identification strategies to isolate the effects of mortgage credit availability during the recent housing cycle. Anenberg et al. (2016) characterize mortgage credit availability as the largest mortgage that a borrower can obtain given his credit score, income and ability to make a down payment, assuming this maximum size is determined by mortgage supply rather than demand. The authors show that tighter credit conditions depress both house prices and new residential construction. Gete and Reher (2016) identify local variations in mortgage credit tightness based on the share of mortgage lending by the largest banks in different areas prior the crisis. They argue that these banks tightened credit more in response to new financial regulations and use the variation in their lending share to show that tight credit helps explains higher residential rents. Finally, Favara and Imbs (2015) use heterogeneity in US bank deregulation to look at the effects of mortgage credit supply on house prices, while DiMaggio and Kermani (2015) use heterogeneity in the effect of predatory lending laws to measure the effect of credit supply on lending, house prices, and employment. Our paper presents yet another way of identifying the effects of mortgage credit availability by focusing explicitly on the variation in lenders' use of minimum credit scores. Unlike all of these other studies, our approach us allows us to measure the effects on individuals rather than just local areas.

In using credit score thresholds, our study is also related to work by Keys et al. (2009, 2010, 2012), who argue that, before the crisis, the greater ease of securitizing mortgages made to borrowers with credit scores above 620 led to lax screening by originators because of moral hazard. Bubb and Kaufman (2014) instead argue that the use of 620 as a threshold arose as a lender response to a fixed cost of screening potential borrowers. During the more recent period we study, lenders' reliance on minimum credit scores clearly does not reflect their difficulty in securitizing these loans. As we describe below, most securitized loans issued around the thresholds since the financial crisis have been guaranteed by the FHA, whose explicit credit score minimums were substantially lower than the thresholds we study. In any case, we are less concerned with the origin of lenders' decision to apply minimum credit scores and more concerned with the effect of these rules on individuals' ability to obtain mortgage credit.

The rest of the paper proceeds as follows: Section 2 describes lenders' use of minimum credit scores, how we observe the effects of these rules in the data, and the construction of our credit availability measure. We present our empirical results on mortgage borrowing and other outcomes in section 3. In section 4 we examine heterogeneity in the effects of credit availability on mortgage borrowing across different demographic and socioeconomic groups, while in section 5 we calculate the cumulative effects of the credit restrictions over various horizons. Finally, section 6 concludes the paper and offers thoughts on directions for future research.

2 Data Sources and the Credit Availability Measure

2.1 A Recent History of Credit Score Thresholds

As noted in the introduction, since the financial crisis, there have been significant discontinuities in the distribution of credit scores on newly originated mortgages. In figure 1, we plot the density and cumulative distribution of credit scores for mortgages originated in 2005, 2008, 2010, and 2012.[4] At certain key scores, there are fewer loans originated to borrowers

[4]The data, which come from Black Knight, are described more fully in section 2.2.

with credit scores just below those thresholds. By 2010 (the blue lines), there were very few loans made to borrowers with credit scores below 620. By 2012 (the green lines), the most significant threshold score was 640.

These discontinuities are largely explained by lenders' changing policies on issuing mortgages guaranteed by the Federal Housing Administration (FHA), which has dominated the market for low-score mortgages since the crisis. In the early 2000s, the FHA's market share fell sharply because of competition from sub-prime lenders who offered comparable mortgages at lower prices. However, by 2008, most of those lenders had disappeared from the market, leaving the FHA program as a last resort for borrowers with low scores. Around the same time, the Economic Stimulus Act of 2008 raised the maximum loan size on FHA mortgages in a further effort to increase the scope of FHA lending and thereby help stabilize the mortgage market.

As house prices continued to decline, losses on the book of mortgages insured by the FHA rose substantially. By the end of 2008, the 90-day delinquency rate on FHA loans reached 6.8 percent and although payments to the owners of these loans were guaranteed by the US government, lenders also bore some risk from these loans. These risks included the increased cost of servicing the delinquent mortgages if they had retained the servicing rights, as well as reputational risks in a market increasingly sensitive to the dangers of risky mortgage lending. In February 2009, two of the nation's largest lenders, Wells Fargo and Taylor, Bean & Whitaker (TBW), announced that they would require credit scores of at least 620 for newly originated loans guaranteed by the FHA and the Department of Veterans Affairs. A Wells Fargo spokesman stated, "This change is a reflection of our commitment to do business with brokers and correspondents who manage to the economics and risks of the mortgage industry" (Inside FHA/VA Lending, 2009b). Over the next six months, the average FICO score on FHA loans climbed 30 points, from 663 in February to 692 in August (Inside FHA/VA Lending, 2009a).

In January 2010, the Department of Housing and Urban Development (HUD) announced its own tightening of FHA standards, including an increase in upfront and ongoing mortgage insurance premiums, a minimum credit score of 500 on all FHA loans, and a minimum score of 580 for borrowers seeking to make down-payments below 10 percent.[5] This introduction of minimum credit scores on FHA mortgages had little impact because lenders were already making very few loans to borrowers with such low scores. More importantly for FHA lenders,

[5]HUD also proposed lowering the percentage of the sale price that sellers were allowed to put towards closing costs or renovations ("seller concessions") from 6 percent to 3 percent.

HUD announced two changes regarding its practice of terminating lenders' eligibility to originate FHA loans. First, HUD announced that it would systematically review the performance of each lender's FHA mortgages and revoke the lender's eligibility as FHA lenders if the overall default rate exceeded a specified threshold. Second, HUD announced that lenders would now also be evaluated based on the performance of the loans made through third-party correspondent lenders whereas previously, only mortgages originated by the lenders themselves were used in these reviews. Both policy changes were phased in gradually over 2010.

In response to the new FHA rules, many lenders tightened their FHA lending, including by imposing new minimum credit scores on the FHA mortgages they were willing to originate themselves, and especially on those originated through third-party correspondents. Two of the largest lenders, Wells Fargo and Bank of America, stopped buying FHA loans made to borrowers with credit scores below 640, though both continued to originate loans to lower-score borrowers through their retail channels (Bloomberg News, 2010). Other lenders reportedly established minimum credit score thresholds as high as 660 (Inside FHA/VA Lending, 2010).

The impact of these changes in lenders' policies around FHA lending is apparent in the distribution of credit scores for newly originated mortgages in figure 2, where the blue lines in the four panels show the distribution of FICO sores for FHA mortgages in 2005, 2008, 2010 and 2012, respectively. In figure 2A, we see the low share of FHA mortgages prior to 2008. Then figure 2B shows the dominance of FHA lending among low-FICO borrowers during 2008 and the absence of any large discontinuities in the distribution, reflecting the limited use of minimum FICO scores by lenders during this period. The announcements by Wells Fargo and TBW in January 2009 that they would stop originating loans below 620 are apparent in figure 2C, which shows a dramatic reduction in the fraction of FHA mortgages to borrowers with scores below 620 in 2010. The size of this reduction suggests that many other lenders also adopted a similar practice. Finally, figure 2D shows that, by 2012, few FHA mortgages—or mortgages of any other type—were made to borrowers with scores below 640, a situation that has remained essentially unchanged since then.

2.2 Measuring Credit Availability

Our analysis uses the discontinuities in the distribution of mortgages at particular credit scores as indications that lenders are using these scores in their underwriting decisions and are exhibiting some reluctance to lend to borrowers with credit scores that fall below this value. Intuitively, if borrowers with credit scores just above the threshold have a similar demand for mortgages compared to borrowers just below the threshold, then the difference in the number of mortgages originated to these two groups must reflect pure differences in the supply of mortgage credit. We can use these differences to identify the effects of credit supply on borrowers. From the distribution of newly originated mortgages, there appear to be many scores that exhibit discontinuities in the number of mortgages originated. However, in the period since the financial crisis, the two most prominent discontinuities occur at 620 and 640 and we focus on these thresholds.

Our credit availability measure is constructed to capture the difference in the ability of borrowers above those thresholds to obtain mortgages compared to borrowers below them. In practice, computing this measure requires two steps. First, we need to estimate the impact of falling above or below the threshold at each point in time. Second, we need to determine how likely it is that each individual would fall below the threshold if she applied for a mortgage.

2.2.1 Credit Score Thresholds in Originated Mortgages

In order to identify the use of the thresholds, we look at the distribution of credit scores on loans originated each quarter, as captured in a data set of mortgages provided by Black Knight Financial Services, formerly known as "LPS" and "McDash". For each mortgage, Black Knight reports detailed information that includes the origination date, the loan-to-value ratio, the debt-to-income ratio, and the borrower's credit score. Importantly for our purposes, the credit score reported in the data is the FICO score used in the lender's mortgage underwriting decision, a point we return to below. As discussed above, figure 1 plots the density and cumulative distribution of FICO scores for mortgages in the Black Knight data originated in 2005, 2008, 2010, and 2012.

We quantify the size of the 620 and 640 thresholds by calculating the ratio of the number of mortgages originated within five points below the threshold compared to the number of mortgages originated within five points above the threshold. Assuming that these two groups of borrowers have similar demand for mortgage credit, differences in the number of new mortgages originations should reflect differences in lenders' willingness to provide credit above and below the threshold. Looking at the black line in figure 1, lenders appear to have used 620 as a relevant threshold in their lending decisions even before the crisis.[6] In 2005, for example, only 70 percent as many mortgages were originated to borrowers just below the

[6] As discussed in the introduction, Keys et al. (2010) argue that the discontinuity existed because loans with credit scores above 620 were easier to securitize, while Bubb and Kaufman (2014) dispute this conclusion.

thresholds compared to those just above. In contrast, the ratio around 640 was about 90 percent, suggesting that 640 was not a particularly important score in underwriting decisions during that time period. These ratios were similar in 2008 (the red line).

By 2010 (the blue line), however, the ratio at 620 had plummeted to just 20 percent, suggesting a dramatic tightening of mortgage credit for borrowers with credit scores under 620. By 2012 (the green line), the ratio at 640 had also fallen sharply, to about 45 percent.[7] These ratios have changed relatively little since 2012.

The discontinuities around these credit score thresholds could in theory emerge from several different kinds of restrictions by lenders. First, it may be that some lenders simply refuse to lend at all to borrowers with credit scores below the threshold values. Low-score borrowers who would have approached these lenders because of their geographic proximity or other reasons would therefore not be able to get a mortgage from their preferred lender and may face search costs that prevent them from turning to other lenders. Alternatively, it may be that lenders impose other restrictions—on loan-to-value (LTV) or debt-to-income (DTI) ratios, e.g.—on borrowers with credit scores below the threshold and these other restrictions limit the demand from these less credit-worthy borrowers. This second explanation would imply that loans originated to borrowers with scores just below the threshold should appear less risky based on other observable characteristics. Indeed, we do find some evidence of this behavior. For example, DTI ratios and LTV ratios are both slightly lower on mortgages originated just below the thresholds compared to mortgages originated just above. In the end, the precise form of the restriction is not important for our analysis as long as the discontinuity reflects differences in the supply of mortgage credit to borrowers above and below the threshold rather than differences in demand.

One additional complication in studying mortgage underwriting decisions during this period is lenders' participation in the FHA's streamline refinance program, which allows borrowers to refinance FHA-guaranteed mortgages into new FHA mortgages without going through the full underwriting process.[8] For example, it may be that there are actually many low-credit score borrowers getting mortgages through this program who appear in the data with missing FICO scores. While we can't observe in the data which mortgages are

[7] As the number of mortgages to borrowers with credit scores between 620 and 640 fell between 2010 and 2012, the ratio at 620 actually rose back to 40 percent, a mechanical response to the decrease in loans to borrowers with scores just above 620, the denominator. A combined measure of the two discontinuities, which calculates the ratio of mortgages just above 640 to the number of mortgages just below 620, shows a clear overall tightening during this period.

[8] In theory, the program allowed FHA mortgages to be refinanced with no underwriting at all, though in practice, many lenders did impose restrictions on which loans they would refinance.

originated through the streamline refinance program, we can study the pool of mortgages with characteristics that would make them likely to part of this program: refinance mortgages guaranteed by the FHA that do not involve any equity extraction.

Reassuringly, the fraction of mortgages in this category with missing FICO scores is only slightly higher than the overall fraction of mortgages in the data with missing scores (14 percent compared to 12 percent overall), making it unlikely that there are a large number of low-score borrowers obtaining mortgages through the program and appearing in the data with missing scores. In contrast, FHA refinances just below the 620 threshold do exhibit other risky characteristics that suggest they were underwritten less stringently, likely because they were disproportionately originated through the streamline program. In particular, FHA refinances with credit scores just below the threshold have higher DTIs and are more likely to lack full documentation of the borrower's income. Again, however, these are supply-driven differences that do not invalidate our identification strategy.

2.2.2 Using Credit Scores in the Consumer Credit Panel

The second, less obvious step in computing our mortgage credit availability measure is identifying whether each individual in the population has a credit score that falls above or below the relevant threshold. In principle, all we would need to do this is to observe the individual's FICO score at a given point in time. In practice, there are two complications.

First, a FICO score is the output of a proprietary scoring model, which has changed over time, applied to data reported by any one of the three credit bureaus. As a result, there is no single "FICO score" for an individual at any given point in time. Moreover, scores change almost continuously as new information is reported to the credit bureaus. The scores reported in the Black Knight data, which we used to construct figure 1, are the results of the particular scoring model and credit bureau data used by the lender at the time of underwriting. For both these reasons, even if we observed *some* FICO score from *around* the same time that a mortgage was originated, it would not necessarily match exactly to the score reported in the Black Knight data. The empirical relevance of the observed 620 and 640 thresholds in a different data set is thus something that we need to test, not something that we can assume.

The second complication is that we do not observe any FICO scores in our main data set for this project, which is the Equifax Consumer Credit Panel from the Federal Reserve Bank of New York. Instead, the CCP contains an "Equifax Risk Score", which is a similar credit score intended to capture the probability that individual will default on any loan. In order to relate the Risk Score in the CCP to a FICO score, we use a linked monthly panel data set that contains both types of credit scores. Using the joint distribution of Equifax Risk Scores and FICO scores, we predict the probability that an individual with a given Risk Score in the CCP would have a FICO score (using the particular model and credit bureau data in the linked data set) that exceeded the a given threshold value.[9] To characterize the relationship between the Equifax Risk Score and the probability that a FICO score exceeds a threshold we estimate logit models using data six months prior to origination. The models allow the relationship between the two scores to vary across years.

2.3 Identification Strategy

Our identification strategy combines these two steps into a specification designed to measure the effect of having a credit score above the threshold in a period when lenders are using that threshold to make lending decisions. To identify this effect, we use a difference-in-difference approach, comparing borrowers above and below the threshold in periods where the threshold is more or less important. For ease of exposition, we begin with a case where there is only one credit score threshold at 620. First, as described in section 2.2.1, our measure of the importance of the threshold in quarter t is given by the ratio of the number of mortgages originated to borrowers just below 620 compared to the number just above:

$$r_t^{620} = \frac{(\text{Loan Count}|FICO \geq 615, FICO < 620)_t}{(\text{Loan Count}|FICO \geq 620, FICO < 625)_t}$$

Second, as described in section 2.2.2, our measure of whether a borrower in the consumer credit panel has a FICO score above 620 is based on their Equifax Risk Score, $Pr(FICO \geq 620|riskscore_{it})_{a(t)}$, with the relationship allowed to vary by year ($a(t)$).[10]

This approach yields an estimating equation of the form

$$\begin{aligned} y_{it} = &\alpha Pr(FICO \geq 620|riskscore_{it})_{a(t)} \\ &+ \beta Pr(FICO \geq 620|riskscore_{it})_{a(t)} \times (1 - r_t^{620}) \\ &+ \delta_t riskscore_{it} + \eta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

[9] The linked data contain information only on mortgage borrowers, which is why we cannot use them for our main estimates.

[10] Throughout the paper we calculate the probability of exceeding a FICO threshold using the Risk Score with which an individual *enters* quarter t, so that the score cannot have already directly responded to the outcome variable. Equifax captures the information in the CCP on the last day of a quarter.

where y_{it} is an outcome variable.[11] The parameter of interest is β, the coefficient on the interaction between one minus the importance of the 620 threshold and the probability that the individual's FICO score is 620 or greater. A similar logic applies for the 640 threshold.

Equation 1 also shows the primary controls that we include in the empirical work below, including 1) quarter fixed effects (η_t), 2) the Equifax Risk Score of the individual interacted with quarter dummies to allow the coefficient (δ_t) to vary over time, and 3) the (un-interacted) probability that the individual's FICO score is 620 or greater.[12] As we note in the introduction, these controls allow us to identify the effects of credit availability using the timing and nonlinearity of the interaction term (or, in practice, our combined credit availability measure). Formally, we require that the interaction term be uncorrelated with any other factors affecting an outcome variable, conditional on the controls. Thus our identification is secure against any confounding factors that 1) vary only in the time series dimension, 2) are correlated with credit score in a linear fashion, even if that linear relationship with credit score shifts over time, or 3) are correlated with the threshold probabilities—which are nonlinear functions of the Risk Scores—but do not shift over time. In particular, our view is that credit *demand* could be correlated over time with the level and slope of many of our outcomes but that it is unlikely to have an effect on those outcomes that happens to shift at the precise times and in the nonlinear ways that the interaction term above does.

2.4 Combined Credit Availability Measure

To help understand how to evaluate mortgage credit availability in periods in which lenders used both the 620 and 640 thresholds in their lending decisions, we introduce a very simple structural model. This model also gives a structural interpretation to the ratio of mortgage originations above around the relevant threshold scores.

To start, we imagine a mortgage market with a large number of lenders, each of whom makes lending decisions based on based on the FICO score of a perspective borrower. All lenders are willing to make loans to borrowers with scores of 640 or greater. A fraction ρ_{640} are willing to make loans to borrowers with scores below 640 and a fraction ρ_{620} of these lenders (i.e., a fraction $\rho_{620} \times \rho_{640}$ of all lenders) are willing to make loans to borrowers with scores below 620. Assume the FICO scores of individuals who would like to purchase a home are uniformly distributed with mass M in each 5-point FICO bin. Each borrower approaches

[11] In practice, many of our outcome variables are binary or counts, so we estimate logistic or negative binomial regressions, rather than linear models.

[12] Note that the quarter fixed effects subsume the un-interacted ratios.

a single lender, drawn at random from the distribution of lenders, and applies for a loan.

Now consider a borrower whose credit score we do not observe but for whom we can calculate $Pr(FICO \geq 620)$ and $Pr(FICO \geq 640)$. The probability that she will be given a loan when she approaches a random lender is

$$P = Pr(FICO \geq 640) + Pr(640 > FICO \geq 620) \times \rho_{640} + Pr(FICO < 620) \times \rho_{620} \times \rho_{640} \quad (2)$$

Next, we discuss how we can estimate ρ_{620} and ρ_{640} from the data. For borrowers with scores between 615 and 619, a fraction $\rho_{620} \times \rho_{640}$ of lenders they approach will make them loans and the total number of loans to borrowers in this range will be $\rho_{620} \times \rho_{640} \times M$. Similarly, the total number of loans originated to borrowers with scores between 620 and 624, and also between 635 and 639, is $\rho_{640} \times M$. Finally, all applicants with scores above 640 will be approved so the total number of loans originated to borrowers with scores between 640 and 644 is M. Therefore we can identify estimators for ρ_{620} and ρ_{640} as

$$\frac{(\text{Loan Count}|FICO \geq 635, FICO < 640)}{(\text{Loan Count}|FICO \geq 640, FICO < 645)} = \frac{\hat{\rho}_{640} \times M}{M} = \hat{\rho}_{640}$$

and
$$\frac{(\text{Loan Count}|FICO \geq 615, FICO < 620)}{(\text{Loan Count}|FICO \geq 620, FICO < 625)} = \frac{\hat{\rho}_{620} \times \hat{\rho}_{640} \times M}{\hat{\rho}_{640} \times M} = \hat{\rho}_{620}.$$

This derivation shows that ratio of the number of mortgages just below the threshold to the number just above it can be interpreted as the fraction of lenders who are willing to lend to borrowers with credit scores below that threshold.[13] That is, $r_t^{620} = \hat{\rho}_{620}$ and $r_t^{640} = \hat{\rho}_{640}$.

To operationalize equation 2 and define our credit availability measure for a given individual, we make two simple substitutions. First, we replace ρ_{620} and ρ_{640} in equation 2 with our estimates r_t^{620} and r_t^{640}. Second, we replace the notional $Pr(FICO \geq 640)$ with the $Pr(FICO \geq 640|riskscore_{it})_{a(t)}$ that we estimate from the linked data described above. These substitutions yield

$$\begin{aligned} credavail_{it} = {} & Pr(FICO \geq 640|riskscore_{it})_{a(t)} \\ & + Pr(640 > FICO \geq 620|riskscore_{it})_{a(t)} \times r_t^{640} \\ & + Pr(FICO < 620|riskscore_{it})_{a(t)} \times r_t^{640} \times r_t^{620}, \end{aligned}$$

[13]A more realistic model could relate the ratio to the number of lenders willing to lend but also the size of those lenders and the cost to borrowers of seeking them out. A small rural lender willing to lend to borrowers with FICO scores below 620 is not likely to be able or willing to draw enough customers to significantly affect the measured ratio or credit supply.

or equivalently,

$$\begin{aligned} credavail_{it} = Pr(FICO \geq 640 | riskscore_{it})_{a(t)} \\ + Pr(FICO < 640 | riskscore_{it})_{a(t)} \times r_t^{640} \\ + Pr(FICO < 620 | riskscore_{it})_{a(t)} \times (r_t^{620} - 1) \times r_t^{640}. \end{aligned}$$

To connect this derivation to the difference-in-difference approach described above, it is instructive to consider two special cases. If $\rho_{640} = 1$ and we estimate $r_t^{640} = 1$—no lenders use 640 as a minimum score—then 620 is the only relevant threshold and

$$\begin{aligned} (credavail_{it} | r_t^{640} = 1) = credavail_{it}^{620} \equiv & Pr(FICO \geq 620 | riskscore_{it})_{a(t)} \\ & + (1 - Pr(FICO \geq 620 | riskscore_{it})_{a(t)}) \times r_t^{620} \\ = & r_t^{620} + Pr(FICO \geq 620 | riskscore_{it})_{a(t)}) \times (1 - r_t^{620}). \end{aligned}$$

Similarly, if $\rho_{620} = 1$—no lenders use 620 as a minimum score—then 640 is the only relevant threshold and

$$\begin{aligned} (credavail_{it} | r_t^{620} = 1) = credavail_{it}^{640} \equiv & Pr(FICO \geq 640 | riskscore_{it})_{a(t)} \\ & + (1 - Pr(FICO \geq 640 | riskscore_{it})_{a(t)}) \times r_t^{640} \\ = & r_t^{640} + Pr(FICO \geq 640 | riskscore_{it})_{a(t)}) \times (1 - r_t^{640}). \end{aligned}$$

Focusing on the last line of the definition of $credavail_{it}^{620}$, we observe that it is precisely the same as the interaction term from equation 1, our difference-in-difference specification, except that it includes the additional un-interacted r_t^{620} term. This un-interacted term is already absorbed into our quarter fixed effects. As a result, if we replaced the interaction term in equation 1 with this credit availability measure, the estimated coefficient would be the same. In other words, when only the 620 threshold is active, we can think of this credit availability measure as simply the interaction term from the standard difference-in-difference specification. The same holds for the 640 threshold.

This derivation shows that our combined credit availability measure has both theoretical motivations and effectively reduces to the standard interaction term from our difference-in-difference specification when only one credit score threshold is active. Our final specification (for a continuous outcome variable) is then

$$\begin{aligned} y_{it} = &\alpha_{620} Pr(FICO \geq 620 | riskscore_{it})_{a(t)} + \alpha_{640} Pr(FICO \geq 640 | riskscore_{it})_{a(t)} \\ &+ \beta credavail_{it} + \delta_t riskscore_{it} + \gamma X_{it} + \eta_t + \varepsilon_{it} \end{aligned} \tag{3}$$

where β is again the parameter of interest, capturing the combined effect of the 620 and 640 thresholds. The specification includes our predicted probabilities of having a FICO score over 620 and 640, to strip out nonlinear, non-time-varying effects of credit score on the outcomes. It also includes the linear effect of the Risk Score, which is allowed to vary over time. Finally, to isolate the effect of current credit availability, we also add as additional controls the first quarterly lag of credit availability for the individual, the first lag of the predicted threshold probabilities, and the first lag of credit score interacted with the quarter dummies, all contained within the vector X_{it}.[14]

Although it is easy to think of $credavail_{it}$ in a binary context—one either has access to credit or one does not—in practice it is a continuous variable with outcomes ranging from 0 to 1, both because the link between Equifax Risk Score and FICO threshold is probabilistic and because our quantification of the importance of the threshold is never actually 0 or 1. Figure 3 shows the evolution of the credit availability measure. The left panel shows the time series of average credit availability for individuals with Equifax Risk Scores between 530 and 730, our estimation sample. The timing of the sharp drops in the series correspond to the narrative provided above and the introduction of the thresholds we identified in the Black Knight data. The three shaded regions denote periods between 2008 and 2011 in which availability was roughly stable.

Taking a different slice through the data, the right panel compares average credit availability, by 10-point Risk Score bin, across those three stable periods of credit availability between the changes in the thresholds. As should be expected, our availability measure dropped most for individuals with low Risk Scores between 2008 (the black line) and 2009:Q2-2010:Q2 (the red line), as the 620 FICO threshold kicked in. By 2011 (the blue line), with the introduction of the 640 threshold, availability fell a bit further for the low end of the Risk Score range plotted here, but also fell noticeably in the middle of the range. Individuals with Risk Scores above 700 saw essentially no change in either period, because we estimate a very low probability of these individuals having a FICO score below 640.

[14] A brief discussion of the estimated coefficients on lagged credit availability is presented in section 3.3.

2.5 Estimation Sample

We estimate the effects of our credit availability measure using the Equifax/FRBNY CCP, which consists of a 5 percent random sample of individuals who have a credit file. For our main results, we use a random sample containing 50 percent of the individuals in the panel, or a 2.5 percent sample of the population. We used a disjoint smaller subset of the CCP as a training sample for the initial data analysis for this paper, in part for ease of computation and in part to avoid reporting results from the same data as our training sample. This approach likely helped us avoid reading too much into results that happened to be economically large or statistically significant in our initial analysis.

We restrict our estimation sample to the years 2008-2011, a period when we can clearly identify changes in credit availability, as discussed above. Ending our sample in 2011 has the further advantage that we are able to observe everyone in our sample through 2015, a full four years after the end of the estimation period, allowing us to estimate longer-term effects of our credit availability measure.[15]

We also restrict our analysis to borrowers within a relatively narrow range of Risk Scores around the thresholds at 620 and 640 that we identified above. This restriction has two motivations. First, borrowers with credit scores far from the threshold values are much less likely to be affected by lender's use of these thresholds in making lending decisions. Results suggesting that such borrowers are significantly affected by these mortgage thresholds are thus more likely to be spurious. Second, the relationship between credit score and mortgage demand is likely nonlinear. However, within a narrow band of scores, a linear function of credit score should be a reasonable control for demand. Our baseline specification uses a sample of borrowers with scores between 530 and 730, but we perform robustness checks around the size of the window in section 3.4.

3 Results

Having constructed a measure of mortgage credit availability for each member of the consumer credit panel, we next explore the relationship between this measure and various outcomes. Depending on the outcome, we use linear regressions, logit models in the case of probabilities, or negative binomial models in the case of count variables. For each outcome

[15]We drop individuals identified in the CCP as dead, those who are reported to be younger than 16 or older than 120, and those whose address is reported as something other than a "street address" or "high-rise". These restrictions removed less than 10 percent of the observations in the CCP.

variable, we consider horizons of 4, 8, 12, and 16 quarters to assess both the short-term and longer-term effects of restrictions on mortgage credit. As laid out above, our baseline specification includes dummy variables for the quarter of observation and also an interaction of this quarter dummy with Risk Score.

In the table for each specification, we report results using the entire sample and also separately for those who had a mortgage in the previous quarter and those who did not. In determining whether someone has a mortgage, we use total outstanding balance on all mortgages appearing on her credit report and say an individual has a mortgage if the total is greater than zero. Because our sample is concentrated towards the bottom of the credit score distribution, the sub-sample of people with no mortgage balance makes up about 85 percent of our estimation sample.

Finally, it is worth noting that the coefficients on our mortgage credit availability measure capture the differences between a borrower with a credit availability of one, meaning she is unaffected by minimum credit scores, and a hypothetical borrower with credit availability of zero, meaning both that she falls below the credit score threshold with certainty and that we observe no mortgages to borrowers with credit scores just below this threshold. In practice, we always estimate some positive probability of an individual with a low Risk Score being above a FICO threshold, and we always see some mortgages issued below the FICO thresholds in the Black Knight data. As a result, our credit availability measure is never less than about 0.2. As shown in figure 3B, for borrowers with scores toward the bottom of our range, credit availability fell from about 0.7 to 0.2 between 2008 and 2011, so the net effect for the most affected group is about half as large as the reported effect.[16]

3.1 Mortgage Borrowing

Our first set of models is intended in part to confirm that our measure of mortgage credit availability actually captures borrowers' ability to obtain a mortgage. In these models, the dependent variable is whether the person takes out one or more new mortgages within the specified horizon and we use a logit specification. We use the CCP's trade-line data on individual mortgages to determine the date on which the mortgage was opened.[17] In addition

[16]We also note that we are cautious about using our measure to compare people with very high credit scores to those with very low credit scores, as our identification comes largely from the curvature in our measure around the credit score thresholds at 620 and 640.

[17]This is a subtle but important step. Many of the aggregate variables in the CCP only update with a lag as the information is reported to Equifax. For example, a change in an individual's reported mortgage balance will typically occur in the data one or two quarters after they actually take out a mortgage. By using the dates from the trade lines, we are able to precisely measure the timing of the mortgage origination.

to considering longer horizons, this first set of regressions also includes specifications in which the outcome variable is whether the individual takes out a mortgage in the current quarter.

We can get a good sense of the data by examining plots of the relationship between credit score and the probability of taking out a mortgage. Figure 4 shows the contemporaneous probability of mortgage attainment by credit score, across the three stable periods of availability in our data. The plot shows that the probability of taking out a new mortgage declined most sharply for those at the bottom of the credit distribution between the 2008 (the black line) and 2009:Q2-2010:Q2 periods (the red line). After lenders began using the 640 threshold, we see that the 2012 probabilities (the blue line) show evidence of a further decline in mortgage originations in the middle of our sample. These patterns mirror the evolution of our credit availability measure, as discussed above and shown in figure 3B.

More formally, our first main result is shown in the first column of panel A of table 1. Even after including the various controls, we estimate that the average marginal effect of our credit availability measure on the probability of taking out a new first mortgage in the current quarter is 1 percentage point, with a standard error of just 0.1 percentage point.[18] This estimate is also very large compared to the average probability in our sample of taking out a new mortgage ("Dep. Var. Mean"), which is just 0.9 percent.

This result confirms both the importance of these credit score thresholds in determining who receives mortgages and also the ability of our credit availability measure to capture these threshold effects. Although this result may be unsurprising given the patterns in the Black Knight data, it is not trivial, for at least two reasons. First, the translation from Equifax Risk Scores to predicted FICO scores could wash out the effect, especially given the controls we include. Second, there are various behaviors that could imply the patterns we observe in the loan-level data without implying similar patterns in the individual data. For example, credit scores could be sufficiently variable from day to day that individuals can easily get a mortgage tomorrow even if their score falls below the threshold today.

The fact that we do find effects using our credit availability measure suggests neither concern is valid. Apparently, the Equifax Risk Score is sufficiently correlated with the FICO scores used in mortgage underwriting that that they are able to capture changes in lenders' reactions to borrowers' FICO scores. Also, these scores appear sufficiently stable that a single observation taken at the end of the quarter does affect the individual's ability to borrow over the following three months. As we wrote in the introduction, establishing these facts seems

[18]Our analysis focuses on first mortgages, which made up the vast majority of mortgages during this period. Nevertheless, all of our results are similar if we include second mortgages as well.

particularly important given the large number of studies that have interpreted these scores as a meaningful measure of individual's access to mortgage credit.

Looking at longer horizons, panel A of table 1 shows the cumulative effect of our credit availability measure on mortgage originations over the subsequent 4, 8, 12 and 16 quarters. In columns 2 through 5, we see that the coefficient on our credit availability measure increases in magnitude through columns 2 and 3 (0-3 quarters and 0-7 quarters, respectively) and then levels off at about 3 to 3.5 percentage points. However, the mean of the dependent variable increases steadily from left to right, suggesting that our measure of mortgage credit access becomes less important over time compared to other factors that determine whether people take out new mortgages. Considering whether people take out any new mortgages up to three quarters ahead, the average marginal effect of our measure is about 3 percentage points, while overall, 3.5 percent of people in the sample take out a mortgage within this period. At a 15-quarter horizon, the average marginal effect of our measure is still about 3 percentage points, but the average probability of taking out a mortgage is 13 percent. While attenuated in relative terms compared to the short run, these effects are still very large, suggesting that the effects of credit availability are quite persistent.

In panel B, we repeat our analysis on the sub-sample of people who have no previous mortgage balance. Because this sub-sample makes up about 85 percent of our estimation sample, the average marginal effects for this group are similar to the effects for the sample as a whole, although they are somewhat larger relative to the average probability of taking out mortgages. For people who already have a mortgage (panel C), the average probability of taking out a new mortgage is considerably higher. Many of these individuals are likely refinancing an existing mortgage during this period of falling interest rates. Moreover, already being homeowners suggests a preference (and financial capacity) for homeownership. For this group, the estimated marginal effects are also much larger, indicating that credit availability boosts mortgage originations by more in percentage point terms. However, as a ratio to their average probabilities, the effects are similar in size those of the entire sample.

In table 2, we consider an alternative measure of new mortgage borrowing, namely the change in the total mortgage balance on an individual's credit record, relative to the quarter prior to that in which we estimate credit availability. Qualitatively, the results are similar to those in table 1. In panel A of table 2, credit availability increased an individual's mortgage balance by about \$3,000 over four quarters and \$6,600 over 16 quarters, where the average increases in mortgage debt over the entire sample are close to zero. The effects are noticeably smaller for those who did not have mortgages previously (panel B) and larger for those who did (panel C). Interestingly,those who did have mortgages previously had $56,000 less in mortgage debt after 16 quarters, on average, either through paying it down or discharging debt through foreclosure or other means. Even if we halve the coefficient on credit availability, to match the actual change in our credit availability measure for low-score borrowers, this result suggests that credit availability attenuates the decline in mortgage balance, perhaps because it allows homeowners to refinance and either take out cash or avoid default.

3.2 Additional Outcomes

Aside from the direct question of whether restrictions on mortgage credit are preventing individuals from obtaining mortgages and how these effects attenuate over time, we are also interested in understanding the broader relevance of credit supply. The richness of the consumer credit panel allows us to explore several additional outcomes.

3.2.1 Mortgage Delinquency

We next consider whether access to mortgage credit can allow individuals to avoid negative credit events. In table 3, we show the results of logit models in which the dependent variable is whether individuals have had at least one mortgage delinquency of 60 days or more. For the full sample in panel A, we find large negative effects: At a horizon of four quarters (column 1), the average probability of being delinquent in at least one quarter is 4.5 percent, while having credit available reduces the probability of delinquency by 2.2 percentage points. The effects are larger at longer horizons, although they are somewhat smaller relative to the increasing average probabilities.

We get can get a better sense of the mechanism at work by looking at panels B and C. In panel B, among people with no prior mortgage balance, we see that credit availability has much more modest effects on delinquency, both in absolute terms and relative to the (smaller) average probabilities of delinquency in this group. In contrast, for those who already have a mortgage balance (panel C), we find that continued access to mortgage credit lowers their probability of being delinquent within four quarters by 7 percentage points, half of the dependent variable mean. The effect is even larger in percentage point terms at longer horizons. These results strongly suggest that having access to credit allows homeowners to avoid delinquency through lowering their mortgage payments by refinancing at a lower interest rate. Since credit availability was declining during this period, it is likely that many homeowners became delinquent because they were unable to refinance in the new environment.[19]

In addition to mortgage delinquency, it also interesting to examine whether mortgage credit availability affects delinquency on other types of loans. Importantly, we do not think that lenders tightened other forms of credit at the same times and at the same credit score thresholds, so our credit availability measure should cleanly identify the spillover effects of having access to mortgage credit specifically. Panel A in table 4 shows that the overall effect of having access to mortgage credit is zero at a horizon of four quarters. At a horizon of 16 quarters, there is a meaningful negative effect (-3.5 percentage points), on an average delinquency probability that reached 52 percent for our sample during this turbulent economic period

As in the previous results, we can better understand the mechanism by separately considering the impact on individuals who did and did not already have a mortgage. Similar to our results for mortgage delinquency, the effects of credit availability on non-mortgage delinquency are uniformly negative for borrowers who already have mortgages (panel C), pointing to the importance of refinancing in avoiding negative credit events. In partial contrast to our results for mortgage delinquency, the effects are also clearly negative for borrowers who did not previously have a mortgage (apart from the short-run effect, which is very close to zero). This pattern suggests that access to mortgage credit for new borrowers ultimately helps avoid delinquency on non-mortgage loans, but that the effect takes time to kick in. This may be because the financial benefits of being a homeowner, such as the ability to withdraw equity or to borrow more cheaply if rates decline, are only realized some time after becoming a homeowner.

3.2.2 Moving and Migration

Because we observe the mailing address of an individual in the CCP down to the Census block, we can also examine the effects of credit availability on moving and migration decisions. The address data in the CCP tend to be unstable because they reflect the most recent address reported to Equifax, which can fluctuate back and forth if that person is receiving bills at more than one address. To try to isolate actual moves, we limit the sample to those individuals whom we can observe in a single location for at least four quarters before we measure their credit availability and who appear to remain in a location for four quarters after the end of whatever horizon we use. As a consequence of this approach, the samples

[19] Although the Home Affordable Refinance Program allowed borrowers, regardless of credit score, to refinance if their mortgage balance was larger than the value of their home, many lenders reportedly imposed minimum-score overlays at the 620 or 640 thresholds.

are smaller. Also, we can only show effects out through 12 quarters, because we cannot establish four-quarter address stability for those who are 16 quarters out from 2011, as our data end in mid-2016.

Table 5 shows the effects on the individual's probability of moving across Census blocks. In panel A, we see small positive effects at short horizons and no effects at longer horizons. As before, however, these estimates mask heterogeneity between those who do and do not already have a mortgage balance. For those who do not (panel B), we see somewhat larger positive effects at shorter horizons. The positive effect for this group is sensible, since non-homeowners who have credit available to them usually have to move to buy a home, which we observed them doing in table 1.[20] For those who do have a mortgage balance (panel C), the effects start small and grow more negative over time, suggesting that having the option to refinance leads some of these homeowners to remain in their homes for longer.

The next table (6) looks at the effects on moving across metropolitan areas.[21] As with moving, panels A and B indicate that credit availability has positive effects on migration behavior, both for the full sample and for those without a previous mortgage balance, although the effects attenuate at longer horizons. The effects in column 1 appear small in percentage point terms, with mortgage credit availability associated with a 1 percent rise in changing CBSAs. However, these estimates are actually fairly large relative to the average probabilities of moving across metro areas, which are under 3 percent.

Arguably the most interesting results in table 6 are in panel C, where we find no significant effects of credit availability on migration among those who did previously have a mortgage, at least of a size that we can detect given our standard errors. Some articles in the popular press have suggested that homeowners could have been "locked in" to their current properties or local areas because they were unable to get a new mortgage, either because they were under water, or wanted to hold on to their current rate, or had credit scores that were too low.[22] Our results suggest that, at least along this last dimension, there is no evidence of this phenomenon: Among prior homeowners, lack of mortgage credit *increases* moving and has no effect on migration. Therefore our analysis provides no support for the hypothesis that the economic recovery was slowed because frictions from the housing market prevented

[20] Of course, individuals without previous mortgage balances can be homeowners, but most people who did not have a balance and then took out a mortgage seem likely to be purchasing and moving to a new home.

[21] Formally, these are known as core-based statistical areas, or CBSAs. We use the 2013 CBSA definitions, merged into the CCP by county of residence.

[22] See the introduction for citations of the academic literature on the impact on migration of being underwater.

unemployed workers from relocating to areas with stronger labor markets.

3.2.3 Auto Loans

Finally, we explore whether we can observe interactions between mortgage borrowing and other kinds of consumer credit. In particular, we consider whether our measure of mortgage credit availability has implications for consumers' use of auto loans. Results from this exercise are shown in table 7, where the dependent variable is the change in the number of auto loans on the individuals credit record, and table 8, where we use the change in the total auto loan balance.

We have no strong prior as to either the sign or magnitude of the effect. On the one hand, individuals who cannot buy a house because they are denied mortgage credit could substitute into cars, while those who get mortgages may substitute away from cars. On the other hand, auto borrowing could be positively correlated with mortgage borrowing because of complementarities between driving and purchasing a home, or because refinancing one's mortgage lowers interest payments and relieves liquidity constraints. On net, looking across both tables, the effects among those who did not previously have a mortgage balance (panel B) are mostly negative, suggesting that the substitution channel dominates. For prior mortgage borrowers (panel C), the effects are uniformly positive, suggesting that refinancing enables some homeowners to purchase cars.

3.3 Lagged Credit Availability

In all of the specifications described above, we include among the controls an individual's credit availability from the previous quarter. Doing so allows us to isolate the effect of having credit availability at a particular point in time, given that credit scores (and thus credit availability) are likely to be highly correlated over time.[23] The lagged effects may be of interest in their own right, however, which is why we included them in our tables.

While the magnitudes vary substantially, the signs of the effects on lagged credit availability are generally the same as on the current measure, likely because credit availability has persistent effects on some outcomes, as we showed above. In addition, to the extent that our current measure of credit availability is noisy, the lagged measure may also pick up some of the effect on the outcome.

[23] The abrupt changes in the credit score thresholds during the 2008-2011 period mean that current and lagged availability may not have been as correlated as during other periods.

In some cases, however, we see different signs on the two coefficients when we focus the analysis on people who do not have a mortgage. In particular, those who appeared to have greater access to mortgage credit in the previous quarter but did not become homeowners subsequently experience less growth in both mortgage balances and higher growth in auto debt (as shown in panel B of tables 2 and 7). This may reflect a selection effect, whereby those who could have obtained a mortgage but chose not to have lower demand for homeownership, and possibly more demand for cars instead.

More generally, we might have expected those who were excluded from the mortgage market in the previous period to display an *increased* demand for mortgages the following period, reflecting pent-up demand. This effect would have appeared as a negative effect of lagged credit availability in the specifications with mortgage originations as the dependent variables. However, this is not what we find, suggesting that if there is pent-up demand of this form, it is offset by the persistence of the positive effects of availability.

3.4 Robustness Checks

We next examine a series of alternative specifications to some of our main results, to ensure that they are robust. Table 9 shows different estimates of the effect of credit availability on the contemporaneous probability of taking out a mortgage, across all borrowers. Column 1 repeats our preferred estimate from column 1 of panel A in table 1. In the second column, we add linear and quadratic terms for the age of the individual, interacted with quarter. Age is an attractive control because it is highly correlated with credit score, as we show in figure 5A (discussed below). Moreover, because age evolves deterministically, it may be a more stable proxy for current and past credit scores. In any event, including age does not change the estimated effect of credit availability.

Next we consider the possibility of changing how we control for the past evolution of credit availability and credit score, via a more direct route than controlling for age. Column 3 shows the result of including the second through fourth lags of credit availability, the second through fourth lags of the predicted threshold probabilities, as well as the second through fourth lags of credit score interacted with quarter dummies. The effects of credit availability and the first lag are nearly unchanged. Similarly, the effect of credit availability is also unchanged in column 4 when we drop all lags, including the first, from the right-hand side.

Finally, columns 5 and 6 show the results of changing the credit score window to include a larger or smaller sample. Our preferred specification in column 1 includes individuals with scores between 530 and 730. We selected that window because scores above 730 or below 530 are very unlikely to be affected by changes in lenders' use of a 620 or 640 threshold. Moreover, we wanted to use a narrow enough window that the linear credit score controls could plausibly pick up variation in mortgage demand by score, since a wider window makes it more likely that the relationship between score and demand would be nonlinear.

Column 5 considerably expands the sample by including all individuals with scores between 500 and 830.[24] The estimated average marginal effect of credit availability is slightly smaller in magnitude, but the mean of the dependent variable is larger, because high-score individuals are so much more likely to take out mortgages. Column 6 does the opposite, narrowing the window to include only individuals with scores between 580 and 680. In this case the mean of the dependent variable is about the same, but the average marginal effect is about half as large as in column 1 and is no longer statistically significantly different than zero. Intuitively, with a more narrow range of scores, nonlinearities play a smaller role and the linear credit score interacted with the time dummy picks up most of the variation. In other words, as the range narrows, it becomes more difficult to separate out the effect of being more likely to be above the credit score threshold from the effect of simply having a higher credit score.

In table 10, we apply the same alternative specifications to the longer-run probability of taking out a mortgage, specifically the model for one to 16 quarters ahead from column 5 of panel A in table 1. Again, column 1 repeats our main result. The next three columns are essentially the same as column 1, the same pattern as in table 9. Unlike in table 9, the "wide range" estimate in column 5 is larger than the baseline, but the "narrow range" estimate in column 6 is again smaller than the baseline and not statistically significant. We find it somewhat comforting that the point estimates in the final columns of both tables 10 and 10 remain positive and large in economic terms. Nevertheless, the size of the standard errors makes clear that we do not have enough power to pin down the magnitude of the effect using a very narrow Risk Score window, given our large set of controls and the concomitant loss of identifying variation.

[24]This expanded sample still drops the roughly 5 percent of individuals who have extremely high or low scores.

4 Heterogeneity

Most of this paper focuses on average effects of credit availability among the total population with Equifax Risk Scores around the 620 and 640 thresholds. However, the importance of the thresholds should vary across demographic and socioeconomic groups, for two reasons. First, credit scores are highly correlated with characteristics like age, race, and income. As a result, some groups—for example, younger adults—are more likely to have scores near the thresholds than others. Second, the estimated effects of credit availability—the salience of the thresholds—can also differ across groups. For example, individuals who do not want to buy a home or cannot afford it should be little affected by the availability of mortgages.

4.1 Heterogeneity by Age

Figure 5 examines heterogeneity in the effects of credit availability by age, focusing on the sample of individuals with no mortgage balance in the prior quarter. The top left panel (5A) shows that credit scores are highly correlated with age: Individuals younger than 35 (the two left-most bins) have an average Equifax Risk Score of around 650, while those 75 and older (the right-most bin) have an average score of around 770. The three lines in the panel, which correspond to the three stable periods of credit availability discussed above, are essentially on top of each other, indicating that scores in each age group were little changed over our sample period, on average.

Moving on to the question of how these differences in credit scores translate into mortgage credit access, the top right panel (5B) shows the average of our credit availability measure in each age bin, across stable periods. Because of the strong correlation between age and credit score, this panel looks fairly similar to figure 3B, where we plotted credit availability against credit score. Credit availability fell dramatically among the younger groups between the first (black) and second (red) periods, as lenders started using the 620 threshold, and then fell somewhat further by 2011 (the blue line), as they moved to a 640 threshold.

Next we consider the possibility that, like the average credit availability measure that we calculate, the salience of credit availability could also differ across age groups. The bottom left panel (5C) shows the average marginal effects of credit availability on the contemporaneous probability of taking out a mortgage, estimated separately for each age bin using a specification otherwise identical to the pooled estimate in column 1 of panel B in table 1. The solid line in the figure gives the point estimates, while the dotted lines indicate a range of two standard errors on either side of that estimate. The impact of mortgage credit availability is low for the youngest group, highest for the 25-34 bin, and thereafter shrinks monotonically with age. This pattern is fairly intuitive: Relatively younger adults are more likely to be constrained by mortgage credit availability, but the very youngest are less likely to want to purchase a home in the first place.[25]

Finally, we combine the information in the previous panels to show how the tightening of mortgage credit over time has differentially impacted different age groups. To isolate these effects, we look at the individuals in 2008:Q1, the first quarter of our sample. Holding constant the credit scores of this group at their 2008:Q1 values, we first recompute how our credit availability measure would have changed for them as lending conditions changed over time, as implied by the changes in the ratios around the 620 and 640 thresholds. Then, holding constant all of the other characteristics and the estimated time fixed effects at their 2008:Q1 values, we use our age bin-specific logit models to predict mortgage attainment for the sample in each quarter through 2012.[26]

In the bottom right panel (5D), we aggregate these predictions to calculate the expected mortgage attainment over each of the three periods defined above. The black line shows the average predicted probabilities given credit availability in 2008, while the red and blue lines show the averages predicted given credit availability in the later stable periods. Not surprisingly given the previous panels, we find the largest shift down in predicted mortgage attainment among younger and middle-aged individuals. Among the oldest adults, the aggregate effects are small, both because they have higher credit scores and credit availability contracted less, and because their average marginal effects are smaller. The aggregate effects are also smaller among the very youngest adults represented in our panel, because while their access to credit contracted considerably, their estimated marginal effects are smaller than for somewhat older groups, as noted above.

4.2 Heterogeneity by Local Racial Distribution and Income

While we would like to repeat this exercise to measure heterogeneity by race, we do not observe race in the credit panel. We do, however, observe mailing addresses, so we break down the sample into four groups according to the percentage of black residents in an individual's

[25] Individuals under 25 are not fully represented in the consumer credit panel, because not all of them have a credit report. This discrepancy between the CCP sample and the population shrinks with age, so there are few 18-year-olds in the panel, but most 25-year-olds are included. As a result, the point estimate shown for the youngest bin is likely an overestimate of the true effect for this age group, because individuals who do not even have a credit card are presumably the least likely to take out mortgages and buy homes.

[26] In a linear model, the bottom right panel could be derived simply by multiplying the marginal effects—which would be the model coefficients themselves—by the changes in the credit availability measure.

census tract in the 2000 Census.[27] Results from this exercise are shown in figure 6. The top left panel (6A) shows that race, like age, is highly correlated with credit score, and that the relationship changed little during our sample period. Accordingly, the top right panel (6B) shows that credit availability declined most for those tracts with the largest share of black residents.

As we did for different age groups, we next estimate the average marginal effects of credit availability on the probability of taking out a mortgage for residents of these four groups of census tracts. The lower left panel (6C) indicates that the marginal effect is constant across the first three bins, containing all tracts with less than half black residents, but it is about half as large in the right-most bin, which contains individuals in tracts with more than half black residents. As a result, the bottom right panel (6D) indicates that the overall implied effect of lower credit availability was somewhat larger in the middle two bins than in the other two. In sum, people living in census tracts with 10 percent or fewer black residents were affected less because they suffered smaller declines in credit availability, while those in areas containing half or more black residents were less affected because of their lower marginal effects, again presumably reflecting a lower demand for homeownership.[28] Of course, the severity of the effects of changing credit availability might differ across these bins in other ways that we do not observe.

A very similar pattern is evident when we group individuals with no prior mortgage balance by quartiles of tract median income. Figure 7 shows that Equifax Risk Scores are positively correlated with tract income (7A) and that credit availability declined most for the lowest income tracts (7B). However, the lowest income tracts have noticeably smaller marginal effects than the other three quartiles (7C). In the end, panel 7D shows that our models predict that changes in credit availability had larger net effects on mortgage attainment for the middle two quartiles than for the top income quartile (for whom credit availability declined least) and the bottom income quartile (who have smaller marginal effects).

[27] The four groups are tracts with 0-10 percent, 10-20 percent, 20-50 percent, and over 50 percent. We selected the bins based on a visual inspection of the distribution, which is highly skewed, so the bins do not contain equal numbers of observations.

[28] In contrast, when we perform a similar analysis for tracts based on their shares of Hispanic residents (not shown), we find offsetting differences in the marginal effects and the reduction in credit availability across the four bins. As a result, there is a parallel downward shift across all four bins in the overall implied effect of lower credit availability over this period.

5 Counterfactual

As a final exercise, we attempt to compute the aggregate direct impact of the 620 and 640 FICO score thresholds on the total number of mortgages originated in the years following the financial crisis. To perform this calculation, we run a simple counterfactual experiment, using estimates of the effects of our credit availability measure on the total number of first mortgages taken out by individuals in the CCP sample. We do so using counts of mortgages taken out by each individual, over various horizons, and estimate negative binomial models to relate these counts to the credit availability measure and our controls. Because many mortgages are taken out jointly by couples, we estimate separate models for joint and individual mortgages, so that we can properly aggregate and avoid double-counting. Importantly, these calculations reflect only the direct effects of the thresholds, and not any other constraints on mortgage credit availability since the financial crisis.

Table 11 shows the effects of credit availability on joint mortgages, while table 12 shows them for individual mortgages. We see large positive effects throughout both tables, with uniformly larger effects for joint mortgages, which have larger average probabilities as well. Comparing panel C from each table to the other makes clear that individuals who already have a mortgage balance on their credit record are much more likely to take out joint mortgages than individual mortgages, and that the effects of credit availability scale up with the average probabilities.

Next we use these models to predict the number of mortgages that would have been originated if the credit availability measure had remained at its level in the first quarter of 2008. Specifically, we take every individual in our sample and recalculate our credit availability measure using her actual Risk Score at each point in time and the 620 and 640 threshold ratios from 2008:Q1, holding all else constant. Then, using the specifications in column 2, panel A, of tables 11 and 12, we predict the number of each type of mortgage that would have been originated zero to three quarters ahead. We divide the number of joint mortgages by two, and then add the two predictions together.

Starting from the first quarter of 2011, when the full effect of the 640 threshold had kicked in, we find that the imposition of the thresholds lowered mortgage originations in our estimation sample—people with Risk Scores between 530 and 730—by about 260,000 in 2011. Comparing this figure to the 1.65 million mortgages that were actually originated in our sample, we conclude that mortgage originations would have been about 16 percent higher without the thresholds. For a broader comparison, we note that first mortgage originations in 2011 to people of all credit scores totaled 7 million, according to data collected under the Home Mortgage Disclosure Act (HMDA). Assuming, somewhat conservatively, that the thresholds had no effect one people with scores outside of the 530 to 730 range, we conclude that total mortgage originations would have been about 3.5 percent higher without the thresholds.

We can take a longer view by doing essentially the same exercise with the specifications in column 5, panel A, of both tables and predicting the number of joint and individual first mortgages that would have been originated zero to 15 quarters ahead. Again starting from the first quarter of 2011, we find that the imposition of the thresholds lowered originations in our sample by about 580,000 between 2011 and 2014. Comparing this figure to the 8.4 million mortgages actually taken out by individuals in our sample indicates that originations would have been about 7 percent higher. Comparing the 580,000 figure to 31 million, the total number of first mortgages originated to all individuals from 2011 to 2014, implies that there would have been about 2 percent more mortgages originated over this period.

6 Conclusion

The question of how tight mortgage credit should be is an important one that forces policy makers to balance concerns in both directions. On the one hand, tight mortgage credit prevents marginal borrowers from realizing the benefits of homeownership and, on a larger scale, reduces economic activity in the housing sector. On the other hand, the recent financial crisis demonstrates the risk of mortgage credit that is too loose: Banks' losses on defaulting mortgages can cause instability in the financial sector, borrowers may take out loans they are unable to repay, and an excess supply of credit can potentially contribute to a bubble in housing prices.

Our paper aims to shed additional light on one of these issues, the effect of mortgage credit on individual borrowers. Exploiting the timing and nonlinear effects of lenders' introduction of minimum credit score thresholds, we find that these thresholds have very large negative effects on borrowing. In other words, borrowers are not able to avoid the thresholds in the short run. We also find that borrowers without current access to mortgage credit are more likely to become delinquent on mortgages they had previously taken out, as well as on other forms of debt. Although these effects attenuate somewhat over time in relative terms, we find that they persist for at least several years, suggesting that the impact of these policies on the welfare of constrained individuals could be quite large. Further research is necessary to study these effects and the other consequences of tight mortgage credit, in order to give policy makers a better understanding of the total effects of policies affecting credit availability.

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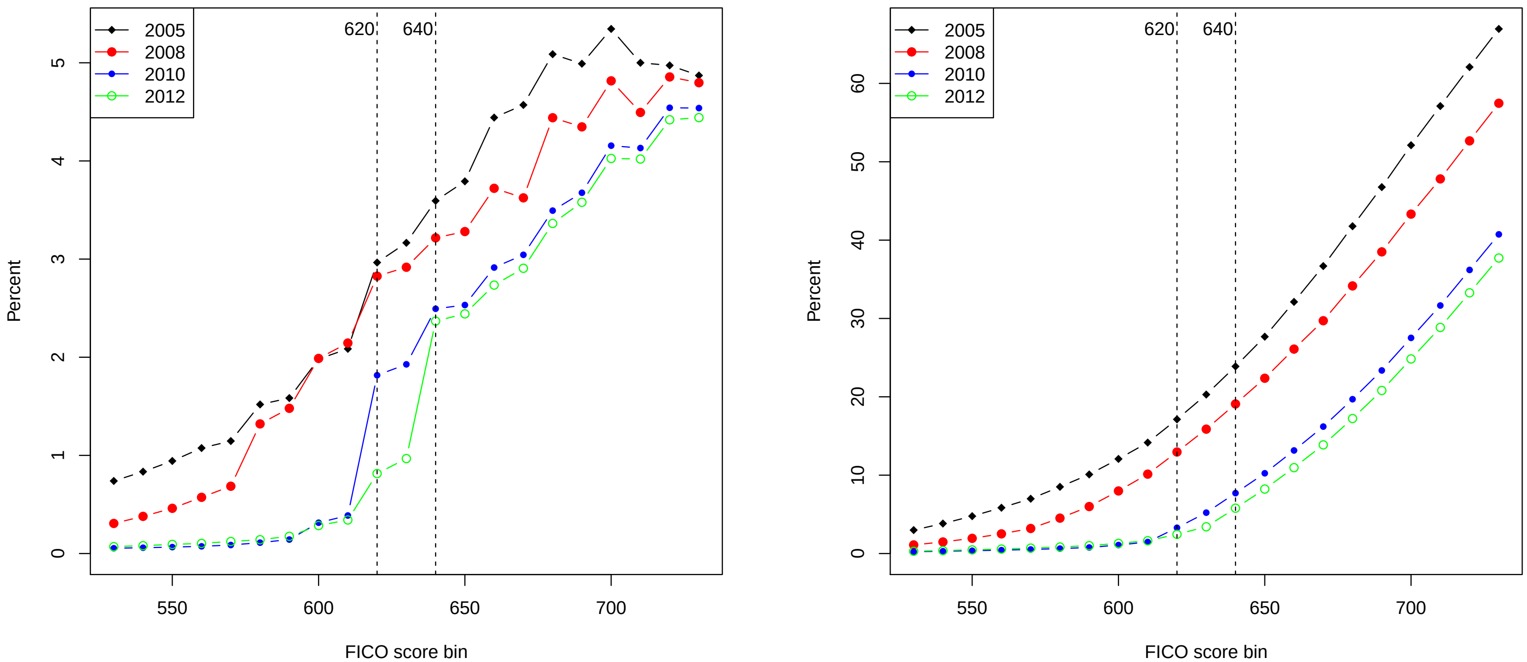
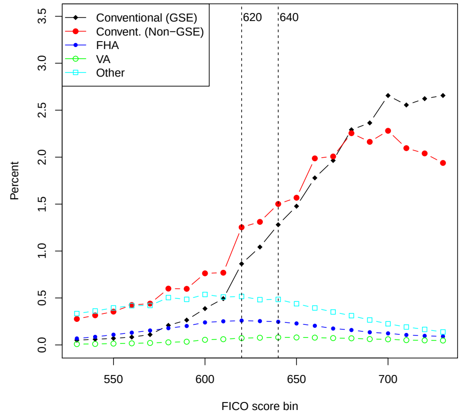


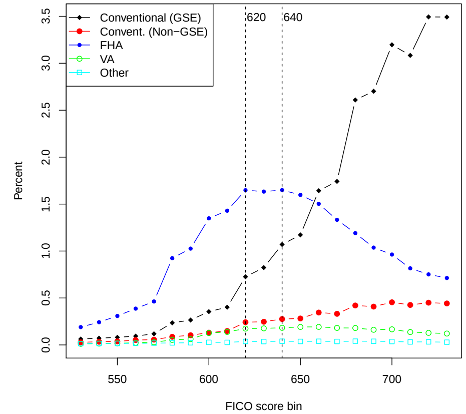
Panel A. Densities

Panel B. Cumulative Distributions

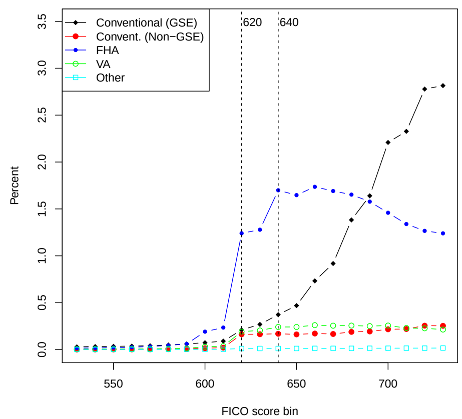
FIG. 1.—Mortgages by FICO Score. This figure plots the densities and cumulative distributions of newly originated first mortgages by 10-point FICO score bin in the Black Knight data set, across four years.



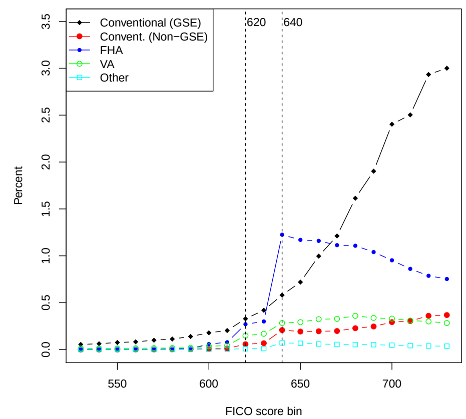
Panel A. 2005



Panel B. 2008

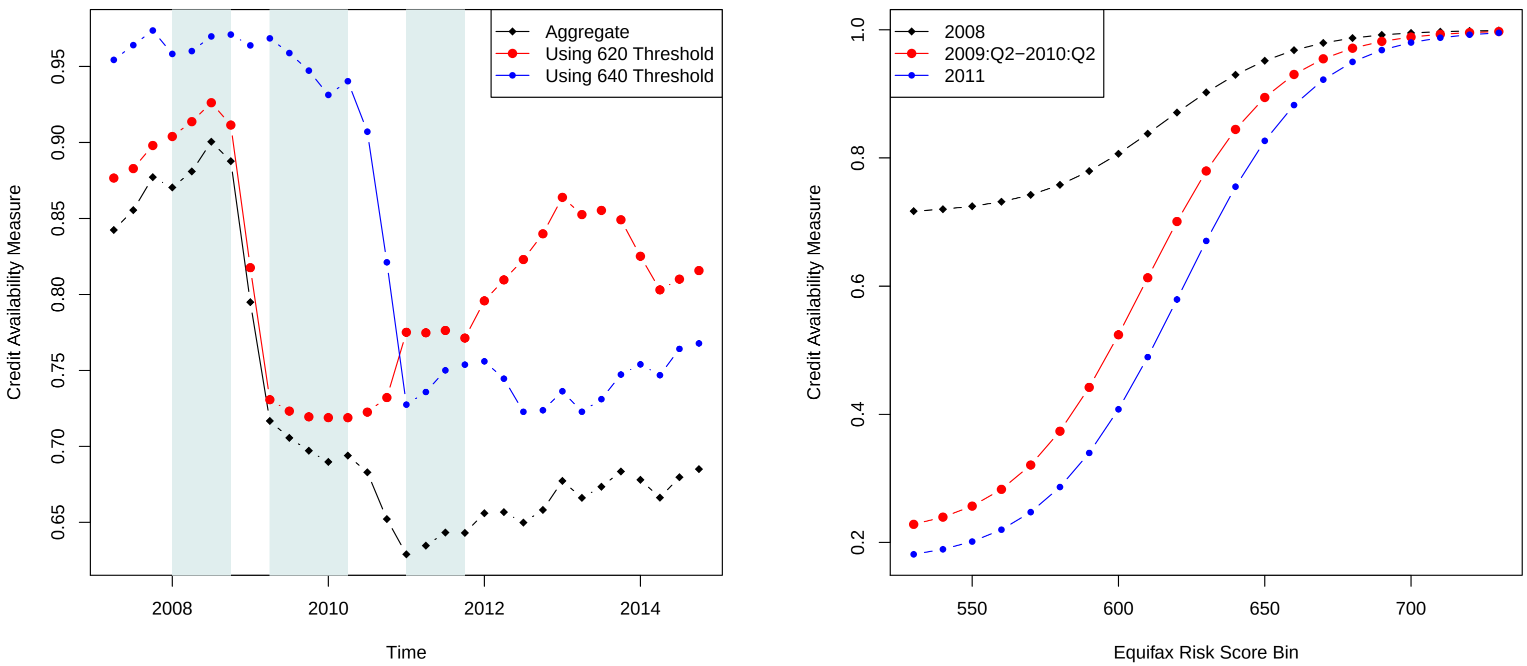


Panel C. 2010



Panel D. 2012

FIG. 2.—Mortgage Densities, across Types. This figure plots the densities of newly originated first mortgages by 10-point FICO score bin in the Black Knight data set, across types of loans. Each panel shows the data from a separate year.



Panel A. Time Series *Panel B. Cross-Section Across Periods*

Fig. 3.—Credit Availability. This figure shows the evolution of the credit availability measure in two different ways. The left panel plots the time series of average credit availability for all individuals with Equifax Risk Scores between 530 and 730. The three shaded regions denote periods between 2008 and 2011 in which availability was roughly stable. The right panel compares average credit availability, by 10-point Equifax Risk Score bin, across the three stable periods of credit availability.

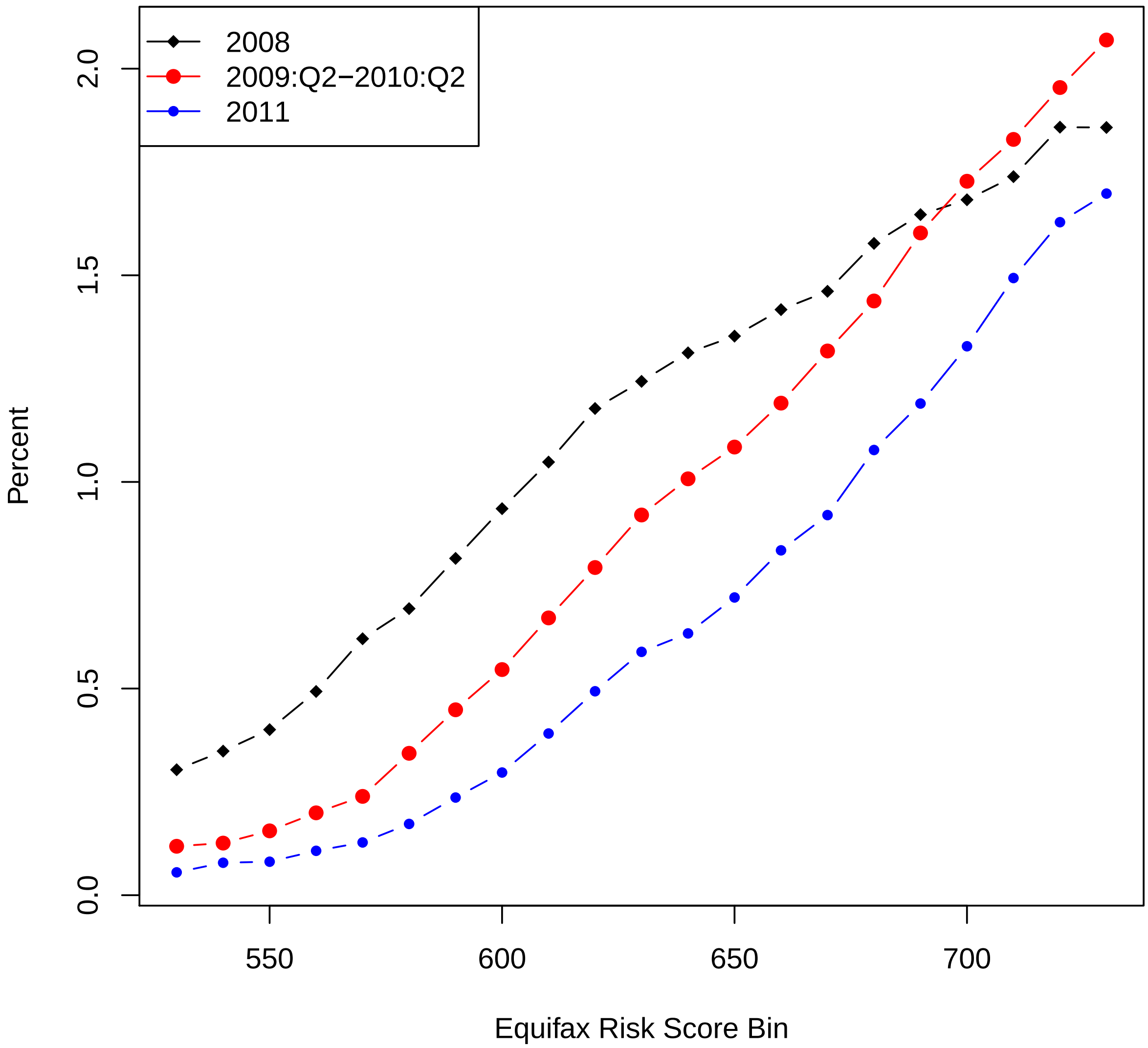
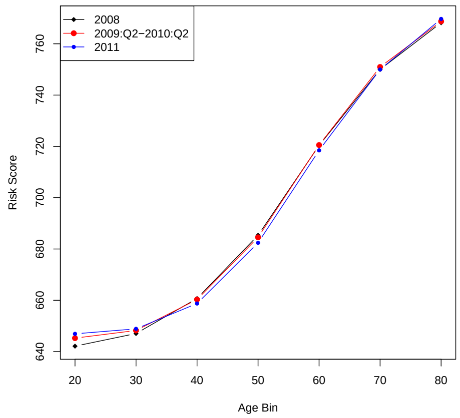
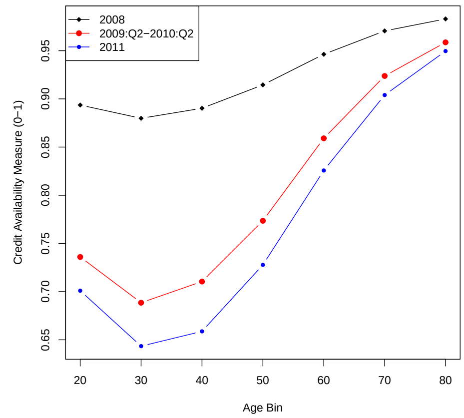


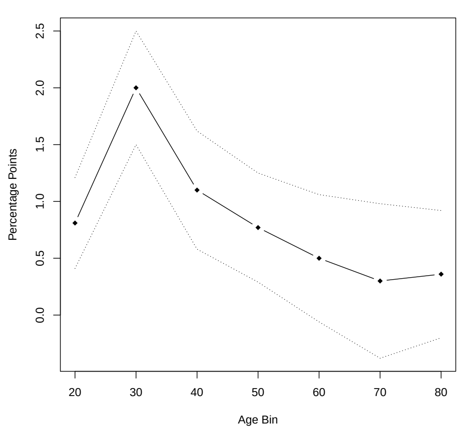
Fig. 4.—Contemporaneous Mortgage Origination Probability. This figure compares the probability of taking out at least one mortgage in the contemporaneous quarter, by 10-point Equifax Risk Score bin, across the three stable periods of credit availability.



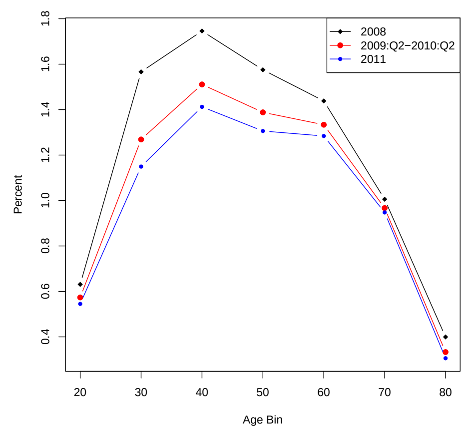
Panel A. Credit Score



Panel B. Credit Availability

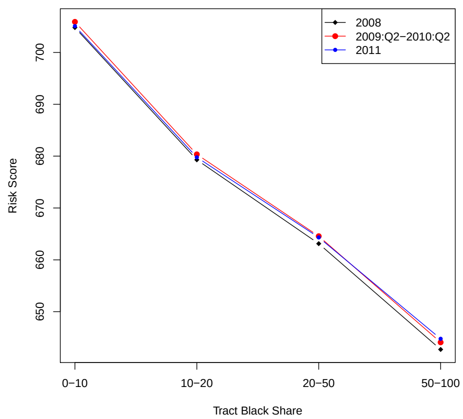


Panel C. Marginal Effects

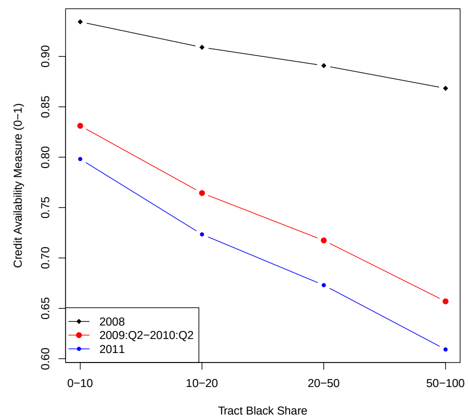


Panel D. Implied Effects

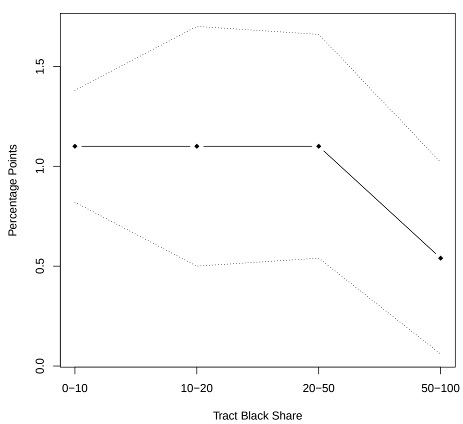
Fig. 5.—Age Heterogeneity. This figure traces out the effects of credit availability by age, for individuals with no initial mortgage balance. Bins are 10 years wide and centered on the bin midpoint, except for 20 and 80, which include all individuals under 25 and over 74, respectively. Panel A shows the average Equifax Risk Score in each bin, across the three stable periods of credit availability. Panel B shows average credit availability in each bin, across periods. Panel C shows the estimated marginal effects of credit availability on the contemporaneous probability of mortgage attainment for each bin (which are assumed to be constant across periods), plus or minus two standard errors. Panel D shows the model-derived contemporaneous probability of mortgage attainment for each bin, allowing credit availability to change over time but holding all else constant at 2008:Q1 levels. See text for details.



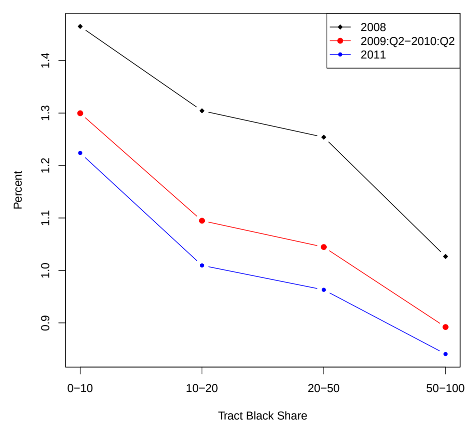
Panel A. Credit Score



Panel B. Credit Availability

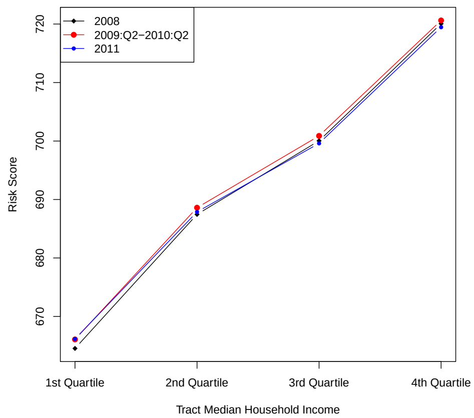


Panel C. Marginal Effects

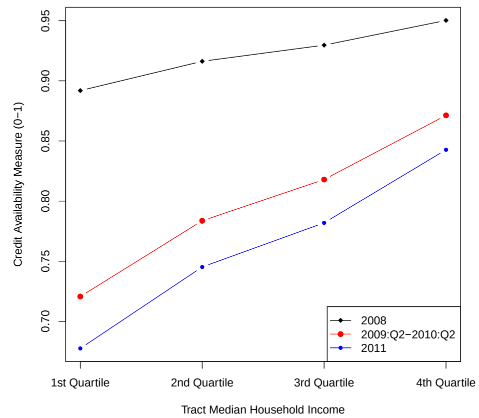


Panel D. Implied Effects

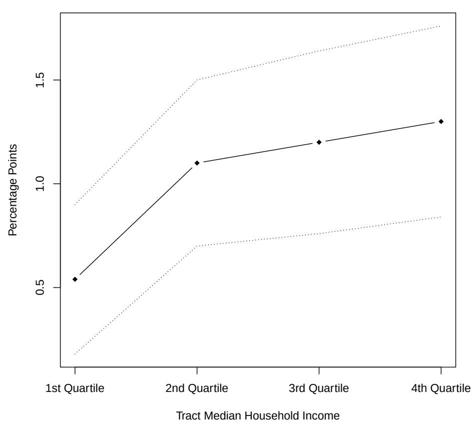
Fig. 6.—Race Heterogeneity. This figure traces out the effects of credit availability by the black share of tract population, for individuals with no initial mortgage balance. Panel A shows the average Equifax Risk Score in each bin, across the three stable periods of credit availability. Panel B shows average credit availability in each bin, across periods. Panel C shows the estimated marginal effects of credit availability on the contemporaneous probability of mortgage attainment for each bin (which are assumed to be constant across periods), plus or minus two standard errors. Panel D shows the model-derived contemporaneous probability of mortgage attainment for each bin, allowing credit availability to change over time but holding all else constant at 2008:Q1 levels. See text for details.



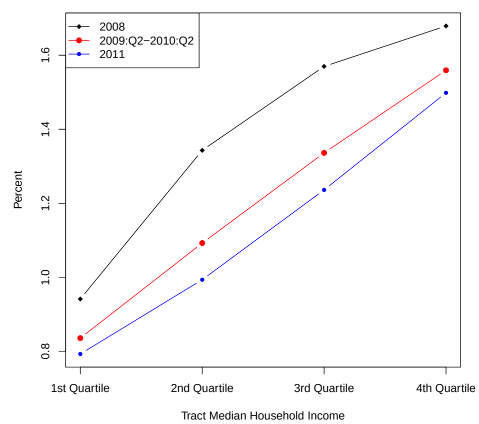
Panel A. Credit Score



Panel B. Credit Availability



Panel C. Marginal Effects



Panel D. Implied Effects

Fig. 7.—Income Heterogeneity. This figure traces out the effects of credit availability by tract median household income quartiles, for individuals with no initial mortgage balance. Panel A shows the average Equifax Risk Score in each quartile, across the three stable periods of credit availability. Panel B shows average credit availability in each quartile, across periods. Panel C shows the estimated marginal effects of credit availability on the contemporaneous probability of mortgage attainment for each quartile (which are assumed to be constant across periods), plus or minus two standard errors. Panel D shows the model-derived contemporaneous probability of mortgage attainment for each quartile, allowing credit availability to change over time but holding all else constant at 2008:Q1 levels. See text for details.

TABLE 1

Effects on Probability of Taking Out a First Mortgage

	(1)	(2)	(3)	(4)	(5)
Horizon in Quarters:	0	0-3	0-7	0-11	0-15
	Panel A: Entire Sample				
Credit Availability	0.010	0.028	0.035	0.034	0.028
	(0.001)	(0.003)	(0.004)	(0.006)	(0.007)
Lagged Availability	0.001	0.003	0.007	0.005	0.006
	(0.001)	(0.003)	(0.005)	(0.007)	(0.009)
Dep. Var. Mean	0.009	0.035	0.068	0.100	0.130
Observations	32,521,878	31,978,664	31,397,303	30,895,003	30,392,255
	Panel B: No Initial Mortgage Balance				
Credit Availability	0.010	0.026	0.033	0.036	0.034
	(0.001)	(0.003)	(0.004)	(0.005)	(0.006)
Lagged Availability	0.000	0.003	0.009	0.010	0.009
	(0.001)	(0.003)	(0.005)	(0.007)	(0.008)
Dep. Var. Mean	0.007	0.027	0.053	0.079	0.100
Observations	27,692,800	27,203,296	26,676,170	26,217,051	25,754,177
	Panel C: Positive Initial Mortgage Balance				
Credit Availability	0.021	0.080	0.110	0.092	0.072
	(0.004)	(0.007)	(0.010)	(0.011)	(0.011)
Lagged Availability	0.016	0.041	0.047	0.037	0.039
	(0.004)	(0.007)	(0.010)	(0.011)	(0.011)
Dep. Var. Mean	0.021	0.079	0.150	0.220	0.280
Observations	4,829,078	4,775,368	4,721,133	4,677,952	4,638,078

Note.—Logit estimates of effect of credit availability on the cumulative probability of taking out a mortgage, over various horizons. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 2
EFFECTS ON CHANGE IN FIRST MORTGAGE BALANCE

	(1)	(2)	(3)	(4)
Horizon in Quarters:	4	8	12	16
	Panel A: Entire Sample			
Credit Availability	3340	5293	6809	6623
	(765)	(1100)	(1318)	(1473)
Lagged Availability	-589	239	1353	0
	(898)	(1366)	(1676)	(1908)
Dep. Var. Mean	-31	-564	-737	-522
Observations	32,037,646	31,612,415	31,292,893	31,002,021
	Panel B: No Initial Mortgage Balance			
Credit Availability	1235	1298	2359	1460
	(432)	(527)	(635)	(733)
Lagged Availability	-2762	-2428	-2697	-3554
	(533)	(620)	(743)	(858)
Dep. Var. Mean	3208	5364	7405	9472
Observations	27,252,549	26,858,940	26,558,765	26,282,176
	Panel C: Positive Initial Mortgage Balance			
Credit Availability	16973	31038	35237	35188
	(2762)	(3834)	(4364)	(4730)
Lagged Availability	16506	24956	28714	26019
	(3052)	(4510)	(5311)	(5959)
Dep. Var. Mean	-18478	-34057	-46415	-56173
Observations	4,785,097	4,753,475	4,734,128	4,719,845

NOTE.—Linear regression estimates of effect of credit availability on the change in an individual's mortgage balance, over various horizons. Standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 3

EFFECTS ON PROBABILITY OF HAVING A DELINQUENT MORTGAGE

	(1)	(2)	(3)	(4)
Horizon in Quarters:	0-3	0-7	0-11	0-15
	Panel A: Entire Sample			
Credit Availability	-0.022	-0.031	-0.036	-0.034
	(0.006)	(0.008)	(0.009)	(0.009)
Lagged Availability	-0.023	-0.035	-0.039	-0.039
	(0.009)	(0.012)	(0.013)	(0.013)
Dep. Var. Mean	0.045	0.068	0.085	0.098
Observations	30,558,656	29,138,671	27,932,190	26,860,384
	Panel B: No Initial Mortgage Balance			
Credit Availability	-0.005	-0.010	-0.012	-0.009
	(0.004)	(0.005)	(0.006)	(0.006)
Lagged Availability	-0.016	-0.021	-0.022	-0.020
	(0.006)	(0.007)	(0.008)	(0.009)
Dep. Var. Mean	0.028	0.041	0.052	0.061
Observations	25,790,250	24,431,303	23,282,082	22,267,892
	Panel C: Positive Initial Mortgage Balance			
Credit Availability	-0.070	-0.089	-0.096	-0.100
	(0.010)	(0.011)	(0.012)	(0.012)
Lagged Availability	-0.087	-0.120	-0.120	-0.120
	(0.013)	(0.015)	(0.016)	(0.016)
Dep. Var. Mean	0.140	0.210	0.250	0.280
Observations	4,768,406	4,707,368	4,650,108	4,592,492

NOTE.—Logit estimates of effect of credit availability on the cumulative probability of having a mortgage delinquent by 60 or more days. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 4

EFFECTS ON PROBABILITY OF HAVING A DELINQUENT NON-MORTGAGE LOAN

	(1)	(2)	(3)	(4)
Horizon in Quarters:	0-3	0-7	0-11	0-15
	Panel A: Entire Sample			
Credit Availability	0.000	-0.034	-0.050	-0.035
	(0.009)	(0.008)	(0.008)	(0.008)
Lagged Availability	-0.037	-0.035	-0.011	0.002
	(0.010)	(0.009)	(0.009)	(0.009)
Dep. Var. Mean	0.31	0.40	0.47	0.52
Observations	31,978,664	31,397,303	30,895,003	30,392,255
	Panel B: No Initial Mortgage Balance			
Credit Availability	0.006	-0.029	-0.048	-0.033
	(0.010)	(0.009)	(0.009)	(0.009)
Lagged Availability	-0.024	-0.025	0.001	0.015
	(0.012)	(0.011)	(0.010)	(0.011)
Dep. Var. Mean	0.32	0.41	0.48	0.54
Observations	27,203,296	26,676,170	26,217,051	25,754,177
	Panel C: Positive Initial Mortgage Balance			
Credit Availability	-0.033	-0.050	-0.042	-0.026
	(0.011)	(0.012)	(0.012)	(0.013)
Lagged Availability	-0.092	-0.085	-0.072	-0.062
	(0.012)	(0.013)	(0.014)	(0.014)
Dep. Var. Mean	0.24	0.33	0.38	0.43
Observations	4,775,368	4,721,133	4,677,952	4,638,078

NOTE.—Logit estimates of effect of credit availability on the cumulative probability of having a non-mortgage loan delinquent by 60 or more days. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 5
EFFECTS ON MOVING TO DIFFERENT CENSUS BLOCK

	(1)	(2)	(3)
Horizon in Quarters:	4	8	12
	Panel A: Entire Sample		
Credit Availability	0.013	-0.001	0.004
	(0.005)	(0.006)	(0.007)
Lagged Availability	0.002	0.009	0.011
	(0.005)	(0.007)	(0.008)
Dep. Var. Mean	0.10	0.19	0.25
Observations	20,414,501	20,379,761	20,257,793
	Panel B: No Init. Mort. Bal.		
Credit Availability	0.018	0.003	0.011
	(0.006)	(0.007)	(0.008)
Lagged Availability	0.002	0.009	0.012
	(0.007)	(0.008)	(0.009)
Dep. Var. Mean	0.11	0.20	0.27
Observations	17,003,743	16,962,731	16,842,345
	Panel C: Pos. Init. Mort. Bal.		
Credit Availability	-0.003	-0.016	-0.034
	(0.007)	(0.009)	(0.010)
Lagged Availability	-0.009	-0.017	-0.028
	(0.007)	(0.009)	(0.010)
Dep. Var. Mean	0.05	0.10	0.14
Observations	3,410,758	3,417,030	3,415,448

NOTE.—Logit estimates of effect of credit availability on the probability of moving to a different census block, at various horizons. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 6

EFFECTS ON MOVING TO DIFFERENT CBSA

	(1)	(2)	(3)
Horizon in Quarters:	4	8	12
	Panel A: Entire Sample		
Credit Availability	0.009	0.006	0.003
	(0.002)	(0.003)	(0.003)
Lagged Availability	0.002	0.001	0.005
	(0.002)	(0.003)	(0.004)
Dep. Var. Mean	0.026	0.048	0.067
Observations	24,467,862	24,175,627	23,901,752
	Panel B: No Init. Mort. Bal.		
Credit Availability	0.010	0.006	0.003
	(0.002)	(0.003)	(0.004)
Lagged Availability	0.001	0.001	0.004
	(0.003)	(0.004)	(0.004)
Dep. Var. Mean	0.029	0.052	0.073
Observations	20,601,775	20,333,093	20,076,915
	Panel C: Pos. Init. Mort. Bal.		
Credit Availability	0.001	-0.001	-0.007
	(0.003)	(0.004)	(0.005)
Lagged Availability	0.000	-0.004	0.000
	(0.003)	(0.004)	(0.005)
Dep. Var. Mean	0.012	0.023	0.034
Observations	3,866,087	3,842,534	3,824,837

NOTE.—Logit estimates of effect of credit availability on the probability of moving to a different core-based statistial area (CBSA), at various horizons. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 7

Effects on Change in Number of Auto Loans

	(1)	(2)	(3)	(4)
Horizon in Quarters:	4	8	12	16
	Panel A: Entire Sample			
Credit Availability	-0.009	-0.021	0.008	0.010
	(0.006)	(0.009)	(0.011)	(0.013)
Lagged Availability	0.004	0.024	0.041	0.021
	(0.007)	(0.010)	(0.013)	(0.015)
Dep. Var. Mean	-0.001	0.000	0.008	0.026
Observations	30,664,032	29,587,609	28,787,215	28,143,066
	Panel B: No Initial Mortgage Balance			
Credit Availability	-0.013	-0.031	-0.004	-0.002
	(0.007)	(0.009)	(0.011)	(0.014)
Lagged Availability	0.001	0.020	0.039	0.016
	(0.007)	(0.010)	(0.013)	(0.015)
Dep. Var. Mean	0.002	0.007	0.019	0.042
Observations	25,886,884	24,852,642	24,089,800	23,481,558
	Panel C: Positive Initial Mortgage Balance			
Credit Availability	0.023	0.035	0.056	0.050
	(0.013)	(0.017)	(0.021)	(0.022)
Lagged Availability	0.036	0.062	0.066	0.049
	(0.013)	(0.018)	(0.021)	(0.023)
Dep. Var. Mean	-0.017	-0.037	-0.050	-0.052
Observations	4,777,148	4,734,967	4,697,415	4,661,508

Note.—Linear regression estimates of effect of credit availability on the change in the number of auto loans on an individual's credit record, over various horizons. Standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 8
EFFECTS ON CHANGE IN AUTO LOAN BALANCE

	(1)	(2)	(3)	(4)
Horizon in Quarters:	4	8	12	16
	Panel A: Entire Sample			
Credit Availability	-113	-149	-46	-13
	(69)	(97)	(117)	(127)
Lagged Availability	46	-12	-31	-188
	(76)	(110)	(127)	(136)
Dep. Var. Mean	-28	-21	71	232
Observations	32,037,646	31,612,415	31,292,893	31,002,021
	Panel B: No Initial Mortgage Balance			
Credit Availability	-151	-304	-279	-221
	(62)	(88)	(106)	(117)
Lagged Availability	-49	-105	-123	-245
	(66)	(97)	(112)	(122)
Dep. Var. Mean	10	61	186	371
Observations	27,252,549	26,858,940	26,558,765	26,282,176
	Panel C: Positive Initial Mortgage Balance			
Credit Availability	317	732	985	645
	(213)	(288)	(328)	(359)
Lagged Availability	903	906	695	205
	(212)	(289)	(324)	(354)
Dep. Var. Mean	-245	-482	-571	-541
Observations	4,785,097	4,753,475	4,734,128	4,719,845

NOTE.—Linear regression estimates of effect of credit availability on the change in an individual's auto loan balance, over various horizons. Standard errors clustered at quarter-riskscore level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term.

TABLE 9

Robustness Checks: Effects on Contemporaneous Quarter Probability of Taking Out a Mortgage

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Baseline	Age Controls	More Lags	No Lags	Wide Range	Narrow Range
Credit Availability	0.010	0.010	0.009	0.010	0.008	0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
1Q Lagged Availability	0.001	0.001	0.001		0.006	-0.001
	(0.001)	(0.001)	(0.001)		(0.001)	(0.004)
Dep. Var. Mean	0.009	0.009	0.009	0.009	0.015	0.008
Score Range	530-730	530-730	530-730	530-730	500-830	580-680
Observations	32,521,878	32,521,878	28,886,923	32,521,878	72,849,732	15,108,112

Note.—Robustness checks for the logit estimate of the effect of credit availability on the cumulative probability of taking out a mortgage in the contemporaneous quarter. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term. Column 1 ("Baseline") is the estimate from Panel A of column 5 of table 1. Column 2 ("Age Controls") includes linear and quadratic age terms interacted with quarter. Column 3 ("More Lags") includes the second through fourth lags of credit availability, the second through fourth lags of probabability of having a score over 620 and 640, as well as the second through fourth lags of the riskscore interacted with quarter. Column 4 ("No Lags") includes no lags. Column 5 ("Wide Range") includes all observations with riskscores between 500 and 830. Column 6 ("Narrow Range") includes only observations with current and lagged riskscores between 580 and 680.

TABLE 10

ROBUSTNESS CHECKS: EFFECTS ON 0-15 QUARTER PROBABILITY OF TAKING OUT A MORTGAGE

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Baseline	Age Controls	More Lags	No Lags	Wide Range	Narrow Range
Credit Availability	0.028	0.030	0.029	0.031	0.052	0.018
	(0.007)	(0.007)	(0.007)	(0.005)	(0.011)	(0.020)
1Q Lagged Availability	0.006	0.012	-0.011		0.026	-0.027
	(0.009)	(0.008)	(0.011)		(0.031)	(0.000)
Dep. Var. Mean	0.13	0.13	0.13	0.13	0.20	0.12
Score Range	530-730	530-730	530-730	530-730	500-830	580-680
Observations	30,392,255	30,392,255	27,136,860	30,392,255	68,818,853	14,093,101

NOTE.—Robustness checks for the logit estimate of the effect of credit availability on the cumulative probability of taking out a mortgage in the contemporaneous quarter. Average marginal effects, with standard errors clustered at quarter-riskscore level in parentheses. All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear riskscore term, and quarter fixed effects interacted with lagged linear riskscore term. Column 1 (“Baseline”) is the estimate from Panel A of column 5 of table 1. Column 2 (“Age Controls”) includes linear and quadratic age terms interacted with quarter. Column 3 (“More Lags”) includes the second through fourth lags of credit availability, the second through fourth lags of probabability of having a score over 620 and 640, as well as the second through fourth lags of the riskscore interacted with quarter. Column 4 (“No Lags”) includes no lags. Column 5 (“Wide Range”) includes all observations with current riskscores between 500 and 830. Column 6 (“Narrow Range”) includes only observations with current and lagged riskscores between 580 and 680.

TABLE 11
EFFECTS ON TOTAL NUMBER OF NEW JOINT FIRST MORTGAGES

	(1)	(2)	(3)	(4)	(5)
Horizon in Quarters:	0	0-3	0-7	0-11	0-15
	Panel A: Entire Sample				
Credit Availability	0.006	0.020	0.028	0.030	0.027
	(0.001)	(0.002)	(0.003)	(0.005)	(0.006)
Lagged Availability	0.002	0.004	0.007	0.005	0.006
	(0.001)	(0.002)	(0.004)	(0.006)	(0.008)
Dep. Var. Mean	0.006	0.023	0.046	0.071	0.097
Observations	32,521,878	31,978,664	31,397,303	30,895,003	30,392,255
	Panel B: No Initial Mortgage Balance				
Credit Availability	0.006	0.017	0.025	0.030	0.033
	(0.001)	(0.002)	(0.003)	(0.004)	(0.004)
Lagged Availability	0.000	0.003	0.006	0.006	0.005
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Dep. Var. Mean	0.004	0.014	0.028	0.043	0.060
Observations	27,692,800	27,203,296	26,676,170	26,217,051	25,754,177
	Panel C: Positive Initial Mortgage Balance				
Credit Availability	0.016	0.078	0.120	0.130	0.120
	(0.004)	(0.008)	(0.012)	(0.015)	(0.017)
Lagged Availability	0.018	0.045	0.067	0.069	0.086
	(0.004)	(0.008)	(0.011)	(0.014)	(0.017)
Dep. Var. Mean	0.019	0.074	0.150	0.230	0.300
Observations	4,829,078	4,775,368	4,721,133	4,677,952	4,638,078

NOTE.—Negative binomial estimates of effect of credit availability on the number of new joint first mortgages taken out, over various horizons. Average marginal effects, with standard errors clustered at quarter-risk score level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear risk score term, and quarter fixed effects interacted with lagged linear risk score term.

TABLE 12
Effects on Total Number of New Individual First Mortgages

	(1)	(2)	(3)	(4)	(5)
Horizon in Quarters:	0	0-3	0-7	0-11	0-15
	Panel A: Entire Sample				
Credit Availability	0.005	0.014	0.019	0.020	0.019
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Lagged Availability	0.000	0.003	0.008	0.012	0.015
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)
Dep. Var. Mean	0.004	0.015	0.030	0.045	0.062
Observations	32,521,878	31,978,664	31,397,303	30,895,003	30,392,255
	Panel B: No Initial Mortgage Balance				
Credit Availability	0.005	0.013	0.017	0.018	0.017
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Lagged Availability	0.000	0.002	0.006	0.010	0.012
	(0.001)	(0.002)	(0.004)	(0.005)	(0.007)
Dep. Var. Mean	0.004	0.015	0.031	0.047	0.065
Observations	27,692,800	27,203,296	26,676,170	26,217,051	25,754,177
	Panel C: Positive Initial Mortgage Balance				
Credit Availability	0.006	0.016	0.025	0.020	0.019
	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)
Lagged Availability	0.001	0.011	0.016	0.019	0.025
	(0.001)	(0.003)	(0.004)	(0.006)	(0.007)
Dep. Var. Mean	0.003	0.011	0.022	0.035	0.049
Observations	4,829,078	4,775,368	4,721,133	4,677,952	4,638,078

Note.—Negative binomial estimates of effect of credit availability on the number of new individual (i.e., non-joint) first mortgages taken out, over various horizons. Average marginal effects, with standard errors clustered at quarter-risk score level in parentheses. Models are estimated separately on the whole sample (panel A) and on samples split by whether the individual has a positive mortgage balance at t=-1 (panels B and C). All models include predicted probablities of having a score over 620 and 640, lagged predicted probability of having a score over 620 and 640, quarter fixed effects, quarter fixed effects interacted with linear risk score term, and quarter fixed effects interacted with lagged linear risk score term.