Is there crowd out in mortgage refinance?*

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ABSTRACT: We examine whether supply-side capacity constraints contribute to the well-documented "failure to refinance" among certain borrowers who would benefit financially from doing so. We find that, conditional on the potential financial benefits of refinancing, "marginal" borrowers (those with low loan balances, low incomes, or low credit scores) are substantially less likely to prepay their mortgage during refinance booms when markets are operating at or near full capacity. In contrast, borrowers with high loan balances, high incomes, or high credit scores prepay at higher rates during these periods. These patterns hold after controlling for a rich set of observable characteristics and among borrowers that are likely able to qualify for a conventional refinance loan. We provide suggestive evidence that marginal borrowers are crowded out from supply-constrained markets before making a formal application for a refinance loan. Overall, our results indicate that in addition to demand-side explanations for differences in refinancing activity, supply-side factors also play an important role.

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1. Introduction

The U.S. has experienced several booms in refinance activity over the past decade. As shown in Figure 1, these booms are largely attributable to movements in interest rates over time. When the market rate falls below levels seen in preceding years (e.g., in March of 2020), new loan applications spike as many borrowers respond to their increased financial incentive to refinance.

While refinance booms are characterized by widespread increases in refinancing, the relative magnitudes of these increases differ across borrower groups. For example, Figure 2 shows that refinance booms coincide with sharp declines in the share of refinance loans originated to borrowers with lower loan amounts, lower income, or lower credit scores. This suggests there are systematic differences across borrowers in either their willingness or ability to refinance during booms, and that some miss out on the financial gains from refinancing when rates are low.

Understanding what drives these disparities is important for a broad set of policy concerns. For consumers, refinancing a mortgage when it is optimal to do so can result in thousands of dollars in savings on interest expenses over the life of the loan (e.g., Keys, Pope, and Pope 2016; Agarwal, Chomsisengphet, Kiefer, Kiefer, and Medina 2021). Household refinancing activity also has implications for the real economy. Several recent studies have highlighted how frictions in mortgage refinancing affect the distributional impact and effectiveness of monetary policy.[1]

What can explain differences in borrowers' refinancing activity during booms? It is well known that many borrowers fail to refinance when they have a financial incentive to do so (e.g., Keys, Pope, and Pope 2016; Gerardi, Willen, and Zhang 2020), and demand-side factors are an important reason why. Differences in borrowers' propensity to refinance have been linked to differences in their financial sophistication, trust in financial institutions, exposure to lenders' advertising or news media, and their social networks.[2]

This paper explores a new explanation for differential patterns in refinance activity during booms: supply-side capacity constraints. When swamped with demand for refinance loans, a capacity-constrained lender may prefer to "…prioritize the processing of easier-to-complete or more profitable loan applications" (Duke 2013). Following this intuition, we hypothesize that

[1] See, for example, Di Maggio et al. (2017); Beraja et al. (2018); Amromin et al. (2020); Gerardi et al. (2020); Berger et al. (2021). Much of this literature highlights the inequitable distribution of efforts to ease credit and stimulate consumption. There are operational concerns as well if, for example, the savings from refinancing predominantly accrue to households with a relatively low marginal propensity to consume.

[2] We review the relevant literature in the Background section.

during booms supply-constrained lenders engage in credit rationing whereby some borrowers are "crowded out" from the refinance loan market and unable to refinance their loan at the prevailing low rates. In contrast, supply-side capacity constraints should have less pronounced (if any) effects on refinance activity of borrowers that lenders perceive as easy-to-underwrite or more profitable, as lenders prioritize loan applications from such borrowers.

To evaluate these hypotheses, we analyze data from two primary sources. The first is loan-level administrative data from the National Mortgage Database (NMDB®). The NMDB is a nationally representative sample of U.S. residential mortgages, with detailed data on loan terms, borrower and property characteristics, and payment history. Second, we use data collected under the Home Mortgage Disclosure Act (HMDA) to construct county-quarter level indicators that proxy for whether capacity constraints are binding. These measures are based on variation in the number of days it takes lenders to process refinance loan applications (as in, e.g., Fuster, Goodman, Lucca, Madar, Molloy, and Willen 2013) and reflect periods where the surge in demand for refinancing exceeds lenders' ability to adjust supply.

We specify linear probability models of loan prepayment in which the key independent variable is the indicator for whether the borrower is located in a county with constrained supply in a given quarter.[3] To better isolate the effects associated with refinancing (as opposed to other forms of prepayment), we allow the effect of being in a capacity constrained market to vary with the borrower's financial incentive to refinance. Reflecting the intuition outlined above, we also let the effects of capacity constraints vary across borrower characteristics. We categorize borrowers using three alternative measures: unpaid principal balance (UPB), income, and credit score. The first directly relates to how profitable a new refinance loan would be to originate; the second and third proxy for lenders' perceptions of whether a borrower is relatively difficult to underwrite or the expected profit from origination the loan. We refer to borrowers in the lowest UPB, income, and credit score groups as "marginal" borrowers; lenders may de-prioritize such borrowers when their resources are constrained.

A challenge for identification in our setting is that capacity constraints typically bind during refinance booms that coincide with recessionary periods when interest rates have dropped. Marginal borrowers may be disproportionately more likely to experience shocks to employment

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[3] NMDB does not currently distinguish refinancing from other reasons for prepayment such as home sales. We show that the variation in prepayments observed in our data is almost entirely attributable to refinances.

or income during recessions, and thus may find it harder to qualify for a new refinance loan. To address this issue, we focus our analysis on borrowers that are very likely able to qualify for a new loan – those that currently have a conventional loan and, since origination of that loan, have not missed a mortgage payment or had their credit score fall below 620. These sample selection criteria limit the scope for our estimated effects of supply-side capacity constraints on refinancing to suffer from downward bias due to unobserved differences in borrowers' ability to qualify for a new mortgage.

A second challenge is that demand for new refinance loans increases during booms, even after conditioning on the potential financial gains. Borrowers are more likely to be "awake" to the possibility of refinancing during booms, based on a model of refinancing behavior that incorporates psychological and information-gathering costs and allows these costs to vary across borrowers and over time (Andersen, Campbell, Nielson, and Ramadorai 2020). Because we do not observe such shifts in demand in our data, our estimates reflect the net impact on prepayment of two opposing factors: (1) the negative effect of supply constraints (the focus of this paper), and (2) the positive effect of concurrent increases in demand.

Our empirical results indicate that when borrowers have a financial incentive to refinance, the overall conditional quarterly likelihood of prepayment is about 0.7 percentage points (pp) higher during refinance booms when capacity constraints bind; this is about 15% of the mean prepayment rate in our sample.[4] This positive effect is consistent with increased demand for refinancing during booms outweighing any dampening effect that supply-constraints have on overall prepayment activity.

In contrast, we find that among marginal borrowers that lenders may prefer to de-prioritize, conditional prepayment rates are substantially *lower* when supply of credit is constrained. For example, among borrowers with low UPB and a financial incentive to refinance, the quarterly probability of prepayment is about 0.8 pp (or 18%) lower when capacity constraints bind. Results are qualitatively similar when categorizing borrowers by income at origination or by credit score. Our estimates imply the cumulative effects of capacity constraints are economically significant. Had capacity constraints not been binding during the most recent refinance boom, cumulative

[4] In the main analyses presented in the paper, our measure of the refinance option value of a loan uses the ratio of the note rate to the borrower's current market interest rate, as in Richard and Roll (1989). As described below, results are robust to using more sophisticated measures of the refinance option value.

prepayment rates over the period 2019Q3 through 2021Q2 would have been roughly 10 to 15 percent higher for the most marginal borrower groups. We interpret these estimates as the lower bound of the "true" effect of capacity constraints, as we cannot account for increased demand that might otherwise increase the likelihood of prepayment.

In supplemental analyses, we examine the ways lenders may ration credit to borrowers they may perceive as less profitable or more difficult to underwrite. Based on analyses of HMDA data, we find little evidence that supply constrained lenders throttle demand by raising prices on loans to marginal borrowers. We find some evidence that constrained lenders de-prioritize the processing of loan applications from such borrowers (as reflected in higher rates of applications being closed or denied for incompleteness) but these effects are small in magnitude.

Instead, we find that when capacity constraints are binding, lower UPB and lower income borrowers in our NMDB sample are substantially less likely to successfully contact and obtain pricing from a mortgage lender, as proxied by the incidence of inquiries for new mortgage credit.[5] This suggests that much of the inhibiting effect of capacity constraints on marginal borrowers' propensity to refinance occurs before a formal loan application is filed, and is consistent with Agarwal et al. (2021), who attribute inequality in refinancing activity to lower income borrowers being underrepresented in the pool of applications received during the post-COVID boom.

Taken together, our estimates indicate that in addition to demand-side factors, supply-side capacity constraints play an important role in explaining why some borrowers fail to refinance during booms. That supply-side crowd out occurs primarily because marginal borrowers find it more difficult to connect with and obtain pricing from constrained lenders has implications for policy, which we discuss in the concluding section.

2. Background

In this section we review the relevant literature on mortgage prepayment and refinancing decisions. We then discuss existing evidence that the supply of mortgage credit is constrained

[5] We view a mortgage credit inquiry as a reliable indication that the borrower has obtained pricing from a lender because credit score is central to loan pricing and a common initial step in a potential refinancing is for the loan officer to request a hard credit check on the borrower(s) expected to submit an application for a new loan.

during refinance booms, and building on this literature, describe the methodology we use to identify markets where such capacity constraints bind.

A. Relevant Literature

The conceptual framework for this analysis is the option based model of mortgage terminations, standard in the economic literature (e.g., Hendershott and Van Order 1987; Kau and Keenan 1995). The model implies that a mortgage holder should exercise her option to refinance when the benefit of doing so exceeds the costs. The benefit from refinancing is primarily the savings on future interest payments achieved by lowering the contract rate. The present value of savings is a function of the borrower's current rate relative to the market rate and also the expected life of the new mortgage. The latter factor may depend on, among other things, future interest rate movements and the borrower's expected tenure in the home. Costs of refinancing include upfront fees charged at origination (e.g., discount points paid, appraisal fees, title fees, other lender charges) and time costs (e.g., searching for a lender and providing the necessary documentation).

It is well-known that many borrowers fail to exercise their refinance option when it is in their financial interest to do so (e.g., Keys et al. 2016). This is especially true among certain segments of the population including lower-income and minority households (Firestone, Van Order, and Zorn 2007; Goodstein 2013; Gerardi et al. 2020; Brevoort 2022).

Differences in borrowers' propensity to refinance have been linked to a variety of demand-side factors including: financial sophistication (e.g. Agarwal, Rosen, and Yao 2016; Bajo and Barbi 2018); consumer inattention (Byrne, Devine, King, McCarthy, and Palmer 2022); trust in financial institutions (Johnson, Meier, and Touba 2019); exposure to lenders' advertising (Grundl and Kim 2019); news media stories about refinancing (Hu, Li, Ngo, and Sosyura 2021); and social networks (Maturana and Nickerson 2018; McCartney and Shah 2022). Particularly relevant here, Andersen et al. (2020) attribute delays in mortgage refinancing to psychological and information-gathering costs that vary across borrowers and over time such that more borrowers are "awake" to their incentive to refinance during low rate periods.[6] This suggests the

[6] Psychological and information-gathering costs may differ over time for various reasons. For example, media coverage of the value of refinancing may increase during booms; Hu et al. (2021) show that exposure to such media coverage can affect refinancing behavior, particularly among lower-income and minority borrowers.

dynamics of who refinances during booms is driven not only by potential financial gains but also differences in the responsiveness to those gains.

Less clear is whether differences in borrowers' propensity to refinance might also be attributable to constrained credit supply. Two earlier papers find that capacity constraints affect the provision of credit to home purchase mortgage borrowers. Sharpe and Sherlund (2016) develop a theoretical model in which capacity constrained lenders prioritize higher credit score and refinance lending (assumed to be less costly to underwrite than home purchase lending). They find that increased "capacity utilization" is associated with a decrease in the number of home purchase loans originated to less credit-worthy borrowers, based on an analysis of GSE lending from 2003 to 2014. Choi, Choi, and Kim (2022) find that, following the 2008 financial crisis, banks with limited "risk capacity" (e.g., due to capital requirements) or "operating capacity" shifted from home purchase to refinance lending, arguing that such banks may prefer safer loans or easier-to-process loan applications. Neither paper considers how supply constraints impact the distribution of borrowers who refinance, the focus of this paper.

B. Capacity Constraints in the Supply of Mortgage Credit

Supply of mortgage credit is not perfectly elastic. Refinance booms are characterized by increases in the price of financial intermediation and longer loan application processing times, consistent with the presence of capacity constraints (Fuster et al. 2013; Fuster, Lo, and Willen 2017). More recently, Fuster, Hizmo, Lambie-Hansen, Vickrey, and Willen (2021) find that capacity constraints were particularly acute after the onset of the COVID-19 pandemic because of related operational and labor market frictions.

In this study, we derive a measure of supply-side capacity constraints using confidential data collected under the Home Mortgage Disclosure Act (HMDA). First, for all first-lien, single family refinance originations reported in years 2010 through 2021, we compute the number of application processing days by taking the difference of the origination date and application date.[7] Figure 3 shows the 50^{th}, 75^{th}, and 90^{th} percentile value of application processing days on refinance loan originations across all counties over our period of analysis. The figure shows that

[7] Publicly available HMDA data do not include the exact application and action (origination) dates. This information is included in the restricted-access HMDA data, generally available only to certain federal regulatory agencies. We are not the first to use application processing days to characterize lender capacity constraints; earlier examples include Fuster et al. (2013), Fuster et al. (2017), Fuster et al. (2021), and Choi et al. (2022).

at each of these points in the distribution, the number of application processing days is positively correlated with the number of refinance applications, and increases sharply during refinance booms.

To proxy for whether capacity constraints are binding in a given local market and time period, we create an indicator variable equal to one if the 75^{th} percentile of application processing days in a given county-quarter exceeds 110% of the average 75^{th} percentile value for the county over the period of analysis.[8] While this approach is admittedly arbitrary, we find it attractive because it reflects cross-sectional as well as time-series variation in mortgage lender capacity constraints, and because the measure accounts for level differences in application processing days across counties.

Figure 4 shows the share of counties in our sample categorized as capacity constrained over our period of analysis. The figure shows that during the most pronounced refinance application booms over the past decade (e.g., 2012-13; 2020), supply of mortgage credit was constrained in nearly every county in our sample. However, during milder booms (e.g. early-2015; mid-2016) capacity constraints were much less widespread across markets.

Figure 5 illustrates that when capacity constraints are binding, refinance mortgage loan credit may be rationed to certain types of borrowers. The figure shows the quarterly incidence of mortgage prepayments for selected quarters in which borrowers' refinance option goes in the money (ITM), separately by borrower credit score.

During periods of moderate refinance activity, quarterly prepayment rates are fairly similar regardless of credit score. For example, among higher credit score borrowers whose refinance option goes ITM in 2016Q1, about 4% prepaid in 2016Q2, and another 4% prepaid in Q3 and in Q4. Prepayment rates were nearly identical among lower credit score borrowers over the same period. (For both groups prepayments fell sharply once rates increased at year-end 2016.)

However, during major refinance booms when supply of credit is widely constrained, pronounced differences arise in prepayment rates between the credit score groups. For example,

[8] We construct the capacity constraint indicator using application data from the three-month window around the month that ends quarter *t,* to reflect the approximate timing of when a borrower would need to submit a loan application in order to complete a refinancing by the end of the next quarter. For example, for a county-quarter observation in 2020Q1, we compute loan application processing days (and the capacity constraint indicator) using loan applications filed in February to April 2020. Further, to ensure we have enough data to reliably construct the capacity constraint measure, we limit to the 1,126 counties in which we observe at least 50 refinance loan originations in every quarter of our analysis period. We drop the 2,168 counties that did not meet this criterion.

compare incidence of prepayment across credit score groups that went ITM in 2019Q3, when rates fell below their post-2017 lows (as shown in Figure 1). In the subsequent two quarters when capacity constraints were not widespread, prepayment rates were similar across lower and higher credit score groups. However, prepayment rates diverged sharply beginning in 2020 Q2 when 9 percent of higher credit score borrowers prepaid, compared to 6 percent for those with lower credit score. This divergence coincided with interest rates dropping to a historically low level in March 2020 with the onset of the Covid-19 pandemic, resulting in a massive increase in refinance applications that lenders struggled to handle.

Of course, the differences in prepayment behavior illustrated in Figure 5 might also be attributable to other differences in market conditions over time. For example, lower-credit score borrowers might have found it relatively difficult to qualify for a refinancing in late-2020 compared to late-2016, if they disproportionately experienced higher unemployment rates or other adverse shocks as a result of the pandemic. Our empirical analysis attempts to control for such factors.

3. Empirical Model

We specify models of the form

$$PP_{bc(t+1)} = [capConstr_{ct} \times refiVal_{bt}^2 \times borrType_{bt}]\beta + X_{bct}\gamma + \mu_c + \varepsilon_{bct} \tag{1}$$

where *b* indexes borrowers, *c* indexes counties, and *t* indexes time (in quarters). We estimate the models using OLS, clustering errors at loan level.[9]

The dependent variable $PP_{bc(t+1)}$ is a binary indicator equal to 1 if the mortgage is prepaid by the end of the next quarter (*t+1*), and 0 otherwise. We analyze prepayment behavior because our data do not distinguish between refinancing and other forms of prepayment (e.g., selling the home). When interpreting our estimation results we treat prepayment as synonymous with refinancing. We believe this approach is reasonable as the variation in mortgage refinancing over

[9] We use linear probability models for computational simplicity. Results using logit (not shown) are similar.

our period of analysis can be explained almost entirely by variation in prepayment behavior.[10] Most other papers in the literature take a similar approach.[11]

The key independent variable is $capConstr_{ct}$, an indicator of whether supply of mortgage credit is capacity constrained in the county-quarter.

To isolate the effect of capacity constraints on refinancing (as opposed to other forms of prepayment), we include an interaction with a quadratic measure of the borrower's economic incentive to refinance ($refiVal_{bt}^2$) at time t. We follow Richard and Roll (1989) in measuring the borrower's option value of refinancing using the ratio of the note rate on the mortgage to the "adjusted" market rate (i.e. the rate the borrower could get on a new refinancing).[12] This is an intuitively simple measure and has a strong positive correlation with the incidence of prepayment in our sample. However, we recognize that this measure does not reflect the full range of factors a borrower might consider and show below that our results are robust to using more sophisticated methods to calculate the borrower's refinance option value.

To allow the effects of supply constraints to differ across borrowers, we interact the supply-constraint measure with a categorical measure of $borrType_{bt}$. We estimate three alternative specifications of equation (1) using the following measures to categorize borrowers: current unpaid principal balance (UPB), income at origination, and current credit score. Each of these measures is a proxy for lenders' perceptions of whether the borrower's refinance loan application would be relatively less profitable or more difficult to underwrite. In particular, because a large portion of underwriting costs are fixed, the profitability of a new refinance loan is increasing in the UPB on the existing loan (which for a rate and term refinancing is approximately equal to the new loan amount). While the borrower's income at origination and credit score do not directly relate to profitability of a new loan, they may be observed or inferred early in the lender-borrower relationship and are likely correlated with other more germane characteristics like past

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[10] To quantify this, we regressed county-quarter level counts of refinance originations (computed from HMDA) on mortgage prepayments (computed from NMDB) using a variety of specifications that varied by the time period being analyzed and by whether other control variables (e.g. county fixed effects; quarterly fixed effects) were included. The R^2 from these regressions exceeded 0.90 in every case and in most cases was above 0.95.

[11] A recent exception to this is Gerardi et al. (2020) who distinguish between prepayments due to refinancing and home sales.

[12] As described in the next section, we compute the "adjusted market" rate available to the borrower as of quarter t using the average prime rate, adjusted to reflect the GSE's loan-loan level pricing adjustment based on the borrower's current credit score and LTV.

credit issues, spottier work histories and amount of documentation required to qualify for the new loan.

The specification also includes county-fixed effects (μ_c) and a vector (X_{bct}) of other controls for borrower and loan characteristics including current loan-to-value (LTV), debt-to-income ratio (DTI) at origination, rate spread at origination, race and ethnicity, first-time homebuyer status, loan purpose, the cumulative number of quarters the loan has been in the money, and the county-level unemployment rate. (Details on the construction of these variables are in the next section.) The vector also includes a linear control for calendar quarter interacted with $borrType_{bt}$, to account for differences across borrowers and over time in demand and in their ability to qualify for a refinance loan.[13]

If our measure of supply-side capacity constraints, $capConstr_{ct}$, is exogenous with respect to the borrower's refinancing decision (conditional on the other controls), the estimates in β can be interpreted as the causal effects of capacity constraints on likelihood of prepayment.

However, a challenge for identification in our setting is that supply-side capacity constraints typically bind during recessionary periods when interest rates are low. During such periods, marginal borrowers (those with lower UPB, income, or credit score) may be disproportionately likely to experience an unobserved shock to employment or income and find it more difficult to qualify for a refinancing.[14] To address this issue, we limit our analysis to borrowers that we argue are very likely able to qualify: those that currently have a conventional loan and, since origination of that loan, have not missed a payment on the mortgage or had their credit score fall below 620.[15] In robustness checks we show results are similar if we further limit the sample to borrowers that have never fallen seriously behind on payments on other trade lines in their credit record, whose current combined LTV is 80 percent or lower, and whose credit score hasn't fallen

[13] We control for time as a continuous variable to reflect the fact that availability of mortgage credit has gradually loosened since the great financial crisis (while arguably remaining tight by historical standards). We do not include calendar-quarter fixed effects because doing so would absorb much of the variation in our indicator of whether capacity constraints are binding, the key explanatory variable of interest.

[14] DeFusco and Mondragon (2020) show that mortgage refinancing activity is constrained by employment documentation and out-of-pocket closing cost requirements, which bind most frequently during recessions.

[15] We focus on conventional loan borrowers because (as discussed below) our measure of the prevailing market interest rate in a given quarter is based on the prevailing rate for a conventional loan. In an analysis of Black Knight's McDash loan-servicing dataset and property records module, we find that over our period of analysis about 97% of conventional loan refinancings were refinanced into another conventional loan. We filter on borrower credit score below 620 because this is the minimum credit score required to qualify for a GSE-eligible loan. We filter on mortgage payment history because, as shown by Keys, Pope, and Pope (2016), mortgage payment history is a high-quality proxy for a borrower's current creditworthiness.

below 660. We argue that with these sample selection criteria in place, there is little scope for our estimated effects of supply-side capacity constraints on refinancing to suffer from downward bias due to unobserved differences in borrowers' ability to qualify for a new mortgage.

A second empirical issue is that (as discussed above) demand for new refinance loans increases during booms, even after conditioning on the potential financial gains from refinancing. Because we cannot fully account for such shifts in demand, the estimates of β reflect the effects of both capacity constraints and concurrent increases in demand. We expect that supply-constrained lenders may prioritize borrowers with higher UPB, lower income, or credit score and for those borrowers the net effect will be positive, i.e., their conditional prepayment propensities will be higher during refinance booms when constraints bind. However, we expect the negative effects of supply constraints to be more pronounced on groups of borrowers de-prioritized by lenders. Among such borrowers (those with lower UPB, income, or credit score), we expect conditional prepayment propensities to increase by a smaller amount or even decline when supply constraints bind.

4. Data

We analyze borrower refinancing behavior using the National Mortgage Database (NMDB®), jointly sponsored by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB).[16] The NMDB is a five percent nationally representative sample of closed-end first-lien residential mortgages in the U.S., with detailed administrative information on mortgage terms, monthly payment streams, property value and characteristics, and credit-related information for all borrowers listed on the mortgage.

We limit our analysis to conventional, 30-year, fixed-rate, home purchase or refinance mortgages on single family, site-built, owner-occupied properties. To focus our analysis on borrowers who are likely to qualify for a new conventional loan refinancing, we drop from the sample all loans with less than full documentation or that are not fully amortizing. We also drop all loan-quarter observations after (and including) the first instance when the borrower's credit score falls below 620 or misses at least one mortgage payment. To reduce computational burden

[16] For more details on the NMDB program see: fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx

we use a 50 percent random sample of loans in the NMDB. We include originations from 2009 to 2020 and observe payment behavior in years 2010 through 2021.

We merge the county-quarter capacity constraint measures (derived from HMDA as described above) into our analysis sample using the county and quarter identifiers in NMDB.[17] We merge in county-level unemployment rates from the Bureau of Labor Statistics (BLS), using the rate as of the month ending each quarter (e.g., March for Q1). Finally, to construct the "market" rate available to a borrower in a given quarter, we merge in data from Freddie Mac's Primary Mortgage Market Survey (PMMS) and loan level pricing adjustment (LLPA) matrices from Fannie Mae. We define the market rate as the minimum of the weekly average prime rate on a conventional 30 year loan (from PMMS) observed over the quarter, adjusted for the LLPA the borrower would have to pay based on the borrower's current credit score and loan-to-value (LTV) ratio.[18]

Our final analysis dataset includes 626,418 unique loans and about 7.37 million loan-quarter observations. Table 1 presents prepayment rates and other selected descriptive statistics for cells defined by refinance option value, the capacity constraint indicator, and borrower characteristics. Panel A shows that overall, 4.5 percent of loan-quarter observations in our sample are prepaid by the end of the next quarter. The borrower's refinance option value is in the money (ITM) on about 53 percent of loan-quarter observations, meaning the ratio of the interest rate on the loan to the adjusted market rate is at least 1.1. As expected, the prepayment rate is higher (6.6 percent) on loan-quarter observations that are ITM (i.e., the "ITM sample").

We focus on the ITM sample in the remainder of Table 1 because, for non-ITM observations, prepayments are less likely to be refinancings. Panel B shows that prepayment rates are increasing in UPB, with the level and gradient increasing during refinance booms when supply constraints are binding. Among ITM borrowers in constrained markets, 4.3 percent of those in the lowest UPB bin (<$90k) prepay, compared to 10.0 percent in the highest UPB bin ($150k+). This is not likely to be driven by the potential benefits from refinancing, as all borrowers in these

[17] We construct the capacity constraint indicator only for the 1,126 counties with at least 50 refinance loans in every quarter of our analysis period, and drop from the sample all loans in counties that did not meet this criterion.

[18] The LLPA is a risk-based pricing adjustment for GSE-securitized loans based on the borrower's credit score, LTV, type of product, and other factors; we use only the LLPA matrices for credit score and LTV in this analysis. We convert the LLPA from an upfront dollar fee (collected by the GSEs upon delivery of the loan) to an interest rate equivalent (i.e., collected through a monthly stream of payments) by multiplying the LLPA by 0.21. (In an analysis of loan pricing menus, Bhutta, Hizmo, and Fuster (2020) show (in their Figure A-2) that the relationship between upfront discount points paid (analogous to LLPAs) and mortgage rates is nearly linear, with a slope of -0.21.)

cells are substantially ITM. Further, while unemployment rates are generally higher when capacity constraints bind, they don't vary much across UPB groups, indicating that lower UPB borrowers don't disproportionately reside in counties that suffer greater economic shocks during recessions.

Panel C shows, for the ITM sample, differences in prepayment rates and other selected descriptive statistics by borrower income at origination.[19] Patterns are generally similar to those in Panel A, in that prepayment rates increase with borrower income, particularly in supply-constrained markets. Patterns are also similar by borrower credit score, as shown in panel D.[20]

Table 2 summarizes distributions of the other control variables used in the analysis using the last quarterly observation for each loan. We focus first on the variables we use to indicate whether a borrower is marginal from the lender's perspective (i.e., relatively more difficult to underwrite or less profitable). About 9 percent of borrowers in the sample have an UPB below $90k and 20 percent have UPB of $90-150k; 7 percent of borrowers are Low income and another 19 percent are Moderate income; and 7 percent of borrowers have credit score between 620-659, and 10 percent between 660-669.

Other control variables include the current loan-to-value (LTV), equal to the current UPB divided by the mark-to-market property value.[21] About 84 percent of loans in the sample have LTV of less than 80 percent as of the last quarterly observation. Following earlier literature, we include a control for spread at origination, equal to the difference between the note rate on the mortgage and the average prime rate (from PMMS) at origination. As noted by Gerardi et al. (2020), spread at origination may proxy for unobserved constraints that may prevent a borrower from being able to refinance at the prime rate. Around 17 percent of the loans in our sample had

[19] Borrower income at origination is calculated relative to the area median family income (MFI): Low income borrowers are those with income below 50 percent of area MFI; Moderate income borrowers between 50 and 80 percent; Middle-High income borrowers 80 percent or more. Area MFI estimates are based on the MSA or state non-MSA where the residence is located. (These estimates, based on Census' American Community Survey, are tabulated by the Federal Financial Institutions Examination Council and are included in the NMDB.)
[20] In cases where there is more than one borrower on the loan, we use the minimum credit score, consistent with GSE guidelines. A limitation of our analysis is that the credit score observed in NMDB is Experian's VantageScore 3.0, not the FICO score typically used in mortgage underwriting. It is not possible to transform the VantageScore 3.0 directly to a FICO score for the borrowers in our sample. However, our analyses of HMDA data (in years 2018+) suggests that, at least on aggregate, the distributions of these scores are similar.
[21] We compute mark-to-market property value using the smoothed FHFA house price index included in the NMDB. For loan-quarter observations in calendar year 2013 and going forward, NMDB provides loan balances on junior liens secured by the same property as the first-lien. We use these data to compute current combined LTV (current CLTV), which we incorporate in robustness checks as detailed below.

a spread at origination of 50 basis points or more. About half of the borrowers in our sample have home purchase loans, and of these, nearly half (or 23.5 percent of all loans) are first-time homebuyers. Finally, we control for the total number of quarters the borrower's refinance option value has been ITM through quarter *t*, as a proxy for borrower awareness of the refinance option.

5. Results

A. Effects of Capacity Constraints on Prepayment

Our primary analysis examines how constraints on credit supply affect borrowers' quarterly probability of prepayment. We hypothesize that when capacity constraints bind, lenders de-prioritize loan applications they perceive as being more costly or less profitable to underwrite and thereby reducing their likelihood of prepayment. We employ three alternative specifications of equation (1) using the following measures to categorize borrowers: (A) current unpaid principal balance (UPB); (B) relative income at origination; and (C) current credit score. In the following discussion we focus on how the impacts of capacity constraints vary across borrower types and with the financial incentive to refinance. Coefficient estimates of other covariates are available in Appendix Table A-1.

Figure 6 plots selected conditional predicted prepayment probabilities generated from OLS estimates of specification (1A). As expected, a borrower's probability of prepayment increases sharply with the value of the refinance option. For example, panel A shows that when capacity constraints aren't binding, the overall predicted quarterly prepayment rate is about 2.9 percent when the refinance option value is not in the money ("not ITM"; $refiVal$=1.0), but increases to 5.5 percent when the option value is in the money ("ITM"; $refiVal$=1.2) and 6.8 percent when the option value is very in the money ("very ITM"; $refiVal$=1.3).[22]

This same gradient in predicted prepayment probability steepens for borrowers in supply-constrained markets. For borrowers that are not ITM, the predicted probability of prepayment is 2.3 percent, or about 0.6 percentage points (pp) lower than being in an unconstrained market.[23]

[22] As discussed above, in our main specifications we measure the borrower's refinance option value $refiVal_{bt}$ using the ratio of the note rate to the borrower's market rate. Throughout the paper we define "not ITM" as a ratio of 1.0, "barely ITM" as a ratio of 1.1, "ITM" as a ratio of 1.2, and "very ITM" as a ratio of 1.3. These definitions are similar to in practice to how Firestone et al. (2007) categorize the refinance option value.

[23] The negative effect of capacity constraints when the refinance option is not ITM likely reflects changes in the demand for other types of prepayment which are not a focus of this paper. The decline in prepayment is consistent

For very ITM borrowers, the predicted prepayment incidence rises to 7.8, or a full percentage point higher than in unconstrained markets. As a result, for the average borrower the direction of the capacity constraint effect turns positive as the value of the refinance option increases. This positive effect is consistent with increased demand for refinancing during booms outweighing any dampening effect that supply-constrained lenders may have on overall prepayment activity.

However, panel B of Figure 6 illustrates that among borrowers with a financial incentive to refinance, the net effect of being in a supply-constrained market differs substantially by the borrower's current UPB. For example, among ITM borrowers with higher UPB ($150k or more), predicted prepayment increases from 6.3 when constraints are not binding to 7.6 percent when constraints are binding. In contrast, among ITM borrowers in the lowest UPB group (<$90k), the predicted prepayment rate is 3.8 percent when constraints are not binding and 3.0 percent when binding. Thus, the marginal effect of being in a capacity-constrained market is -0.8 percentage points (pp) or about 18 percent of the mean prepayment rate in the sample. Among ITM borrowers in the middle UPB group ($90-150k), predicted prepayment decreases from 4.0 to 3.7 percent, a marginal effect of -0.3 pp, or 7 percent of the sample mean.

Results are similar when we categorize borrowers by income at origination or current credit score, as shown in Table 3. The table presents estimated marginal effects of capacity constraints on prepayment likelihood evaluated at specific values of $refiVal$, for each of the alternative specifications. (The estimates in Table 3 are illustrated graphically in Appendix Figure A-1.) In panel A the effects are allowed to vary by UPB, and correspond to the predicted probabilities illustrated in Figure 6 and discussed in the previous paragraph.[24] In panel B, effects of capacity constraints are allowed to vary by borrower income. The estimates indicate that when the refinance option value is ITM, residing in a capacity constrained market increases the probability of prepayment by 1.0 pp among middle-to-high income borrowers, but reduces the probability of prepayment by about 0.6 pp (13 percent) among low-income borrowers and by 0.2 pp (5 percent) among moderate-income borrowers. The estimates are similar when allowing effects to vary by current credit score, as shown in panel C.

with a recession-driven reduction in home sales that coincides with a refinance boom and with the findings of Sharpe and Sherlund (2016) and Choi et al. (2022) who show refinance booms crowd out availability of home purchase mortgage credit.

[24] Specifically, each of the marginal effects in Table 3 panel A is equal to the difference in the corresponding predicted prepayment probabilities between constrained and unconstrained markets presented in Figure 6.

Overall, the estimates in Table 3 support our hypothesis that capacity-constrained lenders ration credit to certain borrowers that they may perceive as less profitable or more difficult or costly to underwrite. Looking across the alternative specifications, the economic impact of this credit rationing is to reduce the quarterly likelihood of prepayment by about 15 percent for the "most marginal" borrowers (UPB < $90k; Low income; credit score < 620) and by about 5 percent for those in the middle groups (UPB of $90-150k; Moderate income; credit score 620-659). As a result of supply-side constraints, these marginal borrowers will disproportionately experience a longer wait for or may even miss out on the gains from refinancing.

We consider these to be lower-bound estimates of the true effect of supply-constraints. As discussed above, these estimates reflect the net impact of two opposing factors: the inhibiting effect that supply-constrained lenders have on refinancing activity (the main focus of this paper), and the concurrent positive effect of increased demand for refinancing during booms. We do not account for (unrealized) increased demand, and absent supply constraints, we'd expect prepayment propensities to increase for all borrowers during booms.

B. Cumulative Effects of Capacity Constraints Over an In-the-Money Spell

To shed light on how much capacity constraints reduce the overall incidence of prepayment among marginal borrowers, we present results from an alternative analysis focusing on borrowers' prepayment behavior during periods when their refinance option value is in the money (ITM).

Specifically, we restructure our dataset as follows. For each loan in our sample we retain the first quarter where it goes ITM ($refiVal \geq 1.1$) and each subsequent quarter until it either leaves the sample (e.g., due to prepayment) or goes out of the money. We refer to this as the loan's first "ITM spell." We do a similar exercise for any subsequent ITM spells the loan may have, so that all loan-quarter observations in the sample are ITM and a loan can have multiple ITM spells. (See the second column of Table 1, panel A for selected descriptive statistics for the ITM sample.)

We estimate equation (2) using this sample; this specification resembles equation (1) except that we no longer interact the quadratic in refinance option value with the capacity constraint and borrower type variables.[25]

$$PP_{bc(t+1)} = [capConstr_{ct} \times borrType_{bt}]\beta + refiVal_{bt}^{2}\delta + X_{bct}\gamma + \mu_c + \varepsilon_{bct} \qquad (2)$$

Table 4 presents the estimation results from this alternative specification and sample, which are qualitatively quite similar to the main results (in Table 3). In panel A the capacity constraint effect is allowed to vary by current UPB. For the highest UPB group ($150k+), the quarterly likelihood of prepayment is 1.3 pp higher when the borrower is in a constrained market, or about 20 percent of the sample mean prepayment rate of 6.6 percent. In contrast, for the lowest UPB group (<$90k), the quarterly likelihood of prepayment is 1.6 pp (or 23 percent) lower when constraints are binding, and about 0.5 pp (or 7 percent) lower for the middle UPB group ($90-150k). Panels B and C of Table 5 show that patterns are similar if we allow effects to vary by borrower income or credit score. Marginal borrowers are less likely to prepay their mortgage when lenders are supply constrained.

We now evaluate how capacity constraints affect the quarterly and cumulative probability of prepayment, using the estimates from Table 4. We calculate predicted quarterly prepayment activity through 2021Q2 under two scenarios: (1) "Actual", i.e., using the observed values for $capConstr_{ct}$; and (2) a "Counterfactual" scenario in which we set $capConstr_{ct} = 0$ for all observations. In both cases all other variables in the model take on their actual values.

As an illustrative example, we focus on prepayment activity by borrower UPB over the most recent refinance boom, specifically the set of loans that were active and ITM as of the end of the third quarter of 2019.[26] Panel A of Figure 7 shows that among borrowers in the lowest UPB group (<$90k), we predict that 3.8 percent prepay by the end of the next quarter (2019Q4) in both the actual and counterfactual scenarios. Predicted prepayments are very similar in the two

[25] Because all loan-quarter observations are ITM, we are less concerned about non-refinance related prepayments affecting our estimates of the capacity constraint effect. Thus we retain the quadratic in $refiVal_{bt}^{2}$ in equation (2) but no longer interact this term with the capacity constraint and borrower type indicators. Results are qualitatively similar if we retain the interaction with refinance option value. Results are also similar if we limit the sample to loan-quarter observations with $refiVal \geq 1.2$.

[26] As of 2019Q3, interest rates were relatively low (as shown in Figure 1) and about 70 percent of all active loans were ITM. Capacity constraints were not widespread until after the onset of the pandemic in March 2020 when rates fell further, as shown in Figure 4. For brevity, we focus this discussion on differences by UPB. Results are qualitatively similar if we allow effects to vary by borrower income or credit score.

scenarios because capacity constraints were not yet widespread. However, once capacity constraints become prevalent in 2020, predicted quarterly prepayment rates differ sharply in the actual and counterfactual scenarios. For example, among loans that are active in 2020Q3, predicted prepayment by 2020Q4 is about 6.2 percent in the actual scenario, about 1.4 pp lower than the counterfactual scenario in which supply constraints don't bind.

Panel B of Figure 7 presents predicted cumulative prepayment probabilities calculated from the predicted quarterly prepayment rates in panel A. In the counterfactual scenario where $capConstr_{ct}$ is set to zero (i.e., supply constraints don't bind), among low UPB borrowers that are ITM and active in 2019Q3, we predict that 36 percent prepay by 2021Q2, about 3 pp (or 9 percent) higher than the prediction based on actual values of $capConstr_{ct}$. As discussed above, this estimate may understate the "true" dampening effect on refinancing that capacity constraints might have had, as the estimate does not reflect increased (but unmet) demand for refinancing among these borrowers. If we assume that borrowers in the low UPB group had the same proportional increase in demand for refinancing during booms as we observe for higher UPB groups, predicted cumulative prepayments by 2021Q2 would have been about 37 percent, or 13 percent higher than the prediction based on actual values.[27]

C. Robustness

We now discuss the robustness of our main results presented in Table 3. First, we revisit the potential concern that refinance booms typically coincide with economic recessions, and that the negative effects of capacity constraints might be attributable to unobserved adverse shocks disproportionately experienced by marginal borrowers. Recall that in our main analysis we address this by focusing on a sample of borrowers that are arguably very likely to qualify for a new loan: conventional loan borrowers with credit scores above 620 that have never missed a mortgage payment. Here we expand on this strategy, exploiting data on borrowers' other credit trade lines available in the NMDB beginning in 2013.

Results are summarized in Table 5; for brevity we focus on effects evaluated at $refiVal$=1.2, i.e., for ITM borrowers. The first column reproduces our results from Table 3 to facilitate

[27] Panel B of Figure 7 shows that among borrowers with UPB of $150k or more, the predicted cumulative probability of prepayment by 2021Q2 was about 53 percent in the counterfactual scenario and 55 percent (or 4 percent higher) in the actual scenario that reflects concurrent increases in demand. Multiplying the predicted counterfactual cumulative prepayment rate among low UPB borrowers by 104 percent yields a cumulative prepayment rate of 37 percent, or 13 percent higher than the predicted value of 33 percent based on actual values.

comparison with the second column where the sample is restricted to payment activity over the 2013-2021 period. This change in sample period is not innocuous; while the capacity constraint effect is similar for more marginal borrowers, it decreases by 15 to 30 percent for the least marginal groups. The third column replaces the first-lien based LTV with the combined LTV (based on all credit obligations associated with the property), and increases the minimum creditworthiness of borrowers in our sample by filtering out borrowers that missed any payments on any trade line reported to the credit bureaus. Across the three panels the point estimates are fairly similar to those in column 2. The fourth column further restricts the sample to borrowers with a combined LTV of no more than 80 percent, and the fifth column further restricts the sample to borrowers with a credit score of at least 660.[28] Results are qualitatively similar in both cases. Taken together, these results indicate that marginal borrowers' lower propensity to prepay during capacity-constrained periods does not simply reflect concurrent difficulty in qualifying for a new refinance.

In other robustness checks, we explored the sensitivity of our results to using alternative measures of the borrower's financial incentive to refinance. As discussed above, our main analysis uses the ratio of the borrower's note rate to the "adjusted" market rate, which while closely correlated with prepayment activity in our empirical data, does not reflect the full range of factors a borrower might consider when deciding whether to refinance. In Appendix Table A-2, we show our main estimates of interest are generally robust to using: (1) the "Call Option" measure (Deng et al. 2000) which compares the present value of remaining mortgage payments discounted at the note rate vs. the market rate; and (2) the closed form refinancing model of Agarwal et al. (2013) that accounts for interest rate volatility, closing costs, inflation, and mobility (among other things).

Finally, our main estimation results are robust to using alternative measures to proxy for whether capacity constraints bind in a given county-quarter. As shown in columns 1 and 3 of Appendix Table A-3, results are similar if we construct the capacity constraint indicator based on the 50th or 90th percentile of application processing days for completed loan applications within a

[28] We filter out loans with CLTV above 80 percent because, above this threshold, GSE guidelines generally require mortgage insurance which increases the borrower's cost of refinancing and may make it more difficult for the lender to process and underwrite the loan application. We filter out credit scores below 660 because, in practice, some lenders may have credit score overlays that are more stringent than the minimum 620 score specified in GSE underwriting guidelines.

county-quarter, instead of the 75th percentile as in our main analysis. Results are also robust to measuring capacity constraints using the share of applications that are "incomplete" as of each quarter end, following Choi et al. (2022). In column 4 of Appendix Table A-3, the capacity constraint indicator is equal to 1 if the share of incomplete applications in the county-quarter exceeds the 75th percentile value over all county-quarter observations in the sample, and in column 5 the capacity constraint indicator is equal to 1 if the share of incomplete applications in the county quarter exceeds 110 percent of the average share within the county over our sample period.[29]

6. Examining Mechanisms

We find that borrowers with lower UPB, lower income, and lower credit scores are less likely to refinance their mortgages during refinance booms when capacity constraints bind. This result is consistent with supply-constrained lenders rationing credit to marginal borrowers they perceive as less profitable or more difficult to underwrite.

By what mechanisms might such credit rationing occur? Based on anecdotal information and prior literature (detailed below), we speculate that supply-constrained lenders might affect borrowers' propensity to refinance in one of the following ways: (A) reduce the likelihood that marginal borrowers will obtain a price quote; (B) increase prices on loans to marginal borrowers in an effort to "throttle" demand; or (C) de-prioritize processing and underwriting of loan applications from marginal borrowers. In this section we present supplemental analyses to assess the quantitative importance of these channels during recent refinance booms.

A. Do Supply Constraints Reduce Marginal Borrowers' Likelihood of Obtaining a Price Quote?

When a borrower becomes aware that a refinancing might be financially worthwhile, the next step in the refinancing process is to contact one or more lenders to learn about the pricing on a

[29] Following Choi et al. (2022), we use restricted-access HMDA data to compute the share of applications that are "incomplete" in a county-quarter, defined as follows: the number of applications filed in the county quarter on which no action has been taken by quarter-end, divided by the total number of applications filed in the county-quarter. Choi et al. (2022) define constrained markets based on the 75th percentile value over all observations (as in Appendix Table A-3, column 3), and in this paper we define constrained markets based on within-county deviations (as in Appendix Table A-3, column 4). In an additional robustness check, results (not shown) are similar if we define a county-quarter observation as constrained if the 75th percentile value of application processing days exceeds the 75th (or 50th, or 90th) percentile value of application processing days over all county-quarter observations in the sample.

new refinance loan. Once the borrower makes contact and provides some basic information (e.g., remaining balance on the current loan, the property location and an estimate of its value, income, authorization to run a credit check) the lender can provide an initial price quote on a new refinance loan.

Supply-constraints might affect this process in two ways. First, when operating at or near capacity, lenders might adjust their marketing strategies, for example by reducing advertisements targeted to borrowers with loans they perceive as less profitable to refinance. This may reduce such borrowers' awareness of their refinance option and the likelihood they attempt to contact a lender for pricing.[30] Second, lenders facing constraints due to surplus demand during booms may triage borrowers' requests for a price quote, for example by screening calls and prioritizing requests from repeat customers. Anecdotal evidence suggests that some lenders engaged in such behavior during the most recent refinance boom, disproportionately affecting marginal borrowers.[31]

Due to data limitations, we are not able to separately evaluate the extent to which supply-constrained lenders might be adjusting their marketing strategies or engaging in triage of borrower requests for price quotes.

Instead, we examine whether capacity constraints affect the overall likelihood that borrowers contact and obtain a price quote from a lender, making use of NMDB data on the incidence of inquiries for new mortgage credit. We view a mortgage credit inquiry as a reliable indication that the borrower has obtained pricing from a lender because credit score is central to loan pricing and a common initial step in a potential refinancing is for the loan officer to request a hard credit check on borrower(s) looking to submit an application for a new loan.

Specifically, we modify equations (1) and (2) so that the dependent variable is an indicator equal to one if any of the borrowers on the current loan had at least one mortgage-related credit

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[30] As discussed above, borrowers' awareness of their refinance option is affected by several factors other than lender marketing, such as financial sophistication, exposure to news media articles or television programming, and social networks. These factors are not likely to be affected by whether lenders are supply-constrained.

[31] For example, a recent Seattle Times (March 14, 2020) article highlights some of the ways lenders might respond to a surplus of demand: "With rates near historic lows as the coronavirus roils markets, lenders are swamped… [t]hey're raising rates to discourage customers, pumping the brakes on marketing campaigns and capping the amount loan officers can lend. Good luck getting someone on the phone — especially if you're not courteous. 'If you're difficult, a negotiator, or a grinder, they're probably not going to call you back,' said Brian Koss, executive vice president at Massachusetts-based Mortgage Network […]. 'We're sorting calls by who are my best customers, who's on top of it, engaged, and giving me all their documents up front.' "

inquiry in the current quarter (*t*), and equal to zero otherwise.[32] We estimate the models using the Full and in-the-money (ITM) samples respectively, with an additional sample restriction of dropping loan-quarter observations subsequent to the first instance of a mortgage credit inquiry.[33]

The first column of Table 6 presents marginal effects of capacity constraints on the probability of a mortgage credit inquiry for the Full sample, evaluated when the refinance option is ITM ($refiVal$=1.2). In panel A the effects are allowed to vary by current UPB. Patterns are qualitatively similar to the main results in Table 3. Among higher UPB borrowers, the likelihood of a mortgage credit inquiry is about 1.8 pp higher when constraints are binding, or about 38 percent of the sample mean inquiry rate of 4.8 percent. In contrast, among borrowers in the lowest and middle UPB groups, capacity constraints lower the likelihood of a mortgage inquiry by 0.6 pp and 0.2 pp (or 12 and 4 percent), respectively. Differences across borrower income groups are similar, as shown in Panel B. Patterns by credit score (panel C) are somewhat different, in that for the lowest credit score group the effect is not statistically different from zero and is positive for the middle credit score group. Nonetheless, in both cases the effect is smaller in magnitude than the large and positive effect for higher credit score borrowers.[34]

Column 2 of Table 6 presents regression results using the modified specification (2) and the ITM sample; using the ITM sample focuses our analysis on mortgage credit inquiries most likely to be related to a refinancing.[35] The pattern of results across the three panels of column 2 is similar to the results in column 1, with slightly larger effect sizes relative to the mean rate of mortgage inquiry for the ITM sample.

[32] Unlike our main specification in which the dependent variable is an indicator for prepayment in the next quarter (*t+1*), here we focus on mortgage credit inquiries in the current period (*t*) because the time it takes to complete a mortgage credit inquiry is not nearly as long as the time it takes to complete a refinancing.

[33] The Full sample refers to the sample used for the main regression results in Table 3, and the ITM sample refers to the sample of loan-quarter observations where the refinance option value is in the money, used for the regression results in Table 4. In some cases we observe a new mortgage inquiry in the quarter that the current loan was originated; we drop these loan-quarters from the sample because we cannot rule out that the inquiry was related to the origination of the current loan.

[34] The different pattern of results by credit score may be attributable in part to a measurement issue, as credit scores are measured at quarter end and could be negatively affected by credit inquiries occurring during the quarter.

[35] Mortgage inquiries may occur for reasons other than a potential refinancing in response to financial incentives, e.g., a potential new home purchase related to an upcoming move. Dropping loan-quarter observations that are not ITM reduces the potential influence of such inquiries on our results.

In the remaining columns of Table 6, we explore the role of borrower awareness. Because we don't directly observe whether a borrower is aware of her option to refinance, we filter the sample to borrowers that: currently have a refinance loan (column 3), live in a high-income census tract (column 4), or live in a county with above-median "Economic Connectedness" (column 5).[36] Borrowers that meet these criteria are arguably more likely to be aware of their option to refinance. The pattern of results in these columns is quite similar to those from the ITM sample in column 2. Even among borrowers that are arguably more homogeneous in their awareness of the refinance option, those with higher UPB, income, and credit score are more likely to have a new mortgage inquiry when constraints are binding, while those with lower UPB, income, and credit score are less likely to do so. This argues against the proposition that the heterogeneity in effects of capacity constraints is attributable to differences in awareness across borrowers.[37]

Overall, the results in Table 6 indicate that lower UPB and lower income borrowers are less likely to successfully contact and obtain pricing from a mortgage lender when capacity constraints are binding, as proxied by the incidence of inquiries for new mortgage credit. Relative to the unconditional quarterly incidence of an inquiry (e.g., 6.9 percent in column 2), the magnitudes of the capacity constraint effects on mortgage inquiries are similar in magnitude to our main estimates of the overall effects of capacity constraints on prepayment. This suggests that much of the inhibiting effect of capacity constraints on marginal borrowers' propensity to refinance occurs early in the process, i.e., prior to their receiving pricing on a potential new refinancing and before a formal loan application is filed.

B. Do Supply-Constrained Lenders Price Out Marginal Borrowers?

During refinance booms, lenders respond to excess demand in part by increasing prices, as reflected in the spread between primary and secondary market rates and in the "gain-on-sale" associated with selling the loan in the secondary market (e.g., Fuster et al. 2017; Fuster et al.

[36] We use county-level measures of Economic Connectedness constructed by Chetty et al. (2022) using privacy-protected data from Facebook, and available for download via socialcapital.org. Conceptually, Economic Connectedness is a measure of the degree to which low-income and high-income people are friends with each other.
[37] In additional analyses (not shown), we linked the administrative NMDB data to the National Survey of Mortgage Originations (NSMO), which contains additional information on the characteristics of borrowers in the sample. We find that results are qualitatively similar (but less precisely estimated) if we limit the sample to borrowers in the NSMO with characteristics that are likely correlated with financial sophistication or awareness, such as those with higher education level or ownership of other financial assets.

2021). It seems plausible that constrained lenders might disproportionately raise prices for loans they perceive as less profitable or more difficult to originate, in an attempt to "throttle" demand from such borrowers. If marginal borrowers face relatively high prices, their financial incentive to refinance will be reduced and in cases where higher prices push their refinance option value entirely out of the money, they'll be effectively excluded from the refinance market.

To explore whether supply-constrained lenders use price as a mechanism to ration credit, we analyze HMDA data on refinance loan originations from January 2018 to September 2021.[38] We limit the analysis to these years because interest rates and origination costs are not observed in HMDA prior to 2018.

Appendix Figure A-2 plots the average interest rate on refinance loan originations by loan amount, borrower income, and credit score in panels A, B, and C, respectively. While not conclusive, these figures suggest that on average, prices did not increase for marginal borrowers relative to non-marginal borrowers beginning in the second quarter of 2020 when supply constraints were widely binding (as shown in Figures 3 and 4).[39]

We formalize the analysis by specifying regression equation (3). The dependent variable is the interest rate on the loan to borrower *b* made by lender *l* in county *c* and month *t*.

$$P_{blct} = [capConstr_{lt} \times borrType_b]\beta + X_b\gamma + \mu_l + \rho_c + \tau_t + \varepsilon_{blct} \tag{3}$$

The key independent variable is an indicator of whether the lender is capacity-constrained in a given month. Analogously to the county-quarter level indicator of capacity constraints used in our main analysis, we categorize a lender as constrained in a given month when the 75th percentile value of processing days on applications received by the lender over the prior three months exceeds 110 percent of the average for the lender over our period of analysis. (See the Appendix for details on the construction of the lender-level capacity constraint indicator and the data used in this analysis.)

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[38] Specifically, we analyze first lien, closed-end, conventional conforming, 30 year term, fixed-rate, fully amortizing, non-cash-out refinance loan originations on owner occupied, site-built, single family properties from January 2018 to September 2021. We omit originations in the 4th quarter of 2021 to deal with right censoring in our computation of application processing days used to categorize lenders as supply-constrained. See the Appendix for more details on the construction of the HMDA sample used in the analyses presented in this section.

[39] In practice, mortgage pricing depends on both the interest rate and upfront costs (discount points). The trends illustrated in Appendix Figure A-2 and regression results described below are very similar if we account for discount points and other loan costs.

We allow the effect of lender-level capacity constraints to differ across borrower types by interacting this indicator with alternative categorical measures of borrower type: (A) loan amount; (B) borrower income; and (C) credit score. The specification includes controls for other loan and borrower characteristics X_{blt} (loan amount, relative borrower income, credit score, combined LTV, DTI, race/ethnicity, and net points paid at closing), as well as fixed effects for lender, county, and application month.[40]

Regression results are presented in Table 7. The estimates in panel A indicate that, conditional on lender, application month, and other controls, interest rates are about 3 bps higher for loans originated in months when the lender is supply-constrained. This is a small effect, and further, rates are no higher on loans to borrowers with lower loan amounts (e.g., <$90k) in lender-months affected by supply-constraints. Results are similar using alternative measures of pricing including rate spread (the difference between the rate on the loan and the corresponding average prime offer rate (APOR)) in Column 2, or rate spread expressed as a percentage of APOR in Column 3. Results are also similar when allowing effects to vary over other borrower characteristics such as income (panel B) or credit score (panel C).

Overall, the results in Table 7 do not support the hypothesis that, when faced with constraints, lenders raise prices to marginal borrowers in an effort to throttle demand. This suggests that most if not all ITM borrowers (calculated using our measure of "adjusted market rate") will find it worthwhile to file a formal application for a new refinance loan once they receive pricing from a lender.

An important caveat to this analysis is that, in the HMDA data we analyze, we observe loan pricing only for applications that result in an origination. Thus, we may understate the extent to which capacity constraints lead to increased prices offered by lenders, if marginal borrowers offered a relatively high price are less likely to complete a new refinancing. That said, our results are consistent with Fuster et al. (2021), who show using Optimal Blue data on mortgage rate offers that the spread in conventional loan mortgage rates between lower and higher credit score borrowers did not increase during the post-pandemic refinance boom.[41]

[40] Following Brevoort (2022), we define net points at closing as the difference between discount points paid and lender credits, expressed as a percentage of the loan amount.

[41] In contrast to the conventional loan market, Fuster et al. (2021) show that for FHA loans, mortgage offer rates increased for lower credit score borrowers relative to higher credit score borrowers during the recent refinance boom. The authors attribute this difference to the fact that lenders are exposed to substantially more default risk in the FHA loan market compared to the conventional loan market.

C. Do Supply-Constrained Lenders De-Prioritize Applications from Marginal Borrowers?

Once the borrower submits a loan application, the lender processes the application and makes an underwriting decision (to approve or deny the application). Processing the application typically requires the lender to obtain detailed documentation from the borrower including current income and assets, employment status and history. In making an underwriting decision, the lender must consider these and other factors such as borrowers' credit history, monthly housing expenses, and monthly payment-to-income and debt-to-income ratios.[42]

We hypothesize that when facing excess demand, lenders may de-prioritize or deny loan applications submitted by borrowers they perceive as less profitable or more difficult to underwrite. We use HMDA data on refinance loan applications reported in years 2018-2021 to assess the extent to which this occurs in practice.[43] Specifically, we examine whether capacity-constrained lenders are more likely to: (1) close or deny applications from marginal borrowers due to incomplete information;[44] (2) deny applications from marginal borrowers for underwriting reasons; or (3) exhibit increased application processing days for applications from marginal borrowers.

We speculate that when faced with excess demand, constrained lenders may put less effort into following up with borrowers to obtain needed documentation, especially those they might perceive as less profitable or more difficult to underwrite. Consistent with this intuition, Appendix Figure A-3 shows that when refinance applications spiked in the 2nd and 3rd quarters of 2020, the share of applications ending as incomplete (i.e., closed or denied for incompleteness) increased disproportionately for applicants with a lower loan amount (panel A) and especially for those with Low-income (panel B). In contrast, Appendix Figure A-4 suggests that denial rates for reasons related to underwriting did not disproportionately increase for applications with lower

[42] The Consumer Financial Protection Bureau outlines specific requirements that lenders must follow in Regulation Z (Ability to Repay).

[43] For this analysis, we limit the dataset to years 2018+ for a few reasons. First, beginning in 2018, lenders are generally required to report the reason for denial (on loan applications that are denied). Prior to 2018, many lenders were not required to report denial reason. Second, beginning in 2018, most loan application records include data on borrower credit score and other important variables that lenders consider when deciding whether to approve the loan application. However, credit score is not observed in HMDA for loan applications that are closed for incompleteness. See the Appendix for additional details about the dataset used in this analysis.

[44] Under the Equal Credit Opportunity Act (ECOA), a creditor may close or deny the application for "incompleteness" for various reasons, generally related to the applicant not providing additional information requested by the lender in a timely fashion. For more details on ECOA (Regulation B), see consumerfinance.gov/rules-policy/regulations/1002/9/#b-2.

loan amounts or from lower income borrowers. Finally, Appendix Figure A-5 shows that during the 2020 refinance boom, the number of application processing days increased for all groups but especially so for borrowers with lower loan amounts, lower income, and lower credit scores.

To examine whether these patterns hold up after accounting for other observable factors, we estimate alternative specifications of equation (3) on the HMDA sample of refinance loan applications described in the previous subsection. Table 8 presents the results. In the first column the dependent variable is a binary indicator that the application ended as incomplete. As shown in Panel A, applications for a loan amount under $90k are about 1.3pp more likely to end as incomplete in months the lender is capacity-constrained, or 11 percent of the incidence of incomplete applications for the sample. Panel B shows that applications from Low-income borrowers are about 2.1pp (18 percent) more likely to end as incomplete.[45]

The second column of Table 8 presents regression results where the dependent variable is an indicator the loan application was denied for underwriting-related reasons.[46] The estimates indicate that applicants in the lowest loan amount and credit score groups are denied at higher rates when the application is filed in months the lender is constrained, but the opposite is true for those in the Low-income group.

Consistent with constrained lenders de-prioritizing certain applications, the third column of Table 8 shows that lender-level constraints are associated with disproportionately longer application processing days for marginal borrowers. For example, panel A shows that among applicants in the highest loan amount group (the omitted category), capacity constraints are associated with about a 10 day increase in processing days which amounts to around 20 percent of the sample mean of 52 days.[47] Applicants in the lowest loan amount group (<$90k) see a further increase of 3 days to the expected processing time. Applicants in the Low-income and low credit score groups (panels B and C) also see relative increases in processing days, although effects are smaller in magnitude.

[45] We omit the analysis allowing effects to vary by credit score (panel C) because credit score is not reported in HMDA for applications the lender designates as incomplete.

[46] Specifically, we consider the application to be "denied for underwriting" if the lender indicates the denial was due to any of the following reasons: (1) Debt-to-income ratio; (2) Employment history; (3) Credit history; (4) Collateral; (5) Insufficient cash for down payment or closing costs; or (6) Unverifiable information.

[47] We note that this main effect is tautological, as the capacity constraint indicator is equal to one in lender-months with high processing days relative to the lender's average over the period of analysis. However, the fact that processing days increases disproportionately for marginal borrowers is not an artifact of how the capacity-constraint indicator is constructed.

Overall, the results in Table 8 suggest that supply constrained lenders are more likely to de-prioritize loan applications from marginal borrowers, as reflected in higher rates of applications being closed or denied for incompleteness and in longer application processing times. However, the effect sizes are small in magnitude, and suggest the economic impact of lenders' de-prioritizing applications from marginal borrowers on their propensity to refinance is of secondary importance.

As a back-of-the envelope illustration of this point, consider that the estimates in Table 8 indicate that when capacity constraints are binding, the likelihood that the lender *accepts* (i.e., fully processes and does not deny) a loan application from a borrower in the lowest loan amount group declines by about (1.25+0.91=) 2.2 pp. This is a 3 percent reduction relative to the sample mean acceptance rate of (100-11.6-8.3=) 80.1 percent, or an order of magnitude smaller than the effect of capacity constraints on the likelihood that a low-UPB borrower will successfully contact and obtain pricing from a lender.[48]

Our finding that capacity constraints have at most a minor effect on lenders' processing of applications from marginal borrowers is qualitatively consistent with Agarwal et al. (2021), though there are some quantitative differences. Specifically, we show that when constraints are binding, applications from marginal borrowers are slightly more likely to end in an incomplete or be denied for underwriting reasons (though our results are mixed on the latter measure), and that application processing days increase slightly for such borrowers. In contrast, Agarwal et al. (2021) use proprietary data from Freddie Mac to show that "funding" rates and processing times on refinancing applications from lower income borrowers were not differentially affected during the pandemic-related refinance boom.[49] Instead the authors attribute inequality in refinancing activity to lower income borrowers being underrepresented in the pool of applications received in this period. This conclusion is consistent with our results in Tables 6, 7, and 8, which cumulatively suggest that when supply-side constraints are binding, the decline in marginal

[48] As discussed above, we use inquiries for new mortgage credit as a proxy for the borrower contacting and receiving a rate quote from a lender. From Table 6, borrowers in the lowest UPB group are about 1.3pp less likely to have a new mortgage inquiry, about 19 percent of the sample mean inquiry rate.
[49] Reconciling our results with Agarawal et al. (2021) is not straightforward, due to differences in empirical methodology and the data being analyzed. Agarwal et al. (2021) use proprietary data from Freddie Mac to compute "funding rates", i.e., the share of loans run through Freddie Mac's automated underwriting software (Loan Product Advisor) that are ultimately funded by Freddie Mac. According to the authors, about 18 percent of all new loans in the market are run through their LPA software.

borrowers' propensity to refinance largely occurs prior to when borrowers submit a formal application for credit.

7. Conclusion

This paper presents new evidence on how supply-side capacity constraints affect borrowers' refinancing activity. We find that, conditional on the financial benefit of refinancing and a rich set of borrower and loan characteristics, "marginal" borrowers (those that lenders may perceive as more difficult to underwrite or less profitable) are less likely to prepay their mortgages during periods when lenders' supply of credit is constrained. In particular, borrowers with lower remaining loan balances, lower income, and lower credit scores are about 0.5 percentage points less likely to prepay their mortgage in a given quarter, which amounts to 15 percent of the mean quarterly prepayment rate in our sample. Our estimates imply that the cumulative effect of capacity constraints over the post-COVID refinancing boom was to reduce prepayment activity of the most marginal borrowers in our sample by about 3 percentage points, or a 9 percent effect relative to a counterfactual scenario in which lenders are not supply constrained. We view these as lower-bound estimates of the true effect of capacity constraints, as we cannot account for unobserved increases in demand (after conditioning on financial incentives) during booms that otherwise lead to higher prepayment rates.

Overall, our findings suggest some scope for public policy to help alleviate the effects of supply-side constraints marginal borrowers' propensity to refinance. About 7 to 9 percent of mortgage-holders in our sample are in the lowest loan balance, income, and credit score groups that are most affected by capacity constraints, and these borrowers are disproportionately likely to be minorities and first-time homebuyers.

One implication of our work is that programs that make it less costly for these marginal borrowers to apply and be underwritten could increase their credit supply, even during refinance booms. A salient example of such a policy is the program the Federal Housing Finance Agency announced in April 2021, where Fannie Mae and Freddie Mac waived the adverse market refinance fee and provided the lender with a credit of up to $500 for an appraisal provided that the borrower has a low to moderate income and the loan meets minimum standards on LTV, credit score, payment history, and other criteria.[50] Another example is a streamlined refinancing program that would waive income and employment documentation requirements for borrowers with existing loans insured by the federal government (Gerardi, Loewenstein, and Willen 2021). By lowering lenders' cost of processing and underwriting their loan applications, these types of interventions could help borrowers with lower loan amounts, lower income, and lower credit scores take advantage of lower rates and substantially reduce their mortgage payments.

However, we caution that the effectiveness of such policies may be limited, to the extent they don't address demand-side and supply-side frictions that inhibit certain borrowers from initiating a new refinancing. On the demand-side, prior literature has established that many borrowers fail to refinance even when the financial incentives to do so are large. Interventions that increase borrowers' awareness of their option to refinance and address behavioral factors such as consumer inattention may be quite effective. For example, results from a field experiment in Ireland indicate that mandatory disclosures of refinancing opportunities and especially subsequent reminder letters can lead to large increases in borrowers' refinancing activity (Byrne et al. 2022).

On the supply-side, this paper shows that capacity constraints inhibit marginal borrowers' ability to refinance during booms, primarily because they are less likely to successfully contact and obtain pricing from a lender when constraints are widespread. Data limitations prevent us from examining exactly why this is the case. One possibility is that, when constraints are binding, lenders may adjust their marketing strategies in ways that de-prioritize reaching consumers they perceive as less profitable. Alternatively, when faced with excess demand for new refinance loans, some lenders may triage borrowers' requests for a price quote, for example by screening calls and prioritizing requests from certain customers, disproportionately affecting marginal borrowers. Distinguishing between these mechanisms is an important topic for future research, with clear implications for the design of policy interventions meant to remove barriers to taking advantage of refinancing opportunities.

[50] The adverse market fee was a 50 basis point surcharge that applied to most mortgage transactions backed by Fannie Mae or Freddie Mac. The fee took effect on December 1, 2020 and was eliminated effective August 1, 2021.

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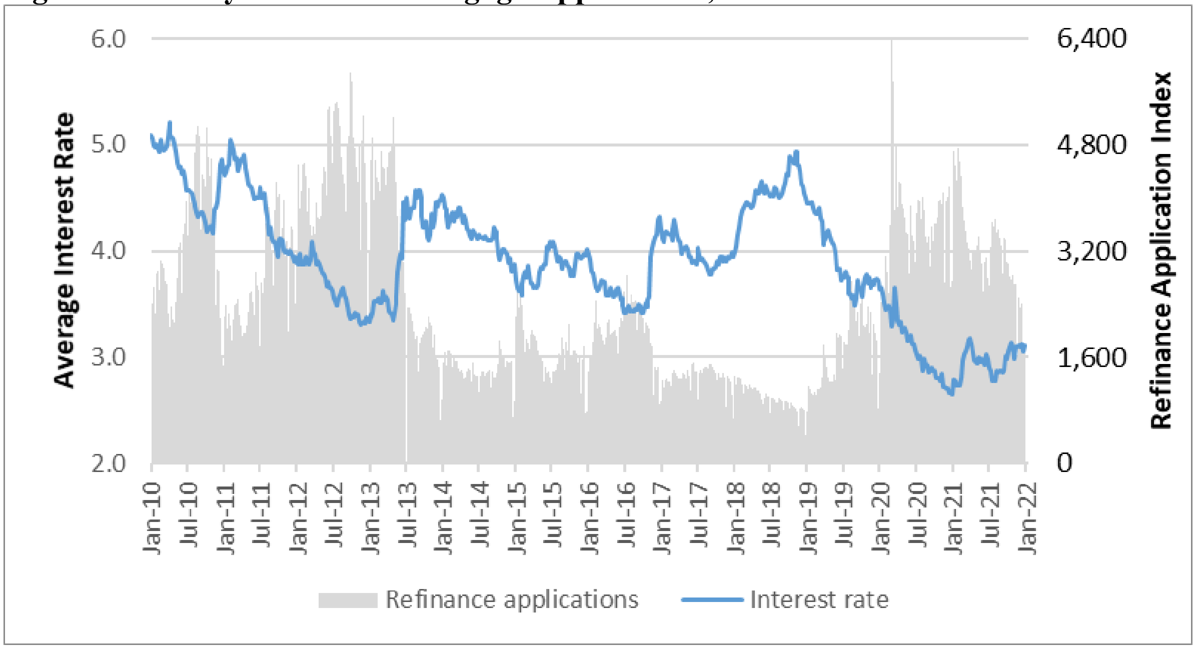
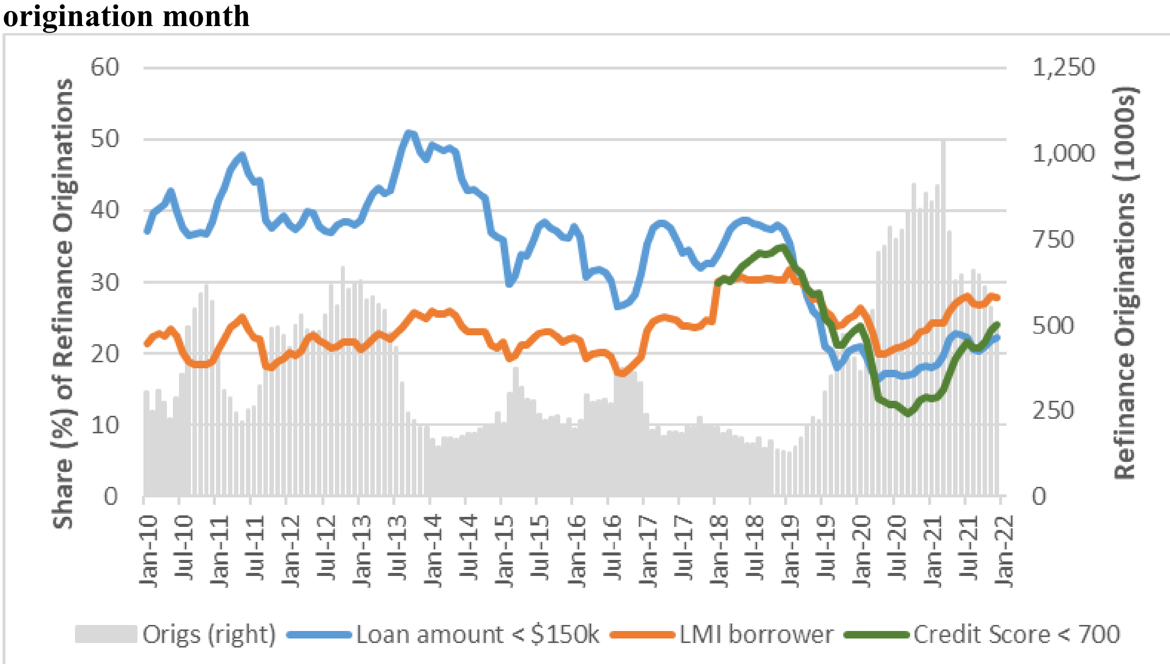
Figure 1: Weekly Refinance Mortgage Applications, 2010 to 2021



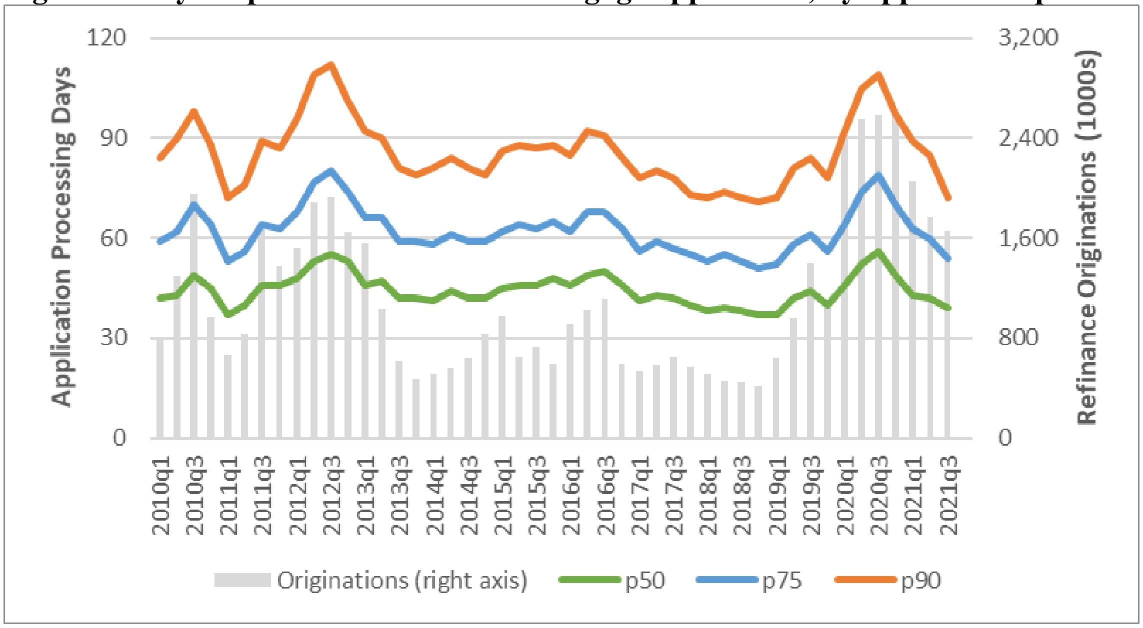
Notes: Refinance mortgage application data are from Mortgage Bankers Association's (MBA) weekly applications survey. Index is equal to 100 for the week of March 16, 1990. Interest rate data are from Freddie Mac's Primary Mortgage Market Survey (PMMS), and reflect the average rate on a 30-year fixed-rate prime conventional conforming mortgage.

Figure 2: Share (%) of refinance originations with selected loan and borrower characteristics, by origination month



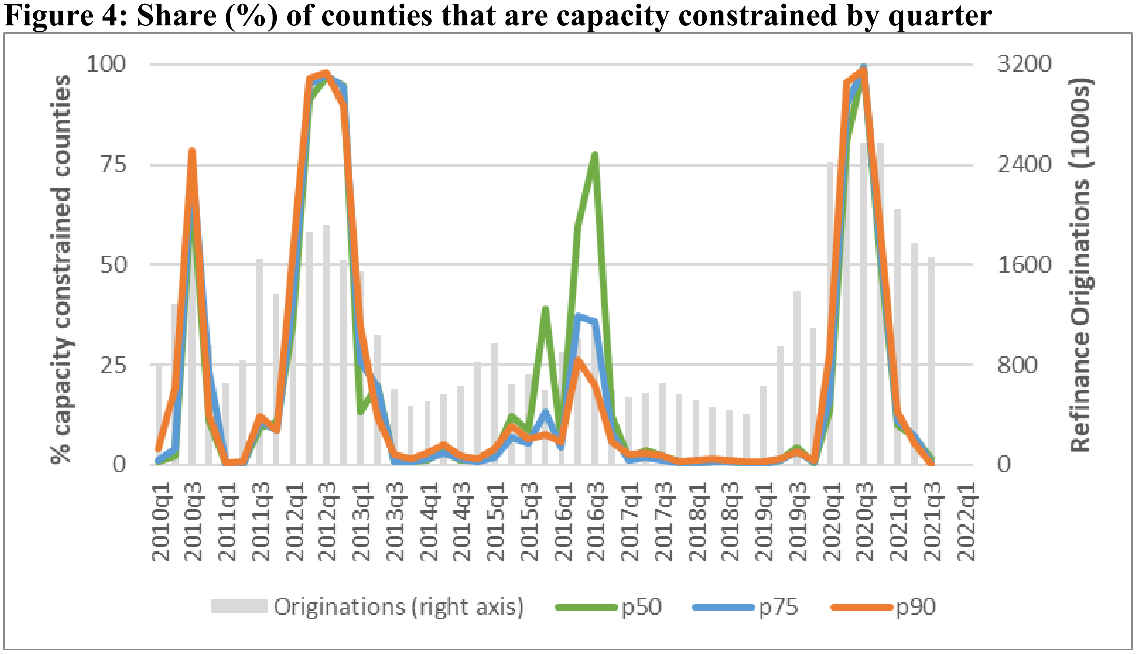
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data. A low- or moderate-income (LMI) borrower has family income less than 80% of the median family income (MFI) in the metropolitan statistical area (MSA) or state non-MSA in which it is located. Borrower credit scores are not observed in HMDA for originations prior to 2018.

Figure 3: Days to process a refinance mortgage application, by application quarter



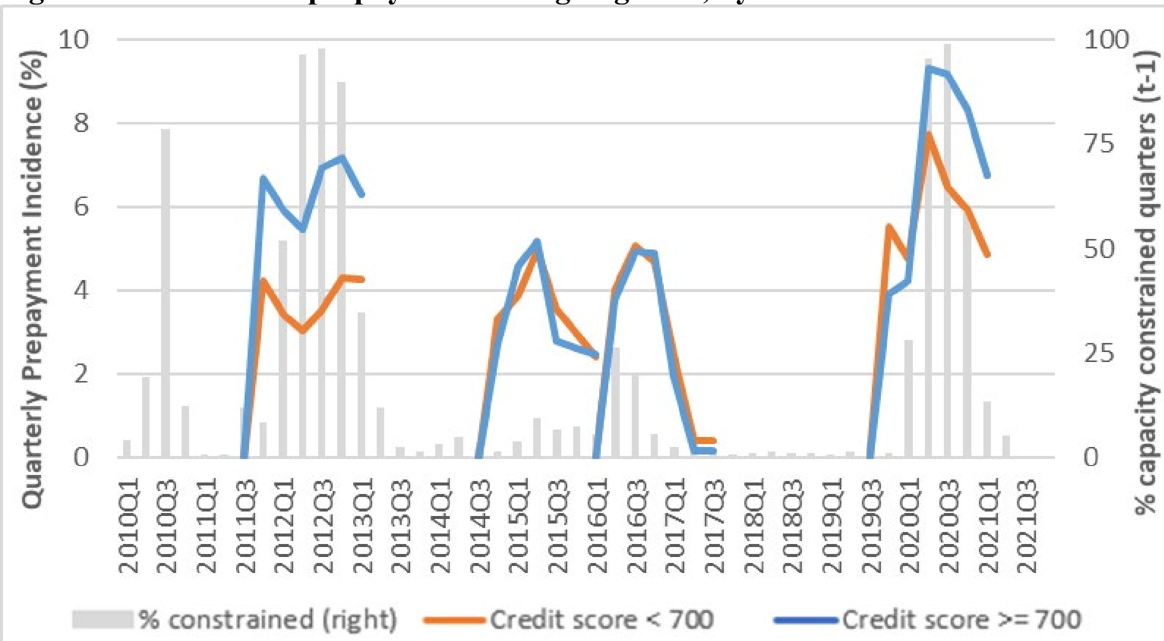
Notes: Authors calculations using HMDA data. Application processing days is the number of days between the date of the application and the date of the origination. The lines reflect the 50th, 75th, and 90th percentile values of application processing days over all first lien refinance loan applications on 1-4 family properties in the quarter that resulted in an origination.

Figure 4: Share (%) of counties that are capacity constrained by quarter



Note: Authors' calculations using HMDA data. A county-quarter is categorized as "capacity constrained" if the 50th (75th; 90th) percentile value of application processing days in that county-quarter exceeds 110% of the average 50th (75th; 90th) percentile value for the county over the period of analysis. Share (%) of counties capacity constrained in a given quarter is weighted by the county-level number of refinance applications in the quarter.

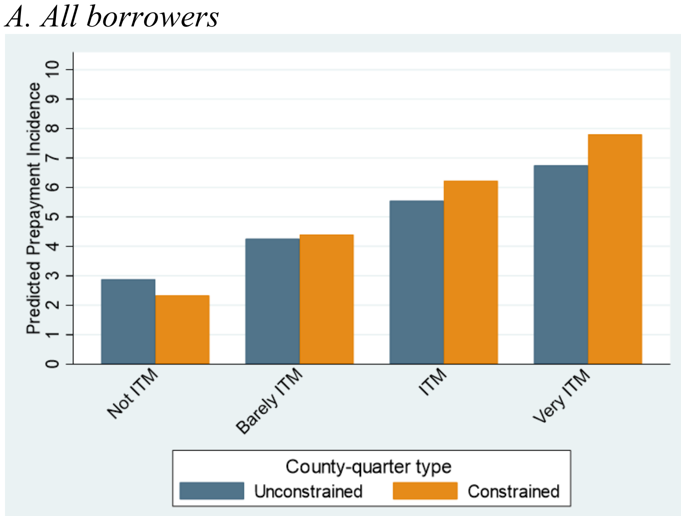
Figure 5: Incidence of prepayment after going ITM, by credit score



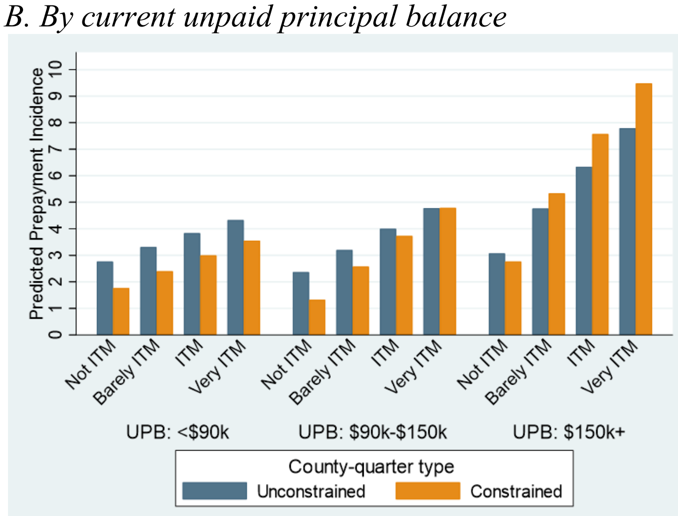
Note: Authors' calculations using data from NMDB and HMDA. This figure illustrates quarterly prepayment incidence for loans on which the refinance option value went in the money (ITM) at selected quarters, separately by whether their credit score in that quarter was above or below 700. We selected these quarters to highlight the observed difference in prepayment that occurs when the majority of counties are capacity constrained (i.e., during refinance booms). Share (%) of counties that are capacity constrained is lagged one quarter (t-1) to reflect the length of time it typically takes to process a refinance application.

Figure 6: Predicted probability of prepayment by capacity constraint, refinance option value, and current unpaid principal balance

A. All borrowers



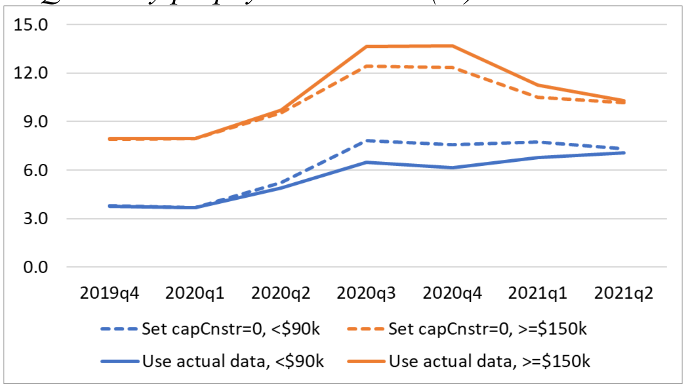
B. By current unpaid principal balance



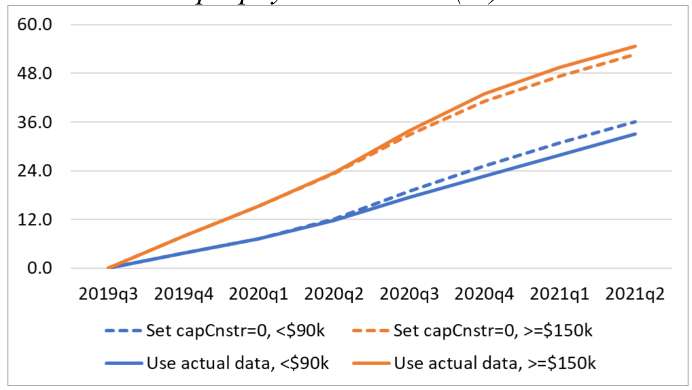
Note: This figure plots quarterly predicted prepayment probabilities by refinance option value, the loan's remaining unpaid principal balance (UPB), and whether the county is capacity constrained this quarter. The predictions are evaluated at refinance option values of 1.0 ("Not ITM"), 1.1 ("Barely ITM"), 1.2 ("ITM"), and 1.3 ("Very ITM"). The predictions are calculated using the coefficient estimates from specification (1), reported in Table 3 and Appendix Table A-1.

Figure 7: Predicted effects of capacity constraints on prepayment for loans that are in the money (ITM) as of 2019Q3, by UPB

A. Quarterly prepayment hazard (%)



B. Cumulative prepayment hazard (%)



Notes: Figure A presents predicted quarterly prepayment hazards for loans that are active and ITM as of 2019q3, separately by UPB. The predictions are calculated using estimates from the ITM model (specification (2) with results in Table 4), under two scenarios. First ("Using actual data"), the variable $capConstr_{ct}$ and all other covariates take on their actual values. Second ("Set capCnstr=0"), the variable $capConstr_{ct}$ is set to zero for all observations, and all other covariates take on their actual values. Figure B presents the corresponding cumulative prepayment hazards through 2021q2. Predictions for the middle UPB category ($90-150k) are omitted for readability.

Table 1: Selected descriptive statistics

A. Full sample by refinance option value	All	ITM sample	Not ITM sample			
Prepaid by next quarter (%)	4.5	6.6	2.3			
Ratio of note to adj. mkt rate (mean)	1.14	1.29	0.97			
% with ratio < 1.1	47.3		100.0			
% with ratio [1.1, 1.3)	33.3	63.2				
% with ratio >= 1.3	19.4	36.8				
County loan processing days (mean)	62.1	65.3	58.6			
County unemployment rate (%)	5.6	6.1	5.07			
Loan-quarter observations	7,369,942	3,880,400	3,489,542			
as % of all loan-quarter obs	100.0	52.7	47.3			
B. ITM sample by capConstr and current UPB	Unconstrained Market			Constrained Market		
	< $90k	$90-150k	$150k+	< $90k	$90-150k	$150k+
Prepaid by next quarter (%)	3.7	4.2	7.1	4.3	5.6	10.0
Ratio of note to adj. mkt rate (mean)	1.3	1.3	1.2	1.4	1.4	1.3
% with ratio [1.1, 1.3)	56.6	66.2	75.1	28.9	39.0	51.3
% with ratio >= 1.3	43.4	33.8	24.9	71.1	61.0	48.7
County loan processing days (mean)	59.6	60.2	61.8	74.4	74.7	76.3
County unemployment rate (%)	5.5	5.5	5.5	7.5	7.5	7.9
Loan-quarter observations	373,969	712,313	1,673,147	130,154	273,943	716,874
as % of ITM loan-quarter obs	9.6	18.4	43.1	3.4	7.1	18.5
C. ITM sample by capConstr and borrower income at origination	Unconstrained Market			Constrained Market		
	Low	Moderate	Mid-High	Low	Moderate	Mid-High
Prepaid by next quarter (%)	3.4	4.6	6.6	4.3	6.2	9.3
Ratio of note to adj. mkt rate (mean)	1.3	1.3	1.3	1.4	1.4	1.3
% with ratio [1.1, 1.3)	62.9	66.9	72.3	36.3	41.2	48.0
% with ratio >= 1.3	37.1	33.1	27.7	63.7	58.8	52.0
County loan processing days (mean)	59.9	60.4	61.5	74.6	75.1	76.0
County unemployment rate (%)	5.3	5.3	5.5	7.5	7.6	7.8
Loan-quarter observations	246,214	589,431	1,923,784	91,114	229,484	800,373
as % of ITM loan-quarter obs	6.3	15.2	49.6	2.3	5.9	20.6
D. ITM sample by capConstr and current credit score	Unconstrained Market			Constrained Market		
	620-659	660-699	700+	620-659	660-699	700+
Prepaid by next quarter (%)	5.8	5.5	5.9	6.0	6.4	8.5
Ratio of note to adj. mkt rate (mean)	1.2	1.3	1.3	1.3	1.3	1.4
% with ratio [1.1, 1.3)	77.5	74.1	69.7	63.0	54.3	44.3
% with ratio >= 1.3	22.5	25.9	30.3	37.0	45.7	55.7
County loan processing days (mean)	61.1	61.0	61.1	75.7	75.4	75.7
County unemployment rate (%)	5.4	5.5	5.5	7.7	7.7	7.7
Loan-quarter observations	78,926	220,217	2,460,286	33,740	87,718	999,513
as % of ITM loan-quarter obs	2.0	5.7	63.4	0.9	2.3	25.8

Notes: Current UPB (unpaid principal balance) and credit score are based on the observed value as of quarter t. Borrower income at origination is expressed relative to the area median family income (AMFI); Low income means the borrower's income is less than 50% of AMFI (moderate: [50-80%); middle-high: 80% or more). "Ratio of note to adj. mkt rate" is the note rate divided by the current market rate, where the market rate is the average prime rate on a 30 year conventional mortgage, adjusted to reflect Fannie Mae's loan level pricing adjustment based on the borrower's current credit score and LTV. The "ITM sample" includes observations where the ratio of the note rate to adjusted market rate is 1.1 or higher, i.e., where the refinance option value is in the money. "Constrained market" includes observations in county-quarters categorized as capacity-constrained. County loan processing days is the 75th percentile value of the number of days between the origination date and application date for first-lien single family refinance loan applications in the county-quarter, computed from restricted-access HMDA data.

Table 2: Sample means for other control variables (loan-level)

		Capacity Constraint	
	All	Yes	No
Count of unique loans	626,418	441,422	610,834
Unpaid principal balance (*t*)			
< $90k	9.2	9.3	9.2
$90-150k	19.7	20.8	19.8
$150k+	71.2	69.8	71.0
Borrower income (*t*=0)			
Low	6.5	6.9	6.5
Moderate	18.5	19.2	18.6
Middle-High	75.0	73.9	74.9
Credit Score (*t*)			
620-659	6.6	4.6	6.5
660-699	9.6	8.8	9.7
700+	83.8	86.5	83.8
Loan purpose (*t*=0)			
Purchase	48.8	46.2	49.1
Refi - not cash out	44.9	46.7	44.7
Refi - cash out	6.4	7.1	6.3
Loan-to-value (*t*)			
< 70	62.5	57.9	62.2
70-79	21.5	22.1	21.5
80-89	11.4	14.2	11.7
90-97	3.1	3.3	3.3
97+	1.4	2.4	1.3
Debt-to-income (*t*=0)			
< 34	47.0	49.3	47.0
34-38	16.6	16.2	16.6
39-43	17.7	16.7	17.7
44-48	12.4	11.5	12.4
49+	5.9	6.0	5.9
unknown	0.3	0.3	0.3
Spread (bps) at origination (*t*=0)			
50+	16.7	15.4	16.6
25 to 49	24.1	23.0	24.1
-25 to 24	51.2	52.4	51.2
< -25	8.1	9.2	8.1
Race and Ethnicity (*t*=0)			
Black	3.8	3.8	3.8
Hispanic (non-black)	8.5	7.8	8.5
Asian (non-Hispanic)	6.9	6.5	6.8
Other (non-Hispanic)	1.6	1.5	1.5
White (non-Hispanic)	79.2	80.4	79.2
First-time homebuyer (*t*=0)	23.1	22.3	23.3
Cumulative quarters ITM (*t*)	6.2	5.9	6.0

Notes: This table presents loan-level sample means of other selected variables, using the last quarterly observation for each loan, whether it was still active, prepaid, or terminated for another reason. Variables labeled with "(*t*)" may vary across loan quarters, while "(t=0)" indicates the variable is observed only in (and does not vary subsequently to) the quarter of origination. Count of unique loans in the "Yes" and "No" capacity constraint columns does not sum to the total number of unique loans because many loans are active in at least one capacity-constrained and unconstrained quarter. Spread at origination is the difference (in basis points) between the note rate and the average prime rate available when the loan was originated. See Table 1 for additional notes.

Table 3: Effects of capacity constraints on probability of prepayment, by refinance option value and borrower type

	Refinance Option Value			
	Not ITM	Barely ITM	ITM	Very ITM
	(1)	(2)	(3)	(4)
A. Current unpaid principal balance				
< $90k	-0.997***	-0.909***	-0.836***	-0.777***
	(0.105)	(0.078)	(0.064)	(0.063)
$90-150k	-1.045***	-0.625***	-0.272***	0.013
	(0.065)	(0.047)	(0.044)	(0.051)
$150k+	-0.310***	0.569***	1.234***	1.685***
	(0.045)	(0.034)	(0.039)	(0.046)
B. Borrower income at origination				
Low	-0.983***	-0.776***	-0.613***	-0.494***
	(0.098)	(0.074)	(0.068)	(0.074)
Moderate	-0.995***	-0.587***	-0.248***	0.020
	(0.074)	(0.050)	(0.052)	(0.062)
Middle-High	-0.093	0.527***	0.997***	1.316***
	(0.067)	(0.040)	(0.046)	(0.053)
C. Current credit score				
620-659	-0.832***	-0.688***	-0.594***	-0.550***
	(0.096)	(0.103)	(0.126)	(0.154)
660-699	-0.501***	-0.347***	-0.231***	-0.151
	(0.084)	(0.069)	(0.083)	(0.102)
700+	-0.110*	0.387***	0.764***	1.021***
	(0.062)	(0.037)	(0.038)	(0.044)

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 1, with errors clustered at loan-level. The estimation sample includes 7,369,942 loan-quarter observations and 626,418 unique loans. Each panel presents results from a separate regression in which the capacity constraint indicator is interacted with a quadratic of the current refinance option value and a categorical variable for: (A) Current unpaid principal balance; (B) borrower income at origination; and (C) Current credit score. In columns (1) to (4) the capacity constraint effect is evaluated at a refinance option value of 1.0 ("Not ITM"), 1.1 ("Barely ITM"), 1.2 ("ITM"), and 1.3 (“Very ITM”), respectively, where ITM stands for “in the money”. Coefficient estimates on all other control variables are provided in Table A1.

Table 4: Effects of capacity constraints on the probability of prepayment by borrower type; limit sample to "in-the-money spells"

Dependent variable	1[Prepay]
A. Current unpaid principal balance	
< $90k	-1.545***
	(0.068)
$90-150k	-0.487***
	(0.057)
$150k+	1.321***
	(0.050)
B. Borrower income at origination	
Low	-1.081***
	(0.081)
Moderate	-0.365***
	(0.063)
Middle-High	0.941***
	(0.047)
C. Current credit score	
620-659	-0.949***
	(0.157)
660-699	-0.484***
	(0.098)
700+	0.654***
	(0.043)

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 2, with errors clustered at loan-level. The estimation sample includes 3,880,400 loan-quarter observations and 498,740 unique loans. Each panel presents results from a separate regression in which the capacity constraint indicator is interacted with a categorical variable for: (A) current unpaid principal balance; (B) borrower income at origination; and (C) current credit score. The specifications include the full set of control variables detailed in Table A-1; coefficient estimates available upon request.

Table 5: Effects of capacity constraints on probability of prepayment by borrower type, additional sample restrictions

Specification	(1)	(2)	(3)	(4)	(5)
A. Current unpaid principal balance					
< $90k	-0.836***	-0.893***	-0.943***	-1.046***	-1.058***
	(0.064)	(0.081)	(0.097)	(0.110)	(0.114)
$90-150k	-0.272***	-0.264***	-0.251***	-0.233***	-0.213**
	(0.044)	(0.059)	(0.068)	(0.081)	(0.084)
$150k+	1.234***	1.054***	1.107***	1.312***	1.419***
	(0.039)	(0.053)	(0.061)	(0.072)	(0.076)
B. Borrower income at origination					
Low	-0.613***	-0.609***	-0.593***	-0.587***	-0.605***
	(0.068)	(0.093)	(0.112)	(0.128)	(0.132)
Moderate	-0.248***	-0.407***	-0.348***	-0.355***	-0.265***
	(0.052)	(0.070)	(0.083)	(0.095)	(0.101)
Middle-High	0.997***	0.766***	0.813***	0.868***	0.943***
	(0.046)	(0.060)	(0.074)	(0.070)	(0.075)
C. Current credit score					
620-659	-0.594***	-0.686***	-0.775***	-1.166***	
	(0.126)	(0.179)	(0.275)	(0.366)	
660-699	-0.231***	-0.440***	-0.447***	-0.657***	-0.584**
	(0.083)	(0.121)	(0.169)	(0.213)	(0.249)
700+	0.764***	0.517***	0.553***	0.608***	0.626***
	(0.038)	(0.050)	(0.060)	(0.056)	(0.059)
Number of observations	7,369,942	6,139,362	4,796,096	3,785,200	3,467,169
Sample restrictions					
Analysis period	2010-2021	2013 - 2021	2013 - 2021	2013 - 2021	2013 - 2021
LTV measure	First-lien	First-lien	Combined	Combined	Combined
Drop if ever DQ on any tradeline	N	N	Y	Y	Y
Drop if CLTV > 80	N	N	N	Y	Y
Drop if credit score < 660	N	N	N	N	Y

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 1, estimated on increasingly restrictive sample filters to retain only the most presumptively creditworthy borrowers. All effects are evaluated at refiVal = 1.2 (i.e., in the money). Estimates of other controls are omitted for brevity. Errors are clustered at loan-level. The first column reproduces the estimates in Table 3, column (3) to facilitate comparison. In the second column we restrict the sample to prepayments made between 2013 and 2021; data on borrowers' other credit obligations are available in the NMDB in years 2013+. In column 3 we include a control for combined LTV (in place of first-lien LTV) and drop any borrower reported as more than 30 days delinquent on any trade line reported to the credit bureaus. In the fourth column we further remove loan quarters where the borrower's combined LTV exceeds 80 percent, and in the fifth column we filter out loan quarters after (and including) the first quarter in that the borrower's credit score falls below 660, if any.

Table 6: Effects of capacity constraints on inquiries for new mortgage credit, by borrower type

Dependent Variable	Credit Inquiry (1)	Credit Inquiry (2)	Credit Inquiry (3)	Credit Inquiry (4)	Credit Inquiry (5)
A. Current unpaid principal balance					
< $90k	-0.611***	-1.327***	-1.223***	-1.358***	-1.25***
	(0.071)	(0.071)	(0.094)	(0.078)	(0.104)
$90-150k	-0.180***	-0.431***	-0.521***	-0.519***	-0.426***
	(0.053)	(0.063)	(0.078)	(0.067)	(0.083)
$150k+	1.816***	1.856***	1.794***	1.836***	1.793***
	(0.045)	(0.055)	(0.067)	(0.058)	(0.065)
B. Borrower income at origination					
Low	-0.514***	-0.979***	-0.968***	-1.101***	-0.988***
	(0.084)	(0.092)	(0.119)	(0.103)	(0.120)
Moderate	-0.050	-0.153**	-0.188**	-0.216***	-0.062
	(0.061)	(0.070)	(0.091)	(0.076)	(0.090)
Middle-High	1.545***	1.408***	1.380***	1.382***	1.54***
	(0.044)	(0.051)	(0.061)	(0.054)	(0.063)
C. Current credit score					
620-659	0.245	-0.172	0.048	-0.009	-0.253
	(0.166)	(0.204)	(0.267)	(0.221)	(0.278)
660-699	0.464***	0.131	0.182	0.094	0.226
	(0.106)	(0.124)	(0.162)	(0.133)	(0.169)
700+	1.154***	0.983***	0.987***	0.981***	1.079***
	(0.038)	(0.046)	(0.054)	(0.049)	(0.055)
Number of observations	5,824,762	3,148,498	1,696,925	2,781,916	1,784,450
Mean, Outcome Variable	4.8	6.9	6.7	6.8	7.3
Sample	Full	ITM	ITM	ITM	ITM
Restrictions	None	None	Refis Only	Middle-Upper Income Tracts only	High Economic Connectedness

Notes: This table presents marginal effects of capacity constraints on the probability of having an inquiry for new mortgage credit (i.e. hard credit checks), computed from OLS regressions with errors clustered at loan-level. Column 1 shows the effects calculated from estimating equation (1) on the Full NMDB sample, evaluated at refiVal = 1.2 (i.e., in the money). Columns 2 to 5 show effects calculated from estimating equation (2) on different cuts of the ITM sample as described in the "Restrictions" row. In column 5 we filter the sample to counties with above median "Economic Connectedness", as measured by Chetty et al. (2022). In all cases we drop loan-quarter observations subsequent to the first instance of a mortgage credit inquiry. Estimates of the other control variables are omitted for brevity.

Table 7: Effects of capacity constraints on loan pricing, by borrower type

Dependent variable	Interest rate (bps)	Rate spread (bps)	Rate spread as % of APOR
	(1)	(2)	(3)
A. Loan Amount (omitted category: >= $150k)			
1(capConstr) * 1(< $90k)	-6.175***	-7.016***	-0.411***
	(0.155)	(0.160)	(0.052)
1(capConstr) * 1($90-150k)	-1.969***	-2.044***	0.021
	(0.071)	(0.073)	(0.024)
1(capConstr)	2.843***	3.408***	1.005***
	(0.031)	(0.032)	(0.010)
1(< $90k)	20.636***	31.208***	9.177***
	(0.121)	(0.125)	(0.041)
1($90-150k)	9.388***	14.117***	4.276***
	(0.058)	(0.060)	(0.020)
B. Borrower income (omitted category: Middle-High)			
1(capConstr) * 1(Low income)	-1.630***	-2.011***	-0.189***
	(0.092)	(0.095)	(0.031)
1(capConstr) * 1(Moderate income)	-0.492***	-0.514***	0.100***
	(0.054)	(0.056)	(0.018)
1(capConstr)	2.720***	3.288***	0.992***
	(0.032)	(0.033)	(0.011)
1(Low income)	0.679***	3.523***	0.938***
	(0.075)	(0.078)	(0.025)
1(Moderate income)	0.367***	2.061***	0.554***
	(0.043)	(0.044)	(0.014)
C. Borrower credit score (omitted category: 700+)			
1(capConstr) * 1(620 to 659)	-3.869***	-4.160***	0.487***
	(0.134)	(0.138)	(0.045)
1(capConstr) * 1(660 to 699)	-2.490***	-3.017***	0.144***
	(0.072)	(0.075)	(0.024)
1(capConstr)	2.884***	3.485***	0.973***
	(0.031)	(0.032)	(0.010)
1(620 to 659)	35.550***	39.512***	11.962***
	(0.096)	(0.099)	(0.032)
1(660 to 699)	20.245***	23.857***	7.296***
	(0.053)	(0.055)	(0.018)
Mean of dependent variable	322.1	11.6	3.8

Notes: Analysis of HMDA data on first lien, closed-end, conventional conforming, 30 year term, fixed-rate, fully amortizing, non-cash out refinance loan applications on owner occupied, site-built 1-4 family properties from March 2018 to September 2021 that resulted in an origination; 4,982,388 observations in total. The capacity constraint indicator is computed at lender-month level; see the data appendix for details. In panels A, B, and C the effects of capacity constraints are allowed to vary by loan amount, income, and credit score, respectively. In column 1 the dependent variable is the interest rate on the loan, in basis points (bps). In column 2 the dependent variable is the difference between the rate on the loan and the average prime offer rate (APOR). In column 3 the dependent variable is the rate spread expressed as a percentage of the APOR. All specifications include controls for net points paid at closing, loan amount, borrower income, credit score, combined LTV, DTI, race/ethnicity, and fixed effects for county, application month, and lender.

Table 8: Effects of capacity constraints on lenders' processing of refinance loan applications by borrower type

Dependent variable	1[Incomplete]	1[Denied for underwriting]	Application processing days
	(1)	(2)	(3)
A. Loan Amount (omitted category: >= $150k)			
1(capConstr) * 1(< $90k)	1.250***	0.908***	3.337***
	(0.153)	(0.139)	(0.200)
1(capConstr) * 1($90-150k)	0.661***	0.142**	1.775***
	(0.076)	(0.069)	(0.090)
1(capConstr)	1.280***	0.384***	9.624***
	(0.037)	(0.034)	(0.042)
1(< $90k)	1.256***	-0.662***	-0.157
	(0.101)	(0.092)	(0.131)
1($90-150k)	0.880***	-2.691***	-0.689***
	(0.053)	(0.048)	(0.062)
B. Borrower income (omitted category: Middle-High)			
1(capConstr) * 1(Low income)	2.143***	-0.976***	0.832***
	(0.088)	(0.080)	(0.117)
1(capConstr) * 1(Moderate income)	-0.262***	0.151***	0.479***
	(0.061)	(0.055)	(0.069)
1(capConstr)	1.263***	0.476***	9.735***
	(0.039)	(0.035)	(0.043)
1(Low income)	1.795***	18.541***	-0.532***
	(0.061)	(0.055)	(0.080)
1(Moderate income)	0.686***	4.989***	-1.048***
	(0.039)	(0.036)	(0.045)
C. Borrower credit score (omitted category: 700+)			
1(capConstr) * 1(620 to 659)		6.219***	1.373***
		(0.102)	(0.181)
1(capConstr) * 1(660 to 699)		1.308***	0.768***
		(0.073)	(0.096)
1(capConstr)		-0.150***	9.774***
		(0.034)	(0.042)
1(620 to 659)		30.846***	4.502***
		(0.063)	(0.104)
1(660 to 699)		7.667***	3.575***
		(0.044)	(0.057)
Sample	All applications	All applications	Originations
Number of observations	6,288,436	6,288,436	4,982,388
Mean of dependent variable	11.6	8.3	52.4

Notes: Analysis of HMDA data on first lien, closed-end, conventional conforming, 30 year term, fixed-rate, fully amortizing, non-cash out refinance loan applications on owner occupied, site-built 1-4 family properties from March 2018 to September 2021. Capacity constraints are measured at lender-month level; see data appendix for details. In panels A, B, and C the effects of capacity constraints are allowed to vary by loan amount, income, and credit score, respectively. Column 1 shows the estimated effects of capacity constraints on the probability that an application is closed or denied for incompleteness (action code = 5 or denial reason code = 7). Borrower credit scores are not reported for loan applications that the lender designates as incomplete. Column 2 shows the effects on the probability that the application is denied for underwriting reasons (denial reason code = 1,2,3,4,5, or 6). Column 3 shows the effects on the number of application processing days; in this column the sample is limited to loan applications that result in an origination. All specifications include controls for loan amount, borrower income, race/ethnicity, and fixed effects for county, application month, and lender. The specification in column 3 also includes controls for net points paid at closing, combined LTV, and DTI.

DATA APPENDIX

In supplemental analyses of whether capacity constraints affect lenders' loan pricing and loan processing and underwriting behavior (described in section 6.B and 6.C), we use data collected under the Home Mortgage Disclosure Act (HMDA) and reported in years 2018 through 2021.

We construct our lender-month level indicator of capacity constraints as follows. First, we filter the HMDA data to first-lien conventional refinance loan originations on owner-occupied, 1-4 family, site-built properties. We further limit the sample to loan applications filed between December 2017 and September 2021 and for each of these applications, we compute the number of processing days by taking the difference (in days) of the loan origination date and loan application date.[54] For each lender-month in the data, we compute the 75th percentile of loan application processing days using applications received over the preceding three months.[55] We then construct a binary indicator for each lender-month equal to one if the 75th percentile value of application processing days exceeds 110 percent of the lenders' average 75th percentile value of application processing days over the sample. Appendix Figure A-6 summarizes the share of lenders in our sample categorized as capacity constrained, by application month. The figure shows that, following the spike in refinance applications beginning in March of 2020, the share of lenders categorized as capacity constrained increases to over 80 percent, compared to less than 10 percent over the 2018-19 period.

We merge our lender-month level indicators of capacity constraints into loan-level HMDA data on first lien, closed-end, conventional conforming, 30 year term, fixed-rate, fully amortizing, non-cash-out refinance loan applications on owner occupied, site-built 1-4 family properties. We limit the sample to applications filed from March 2018 through September 2021 (the months we observe our lender-level capacity constraint indicator). For the loan pricing analysis presented in Table 7, we limit the data to loan originations, as loan pricing is not observed on applications that did not result in an origination. For our analysis of loan

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[54] We drop loan applications filed in months after September 2021 to deal with potential right-censoring in HMDA reporting when computing the number of processing days. For each reporting year in HMDA, lenders report all loan applications on which the action taken (e.g., loan originated; application denied) occurs within the same calendar year. Thus, loan applications filed in October 2021 or later and still in-process as of year-end 2021 are not included in the 2021 HMDA reporting year. We exclude loan applications filed prior to December 2017 for the analogous left-censoring issue.

[55] For example, for a given lender in September 2021, we compute the 75th percentile of application processing days using applications received by that lender between June and August 2021 (and that resulted in an origination). We drop lender-months with less than 30 applications received over the preceding three months.

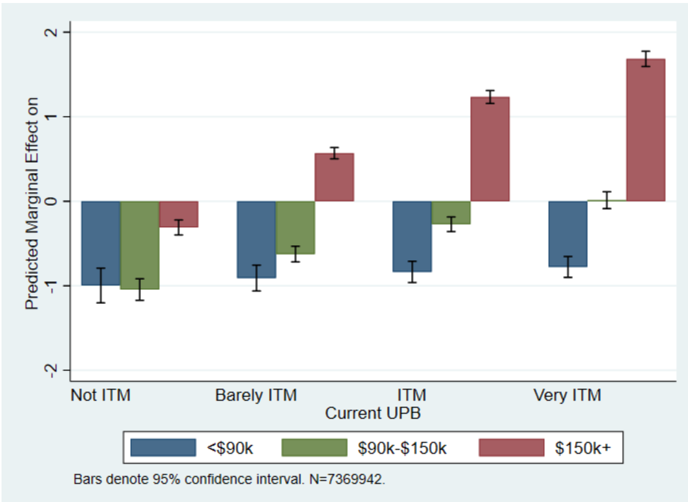
applications being closed for incompleteness or denied for underwriting reasons (Table 8, columns 1 and 2), we limit the sample to loan applications on which the lender made an underwriting determination or closed the loan for incompleteness.[56] For our analysis of application processing days (Table 8, column 3), we limit the sample to applications that resulted in an origination.

Appendix Table A-4 presents sample means for the variables included in the 4.98 million observations used in our pricing analysis and the 6.29 million observations used in our analysis of loan processing and underwriting decisions. Certain fields are not observed in HMDA for loan applications that don't result in an origination, namely credit score, combined loan-to-value, debt-to-income ratio, interest rate, and closing costs (used to calculate net points at origination). These fields are not included as control variables in the specifications we use to analyze loan processing and underwriting outcomes.

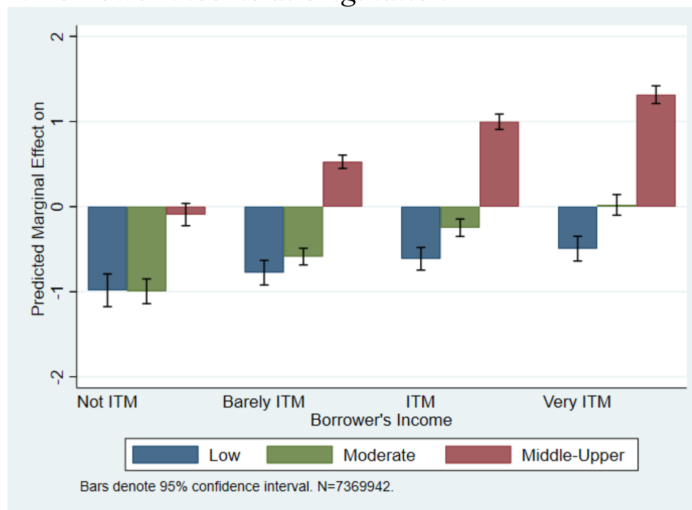
[56] Specifically, for the loan processing and underwriting analysis we retain loan applications with action codes: (1) loan originated; (2) approved but not accepted; (3) denied; and (5) File closed for incompleteness. We categorize an application as closed for incompleteness if the action code is equal to 5 or if the application is denied for reason code 7 (Credit application incomplete).

Appendix Figure A-1: Predicted marginal effects of capacity constraints on prepayment

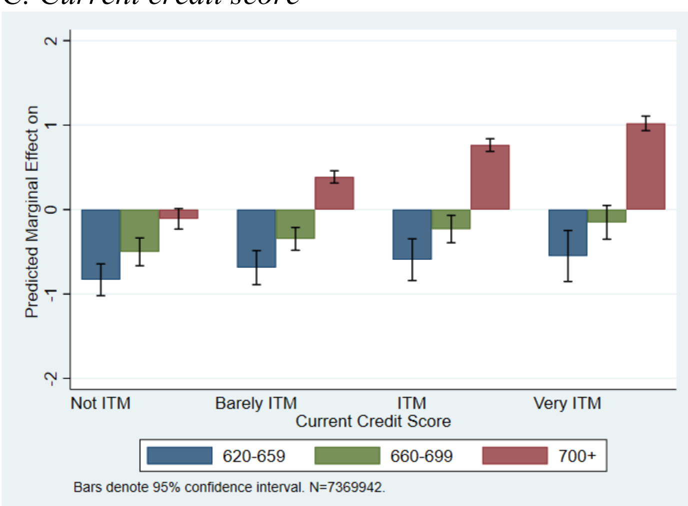
A. Current unpaid principal balance



B. Borrower income at origination



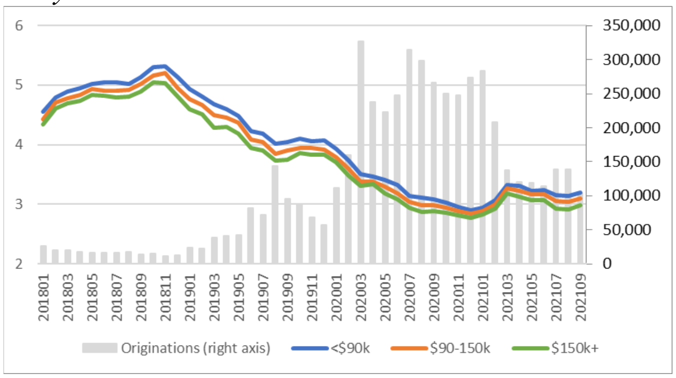
C. Current credit score



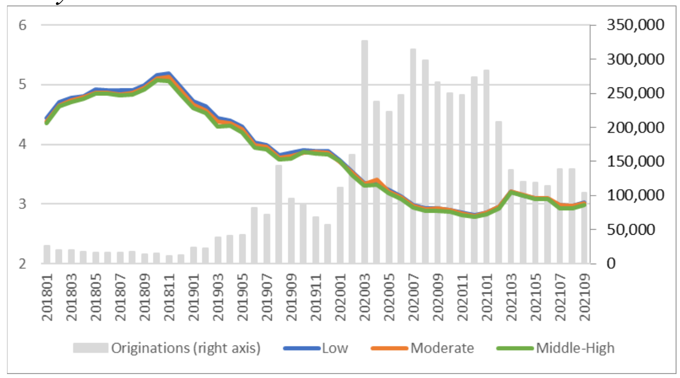
Notes: These figures provide a graphical depiction of the estimates presented in Table 3. The bars illustrate the estimated marginal effects of capacity constraints on the quarterly probability of prepayment (with 95 percent confidence intervals), separately by borrower characteristics and evaluated at different values of the borrower's refinance option. The refinance option value is set to 1.0 for "Not ITM", 1.1 for "Barely ITM", 1.2 for "ITM", and 1.3 for "Very ITM", respectively, where ITM stands for "in the money". See Table 3 for additional notes.

Appendix Figure A-2: Average interest rate on refinance loan originations, by application month and borrower type

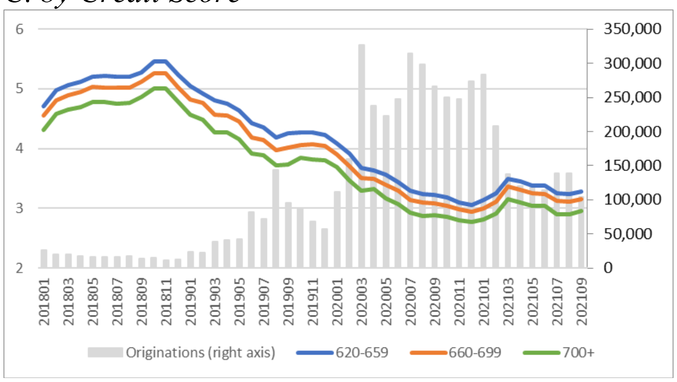
A. by Loan Amount



B. by Borrower Income



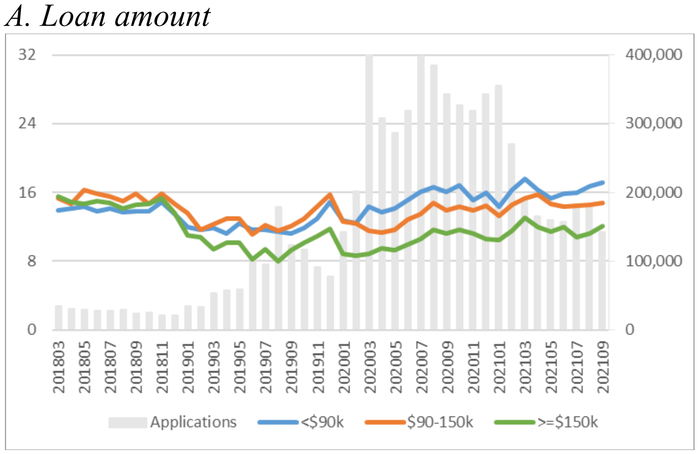
C. by Credit Score



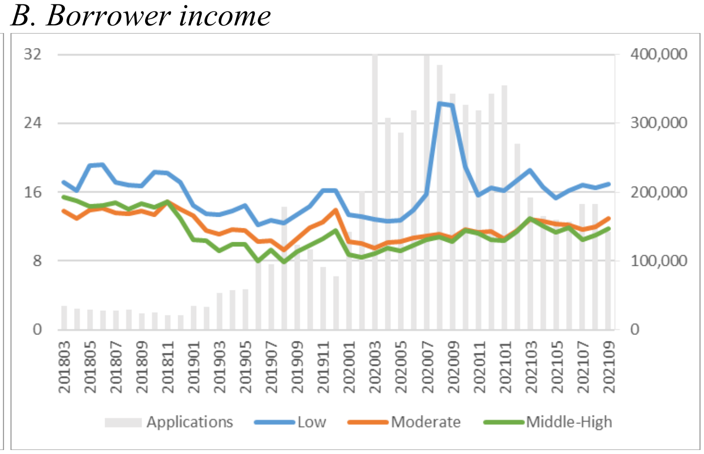
Notes: Analysis of HMDA data on first lien, closed-end, conventional conforming, 30 year term, fixed-rate, fully amortizing, non-cash out refinance loan originations on owner occupied, site-built 1-4 family properties from March 2018 to September 2021 that resulted in an origination; 4,982,388 observations in total. These figures show how various measure of pricing vary by borrower group and with the amount of refinancing activity.

Appendix Figure A-3: Share (%) of refinance loan applications closed or denied for incompleteness, by application month and borrower type

A. Loan amount



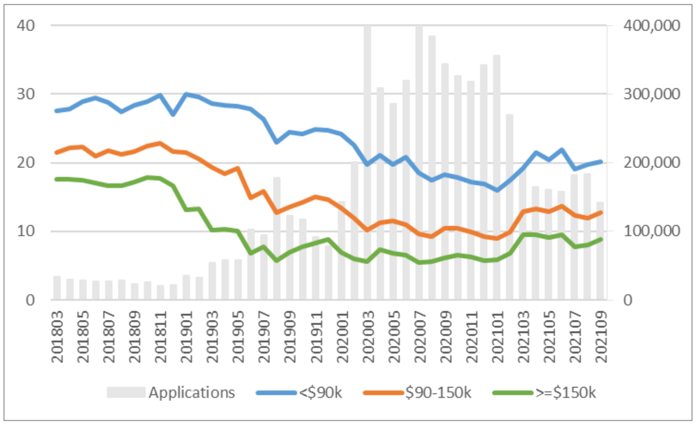
B. Borrower income



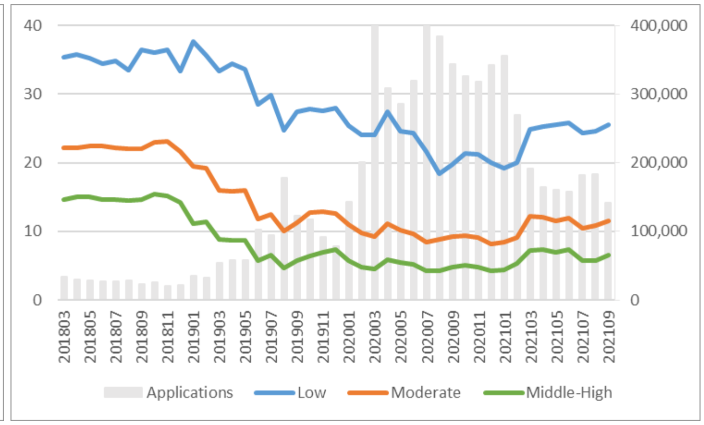
Notes: Authors' calculations using HMDA data on first lien, closed-end, conventional conforming, 30 year term, non-cash out refinance loan applications on owner occupied, site-built properties from March 2018 to September 2021. The figure shows the share of loan applications the lender "Closed for incompleteness" (action code = 5) or denied for reason "Credit application incomplete" (denial reason code = 7). Borrowers are categorized by loan amount and income in panels A and B, respectively. Borrower credit scores are not reported for loan applications the lender designates as incomplete.

Appendix Figure A-4: Share (%) of completed refinance loan applications denied for underwriting reasons, by application month and borrower type

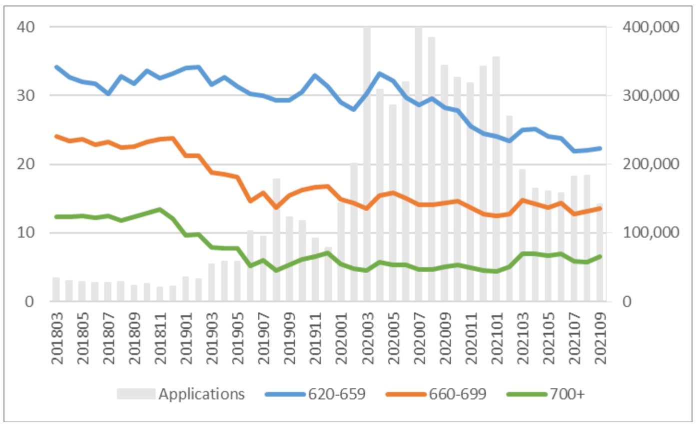
A. Loan amount



B. Borrower income



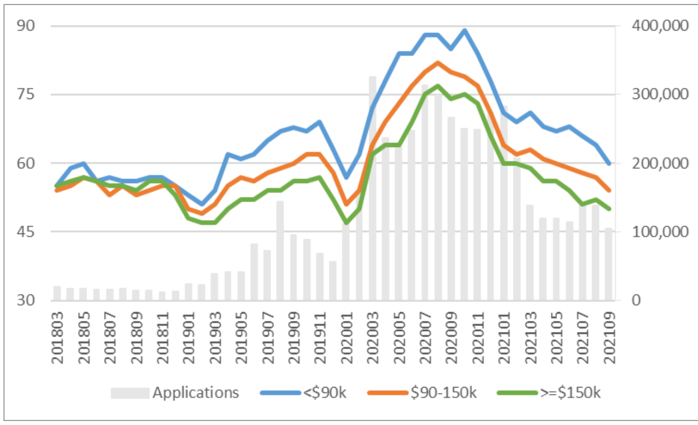
C. Credit score



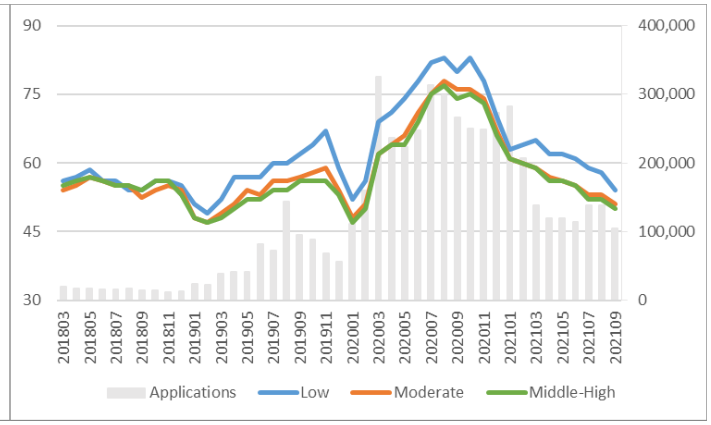
Notes: Authors' calculations using HMDA data on first lien, closed-end, conventional conforming, 30 year term, non-cash out refinance loan applications on owner occupied, site-built properties from March 2018 to September 2021. This figure shows the share of loan applications that are denied by the lender for any of the following reasons: (1) Debt-to-income ratio; (2) Employment history; (3) Credit history; (4) Collateral; (5) Insufficient cash (downpayment, closing costs); or (6) "Unverifable information". Borrowers are categorized by loan amount, income, and credit score in panels A, B, and C, respectively.

Appendix Figure A-5: Number of days to process refinance loan applications by application month and borrower type

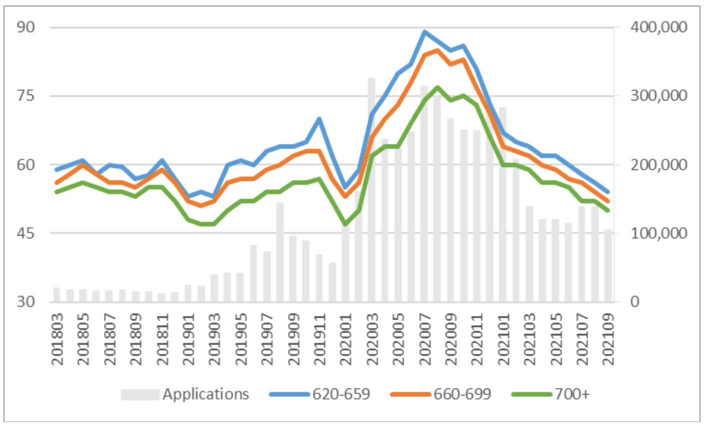
A. Loan amount



B. Borrower income

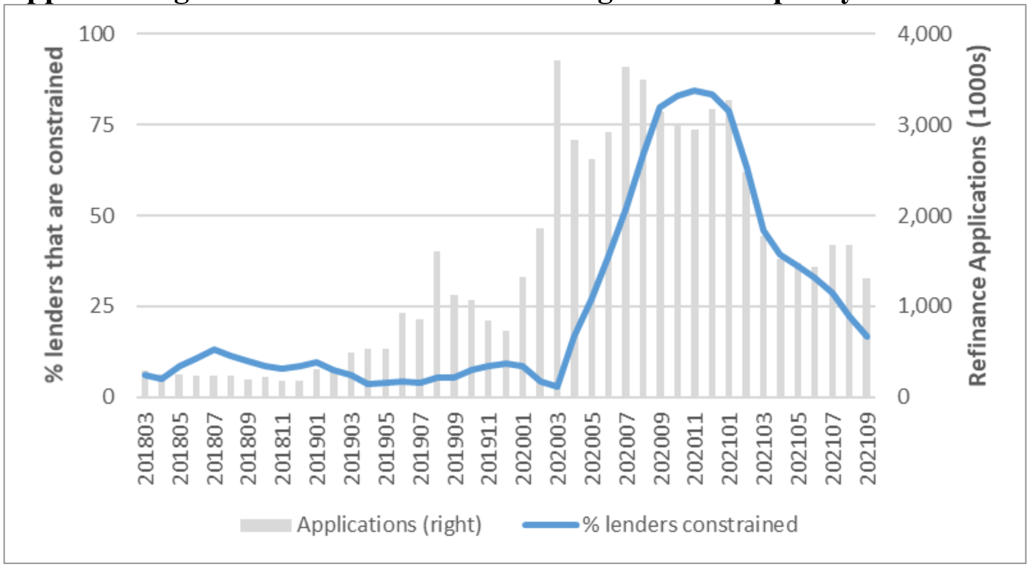


C. Credit score



Notes: Authors' calculations using HMDA data on first-lien conventional loan originations on owner occupied, 1-4 family site-built properties. This set of figures shows the 75th percentile of application processing days (defined as the number of days between the origination date and application date) by application month, for borrowers categorized by loan amount, income, and credit score in panels A, B, and C, respectively.

Appendix Figure A-6: Share of lenders categorized as capacity constrained by application month



Notes: Authors' calculations using HMDA data on first-lien conventional refinance loan originations on owner-occupied, 1-4 family, site-built properties. See the Data Appendix for details on how we construct our lender-month level indicator of capacity constraints.

Table A-1: OLS Estimates of Main Specification, control variable estimates

Borrower Group	Current Unpaid Principal Balance	Borrower Income at Origination	Current Credit Score
	(1)	(2)	(3)
CS: 620-659	1.152***	1.114***	4.602***
	(0.036)	(0.037)	(1.155)
CS: 660-699	0.406***	0.392***	4.066***
	(0.026)	(0.026)	(0.934)
Low (less than 0.5)	-1.785***	14.933***	-1.786***
	(0.031)	(1.046)	(0.032)
Moderate (0.5 to 0.8)	-1.144***	8.326***	-1.120***
	(0.021)	(0.981)	(0.021)
UPB: <$90k	19.602***	-1.401***	-1.447***
	(0.504)	(0.032)	(0.032)
UPB: $90k-$150k	15.750***	-1.345***	-1.307***
	(0.417)	(0.021)	(0.021)
refiVal	29.178***	27.800***	26.514***
	(0.551)	(1.543)	(1.271)
refiVal^2	-5.849***	-5.887***	-5.737***
	(0.249)	(0.659)	(0.533)
Cumulative Qtrs ITM	-0.003	-0.010***	-0.015***
	(0.002)	(0.002)	(0.002)
LTV: 70-79	0.501***	0.528***	0.497***
	(0.021)	(0.021)	(0.021)
LTV: 80-89	-0.194***	-0.144***	-0.180***
	(0.025)	(0.025)	(0.025)
LTV: 90-97	-1.068***	-0.999***	-1.022***
	(0.032)	(0.031)	(0.031)
LTV: 97+	-2.220***	-2.138***	-2.115***
	(0.040)	(0.039)	(0.039)
DTI: 34-38	0.298***	0.291***	0.295***
	(0.022)	(0.022)	(0.022)
DTI: 39-43	0.309***	0.305***	0.316***
	(0.023)	(0.023)	(0.023)
DTI: 44-48	0.341***	0.360***	0.373***
	(0.027)	(0.027)	(0.027)
DTI: 49+	-0.053	0.025	0.036
	(0.035)	(0.034)	(0.034)
DTI: unknown	-0.364***	-0.317***	-0.285**
	(0.112)	(0.107)	(0.111)

Table A-1 [continued]

Borrower Group	Current Unpaid Principal Balance (1)	Borrower Income at Origination (2)	Current Credit Score (3)
Spread: 50bps+	-2.145***	-2.103***	-2.041***
	(0.036)	(0.036)	(0.036)
Spread: 25-49bps	-1.200***	-1.141***	-1.123***
	(0.032)	(0.033)	(0.033)
Spread: -25-25bps	-0.717***	-0.694***	-0.683***
	(0.029)	(0.029)	(0.029)
County unemployment	0.333***	0.349***	0.349***
	(0.005)	(0.005)	(0.005)
Purpose: Refi - not cash out	-0.366***	-0.355***	-0.349***
	(0.021)	(0.021)	(0.021)
Purpose: Refi - cash out	0.023	0.020	0.011
	(0.035)	(0.035)	(0.035)
Black	-1.105***	-1.093***	-1.084***
	(0.038)	(0.038)	(0.038)
Hispanic (non-black)	-0.746***	-0.734***	-0.735***
	(0.030)	(0.030)	(0.030)
Asian (non-hispanic)	0.506***	0.472***	0.461***
	(0.037)	(0.036)	(0.036)
Other (non-hispanic)	0.459***	0.482***	0.490***
	(0.081)	(0.080)	(0.080)
First-time homebuyer	-0.398***	-0.394***	-0.384***
	(0.023)	(0.023)	(0.023)
Loan-Quarter	0.128***	0.123***	0.117***
	(0.001)	(0.001)	(0.001)
Loan age	0.449***	0.461***	0.470***
	(0.005)	(0.005)	(0.005)
(Loan age)^2	-0.220***	-0.217***	-0.220***
	(0.003)	(0.004)	(0.004)
(Loan age)^3	0.024***	0.022***	0.022***
	(0.001)	(0.001)	(0.001)
Constant	-32.162***	-30.365***	-28.655***
	(0.326)	(0.911)	(0.765)
R-squared	0.029	0.028	0.027

Notes: This table presents estimates of the control variables from OLS regressions of Equation 1, with errors clustered at loan-level. The estimation sample includes 7,369,942 loan-quarter observations and 626,418 unique loans. Each column presents results from a different specification, where the capacity constraint indicator is interacted with the categorical borrower group indicated in the column title. In every case the dependent variable is an indicator that the loan was prepaid by the end of the next quarter. See Table 3 for additional notes.

Table A-2: Effect of capacity constraint on P[prepay] when varying the measure of the borrower's financial incentive to refinance

Measure of Refinance Incentive	Int. Rate Ratio - LLPA Adj	Int. Rate Ratio - Not Adj	Call Option	Refi Threshold
	(1)	(2)	(3)	(4)
A. Current unpaid principal balance ($1000s)				
<90	-0.713***	-0.836***	-0.811***	0.581***
	(0.067)	(0.064)	(0.069)	(0.065)
[90,150)	-0.370***	-0.272***	-0.221***	0.089*
	(0.044)	(0.044)	(0.047)	(0.046)
120 or more	0.863***	1.234***	1.439***	1.504***
	(0.034)	(0.039)	(0.037)	(0.039)
B. Borrower income (as % of area median income)				
Low (< 50)	-0.596***	-0.613***	-0.529***	-0.157**
	(0.070)	(0.068)	(0.072)	(0.071)
Moderate [50,80)	-0.389***	-0.248***	-0.134***	0.164***
	(0.049)	(0.052)	(0.052)	(0.060)
Middle (80 or more)	0.733***	0.997***	1.222***	1.294***
	(0.042)	(0.046)	(0.034)	(0.034)
C. Current credit score				
620-659	-0.916***	-0.594***	-0.475***	-0.363***
	(0.098)	(0.126)	(0.113)	(0.123)
660-699	-0.425***	-0.231***	-0.008	0.070
	(0.071)	(0.083)	(0.078)	(0.095)
700 or more	0.573***	0.764***	0.960***	1.161***
	(0.036)	(0.038)	(0.031)	(0.032)

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 1 on the main analysis sample (7,369,942 observations), with errors are clustered at the loan-level. Estimates of other controls are omitted for brevity. The panels are analogous to those in Table 3. The columns report results from separate specifications that use alternative measures of the borrower's incentive to refinance. The first column reproduces the main results from column 3 of Table 3, using the ratio of the note rate to the adjusted market rate and evaluating the marginal effects at refiVal = 1.2. The second column uses the ratio of the note rate to the current prime rate without adjusting for the borrower-specific GSE loan level pricing adjustment (LLPA), evaluating effects at refiVal = 1.2. The third column uses the call option measure from Deng, Quigley, and Van Order (2000) with the refiVal evaluated at a value of 6. The fourth column uses the refinance threshold of Agarwal, Driscoll, and Laibson (2013), calculated using their "square-root rule" and suggested parameter values (including a discount rate of 5 percent, a 28 percent marginal tax rate, and a 10 probability of moving each year), and with the refiVal evaluated at -0.2. In both the third and fourth columns we use the LLPA-adjusted market rate when calculating the refinance incentive.

Appendix Table A-3: Effect of capacity constraint on P[prepay] when varying the capacity constraint measure

Capacity Constraint Measure	75th Pctl of App Processing Days	50th Pctl of App Processing Days	90th Pctl of App Processing Days	High Share of Incomplete Apps	75th Pctl of Incomplete Apps
	(1)	(2)	(3)	(4)	(5)
A. Current unpaid principal balance ($1000s)					
<90	-0.836***	-0.723***	-0.790***	-0.393***	-0.268***
	(0.064)	(0.061)	(0.063)	(0.067)	(0.063)
[90,150)	-0.272***	-0.291***	-0.204***	0.120***	0.356***
	(0.044)	(0.042)	(0.044)	(0.047)	(0.049)
120 or more	1.234***	1.096***	1.432***	2.411***	2.066***
	(0.039)	(0.038)	(0.039)	(0.038)	(0.040)
B. Borrower income (as % of area median income)					
Low (< 50)	-0.613***	-0.548***	-0.532***	-0.358***	-0.489***
	(0.068)	(0.065)	(0.067)	(0.066)	(0.059)
Moderate [50,80)	-0.248***	-0.258***	-0.146***	0.411***	0.129***
	(0.052)	(0.049)	(0.051)	(0.051)	(0.043)
Middle (80 or more)	0.997***	0.862***	1.189***	2.159***	2.486***
	(0.046)	(0.046)	(0.046)	(0.040)	(0.038)
C. Current credit score					
620-659	-0.594***	-0.338***	-0.542***	0.185	-0.041
	(0.126)	(0.124)	(0.125)	(0.132)	(0.125)
660-699	-0.231***	-0.256***	-0.214***	0.491***	0.479***
	(0.083)	(0.080)	(0.083)	(0.082)	(0.078)
700 or more	0.764***	0.626***	0.951***	1.796***	1.712***
	(0.038)	(0.038)	(0.038)	(0.032)	(0.032)
Number of observations	7,369,942	7,369,942	7,369,942	7,369,942	7,369,942
Uses Application Processing Days	Y	Y	Y	N	N
Uses "Share of Apps Incomplete"	N	N	N	Y	Y

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 1 on the main analysis sample (7,369,942 loan-quarter observations), with errors clustered at loan-level. The panels are analogous to those in Table 3. The columns report results from separate specifications that use alternative county-quarter level measures of whether constraints are binding. The first column reproduces the main results from column 3, Table 3 where the indicator equals one when the 75th percentile of application days for refinance loans in the county-quarter lies above 110% of that county's average over the period of analysis (see Background section for more details). The indicator is computed similarly in columns 2 and 3, but using the 50th and 90th percentile value of application processing days, respectively. In the fourth column we follow Choi et al. (2022) and categorize a county-quarter as capacity constrained if the share of applications filed in the quarter that are "incomplete" (meaning no action has been taken) by quarter-end exceeds the 75th percentile value of "share of apps incomplete" over all county-quarter observations in the sample. The indicator in Column 5 is also based on the "share of apps incomplete" measure, but is set equal to 1 if the county-quarter value exceeds 110 percent of that county's average over the sample period.

Appendix Table A-4: Sample means, HMDA-based dataset used in supplemental analyses

Sample	Originations	Applications
	(1)	(2)
Interest rate (bps)	322.1	
Rate spread (bps)	11.6	
Spread as % of APOR	3.8	
% Incomplete		11.6
% Denied for underwriting		8.3
Application processing days	52.4	
% capacity-constrained lender	38.3	39.8
Loan amount		
< $90k	1.8	2.5
$90-150k	9.5	10.6
$150k+	88.7	87.0
Borrower income		
Low	5.5	7.7
Moderate	18.1	18.9
Middle-High	76.5	73.5
Credit score		
[620, 660)	2.4	4.5
[660, 700)	8.8	9.2
700+	88.8	76.4
Unknown	0.0	9.9
Race and ethnicity		
Black	3.4	4.2
Hispanic	6.7	7.2
White non-Hispanic	63.0	59.5
Other	26.9	29.1
Combined loan-to-value		
<= 60	29.0	
(60, 70]	18.0	
(70, 75]	15.9	
(75, 80]	17.4	
(80, 85]	7.3	
(85, 90]	7.2	
(90, 95]	4.0	
95+	1.1	
Debt-to-income		
<= 33	48.2	
(33, 38]	16.4	
(38, 43]	16.3	
(43, 48]	13.6	
48+	5.4	
Net points	0.1	
Action taken		
Loan originated	100.0	76.6
Approved but not accepted		2.6
Application denied		12.2
Closed for incompleteness		8.6
Number of Observations	4,982,388	6,288,436

Notes: This table presents sample means of the variables used in supplemental analyses of HMDA data described in Section 6 of the paper. See the Data Appendix for additional details.