Mortgage Seasonality, Capacity Constraints, and Lender Responses

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Abstract

The housing market is highly seasonal, which implies fluctuations in the number of applications mortgage lenders receive. Using the confidential version of the mortgage application data collected through the Home Mortgage Disclosure Act (HMDA), we examine if lenders ration credits when their mortgage processing capacity is constrained due to an increase in demand during a high home purchase season. We show that seasonal variations in mortgage applications exist both inter-temporally and across geographic areas, coinciding with climate patterns. Using this variation, we find that between 2018 and 2022, refinance applications were more likely to be denied during a high home purchase season compared to a low season even after controlling for extensive sets of loan and credit characteristics. We also find that Black and Hispanic applicants are more likely to be affected by credit rationing due to lender capacity constraints.

This study is the first to examine lenders' response to capacity constraints driven by a demand shift using a novel identification strategy. The identification strategy relies on the fact that the variations in credit characteristics of refinance applications are not correlated with the variations in overall credit demand and the likelihood of capacity constraints during high seasons. We provide suggestive evidence that lenders use soft information or apply discretion differently during high seasons compared to low seasons, disproportionately affecting racial minority borrowers who represent a higher share of marginal applicants. We find that loans originated during high seasons have higher default probability than loans originated during low seasons, implying that the quality of loan officer's work deteriorates when they are overworked.

Keywords: Mortgage, Seasonality, Capacity Constraint, Credit Rationing, Credit Access, Inequality, Soft Information, Mortgage Performance
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1 Introduction

The housing market is highly seasonal. Listings and sales of homes increase during summer and decline during winter because of the weather patterns and school terms.[1] Given that most home purchase transactions are backed by a mortgage in the US[2], the seasonality in housing transactions implies seasonality in the number of applications mortgage lenders receive. Because the housing seasonality is exogenous to the macro-economic environment, driven by weather patterns and administrative calendar effects such as school terms, one can think of such seasonality as a natural experiment that periodically shifts the demand for mortgage credits. In this paper, we use this demand shifter to study how lenders respond to the change in credit demands. We focus on how the mortgage lenders may ration credits when their operating capacities are likely constrained due to the rise in home purchase application volumes during particular time of a year, and whether they are more prone to making errors in underwriting when faced with high workload.

Although lenders are aware of seasonal fluctuations of demand for home purchase loans, they cannot flexibly adjust their labor force throughout the year since hiring and firing mortgage industry workers with highly specialized skills are too costly. Consequently, lenders may suffer from capacity constraints during summer months which potentially results in credit rationing and denying certain groups of borrowers.

Using the confidential version of the mortgage application data collected through the Home Mortgage Disclosure Act (HMDA), we first show that home purchase application volume varies across time and geography. More specifically, seasonal variations in home purchase mortgage application volume are less prominent in milder temperature areas relative to the areas with greater temperature fluctuations. Exploiting the temporal and geographic variations in mortgage application volume as a demand shifter that affects lenders' operating capacity constraints, we study the effects of seasonality on denial rates of applicants. The changes in lenders' operational capacity due to seasonality should not be related to the factors affecting whether an application is denied or not. However, an endogeneity issue arises if applicants' credit characteristics change with seasonality. Our main identification strategy relies on the fact that (1) the demand for home purchase loans increases during high seasons, creating a spillover effect on lenders' capacity to underwrite refinance loans; and (2) unlike the credit characteristics of home purchase applications, those of refinance applications are not correlated

[1] Most real estate professionals are aware of such patterns, and some even advise home buyers when to purchase. For example, see https://www.realtor.com/research/best-time-to-buy-2023/

[2] https://www.redfin.com/news/all-cash-down-payment-april-2023/

with the home purchase seasonality.

We find that the denial rate for refinance loan applications increases by 0.47 percentage points when the seasonal demand for home purchase loans increases by 10 percent relative to the annual average. The finding that the denial rate of refinance applications increases during the home purchase high seasons withstands all of our robustness checks. We rule out that the effect is due to the confounding effects of the changing interest rate environment. During both the stable period of the refinance volume and the subsequent refinance boom period, the effect of mortgage seasonality on application denial rate persists. When lenders' operating capacity is especially constrained due to a refinance boom in low interest rate environments, the denial rates of refinance loans are even higher during home purchase high seasons. Lastly, lenders, whose refinance loans make up a large share of their business, do not ration credits during the home purchase high seasons, validating our underlying assumption of the spillover effect from home purchase seasonality to lenders' overall capacity to process mortgage applications, including applications for refinance loans.

Studying the lenders' response to capacity constrains has serious implications to equal credit access, because lenders' credit rationing does not affect all mortgage applicants equally. Refinance applicants who apply for mortgages at independent mortgage companies are more likely to be impacted during high seasons than those who apply at large banks or credit unions due to credit rationing. Moreover, Black and Hispanic refinance applicants are even more likely than non-Hispanic White applicants to be denied during high seasons, in addition to the preexisting denial rate disparities that are widely documented in the literature (Munnell et al., 1996; Bhutta et al., 2022; Liu and Zhang, 2024) and confirmed in this study. Our back-of-the-envelope calculation implies that approximately 4,200 additional black and 3,100 additional Hispanic refinance applicants were denied relative to white applicants between 2018 and 2022 because of lenders' credit rationing.

We provide suggestive evidence that lenders use soft information or apply discretion differently during high seasons compared to low seasons, disproportionately affecting racial minority borrowers who represent a higher shares of marginal applicants. By examining the mortgage performance, we observe that mortgage loans originated in high seasons are more likely to default than the loans originated in low season. This implies that even though the lenders are forced to ration credits during high seasons, the criteria they apply to screen out additional applicants are not necessarily reflective of the credit risk. Instead, facing higher workload, the quality of their underwriting decisions deteriorates, leading to higher default rates post originations.

One strand of relevant literature is the effect of lenders' capacity constraints on overall credit supply. Lester (2011) and Stiglitz and Weiss (1981) provides a theoretical framework on how a credit rationing occurs. More recent studies examine a crowding out effect stemming from lenders' capacity constraints and credit rationing (Choi et al., 2022; Fieldhouse, 2019; Frazier and Goodstein, 2023; Ma, 2023; Sharpe and Sherlund, 2016). Our main finding is consistent with Sharpe and Sherlund (2016) and Ma (2023) which are closest to our study. However, these and other related studies focus on capacity constraints generated by idiosyncratic changes in interest rates or policy interventions, while our source of capacity constraint is periodic and persistent which could have a broader implication.

Our study also adds to the literature that highlights the importance of the soft information in credit assessment and underwriting decisions (Agarwal et al., 2011; Agarwal and Ben-David, 2018; Agarwal and Hauswald, 2010; Ambrose et al., 2021; Jiang et al., 2022; Liberti and Petersen, 2019). Contrary to the positive views of soft information in the aforementioned work, our finding demonstrates how lender discretion can play a role in limiting credit access for Black and Hispanic applicants.

More broadly, this paper relates to the literature on job performance and decision making under time constraints in various settings. For instance, Agarwal et al. (2017) shows that banks with fewer employees per loan, less training for staff, and longer wait times for phone calls were significantly less likely to modify mortgages to avoid costly foreclosures. Huang (2011) shows that busy appellate court judges exhibit lightened scrutiny over district court decisions. Fitch and Shivdasani (2006) shows that busy boards are associated with weak corporate governance. Coviello et al. (2014) show that judges who juggle too many cases at once have decreased productivity. Iverson (2018) studies how less congested bankruptcy court judges may lead to different Chapter 11 restructuring outcomes, while Yang (2016) examines the effects of court vacancies on criminal justice outcomes.

The study makes four contributions to the literature. First, our study is the first to use a novel identification strategy to examine lenders' response to capacity constraints in mortgage processing to the best of our knowledge. Our key identification strategy relies on the fact that the credit characteristics of refinance applications are not correlated with seasonality, but the probability of lenders reaching the processing capacity limit is, due to a spillover effect from a demand surge for home purchase loans. Secondly, we provide new evidence that minority applicants are more likely to bear the brunt of credit rationing when lenders are capacity constrained. Lenders are more likely to screen out marginal applicants when facing capacity constraints, which potentially has serious implications for fair and equal access to credits for minority borrowers. Third, our study provides suggestive evidence that changes in lenders' reliance on lender discretion serve as a potential mechanism through which lenders ration credits. In other words, lenders are more likely to deny applications on the margin based on either soft information or lender discretion when their mortgage processing capacity tightens. Lastly, by tracing the mortgage performance, we discover that loans originated during high seasons more likely default, implying that the underwriting quality of lenders worsened during high seasons when loan officers are overworked.

The remainder of the chapter is organized as follows. Section 2 presents the dataset and Section 3 presents the background information on housing seasonality and mortgage industry. The theoretical framework and empirical findings are discussed in Section 4 and Section 5. Section 6 and Section 7 present robustness checks and heterogeneous analyses. Section 8 discusses soft information and lender discretion and their roles as potential mechanism through which lenders respond to capacity constraints. Section 9 builds a competing risk model and traces the loan performance of loans originated during different seasons. Section 10 concludes.

2 Data

Our main analysis relies on the confidential HMDA data from 1990 to 2022. In particular, we focus on the HMDA data from 2018 to 2022 in our main specifications. The HMDA data are the most comprehensive source of publicly available information on the U.S. mortgage market, and the only publicly available source of nationwide application-level data on mortgage credit. Significant changes were implemented to the HMDA data starting in 2018 under the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. As part of this change, HMDA began collecting a much more expansive set of information on the applicant and the co-applicant's credit characteristics and loan features which serve as important controls in our models.[3] For privacy reason, some of the newly collected information is not available to the public and is only available in the confidential version which is what we use in this study.

The confidential version of the HMDA data contains the application and action dates of each application, allowing us to study the aggregated seasonal patterns and the length of time for an application to be originated or denied. In addition, unlike the public version, which either excludes certain information such as credit scores and the results of automated

[3] See Liu et al. (2019) for additional details on the changes to the HMDA data collected in 2018 and beyond.

underwriting system (AUS) completely, or modifies the values of some fields in ranges, such as loan amount and debt-to-income ratio (DTI), the confidential version contains the full information that is collected, which could greatly reduce omitted variable bias and mitigate the measurement errors. Lastly, the confidential version also contains the unique IDs of the loan officers that handle the applications. The loan officer ID allows us to compute the number of applications a loan officer processes or are sitting in a loan officer's queue, which is what we use to test capacity constraints.

We use the data on total employment and total number of hours worked in mortgage industry from the Bureau of Labor Statistics to explore seasonality and lender capacity constraints.[4] To explore the mechanism behind the main findings, we use the data from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS).

We use National Mortgage Database (NMDB) to examine how the mortgages originated in different seasons and states may perform differently within the first three years of originations. NMDB is a nationally representative five percent sample of closed-end first-lien residential mortgages in the United States. It is the only nationally representative mortgage data that contain both information at origination and mortgage performance information from origination to termination. [5]

3 Background

Previous literature illustrates the existence of seasonality in housing market. Goodman (1993) documents household moving peaking in summer months and slowing in winter months. Ngai and Tenreyro (2014) and Kajuth and Schmidt (2011) propose a theoretical model underlying the housing price seasonality in the US and UK. The seasonality in moving and housing prices implies a seasonality in mortgage applications, although no studies have formally documented this to the best of our knowledge. In this section, we show the existence of seasonality in home purchase mortgage applications. In addition, such seasonality is more pronounced in areas with a greater temperature variation within a year than areas with more consistent temperature.

[4] Following Sharpe and Sherlund (2016), we use the real estate credit and mortgage and non-mortgage loan broker employment to estimate the total employment and number of hours worked in mortgage industry.

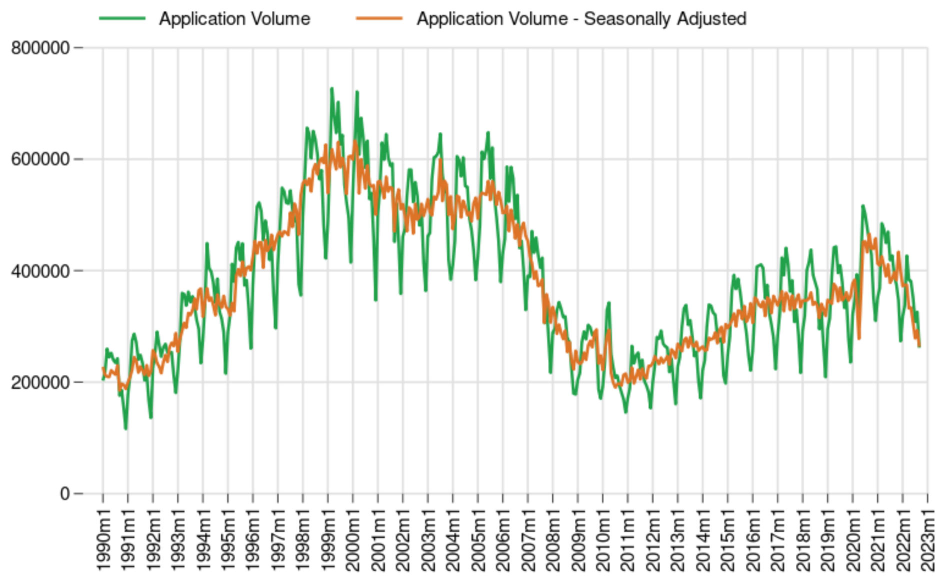
[5] For more information on NMDB, see https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx.

3.1 Measurement of seasonality: Seasonal adjustment factors

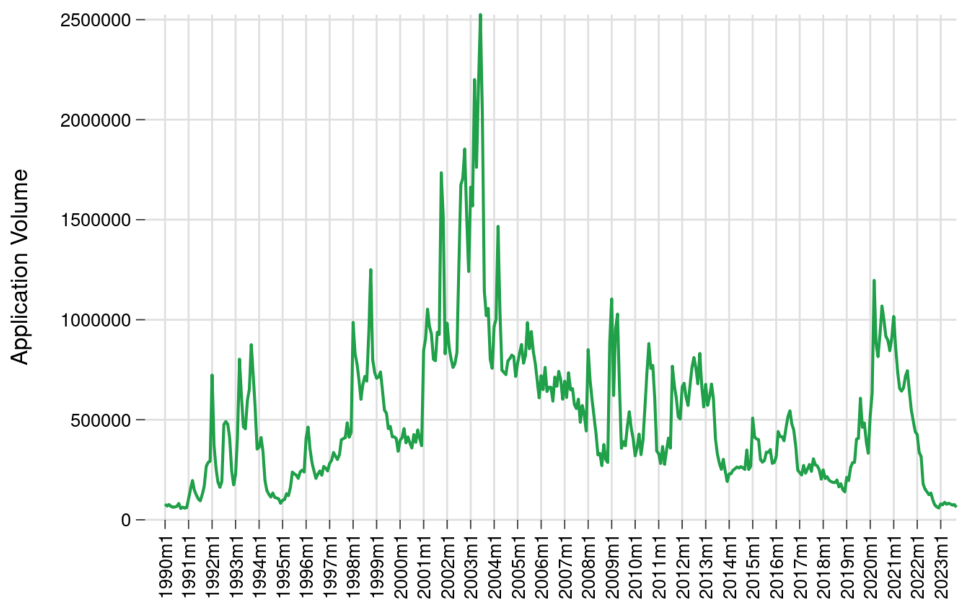
Figure 1 plots the monthly application volumes for home purchase and refinance loans from 1990 to 2022. The home purchase application volume fluctuates cyclically, with the application volume generally high from March through June and low from December through January. This is despite the overall trends and other anomalies that are likely driven by macroeconomic conditions and long-term demographic trends. On the other hand, we do not observe seasonal variations for refinance applications. The demand for refinance loans is typically driven by interest rate environments and has no inherent correlation with weather patterns or other cycles such as school years.

Figure 1: Historical trend of home purchase and refinance applications

(a) Home Purchase



(b) Refinance



Notes: The monthly application volume is from the HMDA data from 1990 to 2022. The sample consists of completed applications with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence.

To formally quantify the seasonal patterns of mortgage applications, we use the Census Bureau's X-13ARIMA-SEATS (X13-A-S) method to compute numeric values called seasonal factors.[6] X-13-A-S enhances upon a long tradition of seasonal adjustment programs by the Census Bureau and is the seasonal adjustment software currently used by the Census Bureau. Most of the official statistics in the US (and in many other countries such as UK) are published with seasonal adjustment using X-13-A-S or its predecessor programs such as X-12-ARIMA. Examples of monthly housing statistics published by the US government and other entities include existing home sales by National Association of Realtors, new home sales by the Census Bureau, house price indices by Federal Housing Finance Agency and Standard & Poor's, and housing starts and permits by the Census Bureau, all of which have strong seasonal patterns and are adjusted with the X13-A-S procedure when being published. Such seasonally adjusted series and not-seasonally-adjusted series are commonly released side-by-side.

We adopt the multiplicative model of X-13-A-S that is most commonly used. Equation 1 describes the basic components of a time series and how it can be decomposed with the help of X-13-A-S procedure. Commonly known as trend-cycle, C represents the long-term trend as well as various business cycles. S represents the seasonal factor, which is a cyclical pattern that evolves as a result of changes associated with the seasons. I represents irregular fluctuations.

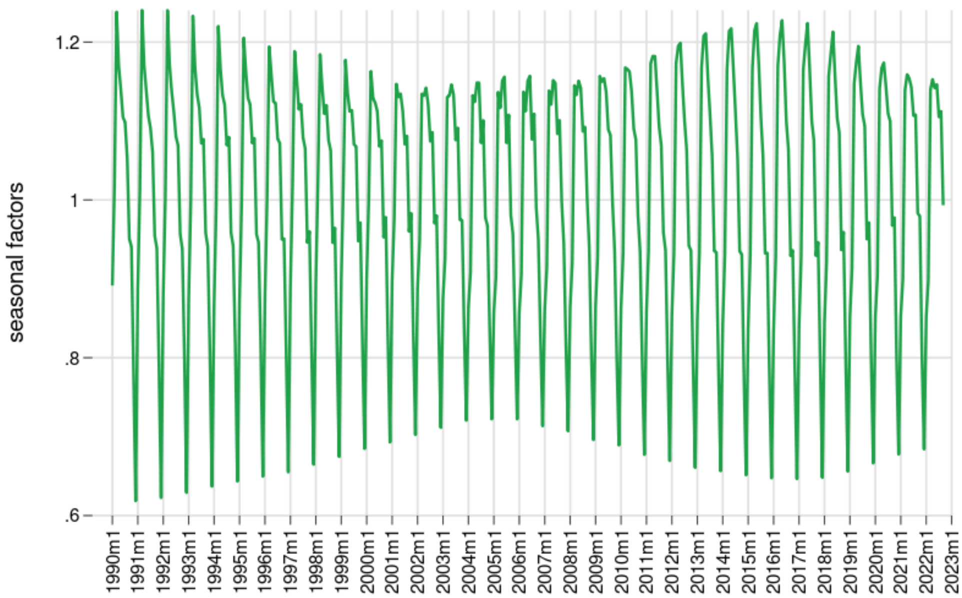
$$Y = C \times S \times I \tag{1}$$

Using the HMDA data from 1990 to 2022 and X-13-A-S procedure, Figure 1 also plots the seasonally adjusted monthly application volume for home purchase loan applications alongside the not-seasonally-adjusted series[7]. The seasonally adjusted series removes the seasonal effects (S) from the Equation 1, and is equal to $C \times I$. Figure 2 plots the seasonal factors of each month, equal to the not-seasonally-adjusted series divided by the seasonally adjusted series.

[6]For more information on X-13-A-S method, see https://www.census.gov/data/software/x13as.html.

[7]We drop the applications taken in the last 3 months of 2022 in all our analyses in this paper. That is because the annual HMDA reporting is based on the date of the action taken on an application. For instance, if an application was received in September 2018 and an underwriting decision such as denial or approval was made in November 2018, that HMDA record would be reported in 2018 HMDA data. If an application was taken in November 2018 and an underwriting decision was not finalized until January 2019, that record would be reported in 2019 HMDA data. For applications in the 1990 to 2022 HMDA data, we are able to stack all HMDA records together and collapse on the "application month", across HMDA reporting years. However, the average time between the date when an application was received and the date when an application was denied between 2018 and 2022 was 38 days, and the average time between the date when an application was received and the date when an application was recorded as originated was 52 days, both with wide dispersion. Consequently, many of the applications taken in the last months of 2022 were not yet reported to the HMDA at the time of this draft. Therefore, we drop the last quarter in 2022 to account for this data censoring problem.

Figure 2: Seasonal adjustment factors of home purchase applications



Notes: The plot is created using the HMDA data from 1990 to 2022. The sample consists of completed applications with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence.

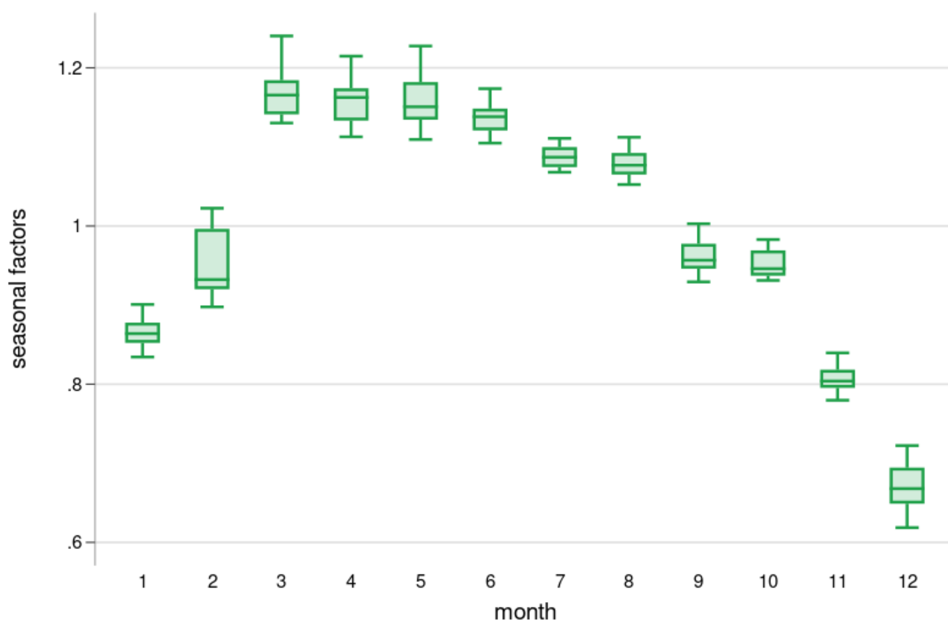
A seasonal factor measures how much of the deviation from the mean in a year can be attributed to the seasonal trends, after de-trending and removing random noises. In the multiplicative model, the seasonal factor S varies around the value of 1. Intuitively, a seasonal factor of a particular month above one implies that for that month the mortgage application volume is higher than the average within a year. In contrast, a seasonal factor below one indicates a month where the volume is lower than the yearly average.

Not only do we compute the seasonal factors of home purchase applications at the national level, we also compute them for each state. For example, when the state seasonal factor is 1.2 in June of 2018, it means that the monthly application volume for June 2018 was 20 percent higher than the 2018 annual average in that state if it is smoothed and de-trended. On the other hand, a state seasonal factor of 0.8 in December of 2019 means that the monthly application volume for that month was 20 percent lower than the 2019 average in that state.

3.2 Seasonality of housing market

To further show the seasonal patterns observed in Figures 1 and 2, Figure 3 presents box plots of the national seasonal adjustment factors against the calendar months for home purchase applications. We illustrate the distribution of the 33 seasonal factors for each calendar month between January and September (one for each year between 1990 and 2022 for 33 years) and 32 seasonal factors for each month between October and December (one for each year between 1990 and 2021 for 32 years) . Figure 3 shows that home purchase application volume is higher in spring and summer months compared to fall and winter months. Nationally, the seasonal demand for home purchase loans is about 15 to 18 percent higher from March to June and about 20 to 30 percent lower from November to January.

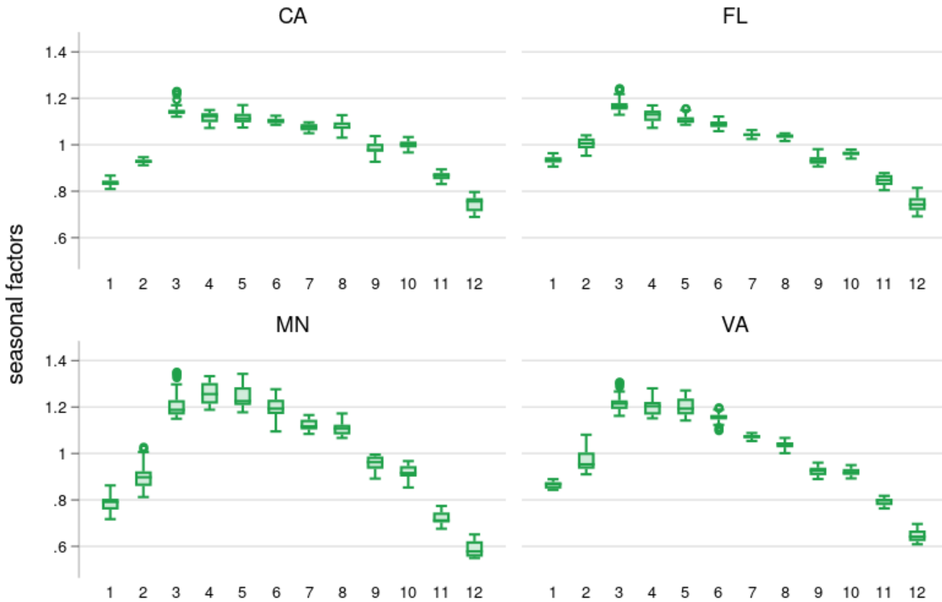
Figure 3: Trends in home purchase application seasonal factors by month



Notes: The monthly application volume is from the HMDA data from 1990 to 2022. The sample consists of completed applications with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The labels on the horizontal axis (1 to 12) represent the months from January to December respectively.

Figures 4 is a reproduction of Figures 3 except that the plots are separated by representative states. Figure 4 shows that states with less temperature fluctuations, such as California and Florida, have home purchase application seasonality that is less pronounced relative to the states with greater temperature fluctuations such as Minnesota and Virginia.

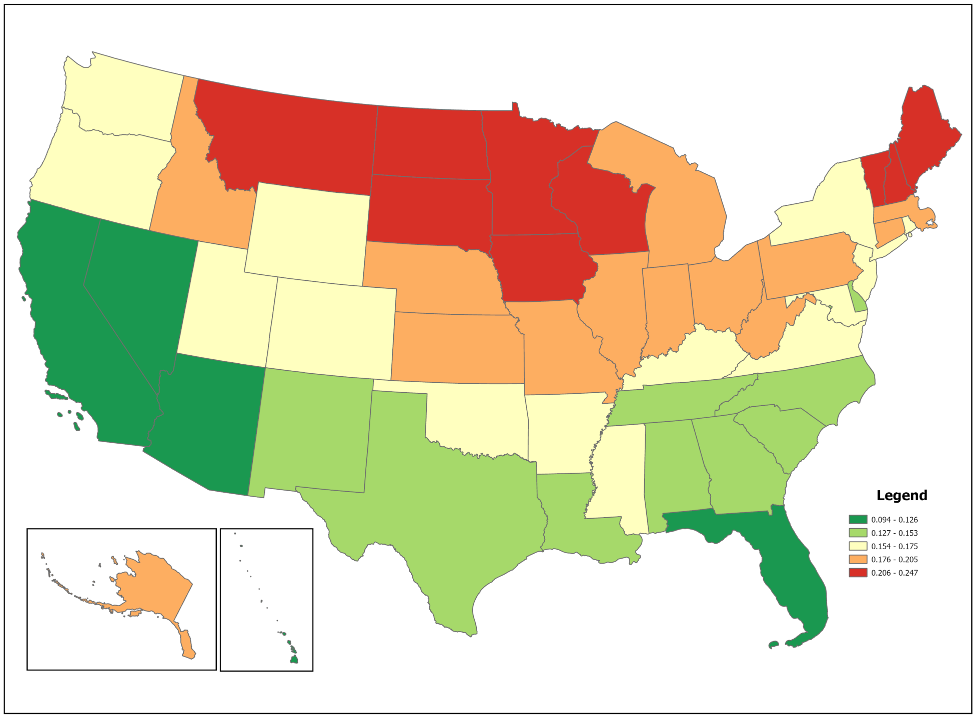
Figure 4: Trends in seasonal factors by state's climates



Notes: The monthly application volume is from the HMDA data from 1990 to 2022. The sample consists of completed applications with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The labels on the horizontal axis (1 to 12) represent the months from January to December respectively.

Figure 5 further demonstrates the geographic variation in seasonality across the nation. The figure is a gradient map of standard deviations in seasonal factors of home purchase applications within each state. The standard deviation is computed over all of the months between 1990 and the first three quarters of 2022. It shows how much the home purchase application volume vary for a particular state. The figure shows a clear pattern of high variability for states with greater temperature fluctuations compared to those with less volatile temperatures.

Figure 5: Geographic variations in application seasonality

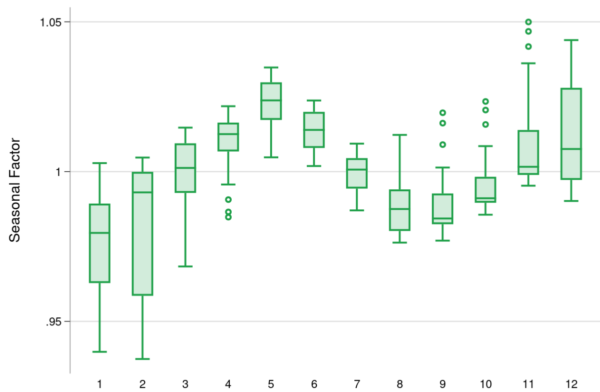


Notes: The geographic variations in volatility of applications is measured by the standard deviation of home purchase mortgage application seasonal factors within each state, from 1990 to 2022. The sample consists of completed applications with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence.

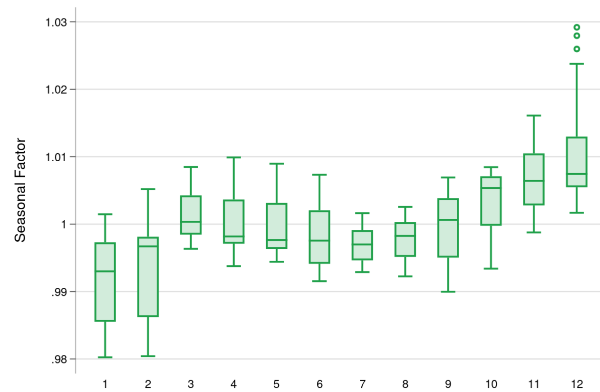
Not only do the application volumes of home purchase loans vary with seasons, the underlying credit characteristics of the application pools also vary. Using the X13-A-S procedure, similar to what we did to the application volume, we also imputed the seasonal factors for applicants' average reported income, shares of Black and Hispanic applicants and the median imputed "loan amount to applicant's income ratio". Figure 6 plots the national seasonal factors of average applicant income, share of black and Hispanic applicants, and median imputed ratio of loan amount divided by the reported income of home purchase applications respectively. We examine these because the HMDA data before 2018 lacked key underwriting variables such as credit score, loan to value ratio (LTV) and DTI, except for income and loan amount. On the other hand, Black and Hispanic applicants have lower credit scores than the population average (Liu et al., 2019). Therefore, for the purpose of considering the composition of applicant pool, the share of black and Hispanic applicants can be used as another proxy. In addition, we divide the loan amount by the reported applicant income. Though not the same as the debt-to-income ratio (DTI) which is defined as the total monthly payment versus income, this imputed variable generally reflects the borrowers' total debt burden in relation to their income and hence still is the best credit characteristics variable that we can derive from the HMDA data before 2018.

Figure 6: Seasonality of home purchase application credit characteristics

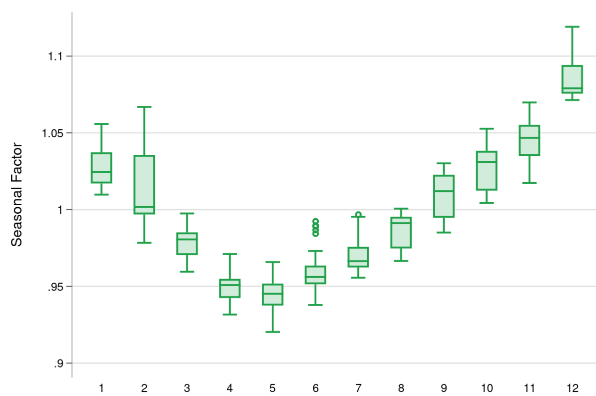
(a) Average Income



(b) Median Loan Amount to Income Ratio



(c) Minority Share



Notes: The figures show box plots of seasonal factors of the average reported income, the median loan amount to income ratio, and the share of minority applicants by calendar months, for home purchase applications. The seasonal factors are computed using the HMDA data from 1990 to 2017. The labels on the horizontal axis (1 to 12) represent the months from January to December respectively.

By comparing Figure 3 with Figure 6, it is apparent that while the overall home purchase application volume is higher in certain months of a year, on average the credit worthiness of the applicant pool in these high months are also higher than the average credit quality of the applicant pool in the low months. This is likely driven by the underlying factors that determine the household mobility in the country. For instance, parents of school-aged children, students, and recent graduates are affected by school terms while others prefer moving during warmer temperature or find it economically advantageous to move when everyone else is moving. As long as these factors persist, it is likely that the composition of the applicant pool of home purchase loans also vary with seasons. This has a strong implication for our identification strategy which we will discuss in Sections 4 and 5.

3.3 Capacity constraints of mortgage lenders driven by seasonality

The previous section demonstrates that the number of home purchase mortgage applications fluctuate from one season to another. Furthermore, this seasonality is more pronounced in states with more volatile temperature changes throughout the year than those with more consistent temperatures. In this section, we explore if mortgage lenders are more likely to face constraints in their capacity to process mortgage applications during busy spring and summer seasons compared to slower fall and winter seasons.

The idea of lenders facing an operational "capacity constraint" is not new. Stiglitz and Weiss (1981) and Lester (2011) proposed the theoretical frameworks for capacity constraints. Previous research has focused on the balance sheet constraints driving banks' capacity constraints (Bernanke and Gertler, 1987; Bernanke and Blinder, 1988; Bernanke, 2007). More recently, several studies examined lenders' response to a demand shock for refinance mortgages that is driven by policy interventions (Choi et al., 2022; Fuster et al., 2021) or low interest environments (Ma, 2023; Sharpe and Sherlund, 2016). Our paper adds to the literature by examining the effect of operating capacity constraint driven by seasonality.

Mortgage lenders rely heavily on highly skilled workforce and thus their ability to quickly respond to demand shifts by adjusting labor force is limited. For example, a typical entry level loan officer position requires a bachelor's degree, completion of pre-licensure courses, obtaining a state license, and passing the Secure and Fair Enforcement Act (SAFE) test. Loan officers are also required to annually complete continuing education coursework and maintain active licenses.[8] Loan processor and underwriter positions also generally require a bachelor's degree and an extensive training.[9] Besides the education and licensing requirements, loan officer positions require extensive knowledge on loan origination process and market conditions. Loan officers (1) collect all of the financial information from borrowers, (2) provide guidance in choosing appropriate loan products and interest rates, (3) ensure all of the documents are correct and (4) coordinate with borrowers and other parties involved— such as processors,

[8] See https://www.indeed.com/career-advice/finding-a-job/how-to-become-a-mortgage-loan-officer Also see https://www.bls.gov/ooh/business-and-financial/loan-officers.htm for the job requirements of loan officers.

[9] https://ca.indeed.com/career-advice/finding-a-job/how-to-become-a-mortgage-underwriter and https://www.indeed.com/career-advice/careers/what-does-a-loan-processor-do

underwriters, appraisers, and title insurance companies—to get the loan approved. Moreover, many loan officers rely heavily on the referrals from real estate agents with whom they have established relationship and build reputation through advertising, hosting seminars and community activities. Such business connections need time to build and maintain, making experienced loan officers highly valuable to lenders.

The fixed costs of hiring and training skilled workers prevent mortgage lenders from flexibly adjusting their labor force based on seasonality. Consequently this could lead to operational capacity constraints during certain seasons. Our conversations with industry experts and loan officers confirm that most lenders are aware of seasonal cycles but keep the number of loan officers stable throughout the year. This stands in contrast to another housing related occupation, the real estate agents. Many real estate agents work part-time or flexibly adjust their hours based on seasonal demands. Loan officers generally do not work part-time and are not assigned to different tasks or departments during low seasons. Instead, since loan officers' compensation is based on a combination of a base salary and commission, loan officers work hard and save during busy months to compensate for the slower months.

Figure 7: Trend in total mortgage industry employment

Notes: The figure is created using the Bureau of Labor Statistics data from 2011 to 2021.

Figure 7 confirms that lenders do not flexibly adjust their workforce based on seasonality. The figure shows that the total number of employees in the mortgage industry do not vary cyclically within a year. Lenders adjust their workforce only if there are large demand shocks that are much greater in magnitude than seasonal variations. Consequently, one can think that there are home purchase low seasons in which the loan officers may partially sit idle and high seasons when the loan officers may be very busy or even overwhelmed.

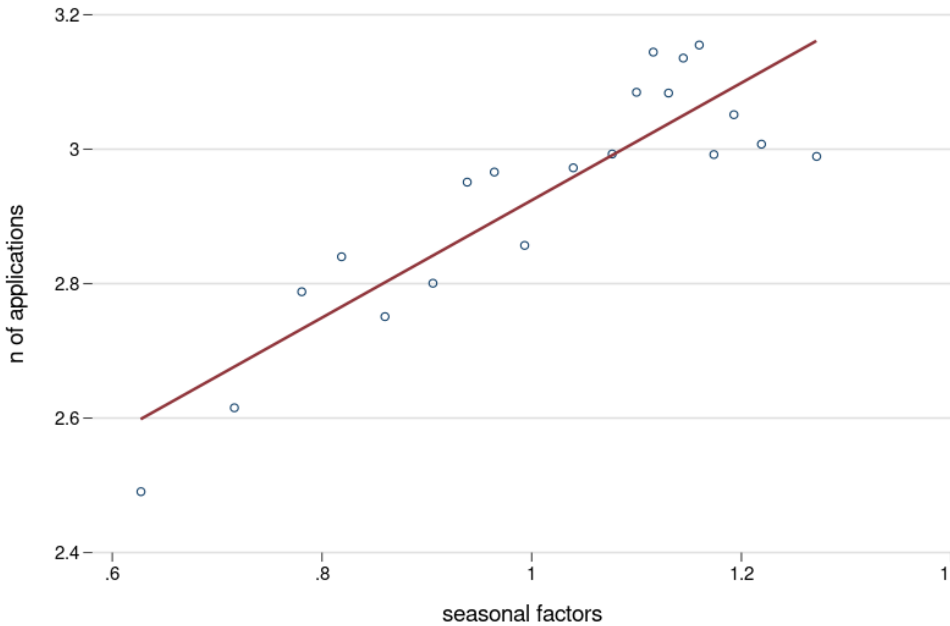
To show that a seasonal demand for home purchase loans constrain lenders' operational capacity during certain time of a year, we use two distinct measures of lenders' operational capacity.[10] First is a measure that estimates the mortgage industry's overall labor capacity to underwrite. Using the unique loan officer IDs in the HMDA data, we compute the total number of mortgage applications a loan officer received in each month.[11] The "average number of applications per loan officer" is then calculated by dividing the total number of applications by the number of loan officers that were associated with those applications taken in that month. Similarly, we compute the average maximum number of applications in each loan officer's queue in a month ("average max queue length"). It is computed by first counting the number of applications that a loan officer has not acted on (approved or denied) on each day. This would be a daily number of applications in the queue (queue length) waiting decisions by each loan officer. Then, we calculate the maximum of the daily queue length in a month. Finally, the maximum queue length of each loan officer is averaged across all loan officers. We expect both measures to increase as lender capacity becomes more constrained.

[10] Few different measures have been proposed to estimate capacity constraint. Choi et al. (2022) use the number of incomplete applications at the end of each quarter as well as the average number of days loan officers spend processing applications.

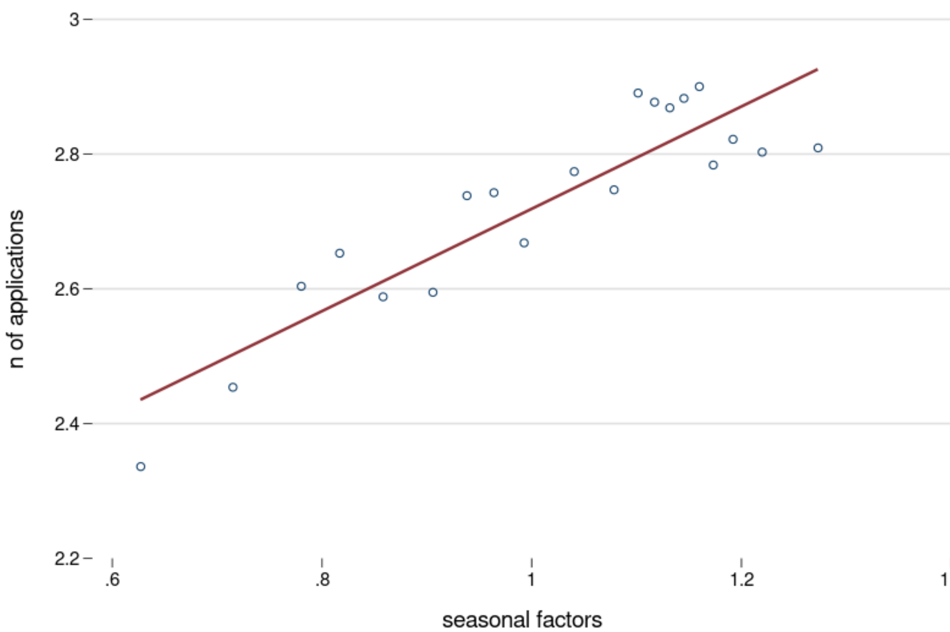
[11] The Secure and Fair Enforcement for Mortgage Licensing Act of 2008 (SAFE Act) is a federal law designed to protect consumers and reduce fraud. The Safe Act requires every mortgage loan originator (MLO) to be registered in the Nationwide Mortgage Licensing System and Registry (NMLSR). Each registered MLO receives a unique ID number that does not change even if the individual changes employers. The restricted version of the HMDA data since 2018 provides the NMLSR ID of the loan officer who handled each application.

Figure 8: The relationship between lender capacity and seasonality

(a) Average Number of Applications Processed per Loan Officer per Month



(b) Average Maximum Number of Applications in a Loan Officer's Queue in a Month



Notes: The sample consists of completed applications from the HMDA data from 2018 to 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Figure 8 provides binned scatter plots of the "average number of applications per loan officer" and “queue length" against the seasonal factors. The figure shows that the measures are positively correlated with the seasonal factors. In other words, lenders are more likely to reach their capacity constraint during high seasons. In the following section, we present the theoretical framework for how lenders respond when faced with capacity constraints.

Finally, the confidential version of HMDA data include the date when the application was taken and the date when the final underwriting decision was made from which we can impute the number of days it took for a denial decision to happen. We find that the number of days to render a denial decision, controlling for all available information in the HMDA data, is positively correlated with the seasonal factors. In other words, the higher the seasonal demand, the longer it takes for lenders to make denial decisions. This constitutes another important piece of evidence that lenders are more likely to be capacity constrained during the high seasons. We discuss the details of the number-of-days analysis in Appendix A.

4 A theoretical model of mortgage seasonality and lenders’ capacity constraints

In this section, we present a stylized model of how the seasonal patterns of home purchase demand may affect the likelihood of lenders reaching their capacity constraints and how this could affect the lenders’ underwriting decisions, for home purchase and refinance application separately.

A probability of a person i applying for a mortgage at a lender j in a state s and a month m is determined by a baseline probability $\bar{P}_{ij}$ times a seasonal factor $F(s,m,C_i)$. The baseline probability is affected by the person i’s income, wealth, and other characteristics, which can be summarized by a single credit characteristic measurement, called a credit score C_i. In this model, we do not allow for lender substitution. In other words, the baseline choice of a borrower i going to a lender j instead of another lender is predetermined, based on an existing banking relationship, proximity, and marketing power of lender j in a community that person i belongs to. Therefore, in the rest of the section, we drop the subscript j. The probability of a person i applying for a home purchase mortgage is,

$$P^{hp}_{ijsm} = \bar{P}_j(C_i, s) \cdot F(s,m,C_i) \tag{2}$$

where $F(s,m,C_i)$ represents the seasonal factor.

We assume that the baseline probability, $\bar{P}$, is an increasing function of credit score C: $\frac{\partial \bar{P}}{\partial C} > 0$. This is based on the well established fact that households' probability of seeking home ownership increases with income, wealth and other credit characteristics. Without loss of generality, we index the month s and state m to ensure that the likelihood of a person applying for a mortgage increases with both s and m monotonically. $\frac{\partial F}{\partial s} > 0$, and $\frac{\partial F}{\partial m} > 0$, as well as $\frac{\partial^2 F}{\partial m \partial s} > 0$.

One crucial assumption lies in whether the variation of the seasonal factor would vary not only with s and m, but also with individual credit characteristics of potential home buyers. Because the household mobility is related to income and wealth and other credit characteristics, if one thinks of the seasonal factor as an amplifier centered around 1 amplifying (or shrinking) the baseline probability of a person purchasing a home in a given state and month, then it is not unreasonable to assume that the magnitude of the amplifier could be even larger for high income, high wealth, high credit score households in home buying high season and state than their low income counterparts in the same season and state, ceteris paribus. In other words, there is a surge in high season across all credit score spectrum, but the surge is more pronounced among high score applicants. Formally, this set of assumptions can be expressed as: $\frac{\partial F}{\partial C} > 0$ as well as $\frac{\partial^2 F}{\partial s \partial C} > 0$ and $\frac{\partial^2 F}{\partial m \partial C} > 0$. As a result of this , the composition of applicant pools for home purchases loans also vary with season.

We assume the population's credit score is normally distributed with mean μ and standard deviation σ: $C \sim \mathcal{N}(\mu, \sigma^2)$.

On the lender side, for a representative firm that operates across all states $s \in S$ in month m, the lender had a preset underwriting standard C_{min} and capacity constrain Ω. One can think of C_{min} as a score cutoff, the minimum credit score the lender would accept. In underwriting, the lender would rank order all the applicants based on credit characteristics C, and reject all applicants whose credit score $C < C_{min}$. That is if the lender is not capacity constrained. For lender j in any period, the lender has maximum processing capacity of only originating no more than Ω loans. If for some reason the lender reached its capacity constraint, the lender then would have to ration the credits, by tightening the lending standard (raising C_{min}) until it reaches a point where the total number of approved applications is equal to Ω.

Here we introduce another critical assumption: for most lenders, it would receive applications for both home purchase and refinance loans and the refinance application volume it receives does not have seasonal patterns.

For person k living in state s likely to apply to lender j for a refinance loan in the month of

m, the probability of the person seeking refinance Q is determined by external factors such as ongoing market interest rates r and borrower credit characteristics C and location s. But the probability is totally orthogonal to the month of a year itself, $Q \perp m$:

$$P_{ksm}^{refi} = Q(C_k, r, s) \tag{3}$$

We assume a person would consider applying for either a home purchase loan or refinance loan, but not both.

Switching to continuous form, aggregating across all states for all population spanning full credit spectrum applying to lender j in month m, the total number of home purchase mortgage applications the lender receives is:

$$N_m^{hp} = \int_{s\in S}\int_{c\in\mathcal{N}} \bar{P}(c,s)\cdot F(s,m,c)dcds \tag{4}$$

The total number of refinance mortgage applications the lender receives is:

$$N_m^{refi} = \int_{s\in S}\int_{c\in\mathcal{N}} Q(c,r,s)dcds \tag{5}$$

Together the total number of mortgage applications the lender receives in month m across all states is:

$$N_m^{all} = \int_{s\in S}\int_{c\in\mathcal{N}} \bar{P}(c,s)\cdot F(s,m,c)dcds + \int_{s\in S}\int_{c\in\mathcal{N}} Q(c,r,s)dcds \tag{6}$$

The total number of approved applications, i.e. originations by lender j in month m is

$$O_m = \max\begin{cases}\int_{s\in S}\int_{c\geq C_{min}} \bar{P}(c,s)\cdot F(s,m,c)dcds + \int_{s\in S}\int_{c\geq C_{min}} Q(c,r,s)dcds \\ \Omega\end{cases} \tag{7}$$

We can solve for increased score cutoff when the lender is capacity constrained and has to ration the credits. The new score cutoff C_{new} in that case has to satisfy:

$$\int_{s\in S}\int_{c\geq C_{new}} \bar{P}(c,s)\cdot F(s,m,c)dcds + \int_{s\in S}\int_{c\geq C_{new}} Q(c,r,s)dcds = \Omega \tag{8}$$

For an individual home purchase loan applicant i in the state of s and month of m with credit score C_i, the probability of his application is rejected is $Prob(C_i < C_{min}^{inplace})$ where $C_{min}^{inplace}$

is the credit score cutoff in place that either is equal to C_{min} when the lender is not capacity constrained or takes on the value of C_{new} determined by equation 8.

$$Prob_i^{hp}(Denial) = \mathbb{1}\{C_i < C_{min}\} \cdot Prob(N_m^{all} <= \Omega) + \mathbb{1}\{C_i < C_{new}\} \cdot Prob(N_m^{all} > \Omega) \quad (9)$$

where N_m^{all} is the total mortgage applications received by the lender in month m as shown in equation 6, C_{new} is the increased credit score cutoff if the lender is capacity constrained that satisfies Equation 8.

A similar equation of denial probability applies to an individual refinance loan applicant k.

$$Prob_k^{refi}(Denial) = \mathbb{1}\{C_k < C_{min}\} \cdot Prob(N_m^{all} <= \Omega) + \mathbb{1}\{C_k < C_{new}|\} \cdot Prob(N_m^{all} > \Omega) \quad (10)$$

In aggregate, the population denial rate of home purchase applications in month m is:

$$DenialRate_m^{hp} = \frac{\int_{s \in S} \int_{c \leq C_{min}^{inplace}} \bar{P}(c,s) \cdot F(s,m,c) dcds}{\int_{s \in S} \int_{c \in \mathcal{N}} \bar{P}(c,s) \cdot F(s,m,c) dcds} \quad (11)$$

while the population denial rate of refinance application in month m is:

$$DenialRate_m^{refi} = \frac{\int_{s \in S} \int_{c \leq C_{min}^{inplace}} Q(c,r,s) dcds}{\int_{s \in S} \int_{c \in \mathcal{N}} Q(c,r,s) dcds} \quad (12)$$

It is straightforward to show that for home purchase applications, $\frac{\partial DenialRate_m^{hp}}{\partial m}$ is indeterminate, while for refinance applications, $\frac{\partial DenialRate_m^{refi}}{\partial m} > 0$.

5 Testing for lender responses to seasonality

As established in Sections 3, there is a seasonal pattern in home purchase mortgage application volumes which provides a natural experiment to test for lenders' response to demand changes. The theoretical model in Section 4 informs us that lenders likely need to ration the credits during high seasons when they face higher probability of capacity constraints. This can be empirically tested by examining the changes in denial rates in relation to the seasonal factors, controlling for credit characteristics of applicants and all other factors that enter lenders' underwriting decisions.

Our main goal is to test whether lenders are more likely to ration credit with higher demand of mortgage applications due to home purchase seasonality. Our evidence of credit rationing lies in possibly higher denial rates for similarly situated mortgage applicants if overall demand is higher. The main specification of the analysis is:

$$Y_i = \alpha X_{1i} + \beta X_{2i} + \epsilon \tag{13}$$

where Y_i is a binary variable of whether an application was denied or not, the main variable of interest X_{1i} is the seasonal factor and X_{2i} is a vector of controls including applicant, loan and property characteristics. The full set of loan characteristic variables available in the HMDA data since 2018 include loan types, loan amounts, loan terms, channels through which an application was submitted, and if a loan is fixed rate. They also include information on the presence of loan features such as balloon payment, interest-only, negative amortization or other non-amortizing features. The credit characteristic variables include credit scores, Combined Loan-to-Value ratio (CLTV), Debt-to-Income ratio (DTI), and the results from Automatic Underwriting System (AUS). Some models also include lender and state fixed effects to account for lender and state specific characteristics. We will discuss these controls in more details later.

Table 1: Summary statistics by loan purpose

	Home Purchase	Refinance	All
Denial rate	0.086	0.167	0.132
	(0.281)	(0.373)	(0.338)
Fixed rate	0.95	0.97	0.96
	(0.22)	(0.17)	(0.19)
Loan amount	302623	275565	286756
	(183650)	(167516)	(174879)
Applicant income (thousands)	106	109	108
	(92)	(148)	(126)
Loan term (months)	352	313	329
	(119)	(187)	(164)
Credit score	727.4	734.7	731.4
	(58.5)	(61.6)	(60.3)
Combined Loan-to-Value ratio (CLTV)	86.7	66.9	75.8
	(14.6)	(18.0)	(19.3)
Debt-to-Income (DTI)	35.3	34.1	34.6
	(10,803.7)	(699.7)	(7,410.7)
Balloon payment	0.00	0.00	0.00
	(0.05)	(0.04)	(0.04)
Interest-only payment	0.02	0.01	0.01
	(0.13)	(0.07)	(0.10)
Negative amortization	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Other non-amortizing features	0.00	0.00	0.00
	(0.03)	(0.02)	(0.02)
Loan type			
Conventional conforming	0.62	0.73	0.69
	(0.49)	(0.44)	(0.46)
Conventional jumbo	0.05	0.03	0.04
	(0.23)	(0.18)	(0.20)
FHA	0.20	0.11	0.14
	(0.40)	(0.31)	(0.35)
VA	0.10	0.13	0.12
	(0.31)	(0.33)	(0.32)
FSA/RHS	0.02	0.00	0.01
	(0.15)	(0.03)	(0.10)

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence.

Table 1 presents the summary statistics of the HMDA data from 2018 to 2022 by loan purpose. The average denial rate for home purchase loan is lower at 9% than that of refinance at 17% during the sample time period. The average loan amount for home purchase loan is slightly higher at about $303,000 compared to that of refinance loan at about $276,000. Refinance applicants overall have slightly better credit characteristics than home purchase applicants with higher income, higher credit scores and lower DTIs.

To allow for the asymmetric response of lenders to the high seasons and low seasons, we spline the seasonal factors at 1. The seasonal factors center around 1[12]. We define high side and low side season factors according to:

$$SF_{high} = \begin{cases} \text{SF}-1, & \text{if } SF > 1 \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

$$SF_{low} = \begin{cases} \text{SF}-1, & \text{if } SF < 1 \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Where SF represents the seasonal factor, SF_{high} represents high side seasonal factor, SF_{low} represents low side seaonal factor. Intuitively, the further away a seasonal factor is above 1, the more likely lenders would reach their capacity constraints, in which case they are more likely to ration credits and we would observe higher denial rates controlling for observables. This is our key variable of interest. On the other hand, when a seasonal factor is below 1 and some lenders' production capacity is underutilized, it is unclear whether lenders would loosen the underwriting standards to bring in more business. The theoretical model presented in Section 4 only considers an upper bound of origination volume due to a capacity constrain as in Equation 7. However, it is also possible to impose a lower bound of origination volume (i.e., minimum quota of production output) that a lender must meet. When a seasonal shift weakens the demand, some idled lenders may respond by relaxing the underwriting standards. We will discuss our findings after the empirical results in the context of soft information and lender discretion in the mortgage underwriting.

In addition to underwriting where the lenders may be forced to ration credits by denying more applications, we also consider the possibility of lenders rationing the credits by increasing the pricing of the loans they offered, forcing some applicants to abandoned the applications. If we call the higher denial rates as extensive margin, we can call potentially the higher pricing intensive margin through which lenders ration the credits. We do not find the evidence of lenders increasing mortgage pricing during the high seasons. We present the mortgage pricing analyses in Append B. For the rest of the paper, we focus on the extensive margin.

Because the seasonal factors vary not only intertemporally but also across regions, we use the state and monthly level seasonal factors for the analysis, which provide sharper variations than national seasonal factors. For a lender that operates in only one state, the seasonal factors

[12]However, mathematically there is no reason that the average of seaonal factors is exactly equal to 1.

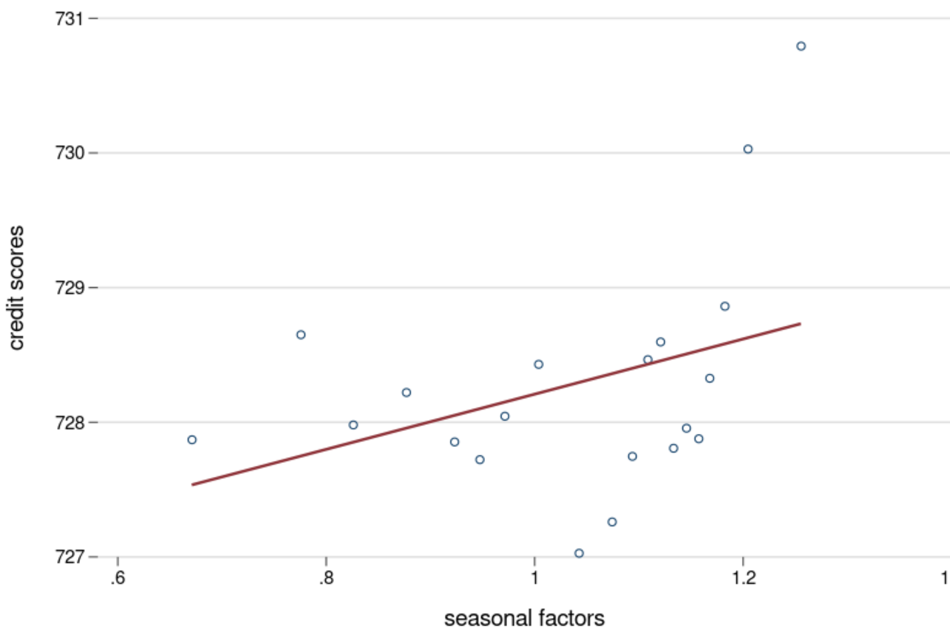
in that state directly capture its exposure to the demand shift. On the other hand, for a lender that operates across multiple states, the overall demand shift that it faces is a weighted exposure of seasonal variations across all states, where the weights are the number of applications that the lender receives in a state in each month. In other words, the overall demand change experienced by a lender is an aggregation of seasonal variations in each state multiplied by the lender's exposure to that state. One can think of our strategy of using state-level seasonal factors as akin to Bartik instrument that was initially introduced by Bartik (1991) and was popularized in Blanchard and Katz (1992). More importantly, we do not require lenders to have different underwriting standards across different states. Just as in the theoretical model in Section 4, each lender applies a within-lender uniform underwriting standard nationwide, which also matches the business practices of most lenders that centralize the underwriting operations in one or few locations according to the industry experts we spoke to.

A potential endogeneity problem exists for home purchase applications. The application volume rises and falls with seasons, shifting the probability that lenders reach capacity constraint as illustrated in Section 3. However, we also find some evidence that the credit characteristics of home purchase applicants are correlated with seasonality in Section 3. Using the credit scores of applicants that are only available in HMDA data starting in 2018, Figures 9 shows a binned scatter plot of credit scores of home purchase applicants against the seasonal factors between 2018 and 2022. The average credit score of home purchase applicants is positively correlated with seasonal factors.

We replicate Figure 9 using the National Mortgage Database (NMDB) in Appendix C1. NMDB is a nationally representative five percent sample of residential mortgages in the US. Even though it is for originated loans only, not for applications, NMDB allows an analysis of the relationship between the credit scores and seasonal factors over a longer time period. The resulting Figure C1 looks consistent with the ones using the HMDA data. [13]

[13] For more information on NMDB, see https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx.

Figure 9: Relationship between the average credit score and seasonal factors, home purchase only



Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Even with the most comprehensive set of controls, not all underwriting variables are available in the HMDA data. The HMDA data since 2018 vastly expanded the information collected on the loan and applicant credit characteristics. However, even though our empirical model includes all of the key factors in the HMDA data since 2018, not all factors that lenders consider in underwriting are available in the data. Examples of information that lenders consider but is not captured in the HMDA data include: detailed loan products or programs under which the underwriting policies and guidelines are set, employment history and income stability, asset and months of reserve, and foreclosure and bankruptcy history etc. The omitted variable bias is one of the greatest challenges that economists face. In the context of single-equation mortgage underwriting model, such challenge is not new. For instance, some have criticized the famous Boston Fed Study on mortgage discrimination (Munnell et al., 1996) on that ground.[14] Importantly, most of the omitted variables are likely correlated with the control variables that we include, which in return are also correlated with the main variable of interest, the seasonal factors.

We illustrate this issue by sequentially including larger sets of control variables in different

[14]See Ross and Yinger (1999) for a summary and response to the criticism.

columns in Table 2 for home purchase applications. Table 2 presents the regression coefficient estimates of the seasonal factors according to the equation 16 in a linear probability model.

Table 2: Likelihood of mortgage application denials, home purchase applications only

	(1)	(2)	(3)	(4)	(5)
Seasonal factor high side (above 1)	-0.049***	-0.027***	-0.021***	-0.017***	0.001
	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
Seasonal factor low side (below 1)	0.021***	0.013***	0.009***	0.007***	-0.005*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Loan & credit characteristics	No	Yes	Yes	Yes	Yes
Channel	No	No	Yes	Yes	Yes
AUS	No	No	Yes	Yes	Yes
Lender FE	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
N. Obs.	20,956,270	19,277,912	19,277,912	19,277,836	19,277,836
Adj. R^2	0.00	0.21	0.28	0.31	0.31

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses.

Column 1 includes no controls, except for the splined seasonal factors SF_{high} on the high side and SF_{low} on the low side. Column 2 includes a rich set of loan and applicant credit characteristics in HMDA. They include loan purpose (home purchase, non-cash-out refinance, cash-out refinance)[15], adjustable rate mortgage (ARM) flag, presence of loan features such as balloon payment, interest only payment, negative amortization or other non-amortizing features, log of loan amount, log of reported income, loan type (conventional conforming, jumbo, FHA, VA, and RHS/FSA), loan term (grouped in 5-year, 10-year, 15-year, 25-year, 30-year, 40-year loans, and other loan terms), credit score bins, CLTV bins, and DTI bins. We note that we are able to leverage off the very large number of observations we have in the 5-year HMDA sample to include the credit score, CLTV and DTI in very fine bins, allowing flexibility to reduce the risk of model misspecifications.

Column 3 includes two more sets of control variables: channel and AUS results. For channel, we use the HMDA field indicating "whether the application was directly submitted to the lender".[16] We also include the full set of automated underwriting system (AUS) results

[15] Even though loan purpose is limited to home purchase in Table 2, we include it in the description because loan purpose is used in regressions in Table 3 and Table 4.

[16] Two fields in the HMDA data since 2018 were designed to capture lending channels: whether the application is directly received by the lender and whether the loan would have been directly payable to the lender had the application been originated.For detailed explanations of how these fields corresponds to retail, wholesale and correspondent channels, see Liu et al. (2019). However, a large number of HMDA reporters have reported the "initially-payable"

in the controls. The AUS results provide the largest lift in explaining underwriting outcomes among all HMDA variables, even more so than credit score, CLTV, and DTI, as documented in an official CFPB report (Consumer Financial Protection Bureau, 2023). The AUS results are also used in Bhutta et al. (2022) and Liu and Zhang (2024) which confirm the importance of AUS results.

Column 5 is our full and preferred specification. It includes both lender and state fixed effects. Different lenders may have different underwriting policies and risk tolerance level. They may also have different capacity constraints and may respond to capacity constraints differently. The lender fixed effects capture these as well as any other lender specific characteristics. The state fixed effects capture all state level specific characteristic beyond the state and monthly level seasonal factors that is the main variable of our interest.

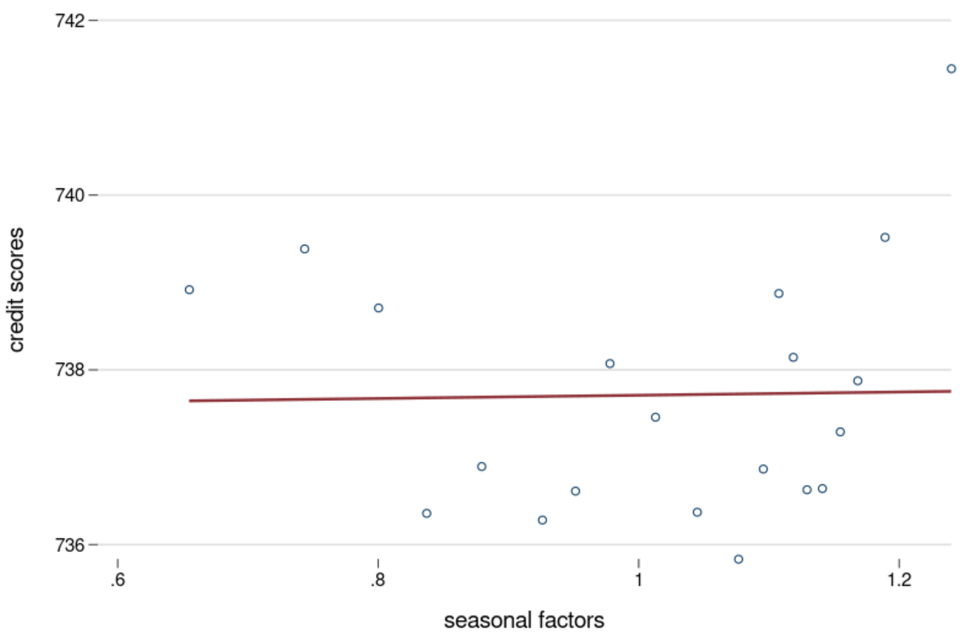
Without any control, the coefficient on high-side seasonal factor is -0.124, meaning for every 10 percentage point increase of mortgage application volume due to seasonal shift, the denial rate of home purchase applications decreases by 1.24 percentage point (Table 2). This implies that the unconditional denial rate of home purchase applications is lower in high seasons and in states with larger upswing of seasonal demand than the denial rates in low seasons and states. This could be the case if the average credit quality of the applicant pool also increases with application volume in high seasons. As we add more controls into the model, from Column 2 to Column 5, however, the magnitude of the high side seasonal factor decreases, still negative in Columns 2 to 4 but becoming smaller in absolute magnitude, until our full preferred specification in Column 5, in which the coefficient becomes near zero and statistically insignificant. Though not conclusive, the direction of the magnitude change in SF_{high} from Columns 1 to 5 implies that if more control variables are added that are missing from HMDA but are legitimate underwriting factors that lenders use, it is possible that the coefficient of SF_{high} would become positive, instead of being insignificant in our full specification. The coefficient on the low side of the seasonal factor is also insignificant in our full specification.

Unlike home purchase applications, there is no reason to believe that the composition of applicant pool for refinance loans is inherently correlated with seasonality. This is because the refinance activities are mostly driven by interest rate environment set regardless of the seasons. Therefore, refinance application volumes and the credit characteristics of refinance applications do not vary with seasonality. To illustrate, Figure 10 is a replicate of Figure 9 except it is limited to refinance applications. Figure 10 shows no trend across seasons for the

field incorrectly in all years since this field was added to HMDA. Therefore, we only use the "directly-submitted" field in our regression to capure channels.

average credit score of refinance applicants. Furthermore, most mortgage lenders receive both home purchase applications and refinance applications. Therefore, as equation 7 in Section 4 points out, the surge in home application volume during home buying high season could constrain the lenders' capacity to process applications and originate loans across the board, even for refinance loans.

Figure 10: Relationship between the average credit score and seasonal factors, refinance only



Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Our key identification assumptions are: 1) There is a seasonal variation in home purchase application volumes. 2) Most lenders receive both home purchase applications and refinance applications and hence the change in home purchase application volume could spill over to the lenders' overall capacity, constraining lenders' capacity to deal with refinance applications. 3) Unlike the home purchase applications, the change of credit characteristics of refinance loan application pool is orthogonal to the home purchase seasonality. In short, since the credit characteristics of refinance applications are not correlated with seasons, the estimate of the relationship between the denial rate and seasonality is much less likely to suffer from an endogeneity issue if we limit the sample to refinance applications.

Table 3: Likelihood of mortgage application denials, refinance applications only

	(1)	(2)	(3)	(4)	(5)
Seasonal factor high side (above 1)	0.006***	-0.002**	-0.003***	0.037***	0.047***
	(0.001)	(0.001)	(0.001)	(0.014)	(0.015)
Seasonal factor low side (below 1)	0.020***	0.010***	0.009***	-0.004	-0.011
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)
Loan & credit characteristics	No	Yes	Yes	Yes	Yes
Channel	No	No	Yes	Yes	Yes
AUS	No	No	Yes	Yes	Yes
Lender FE	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
N. Obs.	27,177,303	22,073,047	22,073,047	22,072,981	22,072,981
Adj. R^2	0.00	0.31	0.38	0.43	0.43

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses.

Table 3 presents our main regression results for refinance applications. The specifications are the same as the ones in Table 2 except that we also include a control for cash-out refinance. Column 5 indicates that the denial rate for refinance loan applications increases by 4.7 percentage points when the seasonal factor increases by one unit on the high side. This means that on average, when the seasonal demand for home purchase loans increased by 10 percent compared to the annual average, the denial rate for refinance loan applications increased by about 0.47 percentage point. As a baseline, during 2018 to 2022 period, the average denial rate of refinance applications is 17% according to Table 1.

This matches our prediction that lenders are likely to impose stricter lending standards and that the same stricter lending standards also apply to refinance loans when their loan processing capacity is constrained during a home-buying high season, resulting in higher denial rates. On the other hand, on the low side, when the seasonal demand of home purchase loans is below annual average, the coefficient on the seasonal factor is statistically insignificant, implying that when the overall demand is weakened and some lenders' capacity is underutilized, they do not or could not relax the underwriting standards to fill in more business.[17]

The main finding is consistent with Sharpe and Sherlund (2016) and Ma (2023). Both studies find that capacity constraints lead to credit rationing which limits access to credits especially for borrowers with higher credit risk. Sharpe and Sherlund (2016) find that when lenders' capacity is constrained due to an increase in refinance volume, lenders prioritize higher credit score

[17] We note that higher lending standards we surmise so far are not necessarily tie to credit risks, but could be implemented through lender discretion, for which we will have thorough discussion in Sections 8 and 9.

borrowers whom require less underwriting resources. Ma (2023) shows that when individual loan officers experience shocks to their capacity, they lend less to home purchase borrowers who require more resources and riskier borrowers. Our finding shows that during months when home purchase volume is high, lenders are more likely to deny refinance applications. Our finding on home purchase applications is inconclusive due to a potential endogeneity issue. We examine heterogeneous effects of capacity constraints in Section 7 .

Table 4: Likelihood of mortgage application denials, home purchase and refinance applications combined

	(1)	(2)	(3)	(4)	(5)
Seasonal factor high side (above 1)	-0.049***	-0.010***	-0.008***	0.013	0.027***
	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)
Seasonal factor low side (below 1)	0.012***	0.012***	0.010***	0.002	-0.008*
	(0.001)	(0.001)	(0.001)	(0.005)	(0.004)
Loan & credit characteristics	No	Yes	Yes	Yes	Yes
Channel	No	No	Yes	Yes	Yes
AUS	No	No	Yes	Yes	Yes
Lender FE	No	No	No	Yes	Yes
State FE	No	No	No	No	Yes
N. Obs.	48,133,573	41,350,959	41,350,959	41,350,915	41,350,915
Adj. R^2	0.00	0.27	0.35	0.39	0.39

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses.

For completeness, Table 4 combines the home purchase and refinance applications. We expand the loan purpose to include home purchase, non-cashout refinance and cash-out refinance as a control in Columns 2-5. In our most complete specification (Column 5), the coefficient of seasonal factor on the high side is 0.027, meaning that when the seasonal demand for home purchase loans increased by 10 percent compared to the annual average, the denial rate for home purchase loan and refinance loan applications combined increased by about 0.27 percentage point. Admittedly, because of the challenges resulted from the correlation between the home purchase application seasonality and composition of home purchase application pools, the combined estimates are not as cleanly identified as the estimates from the regression results on refinance applications alone. Nevertheless, this provides a sense of the overall effects of mortgage seasonality on the entire market, and it is directionally consistent with our predictions. Moreover, on the low side, the coefficient of seasonal factor is statistically insignificant at 5 percent level.

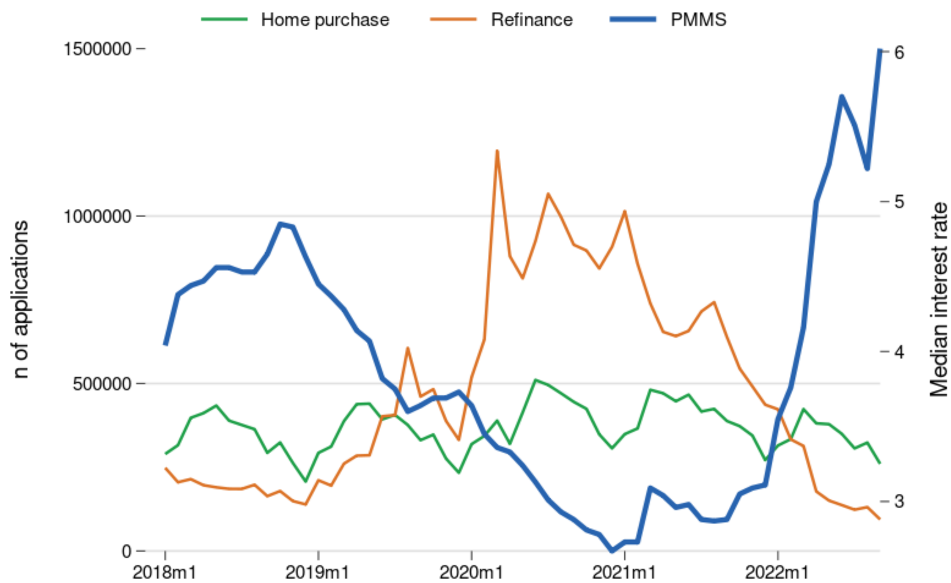
6 Robustness checks

Our key identification strategy using the seasonal factors of home application volumes on refinance application relies on two assumptions: 1) the composition of the refinance applications and volume are not correlated with the home purchase seasonality, and 2) most mortgage lenders are engaged in both home purchase and refinance loan activities. In this section, we conduct two sets of robustness checks against these assumptions.

First, even though we already demonstrate that the home purchase application volume seasonality is exogenous, set by weather patterns and human-induced calendar effects, and we argue that the refinance activities is mostly spurred by interest rate environment with no inherent seasonal component, therefore there should be no correlation between the home purchase seasonality and refinance applications, this assumption could be violated if during our main study period (between 2018 and 2022), the change of refinance activities coincided with the home purchase seasonality accidentally. In that case our identification strategy will be confounded.

Figure 11 plots the monthly volume of refinance applications between January 2018 and December 2022. There are clearly three periods in our main study window: a relatively stable period between January 2018 and December 2018, a refinance boom period between January 2019 and January 2021, and a refinance bust period between February 2021 and the end of 2022. This is clearly driven by the interest rate environment, as shown in the same figure.

Figure 11: Trend in the median 30-year fixed interest rate and the number of refinance and home purchase applications



Notes: The Freddie Mac's Prime Mortgage Market Survey (PMMS) rate is derived from their survey of lenders on weekly mortgage rates that prime borrowers pay. For more information, see https://www.freddiemac.com/research/insight/20221103-freddie-macs-newly-enhanced-mortgage-rate-survey. The number of applications is computed by summing up the number of applications in the HMDA data with the action taken code of 1 (originated), 2(approved but not accepted) and 3 (denied).

Table 6 presents our main estimates separated by the three distinct interest rate environment periods, for refinance applications, with our full specification. The parameter estimate of high side seasonal factor is 0.033 in the stable period. Its magnitude almost doubled, increased to 0.062 in the boom period. The parameter estimate of high side seasonal factor is statistically insignificant and also smallest in magnitude but positive in the last period of our main sample when the entire refinance market tanked.

The Period I in 2018 provides the cleanest test ground for our identification strategy as the refinance volume remained stable throughout. Hence any concern of external factors affecting refinance activity and coinciding with home purchase seasonality in this period should be alleviated. Furthermore, we note that in addition to the time variation by months which consists of only 12 months in Period I, we also use the state level variation of the home purchase seasonality. Therefore, we can identify our key parameter of interest very precisely.

Period II is a time when the market interest rate dropped as the results of Fed's interest rate policy responding to the Covid pandemic and recession. During this period, the refinance volume rose sharply. Sharpe and Sherlund (2016) and Ma (2023) demonstrated that a low

Table 5: Likelihood of mortgage application by time periods, refinance applications only

	(1) 2018m1-2018m12	(2) 2019m1-2021m1	(3) 2021m2-2022m9
Seasonal factor high side (above 1)	0.032***	0.062***	0.017
	(0.012)	(0.018)	(0.016)
Seasonal factor low side (below 1)	-0.029	-0.001	-0.022**
	(0.020)	(0.008)	(0.008)
Loan & credit characteristics	Yes	Yes	Yes
Channel	Yes	Yes	Yes
AUS	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N. Obs.	1,937,044	12,570,795	7,565,023
Adj. R^2	0.42	0.42	0.45

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses.

interest rate led to a demand shock in refinance applications, resulting in capacity constraint of lenders. Therefore, during this period, many lenders' capacities were likely already constrained because of the refinance boom and even small increase in home purchase application volume (smaller in magnitude than the refinance application surge) could further strain the lenders' capacity. In this case therefore it is not surprising to see larger response of lenders to the demand increase during the home purchase high season. Again, because we use both the inter-temporal and geographic variations of seasonality in our specification, even though the refinance boom partially confounds with the inter-temporal variation, the state-level variation of home purchase applications should still be valid.

In Period III, the refinance activities tanked, dropping from a historical high to almost zero near the end of the period, due to the Fed's aggressive interest rate hike combating the inflation. Given the lagged response of lenders' hiring practices we discussed earlier, it is highly likely that, during this period, most lenders' production capacities were underutilized. Figure 7 shows that there was likely excess capacity in 2021 and 2022 because of rapid hiring in prior years to meet the demand shock in refinance activities. As a result, not only did the small bumps of home purchase application volumes during the high season not push most lenders to reach their capacity limits, but such small seasonal bumps from the home purchase loans could actually be welcomed by the lenders, providing a small relief to idled lenders who were facing a significant downturn with very low overall demand. Consequently, it is not surprising that the coefficient of the high-side home purchase seasonal factor is statistically insignificant during this period.

On the low-side, when the seasonal factor is below 1, i.e. when seasonal demand is below the annual average, the coefficients of the seasonal factors are statistically insignificant in both Period I and Period II, matching with our overall results in Table 3. The coefficient of low-side seasonal factor is -0.022 in the Period III and significant. Because of the confounding effects from the refinance bust, it is a bit difficult to interpret this negative coefficient.

Overall, by splitting our main study sample into three (stable, boom and bust) periods, we show that our underlying assumption of refinance activity being orthogonal to the home purchase seasonality holds for the stable period. This assumption is partially confounded during the refinance boom period, but the coefficient estimate during this period matches with our prediction on the condition that the refinancing boom already constrained the lenders' capacity and increased the likelihood that home purchase high seasons could elicit even stronger response from lenders tightening their lending standards. The geographic variation of home purchase application volume also works in our favor regardless of the time period. Conversely, during the refinance bust period most lenders' capacity may have been already idled and therefore we detect a null result of the home purchase seasonality' effects on denial rates.

Another key assumption allowing us to apply the seasonal variation of home purchase applications to refinance applications is that most lenders are engaged in both home purchase loan and refinance loan originations, therefore crowding out of production capacity from the home purchase demand could spill over to the refinance side. This can be directly tested. Out of 5,799 HMDA reporters in our sample, only about 2 percent had less than 1 percent of their originations as home purchase loans. For such refinance specialized lenders, we expect to see a weak or no relationship between their denial rate and home purchase seasonality when the sample is limited to lenders who originate mostly refinance loans.

Table 6 tests this hypothesis by splitting our main refinance application sample to different group of lenders by the share of refinance loans each lender originates and re-estimating our main specification for each of the subgroups. Just as we predict, we find null results among the refinance specialist lenders. Among the lenders who originated more than 99 percent of loans in refinance space (Column 1), the estimated coefficient on high-side home purchase seasonal factor is insignificant. This is similarly the case for lenders whose refinance originations accounted for more than 95 percent of their business (Column 2). When this lender-level refinance specialty threshold is relaxed to 90 percent (Column 3) the coefficient is still statistically insignificant at 5 percent level. On the other hand, when the subsample is limited to lenders whose refinance

Table 6: Likelihood of mortgage application denials by lender's share of refinance loans

	(1) $\geq 99\%$	(2) $\geq 95\%$	(3) $\geq 90\%$	(4) $\geq 80\%$	(5) $\geq 50\%$	(6) $< 50\%$
Seasonal factor high side (above 1)	0.033	0.021	0.054*	0.038**	0.053**	0.030***
	(0.031)	(0.034)	(0.028)	(0.015)	(0.021)	(0.005)
Seasonal factor low side (below 1)	-0.051	-0.048	-0.023*	-0.018**	-0.016*	0.002
	(0.032)	(0.046)	(0.013)	(0.007)	(0.009)	(0.002)
Loan & credit characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Channel	Yes	Yes	Yes	Yes	Yes	Yes
AUS	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	73,025	435,745	1,803,710	6,433,227	15,973,405	6,098,273
Adj. R^2	0.58	0.53	0.51	0.40	0.42	0.45

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses.

share is over 80 percent, the coefficient is significant at 5 percent level and at 0.38 (Column 4). When the sub-sample is limited to lenders with refinance share over 50 percent, the coefficient is significant at 5 percent level and increases to 0.053 (Column 5). Furthermore, when we examine the lenders whose refinance share is less than 50 percent, the statistical significance level increases to 1 percent and our parameter estimate on SF_{high} was 0.30. Such results support our assumption that the spillover effects from the demand shift of home purchase application to the refinance application are real and prevalent.

7 Heterogeneous effects

In this section, we explore the heterogeneity of the lenders' response to mortgage seasonality and its effects on borrowers of difference race and ethnicity.

Table 7 presents the coefficient estimates of the seasonal factors related to denial rates of refinance applications, using our full specification, separated by lender types and different time periods. As the Panel A indicates, in the full study period between January 2018 and September 2022, we observe positive and significant coefficient of SF_{high} for medium-sized banks (with assets between \$10 billions and \$100 billions), small banks (with assets below \$10 billions) and independent mortgage companies, but not for the largest banks with assets over \$1 billion, credit unions and affiliates. The largest coefficient is for the medium-sized banks, at 0.056. The coefficient estimates on the low side seasonal factors are all statistically insignificant at 5% level.

In Period 1, when the mortgage interest rate was stable, the coefficient estimate on high side seasonal factor is statistically significant for independent mortgage companies at 5% level. In period 2, during the refinance boom, just as what is shown in Section 6, the lenders' response to the rise in seasonal home purchase mortgage demand became more significant. In this period, the statistical significance level of the coefficient estimates of SF_{high} for small banks and independent companies increases to 1%, and the statistical significance for medium-sized banks and large credit unions becomes 5%. The size of coefficient estimates also increases from Period 1 to Period 2 for all lender types except for affiliates. In Period 3, during the refinance bust, all coefficient estimates for SF_{high} become insignificant except for medium-sized banks.

Independent mortgage companies made up the largest share of mortgage applications in the entire sample period. Their response to the increase in seasonal demand provides the firmest evidence of credit rationing as we find positive and statistically significant coefficients for them both in the Period 1 and Period 2 as well as when all three periods are combined.

Table 7: Effects of lender response to mortgage seasonality by lender types

	(1) Large Banks	(2) Medium Banks	(3) Small Banks	(4) Large Credit Unions	(5) Small Credit Unions	(6) Independent Mortgage Companies	(7) Others
			Panel A: Sample Period 2018m1 to 2022m9				
Seasonal factor high side (above 1)	0.126	0.057***	0.018***	0.061	0.007	0.036***	-0.008
	(0.081)	(0.021)	(0.006)	(0.041)	(0.005)	(0.008)	(0.037)
Seasonal factor low side (below 1)	-0.036	-0.009	0.002	0.013*	0.005	-0.007	-0.062*
	(0.038)	(0.006)	(0.003)	(0.007)	(0.003)	(0.006)	(0.035)
N. Obs.	3,125,562	1,133,851	1,748,087	430,780	1,512,106	13,255,105	867,490
Adj. R^2	0.52	0.43	0.47	0.52			
			Panel B: Sample Period 2018m1 to 2018m12				
Seasonal factor high side (above 1)	0.060	0.040*	-0.000	-0.040	0.020	0.030**	0.005
	(0.040)	(0.021)	(0.013)	(0.059)	(0.013)	(0.015)	(0.026)
Seasonal factor low side (below 1)	-0.012	-0.039**	-0.014	-0.032	0.001	-0.039	-0.042
	(0.021)	(0.016)	(0.014)	(0.025)	(0.013)	(0.034)	(0.028)
N. Obs.	304,817	118,373	150,376	32,782	145,091	1,100,230	85,374
Adj. R^2	0.52	0.43	0.49	0.48	0.47	0.40	0.45
			Panel C: Sample Period 2019m1 to 2021m1				
Seasonal factor high side (above 1)	0.166	0.071**	0.024***	0.121**	0.007	0.045***	-0.002
	(0.098)	(0.030)	(0.006)	(0.053)	(0.005)	(0.008)	(0.028)
Seasonal factor low side (below 1)	-0.027	-0.005	-0.004	-0.000	0.001	0.004	-0.008
	(0.051)	(0.007)	(0.005)	(0.011)	(0.004)	(0.004)	(0.007)
N. Obs.	1,765,677	695,367	1,111,253	227,003	902,516	7,375,440	493,535
Adj. R^2	0.49	0.42	0.45	0.53	0.48	0.40	0.48
			Panel D: Sample Period 2021m2 to 2022m9				
Seasonal factor high side (above 1)	0.083	0.033**	0.013	0.021	-0.001	0.008	-0.052
	(0.086)	(0.014)	(0.013)	(0.040)	(0.007)	(0.012)	(0.065)
Seasonal factor low side (below 1)	-0.055*	0.000	0.010	0.001	0.006	-0.022**	-0.037**
	(0.028)	(0.010)	(0.008)	(0.015)	(0.005)	(0.010)	(0.016)
N. Obs.	1,055,066	320,108	486,437	170,994	464,440	4,779,398	288,580
Adj. R^2	0.56	0.46	0.49	0.53	0.50	0.43	0.57
Loan & credit characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Channel	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AUS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses. Large banks are defined as commercial banks or thrifts with assets over $100 billion, medium-sized banks have assets between $10 billion and $100 billion, small banks have assets under $10 billion. Large credit unions are credit unions with assets over $10 billion, small credit unions have assets below $10 billion. "Others" are mainly lending institutions that are affiliates of banks, credit unions, or independent mortgage companies.

In Table 8, we present the effects of lenders' response to mortgage seasonality by race and ethnicity. In doing so, we modify equation 16 by adding race and ethnicity dummy variable and interacting that with the seasonal factors. Specifically, we estimate:

$$Y = \alpha_{high} \cdot SF_{high} + \alpha_{low} \cdot SF_{low} + \beta_{race} \cdot Race\_Ethnicity + \gamma_{high} \cdot Race\_Ethnicity \cdot SF_{high} \\ + \gamma_{low} \cdot Race\_Ethnicity \cdot SF_{low} + \delta \cdot Controls + \epsilon \quad (16)$$

where SF_{high} and SF_{low} are the high side and low side seasonal factors, $Race\_Ethnicity$ is a dummy variable for applicant's race and ethnicity.

Using our main specification, we estimate the effects of home purchase demand seasonality on denial rate of refinance applications in Table 8 for the entire study period as well for the three sub-periods.

Not surprisingly, after adding race and ethnicity dummy and interacting them with seasonal factors, the coefficient estimate on the high side seasonal factor alone remains positive for the full sample period from January 2018 to September 2022. It is positive between January 2018 and December 2018. It was exacerbated during the refinance boom period between January 2019 and January 2022 and became statistically insignificant since February 2022.

There is considerable literature examining the disparities in denial rates of mortgage applications across different racial ethnic groups, starting with Munnell et al. (1996). More recent examples using the restricted HMDA data since 2018 include Bhutta et al. (2022), Conklin et al. (2023), and Liu and Zhang (2024). Consistent with these recent studies, we find that during the main study period, Black, Hispanic White and Asian applicants were all more likely to be denied than non-Hispanic white applicants, controlling for all observable information available in the HMDA data, including loan and applicant credit characteristics, lending channel, results of automated underwriting systems, lender fixed effect and state fixed effects. Such disparities were persistent throughout the sample period, both overall and within each sub-period. For example, during the full period between January 2018 and September 2022, excluding the effects of seasonal factors, denial rates were 2.1 percentage points higher for Black applicants, 1.1 percentage points higher for Hispanic applicants, and 1.9 percentage points higher for Asian applicants than non-Hispanic White applicants.[18]

The coefficient estimates of the interaction terms between the race dummies and the seasonal factors measure how much additional change to the probability of being denied (relative to white) for a member of minority group is as a result of the population-wide home purchase

[18]The magnitude of the estimated racial disparities are consistent with those from Bhutta et al. (2022).

demand shift. Such effects are in addition to the average racial disparities that were commonly explored in the literature and captured in the stand-alone racial coefficients in the table.

For the entire study sample, we detect positive effects of the seasonality on the denial probability of Black and Hispanic applicants, but only at 10% significance level. However, when zooming in to the period between January 2018 and December 2018, when the mortgage interest rate was stable and refinance application volume remained normal, the period that we believe provides the best testing ground under our identification strategy, we discover highly significant effects of mortgage seasonality interacting with Black and Hispanic applicant status. In particular, the coefficient estimate of $SF_{high} \cdot Black$ is 0.064 and the coefficient estimate of $SF_{high} \cdot Hispanic$ is 0.055, both were statistically significant at 1% level. These imply that during this period, if the seasonal demand of home purchase application increased by 10% from the annual average, the denial rate of refinance mortgage applications would decrease by additional 0.64 percentage point for Black applicants and 0.55 percentage points for Hispanic applicants, relative to Whites. We also discover a positive coefficient of $SF_{high} \cdot Asian$ at 10% significance level during this period. In Period 2 between January 2019 and January 2021 during the ref boom, the coefficient estimate of $SF_{high} \cdot Hispanic$ is 0.30 and statistically significant at 5% level and the coefficient estimate of $SF_{high} \cdot Black$ is 0.30 as well and statistically significant at 10% level. None of the coefficient estimates for the interaction terms of seasonal factors and race dummies are statistically significant after February 2021, following the sharp decline of refinance volume.

The estimates discussed above are all average treatment effects. The applicants of different racial ethnic groups may be treated with different intensity due to their varying exposure to the seasonal factors, therefore we also estimate the average treatment effects on the treated (ATT) for different groups. During the period between January 2018 and September 2022, the average treatment effect on the treated for Black refinance applicants due to the credit rationing caused by the higher seasonal demand is about 0.17 percentage points, while the average treatment effect on the treated for Hispanic refinance applicants is about 0.13 percentage points. As a baseline, the average denial rates of refinance applications were about 28.7% and 20.7% for Black and Hispanic applicants in the same period respectively. There were about 2.39 million black applicants and 2.31 million Hispanic applicants for refinance loans in our estimation sample between 2018 and 2022. Applying our ATT estimates, that translates to roughly 4,200 more Black applicants and 3,100 more Hispanic refinance applicants that were directly impacted by credit rationing due to seasonality-caused capacity constraint, relative to White applicants.

Our discovery of the heterogeneous effects of the lenders' response to seasonal demand shift on different racial and ethnic groups may have serious implications. On the one hand, it is well known that Black and Hispanic applicants tend to have lower credit scores, higher LTV and higher debt-to-income ratio than White applicants on average. For instance, Liu et al. (2019) documented the distribution of credit score, CLTV and DTI of mortgage applicants by race and ethnicity. To the extent that they are more likely to be among the marginal borrowers whose general credit profiles sit right above the minimum acceptable level of lenders' underwriting standards, when the seasonal demand increases and the lenders have to ration the credits by increasing the cutoff of the underwriting standards, it is possible that Black and Hispanic applicants may be disproportionately affected, accounting for larger shares of those marginal borrowers who fall below the increased score cutoff. This could contribute to the increased racial disparities during the home purchase high seasons that we observe above. On the other hand, if the changes in lending standards when the lenders ration the credit were through mechanism that is mostly opaque and less well understood and documented, then it would in theory increase the likelihood that some of the vulnerable applicants be discriminated, as the lenders apply soft information to screen out additional applicants or simply apply lender discretion rejecting marginal applicants which we discuss in the next section.

Table 8: Effects of lender response to mortgage seasonality by race and ethnicity types

	(1) 2018m1-2022m9	(2) 2018m1-2018m12	(3) 2019m1-2021m1	(4) 2021m2-2022m9
Seasonal factor high side (above 1)	0.036**	0.031**	0.051**	0.006
	(0.017)	(0.012)	(0.019)	(0.018)
Seasonal factor low side (below 1)	-0.008	-0.018	-0.003	-0.015*
	(0.007)	(0.011)	(0.009)	(0.009)
Asian	0.019***	0.026***	0.017***	0.020***
	(0.003)	(0.006)	(0.003)	(0.004)
Black	0.021***	0.023***	0.019***	0.023***
	(0.003)	(0.005)	(0.003)	(0.003)
Hispanic White	0.011***	0.014***	0.008***	0.013***
	(0.004)	(0.004)	(0.003)	(0.004)
Joint	-0.005***	-0.002	-0.004***	-0.005***
	(0.001)	(0.003)	(0.001)	(0.002)
Other	0.028***	0.040***	0.023***	0.029***
	(0.004)	(0.008)	(0.004)	(0.005)
Missing	0.017***	0.024***	0.016***	0.017***
	(0.004)	(0.007)	(0.004)	(0.004)
Asian × SF_{high}	0.020	0.042*	0.017	0.013
	(0.012)	(0.022)	(0.012)	(0.016)
Black × SF_{high}	0.025*	0.064***	0.030*	0.020
	(0.014)	(0.020)	(0.016)	(0.014)
Hispanic White × SF_{high}	0.020*	0.055***	0.030**	0.005
	(0.012)	(0.019)	(0.011)	(0.014)
Joint × SF_{high}	0.014	-0.008	0.018	0.013
	(0.009)	(0.024)	(0.011)	(0.011)
Other × SF_{high}	0.010	0.025	0.018	-0.011
	(0.019)	(0.033)	(0.025)	(0.024)
Missing × SF_{high}	0.004	-0.002	0.001	0.015
	(0.013)	(0.014)	(0.014)	(0.014)
Asian × SF_{low}	0.015**	-0.023	0.018***	0.010
	(0.006)	(0.020)	(0.006)	(0.014)
Black × SF_{low}	-0.020*	-0.028	-0.033***	-0.004
	(0.011)	(0.019)	(0.011)	(0.012)
Hispanic White × SF_{low}	-0.005	-0.054***	-0.003	-0.002
	(0.008)	(0.015)	(0.007)	(0.013)
Joint × SF_{low}	0.007	0.006	0.012*	-0.004
	(0.005)	(0.016)	(0.006)	(0.008)
Other × SF_{low}	-0.014	-0.040	-0.016	0.009
	(0.012)	(0.029)	(0.013)	(0.017)
Missing × SF_{low}	0.001	-0.020	0.005	-0.008
	(0.006)	(0.018)	(0.005)	(0.012)
Loan & credit characteristics	Yes	Yes	Yes	Yes
Channel	Yes	Yes	Yes	Yes
AUS	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N. Obs.	22,072,981	1,937,044	12,570,795	7,565,023
Adj. R^2	0.55	0.57	0.54	0.57

Notes: The sample consists of completed applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 1 (loan originated), 2 (application approved but not accepted), and 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The outcome variable is whether an application was denied. All columns report effects based on OLS estimates of equation (16). Standard errors which are clustered at the state and lender levels are in parentheses. Applications are placed in one category for race and ethnicity. The application is designated as "joint" if one applicant was reported as white and the other was reported as one or more minority races or if the application is designated as white with one Hispanic applicant and one non-Hispanic applicant. If there are two applicants and each reports a different minority race, the application is designated as two or more minority races. If an applicant reports two races and one is white, that applicant is categorized under the minority race. Otherwise, the applicant is categorized under the first race reported. "Missing" refers to applications in which the race of the applicant(s) has not been reported or is not applicable or the application is categorized as white, but ethnicity has not been reported. "Other" consists of applications by American Indians or Alaska Natives, Native Hawaiians or other Pacific Islanders, and borrowers reporting two or more minority races. Note that the omitted racial group is White.

8 The mechanism of lender response and soft information

In the previous sections, we establish that the increase in home purchase application volume during high seasons could increase the likelihood that the lenders reach their capacity constraints. We observe that after controlling for all credit characteristics that we can control using the HMDA data, the lenders' denial rate increases during the high seasons. In this section, we explore how the mechanism could work that leads to the higher denial rate.

Previously we presented a stylized model that lenders increase the underwriting standard to screen out additional applicants during the high seasons due to capacity constraints. However, in practice, the lending standards could be multi-dimensional, with some coded as hard information and some depending upon soft information, and lender discretion could play certain roles in lender decisions as well.

Hard information is quantifiable, not context dependent, and allows lenders to automate a part of credit assessment process by including it in an econometric model (Stein, 2002; Liberti and Petersen, 2019). Some examples of hard information are credit scores, LTVs, and DTIs, all of which are controlled in our regressions. We also control for the results of automated underwriting systems, which provide recommendations to the lenders based on the hard information that the loan officers input. On the other hand, soft information is difficult to measure or quantify and thus context dependent. Because the soft information is collected through personal interactions or based on an experience, it is difficult for others to verify or replicate. An example of soft information would be a loan officer's belief that the documents provided by an applicant are accurate and trustworthy.

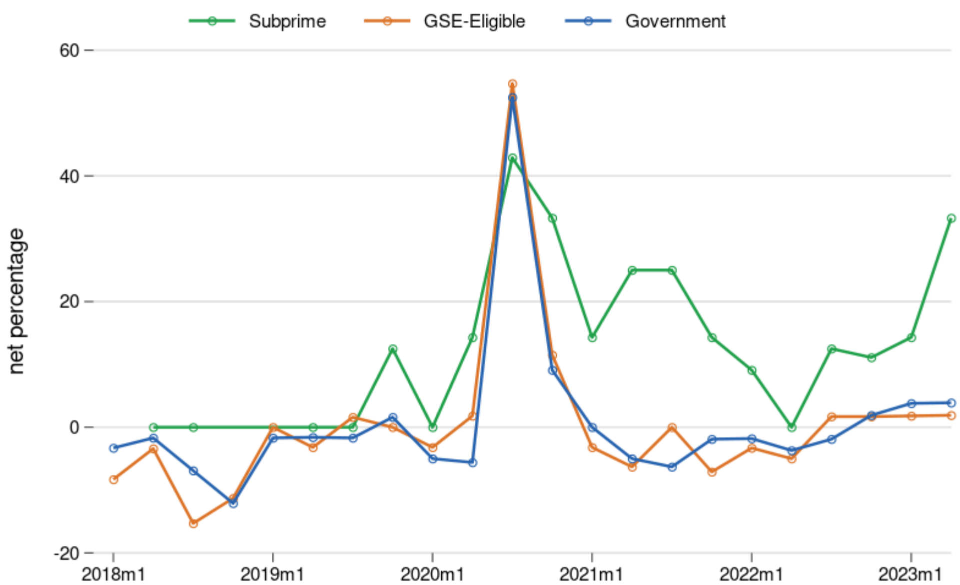
Existing studies highlight the importance of soft information in a credit assessment process and the flexibility of the way it is used by loan officers. Agarwal et al. (2011) find that financial institutions can reduce credit losses by using soft information. Ambrose et al. (2021) and Jiang et al. (2022) showed how loan officers use soft information better in certain situations resulting in differential credit outcomes. More specifically, they found that when the race of borrowers and loan officers match, the racial disparities in mortgage pricing declines because of a better use of soft information. Agarwal and Ben-David (2018) also found that when loan officers were incentivized based on originated loan volume, they overlooked unfavorable soft information during origination process.

Related to soft information, it is also possible that some loan officers may exercise certain discretion when dealing with applicants, especially marginal applicants. Because both soft information and lender discretion are not documented, it is difficult to distinguish them in observed data. Here we posit that soft information still is useful information tied to credit risks that the lenders try to discern outside of the hard information, while lender discretion is based on either random choice (within allowable range of set parameters) or factors not providing informational values to the true underlying risks. One potential policy concern is that some of those factors not only are non-informative, but could be harmful and discriminatory if they are based on prejudice.

Partially consistent with these existing studies of soft information, but with the direction of the impacts reversed, some suggestive evidence exists that loan officers potentially change the way they work with marginal borrowers across seasons. Figure 12 plots the net percentage of domestic banks tightening the residential real estate lending standards from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS).[19] The data from SLOOS - which is typically conducted quarterly to provides information on bank credit availability, loan demand, and lending practices - does not display any seasonal patterns. Therefore, it must be the way in which loan officers either use soft information or apply lender discretion that results in differential denial rates across seasons if the lending standards using hard information do not change. For example, loan officers may potentially spend more time helping out marginal applicants collecting necessary information to get loans approved during low seasons than during high seasons when a large number of applications are waiting in their queues.

[19]We acknowledge some limitations of the fed's SLOOS data for our analysis. The survey is only conducted on a limited sample of 80 large domestically chartered commercial banks that meet the three selection criteria in terms of size, geographic diversity, and mutual independence. In addition, the questions related to residential real estate lending only involves home purchase and not refinance loans. For more information, see https://www.federalreserve.gov/data/sloos/about.htm.

Figure 12: Net percentage of domestic banks tightening standards for mortgage loans



Notes: The figure is created using the data from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). More specifically, the data is derived from the question on the residential real estate lending standards that states "question 13 deals with changes in your bank's credit standards for loans in each of the seven loan categories over the past three months. If your bank's credit standards have not changed over the relevant period, please report them as unchanged even if the standards are either restrictive or accommodative relative to longer-term norms. If your bank's credit standards have tightened or eased over the relevant period, please so report them regardless of how they stand relative to longer-term norms. Also, please report changes in enforcement of existing standards as changes in standards". The "net fraction" (or "net percentage") refers to the fraction of banks that reported having tightened ("tightened considerably" or "tightened somewhat") minus the fraction of banks that reported having eased ("eased considerably" or "eased somewhat"). The seven categories of residential home-purchase loans that banks are asked to consider are government-sponsored enterprise (GSE)-eligible, government, qualified mortgage (QM) non-jumbo non-GSE-eligible, QM jumbo, non-QM jumbo, non-QM non-jumbo, and subprime. However, we only plot three types of loans that make up most of a mortgage market for the ease of readability.

One piece of evidence from our empirical results that supports this soft information / lender discretion theory lies in the asymmetric response of the lenders to the high-side and low-side seasonal factors. We show that when the seasonal factor is above 1, (i.e., when the monthly demand is above the annual average), the higher the seasonal factor, the higher the denial rate is, controlling for all observables. On the other hand, when the seasonal factor is below 1, (i.e., when the monthly demand is below the annual average), the change of the seasonal factor does not affect the probability that a mortgage application is denied. In other words, when the market demand is weak in low season, the lenders do not or cannot loosen the lending standards just to fill in more business. This is consistent with the soft information / lender discretion theory in the sense that lenders do have a minimum requirement of lending standards composed of hard information that they could not relax. In practice, this is typically coded in the underwriting policies and guidelines and in the AUS, with clear cutoffs of credit scores, LTV, DTI and so on and is embedded in the AUS score cutoffs and AUS recommendations that lenders use. Most of such hard cutoffs are either demanded by the investors or the GSEs for the loans that the lenders intend to sell or by the government agencies such as FHA or VA that will insure or guarantee the loans. Lenders themselves could also set cutoffs for portfolio loans or lender overlays beyond what the investors or government loan programs require.

In the main study period we use since 2018, no-doc or low-documentation loans are nearly non-existent in the market, so we expect lenders do hold these minimum requirements tightly. Even if the demand is weak, it is impossible for lenders to relax their minimum requirements. On the other hand, with soft information embedded in the underwriting process, it is always possible for lenders to raise the implicit underwriting standards beyond the hard coded minimum requirements when the situation demands. That fits what we observe in the data, when the demand increases during the high season, lenders on average deny more applications, even though we control for most of the underwriting factors. Alternatively, if lender discretion is allowed, with higher demand, lenders could also randomly toss out marginal applicants, or worse, apply certain prejudice to applicants of certain types.

Another piece of evidence supporting the soft information / lender discretion hypothesis is related to the denial reason code that was reported to the HMDA. Lenders were required to report denial reasons for applications that they denied, starting with the 2018 HMDA data. Prior to that, reporting of denial reasons was optional. Lenders are allowed to report up to four denial reasons according to following list: Code 1: Debt-to-income ratio; Code 2: Employment history; Code 3: Credit history; Code 4: Collateral; Code 5: Insufficient cash (downpayment, closing costs); Code 6: Unverifiable information; Code 7: Credit application incomplete; Code 8: Mortgage insurance denied; Code 9: Other.

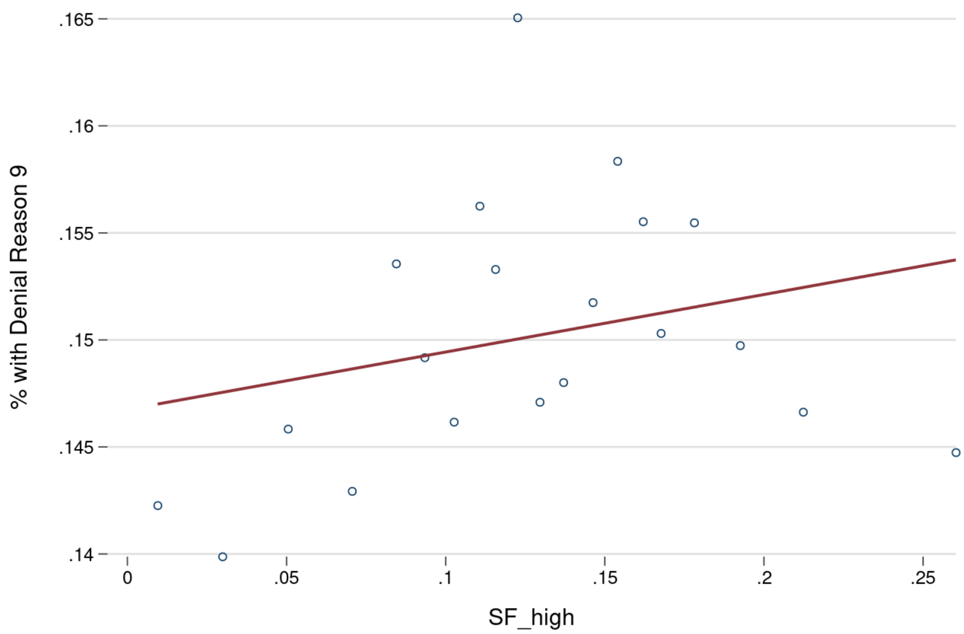
The Code 1 through 8 of the denial reasons are all of standard enumerations that can be interpreted as denials based on hard information and standards. The code 9 "Other" is a catch-all term that lumps all denials that cannot be attributed to the standard reason codes, and hence is rather open to interpretation. It is very possible, though not always true, that some of the denials with denial reason code 9 could be denied based on, or partially based on soft information or lender discretion.

Figure 13 presents two binned scatter plots of the percentage of denials that reported code 9 as a denial reason against the high side seasonal factors, limited to denied refinance applications between January 2018 and September 2022. Panel (a) is the raw plot with no controls. Panel (b) includes all of the control variables in the full specification of our main regression. The differences between the specification of Panel (b) and our full denial regression specification are that in Figure 13 we limit the sample to denied applications instead of all completed applications; we only include applications taken in the month and state for which the seasonal factor of home purchase application volume was above 1; and the dependent variable is the indicator of whether the application received a denial reason code 9.

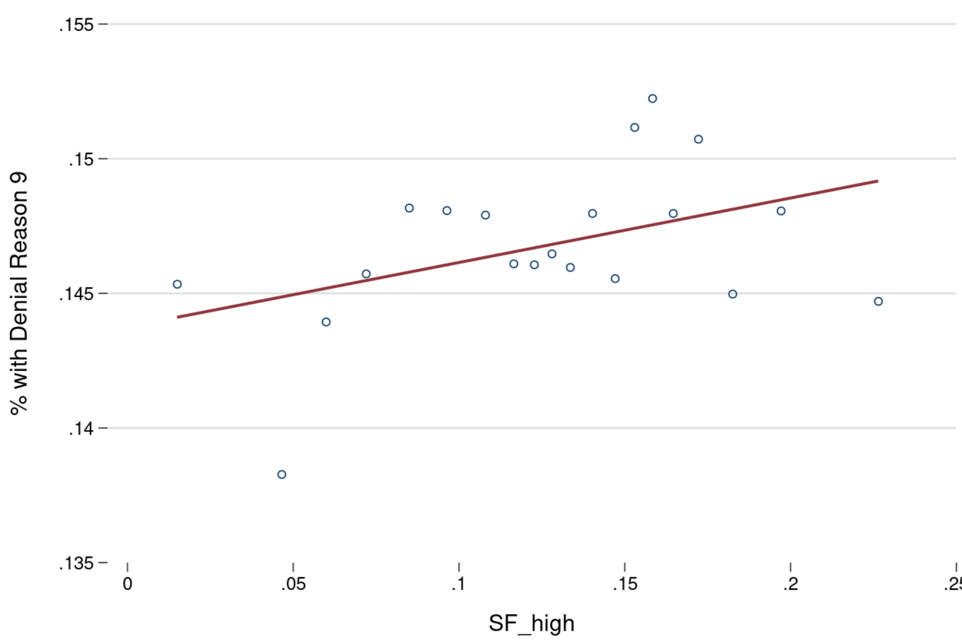
The percentage of denied refinance applications with denial reason code "other" is positively correlated with the seasonal factor, as demonstrated by the upward sloping linear trend curve fitted in Figure 13. The upward trend is consistent regardless of whether no controls are included or a full set of controls from our preferred specification is included. This provides suggestive evidence that lenders may be more likely to deny applications based on soft information or undocumented lender discretion when their capacity is constrained and need to ration credits.

Figure 13: Relationship between denial reason code "other" and high side seasonal factors

(a) No control



(b) Full controls



Notes: The sample consists of denied refinance applications from the HMDA data between 2018 and 2022 with the HMDA action type codes 3 (application denied) for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The sample is limited to denied applications in states and months with home purchase seasonal factor above 1. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Finally, the heterogeneous analysis we conducted in Section 7 by lender type may also be in line with the soft information / lender discretion mechanism. In Section 7, we show that independent mortgage companies respond to increase in seasonal demand by denying more applications, ceteris paribus. But we do not find evidence of credit rationing during the home purchase high seasons for large banks. Compared to independent mortgage companies, large banks generally are more subject to regulators' scrutiny and have stronger compliance system in place that limit the discretion of loan officers making individual decisions. Therefore, it is possible that loan officers in these largest banks are less likely to use soft information to screen out additional applications or apply lender discretion even during the high season when their capacity is constrained. On the contrary, facing less regulatory pressure and less rigorous internal controls, independent mortgage companies may be more likely to adopt soft information in underwriting. [20]

As discussed in Section 7, the denial rate disparities between the Black and White applicants and between the Hispanic and White applicants are even more exacerbated during the home purchase high seasons. One possible explanation is due to the fact that Black and Hispanic applicants account for disproportionately larger share of marginal applicants and hence are more likely to be affected by the tightening of credits. However, even expanded use of soft information as a potential mechanism to screen out additional applicants also means granting more discretion to the loan officers, which in turn could increase the possibility that implicit biases seeped into the underwriting process. One type of implicit biases is the racially based distaste as described by Becker (1957). Because of its vague nature, it could be difficult for lenders and regulators to monitor the use of the lender discretion and reduce the risk of Becker type discrimination. How much the role of soft information and lender discretion play in explaining the exacerbated racial disparities during the high season is one critical area for future research.

9 Mortgage Performance and Seasonality at Origination

In this section we conduct an ultimate outcome test to investigate whether loans originated during high seasons perform differently from those originated during low seasons, inspired by the famous "Becker's test" proposed by Becker (1957) and Becker (1993).

Even though we could not directly observe the changes in decision standards of lenders

[20] We acknowledge that we have not explored the role of Fintech firms related to the mortgage seasonality and many Fintech firms are independent mortgage companies. Nevertheless, we believe most independent mortgage companies are not Fintech firms and our reasoning holds.

towards the marginal applicants during the underwriting stage when their capacity is constrained, observing the downstream outcomes that result from the decisions, on the other hand, could be informative about whether different standards are applied. Becker offers an intuitive example in the context of mortgage lending: if a bank's loans to approved black applicants tend to generate higher profits than its loans to approved white applicants, this may indicate racially biased lending decisions that hold black applicants to a stricter standard beyond what unbiased profit maximization would imply.

Here we adopt a similar strategy, except that our first interest is whether lending standards differ across seasons, instead of races. We examine the default risk of loans originated during different seasons. If we find that loans originated during high seasons are less likely to be delinquent than those originated in low seasons, controlling for all observables, it would bolster the soft information hypothesis that loans originated during high seasons are held to higher standards during underwriting by the lenders in order to ration credits. Vice versa, if we find the loans originated during high seasons are more likely to default post origination, then we could conclude that lenders resort to something else rationing credits, but this something else is not informative of the real credit risk. Instead, it lowers the quality of the lenders' underwriting decisions from a credit risk management perspective.

Our main evidence lies in the post origination default risk of loans that were approved, The main goal of credit underwriting is to screen out potentially high default risk applications. However, prepayment is common occurrence for mortgages. In order to account for prepayment risk simultaneously, we estimate a three-year default-prepayment competing risk model using the NMDB. NMDB contains loan level information at the origination and performance information through the lifetime of the loans. We limit our performance window to within three years of the originations. We choose a 3-year performance window because mortgage default within the first three years more accurately reflects the inherent risks assessed at the time of underwriting than realized default in a longer time window.

We adopt a standard multinomial logit model. The dependent variable has three outcome categories in a given month post origination: (1) current, (2) delinquent, and (3) prepaid. We define delinquent if a loan is in any of the following status in a month: 60 days or more past due, bankrupt, foreclosure proceeding started, deed in lieu, foreclosure, voluntary surrender, repossession, settled, insurance claim, term benefit, government claim, paid by dealer, collection, charge off.

We control for loan and credit characteristics at origination, including log of loan amount, credit scores, LTV, CLTV, DTI, loan terms, loan types, occupancy status, balloon loan status, prepayment flag, full document flag, negative amortization flag and whether the loan is for cashout refinance. We also include county level unemployment rates at originations. These static variables are invariant over performance months.

For each month since origination, we also control for percentage growth of house price index and change of unemployment rate as well as inflation rate. Specifically, NMDB contains the quarterly house price index at the county level, created by combining FHFA's county level annual house price index series with FHFA's state level quarterly house price index and adjusted using smoothing techniques. We transform the quarterly house price index to monthly level by linear interpolation and impute the house price change of each month compared to the house price level at origination. Combining this monthly house price index with the property value at origination for each loan, we update the current property value and include a flag indicating whether a loan is underwater for a given month, i.e. unpaid principal balance (UPB) exceeded the current property value. We control for general inflation by using monthly Consumer Price Index for All Urban Consumers from BLS. To control for labor market conditions, we rely on county level unemployment rate from the BLS's Local Area Unemployment Statistics Program at monthly frequency. We include not only the baseline unemployment rate at the time of origination in a county, but also control for the change of unemployment rate in each month in that county since. Finally, we include the spread between the interest rate of the loan and ongoing market interest rate, using the average 30-year fixed-rate mortgage rate for prime loans from Freddie Mac's Primary Mortgage Market Survey. This affects the incentives of borrower to refinace.

Our main variable of interest is the seasonal factors. We merge the mortgage seasonal factors of home purchase loans based on HMDA data with the NMDB by state and the year and month of the origination. Just as in the sections before, we spline the seasonal factors at 1, allowing possibility of differential effects between mortgage demand high seasons and low seasons. Consistent with our main identification strategy, we limit our NMDB sample to refinance loans while the seasonal factors are all based on home purchase loan applications. We note that the seasonal factors we consider are seasonal factors at the time of originations and are the seasons of the loan performance months. We also control for state and origination year fixed effects.

We present estimates from the competing risk model in Table 9. The main variable of interest is the seasonal factors. Our main estimation sample includes loans originated from

2018 to 2020, reported in Column 1. This sample period is chosen to match with the sample period in the HMDA denial regressions between 2018 and 2022. We have to end the last vintage of our main NMDB sample by Year 2020, since we can not observe the full 3-year performance window for loans originated after 2020 yet due to NMDB reporting lag. Column 2 presents the estimation results for an alternative sample period, with origination vintages between 2011 and 2016. Columns 3 to 5 report separate estimates for each vintage year in 2017, 2018, 2019, and 2020 respectively.

Table 9: Mortgage performance and seasonal factor at origination

	(1) 2018-2020	(2) 2011-2016	(3) 2017	(4) 2018	(5) 2019	(6) 2020
			Panel A: Delinquent			
Seasonal factor high side (above 1)	0.880***	0.371***	0.362***	0.459***	2.296***	-0.790***
	(9.97)	(9.75)	(3.37)	(3.38)	(14.47)	(-4.16)
Seasonal factor low side (below 1)	0.208**	-0.0304	-1.055***	0.184	0.111	0.210
	(3.23)	(-0.96)	(-12.27)	(1.70)	(0.95)	(1.80)
			Panel B: Prepaid			
Seasonal factor high side (above 1)	0.549***	-0.265***	-0.514***	-0.240***	0.414***	1.218***
	(18.11)	(-9.74)	(-7.05)	(-3.60)	(8.41)	(23.94)
Seasonal factor low side (below 1)	0.206***	0.262***	-0.601***	0.191***	0.127***	0.199***
	(9.28)	(11.99)	(-11.22)	(3.35)	(3.75)	(5.77)
N. Obs.	18,691,277	39,211,336	3,976,070	2,504,395	4,006,102	12,180,780

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The sample consists of originated refinance loans from NMDB. The reported parameters are log odds of mortgage becoming delinquent relative to account being current in Panel A and log odds of loan being prepaid relative to current in Panel B, within the first three years of origination.

Table 9 shows that loans originated during high seasons are more likely to be delinquent than loans originated during low seasons, after controlling for all observables at the time of origination and removing the effects of macroeconomic conditions such as house price dynamics, inflation, labor market conditions and interest rate environments after origination. The coefficient estimates of high side seasonal factors of mortgage becoming delinquent in the first three years of originations are positive and statistically significant for all sample periods except for 2020 vintage. Because the 2020 refinance vintage coincided with the beginning of COVID pandemic that substantially impacted the economic conditions and borrower behaviors at the time, it is difficult to interpret the 2020 vintage results. For instance, the pandemic relief and mortgage forbearance program at the time may contaminate the results. Loans originated between 2017 and 2019 may still partially be affected by how COVID period forbearance is treated in the analysis in a portion of their 3-year performance window, even though the issue becomes progressively less severe as we move the vintage year from 2019 to 2017 backward. That is also one reason why in Column 2 we reported alternative sample period with vintage ending in 2016. The 3-year performance windows for all vintage years in this alternative sample period all ended before the onset of the Pandemic.

Regardless, the direction of the default risk parameter estimates are all consistently positive for high side seasonal factors other than the 2020 vintage. The parameter estimates of low side seasonal factors for default risk are either insignificant or acting in different directions, basically implying there is no definite correlation of higher or lower default risk during the mortgage demand low seasons. We include the parameter estimates of prepayment risks in Table 9 as well. We note that the prepayment risks do not reflect the credit risks that lenders assess at the time of underwriting and the prepayment risk estimates are inconsistent across periods. We include them only for completeness purpose.

The finding that loans originated during high seasons actually ended up with high default probability has strongly implications on how lenders respond to capacity constraint during the high season. It means that not only lenders are forced to ration credits due to capacity constrain, they are either less careful in performing their tasks screening out high risk applicants because they are overworked, or resorting to criteria rejecting additional marginal applicants that are both opaque and uninformative to the real underlying credit risk. In other words, we observe that lenders' quality of underwriting during the high seasons worsens as their workload increases.

Such finding fits into a broader literature on job performance and decision making under time constraints. For instance Huang (2011) shows that busy appellate court judges exhibit lightened scrutiny over district court decisions. Fitch and Shivdasani (2006) shows that busy boards are associated with weak corporate governance. Coviello et al. (2014) show that judges who juggle too many cases at once have decreased productivity. This is however the first time that it is extended to the case of mortgage lenders and underwriters.

10 Conclusion

Home ownership plays an important role in household wealth accumulation and their ability to improve socioeconomic status. As a mortgage makes up a significant portion of household debts, it is important to understand lender behavior and its potential implications on household financial well being. Our paper examines how operating capacity constraints driven by seasonal increase in mortgage demand affects lender behaviors and consequently borrowers' access to credits.

Using a novel identification strategy and the confidential mortgage application data, we find that when a lender's capacity is constrained because of an increased demand for home purchase loans during a high season, lenders ration credits by denying applications that could have otherwise been approved during a low season. The effect is robust in the stable period of interest rate environment and is particularly strong during refinance boom period. We also find that independent mortgage companies are more likely to ration credits during high seasons and credit rationing tends to disproportionately affect racial minorities. Lastly, we provide suggestive evidence that lenders' use of soft information likely changes by seasons which leads to credit rationing.

Our main finding is consistent with Sharpe and Sherlund (2016) and Ma (2023). However, one of the main distinction is the source of capacity constraints. Sharpe and Sherlund (2016) examines lenders' capacity constraint driven by an increases in demand for refinance loans due to low interest rates, whereas Ma (2023) investigates individual loan officers' capacity constraints when they experience a demand surge in other markets where they originate loans. In contrast, we examine capacity constraints driven by home purchase seasonality. Since seasonality is periodic and persistent rather than idiosyncratic and temporary, our finding has broader implications for policy makers and borrowers.

The finding also has important implications for equal access to credits especially across different racial groups. Our back of the envelope calculation indicates that about 4,200 additional Black and 3,100 additional Hispanic refinance applicants may have been denied due to lenders' credit rationing during high seasons between 2018 and 2022. Given that soft information plays an important role in Black and Hispanic applicants being approved (Ambrose et al., 2021; Jiang et al., 2022), lenders may unintentionally deny more Black and Hispanic applicants when their loan processing capacity is constrained and they simply do not have a lot of time and resources to spend on each application. Balancing lenders' credit risk assessment and borrowers' equal access to credits is an important policy question that future research can further investigate.

Moreover, by tracking the loan performance, we find that mortgage loans originated during the high seasons are more likely to default, ceteris paribus. The result of such Becker test strongly implies that the quality of underwriting deteriorates during the mortgage demand high seasons, as lenders are overtaxed.

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Appendix

A Days to Denial

In this Appendix section, we discuss the time interval between the date when an application was taken and the date when an underwriting decision was made, and how this relates to the seasonal factors.

The confidential version of HMDA data includes the date when the application was received (“Application Date") and the date when the action was taken (“Action Taken Date") on the application. There are three different action types for complete applications: loan originated, application approved but not accepted, and application denied. For a loan that was originated, the action date is equal to the closing date of the mortgage. Because the loan origination process involves more than underwriting and is affected by many other factors such as a rate lock period, an availability of settlement agents, title insurance, a home inspection in the case of home purchase loans, and ultimately by the home sale transaction date or refinance settlement date, it is difficult to interpret the length of time between the application date and the closing date for originated loans. For loans that were approved but not accepted, the action date depends on when an applicant declined the offer which is arbitrary. Therefore, we focus on the number of days between application date and the date on which a denial decision was rendered, which is solely controlled by the lender.

Figure C2 provides binned scatter plots of the number of days between the application date and the date when a denial decision was made against seasonal factors for denied refinance applications, controlling for all underwriting factors available in HMDA. We adopt the full model that was used in our main specification in Table 3. The figure shows that the number of days between application and being denied are positively correlated with the seasonal factors for the entire sample period as well as for each sub-period we analyze. This provides additional evidence that lenders are more likely to reach their capacity constraints during high seasons which results in a delay in reaching final decisions.

Figure C3 is a replicate of Figure C2 but using denied home purchase applications instead of refinance applications. The figure for Period I when the refinance application volume was largely stable (Figure C3 (b)) is consistent with the overall pattern observed for refinance applications where the number of days until denial decision increases with seasonal factors. For Period

III, which is the refinance bust period (Figure C3 (d)), if we were to focus on the bins when the seasonal factors are above 1 (i.e. during the high season), then the same pattern holds. However, the figure for Period II (Figure C3 (c)) shows an opposite pattern. This time period was unique in a sense that a historically low interest rate environment generated a refinance boom. Existing studies show that loan officers choose to act on loans that are easier to process– such as refinance or low LTV loans– when faced with time and resource constraints (Ma, 2023; Sharpe and Sherlund, 2016). Consistent with this literature, we hypothesize that loan officers quickly denied home purchase loans in order to focus their limited time and resources on processing refinance loans which are easier to process. We leave testing of such a hypothesis to future research. Overall, with all three time periods combined, between January 2018 and September 2022 (Figure C3 (a)), the days between application and denial for home purchase loans increase with seasonal factors when the seasonal factor exceeds 1.05, indicating that home purchase applicants experience a delay in a denial decision during the high season.

B Potential Lender Response through Pricing

Besides denying additional applications, lenders could potentially respond to home purchase high seasons by increasing the price of loans and thus indirectly discouraging applicants from applying or qualifying. In other words, lenders could respond to an increase in application volume by directly increasing the number of loans they deny (extensive margin) or by increasing the price of loans (intensive margin) which could indirectly lead to a reduction in number of approved applications.

Mortgage pricing is highly complex, consisting of the interest rate a borrower pay through the lifetime of the loan, and upfront costs that the borrow must incur in order to obtain the loan. In addition, there are complex tradeoffs between the discount points that the borrower may elect to pay and the interest rate received, while many borrowers are subject to upfront budget constraints. We do not attempt to fully quantify the mortgage pricing in this paper. Nevertheless, the Appendix Table D1 presents estimates from using several measures of loan prices as dependent variables in our preferred specification. The "price margin" is calculated by taking a difference between the interest rate a borrower paid and 10 year treasury yield. The measure provides an approximation of ongoing profit that lenders expect to make during the life of each loan, from the interest revenue minus its funding costs. The "net lender charge" is computed by taking a difference between origination charges and lender credits and measures the one-time dollar amount that lenders expect to make on each loan up front. On the other hand, the “net lender charge share" is calculated by dividing the “net lender charge" by the loan amount and thus estimates how much lenders make on each loan ufront as a share of the loan amount.

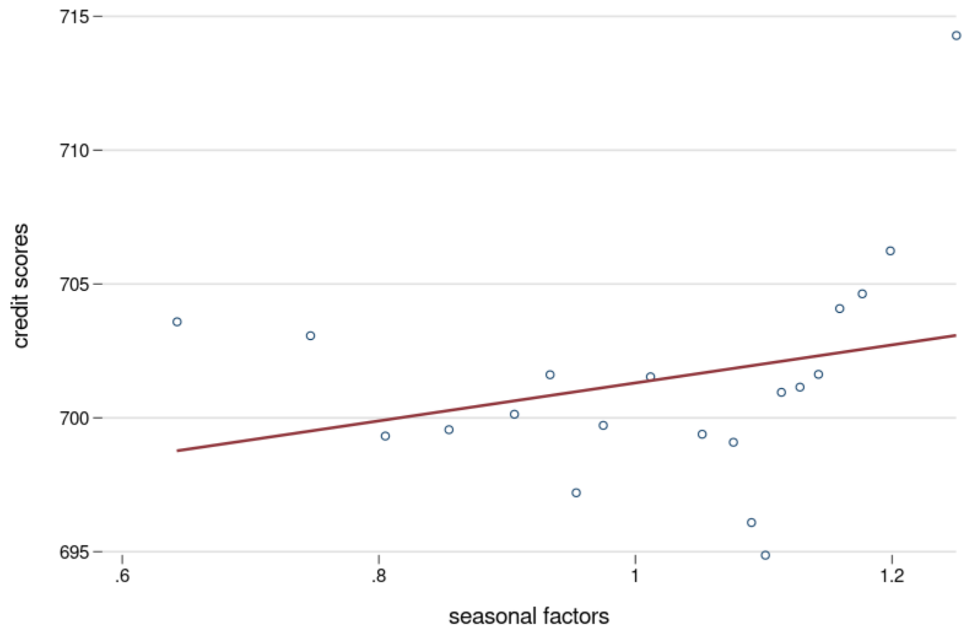
For each of the dependent varaible in Columns 1 to 3, we run an OLS regression controlling, with specification similar to our main denial regressions.

We do not find any evidence that lenders adjust their prices during high seasons to ration credits. None of the estimates for the high seasonal factor are statistically significant. In fact, the direction of the estimates are opposite of what is expected a priori. If lenders charge higher prices during high seasons, the estimates for high seasonal factor should be positive but all of the estimates are negative.

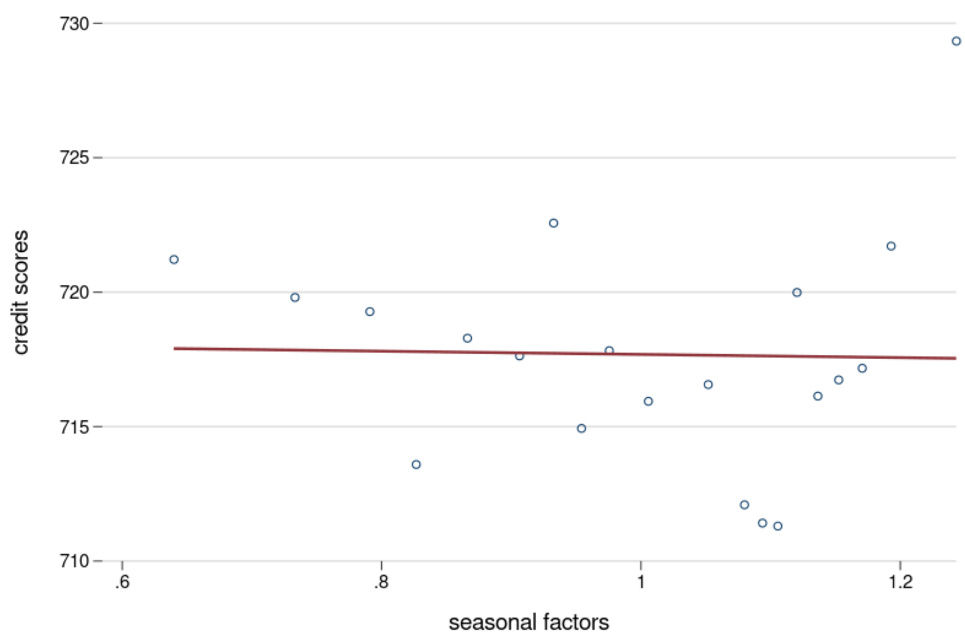
C Appendix Figures

Figure C1: Credit score and seasonal factors

(a) Home purchase

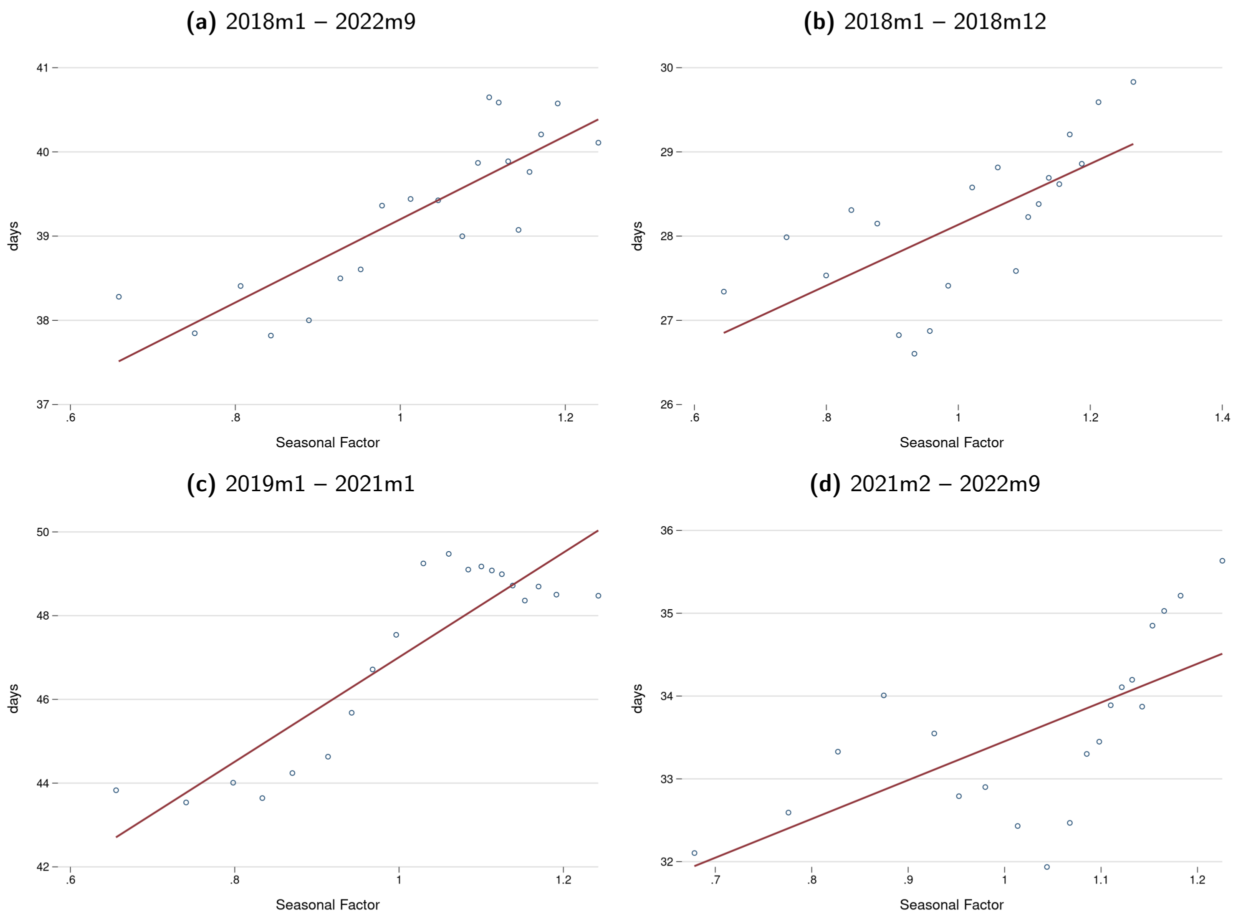


(b) Refinance



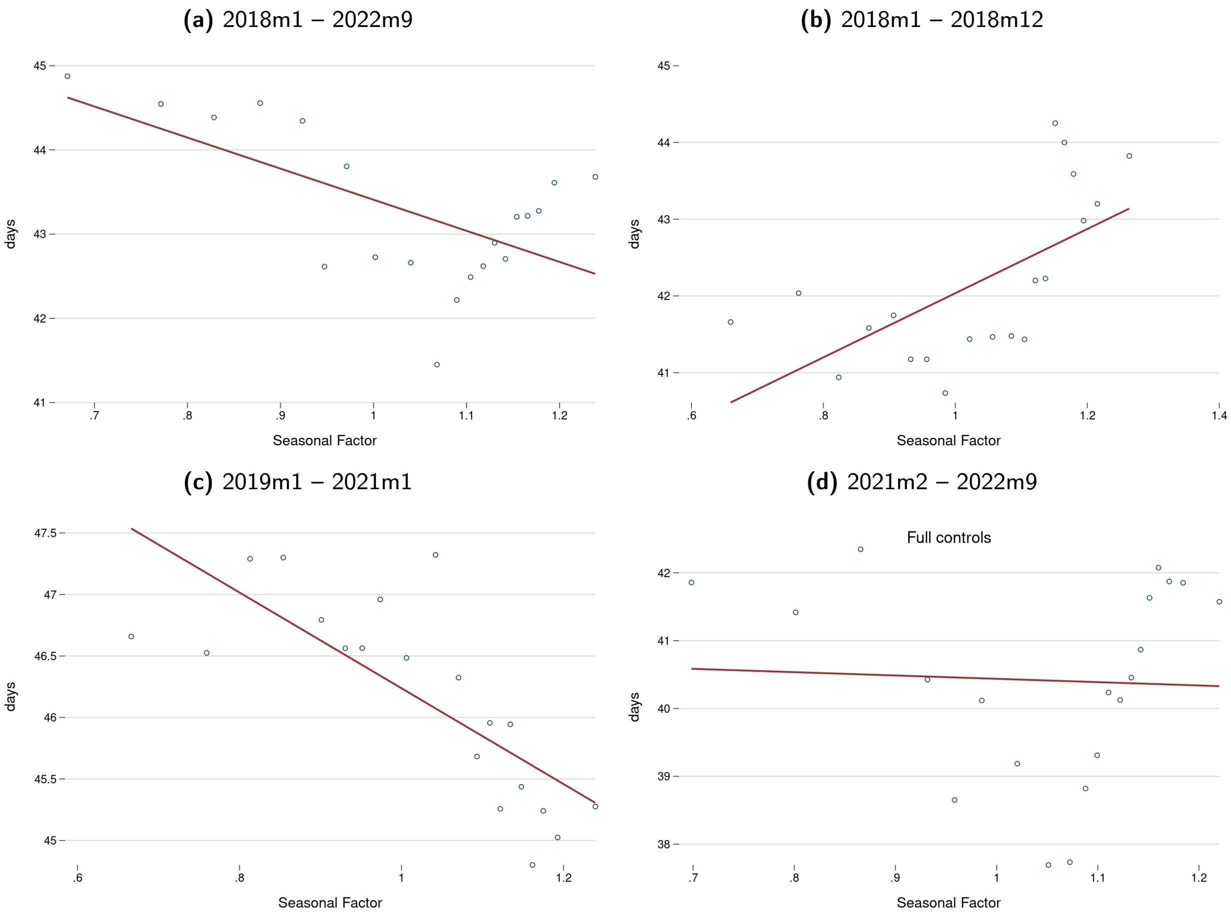
Notes: The sample consists of originated loans from NMDB between January of 1990 and September of 2022 for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Figure C2: Days to denial by time periods, refinance only



Notes: The sample consists of denied refinance loan applications from the HMDA data between 2018 and 2022 for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

Figure C3: Days to denial by time periods, home purchase only



Notes: The sample consists of denied home purchase loan applications from the HMDA data between 2018 and 2022 for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence. The red solid line is a linear trend line fitted over the entire range of the scattered bins.

D Appendix Tables

Table D1: Lender's pricing response to mortgage seasonality

	(1) Price Margin	(2) Net Lender Charge	(3) Share of Net Lender Charge
Seasonal factor high side (above 1)	-0.231	-165.043	-0.000
	(1.504)	(141.894)	(0.001)
Seasonal factor low side (below 1)	1.356	359.952***	0.002***
	(1.009)	(110.408)	(0.000)
Loan & credit characteristics	Yes	Yes	Yes
Channel	Yes	Yes	Yes
AUS	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N. Obs.	16,963,521	16,307,810	16,307,810
Adj. R^2	0.00	0.21	0.03

Notes: The sample consists of refinance orignations from the HMDA data between 2018 and 2022 for closed-end, not reverse mortgages, secured by site-built, single-family, first-lien, principal residence.