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Supply Constraints and Failure to Refinance

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Supply Constraints and Failure to Refinance*

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ABSTRACT: We show that supply-side capacity constraints in the mortgage market contribute to the well-documented "failure to refinance" among borrowers who would benefit financially from doing so. Supply constraints have little impact on most borrowers but substantially reduce the quarterly prepayment rate among "marginal" borrowers (those with lower loan balances, incomes, or credit scores), after accounting for the financial benefit of refinancing and a rich set of observable characteristics. Our estimates imply that supply constraints led to 12 percent of marginal borrowers failing to refinance during the 2020-2021 boom. We provide suggestive evidence that lenders ration credit to these borrowers, particularly in the early stages of the application process.

KEYWORDS: Mortgage Refinance; Credit Supply

JEL CODES: G21; G51; E5

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1. Introduction

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

The dynamics of refinance booms differ across borrower groups. For example, booms coincide with sharp declines in the share of loans to borrowers with lower loan amounts, income, or credit scores (Figure 2). Understanding what drives these differences is important for several reasons. 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 et al. 2024). 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] Policymakers have recently taken actions to make refinancing easier for all homeowners who might benefit from doing so.[2]

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 2023). Demand-side factors are an important reason why. Prior literature has linked borrower refinancing behavior to their financial sophistication, trust in financial institutions, exposure to lenders' advertising or news media, and their social networks, as detailed in the next section.

This paper offers 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

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[1] See, for example, Di Maggio et al. (2017); Beraja et al. (2019); Amromin, Bhutta, and Keys (2020); Berger et al. (2021); Gerardi, Willen, and Zhang (2023). Much of this literature highlights distributional differences in the efficacy 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] For example, the Federal Housing Finance Agency cited differences in borrowers' refinancing behavior in its April 2021 announcement of a program directing Fannie Mae and Freddie Mac to waive the adverse market refinance fee and provided a $500 credit for an appraisal, provided that the borrower has a loan balance under $300,000 or a low to moderate income, and that the loan meets certain underwriting criteria. In September 2022 the Consumer Financial Protection Bureau issued a Request for Information seeking public comment on (among other things) potential new mortgage products that expedite refinancing, especially for homeowners with smaller loan balances.

more profitable loan applications" (Duke 2013). Following this intuition, we hypothesize that during booms supply-constrained lenders de-prioritize certain borrowers, leaving them unable to refinance their loan at the prevailing low rates. In contrast, supply constraints should have less pronounced (if any) effects on refinancing activity among borrowers perceived as more profitable or easy to underwrite.

We analyze 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. We specify a linear probability model of quarterly loan prepayment and estimate the model on a sample of borrowers in the NMDB with a financial incentive to refinance, i.e., borrowers whose refinance option is "in the money".[3] The key independent variable is a categorical measure of mortgage supply constraints that varies at state-quarter level, based on: (i) the number of in-the-money borrowers relative to (ii) the number of active mortgage loan officers available to supply new loans. (We use the NMDB to calculate the former and use loan application data reported under the Home Mortgage Disclosure Act (HMDA) to calculate the latter.) Intuitively, our supply-constraint measure reflects increased congestion in the production of new mortgage loans as potential demand increases relative to supply. A drop in rates increases demand nationally but markets differ in their ability to absorb the new demand and in the elasticity of their supply response.

Our empirical specification allows the effects of capacity constraints to vary across borrowers, consistent with the hypotheses outlined above. 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, and the second and third proxy for lenders' perceptions of whether a borrower is difficult to underwrite or has lower expected profit. We refer to borrowers in the lower UPB, income, and credit score groups as "marginal"; 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.

[3] We estimate models of loan prepayment because the 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. See the Data section for additional information on how we measure the option value of refinancing and how we derive our categorical measure of supply constraints.

Marginal borrowers may be more likely to experience employment or income shocks 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 have not missed a mortgage payment or had their credit score fall below 620 since the origination of that loan. These sample selection criteria limit the scope for bias in our estimated effects of supply-side capacity constraints on refinancing.

A second challenge is how to distinguish the effect of supply constraints from the surge in demand that creates them. Even after accounting for borrowers' increased incentive to refinance, behavioral frictions may cause demand to vary across households in ways that are highly correlated with supply congestion. For example, Andersen et al. (2020) find that borrowers are more likely to be "awake" to the possibility of refinancing during booms and Hu et al. (2021) show that exposure to relevant media coverage can affect refinancing behavior, particularly among lower-income and minority borrowers. To mitigate this issue, we sequentially add controls to proxy for unobserved differences in demand across markets, households, and time. Our preferred specification identifies the effect of capacity constraints by comparing prepayment behavior of borrowers in the same census tract under different levels of market congestion, conditional on their financial incentive to refinance and an extensive set of borrower and loan level attributes.

Our empirical results support the hypothesis that supply-constrained lenders de-prioritize borrowers they may perceive as less profitable or difficult to underwrite. Over the 2018 to 2021 period, the most marginal borrowers were about 3 percentage points less likely to prepay their mortgage when supply was highly congested. This is an economically large effect, over 30 percent of the mean quarterly prepayment rate and similar in magnitude to the predicted effect of a 50 basis point decline in market interest rates. Cumulatively, around 12 percent of marginal borrowers failed to refinance during the 2020-2021 boom because of supply constraints, indicating an effect that persists well after peak market congestion. In contrast, and as expected, we find that supply constraints had little effect on non-marginal borrowers (those with higher loan balances, income, and credit scores) over the same period. Our results are robust to expanding the analysis period to 2010-2021 (i.e., including the previous major refinancing boom), to further filtering the sample based on credit quality, and to several other specification checks.

We examine the ways lenders might prioritize borrowers when they face excess demand. We find no evidence they adjust prices to throttle demand from marginal borrowers, based on an analysis of interest rate spreads on refinance originations reported in HMDA data. Rather, supply-constrained lenders appear to ration credit. Marginal borrowers in our NMDB sample are less likely to successfully connect with a lender and obtain pricing when supply constraints are binding, as proxied by the incidence of inquiries for new mortgage credit. The reduction amounts to around 25 percent of the unconditional quarterly mean suggesting that credit rationing primarily occurs before a refinance application is formally submitted. We further show that supply-constrained lenders de-prioritize their processing of applications from marginal borrowers, as reflected in disproportionately longer processing times and higher rates of applications being closed or denied for incomplete information.

Taken together, our estimates indicate that capacity constraints play an important role in explaining why some borrowers fail to refinance during booms. Our results are consistent with supply-constrained lenders rationing credit to borrowers they perceive as less profitable or more difficult to underwrite. We discuss implications for policy in the concluding section.

2. Background

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 2024). The 2020-2021 refinance boom featured significant intermediation markups that limited pass-through of low rates, likely due to operational and labor market constraints induced by the COVID-19 pandemic (Fuster et al. 2021).

This is the first paper to examine how congestion in mortgage markets affects borrowers' ability to refinance and the mechanisms behind that rationing of credit. Our analysis is related to two earlier papers which show mortgage lenders prioritize refinance loans when supply constraints are binding. Sharpe and Sherlund (2016) develop a theoretical model in which capacity constraints lead lenders to focus on mortgage applications that require less resources to underwrite. Consistent with this intuition, they find that periods of increased capacity utilization are associated with a decrease in the number of home purchase loans originated to less credit-worthy borrowers, based on an analysis of the conforming loan market 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 prefer safer loans or easier-to-process loan applications. Our paper looks within the refinance market to examine whether supply constraints cause lenders to de-prioritize certain borrowers who would otherwise refinance.

This paper also contributes to a well-established literature examining borrowers' apparent failure to exercise their refinance option when it is in their financial interest to do so (e.g., Keys, Pope, and Pope 2016). This failure to refinance is especially prevalent among certain segments of the population including lower-income and minority households (Firestone, Van Order, and Zorn 2007; Goodstein 2013; Brevoort 2022; Gerardi, Willen, and Zhang 2023).[4]

Differences in borrowers' propensity to refinance have been linked to a variety of demand-side factors not directly related to the household's financial incentive including: financial sophistication (e.g. Agarwal, Rosen, and Yao 2016; Bajo and Barbi 2018); consumer inattention (Byrne et al. 2023); trust in financial institutions (Johnson, Meier, and Toubia 2019; Bhutta and Doubinko 2025); exposure to lenders' advertising (Grundl and Kim 2019); news media stories about refinancing (Hu et al. 2021); and social networks (Maturana and Nickerson 2019; McCartney and Shah 2022).

Some of these factors may be especially salient when refinance activity is high, for example the influence of news media or social networks. Consistent with this intuition, Andersen et al. (2020) find that large drops in the market rate can "wake" borrowers up to their option to refinance, based on a model that incorporates psychological and information-gathering costs and allows those costs to vary across borrowers and over time. It follows that the dynamics of who refinances during booms is driven not only by the household's financial gains but also differences across borrowers in their responsiveness to those gains. Our analysis builds on this insight by plausibly accounting for cross-sectional and time-varying differences in borrowers' awareness of their refinance option, as detailed in the next section.

3. Model

[4] Kiefer, Kiefer, and Mayock (2023) argue that transaction costs in mortgage refinancing can partially explain why some borrowers "fail to refinance" when they seemingly should, and that accounting for geographic variation in transaction costs substantially reduces estimates of suboptimal refinancing behavior.

The conceptual framework for this analysis is the option-based model of mortgage terminations (e.g., Hendershott and Van Order 1987; Kau et al. 1995). The model implies a mortgage holder should exercise her option to refinance when the benefit of doing so exceeds the costs. The primary benefit from refinancing is the savings on future interest payments achieved by lowering the contract rate. A lower contract rate reduces the financing cost of the borrowing so long as the new mortgage lasts long enough to recoup the upfront costs of refinancing. The expected life of the new mortgage may depend on, among other things, future interest rate movements and the likelihood of selling the property. Upfront costs of refinancing include 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).

A. Empirical Specification

We specify models of the form

$$PP_{bs(t+1)} = [capConstr_{st} \times borrType_{bt}]\beta + X_{bst}\gamma + refiVal_{bt}\delta + \mu_s + \lambda_{bt} + \varepsilon_{bst} \quad (1)$$

where b indexes borrowers, s indexes the state of the mortgaged property, and t indexes time (in quarters). We estimate the models using OLS, clustering errors at loan level.[5]

The dependent variable $PP_{bs(t+1)}$ 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). We treat prepayment as synonymous with refinancing when interpreting our estimation results, as in most of the prior literature.[6] To facilitate this interpretation, we limit our analysis sample to borrowers whose refinance option is in the money, i.e., who have a financial incentive to refinance. In practice, the variation in mortgage refinancing over our period of analysis can be explained almost entirely by variation in prepayment behavior.[7]

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[5] We use linear probability models for computational simplicity. Results using logit (not shown) are similar.
[6] Two recent exceptions are Lambie-Hanson and Reid (2018) and Gerardi, Willen, and Zhang (2023), who use subsequent changes in the borrower's zip code reported in credit bureau data to infer whether a prepayment is a refinancing or home sale.
[7] To quantify this, we regressed state-quarter level counts of refinance originations (computed from HMDA) on mortgage prepayments (computed from NMDB) using several specifications that varied by the time period being analyzed and by whether other control variables (state fixed effects; quarterly fixed effects) were included. For our main period of analysis (2018 to 2021), the R^2 from these regressions exceeded 0.97 in every case, and for earlier periods (e.g., 2010 to 2013) exceeded 0.90 in nearly every case.

The key independent variable, $capConstr_{st}$, is a categorical measure of mortgage supply constraints. Our preferred measure (detailed in the next section) leverages differences across states and over time in the potential demand for new refinance originations relative to the number of mortgage loan officers (MLOs) available to supply them. This approach captures the congestion created by the relatively inelastic supply of MLOs coping with a surge in refinance activity. Differences in the degree of congestion across states provides variation in the incentive for MLOs to de-prioritize certain borrowers even within a general surge in demand.

We interact this supply-constraint measure with a categorical measure of $borrType_{bt}$ to allow the effects of supply constraints to differ across borrowers. 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.

These measures proxy for a lender's perceptions of how profitable or difficult it would be to underwrite the borrower's refinance loan application. The profitability of a new refinance loan is increasing in the UPB on the existing loan (which is approximately equal to the new loan amount for a rate and term refinancing), because a large portion of underwriting costs are fixed. And 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 by the lender and are likely correlated with other more germane characteristics like past credit issues, spottier work histories and amount of documentation required to qualify for the new loan.

B. Identification

Our analysis tests whether marginal borrowers (those with lower UPB, income, or credit scores) are de-prioritized by lenders when supply is constrained. The key parameter of interest is β, which reflects the differential effect of supply congestion on refinancing activity across borrowers. We assume that $capConstr_{st}$ is exogenous with respect to a borrower's refinancing decision, and our estimates of β can be interpreted as causal. We argue this identification assumption is plausible, based on the rich set of controls and sample selection criteria employed in the analysis.

There are two primary threats to identification in our setting. The first is that supply constraints typically bind during recessionary periods when interest rates are low. During recessions, marginal borrowers may be disproportionately likely to experience an unobserved shock to employment or income and find it more difficult to qualify for a refinancing.[8] This could lead to downward bias in our estimates of β.

We use an extensive set of controls (X_{bst}) and several sample restrictions to mitigate this threat. The controls include the key elements considered in mortgage underwriting, including the borrower's current UPB, income at origination (of the current loan), current credit score, current combined-loan-to-value ratio (CLTV), and debt-to-income ratio (DTI) at origination. We also control for the rate spread at origination of the current loan, to proxy for unobserved differences across borrowers in their credit quality (Gerardi, Willen, and Zhang 2023). We also control for local macroeconomic conditions via the county-level unemployment rate. In addition to these controls, we limit our analysis sample to borrowers who are very likely able to qualify for a new refinance loan: those that currently have a conventional loan and have not missed a payment on the mortgage or had their credit score fall below 620 since their loan was originated.[9] Our results are similar if we further tighten the credit quality of our sample by retaining only borrowers who 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 has remained above 660.

The second challenge in our setting is how to distinguish the effect of supply constraints from the surge in demand that creates them. The first step is to control directly for the household's increased financial incentive to refinance when the market rate falls. However, behavioral frictions may still cause demand to vary unevenly across households in ways that are highly correlated with market congestion, for example due to differences in borrower awareness (Andersen et al. 2020). Failure to account for these shifts in demand would result in estimates of β that are biased upward.

We control for the borrower's financial incentive to refinance, $refiVal_{bt}$, defined as the ratio of the note rate on the mortgage to the rate the borrower could get on a new refinancing

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[8] 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. More generally, Archer, Ling, and McGill (1996) show that income and collateral constraints have an important impact on mortgage prepayment behavior.

[9] We focus on conventional loan borrowers because (as discussed below) our measure of the prevailing market interest rate in each quarter is based on the prevailing rate for a conventional loan. In unreported analysis we find that over our period of analysis about 97 percent 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.

following Richard and Roll (1989).[10] The $refiVal_{bt}$ measure enters the specification quadratically to allow its effect on prepayment to vary with the level of the incentive. We include state fixed effects (μ_s) to account for cross-sectional differences in mortgage markets which may affect a borrower's incentive to refinance, e.g., the state-level variation in closing costs highlighted by Kiefer, Kiefer, and Mayock (2023).

We then sequentially add controls (λ_{bt}) to proxy for additional factors influencing the demand for refinancing. In our baseline model we control for the cumulative number of quarters the refinance option has been in the money, which we expect to be negatively correlated with awareness. Second, we add census-tract fixed effects to account for time-invariant unobserved local factors which may be correlated with borrower awareness, e.g., social networks within neighborhoods. Third, we add a control for the total number of new refinance applications observed in each census tract and quarter (indexed to the 2018-2019 average within each tract, using HMDA data), which should reflect time-variant factors that influence awareness at a local level, such as changes in advertising by lenders and word-of-mouth.

In the fourth and final specification, we add calendar-quarter fixed effects to control for differences across time that are invariant across borrowers, e.g., in national macroeconomic conditions. This specification isolates the variation in market congestion between states by comparing in-the-money borrowers within the same tract and same quarter. This approach identifies the effect of capacity constraints at a cost of amplifying the importance of state-quarter observations outside of the 2020-2021 refinance boom. Congested markets that occur outside of a surge in the number of in-the-money borrowers would likely feature the same type of de-prioritization by MLOs but it opens that possibility of other factors creating congestion that may be less orthogonal to the borrower's decision-making.

In sum, we argue that our empirical strategy mitigates the main threats to identification, and the remaining scope of omitted variable bias is small. It is therefore reasonable to interpret our estimates of β as reflecting the causal effects of capacity constraints on borrowers' likelihood of refinancing.

4. Data

[10] We prefer this intuitively simple measure which has a strong positive correlation with the incidence of prepayment in our sample. Results are robust to using alternative measures, as described in Appendix A.1.

The primary data we use in this study is the National Mortgage Database (NMDB®). 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.[11] We also use several supplementary data sources, including loan application data reported by mortgage lenders pursuant to the Home Mortgage Disclosure Act (HMDA data), and county-level unemployment rates from the Bureau of Labor Statistics (BLS).

The remainder of this section provides a detailed description of how we use these data to measure capacity constraints in mortgage markets, and how we construct the dataset used in our main analyses.

A. Capacity Constraints in the Supply of Mortgage Credit

We derive a new measure of capacity constraints in the supply of mortgage loans that varies at the state-quarter level.[12] Our measure is based on (i) the potential demand for new refinance mortgages, relative to (ii) the number of mortgage loan officers (MLOs) available to supply new loans. Intuitively, this measure reflects increased congestion in the production of new mortgage loans as potential demand increases relative to supply.[13]

We measure potential demand for new refinance mortgages in each state-quarter by counting the number of active mortgage borrowers in NMDB for whom the potential financial gain from refinancing is high, i.e., their refinance option value is "very in the money" (very ITM). We measure the borrower's financial incentive to refinance as the ratio of the note rate on the

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[11] The NMDB is jointly sponsored by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau (CFPB). For more details see: fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx

[12] Using state as the geographic measure of a mortgage market aligns with the statutory requirement that (nonbank) mortgage loan officers must be registered within every state they operate in per the Secure and Fair Enforcement for Mortgage Licensing ("SAFE") Act of 2008. Defining the mortgage market at county level does not qualitatively affect our results.

[13] Sharpe and Sherlund (2016) use a similar measure, defining "capacity utilization" at national level based on the number of refinance loan applications (reported in HMDA) relative to the number of mortgage loan industry employees (based on BLS estimates). In contrast, our measure is at state level and is based on potential demand for refinancings (instead of realized applications). Our results are also robust to measuring capacity constraints analogously to Choi, Choi, and Kim (2022), who measure banks' "operating capacity" based on the percentage of applications received each quarter that remain open (i.e. no underwriting decision has been made) at the end of the quarter. (Results available on request.)

mortgage to the current market rate, following Richard and Roll (1989). Recognizing that loan pricing varies, we calculate a borrower-specific current market rate equal to the average note rate on refinance loans originated in the next quarter to borrowers with a similar credit score and loan-to-value (LTV) ratio.[14] We categorize a borrower's refinance option as ITM if the note rate on their existing mortgage is at least 10 percent higher than their current market rate, and very ITM if the note rate is at least 30 percent higher.[15]

We calculate the number of MLOs in each state-quarter by counting the number of unique MLOs associated with loan applications reported in HMDA. This HMDA-based MLO measure counts all the MLOs who are *actively* originating loans in a state while excluding registered but inactive MLOs. The primary disadvantage of the HMDA-based MLO measure is that it is not observed prior to the 2018 filing year.[16]

To facilitate supplemental analyses of prepayment behavior prior to 2018, we use loan application processing times as an alternative measure of supply-side capacity constraints. Specifically, we compute the number of application processing days by taking the difference of the origination date and application date for all first-lien, single family refinance originations reported in HMDA over our period of analysis. As noted above, prior literature (e.g., Fuster et al. 2013) shows that application processing times increase during periods of high demand, consistent with congestion in the supply of mortgage credit. However, a potential limitation is that application processing days is observed only for loan applications that result in an origination. Thus the processing days measure may not fully reflect the extent to which supply is constrained, because some borrowers may apply for a loan that does not result in an origination,

[14] The actual interest rate a borrower could obtain on a new refinancing is not observable. We use the NMDB to approximate the "current market rate" available to a borrower as follows. We calculate the average note rate on conventional refinance originations by credit score bin (20 point buckets: 620- 639, 640-659, …, >=780), LTV bin (5 point buckets: <=60, 61-65, …, >=96), and calendar quarter. We merge this into the loan-quarter level NMDB data based on the borrower's credit score and LTV as of quarter t, using the average note rate observed over the following quarter $t + 1$. We use the rate from the following quarter to reflect the time lag between application and origination of a new refinance loan. While our measure of the borrower-specific market rate ignores several dimensions of mortgage pricing (e.g., discount points, loan amount, geographic location), in practice it closely follows the variation in interest rates observed on new refinance loans across borrowers and over time.

[15] This approach is consistent with earlier literature (e.g., Firestone, Van Order, and Zorn 2007; Goodstein 2013). Our results are qualitatively similar using alternative measures of a borrower's refinance option value, as detailed in Appendix A.1.

[16] In a robustness check, we measure MLOs using the number of state-licensed or federally-registered MLOs physically located in each state, available in quarterly Mortgage Reports published by the Conference of State Banking Supervisors (CSBS) beginning in 2012Q1. Results using this alternative measure are very similar.

or may attempt to engage with an MLO to inquire about a refinancing without ever filing a formal loan application.[17]

Figure 3 shows how congestion in mortgage supply has varied over time, based on the 75th percentile value of these alternative measures (calculated across states, within each quarter). For example, in 2018Q1 the ITM-MLO ratio was 13.2, meaning there were about 13 very ITM loans for every MLO in the state. By 2020Q2, the peak of the most recent refinance boom, this ratio had increased to 54, or by a factor of about 4.[18] Subsequently, the ITM-MLO ratio declined as borrowers refinanced and additional MLOs entered the market, but generally remained elevated through 2021, after which rates began rising sharply and most borrowers no longer had a financial incentive to refinance.

Looking at the 75th percentile value of application processing days, the variation over the 2018 to 2021 period is similar to the ITM-MLO ratio. And prior to 2018 the number of application processing days closely follows the overall pattern in refinance activity, most notably being quite elevated during the previous refinance boom in 2011-2013.

Our main analysis specification includes a categorical measure of congestion in mortgage loan supply that varies at state-quarter level, using our preferred ITM-MLO ratio measure. The measure is defined as follows: (1) "Low Congestion" if the ITM-MLO ratio is less than or equal to the 75th percentile value over all state-quarter observations over the period of analysis, (2) "Moderate Congestion" if the ITM-MLO ratio is between the 75th and 90th percentile value, and (3) "High Congestion" if the ITM-MLO ratio is above the 90th percentile value. 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.

Figure 4 shows the share of states categorized as capacity constrained over our period of analysis. Every state is Low Congestion in 2018 and early 2019, when interest rates were relatively high and refinance activity was low. But mortgage supply started becoming congested

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[17] Publicly available HMDA data do not include the mortgage loan originator NMLSR identifier, or the exact application and action (origination) dates used to calculate application processing days described below. This information is included in restricted-access HMDA data, available only to certain federal regulatory agencies. For both of these HMDA-derived quarterly measures, we use application data from the three-month window centered on the month that ends quarter *t*, which aligns with the approximate timing of when a borrower would submit a refinance application that would be originated by the end of the next quarter. For example, for observations in 2020Q1 we compute the number of unique MLOs and the 75th percentile value of loan application processing days using loan applications submitted between February and April 2020.

[18] To be clear, the number of MLOs increased between 2018 through 2021. However, this supply response was inelastic relative to the surge in demand for new refinancings.

in late 2019 as rates fell lower. And when rates hit historic lows in 2020 and refinance activity boomed, nearly every state is categorized as Moderate or High Congestion. (Patterns are similar using our alternative measure of supply constraints based on application processing days, as shown in Appendix Figure A.1.)

B. Analysis Dataset

We construct a loan-quarter dataset from NMDB as follows. We first take a 50 percent random sample of loans in the NMDB, to reduce computational burden. We include originations from 2009 to 2020 and focus on payment behavior over the period 2018Q1 through 2022Q1, which spans the most recent refinance boom.

The NMDB does not currently distinguish refinancing from other reasons for prepayment (e.g., home sales). To better isolate the effect of capacity constraints on refinancing, we structure our dataset as follows. For each loan in the sample we retain the first quarterly observation where the borrower's refinance option value goes ITM (as defined above) and each subsequent quarter until it leaves the sample (e.g., due to prepayment) or the refinance option value 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.

We limit our analysis to conventional, 30-year, fixed-rate, home purchase or refinance mortgages on single family, site-built, owner-occupied properties. We exclude borrowers from our analysis that are likely to have difficulty qualifying for a new conventional loan refinancing. Specifically, 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.

Our analysis examines how the effect of capacity constraints on prepayment behavior may differ across borrowers. We use three alternative measures to categorize borrowers: current UPB, income (relative to area median income) at origination of the existing loan, and current credit score. For each of these measures, we categorize each borrower in our analysis dataset relative to others within the same state-quarter as follows: "Very Low" if the measure is less than the 10^{th} percentile value; "Low" if the measure is between the 10^{th} and 25^{th} percentile; and "Higher" if the measure is at the 25th percentile or higher. We collectively refer to those in the Very Low and Low groups as “marginal borrowers”, because lenders may be more likely to de-prioritize their loan applications when supply constraints are binding.

We merge the categorical capacity constraint measures and the borrower-specific current market rates (described above) into our analysis sample using the state and quarter identifiers in NMDB. We merge in county-level unemployment rates from the BLS, using the rate as of the month ending each quarter (e.g., March for Q1). Finally, we merge in HMDA data on the number of new refinance loan applications in the borrower’s census tract and quarter (indexed to the average number of refinance loans over the 2018-2019 period, to remove level differences across tracts).

Our final analysis dataset includes 261,509 unique loans and 1.54 million loan-quarter observations. Table 1, Panel A presents selected descriptive statistics by the level of mortgage supply congestion. Overall, 9.2 percent of loan-quarter observations in our sample are prepaid by the end of the next quarter. When a refinance boom occurs and supply congestion increases from Low to High, the quarterly prepayment rate increases, in part because the average value of the borrower’s refinance option is also increasing.

Panel B of Table 1 shows descriptive statistics by the level of supply suggestion and the borrower’s relative UPB. Prepayment rates are increasing in UPB, with the level and gradient increasing during refinance booms when supply constraints are binding. When supply congestion is low, 4.8 percent of those in the Very-Low UPB group prepay, compared to 9.7 percent in the Higher UPB group. This difference is not driven by the potential benefits from refinancing, as the refinance option value (measured by the ratio of the note rate to market rate) is decreasing in the level of UPB. And 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. Rather, the gradient in prepayment rates by UPB group is likely due to systematic differences in optimal refinancing behavior, as documented in prior literature. Lower UPB borrowers have longer ITM spells on average (as indicated by their higher cumulative number of ITM quarters), meaning they are slower to refinance. One reason why may be that neighborhood refinancing activity, which we argue is linked to an individual borrower's awareness of their refinance option, is relatively low for lower UPB borrowers.[19]

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. Over all the loans in the sample, about 10 percent of borrowers are categorized as Very Low UPB and an additional 14 percent are Low UPB. About 9 percent borrowers are Very Low income and another 14 percent are Low income. And about 8 and 13 percent of borrowers are categorized as Very Low and Low credit score, respectively.[20]

Other control variables include the combined loan-to-value ratio (CLTV), equal to the current UPB on all active mortgages on the property divided by the mark-to-market property value.[21] About 88 percent of loans in the sample have CLTV of less than 80 percent as of the last quarterly observation. We include a control for spread at origination, equal to the difference between the note rate on the mortgage and the average prime rate at origination (based on Freddie Mac's Primary Mortgage Market Survey). Gerardi, Willen, and Zhang (2023) note that spread at origination may proxy for unobserved constraints that may prevent a borrower from being able to refinance at the prime rate. Around 19 percent of the loans in our sample had a spread at origination of 50 basis points or more. About 57 percent of borrowers in our sample have home purchase loans, and of these, nearly half (or 28.3 percent of all loans) are first-time homebuyers.

5. Results

A. Effects of Supply Constraints on Mortgage Prepayment

Our primary analysis examines how supply-side capacity constraints affect borrowers' quarterly probability of mortgage prepayment. We hypothesize that capacity-constrained lenders

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[19] Differences across borrowers categorized by their relative income or relative credit score (not shown for brevity) are qualitatively similar to the differences by UPB presented in Table 1B.

[20] In cases where there is more than one borrower on the loan, we use the minimum credit score, consistent with GSE underwriting 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 forward) 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.

de-prioritize loan applications from borrowers perceived as more difficult to underwrite, thereby reducing those borrowers' likelihood of refinancing.

We first explore how the effects of supply constraints vary across borrowers categorized by the current UPB on their existing loan. We use OLS to estimate four specifications of equation (1) that incrementally add controls to proxy for unobserved factors that influence borrower demand. The full set of coefficient estimates is presented in Appendix Table A.1. Figure 5 plots conditional predicted prepayment probabilities at different levels of market congestion and UPB, generated from the OLS estimates.

Predictions for Higher UPB borrowers are in Panel A. Based on specification (i) with state-level fixed effects, the predicted quarterly probability of prepayment increases substantially with supply congestion, from 10.0 percent in Low Congestion markets to 11.7 percent in High Congestion markets. This counterintuitive pattern demonstrates the challenge in disentangling the effects of supply constraints from the concurrent surge in demand.

However, the addition of controls for demand help isolate the impact of market congestion. Specification (ii) adds census-tract fixed effects and specification (iii) adds a control for local refinancing activity, yielding a more intuitive result: the predicted probability of prepayment declines as supply congestion increases. Specification (iii) is our preferred specification, because it leverages both cross-sectional and time series variation to identify the capacity constraint effect, while controlling for differences across borrowers in demand that arise from both the direct financial incentive and other indirect sources.

Specification (iv) adds calendar-quarter fixed effects which difference out time-related factors that are common across borrowers, e.g., national macroeconomic conditions, comparing borrowers in congested and uncongested states within the same quarter. The predicted prepayment probabilities from this specification are once again increasing in the level of congestion, suggesting that the cross-sectional variation in supply constraints may in part reflect the influence of unobserved factors which also affect demand. That said, the gradient in predicted probability of prepayment from Low to High Congestion markets is quite small in magnitude. Overall, the results in Panel A are consistent with our expectations that supply constraints do not have much of a dampening effect (if any) on Higher UPB borrowers' ability to refinance.

In contrast, we find that supply constraints substantially inhibit refinancing among lower UPB borrowers. Based on the estimates from specification (iii), when supply congestion increases from Low to High, the predicted probability of prepayment falls from 7.3 percent to 4.9 percent among borrowers in the Low UPB group (panel B), and from 6.4 percent to 2.9 percent among Very-Low UPB borrowers (panel C). And while the gradient across the corresponding estimates from specification (iv) is a bit smaller, the results nonetheless indicate that supply constraints have an economically significant dampening effect on refinancing activity among lower UPB borrowers who are relatively less profitable to lenders.[22]

Results are similar when we categorize borrowers by income (at origination of their current loan) or by current credit score. Table 3 presents the estimated marginal effects of capacity constraints on likelihood of prepayment using alternative measures to categorize borrowers. Each panel presents results from a separate regression; for brevity we only report results for specifications (iii) and (iv). In panel A the estimates correspond to the predicted probabilities illustrated in Figure 5 where marginal effects of congestion are allowed to vary by UPB. For example, based on specification (iii) the marginal effect on probability of prepayment of being in a market with High Congestion (relative to Low Congestion) is negative 3.5 percentage points for a Very-Low UPB borrower.[23] This effect is about 38 percent of the mean quarterly prepayment rate over all borrowers in the sample.

In panel B the effects of supply constraints are allowed to vary by borrower income. The estimates from specification (iii) indicate that among Very-Low Income borrowers, being in a market with High Congestion reduces probability of prepayment by 2.9 percentage points. This effect is large in magnitude, about 32 percent of the quarterly prepayment rate over all borrowers in the sample. Supply constraints also have a substantial effect on Low Income borrowers, for example reducing the probability of prepayment by 2.1 percentage points (or 22 percent) in High Congestion markets. And consistent with our expectations, the effects of supply constraints are more muted among Higher Income borrowers, for example reducing probability of prepayment by 0.8 percentage points when supply congestion is High.

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[22] Figure 5 also clearly illustrates substantial differences in the *level* of refinancing activity across UPB groups. This is consistent with earlier literature demonstrating systematic differences across the population in (sub)optimal refinancing behavior (e.g., Keys, Pope, and Pope 2016).

[23] This is equal to the difference in the predicted probabilities of prepayment when supply congestion is Low (2.9 percent) versus High (6.4 percent), as shown in Figure 5.

Panel C shows how effects of supply constraints vary with borrower credit score. Again, results are qualitatively similar to the results by borrower UPB. Supply constraints have an economically significant effect on prepayment probabilities among borrowers with lower credit scores, while effects on higher credit score borrowers are more muted.

Overall, the estimates in Table 3 support our hypothesis that capacity-constrained lenders deprioritize potential refinance borrowers they may perceive as less profitable or more difficult to underwrite. The effects are economically important: high market congestion reduces the quarterly likelihood of prepayment among the most marginal borrowers by 20 to 40 percent, depending on specification. For context, these effects on prepayment are similar in magnitude to the predicted effect of a 50 basis point decline in market interest rates.[24]

B. Cumulative Effects of Supply Constraints Over the 2020-2021 Refinance Boom

Next we quantify the cumulative impact that mortgage supply constraints had on refinancing behavior over the most recent boom, to provide more context on the economic significance of our results. For brevity, we focus on the model that allow effects to vary by borrower UPB and use the estimates from our preferred specification (iii) which includes census-tract fixed effects and controls for local refinance activity (presented in Appendix Table A.1, column 3).

For this analysis we focus on the set of loans that were active and ITM as of the end of the third quarter of 2019.[25] We calculate predicted quarterly prepayment activity on these loans from 2019Q4 through 2022Q1 in: (1) an "Actual" scenario, i.e., using the observed values for $capConstr_{ct}$; and (2) a "Counterfactual" scenario in which supply constraints don't bind, i.e., we set $capConstr_{ct}$ to "Low" for all observations. In both cases all other variables in the model take on their actual values.

Panel A of Figure 6 illustrates the effect of supply constraints on quarterly prepayment rates under the Actual and Counterfactual scenarios. For borrowers in the Very-Low UPB group in 2019Q3, the predicted probability of prepayment by the end of the next quarter (2019Q4) is 3.1

[24] Specifically, our OLS coefficient estimates indicate that reducing the market rate by 50 basis points (which increases borrowers' financial incentive to refinance as measured in $refiVal_{bt}$) would increase the conditional predicted probability of prepayment from 9.2 to 12.8 percent (or about 3.5 percentage points) over all loan-quarter observations in the sample.

[25] As of 2019Q3, interest rates were 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.

percent in the Actual scenario and 3.3 percent in the Counterfactual scenario. These predictions are very similar because supply constraints were not yet widespread.

However, predicted quarterly prepayment rates differ sharply beginning in 2020 when mortgage markets became highly congested. For example, among Very-Low UPB borrowers with an active loan in 2020Q3, predicted prepayment by 2020Q4 is 6.9 percent in the Actual scenario, about 3.1 percentage points lower than the Counterfactual scenario in which supply congestion is set to Low. Among Low UPB borrowers the predicted prepayment rate in the Counterfactual scenario is 2.1 percentage points higher. In contrast, among borrowers with Higher UPB, the difference in Actual and Counterfactual prepayment rates is small (about 0.5 percentage points), reflecting the minimal impact that supply constraints have on this group.

Panel B of Figure 6 presents predicted cumulative prepayment probabilities calculated from the predicted quarterly prepayment rates in panel A. In the counterfactual scenario where supply constraints don't bind ($capConstr_{ct}$ is set to Low), about 29 percent of Very-Low UPB borrowers prepay by 2020Q4, 8 percentage points (or 28 percent) higher than the prediction based on actual values of $capConstr_{ct}$. Among borrowers in the Low UPB group, the predicted cumulative prepayment rate is about 40 percent in the Counterfactual scenario, 5 percentage points (or 14 percent) higher than in the Actual scenario. These differences persist through 2022Q1, after which interest rates rose sharply and most borrowers no longer had a financial incentive to refinance. Ultimately around 4.5 percent of Low UPB and 7.6 percent of Very Low UPB borrowers had not refinanced by the time rates rose. In sum, around 12 percent of marginal borrowers failed to refinance because of lenders' responses to supply constraints.

For context, this effect is over half the magnitude of overall differences in (sub)optimal refinancing behavior documented in previous literature. For example, Keys and Pope (2016) find that as of December 2010, 29 percent of borrowers in the lowest credit score quartile had failed to optimally refinance, 17 percentage points higher than those in the highest credit score quartile. And Gerardi, Willen, and Zhang (2023) show in a counterfactual exercise that as of 2015Q4 (i.e., following the period of relatively low rates in the early 2010s), Black and Hispanic borrowers were around 20 percentage points more likely to be "never refinancers" relative to a control group of White borrowers.

C. Effects of Capacity Constraints from 2010 to 2021

We show that constraints in the supply of mortgage credit made it substantially more difficult for marginal borrowers (those that lenders perceive as less profitable or more difficult to underwrite) to refinance and obtain low market rates during the 2020-2021 boom. And we know that supply constraints were particularly acute during this period due to operational and labor market frictions related to the COVID-19 pandemic (Fuster et al. 2021). A natural question to ask is: did supply constraints similarly inhibit marginal borrowers from refinancing during the previous major refinancing boom of 2011-2013?

To answer this question, we expand our period of analysis to cover years 2010 to 2021, using an alternative measure of mortgage supply constraints based on the number of processing days on refinance loan applications reported in HMDA. (Recall that our preferred measure, the ratio of ITM borrowers to the number of unique MLOs active in each state-quarter, is only observed beginning in 2018.) We construct a categorical measure of congestion in mortgage supply that varies at state-quarter level, just as in our main analysis: (1) "Low Congestion" if the number of processing days is less than or equal to the 75th percentile value over all state-quarter observations over the period of analysis, (2) "Moderate Congestion" if it is between the 75th and 90th percentile value, and (3) "High Congestion" if it is above the 90th percentile value. Using this measure, the share of states categorized as "High" or "Moderate" congestion spikes during the 2011-2013 and 2020-2021 refinance booms, as shown in Appendix Figure A.1.

Table 4 presents the marginal effects of capacity constraints on the likelihood of prepayment separately by analysis period, allowing effects to vary by borrower UPB.[26] The estimates in each panel are from separate regressions of specifications (iii) and (iv). In Panel A the analysis period is 2018 to 2021. These estimates are similar to the estimates from our main analysis (in Table 3, panel A) indicating that our results are robust to using this alternative measure of mortgage supply constraints. For example, the estimate from specification (iii) indicates that a Very Low UPB borrower is 3.0 percentage points less likely to prepay when supply constraints are High (relative to when they are Low). This effect is 33 percent of the mean quarterly prepayment rate.

In Panel B the analysis period is 2010 to 2013, which encompasses the previous major refinancing boom. The estimates generally indicate that lower UPB borrowers were less likely to prepay in supply-constrained markets, but the magnitudes of these effects were somewhat

[26] Results are similar if we allow effects to vary by borrower income or credit score; we omit these from Table 4 for brevity.

smaller than the corresponding estimates for the 2018-2021 period. For example, the estimate from specification (iii) indicates that a Very Low UPB borrower was 1.3 percentage points less likely to prepay when supply constraints were High, about 19 percent of the sample mean prepayment rate over this period.

In Panel C of Table 4 the analysis covers the full 2010 to 2021 period. Again, the results are qualitatively similar to those in Panel A, although the magnitudes of the supply constraint effects are slightly smaller.

In sum, the results in Table 4 are consistent with our hypothesis that when lenders are supply constrained, they de-prioritize marginal borrowers they perceive as less profitable or more difficult to underwrite. This result holds true in each of the previous two major refinancing booms, though the impact appears to have been most pronounced during the 2020-2021 boom. This is perhaps unsurprising, since supply constraints over this period were especially severe due to pandemic-related operational and labor market frictions (Fuster et al. 2024).

D. Robustness

We now discuss the robustness of our results. First, we revisit the potential concern that refinance booms typically occur when rates fall during economic recessions. Specifically, the negative effects of capacity constraints might instead 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 conforming loan borrowers with credit scores above 620 that have never missed a mortgage payment. Here we expand on this strategy by further increasing the credit quality of the borrowers in our sample.

Results are summarized in Table 5. The first column reproduces our results from Table 3 to facilitate comparison. In the second column we limit the sample to borrowers that had never missed a payment on any trade line reported to the credit bureaus, from origination of the existing loan through the last quarter of observation. In the third column we restrict the sample to borrowers with a combined LTV of no more than 80 percent. In the fourth column we restrict the sample to borrowers with a credit score of at least 660.[27] And in the fifth column we apply all of these filters. Looking across the columns shows that the estimated effects of capacity constraints on prepayment are similar in all cases. Taken together, these results indicate our main result that marginal borrowers are less likely to prepay when supply constraints are binding does not instead reflect concurrent difficulty in qualifying for a new refinance loan.

That said, our efforts to mitigate identification concerns over credit quality mean that we exclude a large number of borrowers that could also be de-prioritized by lenders when facing excess demand. For example, borrowers with government loans make up about 20 percent of all active mortgage holders and generally have lower loan amounts, income, and credit scores than those with conventional loans. On the other hand, government loan programs offer streamlined refinancings which reduces the cost of originating a new refinancing and may mitigate a lender's incentive to de-prioritize such borrowers.[28] Which effect dominates is an empirical question.

The sixth and seventh column of Table 5 presents results from the main specification estimated on an expanded sample that includes government loans; the former retains the sample filters from the main analysis and the latter includes the additional sample filters from the fifth column. The point estimates from these specifications are quite similar to those in the first and fifth columns, respectively, suggesting that marginal government loan borrowers are affected in much the same way as conforming loan borrowers when supply constraints are binding.[29]

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 current 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 A.1, we

[27] 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.

[28] Government loan programs include those that are backed by the Federal Housing Administration, the Department of Veterans Affairs, and the U.S. Department of Agriculture. Each of these programs offer a streamlined refinance program with reduced documentation and underwriting requirements. For example, information on the FHA streamlined refinance program is available at: www.hud.gov/hud-partners/single-family-streamline.

[29] In an alternative specification we added an interaction term for loan type to allow the effects of supply constraints on prepayment to differ by borrower type and by whether the current loan is a government or conforming loan. Results (available on request) suggest that borrowers with government loans are, if anything, even more affected by supply constraints than those with conforming loans.

show our main estimates of interest are generally robust to using: (1) the ratio of the note rate to the market average prime rate (instead of our borrower-specific measure of the market rate); (2) the "Call Option" measure (Deng, Quigley, and Van Order 2000) which compares the present value of remaining mortgage payments discounted at the note rate vs. the market rate; and (3) the closed form refinancing model of Agarwal, Driscoll, and Laibson (2013) that accounts for several factors including closing costs and expected inflation, mobility, and interest rate volatility.

Finally, we acknowledge a potential concern over the role of cash-out refinancing, a loan product that is disproportionately taken up by borrowers with lower incomes and credit scores (Goodstein 2013; Amromin, Bhutta, and Keys 2020). Other things equal, a borrower's incentive to take out a cash-out refinance loan increases when market rates are low, much in the same way as a rate-and-term refinancing.[30] However, a borrower's ability to execute a cash-out refinance also requires that she has sufficient equity in the home. If marginal borrowers are disproportionately less likely to have sufficient equity in their home during refinance booms, a preference for cash-out refinancing might dampen their overall incidence of prepayments. To assess whether this is an important concern in practice, we estimated the model on an alternative sample of borrowers with CLTV less than or equal to 70 percent, i.e., borrowers that likely have sufficient equity to take out a cash-out refinance. Estimates for this subsample (available upon request) resemble our main results, suggesting that our estimated effects of capacity constraints on marginal borrowers are not being driven by a fall in demand for cash out refinances among marginal borrowers.[31]

6. Examining Mechanisms

[30] HMDA data show that over the period 2018 to 2021, the number of cash-out refinance loan originations began increasing in 2019 and especially 2020 as market rates decreased. However, because the increase in rate-and-term refinancings was much more pronounced, cash-out refinance originations measured as a share of all originations fell over the same period.

[31] We conducted additional analyses using McDash loan servicing data linked to property records data, which allows us to distinguish between prepayment types (rate-and-term refinance; cash-out refinance; home sale). Focusing on rate-and-term refinancing as the outcome variable, results (available upon request) were quite similar to those presented in this paper. This is further evidence our main finding – that among marginal borrowers the likelihood of prepayment declines during supply-constrained periods – is not attributable to a decline in demand for cash-out refinancing.

We find that borrowers with lower UPB, lower income, and lower credit scores are less likely to refinance when mortgage markets are congested. This result is consistent with lenders responding to excess demand by de-prioritizing borrowers they perceive as less profitable or more difficult to underwrite. In practice, lenders might do so by adjusting their pricing or taking other steps to ration credit. Anecdotally, some lenders engaged in both types of behavior during the most recent refinance boom.[32]

In this section, we examine whether supply-constrained lenders systematically de-prioritize marginal borrowers in any of the following ways: (A) differentially raising prices to "throttle" demand; (B) rationing credit to reduce the number of applications filed; or (C) rationing credit by de-prioritizing the underwriting of loan applications they do receive.

A. 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, Lo, and Willen 2024; Fuster et al. 2021). It seems plausible that constrained lenders might disproportionately raise prices to borrowers they perceive as less profitable or more difficult to originate in order to "throttle" demand. If marginal borrowers face relatively high prices, their financial incentive to refinance will be reduced or eliminated entirely.

To explore whether supply-constrained lenders strategically adjust pricing, we analyze HMDA data on refinance loan originations from 2018 to 2021.[33] We limit the analysis to these years because interest rates and origination fees are not observed in HMDA prior to 2018.

Figure 7 plots the average interest rate spread on refinance loan originations by loan amount and application month. (Interest rate spread is defined as the difference between the Annual

[32] For example, a 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.'"

[33] 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 December 2021. See Appendix A.2 for more details on the construction of the HMDA sample used in the analyses presented in this section.

Percentage Rate (APR) on the loan and the average prime offer rate (APOR) for a comparable transaction as of the date the interest rate is set.) The figure shows that interest rate spreads generally declined during the 2020-2021 refinance boom and that this decline was similar in levels across loan amount groups. Patterns are similar for borrowers categorized by income or credit score, as shown in Appendix Figure A.2. Overall, these figures suggest prices did not increase for marginal borrowers relative to non-marginal borrowers when supply constraints were widely binding.[34]

We formalize the analysis by specifying regression equation (2). The dependent variable is the interest rate spread on the loan to borrower b made by lender l in state s and month t.

$$P_{blst} = [capConstr_{st} \times borrType_b]\beta + X_b\gamma + \mu_l + \rho_s + \tau_t + \varepsilon_{blst} \tag{2}$$

The key estimates of interest are in β, which reflect the differential effects of supply constraints on pricing by borrower type. We use the same state-quarter level measure of congestion in mortgage supply ($capConstr_{st}$) as in equation (1).

We estimate three alternative specifications of (2) where we allow effects to vary across borrowers ($borrType_b$) categorized by: (A) loan amount; (B) borrower income; and (C) credit score. For each of these measures we categorize the loan application relative to others in the same state-quarter as follows: "Very Low" if the measure is less than the 10th percentile value; "Low" if the measure is between the 10th and 25th percentile; and "Higher" if the measure is at the 25th percentile or higher. (This is analogous to how we categorize borrowers in our main analysis.)

In all specifications we include controls for other loan and borrower characteristics X_b (loan amount, relative borrower income, credit score, combined LTV, DTI, race/ethnicity, and net points paid at closing).[35] We also include fixed effects for lender (μ_l), state (ρ_s), and application month (τ_t), so that the supply constraint effects are identified by comparing different types of borrowers within the same lender, state, and month.[36]

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[34] In practice, mortgage pricing depends on both the interest rate and upfront costs (discount points). The trends illustrated in Figure 7 and regression results described below are robust to accounting for discount points and other up-front loan costs.

[35] 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. See the Appendix for additional details on the data used in this analysis.

[36] The results presented in the remainder of this section are robust to alternative specifications, e.g., omitting loan application month fixed effects so that the supply constraint effects are identified using both time series and cross-sectional variation.

Table 6 presents the estimated effects of supply constraints on interest rate spread by borrower type. Borrowers are categorized by loan amount in column A. Overall, the estimated rate spreads are about 26 basis points higher for borrowers in the Very Low loan amount group and 13 basis points higher in the Low loan amount group, relative to the Higher loan amount group. And perhaps surprisingly, rate spreads are slightly lower for borrowers in the Low or Very Low loan amount groups when supply is congested, although the effect sizes are quite small in economic terms. Patterns by borrower income and credit score (columns B and C) are qualitatively similar. Overall, the results in Table 7 do not support the hypothesis that supply-constrained lenders differentially raise prices to marginal borrowers in order to throttle demand.

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.[37]

B. Do Supply-Constrained Lenders Reduce Applications from Marginal Borrowers?

When a borrower becomes aware that a refinancing might be financially worthwhile, the next step is to contact one or more lenders to learn about the pricing on a new refinance loan. Once the borrower 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 quotes a price and the borrower decides whether to proceed with a formal application.

Excess demand for refinancings might affect lender behavior in two ways. First, lenders might adjust their marketing strategies by targeting outreach or advertising to households where refinancing would yield the highest expected profit. Second, they might triage requests for a formal price quote, for example by screening calls and prioritizing easy-to-underwrite customers. We are unable to distinguish between these mechanisms due to data limitations.

[37] 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.

Instead, we use NMDB data on inquiries for new mortgage credit to examine whether supply constraints affect borrowers' overall ability to connect with a lender and submit a formal loan application. A mortgage credit inquiry is a reliable indication of a borrower's ability to do so because loan officers almost always request a hard credit check on potential applicants before providing a formal price quote and (if the borrower chooses to proceed) filing a loan application.

We specify models of the form

$$INQ_{bst} = [capConstr_{st} \times borrType_{bt}]\beta + X_{bst}\gamma + refiVal_{bt}\delta + \mu_s + \lambda_{bt} + \varepsilon_{bst} \quad (3)$$

which are similar to equation (1) except 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 inquiry in the current quarter *t*, and equal to zero otherwise.[38] We estimate the models using the same dataset as in our main analysis, except that we drop any loan-quarter observations subsequent to the first instance of a mortgage credit inquiry. Thus, the analysis evaluates how market congestion influences a borrower's likelihood of contacting a lender and obtaining a price quote, regardless of whether an application is later filed or whether the mortgage is eventually prepaid.

Table 7 presents marginal effects of capacity constraints on the probability of a mortgage credit inquiry. In panel A the effects are allowed to vary by current UPB. Patterns are qualitatively like the results on overall prepayment shown in Table 3. For example, based on specification (iii) which omits calendar-quarter fixed effects, among higher UPB borrowers the likelihood of a mortgage credit inquiry is 1.4 percentage points lower during High congestion. This effect is about 20 percent of the sample mean inquiry rate of 6.7 percent. Effects increase as UPB falls; Very Low UPB borrowers see a reduction in the likelihood of a credit inquiry of 1.8 percentage points when supply is Highly congested, an effect of around 25 percent of the sample mean inquiry rate. Adding calendar-quarter fixed effects in specification (iv) reduces the magnitudes of the point estimates for all UPB groups. For Higher UPB borrowers, the supply congestion effects are very small and not statistically different from zero, while Very Low UPB borrowers still see a reduction of around 0.7 percentage points (or 10 percent) when supply is Highly congested.

[38] We cannot distinguish the purpose of the credit inquiry beyond relating to mortgages and acknowledge that some of the inquiries observed in our data relate to other mortgages or properties (e.g., second liens or second homes). That said, mortgage inquiries are highly correlated with prepayments on the loans in our NMDB sample.

Differences across borrower income and credit score groups are similar, as shown in Panels B and C of Table 7. Supply constraints lead to an economically significant decline in the likelihood of an inquiry for marginal borrowers, and a more modest (or zero) decline for non-marginal borrowers.

Overall, the results in Table 7 indicate that market congestion reduces the likelihood that in-the-money marginal borrowers are able to connect with a mortgage lender and submit a formal refinance loan application (if desired). Relative to the unconditional quarterly incidence of an inquiry (6.7 percent), capacity constraints reduce the likelihood that the most marginal borrowers obtain a mortgage inquiry by about 25 percent. This is over half of the magnitude of the corresponding estimated effect of supply constraints on probability of prepayment, suggesting that lenders' rationing credit prior to loan applications being filed has an economically important impact on marginal borrowers' ability to refinance.

C. Do Supply-Constrained Lenders De-Prioritize the Processing of 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.[39]

We hypothesize that when facing excess demand, lenders may de-prioritize their processing of loan applications they perceive as less profitable or more difficult to underwrite. We use HMDA data on refinance loan applications reported in years 2018 to 2021 to assess the extent to which this occurs in practice, based on two measures: (1) the number of days it takes to process the application, and (2) the share of applications that are closed or denied for incompleteness.

Figure 8 presents the average number of processing days on refinance originations by application month and borrower loan amount. As expected, the average number of processing days increases with overall refinance activity. Further, the increase occurs disproportionately

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

among borrowers in the Very Low and Low loan amount groups, suggesting these borrowers are de-prioritized when lenders get very busy. (Appendix Figure A.3 shows that patterns are similar when we categorize borrowers by income or credit score.)

These results persist after controlling for other loan and borrower characteristics, and for differences across lenders, states, and application month. Table 8 presents results using a regression specification similar to equation (2) except that the dependent variable is the number of application processing days, estimated on HMDA data (as described in Appendix A.2). In column A the effects of supply constraints are allowed to vary by loan amount. When supply constraints are High, the average number of application processing days increases by nearly 4 days for borrowers in the Very Low loan amount group, and by nearly 2 days for those in the Low loan amount group. Results are qualitatively similar (though smaller in magnitude) if we allow the effects of supply constraints to vary by borrower income or credit score, as shown in columns B and C.[40]

Next, we examine whether supply constrained lenders disproportionately close or deny applications from marginal borrowers due to incomplete information.[41] This could occur if lenders with excess demand put less effort into following up with borrowers to obtain needed documentation, especially those they perceive as less profitable or more difficult to underwrite.

Consistent with this intuition, Figure 9 shows that when refinance applications began increasing in late 2019 and into the 2020-2021 refinance boom, the share of applications categorized as incomplete increased disproportionately for applicants with a lower loan amount. (Appendix Figure A.4 shows a similar pattern, if not more pronounced, for borrowers with Very Low income.)

Regression results (Table 9) indicate that, after accounting for other factors, marginal borrowers are disproportionately likely to see their applications closed or denied for incompleteness when constraints are binding. For example, applications for loans with Very Low loan amounts are about 0.9 percentage points to end as an Incomplete in markets with High

[40] One limitation of the application processing days measure used in this analysis is that it is only observed for applications that result in an origination. Thus, we may understate the extent to which capacity constraints lead to delays in processing if, for some marginal borrowers, the delay in processing ultimately results in their loan not being originated.

[41] 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.

congestion, and applications from borrowers with Very Low income are 1.3 percentage more likely to end as an Incomplete. These effects are about 10 to 14 percent of the average rate of incompletes observed in the sample.[42]

Overall, the results in Tables 8 and 9 indicate that when lenders face excess demand, they de-prioritize loan applications from marginal borrowers, as reflected in longer application processing times and higher rates of applications being closed or denied for incompleteness.

What impact does this ultimately have on refinancing activity among marginal borrowers? While this question is not straightforward to answer, our back-of-the-envelope calculations suggest the impact is modest. Specifically, our estimates suggest that supply constraints reduced the cumulative rate of prepayment among Very Low UPB borrowers by about 7 percentage points over the most recent refinancing boom (see Figure 6, panel B). Assume that half of this decline is due to marginal borrowers not being able to connect with and obtain pricing from a lender (as suggested in Table 7), and the remaining half – about 3.5 percent of all Very Low UPB borrowers – were able to do so and then proceeded to file a refinance loan application. The results in Table 9 suggest that about 10 percent of these borrowers had their application closed or denied for incompleteness. This suggests that 0.35 percent of Very Low UPB borrowers would have prepaid their loan if not for capacity constraints leading their lender to close their loan for incompleteness, which is about 5 percent of the total cumulative effect estimated in Figure 6, panel B.

Our finding that capacity constraints have a relatively modest effect on lenders' processing of applications from marginal borrowers is qualitatively consistent with Agarwal et al. (2024), 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 for such borrowers. In contrast, Agarwal et al. (2024) 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

[42] We are not able to analyze how effects vary by credit score, because credit score is not reported in HMDA for applications the lender closes because of incomplete information.

pandemic-related refinance boom.[43] Instead the authors attribute differences 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 7, 8, and 9 which suggest that, when supply-side constraints are binding, the decline in marginal borrowers' propensity to refinance largely occurs before borrowers submit a formal application for credit.

7. Conclusion

This paper presents new evidence that supply-side capacity constraints inhibit certain borrowers from refinancing when they otherwise would. Borrowers with lower remaining loan balances, incomes, or credit scores are about 3 percentage points less likely to prepay their mortgage when markets are highly congested. This effect is over 30 percent of the mean quarterly prepayment rate in our sample. Our estimates are based on a sample of borrowers that is very likely to qualify for a new refinancing and account for the expected financial return from refinancing, a rich set of borrower and loan characteristics, and shifts in demand that occur during refinancing booms.

Our results suggest that when lenders face excess demand they de-prioritize borrowers perceived as less profitable or more difficult to underwrite. We show that lenders do not adjust pricing but instead ration credit to these "marginal" borrowers. In particular, marginal borrowers in highly congested markets are substantially less likely to connect with and obtain pricing from a lender, as proxied by inquiries for new mortgage credit. Constrained lenders also appear to de-prioritize the underwriting of applications from marginal borrowers, as reflected in longer processing times and more applications closed or denied for incomplete information. The result is less credit availability for borrowers with smaller loans, lower credit scores, and lower income, which worsens the distributional equity of gains from refinancing and may lower the efficacy monetary policy operating through the refinance channel.

We find that the cumulative effect of supply constraints over the 2020-2021 refinance boom was to reduce the overall incidence of mortgage refinancing among marginal borrowers by about 12 percentage points, while the effect on non-marginal borrowers was ultimately minimal. This

[43] Differences in empirical methodology and the data being analyzed complicate a straightforward reconciliation between our results with Agarwal et al. (2024). They use proprietary data from Freddie Mac to compute funding rates, i.e., the share of loans run through Freddie Mac's automated underwriting software 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 underwriting software.

difference in refinancing activity is over half the magnitude of overall differences in (sub)optimal refinancing behavior documented in previous literature, indicting that supply-side constraints are an important reason why some borrowers “fail to refinance” during booms.

One implication of this result is that policies designed to improve borrowers’ refinancing behavior by addressing demand-side frictions may not diminish these differences. For example, informational interventions may be an effective way to increase borrower awareness (Bhattacharya et al. 2022; Byrne et al. 2023) but in a congested market could amplify credit rationing and fail to boost refinancing by marginal borrowers.

Alternatively, policies that reduce lender costs or otherwise incentivize the underwriting of marginal borrowers would increase credit availability. A streamlined refinancing program that waives income and employment documentation requirements (e.g., Gerardi, Loewenstein, and Willen 2021; Alexandrov, Goodman, and Tozer 2022) could disproportionately benefit borrowers with lower incomes or spottier work histories, who otherwise may be more costly to underwrite. Further, mortgage servicers could be required to proactively contact all borrowers with a refinancing offer when their potential financial gains from refinancing are large enough (Alexandrov, Goodman, and Tozer 2022). And Bhagat (2021) proposes adding an automatic refinancing feature to the mortgage contract which would eliminate frictions to refinancing entirely. While these programs could meaningfully improve the financial health of many U.S. households, policymakers would need to balance these benefits against any general equilibrium consequences for the overall pricing and availability of mortgage credit.

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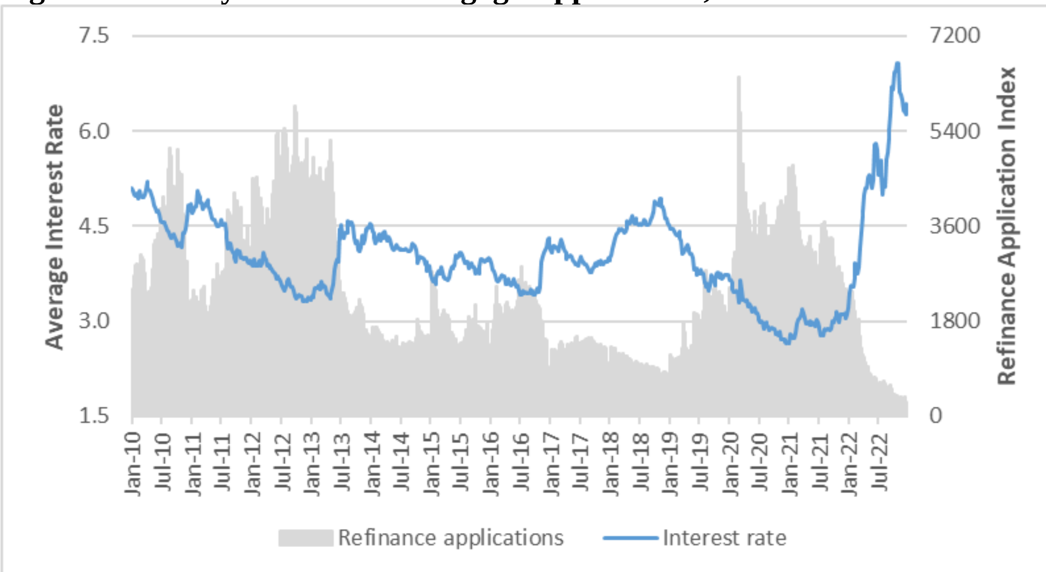
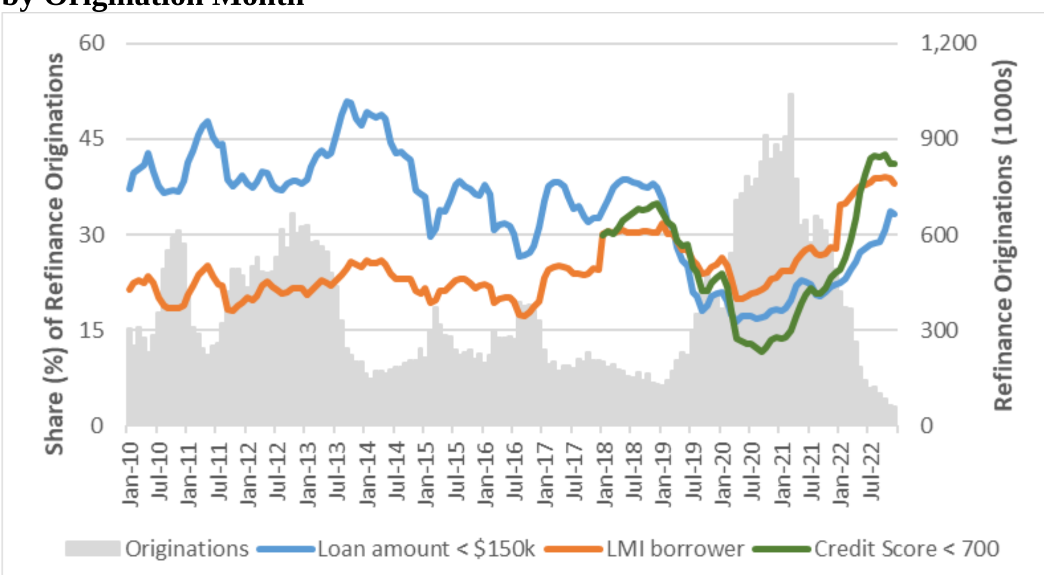
Figure 1: Weekly Refinance Mortgage Applications, 2010 to 2021



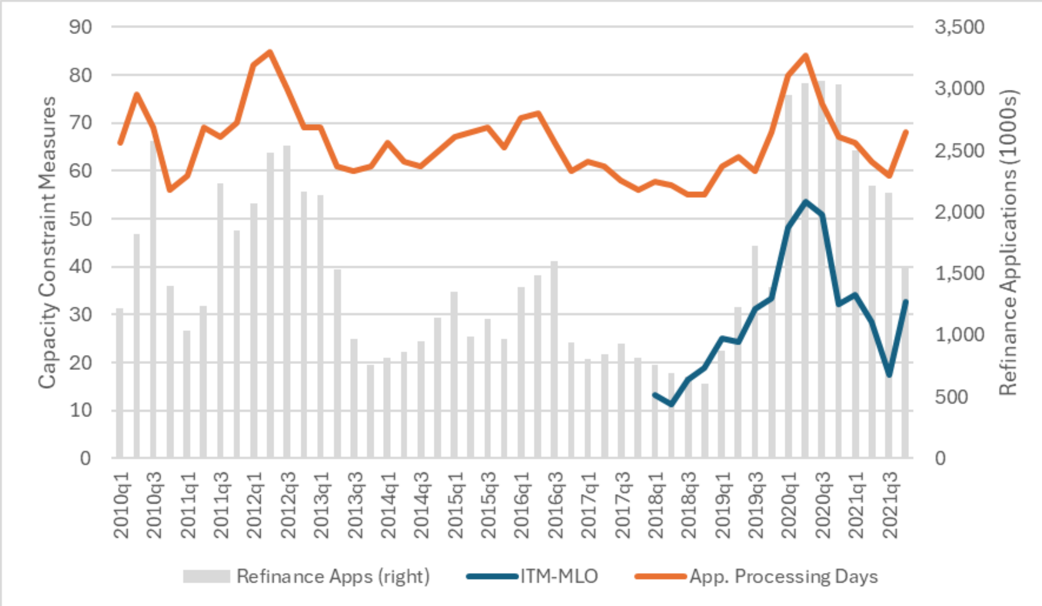
Notes: Refinance mortgage application data are from Mortgage Bankers Association's (MBA) weekly applications survey. Index is equal to 100 for the week of March 16, 1990. Interest rate data are from Freddie Mac's Primary Mortgage Market Survey (PMMS) and reflect the average rate on a 30-year fixed-rate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

Figure 2: Share (%) of Refinance Originations with Selected Loan and Borrower Characteristics, by Origination Month



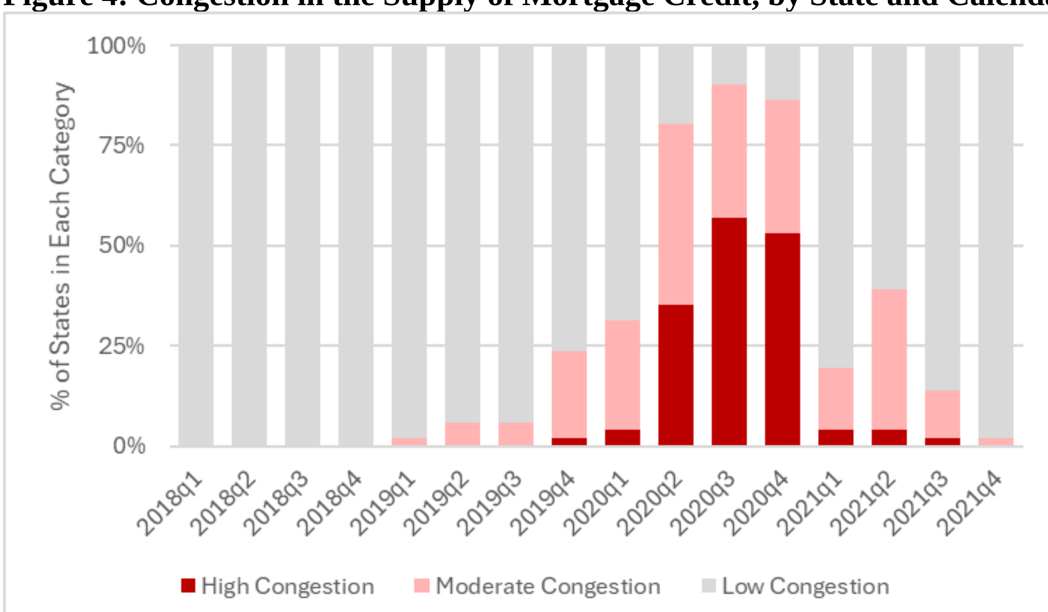
Notes: Authors' calculations using Home Mortgage Disclosure Act (HMDA) data. A low- or moderate-income (LMI) borrower has family income less than 80 percent of the median family income (MFI) in the metropolitan statistical area (MSA) or state non-MSA in which it is located. Borrower credit scores are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

Figure 3: Alternative Supply Constraint Measures, 2010 to 2021



Notes: This figure shows the 75th percentile value across states (within each calendar quarter) for two alternative measures of mortgage supply constraints. The first, ITM-MLO, is the ratio of the number of in-the-money (ITM) mortgages (calculated using the NMDB) to the number of unique mortgage loan officers (MLOs) recorded on loan applications in HMDA data. The second, application processing days, is equal to the number of days between the date of the application and the date of the origination, based on first lien refinance loan applications secured by 1-4 family properties reported in HMDA data. See the Data section for additional details.

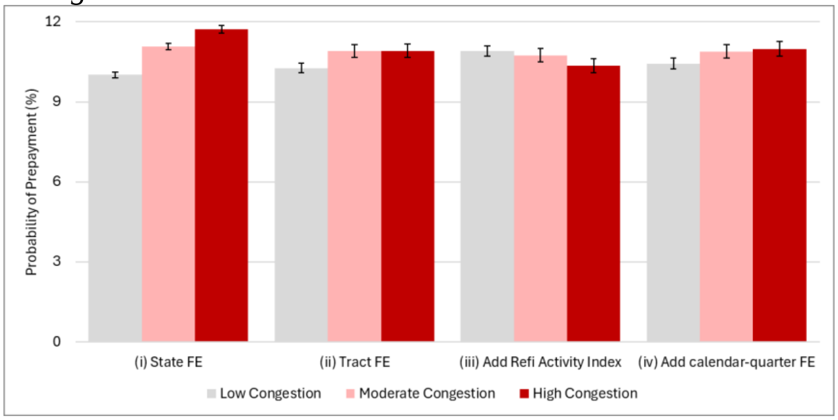
Figure 4: Congestion in the Supply of Mortgage Credit, by State and Calendar Quarter



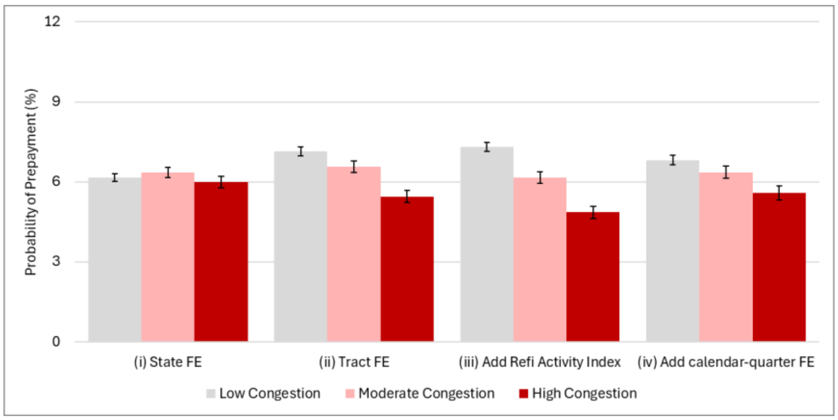
Notes: This figure shows the share of states categorized as capacity constrained over the 2018 to 2021 period. The level of congestion within a state-quarter is categorized as: "Low" if the ITM-MLO ratio is less than or equal to the 75th percentile value over all state-quarter observations over this period ; "Moderate" if the ITM-MLO ratio is between the 75th and 90th percentile value, and (3) "High" if the ITM-MLO ratio is above the 90th percentile value. See the Data section for additional details.

Figure 5: Predicted Probability of Prepayment, by Supply Constraints and Borrower UPB

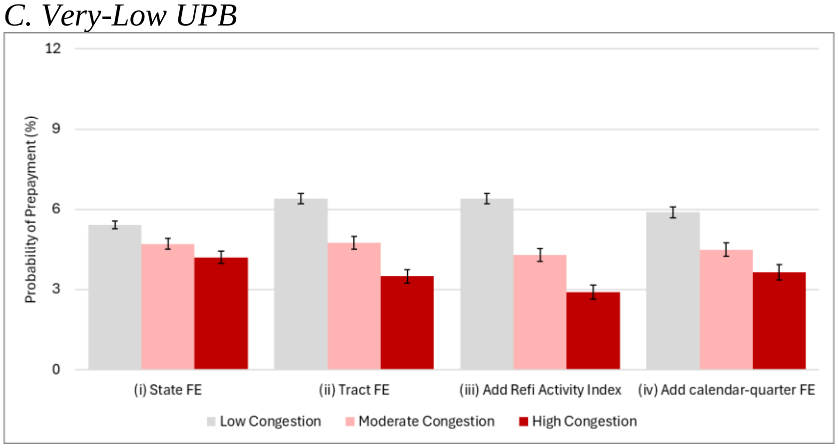
A. Higher UPB



B. Low UPB



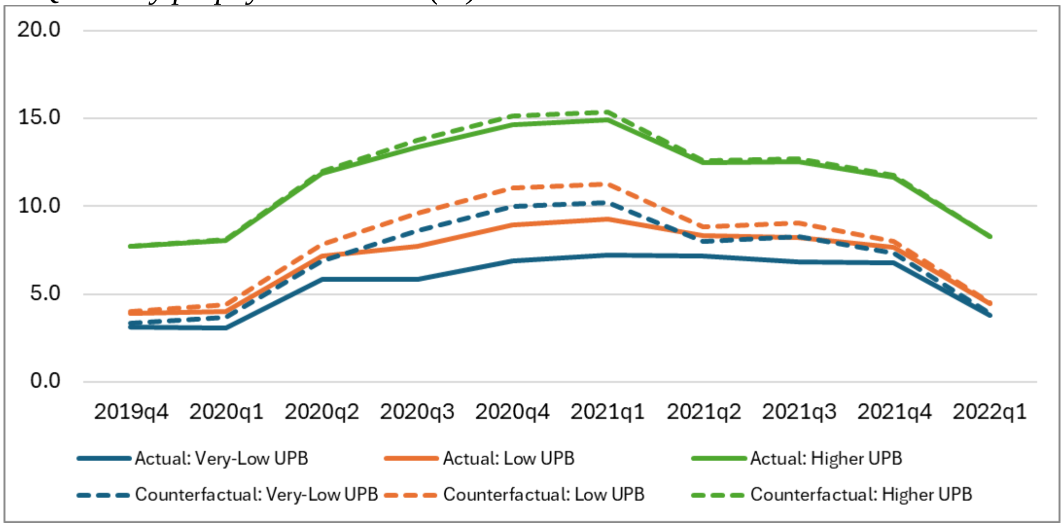
C. Very-Low UPB



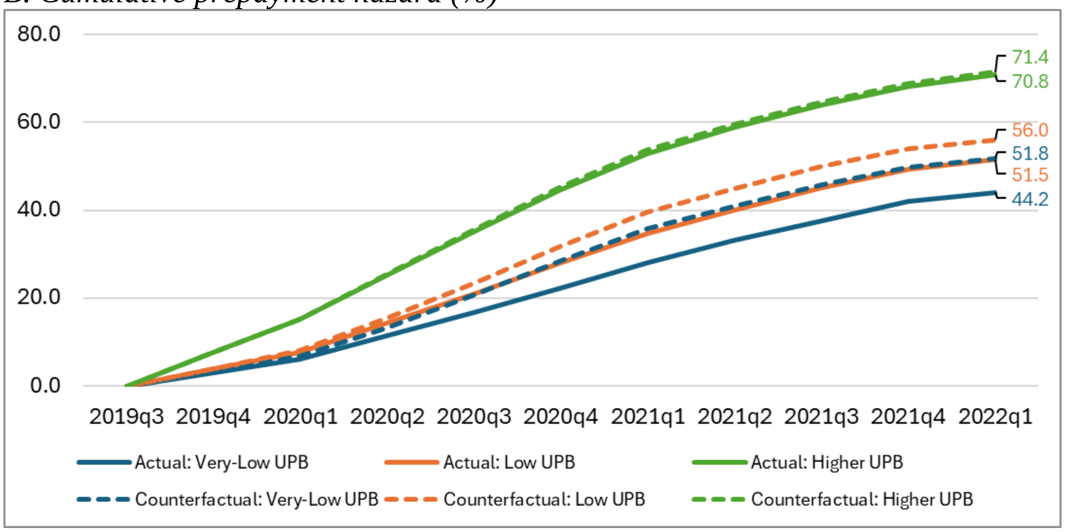
Note: This figure plots quarterly predicted prepayment probabilities by the loan's remaining unpaid principal balance (UPB), the level of market congestion, and empirical specification. The predictions are calculated using the coefficient estimates reported in Appendix Table A.1.

Figure 6: Predicted Effects of Capacity Constraints on Prepayment for Loans That Are Active and In the Money (ITM) as of 2019Q3, by UPB

A. Quarterly prepayment hazard (%)

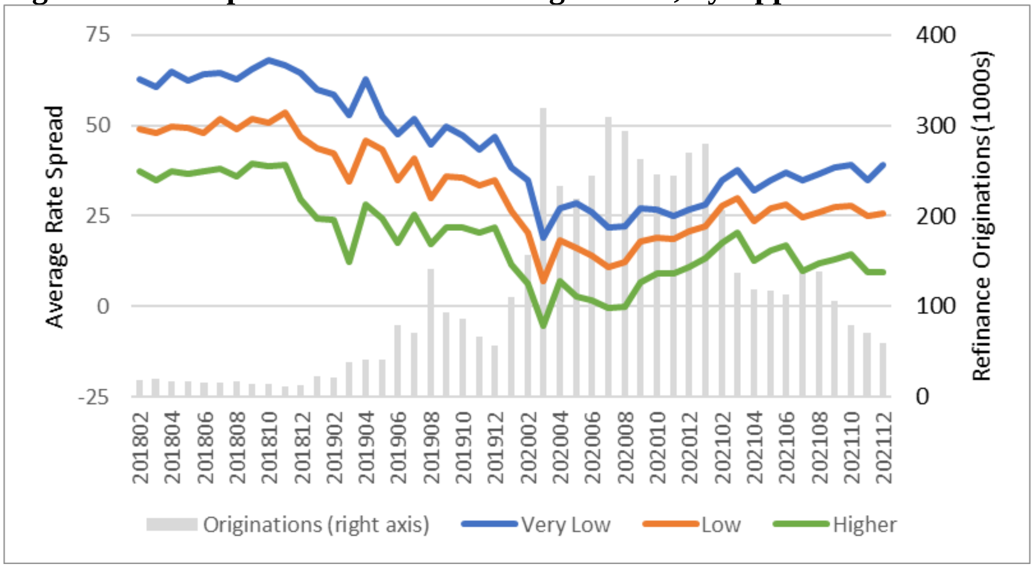


B. Cumulative prepayment hazard (%)



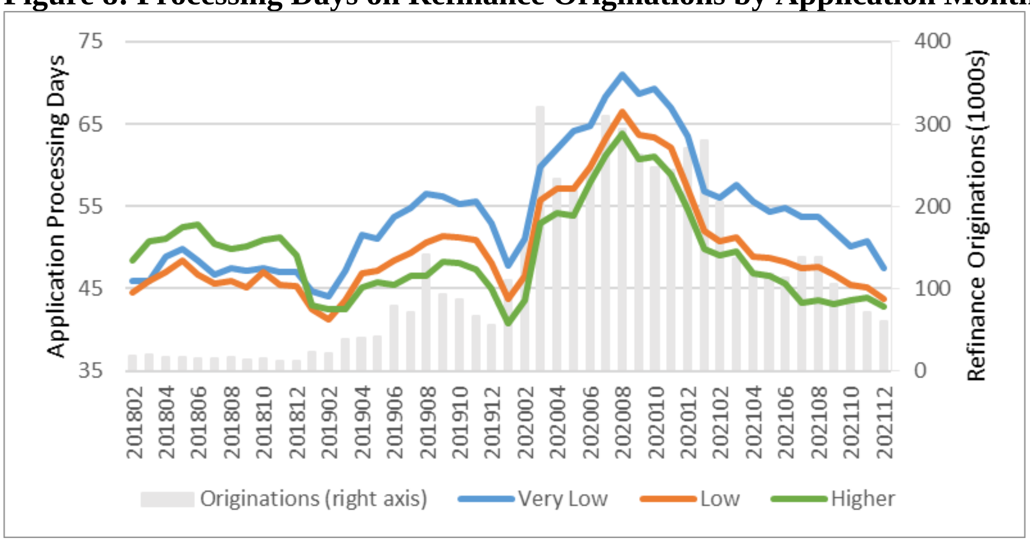
Notes: Figure A presents predicted quarterly prepayment hazards for loans that are active and ITM as of 2019Q3, separately for borrowers categorized by their Unpaid Principal Balance. The predictions are calculated using estimates from specification (iii) (presented in Appendix Table A.1), under two scenarios. In the "Actual" scenario, the variable $capConstr_{st}$ and all other covariates take on their actual values. In the "Counterfactual" scenario the variable $capConstr_{st}$ is set to Low for all observations, and all other covariates take on their actual values. Figure B presents the corresponding cumulative prepayment hazards through 2022Q1.

Figure 7: Rate Spread on Refinance Originations, by Application Month and Loan Amount



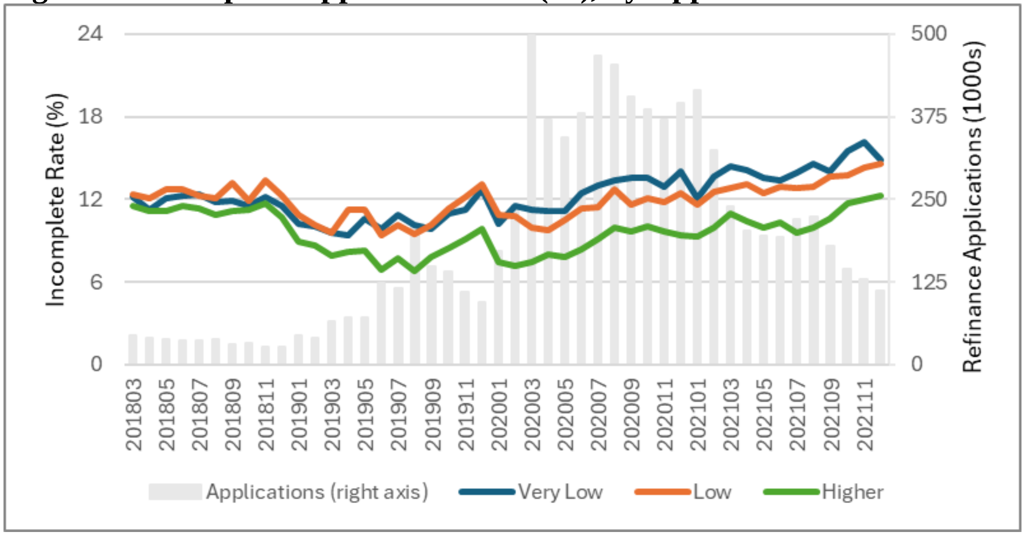
Notes: This figure presents the average interest rate spread on refinance loan applications by month and loan amount. Interest rate spread is defined as the difference between the annual percentage rate (APR) on the loan and the average prime offer rate (APOR) as of the date the interest rate is set. Calculated using HMDA data on first-lien, closed-end, conventional conforming, 30-year term, fixed-rate, fully amortizing, non-cash out refinance loan applications secured by owner-occupied, site-built 1-4 family properties from February 2018 to January 2022 that resulted in an origination.

Figure 8: Processing Days on Refinance Originations by Application Month and Loan Amount



Notes: This figure presents the average application processing days (defined as the difference between the origination date and the application date) by month and loan amount, calculated using HMDA data. See Notes to Figure 7 for additional details.

Figure 9: Incomplete Application Rate (%), by Application Month and Loan Amount



Notes: This figure presents the share (%) of refinance loan applications that are closed or denied for incomplete information by application month and loan amount, calculated using HMDA data. See Notes to Figure 7 for additional details.

Table 1: Selected Sample Means

A. By Supply Congestion

	Supply Congestion			
	Low	Moderate	High	All
Prepaid by Next Quarter (%)	8.3	9.6	10.5	9.2
Ratio, ITM Loans to MLOs	23.1	37.9	57.1	36.3
Ratio, Note Rate to Market Rate	1.27	1.35	1.40	1.33
County-Level Unemployment Rate (%)	4.3	6.0	8.2	5.9
Cumulative # of Quarters ITM	7.6	6.6	5.8	6.8
Index of Tract-Level Refinance Apps	191.8	270.8	315.1	246.0
% Missing, Tract-Level Refinance Apps	3.5	2.4	1.9	2.8
Age of Loan (Quarters)	15.2	15.1	14.7	15.1
Loan-Quarter Observations (Count)	688,191	354,543	412,000	1,454,734
as % of All Observations	47.3	24.4	28.3	100.0

B. By Supply Congestion and Current UPB Group

	I. Supply Congestion = Low			II. Supply Congestion = Moderate			III. Supply Congestion = High		
Borrower UPB Category	Very Low	Low	Higher	Very Low	Low	Higher	Very Low	Low	Higher
Prepaid by Next Quarter (%)	4.8	5.7	9.7	5.2	6.6	11.0	5.4	6.9	12.2
Ratio, ITM Loans to MLOs	22.4	22.9	23.2	37.8	37.8	38.0	56.7	56.9	57.3
Ratio, Note Rate to Market Rate	1.31	1.29	1.26	1.43	1.39	1.33	1.50	1.44	1.38
County-Level Unemployment Rate (%)	4.5	4.5	4.3	6.2	6.1	6.0	8.3	8.3	8.2
Cumulative # of Quarters ITM	13.0	9.3	5.9	11.1	8.1	5.4	10.2	7.2	4.8
Index of Tract-Level Refinance Apps	168.3	181.9	199.5	234.0	250.3	282.2	264.8	285.0	329.8
% Missing, Tract-Level Refinance Apps	8.4	5.0	2.1	6.2	3.5	1.4	5.3	3.0	1.0
Age of Loan (Quarters)	23.5	19.1	12.5	22.7	18.8	12.9	22.3	18.3	12.7
Loan-Quarter Observations (Count)	100,032	123,506	464,653	44,063	59,398	251,082	47,357	66,823	297,820
as % of All Observations	6.9	8.5	31.9	3.0	4.1	17.3	3.3	4.6	20.5

Notes: This table presents mean values for selected variables over the 1,454,734 loan-quarter observations (on 261,509 unique loans) in our main analysis sample. Supply Congestion is measured at state-quarter level based on the ratio of in-the-money (ITM) loans to mortgage loan officers (MLOs) in the state-quarter. Borrower UPB (unpaid principal balance) is based on the observed value as of the end of each quarter. "Ratio, Note Rate to Market Rate" is the note rate divided by the current market rate, where the market rate is equal to the average note rate on refinance loans originated in the next quarter to borrowers with a similar credit score and loan-to-value (LTV) ratio. "Cumulative # of Quarters ITM" is the number of previous quarters the loan has been in-the-money. "Index of Tract-Level Refinance Apps" is the number of new refinance loan applications in the borrower's census tract and quarter, indexed to the census-tract from 2018 to 2019.

Table 2: Sample Means for Other Control Variables (Loan-Level)

		Supply Congestion			
Categorical Variable	Value	Low	Moderate	High	All
Unpaid Principal Balance (*t*)	Very Low	11.1	11.5	11.0	9.9
	Low	15.6	15.9	15.6	14.4
	Higher	73.4	72.6	73.4	75.7
Borrower Income (*t*=0)	Very Low	9.9	10.1	9.8	9.1
	Low	14.7	14.6	14.4	14.0
	Higher	75.3	75.3	75.8	76.9
Credit Score (*t*)	Very Low	7.2	6.5	6.7	7.5
	Low	13.0	12.1	12.2	12.9
	Higher	79.8	81.4	81.1	79.6
Combined Loan-to-value (*t*)	< 70	71.2	69.0	65.5	70.4
	70-79	16.6	17.7	19.0	17.3
	80-89	8.9	10.4	11.7	9.3
	90-97	2.9	2.4	3.2	2.6
	97+	0.4	0.4	0.5	0.4
Debt-to-income (*t*=0)	< 34	44.0	46.5	46.2	44.7
	34-38	17.1	16.8	16.9	17.1
	39-43	18.8	18.2	18.4	18.7
	44-48	14.3	13.2	13.2	13.9
	49+	5.8	5.2	5.2	5.5
	Unknown	0.1	0.1	0.1	0.1
Spread at Origination (bps; *t*=0)	50+	22.2	18.9	17.3	19.2
	25 to 49	28.1	26.6	25.3	26.3
	-25 to 24	46.2	50.1	52.3	50.0
	< -25	3.5	4.4	5.1	4.5
Loan Purpose (*t*=0)	Purchase	57.6	58.2	57.0	57.4
	Refi - not cash out	38.8	38.2	39.0	38.9
	Refi - cash out	3.6	3.6	4.0	3.7
Race and Ethnicity (*t*=0)	Black	4.6	4.7	4.7	4.5
	Hispanic (non-black)	9.4	8.7	9.9	9.3
	Asian (non-Hispanic)	7.4	6.7	8.4	7.8
	Other (non-Hispanic)	1.3	1.2	1.2	1.3
	White (non-Hispanic)	77.3	78.6	75.8	77.1
First-time Homebuyer (*t*=0)	Yes	28.2	28.7	29.1	28.3
Count of Unique Loans		201,501	173,897	157,025	261,509

Notes: This table presents sample means of other selected variables at loan level, using the last quarterly observation for each loan, whether it was still active, prepaid, or exited 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. The count of unique loans in the first to third columns does not sum to the total in column four because loans may be categorized in different levels of supply congestion over time. For Unpaid Principal Balance, Income, and Credit Score, borrowers are categorized relative to others within the same state-quarter; see Data section for details. Spread at origination is the difference between the note rate and the average prime rate available when the loan was originated.

Table 3: Marginal Effects of Supply Constraints on Probability of Prepayment, by Borrower Type

	Specification (iii)		Specification (iv)	
Supply Congestion	Moderate	High	Moderate	High
A. By UPB				
Very Low	-2.113***	-3.502***	-1.402***	-2.244***
	(0.139)	(0.155)	(0.146)	(0.181)
Low	-1.137***	-2.451***	-0.454***	-1.226***
	(0.134)	(0.149)	(0.141)	(0.175)
Higher	-0.163*	-0.555***	0.454***	0.550***
	(0.090)	(0.114)	(0.100)	(0.147)
B. By Income				
Very Low	-1.650***	-2.930***	-0.968***	-1.737***
	(0.152)	(0.167)	(0.158)	(0.191)
Low	-1.178***	-2.069***	-0.520***	-0.900***
	(0.148)	(0.162)	(0.154)	(0.186)
Higher	-0.311***	-0.838***	0.323***	0.291**
	(0.087)	(0.111)	(0.097)	(0.144)
C. By Credit Score				
Very Low	-1.082***	-2.967***	-0.426*	-1.806***
	(0.247)	(0.240)	(0.251)	(0.258)
Low	-1.271***	-2.232***	-0.628***	-1.102***
	(0.179)	(0.187)	(0.184)	(0.210)
Higher	-0.463***	-0.971***	0.175*	0.161
	(0.081)	(0.106)	(0.092)	(0.140)
Control Variables				
Base covariates	Y		Y	
Tract FE	Y		Y	
Index of Tract Refis	Y		Y	
Calendar-Quarter FE			Y	

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment computed from OLS regressions of Equation 1; errors clustered at loan level. The estimation sample includes 1,454,734 loan-quarter observations and 261,509 unique loans. Each panel presents results from a separate regression in which the categorical measure of Supply Congestion is interacted with a categorical measure of the borrower's: (A) Unpaid Principal Balance; (B) Income; or (C) Credit Score. Specification (iii) includes the base covariates in X_{bst}, census tract fixed effects, and an index for the level of refinance activity in the tract. Specification (iv) adds calendar-quarter fixed effects. See Appendix Table A.1 for the full set of coefficient estimates.

Table 4: Effects by Analysis Period and Borrower UPB

	Specification (iii)		Specification (iv)	
Supply Congestion	Moderate	High	Moderate	High
A. Years 2018 to 2021 (1,454,734 observations; mean of dependent variable is 9.2)				
UPB = Very Low	-2.919***	-3.010***	-2.145***	-2.059***
	(0.161)	(0.158)	(0.173)	(0.196)
UPB = Low	-2.025***	-2.507***	-1.262***	-1.589***
	(0.158)	(0.151)	(0.170)	(0.188)
UPB = Higher	-0.474***	-1.174***	0.188	-0.372**
	(0.107)	(0.110)	(0.123)	(0.157)
B. Years 2010 to 2013 (770,943 observations; mean of dependent variable is 6.9)				
UPB = Very Low	-0.129	-1.347***	-0.409**	-1.536***
	(0.163)	(0.177)	(0.173)	(0.209)
UPB = Low	-0.122	-0.322*	-0.320*	-0.459**
	(0.156)	(0.170)	(0.167)	(0.203)
UPB = Higher	0.284***	0.446***	0.135	0.345**
	(0.100)	(0.115)	(0.116)	(0.162)
C. Years 2010 to 2021 (2,870,831 observations; mean of dependent variable is 7.7)				
UPB = Very Low	-1.421***	-2.340***	-1.228***	-1.974***
	(0.096)	(0.102)	(0.102)	(0.121)
UPB = Low	-0.940***	-1.624***	-0.750***	-1.294***
	(0.094)	(0.097)	(0.100)	(0.117)
UPB = Higher	-0.092	-0.416***	0.094	-0.132
	(0.061)	(0.068)	(0.070)	(0.093)
Control Variables				
Base covariates	Y		Y	
Tract FE	Y		Y	
Index of Tract Refis	Y		Y	
Calendar-Quarter FE			Y	

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment during different historical periods by the borrower's Unpaid Principal Balance. The specifications are estimated on the 2018 to 2021 sample in Panel A, the 2010 to 2013 sample in Panel B, and the 2010 to 2021 sample in Panel C. All specifications use an alternative measure to categorize congestion in mortgage markets, based on loan application processing times observed in HMDA data; see the Data section and Appendix Figure A.1 for details. See Table 3 for additional notes.

Table 5: Effects of Capacity Constraints on Probability of Prepayment by Borrower UPB, Estimated using Alternative Samples

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1[capConstr = Moderate] * 1[UPB = Very Low]	-2.113***	-2.307***	-2.108***	-2.110***	-2.280***	-1.968***	-2.220***
	(0.139)	(0.162)	(0.145)	(0.141)	(0.169)	(0.122)	(0.153)
1[capConstr = Moderate] * 1[UPB = Low]	-1.137***	-1.388***	-1.087***	-1.143***	-1.341***	-1.189***	-1.335***
	(0.134)	(0.156)	(0.144)	(0.136)	(0.167)	(0.118)	(0.151)
1[capConstr = Moderate] * 1[UPB = Higher]	-0.163*	-0.184*	-0.027	-0.182**	-0.033	-0.227***	-0.128
	(0.090)	(0.103)	(0.101)	(0.092)	(0.116)	(0.080)	(0.106)
1[capConstr = High] * 1[UPB = Very Low]	-3.502***	-3.958***	-3.494***	-3.586***	-4.000***	-3.371***	-3.885***
	(0.155)	(0.179)	(0.164)	(0.157)	(0.190)	(0.135)	(0.171)
1[capConstr = High] * 1[UPB = Low]	-2.451***	-2.727***	-2.352***	-2.487***	-2.702***	-2.371***	-2.760***
	(0.149)	(0.174)	(0.161)	(0.151)	(0.188)	(0.130)	(0.169)
1[capConstr = High] * 1[UPB = Higher]	-0.555***	-0.567***	-0.264**	-0.539***	-0.220	-0.685***	-0.421***
	(0.114)	(0.130)	(0.128)	(0.116)	(0.147)	(0.100)	(0.133)
Number of Observations	1,454,734	1,158,377	1,226,428	1,413,351	961,615	1,874,061	1,155,163
Mean of Dependent Variable	9.2	9.7	9.6	9.2	9.7	9.5	9.8
Sample Restrictions							
Drop if ever DQ on any tradeline	N	Y	N	N	Y	N	Y
Drop if CLTV > 80	N	N	Y	N	Y	N	Y
Drop if credit score < 660	N	N	N	Y	Y	N	Y
Include Government Loans	N	N	N	N	N	Y	Y

Notes: This table presents marginal effects of capacity constraints on the probability of prepayment by the borrower's Unpaid Principal Balance, computed from OLS regressions of Equation 1 (with all controls except for calendar-quarter fixed effects) on alternative estimation samples. Estimates of other controls are omitted for brevity. Errors are clustered at loan level. The first column reproduces the estimates in Table 3, panel 3(iii). In column (2) we drop borrowers who are ever reported as more than 30 days delinquent on any trade line reported to the credit bureaus, in column (3) we drop all loan quarters where the borrower's combined LTV exceeds 80 percent, and in column (4) we drop any borrower whose minimum credit score falls below 660. In column (5) we enforce all three filters. In the final two columns we expand the sample to include borrowers with government loans; in column (6) we use the sample filters from our main analysis and in column (7) we add the extra three filters.

Table 6: Effects of Capacity Constraints on Interest Rate Spread (bps), by Borrower Type

	Capacity Constraint Effects Vary by…		
	A. Loan Amount	B. Income	C. Credit Score
1[borrType = Very Low] * 1[capConstr = Moderate]	-2.518***	0.325***	0.074
	(0.178)	(0.094)	(0.099)
1[borrType = Very Low] * 1[capConstr = High]	-3.184***	-0.076	-2.674***
	(0.168)	(0.087)	(0.096)
1[borrType = Low] * 1[capConstr = Moderate]	0.403***	0.574***	-0.929***
	(0.102)	(0.077)	(0.070)
1[borrType = Low] * 1[capConstr = High]	-0.725***	0.283***	-2.058***
	(0.094)	(0.070)	(0.065)
1[capConstr = Moderate]	-0.699***	-0.831***	-0.558***
	(0.040)	(0.042)	(0.042)
1[capConstr = High]	0.152***	0.004	0.546***
	(0.058)	(0.059)	(0.059)
1[borrType = Very Low]	26.229***	2.401***	31.308***
	(0.100)	(0.058)	(0.055)
1[borrType = Low]	13.224***	1.923***	15.112***
	(0.061)	(0.045)	(0.040)
Controls			
Loan and Borrower Characteristics	Y	Y	Y
Lender Fixed Effects	Y	Y	Y
State Fixed Effects	Y	Y	Y
Application Month Fixed Effects	Y	Y	Y
R-sq	0.423	0.423	0.424

Notes: This table presents marginal effects of capacity constraints on the interest rate spread observed on originated loans, computed from OLS regressions with errors clustered at loan level. This analysis uses HMDA data on 5,448,753 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 February 2018 to January 2022 that resulted in an origination. The dependent variable is the interest rate spread, defined as the difference between the annual percentage rate (APR) on the loan and the average prime offer rate (APOR) as of the date the interest rate is set. The sample mean of the interest rate spread is 11.8.

Table 7: Effects of Capacity Constraints on Inquiries for New Mortgage Credit, by Borrower Type

	Specification (iii)		Specification (iv)	
Market Congestion	Moderate	High	Moderate	High
A. By UPB				
Very Low	-1.301***	-1.843***	-0.639***	-0.709***
	(0.126)	(0.143)	(0.133)	(0.168)
Low	-0.965***	-1.513***	-0.281**	-0.338**
	(0.130)	(0.143)	(0.136)	(0.168)
Higher	-0.698***	-1.380***	0.010	-0.135
	(0.081)	(0.100)	(0.092)	(0.134)
B. By Income				
Very Low	-0.984***	-1.686***	-0.318**	-0.551***
	(0.150)	(0.162)	(0.156)	(0.185)
Low	-1.038***	-1.453***	-0.359**	-0.276
	(0.141)	(0.153)	(0.147)	(0.177)
Higher	-0.749***	-1.429***	-0.041	-0.190
	(0.078)	(0.098)	(0.089)	(0.132)
C. By Credit Score				
Very Low	-1.270***	-2.613***	-0.605**	-1.443***
	(0.242)	(0.232)	(0.246)	(0.249)
Low	-1.208***	-2.085***	-0.539***	-0.913***
	(0.170)	(0.174)	(0.175)	(0.197)
Higher	-0.721***	-1.265***	-0.024	-0.049
	(0.073)	(0.094)	(0.084)	(0.129)
Control Variables				
Base covariates	Y		Y	
Tract FE	Y		Y	
Index of Tract Refis	Y		Y	
Calendar-Quarter FE			Y	

Notes: This table presents marginal effects of capacity constraints on the probability of having an inquiry for new mortgage credit (i.e., a hard credit check), computed from OLS regressions with errors clustered at loan level. In all cases we drop loan-quarter observations after the first instance of a mortgage credit inquiry; estimation sample has 1,309,354 observations. (The full set of OLS coefficient estimates is available upon request.)

Table 8: Effects of Capacity Constraints on Processing Days, by Borrower Type

	Capacity Constraint Effects Vary by…		
	A. Loan Amount	B. Income	C. Credit Score
1[borrType = Very Low] * 1[capConstr = Moderate]	3.139***	1.071***	1.853***
	(0.228)	(0.120)	(0.126)
1[borrType = Very Low] * 1[capConstr = High]	3.874***	0.720***	3.146***
	(0.214)	(0.111)	(0.123)
1[borrType = Low] * 1[capConstr = Moderate]	1.794***	0.555***	1.089***
	(0.130)	(0.098)	(0.089)
1[borrType = Low] * 1[capConstr = High]	1.824***	0.260***	1.381***
	(0.119)	(0.090)	(0.082)
1[capConstr = Moderate]	-0.790***	-0.761***	-0.946***
	(0.051)	(0.053)	(0.054)
1[capConstr = High]	-0.608***	-0.495***	-0.868***
	(0.074)	(0.075)	(0.075)
1[borrType = Very Low]	-0.294**	1.099***	4.280***
	(0.127)	(0.072)	(0.070)
1[borrType = Low]	-0.868***	-0.023	3.184***
	(0.077)	(0.057)	(0.051)
Controls			
Loan and Borrower Characteristics	Y	Y	Y
Lender Fixed Effects	Y	Y	Y
State Fixed Effects	Y	Y	Y
Application Month Fixed Effects	Y	Y	Y
R-sq	0.219	0.219	0.219

Notes: This table presents marginal effects of capacity constraints on the number of days between mortgage application and origination, computed from OLS regressions with errors clustered at loan level. This analysis uses HMDA data on 5,448,753 first-lien, closed-end, conventional conforming, 30-year term, fixed-rate, fully amortizing, non-cash out refinance loan applications from February 2018 to January 2022 that result in an origination. The dependent variable is the number of application processing days, defined as the difference between the origination date and the application date. The sample mean of application processing days is 52.2.

Table 9: Effects of Capacity Constraints on Incomplete Applications, by Borrower Type

	Capacity Constraint Effects Vary by…	
	A. Loan Amount	B. Income
1[borrType = Very Low] * 1[capConstr = Moderate]	0.539***	0.948***
	(0.136)	(0.074)
1[borrType = Very Low] * 1[capConstr = High]	0.929***	1.335***
	(0.128)	(0.068)
1[borrType = Low] * 1[capConstr = Moderate]	0.305***	0.024
	(0.086)	(0.068)
1[borrType = Low] * 1[capConstr = High]	0.243***	0.011
	(0.079)	(0.062)
1[capConstr = Moderate]	-0.008	-0.081**
	(0.036)	(0.037)
1[capConstr = High]	0.108**	0.003
	(0.051)	(0.052)
1[borrType = Very Low]	1.305***	1.152***
	(0.075)	(0.043)
1[borrType = Low]	1.072***	0.414***
	(0.050)	(0.039)
Controls		
Loan and Borrower Characteristics	Y	Y
Lender Fixed Effects	Y	Y
State Fixed Effects	Y	Y
Application Month Fixed Effects	Y	Y
R-sq	0.163	0.163

Notes: This table presents marginal effects of capacity constraints on incidence of an application ending as marked incomplete, computed from OLS regressions with errors clustered at loan level. This analysis uses HMDA data on 8,732,572 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 February 2018 to January 2022. The dependent variable is equal to 1 if the lender closes or denies the loan application for incomplete information; 9.5 percent of loan applications in the sample are closed or denied for incompleteness. Results by borrower credit score are omitted from this table because credit scores are not reported for loan applications that the lender designates as incomplete.

ONLINE APPENDIX

A.1 Alternative measures of the borrower's financial incentive to refinance

In the main specifications used in this paper, we control for the borrower's financial incentive to refinance, measured as the ratio of the note rate on the mortgage to the current market rate (Richard and Roll 1989). To provide the correct pricing we calculate a borrower-specific current market rate equal to the average note rate on refinance loans originated in the next quarter to borrowers with a similar credit score and loan-to-value (LTV) ratio. (See the Data section for details.)

Here we explore the robustness of our results to using the following alternative measures of the borrower's financial incentive to refinance: (1) the ratio of the note rate to the current prime rate (i.e., assuming all borrowers can qualify for the prime rate)[47]; (2) the "Call Option" measure of Deng, Quigley, and Van Order (2000), which compares the present value of remaining mortgage payments discounted at the borrower's current note rate vs. the borrower-specific current market rate; and (3) the closed-form refinancing rule developed by Agarwal, Driscoll, and Laibson (2013; hereafter "ADL") that accounts for several factors including closing costs and expected inflation, mobility, and interest rate volatility.[48]

Appendix Figure A.5 shows that the quarterly incidence of prepayment observed in our data increases in the value of refinancing for each of these alternative measures, as expected.[49] Further, the gradient is quite similar across the measures, suggesting that in practice they do a similar job of measuring a borrower's financial incentive to refinance (at least on an ordinal basis).

[47] We assume the current prime rate is equal to the quarterly average of the prime rate on a 30-year fixed-rate conventional conforming mortgage, from Freddie Mac's Primary Mortgage Market Survey (PMMS).

[48] Specifically, we use the second-order approximation of the closed-form refinancing decision rule developed by ADL. To compute the threshold above which the borrower should refinance, we use all but one of the parameter values assumed by Gerardi, Willen, and Zhang (2023): closing costs equal to $2000 + 1 percent of the outstanding mortgage balance, a 2 percent discount rate, expected inflation of 2 percent, and expected annual mobility of 4 percent. The one exception is the standard deviation of the mortgage rate, which we set to 0.46 percent, which is the standard deviation of changes in the average monthly Freddie Mac Primary Market Mortgage Survey Rate between 2010 and 2021, our period of analysis. (Gerardi et al. 2023 use a value of 0.95 percent, based on a similar computation but over the period April 1971 to August 2020.) Our estimation results are qualitatively similar using the full set of parameter values from Gerardi, Willen, and Zhang (2023), and several other parameterizations of the ADL rule. In all cases we compute the ADL threshold using the borrower-specific current market rate.

[49] For example, among observations in the fourth decile of the borrower-specific Rate Ratio (ranging from 0.96 to 1.03), the quarterly prepayment rate was 2.9 percent, and in the ninth decile (ranging from 1.33 to 1.46) the prepayment rate was 11.3 percent. Using the Call Option measure, the prepayment rate among observations in the fourth decile (-1.68 to 1.16) was 2.8 percent, and in the ninth decile (10.89 to 14.24) was 11.1 percent.

It follows that the main results presented in this paper are robust to using alternative controls for the borrower's financial incentive to refinance, as shown in Appendix Table A.2. Each panel of the table reports results from a separate specification where the measure of the borrower's refinance option value is indicated in the column header and borrowers are categorized as indicated in the row header. Panel I repeats the results from the main specification of the paper that uses the interest rate ratio based on the borrower-specific market rate, and borrowers are categorized by UPB, income, and credit score in panels A, B, and C, respectively. In Panel II we use an alternative interest rate ratio, where we assume that all borrowers can qualify for the current prime rate. Panel III uses the Call Option measure, and Panel IV uses the ADL measure. The overall pattern of results is not sensitive to the specific refinance option value measure used. As congestion in mortgage supply increases, marginal borrowers (those with lower UPB, income, and credit scores) are substantially less likely to prepay.

A.2 Supplemental HMDA data

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). We limit the sample to 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, filed from February 2018 through January 2022.[50] For our analyses of loan pricing and loan processing days (detailed below), we further limit the sample to applications that resulted in an origination. Finally, we merge into these data our state-quarter categorical measures of supply constraints, calculated from the NMDB and HMDA (as detailed in the Data section).

Appendix Table A.3 presents sample means for the variables included in the 5.45 million loan originations used in our loan pricing and loan processing days analyses, and the 8.73 million loan applications used in our analysis of loan 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

[50] We limit the analysis to applications received from February 2018 to January 2022 because these correspond to the main analysis presented in the paper (which examines borrowers' prepayment behavior in quarters 2018Q2 through 2022Q1, conditional on being active in the preceding quarter 2018Q1 through 2021Q4). To mitigate any potential right censoring issues, we use data from HMDA reporting years 2018 through 2023.

net points at origination). These fields are omitted from the set of control variables in the specifications we use to analyze loan underwriting outcomes.

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Deng, Yongheng, John M. Quigley, and Robert Van Order. 2000. “Mortgage Terminations, Heterogeneity, and the Exercise of Mortgage Options.” *Econometrica* 68(2): 275-307.

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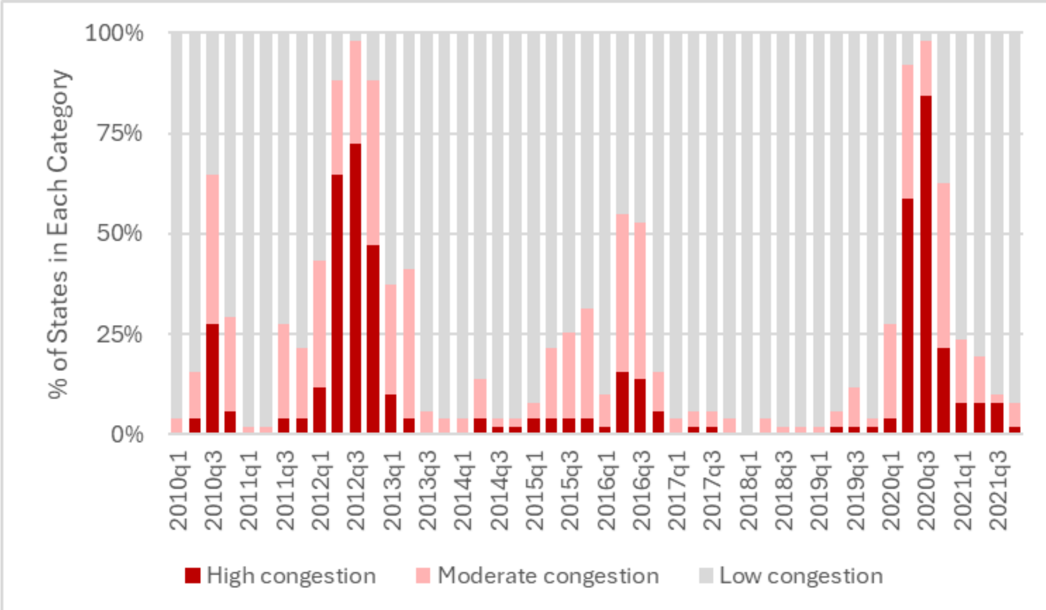
Appendix Figure A.1: Congestion in the Supply of Mortgage Credit Based on Refinance Loan Application Processing Days, by State and Calendar Quarter



Notes: This figure shows the share of states categorized as capacity constrained over the 2010 to 2021 period, based on refinance loan application processing days observed in HMDA. The level of congestion within a state-quarter is categorized as: "Low" if the number of processing days is less than or equal to the 75th percentile value over all state-quarter observations over this period; "Moderate" if it is between the 75th and 90th percentile value, and "High" if it is above the 90th percentile value. See the Data section for additional details.

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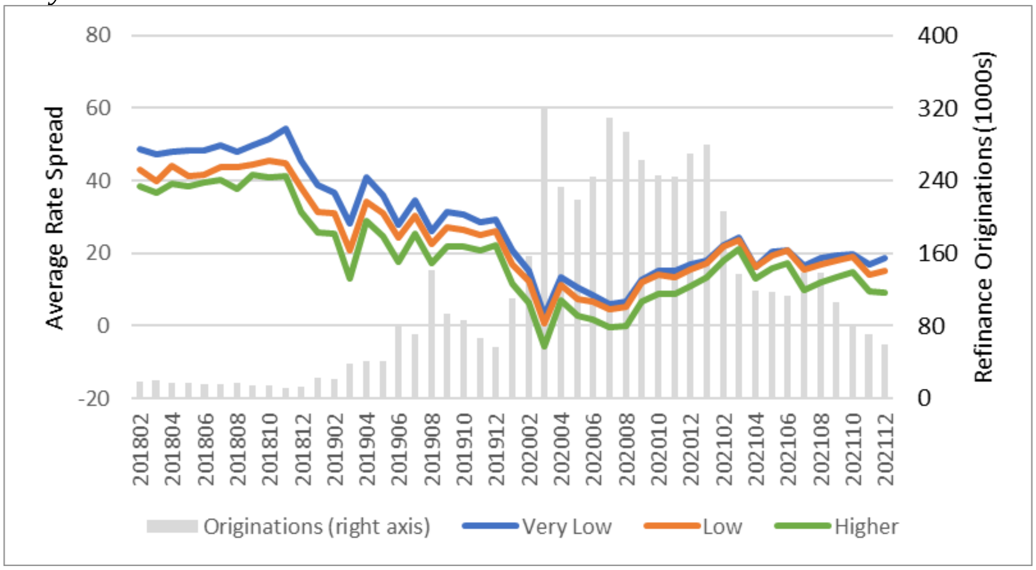
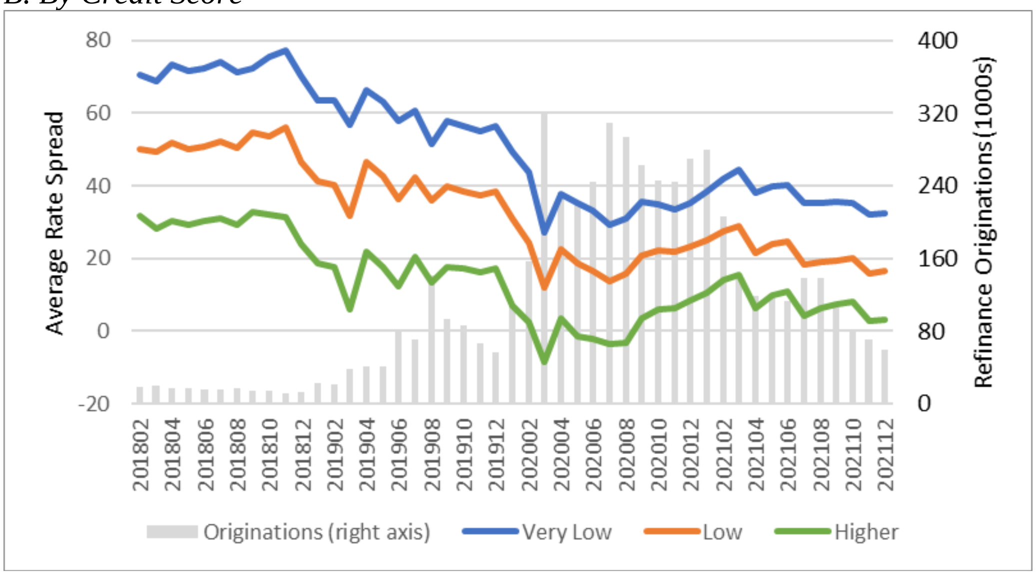
Appendix Figure A.2: Rate Spread on Refinance Originations, by Application Month and Borrower Type

A.By Income



B. By Credit Score



Notes: This figure presents the average interest rate spread on refinance loan applications by month and borrower type. Borrowers are categorized by income in panel A, and by credit score in panel B. Interest rate spread is defined as the difference between the annual percentage rate (APR) on the loan and the average prime offer rate (APOR) as of the date the interest rate is set. Calculated using 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 February 2018 to January 2022 that resulted in an origination.

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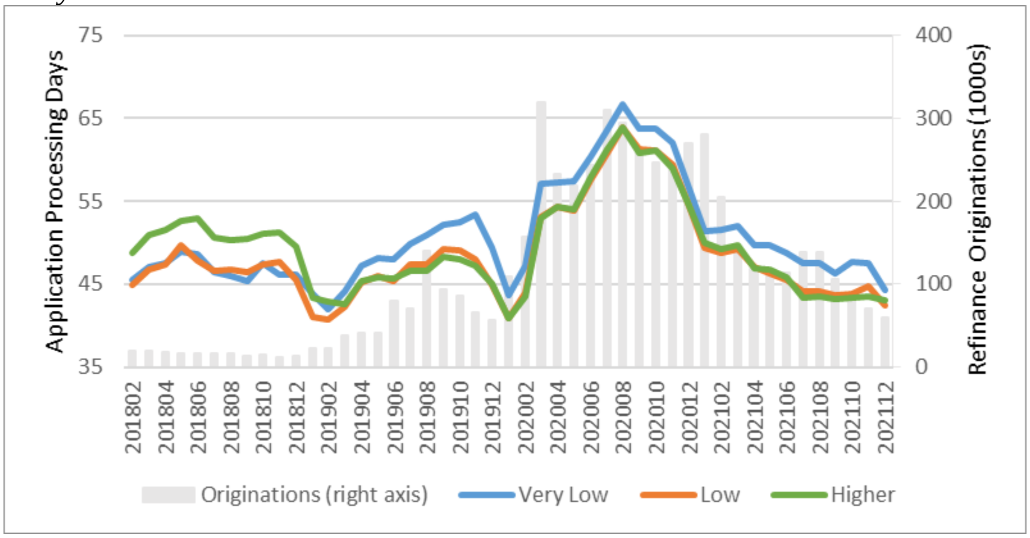
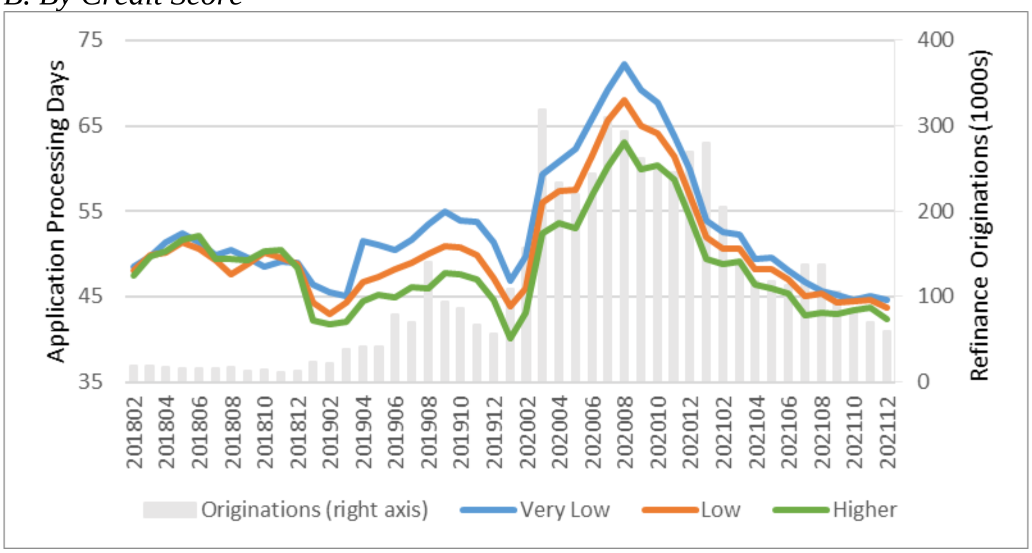
Appendix Figure A.3: Processing Days on Refinance Originations, by Application Month and Borrower Type

A. By Income



B. By Credit Score



Notes: This figure presents the average application processing days (defined as the difference between the origination date and the application date) by month and borrower type. See Notes to Figure A.2 for additional details.

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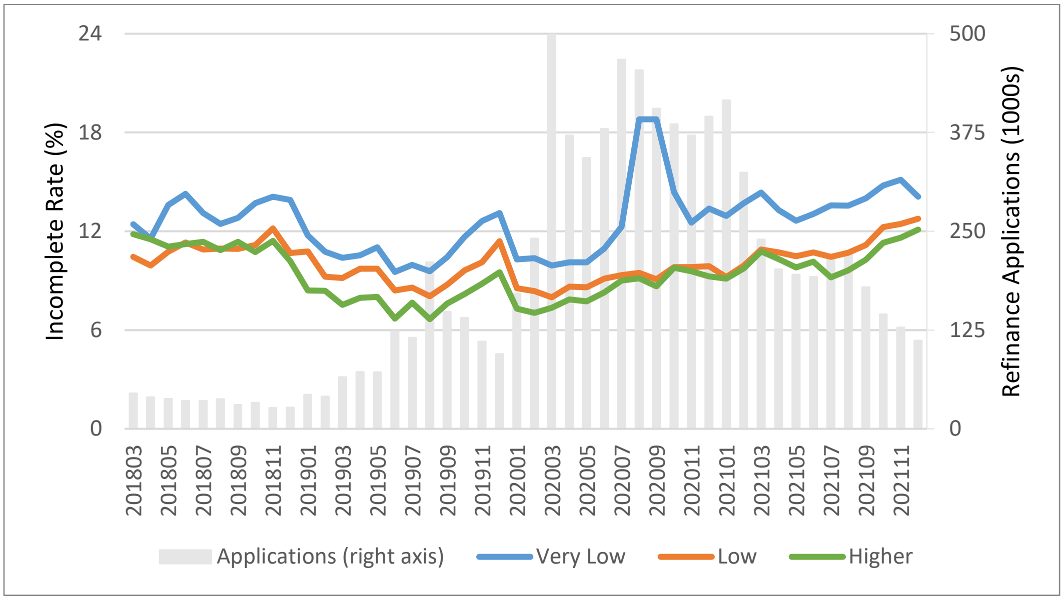
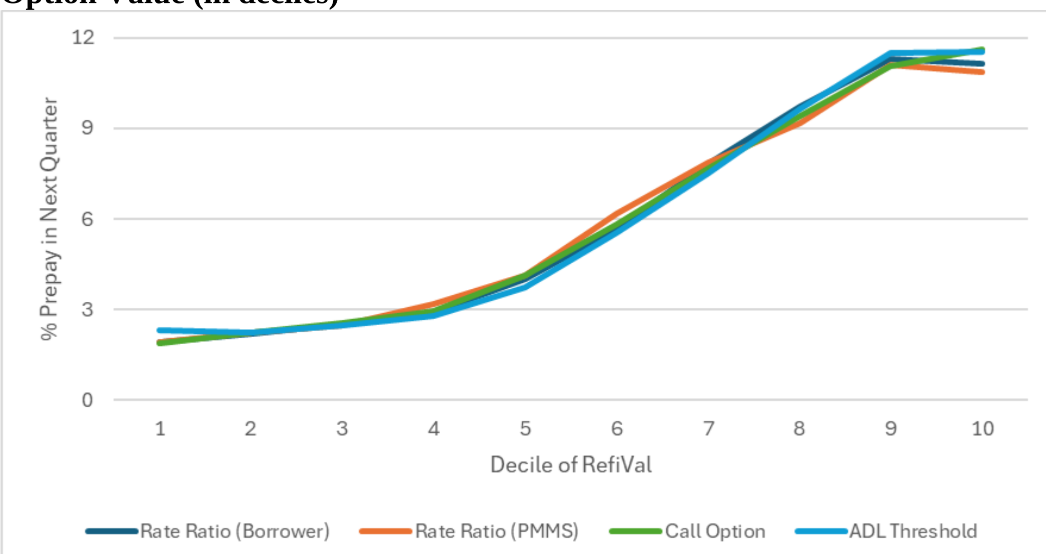
Appendix Figure A.4: Incomplete Application Rate (%), by Application Month and Borrower Income



Notes: This figure presents the share (%) of refinance loan applications that are closed or denied for incomplete information, by borrower income.

Appendix Figure A.5: Quarterly Prepayment Rate by Alternative Measures of the Refinance Option Value (in deciles)



Notes: This figure presents the mean quarterly prepayment rate by decile of four alternative measures of a borrower's refinance option value: (1) Rate Ratio (Borrower) is the ratio of the borrower's note rate to the borrower-specific market rate; (2) Rate Ratio (PMMS) is the ratio of the borrower's note rate to the average prime rate; (3) the Call Option measure from Deng et al. (2000); and (4) the closed form refinancing rule from Agarwal, Driscoll, and Laibson (2013). Calculations are based on a 50 percent sample of loan-quarter observations in NMDB data over the 2018 to 2021 period. See the Data section and Appendix A.1 for additional details.

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Appendix Table A.1: OLS Estimates of Main Specification (Borrowers Categorized by UPB)

	Specification			
	(i)	(ii)	(iii)	(iv)
Supply congestion: Moderate	0.975***	0.469***	-0.163*	0.454***
	(0.082)	(0.085)	(0.090)	(0.100)
Supply congestion: High	1.483***	0.329***	-0.555***	0.550***
	(0.100)	(0.107)	(0.114)	(0.147)
UPB: Very Low	-1.865***	-1.957***	-2.290***	-2.166***
	(0.097)	(0.117)	(0.116)	(0.117)
UPB: Low	-1.304***	-1.389***	-2.321***	-2.287***
	(0.089)	(0.102)	(0.098)	(0.098)
[Supply congestion: Moderate] X [UPB: Very Low]	-1.297***	-1.567***	-1.949***	-1.856***
	(0.157)	(0.164)	(0.155)	(0.155)
[Supply congestion: Moderate] X [UPB: Low]	-0.862***	-1.013***	-0.974***	-0.908***
	(0.154)	(0.161)	(0.150)	(0.149)
[Supply congestion: High] X [UPB: Very Low]	-2.105***	-2.522***	-2.947***	-2.794***
	(0.154)	(0.167)	(0.159)	(0.159)
[Supply congestion: High] X [UPB: Low]	-1.317***	-1.496***	-1.896***	-1.776***
	(0.150)	(0.160)	(0.150)	(0.150)
refiVal	56.540***	69.268***	64.219***	64.078***
	(1.812)	(1.854)	(1.780)	(1.802)
(refiVal)^2	-14.896***	-17.810***	-16.629***	-16.485***
	(0.613)	(0.629)	(0.602)	(0.601)
Credit score: Very Low	-0.155	0.239**	0.119	0.048
	(0.099)	(0.110)	(0.110)	(0.110)
Credit score: Low	0.253***	0.540***	0.471***	0.432***
	(0.076)	(0.082)	(0.082)	(0.082)
Income: Very Low	-3.819***	-3.571***	-3.033***	-2.988***
	(0.075)	(0.099)	(0.097)	(0.098)
Income: Low	-3.518***	-3.119***	-2.052***	-2.033***
	(0.063)	(0.078)	(0.079)	(0.080)
Loan-to-value: 70 to 79	1.278***	1.394***	1.323***	1.512***
	(0.075)	(0.083)	(0.083)	(0.083)
Loan-to-value: 80 to 89	0.370***	0.427***	0.387***	0.666***
	(0.091)	(0.101)	(0.101)	(0.103)
Loan-to-value: 90 to 97	-2.032***	-2.005***	-1.989***	-1.632***
	(0.118)	(0.134)	(0.134)	(0.135)
Loan-to-value: 97+	-3.567***	-3.786***	-3.713***	-3.515***
	(0.220)	(0.266)	(0.266)	(0.268)
Debt-to-income: 34 to 38	0.592***	0.671***	0.689***	0.687***
	(0.070)	(0.081)	(0.081)	(0.082)
Debt-to-income: 39 to 43	0.487***	0.489***	0.527***	0.519***
	(0.069)	(0.080)	(0.080)	(0.081)
Debt-to-income: 44 to 48	0.375***	0.492***	0.557***	0.538***
	(0.079)	(0.091)	(0.091)	(0.092)
Debt-to-income: 49+	-0.202*	-0.251**	-0.125	-0.104
	(0.107)	(0.127)	(0.126)	(0.128)
Debt-to-income: unknown	-3.998***	-4.179***	-4.082***	-4.000***
	(0.353)	(0.575)	(0.570)	(0.575)

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Appendix Table A.1 [continued]

	Specification			
	(i)	(ii)	(iii)	(iv)
Spread at origination: 50bps+	-2.981***	-3.675***	-3.144***	-3.064***
	(0.141)	(0.166)	(0.166)	(0.170)
Spread at origination: 25 to 49bps	-1.549***	-1.735***	-1.471***	-1.421***
	(0.134)	(0.158)	(0.157)	(0.160)
Spread at origination: -25 to 25bps	-0.153	-0.284*	-0.176	-0.191
	(0.128)	(0.151)	(0.151)	(0.153)
County-Level Unemployment Rate (%)	0.018*	0.079***	-0.023*	0.069***
	(0.011)	(0.012)	(0.012)	(0.022)
Purpose: Refi - not cash out	-0.495***	-0.690***	-0.823***	-0.856***
	(0.063)	(0.074)	(0.073)	(0.075)
Purpose: Refi - cash out	-0.128	-0.133	-0.286*	-0.283*
	(0.132)	(0.161)	(0.160)	(0.162)
Black	-1.851***	-1.860***	-1.860***	-1.916***
	(0.102)	(0.140)	(0.139)	(0.141)
Hispanic (non-black)	-1.474***	-1.011***	-1.027***	-1.077***
	(0.083)	(0.107)	(0.106)	(0.108)
Asian (non-hispanic)	0.919***	0.899***	0.864***	0.867***
	(0.107)	(0.128)	(0.128)	(0.129)
Other (non-hispanic)	-0.327	-0.282	-0.280	-0.302
	(0.219)	(0.253)	(0.252)	(0.256)
First-time homebuyer	-0.595***	-0.487***	-0.490***	-0.540***
	(0.065)	(0.075)	(0.075)	(0.076)
Loan age	0.727***	0.906***	0.892***	0.873***
	(0.016)	(0.018)	(0.018)	(0.018)
(Loan age)^2	-0.387***	-0.473***	-0.472***	-0.464***
	(0.009)	(0.010)	(0.010)	(0.010)
(Loan age)^3	0.049***	0.059***	0.059***	0.058***
	(0.001)	(0.002)	(0.002)	(0.002)
Cumulative # of Quarters ITM	-0.062***	-0.013**	0.022***	-0.033***
	(0.005)	(0.006)	(0.006)	(0.007)
Index of Tract-Level Refinance Apps			0.013***	0.014***
			(0.000)	(0.000)
Missing Data, Tract-Level Refinance Apps			2.086***	2.231***
			(0.531)	(0.533)
Constant	-38.501***	-50.909***	-48.794***	-48.296***
	(1.282)	(1.312)	(1.259)	(1.297)
N	1,454,734	1,454,734	1,454,734	1,454,734
R-sq	0.027	0.070	0.071	0.072
Specification Includes…				
State Fixed Effects	Y			
Census Tract Fixed Effects		Y	Y	Y
Loan Quarter Fixed Effects				Y

Notes: This table presents OLS estimates of four alternative specifications of equation (1), with errors clustered at the loan level. The estimation sample includes 1,454,734 loan-quarter observations and 261,509 unique loans. The categorical measure of Supply Congestion is interacted with a categorical measure of the borrower's Unpaid Principal Balance (UPB). All specifications include the base covariates in X_{bst} (detailed in the Model section). Coefficients for alternative borrower categories are available upon request.

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Appendix Table A.2: Marginal Effects of Supply Constraints, Estimated using Alternative Measures of Refinance Option Value

	I. Rate Ratio (Borrower)		II. Rate Ratio (PMMS)		III. Call Option		IV. ADL Threshold	
Supply Congestion	Moderate	High	Moderate	High	Moderate	High	Moderate	High
A. By UPB								
Very Low	-2.113***	-3.502***	-1.615***	-3.111***	-1.793***	-2.964***	-0.916***	-1.705***
	(0.139)	(0.155)	(0.138)	(0.152)	(0.138)	(0.152)	(0.140)	(0.155)
Low	-1.137***	-2.451***	-0.622***	-2.027***	-0.859***	-1.972***	-0.104	-0.820***
	(0.134)	(0.149)	(0.133)	(0.147)	(0.134)	(0.147)	(0.134)	(0.149)
Higher	-0.163*	-0.555***	0.265***	-0.241**	0.089	-0.130	0.578***	0.749***
	(0.090)	(0.114)	(0.089)	(0.112)	(0.090)	(0.113)	(0.090)	(0.113)
B. By Income								
Very Low	-1.650***	-2.930***	-1.207***	-2.599***	-1.354***	-2.426***	-0.635***	-1.349***
	(0.152)	(0.167)	(0.151)	(0.164)	(0.151)	(0.165)	(0.152)	(0.166)
Low	-1.178***	-2.069***	-0.733***	-1.726***	-0.903***	-1.598***	-0.249*	-0.556***
	(0.148)	(0.162)	(0.147)	(0.160)	(0.148)	(0.160)	(0.148)	(0.161)
Higher	-0.311***	-0.838***	0.129	-0.515***	-0.064	-0.425***	0.490***	0.524***
	(0.087)	(0.111)	(0.086)	(0.108)	(0.087)	(0.109)	(0.087)	(0.110)
C. By Credit Score								
Very Low	-1.082***	-2.967***	-0.747***	-2.637***	-0.809***	-2.507***	-0.481*	-1.860***
	(0.247)	(0.240)	(0.246)	(0.239)	(0.247)	(0.239)	(0.247)	(0.239)
Low	-1.271***	-2.232***	-0.882***	-1.963***	-1.004***	-1.769***	-0.585***	-1.046***
	(0.179)	(0.187)	(0.179)	(0.186)	(0.179)	(0.186)	(0.179)	(0.187)
Higher	-0.463***	-0.971***	-0.018	-0.652***	-0.217***	-0.561***	0.417***	0.483***
	(0.081)	(0.106)	(0.079)	(0.103)	(0.080)	(0.104)	(0.081)	(0.105)

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 the loan level, using alternative specifications that vary in the measure used to control for the borrower's financial incentive to refinance. Specifically: (I) Rate Ratio (Borrower) is the ratio of the borrower's note rate to the borrower-specific market rate; (II) Rate Ratio (PMMS) is the ratio of the borrower's note rate to the average prime rate; (III) Call Option is the measure from Deng et al. (2000); and (IV) ADL threshold is the closed form refinancing rule from Agarwal, Driscoll, and Laibson (2013) and the parameterization from Gerardi et al (2023). See Table 3 for additional notes.

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Appendix Table A.3: Sample Means, HMDA Data Used in Supplemental Analyses

Sample	Originations (1)	Applications (2)
Interest rate (bps)	323.0	
Rate spread (bps)	11.8	
Application Processing Days	52.2	
% Incomplete		9.5
Mortgage Supply Congestion (% of obs)		
Low	45.3	
Moderate	23.3	
High	31.4	
Loan amount (% of obs)		
Very Low	2.2	3.1
Low	7.0	8.0
Higher	90.8	88.9
Borrower income (% of obs)		
Very Low	8.5	11.4
Low	13.4	14.0
Higher	78.1	74.6
Credit score (% of obs)		
Very Low	7.6	
Low	17.0	
Higher	75.4	
Race and ethnicity (% of obs)		
Black	3.5	4.6
Hispanic Non-Black	6.9	7.5
Non-Black and Non-Hispanic	89.6	88.0
Combined loan-to-value (% of obs)		
<= 60	29.4	
(60, 70]	18.2	
(70, 75]	15.8	
(75, 80]	17.4	
(80, 85]	7.1	
(85, 90]	7.0	
(90, 95]	3.9	
95+	1.1	
Missing	0.04	
Debt-to-income (% of obs)		
<= 33	47.9	
(33, 38]	16.4	
(38, 43]	16.3	
(43, 48]	13.7	
48+	5.5	
Missing	0.2	
Net points	0.14	
Number of Observations	5,448,753	8,732,572

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. % Incomplete indicates the share of loan applications that the lender closes or denies for incomplete information. Sample means are omitted for variables that are not observed on loan applications that do not result in an origination. E.g., credit scores are not observed on loans the lender designates as incomplete.