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By

Leonel Diego Drukker

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy
in
Business Administration
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Graduate Division
of the
University of California, Berkeley

Committee in charge:

Professor Amir Kermani, Chair
Professor Timothy McQuade
Professor Nancy Wallace
Professor Yuriy Gorodnichenko

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Abstract

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This dissertation studies accessibility to housing along the housing cycle, understanding the inequitable returns to housing by race, and household expectations of the housing market.

The first chapter investigates the mortgage channel of monetary policy transmission to home purchasing behaviors of first-time home buyers and incumbent homeowners. Between 2009 and 2019, the first-time home buyer share of home purchases fell from 35% to 22%, a period in which mortgage rates fell from nearly 7% to 3.5%. First, I construct a new mortgage rate-specific monetary policy shock to use as an IV for mortgage rate changes which predicts future mortgage rates better than existing monetary policy shocks. Next, I provide empirical evidence for three new findings: 1) transacted house prices respond to monetary policy-induced mortgage rate changes within a matter of weeks, indicating a rapid housing demand response to mortgage rates; 2) a negative 25 basis point mortgage rate shock lowers the first-time buyer share of home purchases by 77 b.p. in the first three months after the shock; 3) these results are more pronounced among lower-income households and in areas with higher shares of high LTV-constrained borrowers which tend to be areas with more severe housing crises. Finally, I construct a lifecycle model with a housing ladder, heterogeneous agents, and a system of housing-related taxes calibrated to my empirical findings. I find that a one-time unanticipated negative one p.p. transitory shock to mortgage rates causes potential first-time home buyers to face 0.1% consumption-equivalent welfare losses while incumbent homeowners receive welfare-gains of 0.19%.

The second chapter investigates the financial disparities Black sellers face in the US housing market. Using repeat-sale transactions from 2003 to 2020, we document that Black sellers earn, on average, 0.36% lower annualized unlevered returns on their property sales compared to non-Black sellers. These racial disparities in housing returns are not explained by seller characteristics, property renovations, the buyer's race, seller agent fixed effects, and appraisal measures. However, we find significant racial gaps in listing prices and time on market, which we attribute to intermediaries involved in housing transactions. Controlling for these factors reduces the racial gap in returns to effectively zero. Additionally, we construct a measure of a neighborhood's exposure to buyer agent discriminatory practices using the HUD

Discrimination Survey, and find that the racial gap dissipates for homes less exposed to discriminatory practices. Finally, we find that when homes are sold to iBuyers, where human intermediary bias is removed, the racial gap in housing returns disappears. Our findings suggest that Black sellers experience worse selling outcomes due to higher search frictions caused by human intermediary practices.

The third chapter studies how household expectations shape housing supply and prices. Using survey data on mortgage rate and house price expectations, I document new facts about expectation formation and relate these beliefs to realized housing outcomes. First, I find that homeowners' one-year mortgage rate expectations are state and path-dependent. Second, while house price expectations are typically negatively related to mortgage rates, this relationship reverses in high-rate environments: in low-supply-elasticity states, homeowners who expect rates to fall also expect house prices to rise. Third, I show that homeowners update their house price expectations in response to a mortgage rate shock, demonstrating that homeowners internalize existing information and quickly update their own expectations. I find that annualized metropolitan delistings growth is related to high mortgage rate levels, high shares of homeowners expecting mortgage rate increases, and high shares of households expecting house price decreases. Although delistings are associated with falling house prices, during high periods of mortgage rates, I find that delistings cause prices to rise. The mechanism is simple: rising delistings reduce the effective housing supply which pushes up prices. These results provide new, direct empirical evidence on the positive co-movement of house prices and mortgage rates in 2022–2025.

*To my wife, Amy, to my parents, David and Lily, and to my sister, Isabelita.*

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# Chapter 1

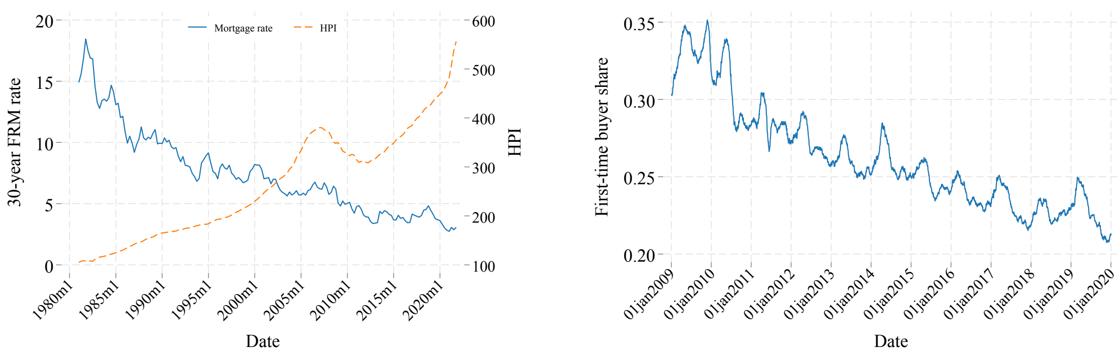
# Do Lower Mortgage Rates Benefit First-Time Homebuyers?

## 1.1 Introduction

US house prices have increased by a factor of five between 1981 and 2021 and tripled since 2000, while at the same time the median age of first-time home buyers increased by four years (NAR (2024)). During that time, average mortgage rates have drastically fallen from a high of 17 percent in the early 1980s to a trough of under 3 percent in 2020 and 2021. Lower mortgage rates, indicating lower borrowing costs, alleviates the debt-to-income (DTI) constraint for households which leads to a surge in demand for home purchasing and boosts house prices, consequently increasing the down payments necessary to obtain a mortgage. This inverse relationship between mortgage rates and prices holds strongly when the impact that mortgage rates have on housing demand exceeds their impact on supply, which is historically the case. In fact, since 2000, the bulk of the growth in house prices occurred in the years 2000–2006 and 2013–2021, when mortgage rates were at their respective historic lows.

At the same time, the first-time homebuyer share of home purchases has fallen from 35% to 22% between the years of 2009 and 2019 as shown in Figure 1.1 Panel (B). This figure tells us that fewer first-time home buyers are purchasing homes relative to incumbent homeowners, despite the lower mortgage rates. Additionally, this figure indicates that incumbent households are steadily increasing the amount of housing in their financial portfolios. Overall, the combination of increased prices, increased age at the time of the first purchase of a home, and fewer potential first-time home buyers purchasing homes suggests that the path to homeownership is not as easy as it was in previous generations. This brings rise to the question: do low mortgage rates benefit or harm the path to home ownership?

Figure 1.1: House prices, mortgage rates, and first-time home buyers




(a) House prices and mortgage rates

(b) First-time home buyer share of home purchases

*Notes*: Panel (a) plots the S& P Corelogic Case-Shiller US National House Price Index and the mean, national realized mortgage rate level at the month date level from January 1981 through 2020. Both data are downloaded via FRED. Panel (b) plots daily national-average first-time homebuyer purchase shares from January 1st, 2009 through December 31st, 2019 using the data sample created using the Fisher Center data described in Section 2. The first-time homebuyer purchase share trends observed in this time series are very similar to those observed in NAR (2024).

The main contributions of the paper are as follows. First, I construct a new mortgage-rate specific monetary policy shock to use as an instrument for mortgage rate changes. Existing monetary policy shocks that capture the longer end of the yield curve fail to accurately predict mortgage rate movements. Factor-driven approaches such as Gürkaynak et al. (2005), Acosta et al. (2024)'s update of the Gürkaynak et al. (2005) factors, and Swanson (2021), all use a variety of financial assets which serve well for giving us an understanding of the expected path of the federal funds rate, but provide an incomplete picture for mortgage markets. The longest duration asset Acosta et al. (2024) tracks movements for are one-year Treasury futures yields, while Swanson (2021)'s data sample includes 30-year Treasuries among many other securities. Neither of their data samples include mortgage-backed securities (MBS). Although the methodology is the same, my monetary policy shock series outperforms these existing factors due to the selection of financial assets. By focusing only on 10-year Treasuries and MBS, I am able to capture the surprise movements in mortgage rates without adding confounding movements from other financial assets.

I focus on 10-year Treasuries and MBS because they directly influence mortgage rate setting. 30-year fixed rate mortgage rates are often tied to 10-year Treasury yields because they have a similar duration due to the high frequency of mortgage prepayment and the less-frequent occurrence of mortgage default. As for MBS, high demand for MBS in the secondary market raises MBS prices implying that mortgage originators may sell their mortgages at a higher price, incentivizing lenders to lower mortgage rates in the hopes of originating more mortgages to sell. Consequently, using intraday 10-year Treasury futures and MBS transactions data, I construct a new monetary policy factor which contains price shocks within 30 minute intervals before and after each Federal Open Market Committee (FOMC) meeting from December 2012 through December 2024.

Second, I provide new empirical evidence that monetary policy-induced mortgage rate changes impact transacted house prices within a matter of weeks. I estimate that on average, a 25 basis point (b.p) fall in mortgage rates yields a 0.42 percent *increase* in transaction prices relative to the their listed. To the best of my knowledge, this is the first paper that demonstrates a high-frequency response in transaction house prices to monetary policy.

Third, I provide novel evidence on how monetary policy affects the composition of homebuyers—specifically, comparing renters, who I observe purchasing their first homes, and incumbent homeowners. The positive relationship between mortgage rates and the first-time buyer share of home purchases observed in Figures 1.1 does not imply causality. There exist several potential confounders such as growing income or wealth inequality. Additionally, mortgage rates are quite endogenous—suggesting the need for an instrumental variable approach. Consequently, I use the new mortgage-rate specific monetary policy shock as an instrument for mortgage rates. With the new shock in hand, I take this question to the data and demonstrate a positive relationship between mortgage rates and the first-time buyer share of home purchases. I find that a negative 25 basis point (b.p.) mortgage rate shock yields an 77 b.p. *decrease* in the first-time home buyer share of home purchases in the first three months after the shock. This result provides strong evidence that monetary policy transmission through the mortgage channel directly impacts first-time home buyers.

The intuition behind this empirical finding is that when interest rates fall, house prices increase and consequently, downpayments increase as well. On the one hand, incumbent homeowners who want to purchase a home already have housing wealth, so they are hedged from downpayment increases. Thus, they are more able take advantage of the opportunity of lower borrowing costs. On the other hand, renters or potential first-time homebuyers who do not have housing wealth are not hedged from the price increases. This implies that renters must save more in order to overcome this higher downpayment friction, pushing their home purchase further into their lifecycle and delaying the point that they are able to purchase a home and receive all of the benefits that homeownership provides. I argue that these are the two mechanisms driving the empirical results. Importantly, I provide direct evidence for the downpayment mechanism by showing that CBSAs with higher shares of loan-to-value (LTV)-constrained purchases prior to a mortgage rate shock exhibit a larger response in first-time purchase shares than CBSAs with lower shares of LTV-constrained purchases. Lastly, I show that these effects are more pronounced among lower-income first-time homebuyers.

For the final contribution of this paper, I construct a lifecycle model with heterogenous agents, a housing ladder, a negatively-skewed income process, and a system of housing-related taxes to quantify the disparate welfare impact of lowering mortgage rates between potential first-time home buyers (renters) and incumbent home owners. The housing ladder consists of four states: a renter state, a starter-home state, a large home state, and a state where the household owns both a large home and an a vacation home which from this point on will be referred to as a second-home. The inclusion of a state where the household owns both a primary home and a second-home is crucial to generate the empirical results in the model. Like much of the recent macro-housing literature, the model exhibits nonlinear dynamics. When I calibrate the model to the main empirical findings and apply an unanticipated transitory negative one p.p. "MIT" shock with low persistence to mortgage rates, prices and down payments rise while, the first-time home purchase shares fall. I find that households who were renters at the time of the shock face lower consumption-equivalent welfare of 0.1% relative to their pre-shock stationary equilibrium versions, while incumbent homeowners receive welfare-gains of 0.19%.

This paper contributes to several strands of macroeconomic and housing literatures. First, I provide a new monetary policy shock series specifically constructed for mortgage rates which predicts future mortgage rate changes better than existing monetary policy shocks aimed towards the longer end of the yield curve. This shock contributes to the existing monetary policy shock literature which uses high-frequency identification, such as to construct policy shocks Gürkaynak et al. (2005), Swanson (2021), Nakamura and Steinsson (2018), Bauer and Swanson (2023), and Acosta et al. (2024). Xu et al. (2012) finds that the 30-year fixed mortgage rate is slow-moving in response to monetary policy surprises, whereas I show that daily mortgage rates respond immediately within one day. This mortgage rate-specific monetary policy shock can be used in virtually any empirical setting for studying monetary policy transmission through the mortgage channel.

The empirical results in this paper contribute to large empirical literature on the mortgage channel of monetary policy transmission, such as Di Maggio et al. (2017), Di Maggio et al. (2020), Bhutta and Ringo (2021), Beraldi and Zhao (2023), Indarte (2023), Ahn et al. (2024), Bosshardt et al. (2024), Gorea et al. (2025). Like Gorea et al. (2025), I find empirical evidence that monetary policy-induced changes to mortgage rates affect house prices within a matter of weeks. My paper serves as a complement to theirs, which only finds a response in listed home prices, by showing that transaction prices respond to mortgage rate changes within a matter of weeks. Like many of these papers, I find that mortgage credit constraints play a vital role in explaining the dynamics found in the empirical analysis. Beraldi and Zhao (2023) show that when local house prices rise, homebuyer income rises and argue that lower-income buyers are priced-out, particularly among first-time homebuyers. My empirical results complement theirs by demonstrating that first-time homebuyer purchase shares fall when mortgage rates fall, with more pronounced effects in LTV-constrained areas and among lower-income households, complimenting those in Mabille (2023).

Overall, this paper adds to the literature by providing direct evidence of the disparate impact of monetary policy on first-time and incumbent home buyers.

This paper relates to several papers with quantitative macro models that focus on the mortgage channel of monetary policy transmission and credit frictions, such as Beraja et al. (2019), Berger et al. (2021), Eichenbaum et al. (2022), Favilukis et al. (2017), Greenwald (2018), Gariga and Hedlund (2020), Gariga et al. (2017), Guren and Greenwald (2025), Guren et al. (2021a), and Guren et al. (2021b). As in Greenwald (2018), the constraint switching effect is present in the transition dynamics of the lifecycle model. When mortgage rates fall, causing housing demand and consequently house prices to rise, the lower borrowing costs alleviates the DTI constraint while the higher prices tightens the LTV constraint. However, renters are more likely to be priced out of purchasing a home due to the tightening LTV constraint and their lack of housing wealth—meanwhile, incumbent homeowners are hedged by the price effects. Beraldi and Zhao (2023) show a similar mechanism in their stylized model. Additionally, as in Favilukis et al. (2017), Greenwald (2018), Guren and Greenwald (2025), and Guren et al. (2021a) financial frictions play a large role in explaining house price movements. This paper also shows that the differential impact of financial frictions on those who have and do not have housing wealth matters in understanding price movements and first-time home purchasing.

Although this paper is not the first to have a macro model with a housing ladder, others include Attanasio et al. (2012), Fonseca et al. (2024), Ortalo-Magné and Rady (2006), to the best of my knowledge it is the first to investigate the disparate impact in the dynamics of a mortgage rate shock comparing potential first-time home buyers and incumbent homeowners. Similar to Attanasio et al. (2012), I find that house price increases caused by a negative shock to mortgage rates increases downsizing because the gains from selling are larger for owners with multiple homes, however unlike their model, I find an increase in housing demand which is a key driver of the price increase. Like their paper, I find that taxes have a large impact on welfare. A key difference is that my paper allows for a third housing state where homeowners own both a large two-unit primary home and a one-unit second-home. The reason for this lies in what we learn from the data, that falling mortgage rates prompt incumbent homeowners to increase their quantity of housing units owned. Including a second-home state in the housing ladder allows the model to better match the empirical results with more reasonable parameters.

Finally, a subset of the empirical results speak to the urban literature documenting heterogeneity across space and types of movers. I find a larger impact in first-time purchase shares in CBSAs with larger housing markets. This result is largely related to the fact that such CBSAs tend to have higher shares of LTV-constrained borrowers. Additionally, I find that results almost entirely come from within-CBSA movers rather than households moving across CBSAs. Finally, I find that the results are not driven by CBSA-level housing supply elasticities.

The rest of the paper is organized as follows. Section 2 describes the data, the data sample construction, and the monetary policy shock construction. Section 3 describes the empirical methodology and presents the results. Section 4 describes the theoretical model, presents the results, and provides a further discussion connecting the model to recent literature along with next steps. Section 5 concludes.

## 1.2 Data

### 1.2.1 Constructing the data to estimate the price response

To construct the sample, I start by obtaining arms-length, full consideration property transactions records from ATTOM, a proprietary data provider that compiles national data from county deed and assessor records. For each property transaction, I observe the transaction date, property type, transaction type, and location. Sales involving non-household sellers (e.g., those made by banks or firms) as well as distressed sales (e.g. foreclosures and short sales) are excluded from the sample.

I use national property listing data between January 2011 and December 2020 from Altos Listing Intel. The property listing data provides weekly updates on the listing price, close price, and days on market. Occasionally, a house on the market may post multiple listings. For these cases, I combine listings for the same property if they are no more than 60 days apart.

I then merge the listing data to the property transaction records using the property address, price, and sale date. This leaves me with a sample of nearly two million housing transactions where I observe the transaction price, the last listing price made prior to sale, the transaction date, the last listing price setting date, and time on market at the time of the last listing price setting date.

### 1.2.2 Constructing the panel

In order to conduct my main empirical analysis, I construct a CBSA-month date panel with the composition of home purchases, national month-averages of daily bank offered mortgage rates, and CBSA characteristics. To the best of my knowledge, this is the first data sample that decomposes the types of home purchases between first-time and incumbent homeowners at a CBSA-month date level of granularity.

To construct the sample, I again start by obtaining arms-length, full consideration property transactions records from ATTOM, a proprietary data provider that compiles national data from county deed and assessor records. For each property transaction, I observe the transaction date, property type, buyer names, transaction type, and location.

I am able to identify whether a buyer is a renter or an incumbent homeowner household using USPS change-of-address tracking data from Data Axle InfoGroup. The data provider tracks households and identifies when a household moves from one location to another based on their submission of a USPS change-of-address form which forwards their mail from their old home to their new home. Importantly, the data provider also includes a key variable which identifies whether a household is a renter or a homeowner. The data is well-populated starting in 2009. With latitude, longitude, and property address information, I am able to match properties from this data to properties in ATTOM. Using the name of the head of household from the tracking data and the name of the buyer from the transactions data, I am able to merge households' mobility and rental-ownership status with the housing transactions data. However, it is important to note that these housing transactions likely excludes many non-primary housing transactions because the tracking data reports moving from one primary home to another.

Finally, I obtain loan-level mortgage origination characteristics from Black Knight McDash and borrower credit file information from Equifax. I combine the borrower ID from Black Knight McDash with the borrower ID from the Equifax borrower credit files using a crosswalk provided by Black Knight McDash. I rely on the borrower identifier to check if a renter purchasing a home has previously purchased a home on their credit file. This check is crucial to ensure that households identified as a renter are indeed a first-time home buyer. Importantly, I can identify whether the originated mortgage for a home is reported to be the owner's primary home or non-primary second-home. I use this as an additional check to ensure that households identified as a first-time buyer are purchasing their primary home. Separately, I am able to obtain origination LTV and DTI ratios for each housing transaction. I construct a CBSA-month date panel containing the shares of borrowers with high LTV and high DTI originations, which is used to demonstrate the downpayment mechanism in Table 1.3.

To merge in the mortgage origination and borrower credit history data I rely on a crosswalk following the same procedure used in Bartlett et al. (2022) and Kermani and Wong (2024). The matching algorithm uses a set of property and transaction attributes such as loan amount, loan purpose, and interest rate to find the k-nearest neighbors. I then keep the matches from the merge with the transactions matched with the tracking data. In an attempt to include non-primary home purchases, I expand the data sample to include additional property purchases identifed in the transactions data that did not match tracking data using the borrower identifier. This allows me to have a dataset that contains property purchases by first-time buyers as well as primary and non-primary purchases made by incumbent homeowners. The merge is available for housing transactions through 2019, giving me a CBSA-month date panel from January 2009 through December 2019.

Although the mortgage origination data contains the mortgage rate for borrowers, this may not resemble the true mortgage rate offered by banks at the time of origination, given that many home buyers lock in their mortgage for up to 30 days. Additionally, a borrower's mortgage rate is impacted by many factors such as their credit score, LTV, DTI, any points paid, and the loan product. Consequently, I obtain daily offered mortgage rates from Bankrate downloaded via a Bloomberg Terminal. These data are overnight averages of offered mortgage rates for 30-year fixed rate mortgages among all banks surveyed by Bankrate.com.

I obtain CBSA-month date level unemployment rates, house price indices, and rent price indices from BLS via FRED as well as national month date-averages of the effective federal funds rate from FRED. Lastly, I obtain month date-averages of the CBOE: Volatility Index Overview (VIX) from Wharton Research Data Services (WRDS). The unemployment rates, policy rates, and VIX are used as controls in the regression specification.

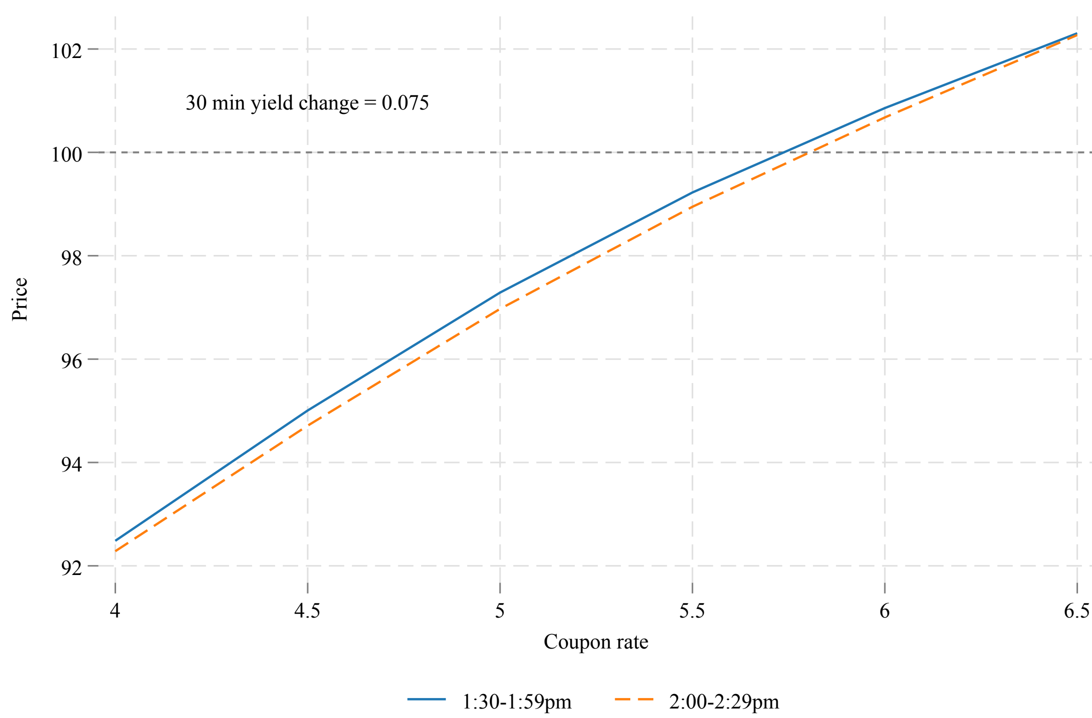
### 1.2.3 Monetary policy shock construction

I construct the mortgage rate-specific monetary policy shock using a factor approach similar to Gürkaynak et al. (2005), Swanson (2021), and Acosta et al. (2024). This data-driven method relies on observing price changes for a set of financial assets between narrow time windows before and after each FOMC announcement and extracting a single factor from the observed changes for each FOMC date. In order to construct a factor that is relevant for mortgage rate changes, my data sample consists of intraday trades for 10-year Treasury futures and MBS. This is the first monetary policy shock that uses MBS price movements in its construction. The inclusion of MBS is vital to study mortgage rate movements given the effects that forward guidance and quantitative easing have in the secondary mortgage market, Krishnamurthy and Vissing-Jorgensen (2011) and Hancock and Passmore (2011).

I obtain intraday 10-year Treasury futures trades from CME Group via DataBento, a data platform that supplies real-time and historical financial data. The data platform provides intraday transaction prices on trades at the nanosecond-level since June 2010.

I obtain intraday 30-year To-Be-Announced (TBA) MBS price and coupon data since December 2012 and 30-year TBA uniform MBS (UMBS) price and coupon data since March 2019.[1] The data are reported to FINRA and downloaded from TRACE via WRDS. TBA MBS and UMBS mortgage pools are not known at the time of trade, but their characteristics such as maturity, coupon, and settlement date are known. I use UMBS when available because they are more liquid FHFA (2020).

Figure 1.2: MBS Prices December 18, 2024




*Notes*: The figure provides LOWESS plots comparing prices and coupon rates for TBA UMBS trades in 30 minute windows before and after the Federal Open Market Committee's 2pm EST monetary policy statement release on December 18th, 2024. The plots provide a graphical explanation for the coupon rate, and consequently the yield, for a hypothetical TBA UMBS which sells at par. The data are downloaded from WRDS's TRACE database.

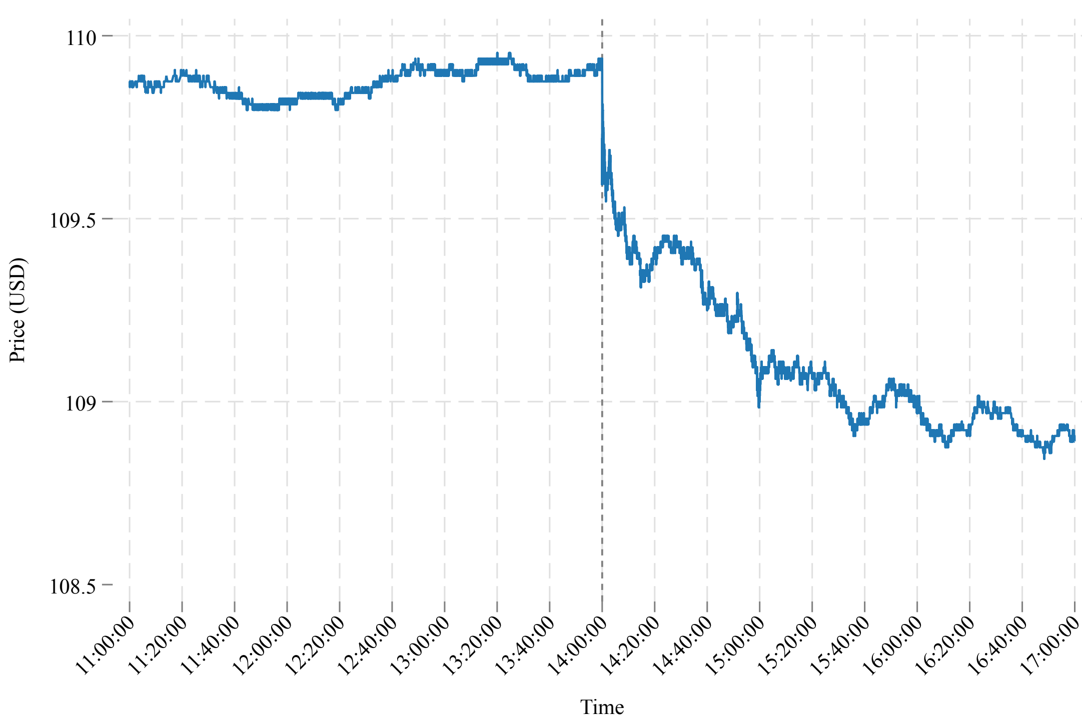
Alternatively, one could use 10-year Treasury futures and MBS yields instead of prices. One way to interpolate MBS yields is to extrapolate the hypothetical coupon rate that sells at par from a curve which compares prices to coupon rates. However, there exist FOMC announcement dates when it is impossible to find two such MBS with coupon rates that trade above and below par, such as May 1, 2013, which adds measurement error. For that reason, I focus on percent changes in prices. Figure 1.2 provides a graphical example with LOWESS plots comparing prices and coupon

[1] Prior to December 2012 I observe very few or no trades.

rates for TBA UMBS trades in 30 minute windows before and after the 2 pm FOMC announcement on December 18, 2024.

The December 18, 2024 monetary policy announcement included a largely expected 25 basis point decrease in the Federal Funds Rate and reduction in LSAPs. However, the announcement also included a large unexpected forward guidance message in the closely watched "dot plots" suggesting that fewer rate decreases were forecasted than previously expected.[2] In line with the Expectations Hypothesis, the higher expected future short-term rates led to an increase in 10-year Treasury note future yields, implying lower prices, as seen in Figure 1.3 and an increase in MBS yields as seen in Figure 1.2.

Figure 1.3: 10-year Treasury Note Prices December 18, 2024



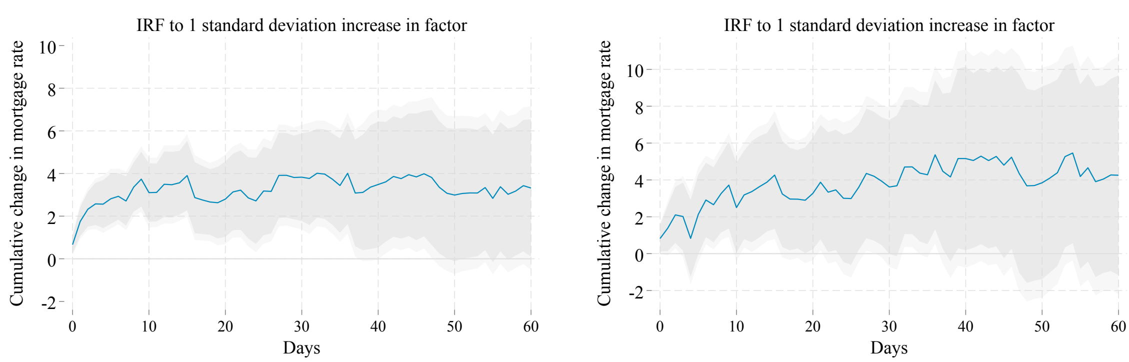

*Notes*: The figure plots intraday prices in Panel (a) and yields in Panel (b) for 10-year Treasury Note futures from the Chicago Mercantile Exchange on December 18th, 2024 before and after the Federal Open Market Committee's 2pm EST monetary policy statement release. The data are downloaded from DataBento's CME Group database.

[2]See Figures 2 from the projection materials for September 2024 and December 2024: `https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20240918.pdf` and `https://www.federalreserve.gov/monetarypolicy/files/fomcprojtabl20241218.pdf`

With the price data in hand for each scheduled and unscheduled FOMC meeting from December 12, 2012 to December 18, 2024, I calculate the average price for 10-year Treasury futures and TBA MBS's in the thirty minutes immediately before the announcement and the thirty minutes immediately after the announcement. This allows me to calculate the average price percent change for both asset types. With these two sets of price responses for each FOMC date, I extract a single factor to serve as the shock. The factor is scaled to equate to one unit standard deviation shock to 1 p.p. ten-year Treasury yield change.

Assuming no outside confounders impact the assets within these narrow time windows, the changes in prices demonstrate the responses to FOMC announcements. Thus, the single factor I extract serves as a monetary policy shock that is specific for mortgage rate setting.

Figure 1.4: Monetary policy factor relevance




(a) Mortgage rate monetary policy factor (b) GSS path factor Acosta et. al 2024 update

*Notes*: The figure plots the estimated coefficient of regressing cumulative difference in mortgage rate change between horizon h=0,...,60 business days and the mortgage rate the day before the FOMC announcement on the factors with 90% and 95% confidence bands. The sample period runs December 2012 through December 2019, which matches the same time period from the empirical analysis in Table 1.2.

Figure 1.4 demonstrates relevance of the new mortgage rate monetary policy factor for predicting future mortgage rate changes for a sample period that contains FOMC announcements from December 2012 to December 2019 which matches the sample period for the main empirical results. I regress the cumulative change in daily mortgage rates on the factor for horizons of 0 to 60 business days and plot the estimated impulse response function estimated from a local projections approach where the shock is the only right-hand side variable. Panel (A) plots the impulse response function (IRF) for the new factor and Panel (B) plots the IRF for the existing path factor from Acosta et al. (2024). Both factors have mean zero, but to improve comparability, the path factor is rescaled to match the variance of the mortgage rate factor. The light gray area plots the 95% confidence band and the dark gray area plots the 90% confidence band. Though the estimated coefficients are quite similar over the 60 business day horizon, the new mortgage rate-specific monetary policy factor is much less noisy as it is statistically significant for approximately three months. Notably, the Zero-Lower Bound (ZLB) period makes up much of the time frame. When expanding the sample to March 2025, mortgage rates are more responsive to monetary policy shocks and the persistence of the effects are statistically significant for one year as seen in Appendix Figure A1.

Separately, I run a horse-race between the 10-year Treasury future and the MBS price shocks on one-day and ten-day cumulative mortgage changes after FOMC announcements to determine which shocks primarily drive mortgage rate movements. During the ZLB period prior to 2016, I find that MBS shocks dominate Treasury shocks in explaining future mortgage rate movements. However after the ZLB period, mortgage rate movements almost entirely load on Treasury shocks.

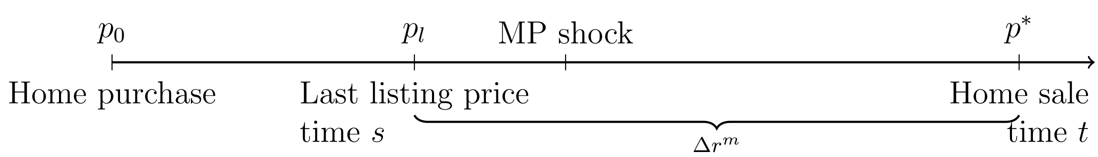
## 1.3 Empirical results

### 1.3.1 House price impact of monetary policy

First, I establish that monetary policy-induced mortgage rate changes pass through to transaction house prices more quickly than previously believed by the prior literature. Some of existing literature tells us no, Kuttner (2013) and Williams (2015), largely due to their data being aggregated and having a low frequency. However, more recent papers such as Gorea et al. (2025) find that listed home prices respond in a matter of weeks. In fact, they find that an exogenous 0.25 p.p. increase in mortgage rates lowers house prices 1.4 percent in two weeks using Swanson (2021)'s forward guidance monetary policy shock and provide evidence that the impact is asymmetric with the bulk of the response coming from expansionary monetary policy. Although Gorea et al. (2025) demonstrates passthrough to listing prices within a matter of weeks, they fail to find this pattern for transaction prices. Showing passthrough to transacted prices is the first empirical contribution of this paper. Figure 1.5 presents the empirical strategy.

Consider a home that was purchased at price $p_0$, is later listed on the market with a most-recent listing price of $p_l$ set on date $s$, and is sold on date $t$ at price $p^*$. Between dates $s$ and $t$, there is a monetary policy shock that impacts mortgage rates. I will regress the log price change between the listed and transaction prices on the change in mortgage rates between dates $s$ and $t$ instrumented by the monetary policy shock. The estimated coefficient will inform us how mortgage rate changes impact the price changes. Effectively, this is a repeat-sales approach but substituting the purchase price with the listing price. The relatively high-frequency approach allows us to more cleanly estimate the impact that mortgage rate changes have on individual transaction prices.

Figure 1.5: Price growth empirical strategy




Equation 1.1 describes the exact specification. For a home $i$ on the market, estimate log growth between the transaction price at date $t$ and the last listed price at date $s$ in response to the instrumented change in mortgage rates between dates $s$ and $t$ using the mortgage rate-specific monetary policy shock. Controls include the mortgage rate for date $s$, time on market at date $s$, the effective federal funds rate for date $s$, and Census Tract-level fixed effects. $\beta$ is the estimated coefficient of interest.

$$\ln(p^*_{i,t}) - \ln(p^l_{i,s}) = \beta \widehat{\Delta^{t-s} r^m} + \boldsymbol{\theta_{i,s} X_{i,s}} + \phi\delta_k + \varepsilon_{i,t} \tag{1.1}$$

Including the national average offered mortgage rate and effective federal funds rate allows us to control for the state of the economy at the time of the price listing.

Controlling for time-on-market allows us to control for homes with different listing experiences—for instance, homes on the market for a longer period of time may be more willing to sell their home at a larger discount—and the Census Tract fixed effects can be though of as a control for neighborhood-level characteristics. The time period of the sample runs from December 2012 through December 2020, though the results are similar if the year 2020 is excluded. The sample excludes homes that were owned for less than two years to remove home flippers and excludes homes extreme transaction values, i.e., homes with sales prices outside of the 1st and 99th percentiles and where the log growth between the last listing price and the transaction price lie outside of the 1st and 99th percentiles.

Table 1.1: Price impact from monetary policy-induced mortgage rate changes

| | All transactions | | | $h < 14$ | $h \in [14, 28)$ | $h \in [29, 42)$ | All transactions | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) OLS | (3) IV | (4) IV | (5) IV | (6) IV | (7) IV | (8) IV |
| Δ Mtg rt | -0.0009** | -0.0015*** | -0.013*** | -0.019*** | -0.014*** | -0.010*** | -0.005 | -0.019*** |
| | (0.0003) | (0.0005) | (0.002) | (0.007) | (0.003) | (0.003) | (0.004) | (0.003) |
| Δ Mtg rt × 90+ LTV shr | | | | | | | -0.011** | |
| | | | | | | | (0.005) | |
| 90+ LTV shr | | | | | | | 0.001*** | |
| | | | | | | | (0.0003) | |
| Δ Mtg rt × Supply elas | | | | | | | | 0.013*** |
| | | | | | | | | (0.005) |
| Observations | 643793 | 643793 | 643793 | 36772 | 116401 | 136891 | 560078 | 356422 |
| Tract FEs | Y | Y | Y | Y | Y | Y | Y | Y |
| Interest rate controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Time-on-mkt control | | Y | Y | Y | Y | Y | Y | Y |
| K-P Fstat | | | 276.46 | 278.00 | 289.40 | 178.54 | 135.72 | 113.04 |

The table provides estimates of the log price change between the listed and transaction prices in response to mortgage rate changes between the time of setting the last listing price and the transaction date. $h$ refers to the number of days post FOMC meeting. Controls include the mortgage rate and effective federal funds rate at the time of listing, time on market at the time of listing, and Census Tract fixed effects. The data sample excludes homes owned for less than two years, extreme transaction values, and extreme price growth between listing and sale, and runs from December 2012 through December 2020. Kleibergen-Paap (Kleibergen and Paap (2006)) F-statistics are reported. Clustered standard errors at the transaction date-level reported in parenthesis
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

There are two candidates to select as the sale date $t$. One date is the transaction date recorded by the county assessor's office observed in the ATTOM data. Though this date is typically after a home deal is finalized which may come after a price is agreed between the two parties. While closing a home may only take a few days for cash buyers, it may take weeks for homes purchased with mortgages. Thus, the other candidate date is the last observed listing date which can be inferred as the last date prior to matching with a buyer at an agreed price. Due to the higher-frequency setting of this empirical framework, using the last observed listing date may give a closer estimate for the actual change in mortgage rates between the last price setting date and the date of price negotiating between the buyer and seller. However, both dates give very similar results.

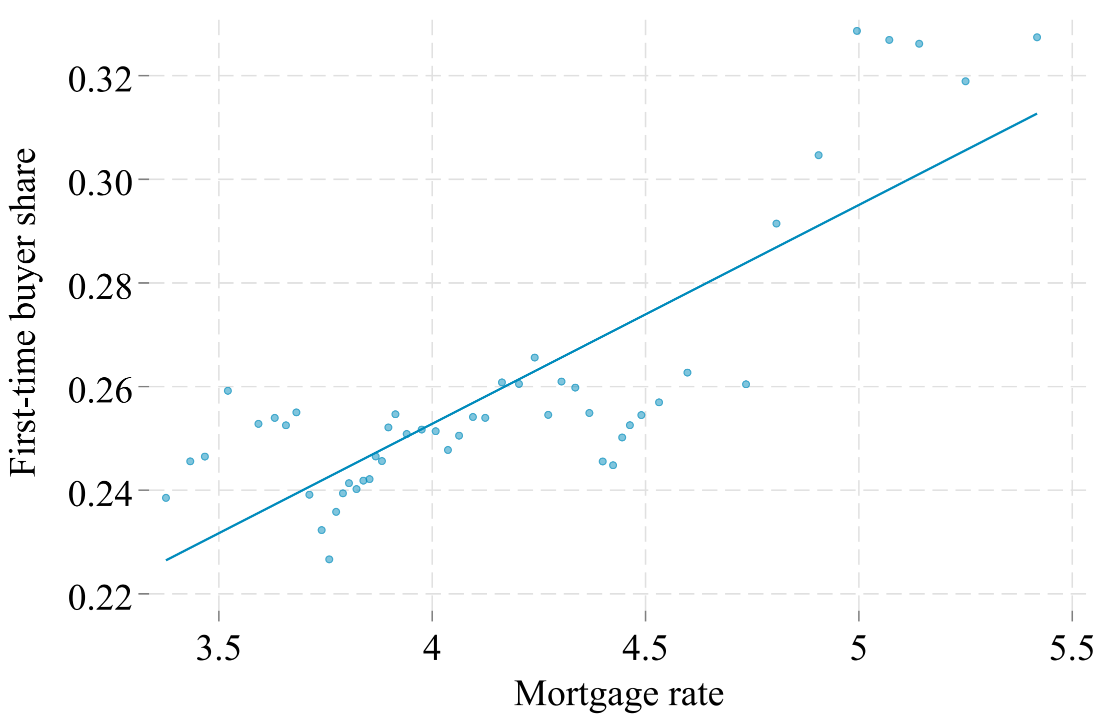
Table 1.1 presents the results using the last listed date as the sale date. All regressions include the interest rate controls and Census Tract fixed effects. Standard errors are clustered at the sale date level and Kleibergen-Paap (Kleibergen and Paap (2006)) F-statistics are reported. $h$ in the column titles refers to the number of days since the shock. Columns (1) and (2) estimate the price response to mortgage rate changes using an OLS approach without and with the time-on-market control, respectively. Column (3) presents the results using the IV approach described above. The estimated coefficient tells us that a one percentage point reduction in mortgage rates, raises the transaction price by about 1.26% relative to the listing price. Given the short time-horizon between listing and finalizing sales, this estimate is quite large. To get a better sense of the response for different time horizon Columns (4), (5), and (6) present the results for pooled $t - s$ horizons of less than 14 days, between 14 and 28 days, and between 28 and 42 days, respectively. For each of these columns, a statistically significant negative coefficient is estimated. The magnitude of these estimates demonstrate that transacted prices show a significant response to mortgage rate changes almost immediately. We can interpret from these results that home buyer demand responds to monetary policy-induced mortgage rate changes within a matter of days or a couple of weeks.

The estimates presented in Column (7) use a similar specification but interacts the instrumented mortgage rate change with the share of origination LTVs greater than 90% in home $i$'s Census Tract for the quarter prior to setting the listing price. The sign of the estimated coefficient tells us that transaction prices grow more in response to falling mortgage rates in neighborhoods where buyers face more binding LTVs. This result is inline with Gorea et al. (2025)'s findings that listing prices in low-income and low house price zip codes are more responsive to mortgage rate changes. While this benefits sellers in neighborhoods with higher shares of LTV-constrained homebuyers, it makes entering the homeownership state more difficult, particularly for LTV-constrained buyers. As a robustness check, I perform the same exercise but with defining the transaction date as the sale date $t$ in Table A1. The estimated coefficients in the table are very similar to those in Table 1.1 demonstrating that these empirical findings are not sensitive to sale date choice.

### 1.3.2 Main results

Figure 1.6 presents binned scatter plots showing first-time homebuyer purchase shares against the level of mortgage rates. The figure demonstrates a positive relationship between the first-time purchase share of housing purchases and mortgage rates. This implies a negative relationship between the total incumbent homeowner purchase share, which includes incumbent primary home purchases and secondary home purchases, and mortgage rates as well.

Figure 1.6: First-time home purchase shares and mortgage rates




*Notes*: Data are at the CBSA-month date level between 2009 and 2019. CBSAs with fewer than 50 transactions are dropped.

These binscatter plots provide suggestive evidence. Mortgage rates are endogenous and impacted by both primary and secondary market demand for mortgages, the financial state of mortgage originators, and other factors. Thus, we cannot conclude that outside factors are not behind the patterns we observe from the binscatter plots. Consequently, we will use a Two-Stage Least-Squares Instrumental Variables approach with the newly constructed monetary policy shocks specifically constructed for mortgage rates as the instrumental variable.

The specification is slightly different from a local projections approach with an IV, though a local projections approach gives very similar estimates. Instead of instrumenting for the mortgage rate or the mortgage rate change at the time of the shock, I instrument for the cumulative mortgage rate change with the monetary policy shock. This specification allows me to use the relevant mortgage rate change for longer horizons. Equation 1.2 shows IV specification. $i$ denotes a CBSA, $t$ denotes the month date of the monetary policy shock, and $h$ denotes the horizon after the shock.

$$\Delta^{12}Y_{i,t+h} - \Delta^{12}Y_{i,t-1} = \alpha_{2,h} + \hat{\beta}_h \widehat{\Delta^h r_t^m} + \boldsymbol{\theta_{2,h} X_{i,t}} + \phi_{2,h}\delta_i + \varepsilon_{i,t,h} \tag{1.2}$$

The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+h$ and the annual change in purchase shares for time $t-1$. I focus on changes in annual differences of purchase shares to account for seasonality in housing markets (Case and Shiller (1989), Goodman (1993), Ngai and Tenreyro (2014)) which is demonstrated in Figure 1.1. The main purchase shares variable of interest is the first-time buyer share of home purchases. The main coefficient of interest is $\hat{\beta}_h$ which tells us the response in the purchase shares to the instrumented change in mortgage rates. The set of controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). We control for the levels of mortgage rates because households behave differently in periods of low and high mortgage rates. Including the EFFR and VIX allows us to control for contemporaneous macroeconomic conditions, and including local unemployment rates gives us an additional control for the state of the local metropolitan area. Because the specification controls for twelve lags of monthly changes in annual differences of first-time purchase shares, I need to ensure that these variables are properly estimated, minimizing measurement error. Thus, I remove any CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions (roughly 3 transactions per day). Finally, to account for common autocorrelated disturbances, Driscoll-Kraay standard errors (Driscoll and Kraay (1998)) are included with four lags.

Table 1.2 reports the estimates of the impact of mortgage rate changes on annual changes in the first-time home buyer share of home purchases for one, two, and three month horizons. Kleibergen-Paap (Kleibergen and Paap (2006)) F-statistics are reported. Mortgage rate shocks are monthly averages, and months without a mortgage rate shock are never counted as a period receiving a monetary policy shock of zero. The sample in the table consists of 2,032 CBSA-month date observations containing 50 total CBSAs.

Table 1.2: First-time buyer share of home purchases regressions

| | $h = 1$ | | $h = 2$ | | $h = 3$ | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV |
| $\Delta$ Mortgage rate | 0.0096** | 0.0359** | 0.0141*** | 0.0298*** | 0.0134*** | 0.0270** |
| | (0.0038) | (0.0140) | (0.0033) | (0.0080) | (0.0030) | (0.0128) |
| Observations | 2032 | 2032 | 2032 | 2032 | 1989 | 1989 |
| K-P Fstat | | 16.84 | | 27.67 | | 15.65 |
| Number of transactions | 3066813 | 3066813 | 3088425 | 3088425 | 3030114 | 3030114 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+h$ and the annual change in purchase shares for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

The main result with the IV estimate is presented in Column (2) showing that a negative 1 percentage point change in the mortgage rate between the month before and after the mortgage rate shock yields a negative 3.59 percentage point change in the annualized first-time buyer share of home purchases in the month after the shock compared to the month before the shock. The estimated coefficient is statistically significant at the 5% level. Finally, the total number of housing transactions used in the calculation of the LHS variable is reported at over 3 million. Column (1) shows a qualitatively similar and statistically significant coefficient for the OLS specification.

Columns (4) and (6) present the estimated coefficients using the IV approach for the two-month and three-month horizons, respectively. The IV regression results in Column (4) reports a similar coefficient estimate of 0.0298 to that in Column (2) which is statistically significant at the 1% level. The reported F-statistic is much higher at 27.67 demonstrating stronger validity of the mortgage rate shock as an instrument. The estimated coefficient in Column (6) drops to 0.0270 and maintains statistical significance at the 5% level; however, the F-statistic also falls to 15.65. The fall in the magnitude of the coefficient, the statistical significance, and the F-statistic are not surprising given that there are likely 2-3 FOMC meetings by the third month horizon which likely diminish the impact of the original shock. Columns (3) and (5) present the OLS estimated coefficients for the two and three-month horizons, respectively, reporting statistically significant coefficients of similar magnitude to that in reported in Column (1). Appendix Figure A2 plots the estimated coefficients of the IRF using a local projections approach (Jordà (2005)) with the mortgage rate shock IV with the same set of controls. The figure shows that the effects are persistent and statistically significant for six months after the monetary policy shock.

At a high level, by comparing the volume response between first-time and incumbent buyers it appears that the results are largely explained by an immediate response from incumbent homeowners rather than first-time buyers as seen in Appendix Table A3. Again, due to high seasonality in housing markets, the dependent variable is log changes in annual log differences of purchase volumes. I do not find a statistically significant response in total volumes one month after the mortgage rate shock—though as we know from Table 1.2 the difference between first-time and incumbent buyers is statistically significant. However, I do estimate statistically significant total and incumbent volume increases in response to a mortgage rate decline for the second and third month horizons. The lack of a negative statistically significant coefficient for first-time buyer volumes in the first two months after the shock is an important result. While incumbent homeowners adjust the amount of housing in their portfolio within the first two months after the shock, we fail to provide evidence of first-time buyers doing the same until three months after the shock, which is still a lower response compared to incumbent homeowners. It is important to note that the composition of first-time buyers can change as well. Specifically, I discuss how the actual first-time buyer response depends on the first-time buyers' liquidity constraints in the following subsection.

Appendix Table A5 reports the estimated coefficients using the same specification from Table 1.2 but with the Acosta et al. (2024) update of the Gürkaynak et al. (2005) path factor as the IV. Though qualitatively similar, the IV regression coefficients in Columns (2), (4), and (6) lack statistical significance. This is likely due to the lack of validity the path factor serves as an instrument which is observed from the reported F-statistics and from Figure 1.4 Panel (B).

The mechanism argued in the paper is one that lowering mortgage rates increases house prices and consequently increases down payments. This downpayment increase differentially affects renters (potential first-time home buyers) and incumbent homeowners LTV constraints. Incumbents already have housing wealth, so their housing wealth co-moves with downpayments, allowing them to take advantage of the opportunity of lower mortgage borrowing costs. However, renters who were on the margin of overcoming the down payment friction are suddenly more LTV-constrained and may need to forgo the house purchase to save more, despite the lower borrowing costs. Recent papers such as Gorea et al. (2025) and the analysis shown in Table 1.1, tell us that house prices respond to monetary policy-induced mortgage rate changes within a matter of weeks. Applying a back-of-the-envelope calculation of a 0.25 p.p. mortgage rate cut to a $400,000 dollar house with a 20% downpayment would raise the downpayment by over one thousand dollars with the Table 1.1 Column (3) estimate of average house price response, which is not an insignificant impact.

To get a sense of the impact that monetary policy-induced mortgage rate changes have on house prices at an annual frequency, I perform a similar exercise to that of Gorea et al. (2025) estimating local projections (Jordà (2005)) with this paper's new mortgage-rate specific monetary policy shock as the instrument. Appendix Figure A3 plots house price IRF. I estimate the cumulative changes in annual log differences of CBSA-level house prices and house price to rent ratios on the mortgage rate change instrumented with the mortgage rate-specific monetary policy factor. The specification is the same as above except that the instrumented variable of interest is the change in average mortgage rates one month before and after the shock instead of the cumulative change. I do this because house prices are typically very persistent as opposed to purchase shares.

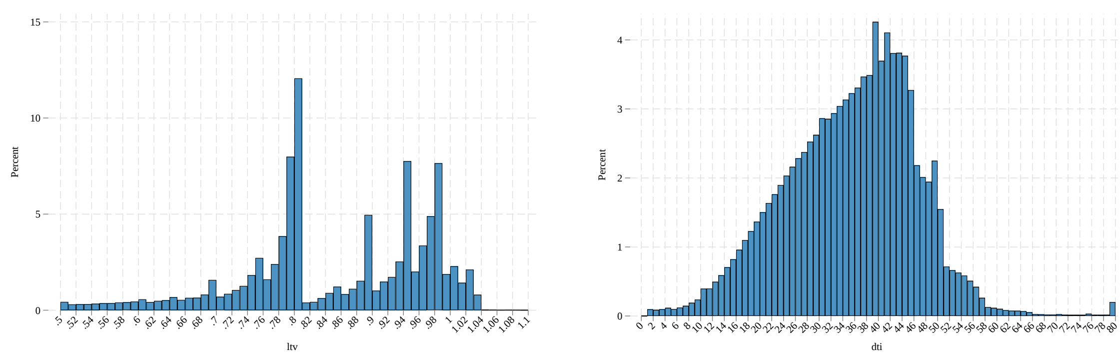
Not surprisingly, the immediate response is slow. The data sample is monthly with house price indices aggregated at the CBSA-level. The important takeaways are twofold. First, the twelve-month response to an exogenous 1 p.p. decrease in mortgage rates yields a 4% increase in annualized house price growth. Second, the response persists and increases to 10% two years after the shock.

### 1.3.3 LTV and DTI

To understand the mechanism behind the main results, I explore how the results vary when focusing on CBSAs with more constrained borrowers. In particular, I examine the role that LTV and DTI constraints play in explaining these results. First, I examine the LTV and DTI distributions for mortgages in my sample period as shown in Figure 1.7.

Although, there are many different types of loan products, in Panel (A) find LTV bunching around the 80% level as well at several levels at and above 90%. Over 20% of mortgages originate with an LTV between 79 and 81% while over 30% are between 90 and 100%. The bunching around the 80% level indicates many households are up against the LTV mortgage constraint which avoids paying private mortgage insurance (PMI). The large mass with LTVs between 90 and 100% tells us that many households are up against the LTV constraint to obtain a mortgage. CBSAs are very heterogeneous in their shares of home purchases with mortgage originations that have high LTVs. In the data sample for Table 1.2, the mean share of high LTV originations between 90 and 100% is 47% with a standard deviation of 12. If the mechanism behind the main regression results is that higher prices and consequently higher down payments cause the LTV constraint to bind or fail to be satisfied, we would expect starker results in magnitude among CBSAs with a history of more LTV constrained buyers. Table 1.3 Columns (1)–(4) demonstrates this exact pattern in its results.

Figure 1.7: LTV and DTI Distributions




LTV Distribution DTI Distribution

*Notes*: Data sample consists of 10 million purchase loan originations between 2009 and 2019. Mortgages with LTVs higher than 1.1 and DTIs higher than 80% are excluded.

In Panel (B) I find that the DTI distribution largely resembles that shown in Bosshardt et al. (2024) in that there are steep cliffs after the 45% and 50% DTI levels. One might expect to see a cliff at the 36% level given Fannie Mae's default DTI maximum limit; however, Fannie Mae allows a maximum limit of 45% if the borrower provides a higher level of credit worthiness. Additionally, Fannie Mae allows a higher DTI limit of 50% for mortgages underwritten using their Desktop Underwriting automated process if the full set of the borrower's characteristics (application data, income, financial assets, credit history, and employment history) satisfies their eligibility model. Approximately 20% of mortgages originated in the data have a DTI greater than 45%. One might expect that CBSAs with higher shares of high DTI mortgages originated would strongly react with higher first-time home purchase shares in the event of a mortgage rate decrease. The results in Table 1.3 Columns (5)–(8) show that this is not the case.

Table 1.3: First-time purchase shares by LTV and DTI shares

| | LTV shares | | | DTI shares | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $h = 1$ | $h = 2$ | $h = 3$ | $h = 1$ | $h = 2$ | $h = 3$ |
| Δ Mortgage rate × L.LTV 90s shr | 0.0919** | 0.0757*** | 0.0564** | | | |
| | (0.0355) | (0.0245) | (0.0275) | | | |
| Δ Mortgage rate × L.DTI 45+ shr | | | | 0.1695** | 0.1529*** | 0.1099* |
| | | | | (0.0701) | (0.0455) | (0.0575) |
| Observations | 2032 | 2032 | 1989 | 2032 | 2032 | 1989 |
| K-P Fstat | 15.89 | 28.23 | 15.28 | 20.83 | 26.84 | 15.88 |
| Number of transactions | 3066813 | 3088425 | 3030114 | 3066813 | 3088425 | 3030114 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes interacted with CBSA-level shares of high origination LTVs (Columns (1)–(3)) and of high origination DTIs (Columns (4)–(6)) for the month prior to the shock instrumented by the mortgage rate-specific monetary policy shock. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+h$ and the annual change in purchase shares for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table 1.3 presents the regression results using the same specification from Table 1.2 but interacting the instrumented mortgage rate change with the CBSA share of high LTV buyers in Columns (1)–(3) and the share of high DTI buyers in Columns (4)–(6) from the month prior to the monetary policy shock. I define a CBSA's share of constrained LTV borrowers as the share of mortgages originated with an LTV between 90 and 100% in that month. Similarly, I define a CBSA's share of constrained DTI borrowers as the share of mortgages originated with a DTI greater than 45% in that month.

The results in Columns (1)–(3) indicate that CBSAs with higher constrained LTV shares in the prior month faced larger decreases in first-time home purchase shares when mortgage rates fall relative to their less-constrained counterparts. These results provide direct evidence for the mechanism behind the Table 1.2 results that the increased downpayment friction which binds the LTV constraint impedes potential first-time home buyers abilities to purchasing their first home—thus lowering the first-time home purchase share. Appendix Table A6 further supports this by showing similar results by interacting the instrumented mortgage rate change with the CBSA share of high combined LTV (CLTV) buyers.

When borrowing costs fall, one might expect previous DTI-constrained borrowers to have a higher ability to obtain a mortgage and thus we would expect that the impact of the mortgage rate changes to be lower for CBSAs with higher DTI-constrained borrowers given that first-time buyers would be more responsive. Surprisingly, the results in Columns (4)–(6) are contrary to what was initially hypothesized with the estimated coefficients telling a similar story to those in Columns (1)–(3). The rationale behind these results lies in the data. First, borrowers who are DTI-constrained tend to be LTV-constrained as well. So CBSAs with higher shares of LTV-constrained borrowers also tend to have higher shares of DTI-constrained borrowers. Second, the DTI distribution in Figure 1.7 Panel (B) tells us that borrowers seem to have relatively little difficulty in overcoming Fannie Mae's lower 36% DTI limit by providing evidence of credit worthiness and by searching for non-conventional mortgage products, while a sudden increase in a down payment caused by higher house prices may be a more difficult barrier to overcome.

Table A4 regresses log changes in annual log differenced-volumes for first-time buyers with FHA loans to instrumented mortgage rate changes by the CBSA's high LTV share quartile the month prior to the mortgage rate shock. The results are telling, particularly in the one month horizon. In Column (4), I estimate a statistically significant coefficient indicating that a one percentage point mortgage rate drop yields a 37.9% decrease in first-time purchases by buyers with high LTVs. As previously discussed, typically when mortgage rates fall, housing demand rises which causes house prices rise. Given that I do not estimate an statistically significant increase in purchase volumes for these types of home buyers in response to lowering mortgage rates, the empirical evidence suggests that many first-time buyers are relatively priced out of the home purchasing market.

Combined with the prior results, the empirical results indicate that most of the initial increased buyer demand for housing that causes prices to rise comes more from incumbent homeowners and less from first-time buyers. Additionally, the less-affluent high LTV first-time home buyer purchase volumes actually decrease in the one month horizon in CBSAs with higher shares of LTV-constrained buyers. Overall, the results tell a stark story that when mortgage borrowing costs fall, the "haves" (households that own housing) buy more of the housing shock relative to the "have-nots" (potential first-time homebuyers).

### 1.3.4 Additional Heterogeneity

This subsection explores the heterogenous impact of mortgage rate changes on the first-time homebuyer share by income groups, by housing market size, and by original location prior to purchasing a home.

A natural question to ask after seeing how first-time homebuyer purchase share results depend on mortgage constraints is how do the results vary by income. Given the results from Table 1.3, one would expect that lower income first-time homebuyers' purchasing behaviors are more sensitive to price shocks than higher-income first-time homebuyers' purchasing behaviors because they tend to be more liquidity-constrained. Table 1.4 demonstrates evidence showing this is likely the true story.

I estimate homebuyer income in two ways. First, I use the income reported from homebuyers' credit records estimated from their personal income model (PIM). Second, I impute income by dividing a homebuyer's total liabilities by the DTI ratio at origination. Total liabilities are calculated as the sum of all monthly mortgage and non-mortgage debt payments observed in the credit records and the monthly property tax payment the year prior to the home purchase. Miscellaneous liabilities such as child support payments are not included, though these types of liabilities are not typical. Homebuyers are arranged into low, moderate, upper, and highest income groups if their income is less than 50% of their county's median household income, between 50 and 80% of their county's median household income, between 80 and 120% of their county's median household income, and over 120% of their county's median household income, respectively. The first-time homebuyer purchase shares by income group relate the number of first-time homebuyers for an income group by the total number of homebuyers for whom I estimate their income.

Table 1.4: First-time buyer share of home purchases regressions—Income

| | Income via DTI | | | | Income via PIM | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) Low | (2) Moderate | (3) Upper | (4) Highest | (5) Low | (6) Moderate | (7) Upper | (8) Highest |
| Δ Mortgage rate | 0.0917*** | 0.0214*** | -0.0004 | -0.0115** | 0.0314*** | 0.0185 | 0.0159*** | -0.0038** |
| | (0.0309) | (0.0074) | (0.0058) | (0.0055) | (0.0096) | (0.0199) | (0.0054) | (0.0017) |
| Observations | 1568 | 1568 | 1568 | 1568 | 2032 | 2032 | 2032 | 2032 |
| K-P Fstat | 18.34 | 19.13 | 18.78 | 19.14 | 15.46 | 16.60 | 16.44 | 16.72 |
| Number of transactions | 2629613 | 2629613 | 2629613 | 2629613 | 3066814 | 3066814 | 3066814 | 3066814 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock by income groups. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+1$ and the annual change in purchase shares for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 25 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 1.4 presents the analysis using the same specification for the IV regressions in Table 1.2 home buyer income group at the one-month horizon. Columns (1)–(4) display the estimates for the Iow, moderate, upper, and highest income groups, respectively, using the DTI-inferred income. Columns (5)–(8) display the estimates for the Iow, moderate, upper, and highest income groups, respectively, using the PIM-inferred income. Qualitatively, the results are consistent across both income estimates. Columns (1) and (5) indicate that when mortgage rates fall, low-income first-time homebuyer purchase shares fall by more compared to all other income groups, agreeing with the hypothesis that credit constraints matter. The estimated coefficients are lower for higher-income first-time buyers. Columns (4) and (8) indicate that when mortgage rates fall, the highest-income first-time homebuyer purchase shares actually increase, a result that we observed for incumbent homebuyers in the main table regressions. These households are less liquidity constrained, and therefore less sensitive to house price shocks caused by mortgage rate changes. These results complement those in Beraldi and Zhao (2023) by showing that lower mortgage rates price-out lower-income first-time homebuyers.

Alternatively, one may ask how these results vary over different types of metropolitan areas—specifically, those with smaller and larger housing markets. Larger cities typically have larger housing markets that are more liquid and have higher prices. They also tend to have a higher liquidity supply or inflow rate of buyers (Jiang et al. (2024)). Consequently it is not surprising that that CBSAs with larger housing markets have more sensitive first-time homebuyer share rates as shown in Table 1.5. I define the size of a CBSA's housing market based on the number of housing transactions between 2009 and 2019, and divide the data sample into three groups: large market CBSAs with a top ten market size, medium market CBSAs that rank between 11 and 50, and small market CBSAs outside of the top 50. The same specification from Table 1.2 is used; however, I reduce the restriction on the minimum number of transactions from 150 to 25 to include the smaller CBSAs. This allows the sample sizes to be large enough for each sub-sample.

Table 1.5: First-time buyer share of home purchases regressions—Market size

| | Mkt rank $> 50$ | | | Mkt rank 11–50 | | | Mkt rank $\leq 10$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) $h=1$ | (2) $h=2$ | (3) $h=3$ | (4) $h=1$ | (5) $h=2$ | (6) $h=3$ | (7) $h=1$ | (8) $h=2$ | (9) $h=3$ |
| $\Delta$ Mortgage rate | -0.0011 | 0.0067 | 0.0137 | 0.0306** | 0.0301*** | 0.0216* | 0.0390*** | 0.0352*** | 0.0571*** |
| | (0.0123) | (0.0098) | (0.0180) | (0.0140) | (0.0096) | (0.0126) | (0.0142) | (0.0119) | (0.0190) |
| Observations | 4610 | 4610 | 4508 | 1961 | 1961 | 1924 | 636 | 636 | 624 |
| K-P Fstat | 15.19 | 24.72 | 12.79 | 15.63 | 26.64 | 14.31 | 17.71 | 28.10 | 14.19 |
| Num. of trans | 927289 | 932643 | 915964 | 1590605 | 1602805 | 1571324 | 1657077 | 1669421 | 1637211 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock by housing market size. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+h$ and the annual change in purchase shares for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 25 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Columns (1)–(3), Columns (4)–(6), and Columns (7)–(9) report the coefficient estimates for small, medium, and large housing markets respectively. The estimated coefficients for the large market CBSAs are the greatest in magnitude and statistically significant for all three horizons with the reported F-statistic meaningfully large for the first two months post-shock. Similarly, the estimated coefficients for CBSAs with housing markets that rank 11–50 are economically significant in magnitude and statistically significant for the first two post-shock months. Finally, the estimated coefficients for the small market CBSAs are lower in magnitude and are not statistically significant. These results are not very surprising given that CBSAs with larger housing markets tend to have higher house prices and more constrained LTV borrowers. Overall, the results from this table suggest that the positive relationship between mortgage rates and the first-time buyer share is largely driven by characteristics in metropolitan areas with larger housing markets.

Table 1.6: First-time buyer share of home purchases regressions—Migration

| | Within CBSA | | | Into CBSA | | |
|---|---|---|---|---|---|---|
| | (1) $h = 1$ | (2) $h = 2$ | (3) $h = 3$ | (4) $h = 1$ | (5) $h = 2$ | (6) $h = 3$ |
| $\Delta$ Mortgage rate | 0.0387** | 0.0274*** | 0.0254** | -0.0028 | 0.0030 | 0.0014 |
| | (0.0146) | (0.0076) | (0.0124) | (0.0032) | (0.0031) | (0.0042) |
| Observations | 2032 | 2032 | 1989 | 2032 | 2032 | 1989 |
| K-P Fstat | 17.08 | 29.32 | 16.75 | 17.36 | 28.29 | 16.01 |
| Number of transactions | 3066813 | 3088425 | 3030114 | 3066813 | 3088425 | 3030114 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock by whether home buyers are moving within their CBSA or into a new CBSA. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t + h$ and the annual change in purchase shares for time $t - 1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

There is a stark difference in the first-time homebuyer response when comparing households who purchase their first home within the CBSA they currently inhabit and those who move to a different CBSA. Table 1.6 reports the estimated IV coefficients for the different migration populations. The IV specification is the same from Equation 1.2, but changes the numerator of the dependent variable to buyers who move within their CBSA and to buyers who move into a different CBSA. Columns (1)–(3) report the estimated coefficients for the within-CBSA buyers and Columns (4)–(6) report the estimated coefficients for the buyers who move into their new CBSA.

One might expect a stark difference when comparing CBSAs with different levels of supply elasticities, since, we would observe larger effects in areas with lower supply elasticities, i.e., areas with a lower housing quantity increase in response to a price increase. Surprisingly, this is not exactly the case. Table A7 presents the results where the sample is divided between CBSAs with above and below median housing supply elasticities from Baum-Snow and Han (2024). The housing supply elasticities used are those aggregated at the MSA-level. To convert the geography level to the CBSA-level, I merge in the county using a data crosswalk from the Centers for Medicare and Medicaid Services, and merge in the CBSA using a data crosswalk available via the NBER. The results are mixed given that the estimated coefficients are larger for high supply elasticity CBSAs for the one and two-month horizons, while we observe the expected result for the three-month horizon. These results may be explained in that the regressions focus on a short-run horizon rather than a long-run horizon. Additionally, the results in the table confirm that the impact of mortgage rate changes on first-time home buyer shares is not driven by housing supply elasticities.

## 1.4 Model

I construct a quantitative life-cycle model with a housing ladder, a system of housing-related taxes, a negatively-skewed income process with uninsurable income risk, and long-term mortgage debt. Interest rates are exogenous and house prices clear the market at each point in time.

### 1.4.1 Environment

Time is discrete and indexed by $t$ while age is indexed by $a$. Households live for $T$ periods, with one period equating to one year, and have preferences over non-durable consumption $C$ and illiquid housing $H$

$$U(C_{a,j,t}, H_{a,j,t}) = \frac{C_{a,j,t}^{1-\gamma}}{1-\gamma} + \phi H_{a,j,t}$$

where $\gamma$ is the risk aversion parameter and $\phi$ is the housing taste parameter. In each period, households receive working or retirement income and make consumption, savings, and housing decisions to maximize utility over their remaining life. Households are heterogeneous in their age, wealth, income state, moving state, housing state, and the age at which they purchased their most recent house. Without loss of generality, denote a household's state with $j$. The economy is made up of a unit mass of overlapping generations of these $j$ heterogeneous households.

At the beginning of each period, new working households are born, shocks are realized, and then income is earned. Households then make consumption and housing decisions, which clears the housing market, and realize utility. The period ends with households aging one year—those who lived for $T$ periods with terminal wealth $A_j$ and housing $H_j$ realize utility with a bequest benefit

$$\frac{B_0}{1-\gamma}\left(A_j + p_t H_j + B_1\right)^{1-\gamma}$$

where $p_t$ is the housing price, $B_0$ is the bequest motive multiplier, and $B_1$ is the bequest motive shifter. The housing portion a household's bequest benefit is sold at market price $p_t$. Households begin their working life as a renter with no ownership of housing, zero liquid wealth, at a random income state, and no desire to move. Only after their first working year are moving shocks realized. In each period $t$, age $a$, and state $j$, households maximize expected remaining lifetime utility

$$E_t\left[\sum_{k=a}^{T}\beta^{k-a}U(C_k, H_k) + \beta^{T-k}B(A_T, H_T)\right].$$

In each working period, households earn an exogenous time-varying wage depending on their age and income state, choose how much to consume and save liquid wealth at an exogenously given risk-free rate $r = \{r^{rf}, r^b\}$. Households with positive liquid wealth earn interest $r^{rf} > 0$, while those who carry liquid debt borrow at rate $r^b$. Households begin working at age 25, retire at age 61, and reach their end of life at age 65.

### 1.4.2 Housing

The set of housing outcomes $\mathcal{H}$ comprises of four states: a renter state, a starter homeowner state, a large homeowner state, and a second-homeowner state. The aggregate stock of non-rental housing is fixed, i.e., there is no housing construction or depreciation, and non-rental housing is owned entirely by households. Following the results from Guren and Greenwald (2025), rental markets are perfectly segmented and, for simplicity, I further assume that the stock of rental housing perfectly matches rental demand and is owned by outside landlords who charge a fixed per-period rental price $q$. Given the empirical results shown in Appendix Figure A3 that the majority of the response to changes in the house price-to-rent ratio from mortgage rate shocks are due to house price movements and not rent price movements, I only solve for house prices and assume rental prices are exogenously set. In each period, homeowners pay property taxes on the number of total housing units they own at the current market price and tax rate $\tau^p$. Households have the option to change their housing state if they receive a Calvo moving shock with probability $\xi$. Upon receiving a moving shock, households in the renter state may choose to obtain a mortgage in order to purchase a one-unit starter home, owners of a starter home may choose to pre-pay their mortgage and sell their home in order to obtain a new mortgage to purchase a two-unit large home, owners of a large home may choose to pre-pay their large home mortgage in order to obtain a new mortgage to purchase an additional starter home to treat as their second-home, and second-home owners may choose to "downsize" by selling both their large and second-homes and obtain a new mortgage to purchase a new large home. Mortgages originated in time $t$ at age $b$ with an initial balance of $M_0$ amortize over the course of a household's remaining life with interest rate $r_t^m > r^{rf}$ and fixed payments

$$x = \left( \frac{M_0}{T-b} \sum_{a=b}^{T} (1 + r^m_{t-(a-b)})^{a-b+1} \right)^{-1}.$$

Moving households are subject to a variable moving cost $c_m$, and pre-paying a mortgage entails paying off the remaining balance plus $c_p$ percent of the remaining balance. Any housing returns are also subject to a capital gains tax of $\tau^{cg}$. Houses are homogenous in all but their unit size and provide flow utility of $\phi$ times the total number of units owned. For simplicity, I abstract away from any additional consumption benefits that typical owner-occupied housing may provide over rental housing and assume that rental units provide the same consumption utility as a starter home.

When originating a mortgage for a home of unit size $H$ and price $p$, households make a downpayment $\theta^{LTV}pH$, borrow $M_0 = (1-\theta^{LTV})pH$, and must satisfy a debt-to income (DTI) ratio

$$\frac{M_0 r^m + \mathbb{I}(A<0)\cdot |A| r^b + \tau^p p H^{total}}{Y} \leq \theta^{DTI}$$

where $Y$ is the households pre-tax income, $\tau^p$ is the property tax rate, $H^{total}$ is the total number of housing units owned, and $\theta^{DTI}$ is the maximum DTI ratio. The DTI constraint tells us that the household's financial obligations relative to their pre-tax income cannot be too high. To satisfy the DTI constraint, the sum of household's mortgage payment, liquid debt payment, and total property tax payments scaled by their income must not exceed $\theta^{DTI}$.

### 1.4.3 Income process

Pre-tax income follows a simplified and discretized version of the benchmark process recommended in Guvenen et al. (2021). Income follows a Markov process which varies by age. As shown in Equation 1.3, age $a$ income for household $j$ consists of a lifecycle component $g(a)$, discretized states combining the persistent $z_a^j$ and transitory shocks $\epsilon_a^j$, and an additional individual time-varying transitory effect $\beta_a^j$ drawn from $\mathcal{N}(0, \sigma_\beta)$. The persistent component $z_a^j$ follows an AR(1) process (Equation 1.4) with shock $\eta_a^j$ drawn from a mixture of normals (Equation 1.5). The transitory component $\epsilon_a^j$ is an innovation also drawn from a mixture of normals (Equation 1.6). First, I discretize the persistent and transitory shocks into three bins each using quadrature methods. I apply Tauchen's method (Tauchen (1986)) over the mixture-quadrature nodes to create the transition matrix for the persistent shocks. I then use K-means clusters to collapse the joint income distribution of persistent and transitory shocks for each working year into three bins. Transitioning between the income states across time follows a Markov process which varies over time.

$$Y_{a,j} = \exp\{g(a) + \beta_a^j + z_a^j + \epsilon_a^j\} \tag{1.3}$$

$$z_a^j = \rho^p z_{a-1}^j + \eta_a^j \tag{1.4}$$

$$\eta_a^j \sim \begin{cases} \mathcal{N}(\mu_{\eta 1}, \sigma_{\eta 1}) & \text{with prob. } p_z \\ \mathcal{N}(\mu_{\eta 2}, \sigma_{\eta 2}) & \text{with prob. } 1 - p_z \end{cases} \tag{1.5}$$

$$\epsilon_a^j \sim \begin{cases} \mathcal{N}(\mu_{\epsilon 1}, \sigma_{\epsilon 1}) & \text{with prob. } p_\epsilon \\ \mathcal{N}(\mu_{\epsilon 2}, \sigma_{\epsilon 2}) & \text{with prob. } 1 - p_\epsilon \end{cases} \tag{1.6}$$

For simplicity, I do not include non-employment shocks nor do I include individual fixed effects which are present in the benchmark process in Guvenen et al. (2021). I am able to generate negative skewness and high kurtosis in my discretized version of the process without them. Secondly, if one were to include the time-varying component in the model, one would need to track this in the backward induction code, which would add to the already significant state space. Finally, one could discretize the persistent and transitory innovations separately, but that would increase the state space to more than what is necessary to generate the income process with negative skewness and high kurtosis.

Income is taxable following a progressive tax function 1.7 as in Heathcote et al. (2017) and Guren et al. (2021a). Additionally, households with mortgages deduct mortgage interest payments from their current mortgage balance $M_{a,b}$ (where $a$ is their current age and $b$ is their age at origination) from their taxable income. Once households reach retirement age, their remaining income stream is a constant fraction of the income from their last working age. Specifically, I set retirement log income to the last working age income minus $\rho$. Finally, income is scaled so that mean post-tax income, absent any mortgage interest deduction, is one.

$$\text{Post-tax income} = \begin{cases} \tau(Y_{a,i}) = Y_{a,i} - \tau_0 Y_{a,i}^{1-\tau_1}, & H = 0 \\ \tau(Y_{a,i} - M_{a,b}r^m) = (Y_{a,i} - M_{a,b}r^m) - \tau_0(Y_{a,i} - M_{a,b}r^m)^{1-\tau_1}, & H > 0 \end{cases} \tag{1.7}$$

### 1.4.4 Household decisions

Every period, households make consumption and housing decisions. The exogenous state variables for households are their age, income state, and their moving state, and the endogenous state variables are their liquid wealth, housing state, and age at which they purchased their current house. Consequently, the latter two along with the household's age imply the level of their mortgage balance and their constant mortgage payments.

First, consider a renter at age $a$ who enters time $t$ with liquid savings $A_{a-1,i_{t-1},h=0,t-1}$ and income state $i$ who earns pre-tax income $Y_{a,i}$. If they choose to stay as a renter, they pay rent $q$ to live in a one-unit home owned by some outside landlord and choose consumption $C_{a,i,h=0,t}$ to maximize flow and remaining lifetime utility subject to their budget constraint

$$C_{a,i,h=0,t} + A_{a,i,t} = \tau(Y_{a,i}) - q + A_{a-1,i_{t-1},t-1}(1+r).$$

If the renter receives a moving shock, is able to satisfy the DTI constraint, and chooses to climb the housing ladder, they make a downpayment $\theta^{LTV}$ to originate a fixed-rate mortgage with mortgage rate $r_t^m$ where they will make constant annual payments $x_{a,b}^{h=1}(r_{t-(a-b)}^m)$ over the course of their remaining life to purchase a one-unit home at price $p_t$.[3] They will pay a one-time moving cost $c_m p_t$ and start paying property taxes every period. Finally, they choose consumption $C_{a,i,h=1,b,t}$ to maximize flow and remaining lifetime utility subject to their budget constraint

[3]Note that $b$ is the age of mortgage origination, so the household's reference mortgage rate is $r_{t-(a-b)}^m$.

$$\begin{aligned}C_{a,i,h=1,b,t} + A_{a,i,h=1,b,t} = {} & \tau(Y_{a,i} - M_{a,b}r_t^m) + A_{a-1,i_{t-1},t-1}(1+r) \\ & - \theta^{LTV}p_t - x_{a,b}^{h=1}(r_{t-(a-b)}^m) - c_m p_t - \tau^p p_t.\end{aligned}$$

Next consider an age $a$ household who enters period $t$ owning a starter home purchased at age $b$ with liquid savings $A_{a-1,i_{t-1},h=1,b,t-1}$ and in income state $i$. If they choose to stay as a starter owner, they continue to pay down their mortgage and choose consumption $C_{a,i,h=1,b,t}$ to maximize flow and remaining life utility subject to their budget constraint

$$\begin{aligned}C_{a,i,h=1,b,t} + A_{a,i,h=1,b,t} = {} & \tau(Y_{a,i} - M_{a,b}r_{t-(a-b)}^m) + A_{a-1,i_{t-1},h=1,b,t-1}(1+r) \\ & - x_{a,b}^{h=1}(r_{t-(a-b)}^m) - \tau^p p_t.\end{aligned}$$

If the household receives a moving shock, satisfies the DTI constraint for a large, two-unit home mortgage, and chooses to purchase a new two-unit home, they will prepay their original mortgage and face a prepayment penalty $c_p$,sell their starter home and pay a capital gains tax on their housing returns, pay a moving cost, and obtain a new mortgage in order to purchase their new home while choosing consumption $C_{a,i,h=2,b,t}$ to maximize flow and remaining lifetime utility subject to their budget constraint

$$\begin{aligned}C_{a,i,h=2,b,t} + A_{a,i,h=2,b,t} = {} & \tau(Y_{a,i} - M_{a,b}^{h=2}r_{t-(a-b)}^m) + A_{a-1,i_{t-1},h=1,b,t-1}(1+r) \\ & - 2\theta^{LTV}p_t - x_{a,b}^{h=2}(r_{t-(a-b)}^m) \\ & - M_{a,b}^{h=1}(1+c_p) + (p_t - \tau^{cg}(p_t - p_{orig})) - 2c_m p_t - 2\tau^p p_t.\end{aligned}$$

Next consider an age $a$ household who enters period $t$ owning a large home purchased at age $b$ with liquid savings $A_{a-1,i_{t-1},h=2,b,t-1}$ and in income state $i$. If they choose to stay as a large home owner, they continue to pay down their mortgage and choose consumption $C_{a,i,h=2,b,t}$ to maximize flow and remaining life utility subject to their budget constraint

$$\begin{aligned} C_{a,i,h=2,b,t} + A_{a,i,h=2,b,t} = &\ \tau(Y_{a,i} - M_{a,b}r^m_{t-(a-b)}) + A_{a-1,i_{t-1},h=2,b,t-1}(1+r) \\ &- x^{h=2}_{a,b}(r^m_{t-(a-b)}) - 2\tau^p p_t. \end{aligned}$$

If the household receives a moving shock, satisfies the DTI constraint for a one-unit home mortgage, and chooses to purchase a one-unit home to be their vacation (second) home, they will pre-pay their original large home mortgage and obtain a new mortgage in order to purchase their secondhome. The second-home owners will make property tax payments for both of their homes and also list their home for short-term rentals for a part of their receiving an income of $w_{2nd}$. Given this action, they will choose consumption $C_{a,i,h=3,b,t}$ to maximize flow and remaining lifetime utility subject to their budget constraint

$$\begin{aligned} C_{a,i,h=3,b,t} + A_{a,i,h=3,b,t} = &\ \tau(Y_{a,i} - M^{h=1}_{a,b}r^m_{t-(a-b)}) + A_{a-1,i_{t-1},h=1,b,t-1}(1+r) \\ &- \theta^{LTV} p_t - x^{h=1}_{a,b}(r^m_{t-(a-b)}) \\ &- M^{h=2}_{a,b}(1+c_p) - 3c_m p_t - 3\tau^p p_t + w_{2nd} \end{aligned}$$

Finally, consider an age $a$ household who enters period $t$ owning a large home and a home purchased at age $b$ with liquid savings $A_{a-1,i_{t-1},h=3,b,t-1}$ and in income state $i$. If they choose to stay as an large home owner, they continue to pay down their mortgage and choose consumption $C_{a,i,h=3,b,t}$ to maximize flow and remaining life utility subject to their budget constraint

$$\begin{aligned} C_{a,i,h=3,b,t} + A_{a,i,h=2,b,t} = &\ \tau(Y_{a,i} - M_{a,b}r^m_{t-(a-b)}) + A_{a-1,i_{t-1},h=2,b,t-1}(1+r) \\ &- x^{h=2}_{a,b}(r^m_{t-(a-b)}) - 3\tau^p p_t + w_{2nd}. \end{aligned}$$

If the household receives a moving shock, satisfies the DTI constraint for a two-unit home mortgage, and chooses to downsize from a large home and second home to a new large, two-unit home to be their second-home, they will pre-pay their second-home mortgage, sell both of their homes, and obtain a new mortgage in order to purchase their new two-unit home. Given this action, they will choose consumption $C_{a,i,h=2,b,t}$ to maximize flow and remaining lifetime utility subject to their budget constraint

$$\begin{aligned} C_{a,i,h=3,b,t} + A_{a,i,h=3,b,t} &= \tau(Y_{a,i} - M_{a,b}^{h=1} r_{t-(a-b)}^{m}) + A_{a-1,i_{t-1},h=1,b,t-1}(1+r) \\ &- 2\theta^{LTV} p_t - x_{a,b}^{h=2}(r_{t-(a-b)}^{m}) \\ &- M_{a,b}^{h=1}(1+c_p) - 3c_m p_t - 2\tau^p p_t. \end{aligned}$$

### 1.4.5 Stationary Equilibrium

Given an exogenous set of interest rates $\{r^{rf}, r^b, r^m\}$ and tax rates $\{\tau^p, \tau^{cg}, \tau_0, \tau_1\}$, a fixed stock of housing, a stochastic income process with an initial income distribution, and a set of moving shocks, a competitive equilibrium consists of house prices $\{p_t\}$, aggregate allocations $\{H_t\}$, and decision functions $\{\sigma_C(C_t(a,w,h,m)), \sigma_H(H_t(a,w,h,m))\}$ such that households optimize, housing markets clear, and cross-sectional distributions are consistent with household behavior.

### 1.4.6 Solution method

All households are forward-looking and have perfect foresight. I first use backward induction to calculate a household's consumption and housing policy function at each given state and age for some house price. I then simulate the model 250,000 times over the entire course of their working and retired lives. I define each simulation-age pair as an instance. Given the large number of simulations and that the model is in a stationary equilibrium, I treat each instance as an individual household in the economy with each household receiving equal weight, although some instances occur many times, such as the first-working age instance where households wake up as renters with zero liquid wealth and divided equally across the different income states.

A simulation-age pair instance or household that lives in a starter home owns one unit of housing, a household that lives in a large home owns two units of housing, and a household that lives in a large home and owns a second-home owns three units of housing. Renters own zero units of housing. I calculate the total stock of owned housing units per household by summing the number of total units owned in the economy across simulation-age pair instances and divide by the number of simulations times the total number of years households live to calculate the total stock of homes per household in the economy.

By construction, the intra-temporal demand for housing equals the intra-temporal supply of housing because for each simulation-age pair that increases the amount of housing they own, there exists another simulation-age pair (later on in that simulation's "life") that sells or dies with that same amount of housing—a feature one would expect within a stationary equilibrium. However, the total stock of owned housing units in the model changes in response to the house price. Thus, to solve for the equilibrium house price, I solve for the price which matches the calibration target of 1.14 units of owned housing per household. Note that by targeting the total number of homes per household, I allow the homeownership rate to vary. Alternatively, the homeownership rate can be targeted instead.

The solution method for the model where I apply a negative 1 p.p. "MIT" shock to the mortgage rate with low persistence is similar to the solution method for the stationary equilibrium. First, I solve the model for the stationary equilibrium prior to the mortgage rate shock. Then I take the exogenously given mortgage rate path and guess a corresponding house price for some horizon $T_h$ and use backward induction again to calculate a household's consumption and housing policy function at each given state, age, and post-shock time period. I then do a forward sweep and simulate the model again for both existing households prior to the mortgage rate shock and new households who are born after the shock. Each newborn household "replaces" a household who dies and faces the same set of lifecycle shocks without *ex ante* knowledge of receiving them. By doing this, I am able to compare households in the post-shock state to their counterfactual pre-shock stationary equilibrium versions.

### 1.4.7 Calibration

Table 1.7 reports the parameters for the model. Each period in the model represents one year so the discount factor is set to 0.96. The risk-free rate for positive liquid wealth saving is 2% and the borrowing rate is 25%—similar to that of a credit card for revolving debt. The tax function is calibrated as in Heathcote et al. (2017) and Guren et al. (2021a) where the scalar is set to $\tau_0 = 0.8$ and the parameter guiding the curvature of the function is set to $\tau_1 = 0.18$. The parameter that guides log income decline in retirement $\rho$ is set to 0.35 as in Guren et al. (2021a).

Table 1.7: Calibration of Main Parameters

| Parameter | Value | Description | Parameter | Value | Description |
|---|---|---|---|---|---|
| $\beta$ | 0.96 | Discount factor | $\phi$ | 0.4 | Housing taste |
| $\gamma$ | 2 | CRRA | $\theta^{DTI}$ | 0.45 | Maximum Debt-to-Income |
| $r^f$ | 2% | Risk-free rate | $\theta^{LTV}$ | 20% | Downpayment |
| $r^b$ | 25% | Borrowing rate | $\tau^p$ | 1% | Property tax |
| $\rho$ | 0.35 | Log income decline in retirement | $c_m$ | 3% | Variable moving cost |
| $\tau_0$ | 0.8 | Constant in tax function | $c_p$ | 1% | Variable pre-payment cost |
| $\tau_1$ | 0.18 | Curvature in tax function | $\tau^{cg}$ | 15% | Capital gains tax on home sales |
| $B_0$ | 85 | Bequest multiplier | rent | 0.1021 | Minimum pre-tax income value |
| $B_1$ | 1.75 | Bequest additive scalar | $w_2$ | rent/24 | Income from 2nd home |
| | 36 | Working years | $\xi$ | 50% | Moving shock |
| | 5 | Years retired | | 1.14 | Total house supply per household |
| **Stationary equilibrium targets** | | | **Transition target** | | |
| | **Value** | **Description** | | **Value** | **Description** |
| | 62.4% | Homeownership rate | | 3% | Initial 1st-time buyer purchase shr. change |
| | 8.5% | Incumbent homeowner moving rate | | | |

Notes: Benchmark parameter values used in the baseline calibration.

Rent is set to the lowest working-age pre-tax income value before accounting for any time-varying individual heterogeneity, implying that low income retired renters will need to save to account for rent exceeding their retirement income. $\rho$ which governs retirement income is taken from Guren et al. (2021a). The LTV constraint parameter $\theta^{LTV}$ is set to 20% which is the most common LTV ratio used, implying that households face the same mortgage rate and do not make additional payments for PMI, and the DTI constraint parameter $\theta^{DTI}$ is set to 0.45 given the bunching observed in Figure 1.7. Although, this parameter is different from that set in Greenwald (2018) which sets the maximum DTI to 36% and compares the model results to a maximum DTI of 43%, it does not affect the results by much—however, like in Greenwald (2018) the model confirms that higher DTI maximums work well as a countercyclical tool. The variable moving and prepayment penalty costs are also taken from Guren et al. (2021a). The bequest multiplier $B_0$ and bequest shifter $B_1$ parameters guide the utility weight and the motive for bequests, respectively. Increasing $B_0$ incentivizes additional bequest saving and increasing $B_1$ raises the luxury status of bequests, lowering the incentives to make smaller bequests. The parameters are set to values from the lifecycle model in Guren et al. (2021b). The median net-worth for households age 60 relative to households age 45 is 2.4, similar to the 2.1 value in Guren et al. (2021a).

Finally, the housing taste parameter $\phi$, the Calvo moving shock parameter $\xi$, and the constant income from short-term rentals of a second-home parameters are jointly used to calibrate the model to match a homeownership rate of 62% in the stationary equilibrium absent the MIT shock, the homeowner moving rate who moves once every twelve years according to Redfin data,[4] and to match the main empirical results. I choose to estimate the model with an equilibrium mortgage rate set at 5%. The homeownership rate target and the mortgage rate chosen match the U.S. national average in the beginning of 2010. Though housing taste parameter is high compared to the values used in Guren et al. (2021b) and Guren et al. (2021a), the reason for this is to encourage large homeowners to purchase additional housing. The higher housing taste parameter raises the flow utility from housing, overcoming the financial burden of purchasing an additional housing unit at the end of a household's life which could instead be used for additional consumption. In this model, low housing taste parameter values are sufficient to encourage starter and large home purchases, but they lower the incumbent homeowner moving rate and provide insufficient incentives to encourage purchasing second-homes which are typically purchased closer to a household's end of life. On the other hand, a housing taste parameter that is too high incentives too much additional, non-primary home purchases and lowers the homeownership rate. An untargeted moment, the price-to-rent ratio, is about 23 which is comparable to Austin, Texas in the mid-2010s.

I calibrate the income process to match the second and third moments of five-year income growth for median income earners using data provided in the Guvenen

[4]`https://www.redfin.com/news/homeowner-tenure-2022/`

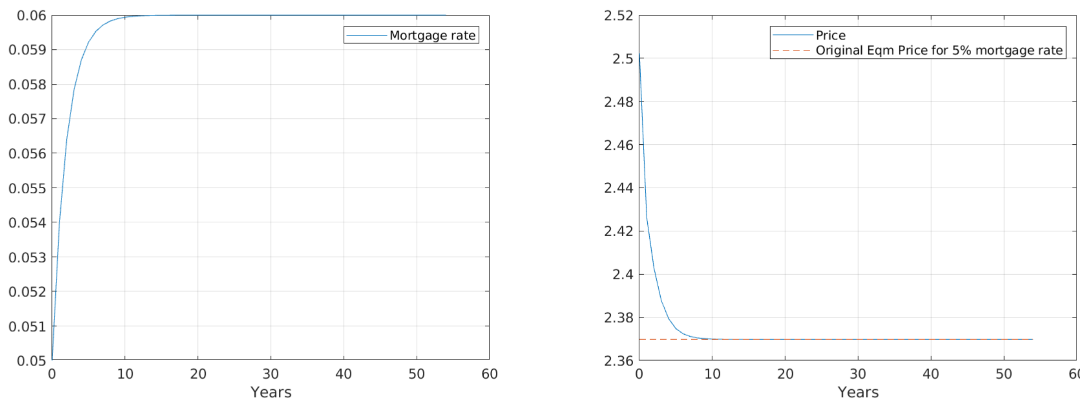
et al. (2021)'s supplementary files as shown in Appendix Table A9. As mentioned in their paper, discretizing their process is difficult because the nonnormalities raises the possibility of needing irregular placement for the grid points. In an attempt to overcome this, I adjust the width of the state space for the persistent shock to be 1.18 standard deviations of the stationary distribution. Although this is small, it can be enlarged when increasing the number of income states. I also adjust the probability of receiving the transitory shock $p_\epsilon$ to 0.353 and the standard deviation of the first set of normals governing the transitory shock $\sigma_{\epsilon 1}$ to 0.35. The rest of the parameter values are taken from Guvenen et al. (2021)'s recommended Model 6 values, though the process is robust to values taken from the other models in their paper. $\mu_{\eta 2}$ and $\mu_{\epsilon 2}$ are calculated such that the innovations have mean zero. Appendix Table A8 reports all of these values.

### 1.4.8 Model results

Assuming a pre-shock stationary equilibrium mortgage rate of 5%, I apply a negative 1 p.p. shock to the mortgage rate with low persistence following the process $\eta_t = 0.6^{t-1}\eta_0$ where $\eta_0 = -1$. After the initial shock period, mortgage rates quickly converge back to their stationary equilibrium level of 5% as shown in Figure 1.8 Panel (a). All households have perfect foresight, so the mortgage rate and house price paths are known. Panel (b) plots the price path dynamics which are the market prices setting demand equal to supply for each post-shock period. Knowing that mortgage rates will rise after the initial shock, household demand for housing increases which raises prices as shown in Panel (b). We can see that housing demand at the time of the shock is higher than housing demand in the stationary equilibrium with a 4% mortgage rate because the initial house price level is higher than the stationary equilibrium price level with a 4% mortgage rate.

Figure 1.9 plots the transition path of the first-time buyer share of home purchases. In the initial shock year, the first-time buyer share falls by 2.8%, in line with the empirical results. The rebound in first-time home purchases three years after the shock reflects the increase of first-time homebuyers entering the market relative to in-

Figure 1.8: Mortgage rate and price paths




(a) Mortgage rate path (b) Price path

*Notes*: Panel (a) plots the mortgage rate path and Panel (b) plots the price path for post-mortgage rate shock horizons 0 to 55 years.

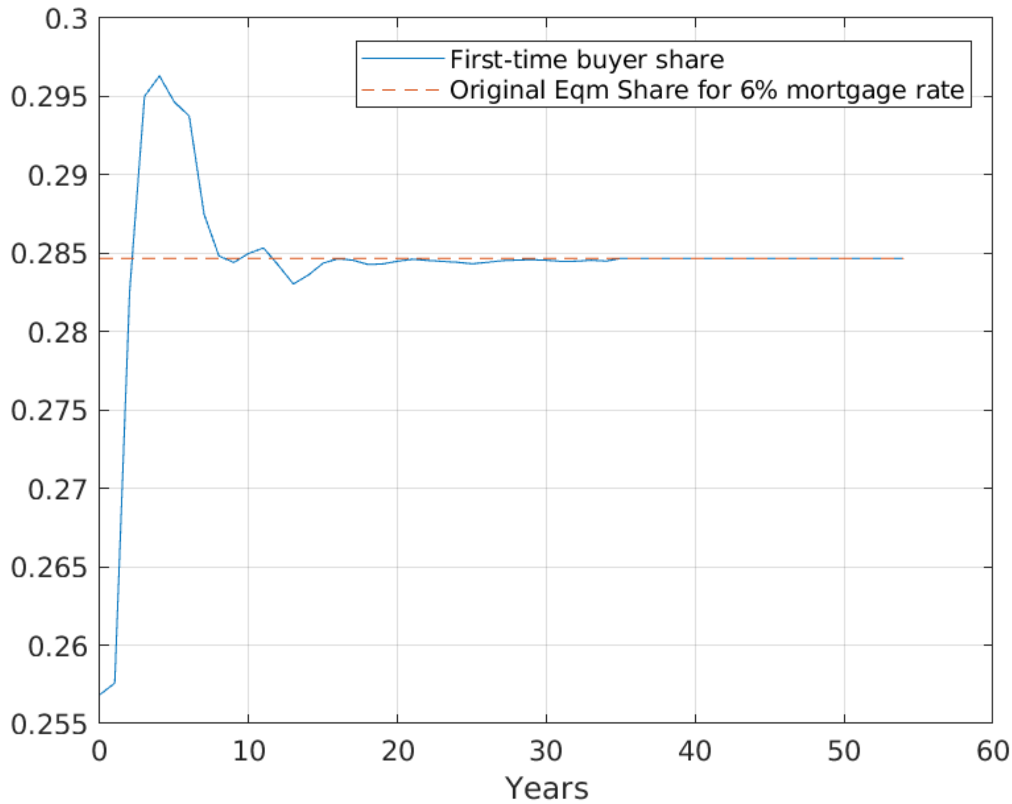
cumbent homeowners. This spike occurs because many incumbent homeowners their next home purchase earlier in their lifecycle to take advantage of the low mortgage rates. As mortgage rates rise and prices fall back to their pre-shock levels, we see that the renter share rises back to its pre-shock level as well.

Following Chatterjee et al. (2007), I calculate consumption-equivalent welfare by finding the percent change to consumption in all periods in the no shock scenario such that households are indifferent between the no shock scenario and the shock scenario. I do this by housing status prior to the shock and denote $\lambda$ as the consumption change scalar

$$\frac{\sum_i \sum_{a=1}^{T} \sum_{s=a}^{T} \beta^{s-a} U\left((1+\lambda) \cdot C_{i,a,s}, H_{i,a,s}\right)}{\sum_i \sum_{a=1}^{T} \sum_{s=a}^{T} \beta^{s-a} \cdot U\left(C'_{i,a,s}, H'_{i,a,s}\right)} = 1.$$

Figure 1.10 below compares the mean post-shock welfare of households by pre-shock housing status relative to the no-shock world. I define a household's welfare as their lifetime's remaining utility at the time of the shock (happy to discuss welfare definitions more). Households who are renters at the time of the shock are -.1% worse off relative to renters in the no-shock world, while households who owned starter homes at the time of the shock are the biggest winners receiving welfare gains of 0.24% on average. Households who own large homes and households who own large

Figure 1.9: First-time buyer share impulse response



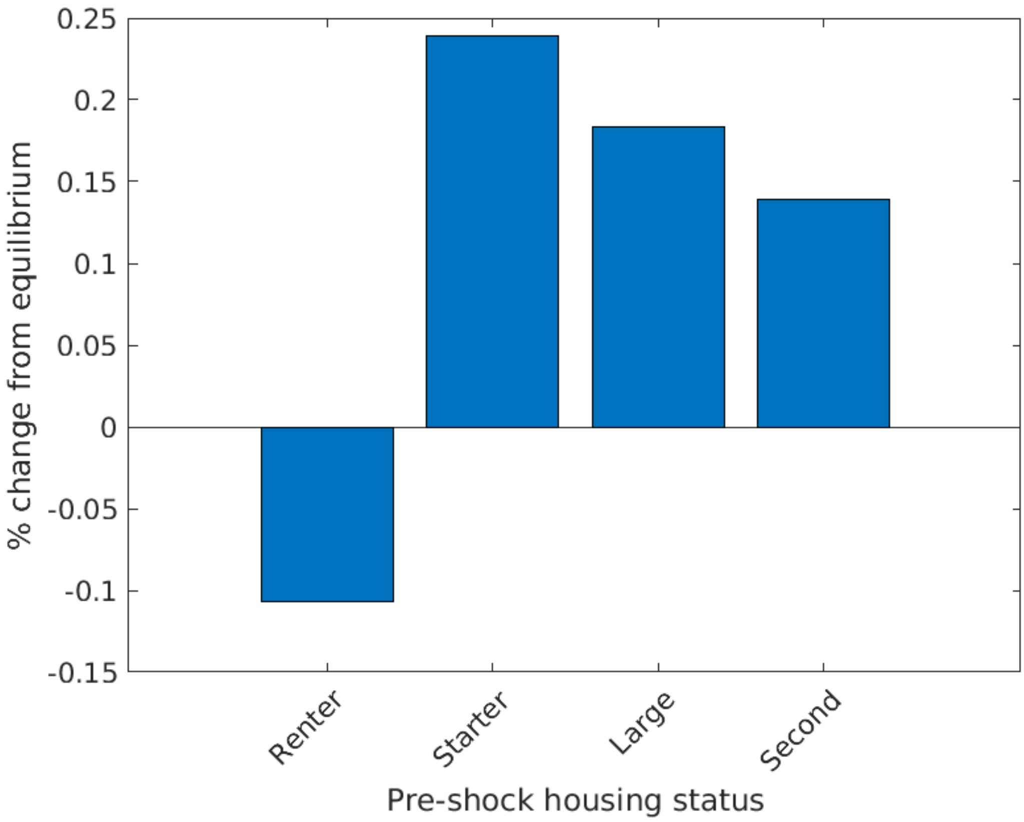

*Notes*: The figure plots the transition path of the first-time buyer share of home purchases for post-mortgage rate shock horizons 0 to 55 years

and multiple homes receive welfare gains of 0.18% and 0.13%, respectively. Overall, the model results clearly depict that there are in fact, winners and losers of mortgage rate decreases. Households without housing wealth are worse off due to the price increases and households with housing wealth are better off.

### 1.4.9 Counterfactual policies

In this subsection, I explore a set of tax-related and subsidy-related counterfactual policies. The tax-related policies explored raise the relative cost of housing for second-home owners which dampens their demand for additional housing and mutes the price effects from mortgage rate decreases. I find that raising property taxes on non-primary homes reduces equilibrium prices and mutes the price response to mortgage rate shocks. Raising the capital gains tax for second home sales has similar, but smaller

Figure 1.10: Relative welfare to pre-shock stationary equilibrium




*Notes*: The figure plots the consumption-equivalent gains and losses for households of different housing status (prior to the mortgage rate shock) relative to their no-shock stationary equilibrium versions.

price effects. Note that due to the construction of the model, prices are constant in equilibrium, implying that capital gains on housing are zero in equilibrium. If price dispersion were introduced, capital gains tax policy may be more effective in lowering house prices. Removing mortgage interest deduction for second homes has the lowest impact on prices. Overall, these price results are similar to those in Coven et al. (2025).

In future versions of this paper, I will explore subsidy-related counterfactual policies. Providing a downpayment subsidy for first-time buyers, such as those proposed by recent presidential candidates, will increase potential first-time buyers' abilities to purchasing their first home—though their increased housing demand will generate a price increase, lowering their future consumption. I suspect that raising property taxes and capital gains tax rates for second-homeowners will generate higher welfare gains for potential first-time home buyers in the event of a mortgage rate decrease relative to providing the equivalent of a \$10,000 subsidy for downpayment assistance.

### 1.4.10 Discussion

This paper attempts to capture as many of the benefits and nuances of housing as feasibly possible. A home provides many benefits for its owners, since it is a unique financial asset which is also consumed. On the consumption side, households derive flow utility from living in their dwelling. A key feature in the model is that households derive additional utility from larger homes and from vacation homes. Unfortunately, due to limits in working with a feasible state space, the model leaves out housing quality which is left for future work—though this is not believed to be of first-order importance.

On the financial side, paying down a mortgage in the US, which typically has a fixed mortgage rate and monthly payments, is not subject to rental market price increases. Mortgage amortization schedules also serve as a savings plan critical for wealth building (Bernstein and Koudijs (2024)). Once a mortgage is paid off, the owners essentially receive a dividend payment in the form of a \$0 rental payment. Finally, homes are unique as a financial asset with many tax benefits. First, primary and second-home mortgage payers may deduct up to \$750,000 of mortgage interest payments from their taxes—increasing the flow returns from "saving" into their housing wealth. Second, selling a home often yields capital gains subject to capital gains taxes. However, there exist tax exemptions for sales on primary homes. Single filers are exempt from capital gains taxes on the first \$250,000, while married filers are exempt on the first \$500,000. Additionally, occupying a second-home for over two weeks allow owners to claim the home as their primary residence—enabling them to take advantage of the capital gains tax exemption as well.

Though this paper studies the welfare impact of capital gains taxes, it does not look at capital gains tax exemptions. To include this feature in the model, one would need to add price dispersion in the model. Unfortunately, this greatly increases the state space because one would need to keep track of prices for both primary and secondary homes that are purchased and sold—making it difficult to study when looking at transition dynamics. However, when comparing stationary equilibrium with high and low mortgage rates and calibrating the exemptions to pre-Covid levels I find that removing exemptions for second-homes is welfare improving for renters because equilibrium prices fall, easing the path to homeownership. Finally, when a homeowner passes away and their home is bequeathed, the cost-basis is reset to the market value at time of death instead of the original purchase price. The model assumes that homes are sold immediately upon death and thus no capital gains taxes are paid.

This paper ignores the existence of trusts which are a useful tool for passing down wealth to future generations with large tax benefits, because to study them properly, one would need to adjust the lifecycle model to allow for legacy households who inherit properties and wealth at some point in their lifetime—further complicating the model. Additionally, this paper has an income process that does not vary as mortgage rates change. Accounting for the increasing income gap would likely augment the model results as renters would face increased sensitivity to the LTV constraint, suggesting that the welfare implications are in fact a lower bound.

The main model results compare outcomes from a stationary equilibrium to the transition dynamics caused by applying a transitory MIT shock to mortgage rates—however, in reality, we likely are never in a true stationary state. Just as Eichenbaum et al. (2022) and Berger et al. (2021) demonstrate a strong state and path-dependency in the consumption response to a fall in mortgage rates, further research is needed to understand the state-dependent nature of the disparate impact monetary policy transmits to first-time and incumbent home buyers.

Finally, the constructed model is tailored to answer questions for contexts when the demand impact of mortgage rate changes exceeds the impact on supply—a feature which on average is consistent with the data as seen from the empirical results. As a result, we are able to study periods such as the early 2020s when we observed record-low mortgage rate levels leading to high house price growth. However, when mortgage rates rose in 2022 and 2023, prices did not fall, a feature the current calibrated model does not capture. This is likely a result of several economic forces. First, households' expectations matter. Households may have expected only a short period of high mortgage rates with the hope that the high federal funds rate would cause inflation to quickly fall—consequently causing a fall in the short rate and a fall in the longer end of the yield curve. If households were to assume high mortgage rates for a short period of time, they may believe that the option value to not selling in a high rate period and waiting to sell in a low mortgage rate period exceeds the value of selling in the high mortgage rate period. If households were aware of the long high mortgage rate period *a priori* we would likely have observed lower prices. Though I am not aware of any paper that demonstrates this, the model in this paper can be adjusted to show this by adding an additional "sell option state" where incumbent home buyers have the option to wait on selling their previous home—effectively limiting the housing supply. I plan to investigate this further in future research. This phenomenon of higher vacancy levels and higher prices is contrary to Wheaton (1990) because it is a transitory outcome not an equilibrium outcome. Second, Fonseca et al. (2024) argue that high housing demand during low mortgage rate periods "lock-in" households during high rate periods, consequently lowering mobility. The lower mobility decreases downsizing and exits from homeownership, which raises net demand for housing and, as a result, prices.

## 1.5 Conclusion

In this paper, I first establish that that transacted house prices respond to monetary policy-induced mortgage rate changes within a matter of weeks, indicating that housing demand and transacted house prices respond to mortgage rate changes faster than previously believed in the literature. Then I show a positive relationship between mortgage rates and the first-time homebuyer share of home purchases estimating that an exogenous negative 0.25 b.p. shock to mortgage rates reduces the first-time home buyer share by 77 b.p.s. These results are more pronounced in areas with higher shares of high LTV buyers, suggesting that a very responsive incumbent homeowner demand and higher down payment frictions due to lower mortgage rates relatively price-out potential first-time home buyers. The link demonstrates the direct impact of monetary policy transmission through the mortgage channel to first-time home buyers. To estimate these results, I construct a new mortgage rate-specific monetary policy shock using intraday 10-year Treasury and MBS transactions data.

To quantify the welfare impact from an exogenous mortgage rate reduction, I construct a quantitative lifecycle model with heterogenous agents that incorporates a housing ladder and a negatively-skewed income process. Agents differ in their housing, income, wealth, age, and age of home purchase states. I find that applying a negative one p.p. transitory MIT shock to mortgage rates with low persistence to my calibrated model lowers potential first-time buyers' consumption-equivalent welfare by 0.05%. The model results indicate that 1) large homeowners and multiple homeowners benefit much more from mortgage rate reductions than first-time buyers, and 2) lower mortgage rates fail to provide consumption-equivalent welfare benefits for first-time homebuyers due to the house price increases caused by increased housing demand from lower mortgage rates.

Overall, my results suggest that central banks should be aware of the power that forward guidance and Quantitative Easing pass-through have on housing demand through the mortgage channel and its direct implications on growing housing wealth inequality. Policies that mitigate incumbent homeowner demand swings relative to first-time buyers are solutions that likely rebalance the relative welfare outcomes between incumbent homeowners and first-time buyers.

# Chapter 2

# Racial Disparities in Home Selling

This chapter is coauthored with my friend, Lei Ma.

## 2.1 Introduction

Housing wealth is a crucial vehicle for households to build and accumulate wealth. Historically, various forms of structural discrimination have impeded Black households from entering homeownership and receiving its wealth appreciation benefits. While it might be expected that such discriminatory practices are no longer relevant today, recent research suggests that Black households continue to face higher mortgage rejection rates (Bhutta et al. (2022)), pay higher purchase prices (Bayer et al. (2017)), and realize lower total returns due to disparities in experiencing distressed property sales (Kermani and Wong (2024)).

In this paper, we focus on the home selling process and consider homes as financial assets that yield capital gains returns. One would expect that identical houses in the same neighborhood should sell for the same price and experience similar price growth over time on average. Conditional on the same property characteristics and market conditions, one would expect that the race of the homeowner should have no impact on the average selling outcomes. However, our findings suggest otherwise. We first show that racial disparities exist in the selling process and then provide empirical evidence for the underlying mechanisms driving these racial disparities. We provide several pieces of evidence that strongly suggest that the racial gap in housing returns is driven by racial differences in human intermediary practices. We believe this paper to be unique in that we demonstrate which mechanisms explain and do not explain these racial disparities.

We use repeat-sale transactions to estimate the racial gap in housing returns for regular, non-distressed sales. By comparing housing returns of properties within the same Census tract, sold in the same year and quarter, where one property is owned by a Black household and the other by a non-Black household, we effectively control for time-invariant property characteristics and market conditions. The repeat-sale approach mitigates the omitted variable bias that may be present in hedonic models. To identify the race of the sellers and buyers, we merge property transaction data with self-reported race from the Home Mortgage Disclosure Act (HMDA) data.

Using over 1.1 million repeat-sale transactions from ATTOM, a commercial data vendor that compiles nearly all property transaction data in the US, we find that Black households, on average, earn 1.74–1.88% lower total unlevered capital gains when selling their homes. To account for the varying duration of homeownership, we also calculate the annualized capital gains. Our results indicate that the annualized unlevered return gap for Black sellers ranges between -0.36% and -0.38%. These gaps are approximately 10% of the mean total and annualized returns to housing. Importantly, our analysis includes both Census tract and year-quarter sale date fixed effects, ruling out differences in neighborhood amenities and market timing as explanations for the observed racial gap.

We then explore the sources of the racial gap. Our main contributions to the existing literature are 1) identifying the specific factors that do and do not explain this racial gap and 2) demonstrating that this racial gap is systemic, caused by disparities stemming from human intermediary practices. The home-selling process involves multiple parties including sellers, potential buyers, and intermediaries such as realtors and appraisers. Discrimination can occur during interactions among these parties. Moreover, unobserved property characteristics, potentially correlated with race, can contribute to differential selling outcomes. We examine each of these factors to determine which ones contribute most to the existence of the gap.

We first examine the sellers' reasons for selling. Liquidity-constrained sellers may be willing to sell at lower prices to ease their financial constraints. To investigate this mechanism, we merge property transaction data with mortgage performance data from Black Knight McDash. Using the seller's mortgage delinquency status as a proxy for liquidity constraints, we find that the racial gap in annualized housing returns continues to exist.

We also explore whether unobserved housing quality can account for the differential returns. Although we observe a detailed set of structural property characteristics, there exist other property features that impact property values but are not observed in the data. Examples include the age of appliances, aesthetic appeal, and the number of parking spaces. To the best of our knowledge, a comprehensive dataset covering all these variables does not exist, so we focus on substantial renovations and remodeling to capture differences in housing quality. If Black homeowners systematically invest less in maintaining and renovating their homes, it would be reasonable to expect lower housing returns. We use property-level building permit data to obtain the renovation status of properties two years prior to the home sale. We find that property renovations do not explain the racial gap.

Next, we investigate whether potential racial prejudices by White buyers can explain the gap. One may speculate that White buyers hold prejudiced beliefs against Black sellers and thus offer lower prices. However, after controlling for the race of the buyer, we find that Black sellers experience lower housing returns regardless of the buyer's race. This finding suggests that any possible direct discrimination between the seller and the buyer is not a predominant factor driving the racial gap. It is also important to note that racial prejudices from potential buyers may indirectly affect this gap if they are unwilling to purchase homes from Black sellers or prefer homes owned by White sellers. Such biases would introduce additional search frictions for Black sellers to be matched with a buyer.

Given that none of the characteristics of the property, seller, or buyer explain much of the gap, we shift our focus to intermediaries. We begin by examining the role of real estate agents and brokers, who charge commission fees to sellers for their services in facilitating housing transactions. If the realtor holds prejudiced biases against Black sellers or believes that Black-owned homes are of inferior quality, they may recommend lower selling prices or exert less effort in selling the property. On the other hand, if Black sellers select agents who are less experienced or of lower quality, this can also lead to worse selling outcomes. To test the mechanism, we merge in property listing data to control for real estate agents and brokerage office fixed effects. Our findings show that controlling for real estate agents and brokerage offices only marginally reduces the racial gap.

Additionally, we examine the role of another key intermediary in the selling process: appraisers. Appraisers are expected to provide objective market valuations of properties, which can help lenders, sellers, and buyers determine a fair price. A report from Freddie Mac (Mac (2021)) finds that homes in predominantly Black neighborhoods often receive much lower appraisal values compared to similar homes in predominantly White neighborhoods. Motivated by this fact, we aim to control for the appraisal value at the time of sale. Unfortunately, we do not directly observe the actual appraisal estimates at the time of sale, so we calculate an implied appraisal value by multiplying the appraisal value at the time the seller refinances their mortgage with the tract-level house price growth rate. The implied appraisal values indicate that, on average, Black-owned homes are not valued lower than non-Black-owned homes – in fact, the implied impraisal values suggest that on average, Black-owned homes are valued more than non-Black-owned homes. Moreover, controlling for this appraisal value does not explain the racial gap.

Lastly, we examine the racial differences during the listing process. We find that Black sellers often set lower initial listing prices, reduce listing prices before the sale, offer greater price discounts between the final sale price and the listing price, and take longer to sell their properties. These patterns suggest that Black sellers may experience higher search frictions, compelling them to reduce listing prices to increase the probability of sale. Within the context of a search model framework, our findings suggest that Black sellers face a different level of market tightness than non-Black sellers, contributing to the price disparity. To test this hypothesis, we control for listing price and days on market when estimating the racial gap. Controlling for the listing price accounts for approximately three-fourths of the racial gap, and the racial gap reduces to almost zero after accounting for both factors.

However, it is important to note that the listing price is a noisy measure of a home's true market value, as it can be influenced by biases from various parties. Sellers may tie the listing price to the appraised value they observe, meaning any biases from appraisers would be reflected in the listing price. Additionally, real estate agents or sellers may lower listing prices if they believe that the market tends to discount Black-owned homes or that such homes tend to stay on the market longer. This suggests that listing prices are also influenced by differences in time on market, which are likely driven by differences in search frictions. Consequently, we argue that the estimated 25% direct contribution of search frictions in explaining the racial gap is a lower bound due to the indirect impact that longer time on market has on listing prices. When applying a stricter definition to identify potential short-sale transactions, we find that time-on-market explains 50% of the racial gap.

Overall, our results are consistent with previous studies using Department of Housing and Urban Development Discrimination Survey (HUDDS) data, which provide evidence of racial steering, agents showing Black home buyers fewer homes, and agents catering to prejudiced demands of White buyers (Ondrich et al. (1998), Yinger (1998), Galster and Godfrey (2005), Zhao et al. (2006), Christensen and Timmins (2022), and Christensen and Timmins (2023)). Each of these forces yield larger search frictions for Black sellers. To directly measure this, we combine our listings data with the publicly-available HUDDS data to construct a measure that is a form of market tightness which exhibits the severity of buyer agent discriminatory practices. Our results show that Black sellers no longer face lower housing returns relative to non-Black sellers in zip codes with higher Black buyer home visits relative to listings.

We provide additional evidence that intermediaries are responsible for the racial gap in housing returns by examining the impact of iBuyers, intermediaries who use algorithms to price and purchase homes with the goal of reselling, on housing returns. iBuyers use housing and property characteristics to price homes, removing real estate agents from the process and eliminating their influence on both search and pricing. We restrict the data to zip codes where iBuyers purchase homes, and find that homes purchased by iBuyers do not exhibit a racial gap in housing returns.

In our heterogeneity analysis, we find that the racial gap is larger in neighborhoods with longer seller search duration and when sellers face more within-neighborhood competition. Conditional on buyer demand, our results suggest that the racial gap widens when local markets are more slack. Additionally, we estimate larger racial gaps when Black sellers experience higher neighborhood-level price growth. We also provide estimates of the racial gap in neighborhoods with different socioeconomic characteristics. We categorize neighborhoods into quartiles based on their racial composition, education, income, and homeownership rate. Our findings reveal that the racial gap is economically significant in all types of neighborhoods. However, the racial gap is larger in neighborhoods with higher proportion of Black residents and lower household incomes.

Section 2 describes the data used in the analysis. Section 3 outlines our empirical strategy to identify the racial gap and presents the baseline results. Section 4 explores the sources of the racial gap. Section 5 provides heterogeneity analysis. Section 6 concludes.

**Related literature**

Our paper contributes to the growing literature documenting racial disparities in housing transactions. Kermani and Wong (2024) find that minority home sellers are more likely to enter into distressed sales and when they do, they lose more of their home values compared to White homeowners. Furthermore, our baseline estimates of the annualized unlevered returns gaps for non-distressed sales are of similar magnitudes to their estimates. Bayer et al. (2016) find similar results that minority homeowners are less likely to sustain homeownership when facing adverse economic shocks. However, Diamond and Diamond (2024) find that Black homeowners face higher total housing returns, largely due to experiencing higher rental yields. Instead of analyzing racial gaps in total returns, our paper focuses on the racial gap in capital gains, namely, the home selling process for regular non-distressed home sales. We merge several micro datasets, including building permits, mortgage origination and performance, property listing data, and publicly-available survey datasets to gain a comprehensive understanding of the scope and sources of the racial gap in selling.

Bayer et al. (2017) and Couillard and Christensen (2024) focus on the home buying process and find that Black and Hispanic home buyers pay a premium when purchasing similar housing in the same neighborhood. Courant (1978) demonstrates how this premium can arise in a search model where White sellers are unwilling to sell to Black buyers. We provide additional results using a hedonic approach in Table B1 to show that the gap we estimate comes from the discounting Black homes and not solely from Black buyer paying a premium for their homes. The main contribution of our paper is to investigate and explain where this selling gap comes from. We find that Black home sellers face substantial search frictions during selling.

Our paper is also related to the literature that examines the role of real estate agents in housing transactions. Several papers (such as Ondrich et al. (1998), Yinger (1998), Galster and Godfrey (2005), Zhao et al. (2006), Christensen and Timmins (2022), and Christensen and Timmins (2023)) use the audit studies from the HUDDS data to investigate the prevalence of discriminatory practices by real estate brokers. They find that real estate brokers show fewer homes to Black households, steer them toward less desirable neighborhoods, and cater to the prejudiced beliefs of White buyers. Additionally, Gilbukh and Goldsmith-Pinkham (2023) show that inexperienced real estate agents often cause worse selling outcomes for their clients. By using property listing data, we control for seller real estate agent fixed effects and investigate the extent to which seller agents contribute to the racial gap in housing returns. We find little evidence suggesting that seller agents are directly responsible for the racial gap, but we acknowledge that our sample size for this analysis is relatively small, which may potentially produce inaccurate estimates. We combine the publicly-available HUDDS data with our listings data to create a zip code and quarter date-level measure of buyer agent discriminatory practices in order to analyze role that buyer agents play in causing the racial gap in housing returns. We believe we are the first to create such a measure.

Our study adds to the growing body of literature that uses high-quality microdata to explore the persistent racial disparities in the housing and financial markets. Avenancio-León and Howard (2022) show that Black homeowners pay higher property taxes due to inflated property assessment values for tax purposes. Bhutta et al. (2022), Frame et al. (2021), Gerardi et al. (2023), and Zhang and Willen (2020) find that minority borrowers are less likely to get mortgage approvals and are charged higher interest rates. Butler et al. (2022), Argyle et al. (2023), Christensen et al. (2021), and Laouénan and Rathelot (2022) find that Black households face racial discrimination in the auto loan market, short-term rental market, and personal bankruptcy courts.

Our paper is also closely related to papers that study differential housing outcomes for different demographic groups. For example, Goldsmith-Pinkham and Shue (2023) find that single women experience a 1.5% lower annualized housing returns compared to single men. Similar to Goldsmith-Pinkham and Shue (2023), we explore various channels that can drive the gap by utilizing detailed property transactions and listing data.

## 2.2 Data

We compile data from various sources to gain a comprehensive view of the sales process and the key players involved. In addition to sales records, we also gather information on the renovation status of the property, the sellers' mortgage payment history, and property listing details.

**Property transactions and characteristics.** The property-level transactions records are from ATTOM, a proprietary data provider that compiles national data from county deed and assessor records. For each property transaction, we observe the transaction date, sale price, deed type, property type, transaction type, property address, and distressed status of the sale (i.e., foreclosure, short sale). We restrict our sample to repeat-sale transactions, that is, properties that have been sold at least twice during our sample period. We exclude non-arms length transactions and partial-consideration sales, as well as sales involving non-individual sellers. We also merge the property transaction data with ATTOM's assessor panel to get detailed property characteristics, such as the number of bedrooms, bathrooms, and assessment values. This allows us to exclude homes that construct additional bed and bathrooms from the repeat-sales analysis.

**Identifying sellers and buyers.** While the property transaction records provide the names of the sellers and buyers, their race is not recorded in the dataset. We merge the self-reported race of mortgage applicants from the Home Mortgage Disclosure Act (HMDA) to the ATTOM dataset. We follow the same merging procedure used in previous studies, such as Bayer et al. (2017), Bartlett et al. (2022), Kermani and Wong (2024), and Avenancio-León and Howard (2022). We link each property transaction to its respective mortgage origination record using the time and amount of the property transaction, as well as the Census tract where the property is located[1]. To identify the race of the seller, we use the race of the buyer from the previous transaction, where the current seller was the prior buyer.

Given that multiple individuals may be involved in selling and purchasing the home, such as a married couple, we differentiate between mixed-race households and households consisting of members from a single race. We define a household to be black if either the main applicant or any of the co-applicants are Black, so Black households can include mixed-race households by definition. We define a household to be Black-only if both the main applicant and co-applicants are Black. White and White-only households are defined in a similar manner.

We identify iBuyers companies by using their names and their corresponding mailing addresses following the approach in Buchak et al. (2022) using the ATTOM dataset.

**Borrowers and appraisals.** We get loan-level mortgage performance data from Black Knight McDash. It provides monthly mortgage payment history for each mortgage, and appraisal values if the mortgage was refinanced. We merge the loan-level information to property transaction data from ATTOM following the same procedure used in Issler et al. (2023) and Kermani and Wong (2024). The matching algorithm uses a set of property and transaction attributes, such as loan amount, loan purpose, and interest rate, to find the k-nearest neighbors. We use the mortgage delinquency status as a measure of liquidity constraints for sellers. Specifically, we create an

[1]Note that we are only able to match properties that were purchased with a mortgage. Moreover, the merge is only up to 2016 because HMDA rounds property values to the nearest $10,000s which makes it more challenging to find perfect matches. So our sample does not include selling transactions where the seller purchased their home after 2016. Combined with the transaction data, we are able to observe the race of buyers between 2003 and 2016 and consequently, the race of sellers conditional on purchasing their home between 2003 and 2016.

indicator variable to determine whether the seller was delinquent for 90 days within twelve months before selling their home. If the seller's mortgage was refinanced within two years of the sale, we use the appraisal value at refinance to impute the appraisal value at the time of sale by multiplying it with tract-level housing price growth rate between the appraisal date and the sale date.

**Building permits.** We use national-level building permits data from BuildFax. We construct indicator variables for properties that have undergone significant improvements two years before the sale date. The improvements we consider include roof replacement, home remodeling, and other substantial renovations that require a permit. For the subsample used in the empirical analysis, we drop property transactions in Census tracts that have zero building permits.

**Property listings.** We use national property listing data between January 2011 and December 2020 from Altos Listing Intel. The property listing data provides weekly updates on the listing price, close price, days on market, and names of sellers' real estate agents and broker offices. We merge the listing data to the property transaction records using the property address, price, and sale date.

**House price indices.** We use the developmental Census tract and year-level FHFA House Price Index data (`https://www.fhfa.gov/data/hpi/datasets?tab=additional-data`) to measure Census tract-level price growth between purchase and sale year.

**Buyer agent showings.** We use the latest HUDDS data published in 2012 to create an aggregate count of homes shown to Black buyers at the zip code and quarter date level. Merging this into our sample allows us to create a measure for Black showings per listing at the Census tract and quarter date level.

**Neighborhood characteristics.** We use the 2010 American Community Survey 5-year estimates from IPUMS to obtain sociodemographic characteristics at the Census tract level. The neighborhood characteristics we use include racial composition, median household income, median education level, and homeownership share.

**Final data sample.** Our main sample consists of 1.1 million repeat-sale transactions of single-family homes between 2003 and 2020. We restrict our sample to non-distressed, arms-length, and full-consideration sales. We drop properties that have undergone structural modifications, that is, properties with different numbers of bedrooms and bathrooms between the two transactions. We also exclude transactions with price differences that exceed 100% or fall below -100% to remove outliers. Finally, we exclude transactions in which the property was bought and sold in less than two years to remove potential flip sales.

## 2.3 The racial gap in housing returns

This section describes our empirical strategy to identify the racial gap in housing returns during property sales and presents our baseline results.

### 2.3.1 Empirical strategy

The ideal experiment is to compare the selling outcomes of two identical homes sold by sellers of different races in the same market. To replicate the ideal experiment as much as possible, we use a repeat-sales approach. The key advantage of the repeat-sales approach is that it controls for any time-invariant property characteristics between the two transactions, including unobserved property characteristics. We focus on comparing the growth in prices between homes within the same neighborhood while controlling for the timing of the sale and the mean house price growth between purchase and sale dates. This allows us to control for differences in neighborhood amenities and time-varying market conditions.

Our baseline specification estimates whether sellers of different races earn different housing returns. For property $i$ located in neighborhood $c$ sold in time $t_1$ and purchased in time $t_0$, we run the following regression

$$r_{i,c,t_0,t_1} = \beta \mathbf{1}(SellerRace_{i,c,t_1} = Black) + \gamma X_{i,c,t_0,t_1} + \alpha_{c,t_1} + \epsilon_{i,c,t}. \tag{2.1}$$

The dependent variable is the housing return on property $i$. The parameter of interest is $\beta$, which captures differential housing returns attributed to the race of the seller in the transaction occurring at time $t_1$. $X_{i,c,t_0,t_1}$ denotes the control variable we use, specifically the Census-tract level housing price growth rate, calculated between the year the home was sold and the year the home was purchased. The control variable allows us to directly control for differential house price growth trends across different neighborhoods. $\alpha_{c,t_1}$ denotes neighborhood-by-time fixed effects, capturing unobserved shocks at neighborhood-time levels. For example, a neighborhood may start with few nice amenities but experience positive amenity shocks five years later, possibly due to the opening of a new school or a beautiful park. In our estimation, we use Census tracts to define neighborhoods $c$ and year-quarter of sale date to define time $t_1$.

We use two measures of housing returns. The first is the total unlevered capital gains between the sale date $t_1$ and purchase date $t_0$, measured as the log price difference between the two transactions,

$$r^{tot}_{i,c,t_0,t_1} = \ln P_{i,c,t_1} - \ln P_{i,c,t_0}.$$

Our preferred measure is the annualized returns to standardize housing returns across transactions with varying holding periods. Unlike total capital gains, which do not differentiate the lengths of ownership, the annualized measure explicitly accounts for the variation in the lengths of asset holding. We define the annualized unlevered capital returns similar to Goldsmith-Pinkham and Shue (2023) and Kermani and Wong (2024). It is defined as

$$r^{ann}_{i,c,t_0,t_1} = \left(\frac{P_{i,c,t_1}}{P_{i,c,t_0}}\right)^{365/(t_1-t_0)} - 1$$

where the difference between the two transaction dates $t_1$ and $t_0$ is measured in days.

### 2.3.2 Baseline results

Table 2.1 presents the average racial gap in total and annualized capital gains from housing using the baseline regression from Equation 2.1. Intuitively, the regression compares the price growth of homes located in the same neighborhood and sold in the same year-quarter date while controlling for the price growth between purchase and sale dates, differing only in being owned by Black versus non-Black homeowners. In all specifications, we cluster standard errors at the Census tract level. As discussed in Section 2, we use two measures to categorize the race of the seller: whether at least one member of the sellers is Black, and whether all sellers involved in the transaction are Black.

Column (1) shows that on average, Black sellers realize 1.74% lower total capital gains when selling their houses compared to non-Black sellers. Additionally, Column (2) shows that sellers identified as Black-only, on average, realize total capital gains 1.88% lower compared to non-Black-only sellers. Columns (3) and (4) present the average gap in annualized capital gains for Black and Black-only sellers, respectively. We find that the average gap in annualized capital gains of a Black seller is 0.36% lower than that of non-Black sellers, and 0.38% lower for Black-only sellers than that of non-Black-only sellers.

Table 2.1: Racial gap in returns to housing

| | Capital gains returns | | Annualized returns | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Black seller | -0.0174*** | | -0.0036*** | |
| | (0.0011) | | (0.0003) | |
| Black-only seller | | -0.0188*** | | -0.0038*** |
| | | (0.0013) | | (0.0003) |
| Observations | 1151718 | 1151718 | 1151718 | 1151718 |
| $R^2$ | 0.701 | 0.701 | 0.680 | 0.680 |

*Notes*: This table presents the average racial gap in total and annualized capital gains using the baseline regression Equation 2.1. Columns (1) and (2) report the gap in total capital gains, while Columns (3) and (4) report the gap in annualized returns. Black sellers are defined as sellers that include at least one Black individual, and Black-only sellers are defined as sellers that are all Black individuals. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

To assess the magnitude of the gap in dollar terms, we conduct a simple back-of-envelope calculation. Imagine two homes, both in the same neighborhood and each bought for $250,000 in February 2012, but one was purchased by a Black-only household, while the other one was purchased by a non-Black-only household. Furthermore, imagine these two homes were sold after eight years, approximately the average duration of homeownership. In this time period, mean house price growth in the US was approximately 60%. If the non-Black household's home was sold for $400,000, our baseline annualized results suggest that the Black-only household would have received $11,323 less when selling the home.

One potential concern with our findings is the possibility that the gap solely arises from Bayer et al. (2017)'s results that Black home buyers tend to pay more for their homes, thereby mechanically reducing their housing returns. If this were the case, we would expect to find no racial gap on the seller's transactions when using a hedonic approach. We shed light on this matter by estimating a simple hedonic regression by regressing the log sale price on a binary variable for the race of the seller along with characteristics of the seller's home and interacted Census tract and year-quarter sale date fixed effects. The characteristics of the home controlled for include the building square footage and lot area, age, heating and cooling systems, pools, garages, and categorical dummies for the number of bedrooms and bathrooms. Because the specification is only conditional on a home's characteristics at the time of sale, we do not need to exclude transactions with changes in the home's characteristics. This significantly increases the sample size by a factor of two.

Appendix Table B1 displays the regression results. Column (1) presents the results comparing Black and non-Black sellers and Column (2) presents the results for Black-only and non-Black-only sellers. The hedonic regression specification finds approximately a -4.1% racial gap in sales price for Black sellers and a -4.6% racial gap in sales price for Black-only sellers. Overall, we interpret these results as evidence that the racial gaps in housing returns that Black sellers experience are not solely explained by a racial gap on the purchasing side.

## 2.4 Explanations of the racial gap

In the last section, we document that, on average, Black households receive lower returns on their homes relative to non-Black households. We explore the underlying mechanisms driving the gap in this section. We use the annualized housing return as the outcome variable to account for any differences in holding periods. We find that this negative gap in returns is not explained by liquidity constraints, nor by observable differences in housing renovations. On average, the race of the buyer does not appear to explain the racial gap either. Using proxy measures for appraisals, we also find no evidence that appraisal values explain away the gap. Additionally, controlling for seller agent and brokerage office fixed effects does not rationalize the racial gap.

However, controlling for listing price and time on market, which is likely influenced by real estate agents involved in a housing transaction, effectively explains the entire gap. Additionally, less exposure to buyer agent discriminatory practices mitigates the returns gap. Finally, we observe no racial gap among housing transactions that involve an iBuyer purchasing the property, i.e., transactions where buyer real estate agents are not directly involved in the matching process. The results strongly suggest that Black sellers' disparities in search frictions, caused by real estate agent practices, are the main driver of the racial gap.

### 2.4.1 Seller and property characteristics channel

We begin by examining the role of the seller's liquidity position on sale price differences. If the seller is liquidity-constrained, they may be willing to accept lower prices to sell the house faster. To test the mechanism, we bring in additional data from Black Knight McDash's mortgage performance data. We use the seller's mortgage delinquency status as a proxy for the seller's liquidity position. If a seller has been delinquent on their mortgage payments for more than 90 days, they are nearing default and face the high risk of losing their home soon. Consequently, a liquidity-constrained seller might prioritize a quick sale over finding a buyer with a higher offer to ease their financial burden. We construct an indicator variable of whether the seller was at least 90 days delinquent on their mortgage within 12 months of selling the home.

On the other hand, the disparities in housing returns might be attributable to differences in unobserved property characteristics correlated with race. Any relation between differential investment in a seller's home and their race could potentially generate a racial gap. We test the validity of this claim by merging building permit data from BuildFax. We create three indicator variables to capture the renovation status of a property: the installation of a new roof, the presence of home remodeling, and other types of replacements that require a permit. We measure these variables within two years before the sale. We acknowledge that there exist many property features that can impact property values but are not observed in the data. Examples include the aesthetic appeal of the house, the availability of a central air conditioning system, the age of appliances, and the status of the basement finishing. To the best of our knowledge, a complete dataset including all property features does not exist. Therefore, we focus on significant renovations and remodeling to capture differences in housing quality, as these factors are likely to have a more pronounced impact on property values compared to other minor property features.

Table 2.2 presents estimates of the annualized racial gap, after controlling for the seller's liquidity status and the renovation status of the properties. Since we merge the main transactions sample with mortgage performance and permits data from the Black Knight McDash and BuildFax, respectively, the size of the merged dataset drops from 1.1 million to about 600,000 observations. In Columns (1) and (4), we rerun the baseline regression Equation 2.1 using the newly merged sample. The coefficients estimated from the newly merged samples have similar magnitudes to those in the baseline sample, shown in Columns (3) and (4) of Table 2.1. The similarity suggests that the characteristics of the newly merged samples closely align with those in the baseline sample.

In Columns (2) and (5), we control for the mortgage delinquency status of the seller. The estimated racial gap in annualized housing returns is -0.29%, which is very similar to the baseline estimates of -0.32% in Columns (1) and (4). This suggests that the differences in need for liquidity between Black and non-Black sellers do not substantially account for the gap in final housing returns. We further add controls for property improvements in Columns (3) and (6). The estimated annualized racial gap remains at -0.29%, the same as the estimates in Columns (2) and (5). The results indicate that neither the seller liquidity nor property renovations explain an economically significant part of the observed racial gap.

Table 2.2: Seller and property characteristics channel

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Black seller | -0.0032*** | -0.0029*** | -0.0029*** | | | |
| | (0.0003) | (0.0003) | (0.0003) | | | |
| Delinquent 90d+ | | -0.0098*** | -0.0098*** | | -0.0098*** | -0.0098*** |
| | | (0.0003) | (0.0003) | | (0.0003) | (0.0003) |
| Roof | | | 0.0030*** | | | 0.0030*** |
| | | | (0.0005) | | | (0.0005) |
| Replacement | | | 0.0028*** | | | 0.0028*** |
| | | | (0.0004) | | | (0.0004) |
| Remodel | | | 0.0114*** | | | 0.0114*** |
| | | | (0.0008) | | | (0.0008) |
| Black-only seller | | | | -0.0032*** | -0.0029*** | -0.0029*** |
| | | | | (0.0003) | (0.0003) | (0.0003) |
| Observations | 593895 | 593895 | 593895 | 593895 | 593895 | 593895 |
| $R^2$ | 0.723 | 0.723 | 0.724 | 0.723 | 0.723 | 0.724 |

*Notes*: This table presents the estimates of the racial gap in annualized returns when we control for seller's mortgage delinquency status and property renovations. All regressions follow the same specification in Equation 2.1. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. The first three columns show the estimates for Black sellers, while the last three columns show the estimates for Black-only sellers. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

### 2.4.2 Race of buyers

Next, we examine the role of the buyer, with a specific focus on the buyer's race. Given the historical prevalence of prejudice against Black households by White individuals, we assess whether Black sellers receive lower housing returns when selling their homes to White buyers. If White buyers hold prejudiced beliefs against Black sellers or their homes, they may offer lower prices. The race of the buyer is determined by the self-reported race from HMDA. We classify a buyer as White if the household is exclusively White, meaning the household is not mixed-race.

Table 2.3 presents the results while accounting for the race of the buyer. The specifications are similar to our baseline regressions, with an additional interaction term between the seller's race and the buyer's race. Columns (1) and (3) follow the same specifications as the baseline regressions shown in Columns (3) and (4) of Table 2.1, respectively. The sample including the buyer's race is smaller because we are not always able to identify the race of the buyer when we merge the baseline sample with HMDA. The magnitudes of the racial gap are slightly smaller in this subset of the data, but they remain economically meaningful.

Columns (2) and (4) present results where we explore the role of White buyers in explaining the racial gap by interacting the race of the seller with the race of the buyer. We find that the interaction does not absorb the racial gap estimate for Black sellers. If the racial gap was primarily caused by potentially prejudiced White buyers, then the interaction term between a Black seller and a White buyer would yield a statistically significant negative estimate that absorbs the coefficient of the Black seller indicator. However, the estimate on the interaction term is close to zero and is neither statistically nor economically significant. Also, the estimated racial gaps in annualized housing returns are -0.23% for Black sellers and -0.30% for Black-only sellers. The magnitudes are similar to the baseline regressions without accounting for the race of the buyer. Overall, Black sellers experience lower housing returns regardless of the race of the buyer, suggesting that any potential direct discrimination between the seller and the buyer is not a dominating force driving the racial gap.

### 2.4.3 Seller real estate agent and broker office

The majority of real estate transactions in the US are facilitated by real estate agents. Specifically, the listing agent, who represents the seller, plays a crucial role in shaping the selling outcomes. The listing agent provides a range of services, including advising on the list price, staging and advertising the property, showing homes to potential buyers, and negotiating the close price on behalf of the seller. If Black sellers work with realtors who exert lower efforts due to racial prejudice, inexperience, or lower intrinsic quality, Black sellers may experience worse selling outcomes. In this section, we use detailed property listing data from Altos Listing Intel to investigate how much of the gap can be attributed to seller real estate agents.

Occasionally, real estate agent and office names are shortened, re-arranged, or misspelled. We first manually standardize these names to minimize instances of the same agent/office being assigned multiple id numbers, such as instances like "Century

Table 2.3: Race of buyers

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Black seller | -0.0027*** | -0.0023** | | |
| | (0.0005) | (0.0008) | | |
| Black seller × White buyer | | -0.0007 | | |
| | | (0.0011) | | |
| Black-only seller | | | -0.0032*** | -0.0030*** |
| | | | (0.0006) | (0.0009) |
| Black-only seller × White buyer | | | | -0.0002 |
| | | | | (0.0012) |
| White buyer | | 0.0005** | | 0.0005** |
| | | (0.0002) | | (0.0002) |
| Observations | 412203 | 412203 | 412203 | 412203 |
| $R^2$ | 0.737 | 0.737 | 0.737 | 0.737 |

*Notes*: This table presents the estimates of the racial gap when we control for buyer's race. We use the subsample that we can identify the buyer's race for this table. In Columns (1) and (3), we rerun the baseline regression for Black and Black-only sellers to get the baseline racial gap. We include an interaction term between the race of the seller and the race of the buyer in Columns (2) and (4). All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

21" and "Century twenty-one". We then use a bigram decomposition algorithm to fuzzy-match similar agent name string and siminlar office name strings within a CBSA.

We rerun our baseline regression using the repeat-sale sample of the matched transaction-listing data. To isolate the role of real estate agents, we control for listing agent fixed effects. The names of real estate agents are often missing in the data, so we exclude listings and associated transactions without agent names. The sampling criteria shrink our sample size significantly, with the subsample with real estate agent information dropping to less than 50,000 observations. This reduction in sample size is due to the lack of data reporting issues in Altos, rather than a lack of representations of real estate agents in these transactions. So we create another subsample where we observe brokerage offices and include them as fixed effects. The results for annualized returns are presented in Table 2.4. In Columns (1) to (4), we use the sample in which we can identify the real estate agents on the listings. Analogously, Columns (5) to (8) use the sample where we can identify the brokerage office. To ensure the subsamples are comparable to our primary sample, we rerun the baseline regressions without agent and brokerage controls. The results are shown in Columns (1), (3), (5), and (7). The estimated racial gaps in the subsamples are around -0.30% to -0.38%, which are very similar to our baseline results shown in Table 2.1.

Table 2.4: Role of listing agent and broker offices

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Black seller | -0.0030** | -0.0024 | | | -0.0038*** | -0.0035*** | | |
| | (0.0011) | (0.0014) | | | (0.0005) | (0.0005) | | |
| Black-only seller | | | -0.0036** | -0.0033* | | | -0.0038*** | -0.0036*** |
| | | | (0.0013) | (0.0017) | | | (0.0006) | (0.0006) |
| Observations | 48852 | 48852 | 48852 | 48852 | 231727 | 231727 | 231727 | 231727 |
| $R^2$ | 0.735 | 0.846 | 0.735 | 0.846 | 0.714 | 0.743 | 0.714 | 0.743 |
| FE | | agent | | agent | | office | | office |

Notes: This table presents estimates of the racial gap in annualized returns when we control for real estate agents and brokerage office fixed effects. Columns (1) to (4) use the matched transaction-listing sample in which the real estate agent information is available. Columns (5) to (8) use the matched transaction-listing sample in which the brokerage office is available. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Columns (2) and (4) estimate the racial gap including listing agent fixed effects. We find that adding listing agent fixed effects attenuates the racial gap to some extent, reducing the annualized gap by 0.06% for Black sellers and 0.03% for Black-only sellers. However, they still do not fully explain the racial gap. Columns (6) and (8) estimate the racial gap including brokerage office fixed effects. We find that adding brokerage office fixed effects only reduces the gap marginally, reducing the annualized gap by 0.03% for Black-sellers and 0.02% for Black-only sellers. We conclude that on average, any direct discrimination from real estate agents towards their Black clients does not contribute significantly to the gap in housing returns.

### 2.4.4 Appraisal measures

Appraisals play a crucial role in real estate transactions by providing objective accurate evaluations of a property's market value. The appraisal estimates are widely used in housing transactions. For example, sellers use appraisal values as benchmarks for setting listing prices, lenders use them to assess the collateral value, and buyers use them as references when negotiating the final sale prices with sellers.

When appraising a home, appraisers fill out a form detailing the characteristics of a home and provide an estimate of the fair market value. The appraisers record structural features such as the number of bedrooms and bathrooms. These objective measures leave little room for any sort of bias. However, other subjective measures such as the perceived quality of the home's feature, opens the possibility for subjective racial biases to influence fair evaluations. Recent newspaper stories have reported instances in which the appraisal value rose by over $30,000 after a Black couple removed family photos and other personal items (Romo (2023)). It should be noted that some subjective measures, such as the drive to a home, are more likely to affect neighborhood-level differences in the racial gap as shown in FHFA blog posts (Broadnax and Wylie (2021) and Vajja (2023)), but they are less likely to affect the within-neighborhood gap that we estimate.

Although we do not have data on the actual appraisal estimates received by home sellers before listing their homes on the market, as well as the appraisal estimates requested by lenders for buyers, we impute a measure that is likely highly correlated with these actual appraisal estimates.

We impute an implied appraisal value based on the appraisal values the seller receives when they refinance their property. For households who refinance their mortgages, the lender re-appraises the property value in order to determine the loan terms of the new mortgage. Using loan characteristics data from Black Knight McDash, we are able to obtain the appraised property value ordered by the lenders for refinancing purposes. We then multiply the appraisal value by the FHFA's house price growth rate at the Census tract level to impute the appraisal value at the time of sale. The key assumptions made are that the appraisal values grow at the same rate as the average price growth rate and that the racial gap in the appraisals does not vary between refinancing a mortgage and selling a home.

We first re-estimate the racial gap in housing returns if sellers were to receive sale prices equal to the imputed appraisal values. Table 2.5 presents the results. We recalculate annualized returns using the implied appraisal value as the numerator, and rerun the baseline regressions. Columns (1) and (2) report a positive racial gap of 0.44% for Black sellers and 0.48% for Black-only sellers if sale prices equal to the implied refinance appraisal values. This result is the opposite of the racial gap in returns to housing which we have been finding and strongly suggests that, on average, the value of homes Black owners sell is not less than the value of homes White owners sell. We view this as strong evidence that homes sold by Black sellers should, on average, grow in value by at least as much as, if not more than, homes sold by non-Black sellers; in other words, these results strongly suggest that racial differences in unobserved home investment or depreciation are likely not valid explanations for the racial gap in housing returns. It is important to note that this data sample restricts sellers to those who refinanced their mortgage. The next step is to first see if a racial gap exists with this subset of the data, and then see if controlling for these implied appraisal values absorbs the racial gap.

Table 2.5: Racial gap in appraisals

| | (1) | (2) |
|---|---|---|
| Black seller | 0.0044* | |
| | (0.0019) | |
| Black-only seller | | 0.0048* |
| | | (0.0021) |
| Observations | 117027 | 117027 |
| $R^2$ | 0.584 | 0.584 |

*Notes*: This table presents the estimates of the racial gap in annualized housing returns if the transaction price were the imputed appraisal value based on the appraised value the seller received when they refinance their mortgage. In other words, the left-hand side variable is the annualized return from purchasing at the actual purchased value and selling at the imputed appraisal value. The appraised value received at the time of refinancing is adjusted by house price growth between the appraisal date and sale date. All regressions include Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

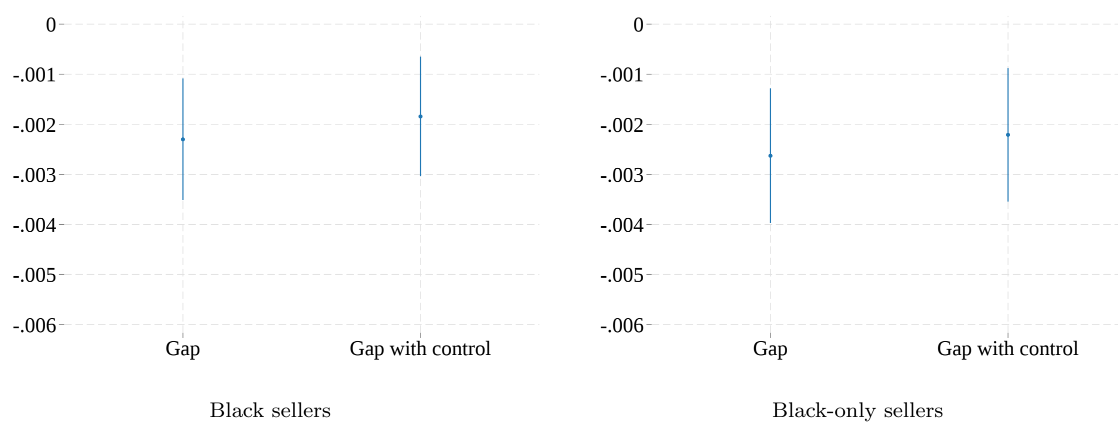
Figure 2.1 presents the point estimates and 95% confidence intervals for the annualized racial gap after controlling for the implied appraisal measure. We do not control for house price growth in the plots.[2] The left panel shows the results for Black sellers, and the right panel shows the results for Black-only sellers. In each plot, the first coefficient provides the annualized gap without controls, and the second coefficient

[2]We exclude the FHFA house price growth control because the price growth from our appraisal measures and the seller's purchase price serve the same role.

provides the annualized gap after controlling for the appraisal measure.

The annualized gaps without controlling for appraisal values are -0.22% and -0.27% for Black and Black-only sellers, respectively, smaller than the estimates provided in Columns (2) and (4) of Table 2.1, but they are still statistically significant at the 95% level. The estimated gaps after including the implied appraisal values have similar magnitudes, with values -0.19% and -0.22%, respectively. The results suggest that, on average, appraisers likely do not play a major role in explaining the racial gap.

Figure 2.1: Racial gap in housing returns controlling for appraisals




*Notes*: This figure plots the point estimates and 95% confidence intervals for the racial gap in annualized housing returns after controlling for appraisal measures. The implied appraisal values are derived from the appraisal value at mortgage refinancing multiplied by average price growth rate at the Census tract level. Each plot shows the estimates without and with appraisal controls for Black and Black-only sellers. All regressions include the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels.

### 2.4.5 Search frictions

This section investigates the role of listing prices and time on market in explaining the gap Black homeowners face when selling their homes. We find that accounting for both the time on market and listing price can explain nearly all of the racial gap.

We first document a few key facts about racial differences in listing outcomes shown in Table 2.6. The listing price and time on market information are merged in from Altos Listing Intel data. We use the baseline regression specification shown in Equation 2.1, but replace outcome variables with listing characteristics.

Listing price is an estimate of the market value of a home, and it is often closely tied to an appraised value sellers receive. A seller's agent may also provide input on the listing price – for instance, if an agent believes that it would be difficult to find a buyer for a house, and thus be on the market for an extended period of time, they may suggest lowering the listing price. Additionally, sellers themselves may have their own views on what the listing price should be – potentially lowering the listing price themselves if their home is listed for a long period of time without receiving a sufficient offer. As a result, a listing price may be influenced by the bias of several players. If these biases are correlated with race of the seller, they are likely to influence the relative difference in sale prices between Black and non-Black sellers.

The regression specification in Columns (1) and (2) is similar to that in Table 2.5 where we re-estimate the racial gap in housing returns if sellers were to receive sale prices equal to the last listing price we observe prior to sale. The results indicate that Black sellers would face lower annualized returns implied by our listing price measure. Given our findings from Section 2.4.4, we suspect that racial differences in listing price are likely due to the influence of biased parties and not due to unobserved quality of the home.

Table 2.6: Listings characteristics gaps

| | Listing price gap | | Listing price change | | Sale-listing gap | | Days on market | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Black seller | -0.0033*** | | -0.0006** | | -0.0024** | | 8.4589*** | |
| | (0.0005) | | (0.0002) | | (0.0008) | | (0.8008) | |
| Black-only seller | | -0.0032*** | | -0.0006* | | -0.0031*** | | 9.4490*** |
| | | (0.0005) | | (0.0003) | | (0.0009) | | (0.9259) |
| Observations | 296052 | 296052 | 595242 | 595242 | 595245 | 595245 | 595249 | 595249 |
| $R^2$ | 0.705 | 0.705 | 0.348 | 0.348 | 0.411 | 0.411 | 0.458 | 0.458 |

*Notes*: This table presents the racial differences in listing outcomes using the matched transaction-listing sample. The first two columns show the racial difference in listing price adjustment, measured by the log difference between the first and final listing prices. The third and fourth columns show the racial difference in the sale-listing price gap, measured as the difference between the sale price and the final listing price. The last two columns show the racial difference in the number of days on market. All regressions include the Census tract by sale year-quarter fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Columns (3) and (4) regress the log change between the final listing price and the first listing price on the race of the seller. We find that Black and Black-only sellers lower their listing prices by 0.06% more than non-Black and non-Black-only sellers, respectively. Columns (5) and (6) regress the log difference between the final sale price and the final listing price on the race of the seller. The regression results indicate that Black and Black-only sellers sell their homes at larger discounts of -0.24% and -0.31% relative to non-Black sellers.

Columns (7) and (8) regress the number of days it takes to sell the house on the race of the seller. We find that Black homes are listed on the market for over a week longer than non-Black homes. Given that we include interacted neighborhood and time of sale fixed effects, the difference in days on market between Black and non-Black sellers is particularly stark. The results show that Black sellers face lower probabilities of matching with a potential buyer, suggesting that Black sellers may face higher search frictions during the selling process. Additionally, this racial difference in time on market likely explains much of the racial difference in listing prices we display in Columns (1) and (2). Within the context of a search model, our findings suggest that Black sellers face a different level of market tightness than non-Black sellers. This result is consistent with the results from the literature that uses the HUDDS data to show that real estate agents have racially steered buyers, shown Black home buyers fewer homes, and catered to prejudiced preferences of home buyers (Galster and Godfrey (2005), Ondrich et al. (1998), Yinger (1998), Zhao et al. (2006), Turner et al. (2013)).

Several factors can explain the racial gap in listing outcomes. First, Black sellers learn about their true property values during the listing process. If the house receives few visits and offers from buyers, the Black seller may learn that they need to adjust prices to attract buyers. Second, the listing agent may put less effort in facilitating the sale of the Black-owned properties, lowering the probability of sale. As a result, the Black seller may respond by lowering listing prices to increase the probability of sale. Third, Black sellers may have less negotiating power when closing the sale, and this can explain why there is a gap between the final sale price and final listing prices. The difference in negotiation skills can be due to bad recommendations by the listing agent, inexperience by sellers, or property defects found during home inspections. Results in the following subsections suggest the former.

Our next set of results tests whether listing behaviors can explain the racial gap. Table 2.7 uses our baseline specification, and we incrementally add controls for listing price growth and time on market.[3] The sample is smaller than the baseline sample because we are not able to find matches for all transactions when merging with the listings data.

Table 2.7: Search frictions regressions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Black seller | -0.0041*** | -0.0010* | -0.0004 | | | |
| | (0.0004) | (0.0004) | (0.0004) | | | |
| Black seller × 1/Time on mkt | | | -0.0013** | | | |
| | | | (0.0005) | | | |
| Black-only seller | | | | -0.0043*** | -0.0010* | -0.0004 |
| | | | | (0.0004) | (0.0005) | (0.0004) |
| Black-only seller × 1/Time on mkt | | | | | | -0.0015** |
| | | | | | | (0.0005) |
| Listing price growth | | 0.7793*** | 0.7773*** | | 0.7793*** | 0.7773*** |
| | | (0.1031) | (0.1030) | | (0.1031) | (0.1030) |
| 1/Time on mkt | | | 0.0079*** | | | 0.0079*** |
| | | | (0.0007) | | | (0.0007) |
| Observations | 440386 | 440386 | 440386 | 440386 | 440386 | 440386 |
| $R^2$ | 0.543 | 0.905 | 0.907 | 0.543 | 0.905 | 0.907 |

*Notes*: This table presents the estimates of the racial gap in annualized returns after controlling for listing price difference and weeks on market. All regressions include the Census tract by sale year-quarter date fixed effects. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

In Columns (1) and (4), we rerun the baseline regression using the new subsamples. The estimated racial gaps are of similar magnitudes as the results in Table 2.1. We control for the annualized price growth between the final listing price and purchase price in Columns (2) and (5). Here, the racial gap in annualized returns decreases substantially, from -0.4% to -0.1%. Including the listing price reduces the gap for two main reasons. First, any bias inherent in the listing price can transmit to the racial gap in the final returns. Second, the listing price reflects unobserved heterogeneity of the property itself. Although we cannot disentangle these two forces from the listing price, our results from Section 2.4.4 suggest the latter explanation is less likely to be legitimate. Additionally, listing price may be lower precisely because Black sellers'

[3]We exclude the FHFA house price growth control because the price growth from listing price and the seller's purchase price serves a similar role.

homes spend more time on the market – suggesting that search frictions may directly play a role in the lower listing prices Black sellers set.

Columns (3) and (6) include the inverse of the total weeks the home is on the market as well as its interaction with the race of the seller and the listing price control. We include the inverse of time on market because it directly maps to the probability of matching with a buyer. We find that accounting for both the listing price and time on market reduces the racial gap by a factor of ten, and it removes the statistical significance of the estimate as well. We interpret these results as evidence that accounting for the differential search frictions Black sellers face explains the price disparity. When the time on market decreases, that is, it takes a short time to find a buyer, non-Black sellers see a higher increase in their annualized returns than Black sellers due to the negative coefficient in the interaction term. For instance, the median number of weeks on market in our data is approximately 5 weeks, and the results in Table 2.6 give the average within-neighborhood difference estimates in time on market between Black and non-Black sellers and Black-only and non-Black-only sellers of 8.5 and 9.4 days or close to one and half weeks. If it took a Black seller 5 weeks to match with a buyer, a difference in time on market of one and a half weeks between Black and non-Black sellers and Black-only and non-Black-only sellers yields a difference in annualized returns of approximately 0.09% and 0.1%, respectively. This equates to roughly one-quarter of the total racial gap we estimate. However, longer time-on-market can lead sellers to lower their listing price – thus, racial differences in time on market are likely to impact listing prices. Consequently, we believe our estimates of search frictions explaining the racial gap to be a lower bound.

### 2.4.6 Buyer agent discriminatory practices

In this section, we construct a measure of exposure to discriminatory practices by real estate agents, using data from the HUD Discrimination Study (Turner et al. (2013)). We then assess its impact on the racial gap in housing returns. The HUD experiment uses paired testing to detect discriminatory practices among real estate agents. It arranges pairs of potential home buyers of different races to contact real estate agents and inquire about a randomly selected set of homes. This experiment conducted over 8,000 tests in 28 metropolitan areas nationwide in 2011 and 2012. The study finds that real estate agents practice racial steering and show Black home seekers 17.7% fewer homes than White buyers, despite both groups being equally qualified. These discriminatory practices directly impact home sellers' sale prices, especially for those more exposed to these practices, as they reduce the probability of matching with a potential buyer.

Therefore, we construct a zip code-quarter date-level measure to quantify the extent of these discriminatory practices. Using HUDDS data, we compute the number of showings to Black home seekers for each zip code and divide it by the number of available listings in the same area, as recorded in the Altos listings data. This measure is constructed analogously to market tightness. A lower value indicates a higher prevalence of discriminatory practices, not only reflecting greater difficulty for Black home buyers to find a match, but combined with the racial steering results directly impacts the match probability for Black sellers as well, consequently lowering house prices because of greater search frictions. Additionally, these discriminatory practices may have larger consequences for Black sellers in states that allow for dual agents.

Table 2.8 illustrates the impact of such discriminatory practices on the racial disparities in annualized housing returns. The regression is the same as our baseline specification in Table 2.1 except that we interact the measure with the race of the seller. Due to the data limitations of the HUDDS study as well as the time period having relatively few transactions not involving a distressed sale, the sample size for this analysis is much smaller. The sample includes 6,095 repeat-sale transactions across 831 zip codes in 25 CBSAs. All regressions include zip-code and sale year-quarter fixed effects, with standard errors clustered at the zip-code level.

Column (1) reports the racial gap in annualized housing returns for this analysis sample. Consistent with our baseline results, Black sellers earn about 1% lower returns compared to non-Black sellers. In Column (2), we control for the measure of buyer agent discriminatory practices. The key coefficient of interest is the interaction term between the Black seller indicator variable and the discriminatory measure con-

Table 2.8: Controlling for Buyer Agent's Discriminatory Practices

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Black seller | -0.0101* | -0.0162** | | |
| | (0.0044) | (0.0053) | | |
| Black seller × Black showings/listings | | 0.0936* | | |
| | | (0.0457) | | |
| Black-only seller | | | -0.0114* | -0.0200** |
| | | | (0.0058) | (0.0064) |
| Black-only seller × Black showings/listings | | | | 0.1350** |
| | | | | (0.0475) |
| Black showings/listings | | 0.0003 | | 0.0001 |
| | | (0.0044) | | (0.0045) |
| Observations | 6095 | 6095 | 6095 | 6095 |
| $R^2$ | 0.361 | 0.363 | 0.361 | 0.364 |

Regressions include zipcode and year-quarter date of sale fixed effects. Due to the nature of the HUD Discrimination Study experiment, regressions are weighed by the number of tester-home pairs within a zipcode. Regressions include control for tract-level annualized house price growth between year of purchase and year of sale. Sample period spans 2011-2012 – the period of the HUD Discrimination Survey. Reported standard errors are clustered at the zipcode level. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

structed from HUD data. The positive coefficient on the interactive term indicates that increasing the number of showings to Black home seekers reduces the racial gap in housing returns. Specifically, increasing the Black showing-to-listing ratio by 1 is associated with a 9% increase in housing returns, offsetting the negative racial gap for Black sellers. Columns (3) and (4) replicate the analyses from Columns (1) and (2), but replace the Black home seller indicator with a Black-only seller indicator. Although the magnitudes are larger relative to those previously estimated in this paper, likely reflecting both contemporary market conditions with high price volatility and some measurement error, the stark results are in line with those in Section 2.4.5 suggesting that Buyer agents play a large role in explaining the racial gap in housing returns.

### 2.4.7 iBuyers

In this section, we examine the racial gap when a buyers' agent is removed from the selling process. In order to do this, we examine homes purchased by iBuyers – companies that use algorithms to make instant offers to buy and sell properties. By removing buyers' agents from the selling process, we eliminate key historical discriminatory practices which lead to differences in search frictions and directly impact prices like racial steering, black homes being shown to fewer buyers, and catering to prejudiced demands of buyers as documented in the literature using the HUD Discrimination Survey (Ondrich et al. (1998), Yinger (1998), Galster and Godfrey (2005), Zhao et al. (2006), Turner et al. (2013), Christensen and Timmins (2022), and Christensen and Timmins (2023)).

We identify iBuyer purchases by name and mailing address following the approach described in Buchak et al. (2022). iBuyers typically purchase homes that they believe are relatively easy to sell. As described in Buchak et al. (2022), we focus on a data sample of homes that are in an accessible price range that are relatively young. Consequently, we restrict the data sample to include transactions where the transaction value is within \$150,000–\$350,000 and where the age of the home is no more than 40 years old.

The regression specification is the same as Equation 2.1 except that we interact the race of the seller with a binary indicator for whether the home was purchased by an iBuyer. Due to the relatively small number of iBuyer home purchases, we use zip code by year of sale fixed effects and control for zip code-level annualized mean house price index growth between purchase year and sale year. Table 2.9 presents the results for Black sellers in Column (1) and Black-only sellers in Column (2). The coefficient estimates for the black seller indicator and the iBuyer indicators are negative in both columns. The magnitude of the racial gap is in line with previous results, and the magnitude of the iBuyer coefficient denotes the annualized discount sellers observe from selling to an iBuyer. However, the coefficient for the interaction is positive and offsets the negative racial gap suggesting that when we remove players who potentially impact prices, such as buyers' agents, the racial gap is, on average, eliminated. Overall, this set of results combined with the results from Tables 2.7 and 2.8 provide strong evidence for the role that real estate agents have in creating this racial disparity in housing returns.

Table 2.9: iBuyer impact

| | (1) | (2) |
|---|---|---|
| Black seller | -0.0025*** | |
| | (0.0004) | |
| Black-only seller | | -0.0029*** |
| | | (0.0004) |
| iBuy | -0.0055*** | -0.0054*** |
| | (0.0005) | (0.0005) |
| Black seller × iBuy | 0.0037* | |
| | (0.0019) | |
| Black-only seller × iBuy | | 0.0036 |
| | | (0.0020) |
| Observations | 218324 | 218324 |
| $R^2$ | 0.695 | 0.695 |

*Notes*: Regressions include zip code-level annualized mean house price index growth between purchase year and sale year as well as zip code tract × year of sale date fixed effects. Reported standard errors are clustered at the zip code level. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

### 2.4.8 Robustness

#### Alternative delinquency definitions

As a robustness check, we replicate the results from Table 2.2 with alternative measures of seller delinquency status. Table B2 reports the results where we proxy liquidity constraints with any 30 day or longer delinquency on the sellers' mortgage within a year of selling their property, Table B3 reports the results where we proxy liquidity constraints with any 90 day or longer delinquency on the sellers' mortgage within one month of selling their property, and Table B4 reports the results where we proxy liquidity constraints with any 30 day or longer delinquency on the sellers' mortgage within one month of selling their property. Overall, the results do not change from those in Table 2.2, demonstrating the robustness of our liquidity constraint result.

#### Restricting additional potential short-sales

The data sample used in our main analysis identifies and excludes short sales using a proprietary algorithm from ATTOM. In this section, we perform the same analysis from the main sections of the paper with more restrictive exclusion of property transactions that are potentially short-sales. Figure B1 presents these results. First, we exclude transactions that ATTOM identifies as a short sale. Second, we add an additional exclusion rule by excluding transactions identified by an algorithm first used in Ferreira and Gyourko (2015). This algorithm identifies transactions as a short sale if the transaction value is less than 90% of the initial unpaid principle balance. Like Kermani and Wong (2024), we find that the definition of short sale does not qualitatively change the results. However, the results in this potentially cleaner sub-sample suggest time-on-market explains 50% of the racial gap for Black sellers.

First, we replicate the baseline regression from Table 2.1 in the first plotted coefficient and estimate a racial gap in housing returns of -0.28% annually. Next, we estimate the racial gap after controlling for delinquency status and renovations in the third plot using the same specification from Table 2.2 with the second plot being the racial gap on the same sample without the seller characteristics controls. The fifth coefficient plots the racial gap after controlling for white buyers using the same specification from Table 2.3 with the fourth plot being the estimated racial gap on the same sample without controlling for the buyers' race. The seventh coefficient plots the racial gap after controlling the implied growth imputed from the values observed up refinancing one's home using the same specification from Figure 2.1 with the sixth plot being the estimated racial gap on the same sample without the appraisal control. Finally, the tenth and last coefficient plots the racial gap after controlling for the inverse of listed time-on-market and listing price using the same specification from Table 2.7 with the ninth plot being the estimated racial gap on the same sample without the listing price control and the eighth plot being the estimated racial gap on the same sample without either controls.[4]

To summarize, we find that controlling for seller characteristics, the race of the buyer, and appraisal values, do not explain any large portion of the racial gap in unlevered housing returns. Additionally, we see that accounting for time-on-market reduces the racial gap by approximately 50% in this sub-sample.

[4] There was very little power in the regressions with the agent fixed effects so the results are not included.

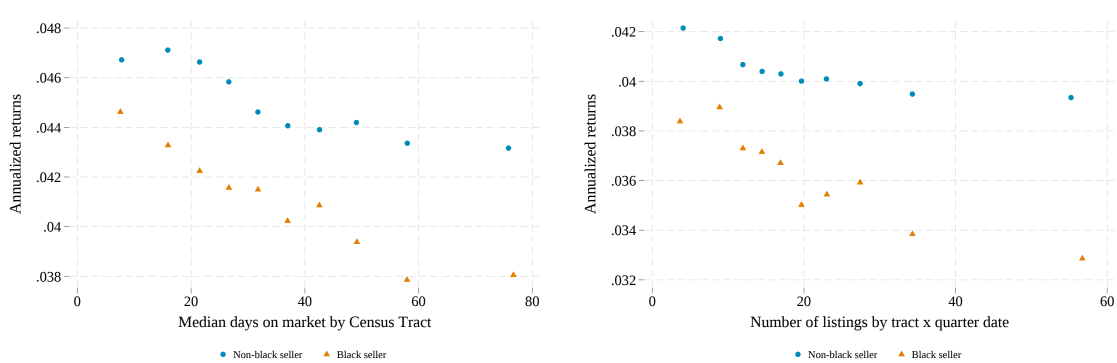
## 2.5 Heterogeneity

### 2.5.1 Market heterogeneity

In Figure 2.2, we present binscatter plots showing annualized housing returns for Black and non-Black sellers in Census tracts with different levels of market characteristics that reflect search. We use two measures: Panel (a) uses median days on market of housing transactions at the Census tract level, while panel (b) uses the number of active regular, non-distressed listings by Census tract and sale year-quarter. Both plots consistently show that Black sellers experience lower housing returns than non-Black sellers. Conditional on housing demand, both Black and non-Black sellers tend to experience lower returns in neighborhoods with more slack markets, characterized either by lower probabilities of sellers matching with a buyer or increased competition in the local housing market. Crucially, the plots show that as local markets become more slack, the racial gap not only persists but also widens. This trend suggests that Black sellers encounter greater search frictions in more competitive housing markets for sellers. These findings highlight that the racial disparities in housing returns are exacerbated under unfavorable market conditions for sellers.

Figure 2.2: Annualized housing return gaps by market characteristics

(a) Median days on market (b) Number of active listings



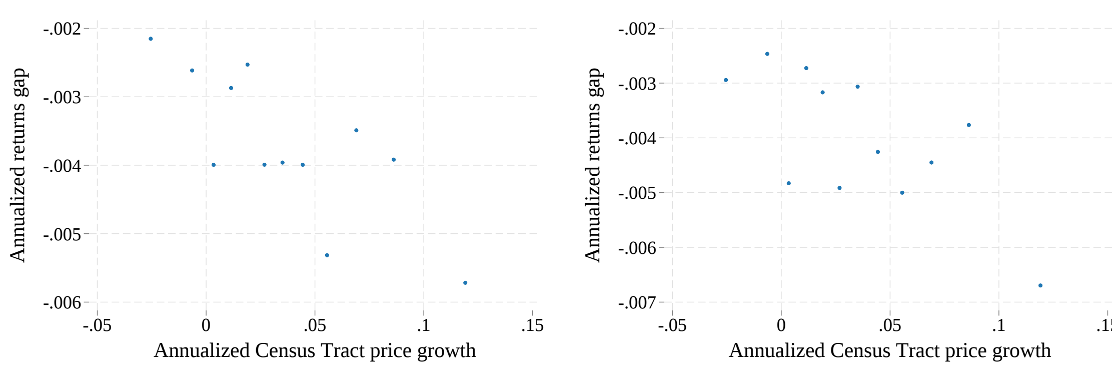

*Notes*: This Figure presents a binscatter of the annualized housing returns by Census tract market characteristics for Black and non-Black sellers. Panel (a) Plots the annualized returns by the median number of days on market within a home's Census tract and Panel (b) plots the annualized returns by the number of active listings by Census tract and year-quarter date of sale. All regressions control for Census tract-level house price index growth between purchase year and sale year and include year-quarter date of sale fixed effects.

### 2.5.2 Price-growth heterogeneity

In Figure 2.3, we present a binned regression plot showing the annualized returns gap for Black and Black-only sellers over twelve quantiles of Census tract-level annualized house price growth between purchase and sale year. The x-axis value refers to the median value within its respective quantile. The plot shows a negative returns gap at each quantile, increasing in magnitude as annualized Census tract-level price growth increases. Black and Black-only sellers in the highest do-deciles of price growth experience an average negative returns gap of -0.57% and -0.67%, respectively, significantly larger than the baseline estimates in Table 2.1. Overall, these results demonstrate that racial disparities in housing returns worsen when Black sellers experience higher neighborhood house price growth.

Figure 2.3: Annualized returns gap by annualized price growth

(a) Black sellers (b) Black-only sellers




*Notes*: This figure plots the annualized housing returns gap between Black and non-Black sellers for each do-decile of Census Tract-level annualized house price growth between purchase and sale where the x-values are the median annualized house price growth within each quantile. Regressions include Census tract-level annualized mean house price index growth between purchase year and sale year and Census tract $\times$ year-quarter of sale fixed effects.

### 2.5.3 Neighborhood heterogeneity

This section provides heterogeneity analysis at the Census tract level. We define neighborhoods using Census tracts, a common definition used in the literature. Our neighborhood-level analysis provides estimates of the racial gap in annualized unlevered returns to housing across neighborhoods with different socioeconomic characteristics. These estimates give us an understanding on which types of neighborhoods have higher or lower estimated racial gaps.

We use neighborhood characteristics from the 2010 American Community Survey 5-year estimates. We group Census tracts into quartiles based on the share of Black residents, the share of White residents, the homeownership rate, the share of residents with a college degree, and the median household income. Figure B2 displays the racial gap estimates in annualized unlevered housing returns across neighborhoods for each of our socioeconomic characteristics. Overall, we find that the annualized gap persists in each quartile group of Census tracts for every socioeconomic variable we examine.

Figure B2 Panel (a) displays the racial gap estimates across neighborhoods with different Black population shares. Neighborhoods with a higher share of Black population experience larger racial gaps in housing returns. In neighborhoods at the bottom quartile of Black population, the racial gaps are approximately -0.29% for Black sellers and -0.32% for Black-only sellers, and the estimates are statistically significant. However, although we estimate negative gaps in the second quartile, the estimates are statistically insignificant. The statistical insignificance is probably due to the mechanical fact that these neighborhoods have very few Black sellers. In neighborhoods at the top quartile of Black population, the racial gap increases to -0.39% for Black sellers and -0.42% for Black-only sellers. We believe this is due to search frictions negatively impacting Black sellers more in neighborhoods with higher Black populations. Additionally, we find that the racial gaps are generally higher for households identified as Black-only.

Figure B2 Panel (b) displays the racial gap estimates across neighborhoods with different shares of White residents. We find lower gaps in annualized housing returns in neighborhoods with the lowest shares of minority residents, though the relationship does not appear to be linear. The results show that the estimated gaps are consistently negative.

Figure B2 Panels (c) and (d) display the racial gap estimates by the quartile groups of neighborhood homeownership rates and of median household income, respectively. We find that the largest gaps are in neighborhoods in the bottom quartiles of median household income with estimates as large as -0.39% and -0.42% for Black and Black-only sellers, respectively. This is likely because neighborhoods with low levels of income typically have higher minority populations. Given this relationship, it is likely that search frictions negatively impact Black sellers more in neighborhoods with lowest income levels than in neighborhoods with higher income levels. We find a flatter relationship between homeownership rates and the racial gap in housing returns. Overall, the results show that the estimated gaps are consistently negative across these types of neighborhoods.

Finally, Figure B2 Panel (e) displays the racial gap estimates by the quartile groups of neighborhood shares with college education. In short, we find a flatter relationship between college education levels of a neighborhood and the racial gap in housing returns. We find that Black sellers realize lower housing returns if their properties are in neighborhoods with lower education levels ranging from -0.43% to -0.26%. However, the gaps for Black-only sellers do not follow a similar pattern. One consistency is that the estimated gaps are slightly larger for Black-only sellers compared to Black sellers realizing an average racial gap of up to -0.46%.

To summarize, we find that both Black and Black-only sellers have realized lower housing returns in all quartiles of neighborhoods for each of the neighborhood characteristics we examine. This indicates that the racial disparity in housing returns is not confined to certain neighborhoods, but is broadly evident across various geographical areas. We also find that the gap tends to be larger in neighborhoods with higher shares of Black residents and lower incomes.

## 2.6 Conclusion

This paper investigates whether there exists a racial gap in unlevered housing returns for regular non-distressed sales. Although many papers have studied racial disparities in the housing market, no one has focused on the within-neighborhood disparities during the home-selling process for non-distressed home sales nor provided a detailed empirical explanation of the main causes for the disparities. We use over 1.1 million repeat-sale transactions between 2003 and 2020 in our analysis. When estimating the differences in housing returns between Black and non-Black sellers, we control for Census tract by sale year-quarter fixed effects and tract-level house price growth between purchase and sale dates. Our main findings are that Black and Black-only sellers on average realize 1.7% and 1.9% lower total capital gains, and 0.36% and 0.38% lower annualized returns, respectively, when selling their homes, and our explanations of what does and does not explain these gaps. We also find that the gap exists in all types of neighborhoods.

To explore the sources of the gap, we bring in additional data from various sources to examine the roles of seller's liquidity, property renovations, race of the buyer, real estate agents, and appraisers on the racial gap. We find that none of these factors can explain much of the gap. However, our appraisal analysis strongly suggests that, on average, Black homes are not valued less than non-Black homes.

We find that Black sellers tend to set lower listing prices and experience longer time on market. These results suggest that Black sellers face different levels market tightness than their non-Black neighbors. Motivated by this new set of facts, we investigate the role of search frictions. Within the context of a simple search model, different levels of market tightness implies different levels of prices. Accounting for listed prices is key because it is a measure of a home's market value that can be influenced by the biases of several players such as home appraisers, real estate agents, and sellers who likely internalize the racial differences in time on market. As a result, we control for listing prices and days on market, and find that the racial gap drops to near zero, suggesting that both the biases behind listing prices and the search frictions faced by Black sellers are the dominating factors contributing to the gap. In a complementary set of analyses, we find that Black sellers living zip codes less exposed to buyer agent discriminatory practices realize a lower returns gap relative to non-Black sellers. Finally, we find that when intermediaries such as buyer agents, whose involvement we argue causes racial differences in search frictions and consequently in housing returns, are absent, the racial gap in housing returns is eliminated. Overall, the results in this paper provide strong evidence for the significant role that human intermediaries, such as buyers' real estate agents, in creating this racial disparity in housing returns.

# Chapter 3

# Expectations, Expectations, Expectations

## 3.1 Introduction

Every decision behind buying or selling a house requires a large set of inferences made from a broad pool of information. Home buyers internalize information such as mortgage rates, house prices, their own income, their credit worthiness, heterogenous mortgage products, and consider the option of paying points, all while searching for a house that best matches their preferences. Home sellers attempt to infer the buyers' information set to generate their own understanding of housing demand. These decisions are not static either, but dynamic, further complicating the decision-making process. Home buyers also consider the question "should I buy today or later.' Home sellers infer home buyers' answer to their question and face a similar option, "should I sell today or later". Thus, if we want to understand housing market dynamics, the expectations channel matters.

This paper studies how mortgage rate and house price expectations affect housing supply through delistings behavior and, ultimately, house prices. In this paper, I document new facts about household expectation formation of the housing market and relate their expectations to realized housing outcomes with a focus on the supply-side of the housing market.

First, using individual respondent data from the Fannie Mae National Housing Survey (NHS), I find that homeowners' one-year mortgage rate expectations are state and path-dependent. When mortgage rates are relatively stable and above or below recent historic averages, homeowners expect mortgage rates to mean revert. I find that when mortgage rates are trending in a certain direction, homeowner mortgage rate expectations tend to follow the trend. I focus on homeowner responses because I later relate expectations to home delistings growth patterns. Since renters do not own homes to list on the market, they are excluded. Additionally, similar to Adelino et al. (2018), I find noticeable differences in the dispersion of housing market expectations between owners and renters in the NHS data.

Second, I relate household one-year mortgage rate expectations to their one-year house price expectations. The survey data confirms that, all else equal, house price expectations are negatively related to mortgage rate levels. However, during periods of high mortgage rates, homeowners in low housing supply elasticity states tend to expect house prices to rise when they expect mortgage rates to fall . This pattern fails to emerge when for households in higher supply elasticity areas. The results suggest spatial heterogeneity in households relation between future mortgage rate changes to future house prices. Although a dataset with finer location variables, allowing me to better control for local market experiences (Kuchler and Zafar (2019)), and additional individual characteristics may help explain this.

Third, using the New York Federal Reserve Bank's Survey of Consumer Expectations, I show that homeowners update their house price expectations in response to a mortgage rate shock. Using the mortgage rate-specific monetary policy shock described in Chapter 1 as an instrument, I show that a negative mortgage rate shock causes homeowners to increase their price expectations. While Ahn et al. (2024) show the effects of monetary policy shocks through the mortgage rate channel impacting inflation expectations, these results show similar results on house prices. The results demonstrate that homeowners internalize existing information and quickly update their own expectations, complementing the findings of Fuster et al. (2026) who demonstrate households have high levels of informedness of mortgage rate changes.

Fourth, I link house price expectations to housing market purchase and selling beliefs. NHS respondents are also asked if they believe it is a good time to buy and if they believe it is a good time to sell at the time of responding to the survey. During high mortgage rate periods, homeowners demonstrate a logical understanding of when is a good time to sell one's home given the known level and history of mortgage rates and their expectations of future house prices. I find that when mortgage rate levels are high, respondents who expect house prices to rise are less likely to believe that it is a good time to sell, while respondents who expect prices to fall are more likely to report that it is a good time to sell. This result is crucial because it gives us intuition for the sharp rise of home delistings in 2022 and 2023.

Surprisingly, I fail to estimate an analogous set of coefficients demonstrating that homeowners combine house price expectations and knowledge of mortgage rates to generate rational decision on when is a good time to buy a house. In fact, I find that when mortgage rates are high, homeowners who expect house prices to fall are more likely to report that it is a good time to buy. In other words, during periods when the debt-to-income constraint is more binding and when the loan-to-value (LTV) constraint is more binding relative to the expected future LTV constraint, these households are more likely to respond by saying it is a good time to buy. As a robustness check, I replicate these findings using the University of Michigan's Survey of Consumers, and find these patterns are stronger when homeowners report that it is a good time to sell for price reasons using a similar decomposition of reasons to Piazzesi and Schneider (2009).

After establishing the new set of empirical facts regarding housing market expectations, I relate aggregated homeowner expectations shares to realized housing outcomes. Using metropolitan-month date delistings data from Redfin, a national real estate brokerage, one can see that delistings growth plummeted during the low-rate Covid era and skyrocketed during the post-Covid rate hike period. I find that annualized metropolitan delistings growth is related to high mortgage rate levels, high shares of homeowners expecting mortgage rate increases, and high shares of households expecting house price decreases. These results are consistent with those from relating the interaction of mortgage rates and homeowner price expectations to whether they think it is a good time to sell.

Finally, I show that delistings growth has important implications for realized house price growth. The results indicate a result widely known to the literature that delistings growth and mortgage rates are negatively related to house price growth. However, the sign of interaction between mortgage rates and delistings growth tells a different story. During periods of high mortgage rates, positive delistings growth is associated with positive house price growth. The mechanism is simple: rising delistings reduce the effective housing supply which pushes up prices. These results provide new empirical evidence for an additional explanation on why house prices rose when mortgage rates rose in 2022 and 2023.

The empirical evidence highlight a new supply-side channel through which expectations shape housing market dynamics. While much of the literature has focused on the effects of mortgage rate lock-in as an explanation for the positive correlation between house prices and mortgage rates, it is difficult to disentangle the demand effects from the supply effect. By focusing on delistings, this paper hones in on the supply effects of high mortgage rates through our newly-gained understanding of the role of expectations. Although, mortgage rate lock-in may contribute to the delistings results, it is largely believed that lock-in effects impact the moving decision prior to listing one's home (Fonseca and Liu (2024), Fonseca et al. (2024)). So the lock-in effects likely have a small effect on the decision to delistings relative to active listings and new-listings. The fact that, in addition to delistings levels, ratios such as delistings-to-active listings and delistings-to-new listings still grew when mortgage rates rose supports this claim.

As demonstrated in Chapter 1, households' home-purchasing behaviors are quite responsive to contemporary mortgage rates. However, a key piece of information missing from the literature is understanding the role of household mortgage rate expectations in explaining household decision-making and dynamics in housing markets. Ultimately, understanding household expectations can further our understanding of housing markets. This paper focuses on how these expectations impact the supply of housing. Just as the decision to move is crucial to understand the supply of housing (Ngai and Sheedy (2020)), the decision to delist is especially crucial to understand housing supply dynamics.

Other related papers include Piccolo and Gorodnichenko (2025) who relate homeownership status to inflation expectations and Adelino et al. (2018) who argue housing decisions vary by perceptions of house price risk. This paper contributes to the literature that connects household expectations to realized outcomes in housing markets (Burnside et al. (2016), Glaeser and Nathanson (2017), Bailey et al. (2019),Chodorow-Reich et al. (2024)). Lastly, many of the new empirical facts established in this paper, complement those described in Kuchler et al. (2023).

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 describes the empirical methodology and presents the results. Section 4 concludes.

## 3.2 Data

I obtain individual respondent microdata for the Fannie Mae National Housing Survey (NHS) from the database Roper from January 2011 through March 2025. The NHS randomly surveys approximately 1,000 households every month, asking them to answer questions about the current state of the housing market, their expectations of the housing market, and basic characteristics about themselves. Questions of interest for this paper are those that ask households about their one-year mortgage rate expectations, one-year house price expectations, whether they think it is a good time to buy and to sell at the time of responding, and their housing status (i.e., whether they outright own their home, own their home with a mortgage, rent, or other). The key advantage of this survey is that it is the only existing survey that provides mortgage rate expectations during this 14 year span. Though it does not ask respondents to report their mortgage rate expectations in percentage points (p.p.), their binary measure of mortgage rate expectations, whether respondents believe mortgage rates will rise or fall in one year, is full of important and not-fully explored information. Respondent state is not available until March 2016 and respondent Metropolitan Statistical Area (MSA) is available until May 2016. I infer respondent state prior to March 2016 from the MSA for respondents in living in MSAs that are fully contained within one state's borders.

The University of Michigan Survey of Consumers randomly surveys households every month, asking them questions about the current state of the housing market, their expectations of house prices, and basic characteristics about themselves. I obtain a sample of these data spanning January 2011 through October 2024. Questions of interest for this paper are those that ask households about their one-year house price expectations, whether they think it is a good time to buy and to sell at the time of responding, and their housing status (i.e., whether they own their home or rent). A key advantage of this survey, is that they ask households follow-up questions on their buying a selling beliefs which allows us researchers to understand the reasoning behind their answers. The survey asks whether households believe it is or is not a good time to buy or sell a home for interest rate, price, credit, affordability, or other reasons.

The New York Federal Reserve Survey of Consumer Expectations randomly surveys households, asking them questions about the current state of the housing market, their expectations of house prices, and basic characteristics about themselves. I obtain a sample of these data spanning June 2013 through December 2024. Questions of interest for this paper are those that ask households about their one-year house price expectations and their housing status (i.e., whether they own their home or rent). The key advantage of this survey is that they follow households for approximately one year, allowing one to observe how households update their expectations.

I obtain aggregated metropolitan-month date level data on listings from Redfin, a national real estate brokerage. My data sample contain counts of active listings, new listings, delistings, and listings sold from January 2016 through September 2025. Redfin defines a delisting as a home listing that was once active and observed to be taken off the market.

Daily offered mortgage rate levels are from Bankrate.com downloaded via Bloomberg Terminal. Housing supply elasticity estimates are obtained from Baum-Snow and Han (2024).

## 3.3 Empirical results

### 3.3.1 Mortgage rates and house price expectations

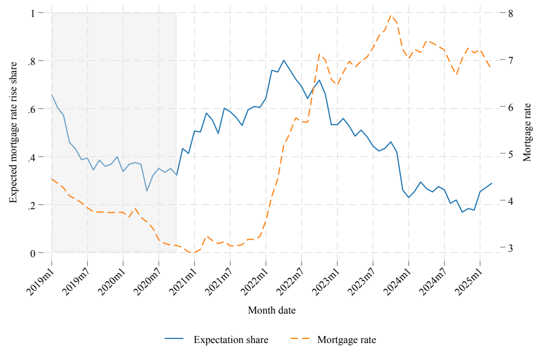
A key piece of information missing from the literature is understanding the role of household mortgage rate expectations in explaining household decision-making and dynamics in housing markets. Understanding mortgage rate expectations can help us infer house price expectations, and ultimately, further our understanding of housing markets. Figure 3.1 presents visual evidence of the first contribution of this paper. Spanning January 2019 through March 2025, the figure breaks down the monthly time series of national-level share of homeowners expecting a mortgage rate increase over twelve months into four segments. I compare the trends of expected mortgage rate increase shares to the trends of mortgage rate levels in each panel.

In Panel (A), between January 2019 and October 2020, a period of falling mortgage rates, the share of homeowners expecting a mortgage rate increase also fell. In Panel (B), between November 2020 and August 2021, a period of stable and historically-low mortgage rates, the share of homeowners expecting a mortgage rate increase rose—demonstrating an expectation of mean-reversion. In Panel (C), between September 2021 and October 2022, a period of rapidly rising mortgage rates, the share of homeowners expecting a mortgage rate increase rose—once again following the trend of mortgage rate levels. Finally, in Panel (D), between November 2022 and March 2025, a period of stable and high mortgage rates, the share of homeowners expecting a mortgage increase fell—again demonstrating and expectation of mean-reversion.

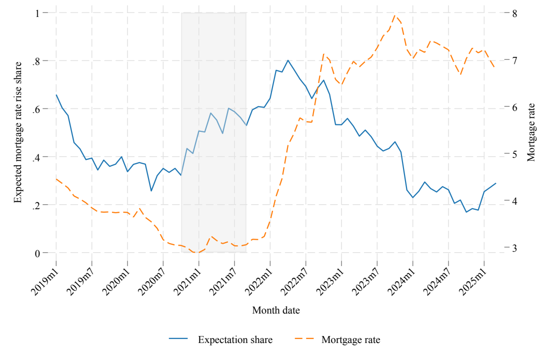
These patterns emerge when explicitly regressing mortgage rate expectations on the state and recent path of mortgage rates. In Table 3.1 and Appendix Table C1, I test the hypothesis of mortgage rate expectation state-dependence empirically at the individual micro data-level and at the national-level, respectively. In Table 3.1, the dependent variables of the logistic regressions are a binary indicator for whether a homeowner expects mortgage rates to increase in 12 months in Columns (1) and (2), and a binary indicator for whether a homeowner expects mortgage rates to decrease in 12 months in Columns (3) and (4). The regressors are the month-average mortgage rate at the time of response, the one-month lagged mortgage rate, and a six-month

Figure 3.1: Mortgage rates and mortgage rate expectations

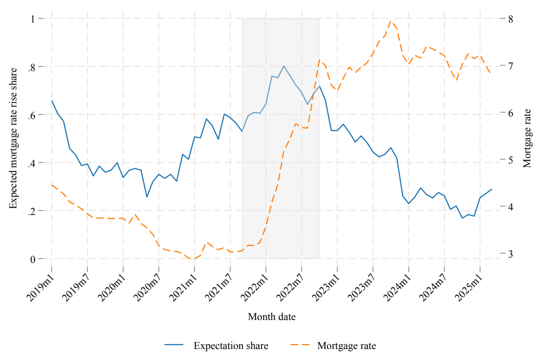
(a) Falling rates and expectations



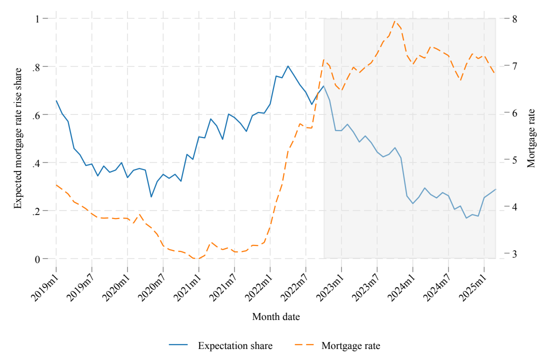

(b) Stable [low] rates and rising expectations




(c) Rising rates and expectations




(d) Stable [high] rates and falling expectations




National-average monthly time series panels plot the mortgage rate level and the share of homeowners expecting a mortgage rate increase 12 months after responding from January 2019 through March 2025. Expectations data are obtained from the Fannie Mae National Housing Survey. Mortgage rate data are obtained from Bankrate.com via Bloomberg Terminal.

rolling average of monthly mortgage rate changes.

The positive constant estimate in Columns (1) and (2) indicates that if mortgage rates were at a hypothetical level of zero percent, households are more likely to expect a mortgage rate increase. The negative coefficients for mortgage rate levels tells us that as mortgage rate levels increase, households are less likely to expect mortgage rate increases. In Columns (3) and (4), the negative constant estimate indicates that if mortgage rates were at a hypothetical level of zero percent, households are less likely to expect a mortgage rate decrease. The positive coefficients for mortgage rate levels in Columns (3) and (4) tells us that as mortgage rates increase, households are more likely to expect mortgage rate decreases. These results support the hypothesis of mean-reverting mortgage rate expectations during stable rate periods.

Table 3.1: Mortgage rate expectations vs mortgage rates

| | Expecting mortgage rate increase | | Expecting mortgage rate decrease | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $r^m$ | -0.2567*** | | 0.5780*** | |
| | (0.0228) | | (0.0352) | |
| L.$r^m$ | | -0.2522*** | | 0.5746*** |
| | | (0.0217) | | (0.0330) |
| 6-mon. roll. avg. $r^m$ | 4.9631*** | 4.7070*** | -5.1538*** | -4.7204*** |
| | (0.3218) | (0.3056) | (0.5095) | (0.4896) |
| Constant | 1.0973*** | 1.0785*** | -4.9386*** | -4.9286*** |
| | (0.1046) | (0.1001) | (0.1786) | (0.1706) |
| Observations | 115270 | 115270 | 115270 | 115270 |

The table presents estimated coefficients of a logistic regression estimating the effect that mortgage rates and 6-month rolling averages of monthly mortgage changes on binary indicators of one-year homeowner mortgage rate expectations. The data sample spans January 2011 through March 2025. Data are obtained from the Fannie Mae National Housing Survey. Clustered standard errors at the month date level reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

I estimate a positive and statistically significant coefficient for the impact of six-month rolling average of monthly mortgage rate changes on the likelihood of a household expecting a mortgage rate increase. Similarly, I estimate an analogous, negative coefficient for the same variable on the likelihood of expecting a mortgage rate decrease. These estimates indicate that household mortgage rate expectations tend to closely follow the trend of recent mortgage rate movements.

Appendix Table C1 shows similar results using data aggregated at the national-level. The dependent variables are the share of homeowners expecting a mortgage rate increase, the share of homeowners expecting a mortgage rate decrease, and the net difference of the two in Columns (1) and (2), (3) and (4), and (5) and (6), respectively. I regress the shares of mortgage rate expectations on the same set of mortgage rate variables. Each column points to the same story—mortgage rate expectations tend to follow the recent trend of mortgage rates and also tend to mean-revert, though the mean-reversion argument shows up strongest in the net share regressions for mortgage rate levels above 7 p.p.

Next I relate homeowner mortgage rate expectations to house price expectations. Demonstrating this relationship is difficult because housing markets are heterogenous across space. Unfortunately, the NHS survey data does not provide detailed location data of respondents for the majority of the survey. Though I am able to observe respondent state since March 2016, I can only observe respondent metropolitan area until May 2016. Observing metropolitan area over the entire sample period would allow me to better account for heterogeneity across space. Further complicating the matter is that the NHS survey data available does not ask households to express their one-year mortgage rate expectations in a continuous measure nor do they ask households what they perceive mortgage rates to be.

Table 3.2 presents the results relating household house price expectations to mortgage rate expectations with the individual respondent microdata. Columns (1)–(4) report the results for the eight states with the lowest housing supply estimates and Columns (5)–(8) report the results for the other states. The dependent variable for Columns (1), (2), (5), (6) is the percent households expect house prices to change over the 12 months after responding to the survey. The dependent variable for Columns (3) and (7) is the binary indicator for whether a household expects house prices to increase over the next 12 months and the dependent variable for Columns (4) and (8) is the binary indicator for whether a household expects house prices to decrease over the next 12 months. Households with responses "Prices will remain about the same" are coded with zeros for both the binary and continuous measures, while households with responses "Don't know" are coded with zeros for the binary indicator variables and excluded from the continuous measures of price expectations. The regressors are the mean mortgage rate for the month of response, a binary indicator for the direction of a household's 12-month mortgage rate expectation, and the interaction between the two variables. Note that expectation responses for "about the same" and "I don't know" are coded as zero for the mortgage rate expectations variables. State-level housing supply elasticities are obtained by aggregating Baum-Snow and Han (2024) Census tract-level housing supply elasticity estimates to the state level.

The sign of the mortgage rate coefficient suggests that homeowners demonstrate awareness of current mortgage rate levels and knowledge of the general inverse relationship between house prices and mortgage rates levels, though it fails to be statistically significant in most of regressions where households are asked to report their expected house price changes in percentage points. However, households do well

Table 3.2: House price expectations vs mortgage rate expectations

| | Lowest supply elasticity | | | | ¬ Lowest supply elasticity | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) % | (2) % | (3) $E[hp]\uparrow$ | (4) $E[hp]\downarrow$ | (5) % | (6) % | (7) $E[hp]\uparrow$ | (8) $E[hp]\downarrow$ |
| $r^m$ | -0.267 | -0.199 | -0.099** | 0.079* | -0.166 | -0.507*** | -0.051* | 0.234*** |
| | (0.2066) | (0.1641) | (0.0445) | (0.0477) | (0.1711) | (0.1093) | (0.0292) | (0.0395) |
| $E[r^m]\downarrow$=1 | -7.220*** | | -1.900*** | | -1.310 | | -0.351* | |
| | (1.8942) | | (0.3168) | | (0.9304) | | (0.1801) | |
| $E[r^m]\uparrow$=1 | | 1.158 | | -0.900** | | -1.003 | | 0.017 |
| | | (1.3400) | | (0.4111) | | (0.9415) | | (0.3023) |
| $E[r^m]\downarrow$=1 × $r^m$ | 0.863*** | | 0.280*** | | -0.279 | | -0.048 | |
| | (0.2851) | | (0.0554) | | (0.1697) | | (0.0308) | |
| $E[r^m]\uparrow$=1 × $r^m$ | | -0.051 | | 0.173** | | 0.486** | | -0.035 |
| | | (0.2934) | | (0.0859) | | (0.2309) | | (0.0623) |
| Constant | 2.795*** | 1.722** | 0.250 | -1.889*** | 2.799*** | 3.462*** | 0.069 | -2.741*** |
| | (0.8330) | (0.8066) | (0.1916) | (0.2531) | (0.6665) | (0.5332) | (0.1266) | (0.2228) |
| Observations | 9796 | 9796 | 11122 | 11122 | 39797 | 39797 | 45631 | 45631 |

The table contains estimated coefficients regressing the continuous measure of homeowners one-year house price expectations and the binary measure of homeowners expecting house price increases or decreases in one year on mortgage rate levels, the binary measure of expecting a mortgage rate increase or decrease in one year, and their interaction at the individual respondent-level. Data are obtained from the Fannie Mae National Housing Survey. Clustered standard errors at the month date level reported in parenthesis
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

in showing this when relating the direction of expected house prices to mortgage rates levels. The interesting part of the tables lies in what we learn from the first four columns. During high mortgage rate periods, homeowners living in states with the lowest supply elasticities tend to expect house price decreases when they expect mortgage rate increases as shown in Column (4). Similarly, in Column (3), we see that during high mortgage rate periods when these homeowners expect mortgage rate decreases, they are more likely to expect a house price increase. Column (1) demonstrates a similar result for the continuous measure of house price expectations. Including the interaction of mortgage rate expectations with the mortgage rate level is crucial because household expectations vary over in the time-series Kuchler et al. (2023).

The magnitude of the estimated coefficients for expected mortgage rate decreases and the tighter standard errors around them suggests that households may have an easier time relating the impact of expected mortgage rate decreases to expected price increases than related the impact of expected mortgage rate increases to expected house price movements. This may be due to observing that house prices may still increase during rate hike periods (though house price growth tends to fall).

The interaction between mortgage rate levels and expected mortgage rate movements does little to explain expected house prices in states with more elastic housing supply (Columns 5–8), where house prices are less volatile on average. Overall, on average homeowners believe there is an inverse relationship between mortgage rate levels and expected house prices. Additionally, homeowners living in low supply elasticity areas, potentially with different housing market experiences, believe there is an inverse relationship between mortgage rate expectations and expected house prices during high mortgage rate periods.

The results suggest spatial heterogeneity in the relationship between mortgage rate expectations and house price expectations. A dataset with finer location variables, allowing me to better control for local market experiences (Kuchler and Zafar (2019)), and additional individual characteristics may help explain this.

Appendix Table C2 shows similar results with the data aggregated to the national level. The aggregated survey data represents shares of households expecting a house price increase or decrease in one year and shares of households expecting a mortgage rate increase or decrease in one year. During high mortgage rate periods, there is an inverse relationship between house price expectations and mortgage rate expectations.

One may ask how quickly households update their expectations. Though Figure 3.1 visually shows that homeowners update their price expectations, it is difficult to measure how households' update in response to shocks. Unfortunately, the NHS data does not follow households over time preventing me from measuring individual mortgage rate changes over time. However, I am able to calculate changes in individual homeowner house price expectations using the New York Federal Reserve's Survey of Consumer Expectations data which follows households over the course of a year.

Another advantage of this data is that the exact date of responding to the survey is reported. Knowing this allows me to merge in the exact offered mortgage rate for that day. Using a similar specification for the house price impact of monetary policy described in Chapter 1, these data allow me to measure how homeowners change their price expectations in response to mortgage rate shocks. I focus on homeowner responses made prior to an FOMC meeting where I observe a response after the FOMC meeting. This allows me to calculate the p. p. change in one-year house price expectations and the change in mortgage rates between the two response dates. I regress the change in one-year price expectations on the mortgage rate change instrumented by the mortgage rate-specific monetary policy shock described in Chapter 1.

Table 3.3 presents the results. Controls include the effective federal funds rate and VIX. Standard errors are clustered at the date of the post-FOMC meeting response and Kleibergen-Paap F-statistics are reported for the IV regressions. All data samples outside of Column (7) restrict the data to homeowners with price expectations within the 5th percentile and 95th percentile of the data sample. Homeowners with owning multiple homes are excluded, though they represent a small share of the sample. The data sample for Column (7) includes renters.

Table 3.3: Updating house price expectations

| | P.P. change in 1yr HP expectations | | | | | | Chg in binary 1yr HP exp. | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\Delta r^m$ | -0.2569 | -0.8190* | -0.2510 | -0.8670** | -1.2960** | 1.8247** | -0.1752** | -0.1764** |
| | (0.1628) | (0.4316) | (0.1630) | (0.4300) | (0.6586) | (0.9010) | (0.0819) | (0.0821) |
| Homeowner=1 × $\Delta r^m$ | | | | | | -2.5409*** | | |
| | | | | | | (0.9456) | | |
| Homeowner=1 | | | | | | 0.2027*** | | |
| | | | | | | (0.0679) | | |
| cut1 | | | | | | | -2.6631*** | -2.6747*** |
| | | | | | | | (0.0258) | (0.1263) |
| cut2 | | | | | | | 2.6503*** | 2.6383*** |
| | | | | | | | (0.0245) | (0.1252) |
| Observations | 53445 | 53445 | 53421 | 53421 | 52210 | 85309 | 70103 | 70069 |
| Regression type | OLS | IV | OLS | IV | IV | IV | OLOGIT | OLOGIT |
| Controls | | | Y | Y | Y | Y | | Y |
| Respondent FE | | | | | Y | | | |
| K-P Fstat | | 284.23 | | 277.66 | 213.09 | 104.24 | | |

The table contains estimated coefficients regressing changes of homeowners one-year house price expectations on changes in daily mortgage rate levels between response dates instrumented by the Drukker (2026) mortgage rate-specific monetary policy shock at the individual respondent-level. The dependent variable for Columns (1)–(6) is changes in the continuous measure of homeowners one-year house price expectations and the dependent variable for Columns (7) and (8) is changes in the categorial measure of homeowners one-year house price expectations. Controls include effective federal funds rate and VIX. Expectations data are obtained from the New York Federal Reserve Bank Survey of Consumer Expectations. Daily offered mortgage rate data is from Bankrate.com downloaded via Bloomberg Terminal. Clustered standard errors at the post-FOMC date level reported in parenthesis $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Columns (1) and (3) present the results for the OLS regression. The sign of the coefficients indicates that when mortgage rates fall, homeowners increase their one-year price expectations. However, the estimates do not demonstrate statistical significance. Column (2) presents the results for the IV regression without any controls. I estimate that a negative one p.p. mortgage rate shock increases one-year price expectations by an average of 0.82 p.p.s. Column (4) shows that the IV regression with controls yields a similar estimated coefficient. Column (5) presents the IV regression with controls and individual respondent FEs. I estimate that a negative one p.p. mortgage rate shock increases one-year price expectations by an average of 1.3 p.p.s. Column (6) presents the results for the IV regression with controls and includes an interaction between mortgage rates and a binary indicator of being a homeowner. This regression demonstrates that renters update their price beliefs in line with mortgage rate changes while homeowners continue to update in the opposite direction from mortgage rate shocks. One thing to note is that I am unable to differentiate between renters who are not buying a home and renters who are buying a home. Renters who are buying a home are likely more knowledgable of the housing market and the home-buying process, and are therefore more likely to update like homeowners do. One thing to note is that the magnitudes of these coefficients suggest that households under-extrapolate the one-year price response to mortgage rate changes given the findings of the IRF in Chapter 1 Appendix Figure A3.

The survey also asks households to report the direction that they expect house prices to change. Among those with responses for "increase", "decrease", and "no change", I can observe how their responses to this question changes over time by creating a new categorical variable for changing in a negative direction, changing in a positive direction, and no change in direction. Because these categories contain a clear order, I can relate these categories to mortgage rate changes using an ordered logistic regression. Columns (7) and (8) report the estimates without and with controls, respectively. Once again, the results demonstrate a negative relationship between mortgage rate changes and updating price expectation in the positive direction.

These findings complement those of Fuster et al. (2026) who show that high levels of informedness of mortgage rate changes. Overall, the results demonstrate that homeowners internalize existing information and quickly update their own expectations.

### 3.3.2 Good times to buy and sell

Now that I have established some facts about homeowners' mortgage rate expectations and how they translate to their house price expectations, I relate house price expectations to beliefs on home purchasing and selling timing. NHS respondents are asked, at the time of responding to the survey, if they believe it is a good time to buy a home and if they believe it is a good time to sell a home. Table 3.4 estimates a logistic regression to relate a binary indicator that takes the value of one when households believe it is a good time to buy (Columns (1) and (2)) and a good time to sell a home (Columns (3) and (4)) to mortgage rates and whether households believe house prices in the next 12 months will be higher than house prices at the time of responding. Note that the left-hand side variable asks whether households believe it is a good time to buy or sell at the time of responding. Relating this to housing market expectations informs us how expectations of the future impact real-time decisions.

Table 3.4: Good time to today to Buy/Sell vs expectations

| | Good time to buy | | Good time to sell | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $r^m$ | -0.5360*** | -0.5579*** | 0.0871* | 0.0058 |
| | (0.0517) | (0.0470) | (0.0453) | (0.0393) |
| E[hp] ↑=1 | 0.3768*** | | 1.0848*** | |
| | (0.1048) | | (0.1347) | |
| E[hp] ↑=1 × $r^m$ | 0.0001 | | -0.1537*** | |
| | (0.0197) | | (0.0243) | |
| E[hp] ↓=1 | | -1.6915*** | | -0.6411*** |
| | | (0.1217) | | (0.1990) |
| E[hp] ↓=1 × $r^m$ | | 0.1753*** | | 0.0909*** |
| | | (0.0229) | | (0.0330) |
| 6-mon. roll. avg. $r^m$ | -2.0681*** | -1.9635*** | 2.1329*** | 2.2456*** |
| | (0.5531) | (0.5424) | (0.6696) | (0.6860) |
| Constant | 2.7402*** | 3.1316*** | -0.3696 | 0.1941 |
| | (0.2632) | (0.2365) | (0.2432) | (0.1997) |
| Observations | 112990 | 112990 | 111778 | 111778 |

The table presents estimated coefficients of a logistic regression estimating the effect that mortgage rates, 6-month rolling averages of monthly mortgage changes, the binary measure of homeowners expecting house price increases or decreases in one year and their interaction with mortgage rates on binary indicators of one-year homeowner mortgage rate expectations. The data sample spans January 2011 through March 2025. Data are obtained from the Fannie Mae National Housing Survey. Clustered standard errors at the month date level reported in parenthesis $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

First, the results in Columns (1) and (2) demonstrate a strong, negative relationship between mortgage rates and home-buying attitudes and the results in Columns (3) and (4) demonstrate a weak, positive relationship between mortgage rates and selling attitudes. Not surprisingly, when sellers expect high prices, they are more likely to believe that it is a good time to sell in general. However, during high mortgage rate periods, the expectations channel appears to drive inter-temporal comparisons in selling beliefs. Homeowners demonstrate a logical understanding of when is a good time to sell one's home given the known level and history of mortgage rates and their expectations of future house prices. I find when mortgage rate levels are high, respondents who expect house prices to fall are more likely to believe that it is a good time to sell today, relative to selling in the future. In a similar vein, respondents who expect prices to rise are less likely to report that it is a good time to sell.

This result is crucial because it gives us intuition for the sharp rise of home delistings in 2022 and 2023. Appendix Figure C1 shows that during 2022 and 2023, the years with the highest delistings growth, although the homeowner share of expecting a price increase was falling, it was still larger than the share of homeowners expecting a price decrease. Thus, the Column (3) estimates provide important context connect mortgage rates, price expectations, selling beliefs and delistings which will be explored in the following subsection.

The home-buying attitudes in relation to house price expectations suggests that buyers are both mortgage rate and price sensitive. The Column (1) results suggest that when homeowners believe prices will rise in the future, they will be more likely to report that it is a good time to buy, relative to the future, when responding to the survey. Similarly, the Column (2) results suggest that when homeowners believe prices will fall in the future, they will be less likely to report that it is a good time to buy, relative to the future, when responding to the survey. The interaction with downward price expectations and mortgage rate levels has the opposite sign, though it is lower in relative magnitude to the price expectations coefficient—potentially signaling that there is some omitted variable bias. If taken seriously, the concern is that during periods when the debt-to-income constraint is more binding and when the loan-to-value (LTV) constraint is more binding relative to the expected future

LTV constraint, these households are more likely to respond by saying it is a good time to buy.

Fortunately, other publicly-available surveys exist that ask households about their house price expectations and their home buying and selling beliefs. As a robustness check, I estimate the same logistic regression with the same specification using data from the University of Michigan Survey of Consumers in Table 3.5. The data spans January 2011 through October 2024. The results are qualitatively the same with the signs and relative magnitudes matching most of those in Table 3.4. The only significant difference is that the coefficients for mortgage rates in Columns (3) and (4) are estimated to be negative, which makes more intuitive sense given the general negative relationship between mortgage rates and prices.

Table 3.5: Good time to today to Buy/Sell vs expectations – SoC Micro data

| | Good time to buy | | Good time to sell | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $r^m$ | -0.6294$^{***}$ | -0.6184$^{***}$ | -0.0099 | -0.0768$^{*}$ |
| | (0.0558) | (0.0562) | (0.0424) | (0.0392) |
| E[hp] $\uparrow$=1 | 0.1447 | | 1.4498$^{***}$ | |
| | (0.1336) | | (0.1038) | |
| E[hp] $\uparrow$=1 $\times$ $r^m$ | 0.0381 | | -0.1286$^{***}$ | |
| | (0.0240) | | (0.0193) | |
| E[hp] $\downarrow$=1 | | -1.2882$^{***}$ | | -1.2403$^{***}$ |
| | | (0.1325) | | (0.1345) |
| E[hp] $\downarrow$=1 $\times$ $r^m$ | | 0.0780$^{***}$ | | 0.1164$^{***}$ |
| | | (0.0276) | | (0.0259) |
| 6-mon. roll. avg. $r^m$ | -1.3763$^{**}$ | -1.3255$^{**}$ | 2.3155$^{***}$ | 2.4731$^{***}$ |
| | (0.5461) | (0.5440) | (0.6072) | (0.6501) |
| Constant | 3.2632$^{***}$ | 3.4606$^{***}$ | -0.0546 | 0.6846$^{***}$ |
| | (0.2692) | (0.2835) | (0.2287) | (0.2094) |
| Observations | 69485 | 69485 | 68868 | 68868 |

The table presents estimated coefficients of a logistic regression estimating the effect that mortgage rates, 6-month rolling averages of monthly mortgage changes, the binary measure of homeowners expecting house price increases or decreases in one year and their interaction with mortgage rates on binary indicators of homeowner beliefs for it being a good time to buy and sell a home. The data sample spans January 2011 through October 2024. Data are obtained from the University of Michigan Survey of Consumers. Clustered standard errors at the month date level reported in parenthesis

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

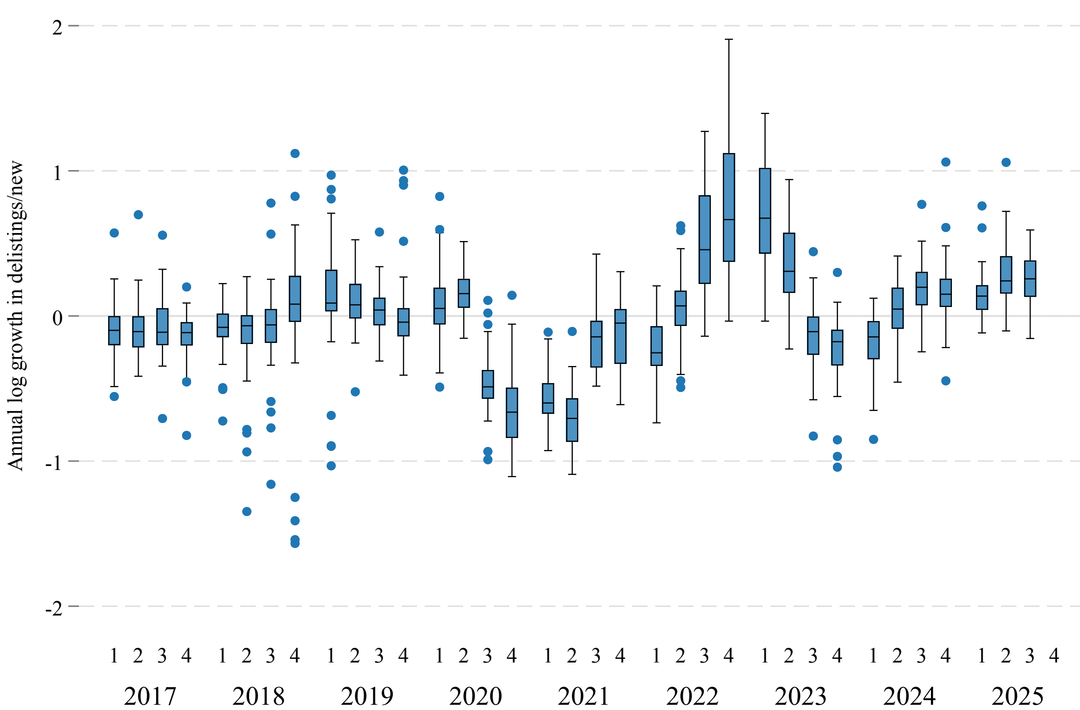
Appendix Table C3 provides results relating the reasons behind household's selling beliefs to mortgage rates and their price expectations. The specification for the logistic regression is the same as in Tables 3.4 and 3.5. Columns (1) and (2) provide the estimates for the binary indicator of when homeowners report that it is a good time to sell due to price reasons. Aside from the sign for the mortgage rate level, these results are qualitatively the same as those in Tables 3.4 and 3.5 suggesting the hypothesis described above.

Columns (3) and (4) provide the estimates for the binary indicator of when homeowners report that it is a good time to sell due to interest rate reasons. I find that the estimated coefficients for the price expectations variables have the opposite sign from those in the first two columns. Given the inverse relationship between prices and rates, these coefficients make sense. Columns (5) and (6) relate binary indicators of when homeowners report that it is a good time to sell for affordability reasons. Propensity of responding that it is a good time to sell due to affordability reasons is very responsive to the current mortgage rate levels. There is also a positive relationship between reporting that it is a good time to sell for affordability reasons and positive price expectations. Columns (7) and (8) relate binary indicators of when homeowners report that it is a good time to sell for other reasons. Not much is learned here given that these reasons tend to be miscellaneous.

### 3.3.3 Delistings and price expectations

Understanding when sellers delist their homes can inform us about housing market dynamics. Figure C3 plots the distribution of log year-on-year growth in metropolitan delistings by year-quarter date using Redfin listings data. The figure shows that annual growth in delistings relative to new listings is relatively stable with less dispersion prior to Covid. When interest rates fell during the beginning of Covid, there was a sharp decline in delistings, as sellers were aware of the surge in homebuyer demand which pushed up prices. In 2022 and 2023 when interest rates sharply rose, delistings dramatically grew in response. This increase in delistings squeezed the market supply and likely drove much of the price increases that occurred despite the lower buyer demand caused by high mortgage rates visible in Appendix Figure C2. After the initial rate hike period, delistings growth fell for a short period but resumed to growing in 2024 likely when sellers realized high mortgage rates were here to stay for the foreseeable future. Appendix Figures 3.2 and C4 show very similar patterns for delistings-to-new and delistings-to-active log year-on-year growth, respectively.

Figure 3.2: Delistings vs new listings: Log yr-on-yr growth




The figure plots the distribution of metropolitan-quarter date log year-on-year growth in delistings from 2017Q1 through 2025Q3. Data originate from Redfin, a national real estate brokerage.

This begs the question, do housing market expectations drive a seller's decision to delist their home from the market? Listing a home is costly and homes that have been listed on the market for months are more likely to sell at a discount due to buyers perceiving time-on-market as a negative signal of the house. By delisting their home and re-listing at a future date, sellers can restart the process with a newly listed home. If they match with a buyer quickly, they can sell at a competitive price without facing an old-listing discount. Sellers observe the path of mortgage rates and the current housing market environment. In order to make listing decisions, sellers compare prices today to prices in the future. Inferences of the future housing market environment are made by developing expectations of future mortgage rates and house prices. The following table relates delisting decisions to these expectations.

Table 3.6 relates various metropolitan delistings year-on-year log growth measures to mortgage rates and housing market expectations. Delistings growth measures include the delistings-to-active listings ratio in Columns (1)–(3), the delistings-to-new listings ratio in Columns (4)–(6), delistings in Columns (7)–(9), and the delistings-to-sold ratio in Columns (10)–(12). Higher annual growth in delistings and delistings relative to new, active, and sold listings are associated with higher mortgage rates, higher shares of homeowners expecting mortgage rate increases, lower shares of homeowners expecting price decreases, and higher shares of homeowners expecting price increases net expecting price decreases. The delistings sensitivity to both current mortgage rate levels and mortgage rate and house price expectations demonstrates that sellers' incorporate both current information and the expected future market environment when making the decision to delist their home. Appendix Table C4 presents the results from the same regressions at the national level. Results are qualitatively the same.

Table 3.6: Delistings vs House price + mortgage rate expectations

| | $\Delta^{12}\ln(delist/active)$ | | | $\Delta^{12}\ln(delist/new)$ | | | $\Delta^{12}\ln(delist)$ | | | $\Delta^{12}\ln(delist/sold)$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Shr. $E[r^m]\uparrow$ | 0.43*** | | | 0.43*** | | | 0.28*** | | | 0.74*** | | |
| | (0.07) | | | (0.07) | | | (0.09) | | | (0.15) | | |
| Shr. $E[r^m]\downarrow$ | | -0.55*** | | | -0.72*** | | | -0.24 | | | -0.96*** | |
| | | (0.13) | | | (0.23) | | | (0.18) | | | (0.28) | |
| Shr. $E[r^m]$ net | | | 0.26*** | | | 0.35*** | | | 0.15** | | | 0.45*** |
| | | | (0.04) | | | (0.08) | | | (0.06) | | | (0.10) |
| $r^m$ | 0.04*** | 0.06*** | 0.05*** | 0.04*** | 0.12*** | 0.11*** | 0.09*** | 0.09*** | 0.09*** | 0.13*** | 0.15*** | 0.14*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.03) | (0.02) | (0.01) | (0.02) | (0.02) | (0.02) | (0.03) | (0.03) |
| E[hp] $\uparrow$ | -0.87*** | -0.78*** | -0.85*** | -0.87*** | -1.18*** | -1.27*** | -0.54*** | -0.46*** | -0.51*** | -1.43*** | -1.27*** | -1.39*** |
| | (0.13) | (0.15) | (0.13) | (0.13) | (0.28) | (0.27) | (0.16) | (0.17) | (0.16) | (0.29) | (0.31) | (0.30) |
| Constant | -0.04 | 0.14 | 0.03 | -0.04 | 0.01 | -0.13 | -0.38*** | -0.26** | -0.33*** | -0.38* | -0.09 | -0.27 |
| | (0.10) | (0.10) | (0.10) | (0.10) | (0.20) | (0.20) | (0.12) | (0.12) | (0.12) | (0.21) | (0.21) | (0.21) |
| Observations | 5031 | 5031 | 5031 | 5031 | 5031 | 5031 | 5031 | 5031 | 5031 | 5019 | 5019 | 5019 |
| $R^2$ | 0.471 | 0.409 | 0.455 | 0.471 | 0.446 | 0.472 | 0.464 | 0.439 | 0.454 | 0.318 | 0.296 | 0.312 |

The table presents estimated coefficients from regressing various metropolitan delistings annual log growth measures on mortgage rates and national homeowner expectation shares of mortgage rate increases, mortgage rate decreases, and house price increases. Delistings growth measures include the delistings-to-active listings ratio, the delistings-to-new listings ratio, delistings, and the delistings-to-sold ratio. The data sample spans January 2017 through September 2025. Delistings data originate from Redfin, a national real estate brokerage. Expectations data are from Fannie Mae NHS. Clustered standard errors at the month date level reported in parenthesis
$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

As shown in Table 3.5, homeowner expectations influence homeowner beliefs of whether it is a good time to sell a home. Thus, one can directly relate realized delistings to aggregate homeowner beliefs of whether it is a good time to sell. Table 3.7 relates various metropolitan delistings year-on-year log growth to mortgage rates and housing market expectations. Delistings growth measures include the delistings-to-active listings ratio in Column (1), the delistings-to-new listings ratio in Column (2), delistings in Column (3), and the delistings-to-sold ratio in Column (4). Higher annual growth in delistings and delistings relative to new, active, and sold listings occurs when homeowners do not believe it is a good time to sell a home. Appendix Table C4 presents the results from the same regressions at the national level. Results are qualitatively the same.

Table 3.7: Delistings vs Good time to sell

| | (1) $\Delta^{12}\ln(delist/active)$ | (2) $\Delta^{12}\ln(delist/new)$ | (3) $\Delta^{12}\ln(delist)$ | (4) $\Delta^{12}\ln(delist/sold)$ |
|---|---|---|---|---|
| Good time to sell | -0.6127*** | -1.3292*** | -0.7310*** | -1.5249*** |
| | (0.1802) | (0.3367) | (0.2710) | (0.3811) |
| Constant | 0.4367*** | 0.9274*** | 0.4873** | 1.0665*** |
| | (0.1347) | (0.2519) | (0.2026) | (0.2855) |
| Observations | 4950 | 4950 | 4950 | 4950 |
| $R^2$ | 0.121 | 0.164 | 0.089 | 0.113 |

The table presents estimated coefficients from regressing various metropolitan delistings annual log growth measures on nationally-aggregated shares of whether homeowners believe it is a good time to sell. Delistings growth measures include the delistings-to-active listings ratio, the delistings-to-new listings ratio, delistings, and the delistings-to-sold ratio. The data sample spans January 2017 through September 2025. Delistings data originate from Redfin, a national real estate brokerage. Selling beliefs data are from Fannie Mae NHS. Clustered standard errors at the month date level reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

We have now related mortgage rates to mortgage rate expectations, mortgage rates and mortgage rate expectations to house price expectations, mortgage rates and expectations to selling beliefs, and all of the above to realized delisting decisions. The results indicate that the level and path of mortgage rates can tell us about housing market expectations, selling beliefs, and delisting decisions. The last set of exercises that remains is relating realized delistings to realized house prices. The table below demonstrates that the state of mortgage rates, once again, matters in understanding the relation.

Table 3.8 relates annual metropolitan house price growth to mortgage rates and various annual delistings growth measures. The results indicate a result widely known to the literature that house price growth and mortgage rates, in general, are negatively related. The coefficients for the delistings growth variables demonstrate an expected, negative relationship with house price growth. Generally, sellers delist their homes during weak periods of the housing market. Conversely, sellers reduce their propensity to delist when there is strong housing demand, such as during the low mortgage rate period in 2020 and 2021 shown in Figure 3.2. However, the sign of interaction between mortgage rates and delistings growth tells a different story. During periods of high mortgage rates, positive delistings growth is associated with positive house price growth.[1]

Table 3.8: Log yr-on-yr house price growth vs delistings

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $r^m$ | -0.0088*** | -0.0119*** | -0.0083*** | -0.0095*** |
| | (0.0022) | (0.0024) | (0.0025) | (0.0021) |
| $\Delta^{12}\ln(delist/new)$ | -0.0816*** | | | |
| | (0.0289) | | | |
| $\Delta^{12}\ln(delist/new) \times r^m$ | 0.0098* | | | |
| | (0.0054) | | | |
| $\Delta^{12}\ln(delist/active)$ | | -0.0777 | | |
| | | (0.0665) | | |
| $\Delta^{12}\ln(delist/active) \times r^m$ | | 0.0126 | | |
| | | (0.0114) | | |
| $\Delta^{12}\ln(delist)$ | | | -0.1350*** | |
| | | | (0.0410) | |
| $\Delta^{12}\ln(delist) \times r^m$ | | | 0.0191*** | |
| | | | (0.0072) | |
| $\Delta^{12}\ln(delist/sold)$ | | | | -0.0571*** |
| | | | | (0.0168) |
| $\Delta^{12}\ln(delist/sold) \times r^m$ | | | | 0.0072** |
| | | | | (0.0031) |
| Constant | 0.1137*** | 0.1304*** | 0.1088*** | 0.1173*** |
| | (0.0139) | (0.0147) | (0.0153) | (0.0127) |
| Observations | 3705 | 3705 | 3705 | 3705 |
| $R^2$ | 0.243 | 0.214 | 0.245 | 0.246 |

The table presents estimated coefficients from regressing metropolitan annual log changes in house prices on annual log changes in various delistings and mortgage rate levels. Delistings growth measures include the delistings-to-active listings ratio, the delistings-to-new listings ratio, delistings, and the delistings-to-sold ratio. The data sample spans January 2017 through September 2025. House prices are obtained from Freddie Mac. Delistings data originate from Redfin, a national real estate brokerage. Clustered standard errors at the month date level reported in parenthesis
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

[1]Note that the lack of statistical significance for the log growth in the delistings-to-active ratio coefficients suggest that relating delistings, which is a flow, to active listings, which is a stock, may be less informative than delistings on it's own and relating delistings to another flow (e.g., new listings or sold listings).

The intuition for the positive estimate of the interaction term comes from the supply effect from delisting homes. During the beginning of the post-Covid, rate-hike period, the median metropolitan delistings annual growth rate exceeded 50% for three quarters. We see a similar pattern for delistings-to-new listings growth during the same period. Within the context of a search and matching model, one can see how the supply impact can exceed the demand impact, causing prices to rise. We can observe that house prices continue to grow in most metropolitan areas during the rate-hike period in Appendix Figure C2. These results provide new empirical evidence for an additional explanation on why house prices rose when mortgage rates rose in 2022 and 2023. While much of the literature has focused on the effects of mortgage rate lock-in as an explanation for the positive correlation between house prices and mortgage rates, it is difficult to disentangle the demand effects from the supply effect. By focusing on delistings, the paper hones in on the supply effects of high mortgage rates through our newly-gained understanding of the role of expectations.

## 3.4 Conclusion

In this paper, I document that mortgage rate expectations follow the trend of mortgage rates and tend to be mean-reverting. Additionally, I show that mortgage rate expectations are related to house price expectations, and show that house price expectations impact selling beliefs. This set of housing market expectations and selling beliefs translate to realized delistings outcomes. Specifically, I find that delistings grow in response to higher mortgage rates, higher mortgage rate expectations, lower house price expectations, and when homeowners believe that it is not a good time to sell a house.

Typically, delistings tend to lower house prices. However, during high periods of mortgage rates, I find that delistings cause prices to rise, likely by squeezing the supply of housing. These results provide new empirical evidence for an additional explanation on why house prices rose when mortgage rates rose in 2022 and 2023. Future versions of this paper will include a model that will allow me to isolate the impact of changes in expectations on house prices through delistings decisions.

# Bibliography

Acosta, M., Brennan, C. M., and Jacobson, M. M. (2024). Constructing high-frequency monetary policy surprises from sofr futures. *Economics Letters*, 242:55–93.

Adelino, M., Schoar, A., and Severino, F. (2018). Perception of house price risk and homeownership. *NBER Working paper No. 25090.*

Ahn, H. J., Xie, S., and Yang, C. (2024). Effects of monetary policy on household expectations: The role of homeownership. *Journal of Monetary Economics*, 147.

Argyle, B., Indarte, S., Iverson, B., and Palmer, C. (2023). Explaining Racial Disparities in Personal Bankruptcy Outcomes.

Attanasio, O. P., Bottazzi, R., Low, H. W., and Neshiam, L. (2012). Modelling the demand for housing over the life cycle. *Review of Economic Dynamics*, 15(1):1–18.

Avenancio-León, C. F. and Howard, T. (2022). The Assessment Gap: Racial Inequalities in Property Taxation. *The Quarterly Journal of Economics*, 137(3):1383–1434.

Bailey, M., Dávila, E., Kuchler, T., and Stroebel, J. (2019). House price beliefs and mortgage leverage choice. *Review of Economic Studies*, 86:2403–2452.

Bartlett, R., Morse, A., Stanton, R., and Wallace, N. (2022). Consumer-lending discrimination in the FinTech Era. *Journal of Financial Economics*, 143(1):30–56.

Bauer, M. and Swanson, E. (2023). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual*, 37.

Baum-Snow, N. and Han, L. (2024). The microgeography of housing supply. *Journal of Political Economy*, 132:1897–1946.

Bayer, P., Casey, M., Ferreira, F., and McMillan, R. (2017). Racial and ethnic price differentials in the housing market. *Journal of Urban Economics*, 102:91–105.

Bayer, P., Ferreira, F., and Ross, S. L. (2016). The Vulnerability of Minority Homeowners in the Housing Boom and Bust. *American Economic Journal: Economic Policy*, 8(1):1–27.

Beraja, M., Fuster, A., Hurst, E., and Vavra, J. (2019). Regional heterogeneity and the refinancing channel of monetary policy. *The Quarterly Journal of Economics*, 134:109–183.

Beraldi, F. and Zhao, Y. (2023). The pricing-out phenomenon in the u.s. housing market. *IMF Working Paper*, Working Paper No. 2023.

Berger, D., Milbradt, K., Tourre, F., and Vavra, J. (2021). Mortgage prepayment and path-dependent effects of monetary policy. *American Economic Review*, 111:277–321.

Bernstein, A. and Koudijs, P. (2024). The mortgage piggybank: Building wealth through amortization. *The Quarterly Journal of Economics*, 139:1767–1825.

Bhutta, N., Hizmo, A., and Ringo, D. (2022). How much does racial bias affect mortgage lending? evidence from human and algorithmic credit decisions. *Finance and Economics Discussion Series*, pages 1–44.

Bhutta, N. and Ringo, D. (2021). The effect of interest rates on home buying: Evidence from a shock to mortgage insurance premiums. *Journal of Monetary Economics*, 118:195–211.

Bosshardt, J., Di Maggio, M., Kakhbod, A., and Kermani, A. (2024). The credit supply channel of monetary policy tightening and its distributional impacts. *Journal of Financial Economics*, 160.

Broadnax, C. and Wylie, J. (2021). Reducing Valuation Bias by Addressing Appraiser and Property Valuation Commentary.

Buchak, G., Matvos, G., Piskorski, T., and Seru, A. (2022). Why is Intermediating Houses So Difficult? Evidence from iBuyers.

Burnside, C., Eichenbaum, M., and Rebelo, S. (2016). Understanding booms and busts in housing markets. *Journal of Political Economy*, 124:1088–1147.

Butler, A. W., Mayer, E. J., and Weston, J. P. (2022). Racial Disparities in the Auto Loan Market. *The Review of Financial Studies*, 36(1):1–41.

Case, K. and Shiller, R. (1989). The efficiency of the market for single-family homes. *American Economic Review*, 79(1):125–137.

Chatterjee, S., Corbae, D., Nakajima, M., and Ríos-Rull, J.-V. (2007). A quantitative theory of unsecured consumer credit with risk of default. *Econometrica*, 75:1525–1589.

Chodorow-Reich, G., Guren, A. M., and McQuade, T. J. (2024). The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. *Review of Economic Studies*, 91:785–816.

Christensen, P., Sarmiento-Barbieri, I., and Timmins (2021). Racial Discrimination in the United States Rental Market. *NBER Working Paper*, (29516).

Christensen, P. and Timmins, C. (2022). Sorting or Steering: The Effects of Housing Discrimination on Neighborhood Choice. *Journal of Political Economy*, 130(8):2110–2163.

Christensen, P. and Timmins, C. (2023). The Damages and Distortions from Discrimination in the Rental Housing Market.

Couillard, S. and Christensen, P. (2024). Racial Housing Price Differentials and Neighborhood Segregation. *NBER Working Paper*, (32815).

Courant, P. N. (1978). Racial prejudice in a search model of the urban housing market. *Journal of Urban Economics*, 5(3):329–345.

Coven, J., Golder, S., Gupta, A., and Ndiaye, A. (2025). Property taxes and housing allocation under financial constraints. Available at SSRN: `https://ssrn.com/abstract=4880480`.

Di Maggio, M., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., and Yao, V. (2017). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, 107(11):3550–3588.

Di Maggio, M., Kermani, A., and Palmer, C. (2020). How quantitative easing works: Evidence on the refinancing channel. *Review of Economic Studies*, 87(3):1498–1528.

Diamond, R. and Diamond, W. F. (2024). Racial Differences in the Total Rate of Return on Owner-Occupied Housing. *NBER Working Paper*, (32916).

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent data. *Review of Economics and Statistics*, 80:549–560.

Eichenbaum, M., Rebelo, S., and Wong, A. (2022). State-dependent effects of monetary policy: The refinancing channel. *American Economic Review*, 112(3):721–761.

Favilukis, J., Ludvigson, S. C., and Nieuwerburgh, S. V. (2017). The macroeconomic effects of housing wealth, housing finance, and limited risk sharing in general equilibrium. *Journal of Political Economy*, 125:140–223.

Ferreira, F. and Gyourko, J. (2015). A New Look at the U.S. Foreclosure Crisis: Panel Data Evidence of Prime and Subprime Borrowers from 1997 to 2012.

FHFA (2020). Fannie mae and freddie mac uniform mortgage-backed securities.

Fonseca, J. and Liu, L. (2024). Mortgage lock-in, mobility, and labor reallocation. *The Journal of Finance*, 79.

Fonseca, J., Liu, L., and Mabille, P. (2024). Unlocking mortgage lock-in: Evidence from a spatial housing ladder model. *SSRN*.

Frame, W. S., Huang, R., Mayer, E. J., and Sunderam, A. (2021). The Impact of Minority Representation at Mortgage Lenders.

Fuster, A., Gianinazzi, V., Hackethal, A., Schnorpfeil, P., and Weber, M. (2026). The response of debtors to rate changes. *NBER Working paper No. 34752*.

Galster, G. and Godfrey, E. (2005). By Words and Deeds: Racial Steering by Real Estate Agents in the U.S. in 2000. *Journal of the American Planning Association*, 71(3):251–268.

Gariga, C. and Hedlund, A. (2020). Mortgage debt, consumption, and illiquid housing markets in the great recession. *American Economic Review*, 110(6):1603–1634.

Gariga, C., Kydland, F. E., and Šustek, R. (2017). Mortgages and monetary policy. *Review of Financial Studies*, 30(10):3337–3375.

Gerardi, K., Willen, P., and Zhang, D. H. (2023). Mortgage prepayment, race, and monetary policy. *Journal of Financial Economics*, 147(3):498–524.

Gilbukh, S. and Goldsmith-Pinkham, P. (2023). Heterogeneous Real Estate Agents and the Housing Cycle.

Glaeser, E. L. and Nathanson, C. G. (2017). An extrapolative model of house price dynamics. *Journal of Financial Economics*, 126:147–170.

Goldsmith-Pinkham, P. and Shue, K. (2023). The gender gap in housing returns. *The Journal of Finance*, 78:1097–1145.

Goodman, J. (1993). A housing market matching model of the seasonality in geographic mobility. *Journal of Real Estate Research*, 8(1):117–137.

Gorea, D., Krysvtsov, O., and Kudlyak, M. (2025). House price responses to monetary policy surprises: Evidence from the u.s. listings data.

Greenwald, D. L. (2018). The mortgage credit channel of macroeconomic transmission.

Guren, A. and Greenwald, D. L. (2025). Do credit conditions move house prices? *American Economic Review*, 115(10):3559–3596.

Guren, A., Krishnamurthy, A., and McQuade, T. J. (2021a). Mortgage design in an equilibrium model of the housing market. *The Journal of Finance*, 76(1):113–168.

Guren, A., McKay, A., Nakamura, E., and Steinsson, J. (2021b). Housing wealth effects: The long view. *Review of Economic Studies*, 88:669–707.

Gürkaynak, R. S., Sack, B., and Swanson, E. (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, 1:55–93.

Guvenen, F., Karahan, F., Ozkan, S., and Song, J. (2021). What do data on millions of u.s. workings reveal about lifecycle earnings dynamics? *Econometrica*, 89(5):2303–2339.

Hancock, D. and Passmore, W. (2011). Did the federal reserve's mbs purchase program lower mortgage rates? *Journal of Monetary Economics*, 58(5):498–514.

Heathcote, J., Storesletten, K., and Violante, G. L. (2017). Optimal tax progressively: An analytical framework. *The Quarterly Journal of Economics*, 132(4):1693–1754.

Indarte, S. (2023). Financial crises and the transmission of monetary policy to consumer credit markets. *The Review of Financial Studies*, 36:4045–4081.

Issler, P., Stanton, R., Vergara-Alert, C., and Wallace, N. (2023). Housing and Mortgage Markets with Climate-Change Risk: Evidence from Wildfires in California. *Working paper*.

Jiang, E. X., Kotova, N., and Zhang, A. L. (2024). Liquidity in residential real estate markets.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Kermani, A. and Wong, F. (2024). Racial Disparities in Housing Returns. *American Economic Review*, 116:287–331.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133(1):97–126.

Krishnamurthy, A. and Vissing-Jorgensen, A. (2011). The effects of quantitative easing on interest rates: Channels and implications for policy. *Brookings Papers on Economic Activity*.

Kuchler, T., Piazzesi, M., and Stroebel, J. (2023). Chapter 6 - housing market expectations. In Bachmann, R., Topa, G., and van der Klaauw, W., editors, *Handbook of Economic Expectations*, pages 163–191. Academic Press.

Kuchler, T. and Zafar, B. (2019). Personal experiences and expectations about aggregate outcomes. *The Journal of Finance*, 74.

Kuttner, K. N. (2013). Low interest rates and housing bubbles: Still no smoking gun. *The Role of Central Banks in Financial Stability: How Has It Changed?*, pages 159–185.

Laouénan, M. and Rathelot, R. (2022). Can Information Reduce Ethnic Discrimination? Evidence from Airbnb. *American Economic Journal: Applied Economics*, 14(1):107–132.

Mabille, P. (2023). The missing homebuyers: Regional heterogeneity and credit contractions. *The Review of Financial Studies*, 36:2756–2796.

Mac, F. (2021). Racial and Ethnic Valuation Gaps In Home Purchase Appraisals. *Freddie Mac Economics & Housing Research Note*.

Manson, S., Schroeder, J., Riper, D. V., Knowles, K., Kugler, T., Roberts, F., and Ruggles, S. (2023). IPUMS National Historical Geographic Information System: Version 18.0 Database. http://doi.org/10.18128/D050.V18.0.

Nakamura, E. and Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330.

NAR (2024). Profile of home buyers and sellers. `https://www.nar.realtor/research-and-statistics/research-reports/highlights-from-the-profile-of-home-buyers-and-sellers`. [Last accessed online November 3, 2025].

Ngai, L. R. and Tenreyro, S. (2014). Hot and cold seasons in the housing market. *American Economic Review*, 104(12):3991–4026.

Ngai, R. L. and Sheedy, K. D. (2020). The decision to move house and aggregate housing-market dynamics. *Journal of the European Economic Association*, 18:2487–2531.

Ondrich, J., Stricker, A., and Yinger, J. (1998). Do Real Estate Brokers Choose to Discriminate? Evidence from the 1989 Housing Discrimination Study. *Southern Economic Journal*, 64(4):880–901.

Ortalo-Magné, F. and Rady, S. (2006). Housing market dynamics: On the contribution of income shocks and credit constraints. *Review of Economic Studies*, 73:459–485.

Piazzesi, M. and Schneider, M. (2009). Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review: Papers & Proceedings*, 99:406–411.

Piccolo, J. and Gorodnichenko, Y. (2025). Homeownership and attention to inflation: Evidence from information treatments. *NBER Working paper No. 33595*.

Romo, V. (2023). Black couple settles lawsuit claiming their home appraisal was lowballed due to bias. *NPR*.

Swanson, E. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 118:32–53.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economic Letters*, 20(2):177–181.

Turner, M. A., Santos, R., Levy, D. K., Wissoker, D., Aranda, C., Pitingolo, R., and Institute, T. U. (2013). Housing Discrimination Against Racial and Ethnic Minorities 2012. *U.S. Department of Housing and Urban Development, Office of Policy Development and Research*.

Vajja, A. (2023). Have Racial and Ethnic Valuation Gaps in Home Purchase Narrowed?

Wheaton, B. (1990). Vacancy, search, and prices in a housing market matching model. *Journal of Political Economics*, 98:1270–1292.

Williams, J. C. (2015). Measuring monetary policy's effect on house prices. *FRBSF Economic Letter: Federal Reserve Bank of San Francisco*.

Xu, P., Han, Y., and Yang, J. (2012). U. s. monetary policy surprises and mortgage rates. *Real Estate Economics*, 40:461–507.

Yinger, J. (1998). Evidence on Discrimination in Consumer Markets. *Journal of Economic Perspectives*, 12:23–40.

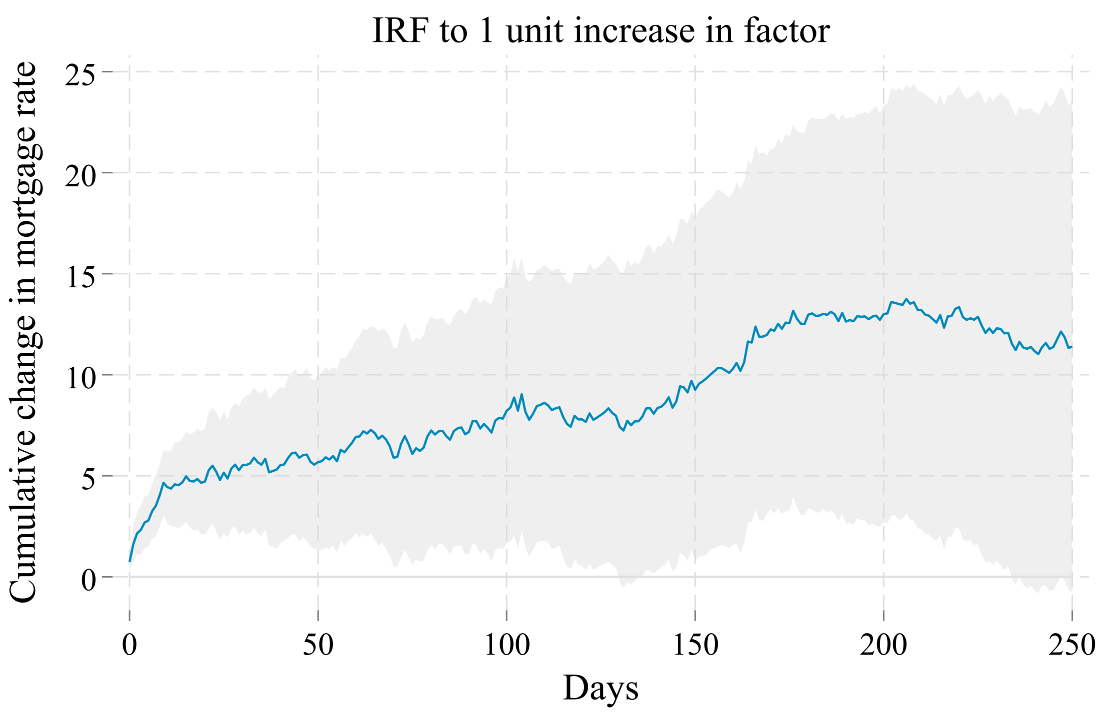
Zhang, D. and Willen, P. (2020). Do Lenders Still Discriminate? A Robust Approach for Assessing Differences in Menus. Federal Reserve Bank of Boston Research Department Working Papers, Federal Reserve Bank of Boston. Series: Federal Reserve Bank of Boston Research Department Working Papers.

Zhao, B., Ondrich, J., and Yinger, J. (2006). Why do real estate brokers continue to discriminate? Evidence from the 2000 Housing Discrimination Study. *Journal of Urban Economics*, 59(3):394–419.

# Appendix A

# Appendices to Chapter 1

Figure A1: Monetary policy factor relevance




*Notes*: The figure plots the estimated coefficient of regressing cumulative difference in mortgage rate change between horizon h=0,...,250 business days (approximately one year) and the mortgage rate the day before the FOMC announcement on the factors with 95% confidence bands. The sample period runs December 2012 through March 2025.

Table A1: Price impact from monetary policy-induced mortgage rate changes

| | All transactions | | | $h < 20$ | $h \in [20, 40)$ | $h \in [40, 60)$ | All transactions | |
|---|---|---|---|---|---|---|---|---|
| | (1) OLS | (2) OLS | (3) IV | (4) IV | (5) IV | (6) IV | (7) IV | (8) IV |
| Δ Mtg rt | -0.0058*** | -0.0056*** | -0.010*** | -0.006 | -0.010*** | -0.008*** | -0.005* | -0.015*** |
| | (0.0004) | (0.0004) | (0.0019) | (0.010) | (0.003) | (0.001) | (0.003) | (0.003) |
| Δ Mtg rt × 90+ LTV shr | | | | | | | -0.009*** | |
| | | | | | | | (0.003) | |
| 90+ LTV shr | | | | | | | 0.001** | |
| | | | | | | | (0.0002) | |
| Δ Mtg rt × Supply elas | | | | | | | | 0.007** |
| | | | | | | | | (0.003) |
| Observations | 1104497 | 1104497 | 1104497 | 13500 | 294223 | 400568 | 930349 | 614963 |
| Tract FEs | Y | Y | Y | Y | Y | Y | Y | Y |
| Interest rate controls | Y | Y | Y | Y | Y | Y | Y | Y |
| Time-on-mkt control | | Y | Y | Y | Y | Y | Y | Y |
| K-P Fstat | | | 393.04 | 143.46 | 145.12 | 215.83 | 211.49 | 196.62 |

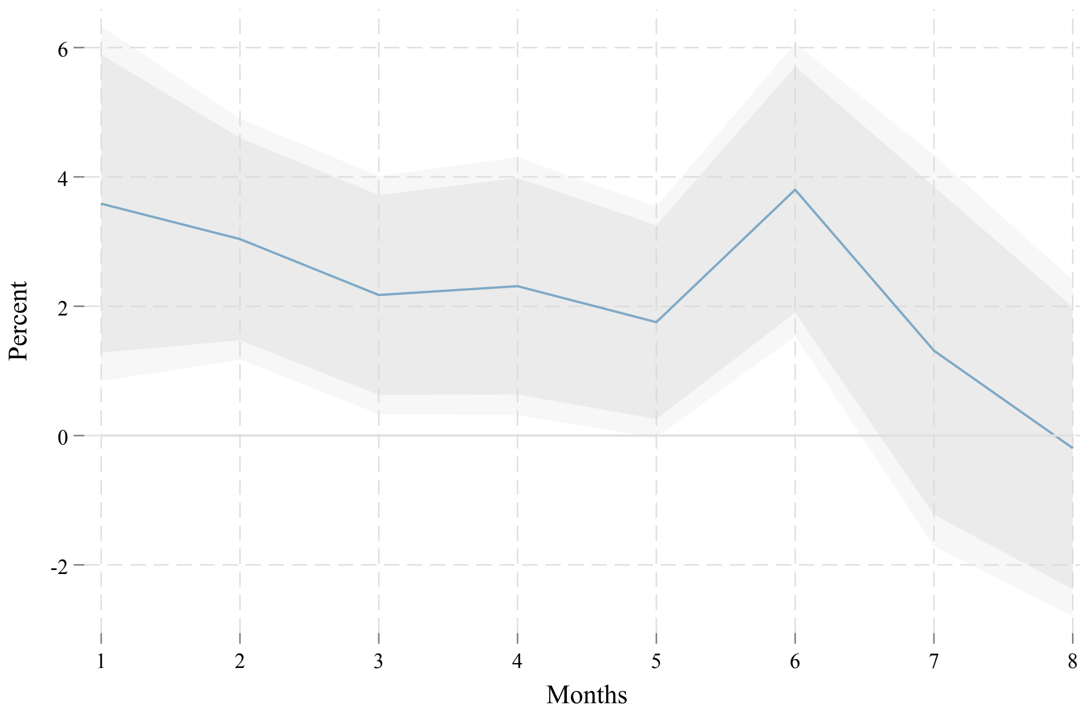
The table provides estimates of the log price change between the listed and transaction prices in response to mortgage rate changes between the time of setting the last listing price and the transaction date. Controls include the mortgage rate and effective federal funds rate at the time of listing, time on market at the time of listing, and Census Tract fixed effects. The data sample excludes homes owned for less than two years, extreme transaction values, and extreme price growth between listing and sale, and runs from December 2012 through December 2020. Kleibergen-Paap (Kleibergen and Paap (2006)) F-statistics are reported. Clustered standard errors at the transaction date-level reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table A2: First-time buyer share of home purchases vs mortgage rates 1st stage regressions

| | $h = 1$ | $h = 2$ | $h = 3$ |
|---|---|---|---|
| | (1) | (2) | (3) |
| MP Shock | 0.0725*** | 0.0736*** | 0.0591*** |
| | (0.0179) | (0.0147) | (0.0154) |
| Observations | 2003 | 2003 | 1962 |

The table provides estimates for the first stage of the Column (2), (4), and (6) regressions in Table 1.2. Driscoll-Kraay standard errors reported in parenthesis.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Figure A2: First-Time Buyer Share of Home Purchases IRF




*Notes*: The figure plots the local projection IRF estimated coefficient of regressing changes in annual differences of first-time buyer share in response to a 1 p.p. mortgage rate increase instrumented by the mortgage rate-specific monetary policy shock at the CBSA-month date level. 90% and 95% confidence bands using Driscoll-Kraay standard errors are included. Controls include 12 months of lags of monthly log price changes and the local unemployment rate, the three previous shocks, lags for the month prior to the shock for the effective federal funds rate and month-average VIX level, and CBSA fixed effects. The data sample spans December 2012 through December 2019.

Table A3: Volume regressions

| | Total volume | | | 1st-time buyer volume | | | Incumbent volume | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) $h=1$ | (2) $h=2$ | (3) $h=3$ | (4) $h=1$ | (5) $h=2$ | (6) $h=3$ | (7) $h=1$ | (8) $h=2$ | (9) $h=3$ |
| Δ Mtg rt | -0.0509 | -0.3061** | -0.4191*** | 0.0799 | -0.1731 | -0.3525*** | -0.0981 | -0.3244*** | -0.5009*** |
| | (0.1198) | (0.1181) | (0.1287) | (0.1336) | (0.1299) | (0.1101) | (0.1235) | (0.1146) | (0.1538) |
| Observations | 2032 | 2032 | 1989 | 2032 | 2032 | 1989 | 2032 | 2032 | 1989 |
| K-P Fstat | 24.98 | 27.76 | 15.45 | 20.18 | 25.85 | 14.57 | 24.66 | 29.24 | 16.10 |
| Nbr of trans. | 3066813 | 3088425 | 3030114 | 3066813 | 3088425 | 3030114 | 3066813 | 3088425 | 3030114 |

The table provides estimates for changes in home purchase volumes in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock for the one, two, and three month horizons. The left-hand side of the IV regression is the change between the annual differences in purchase volumes for time $t+h$ and the annual change in purchase volumes for time $t-1$. Columns (1)–(3), (4)–(6), and (7)–(9) present the results for all buyers, first-time buyers, and incumbent buyers, respectively. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis. $^{*}p<0.10,^{**}p<0.05,^{***}p<0.01$.

Table A4: First-time FHA volume by LTV share regressions

| | $h=1$ | | $h=2$ | | $h=3$ | |
|---|---|---|---|---|---|---|
| | (1) Low LTV shr | (2) High LTV shr | (3) Low LTV shr | (4) High LTV shr | (5) Low LTV shr | (6) High LTV shr |
| $\Delta$ Mtg rt | 0.0698 | 0.3789** | 0.0032 | -0.0372 | -0.2534 | -0.1804 |
| | (0.1764) | (0.1700) | (0.1679) | (0.1904) | (0.2062) | (0.2590) |
| Observations | 1029 | 1001 | 1029 | 1001 | 1006 | 980 |
| K-P Fstat | 21.85 | 18.72 | 27.66 | 25.37 | 17.49 | 14.25 |

The table provides estimates for changes in first-time buyer FHA home purchase volumes in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock for the one, two, and three month horizons restricting the data to above and below-median CBSA shares of high LTV borrowers prior to the shock. The left-hand side of the IV regression is the change between the annual differences in purchase volumes for time $t+h$ and the annual change in purchase volumes for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis. $^{*}p<0.10, ^{**}p<0.05, ^{***}p<0.01$.

Table A5: First-time buyer share of home purchases regressions—GSS path factor

| | $h=1$ | | $h=2$ | | $h=3$ | |
|---|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) OLS | (4) IV | (5) OLS | (6) IV |
| $\Delta$ Mortgage rate | 0.0050 | 0.0297 | 0.0082*** | 0.0384* | 0.0087*** | 0.0233 |
| | (0.0035) | (0.0186) | (0.0031) | (0.0201) | (0.0030) | (0.0155) |
| Observations | 2129 | 2129 | 2129 | 2129 | 2086 | 2086 |
| K-P Fstat | | 7.39 | | 8.81 | | 9.72 |
| Number of transactions | 3179077 | 3179077 | 3201048 | 3201048 | 3142847 | 3142847 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the Acosta et al. (2024) update of the Gürkaynak et al. (2005) path factor. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t+h$ and the annual change in purchase shares for time $t-1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis $^{*}p<0.10, ^{**}p<0.05, ^{***}p<0.01$.

Table A6: First-time purchase shares by CLTV shares

| | (1)<br>$h = 1$ | (2)<br>$h = 2$ | (3)<br>$h = 3$ |
|---|---|---|---|
| $\Delta$ Mortgage rate $\times$ L.CLTV 90s shr | $0.0885^{**}$ | $0.0727^{***}$ | $0.0549^{**}$ |
| | (0.0340) | (0.0234) | (0.0266) |
| Observations | 2032 | 2032 | 1989 |
| K-P Fstat | 16.35 | 28.71 | 15.25 |
| Number of transactions | 3066814 | 3088434 | 3030128 |

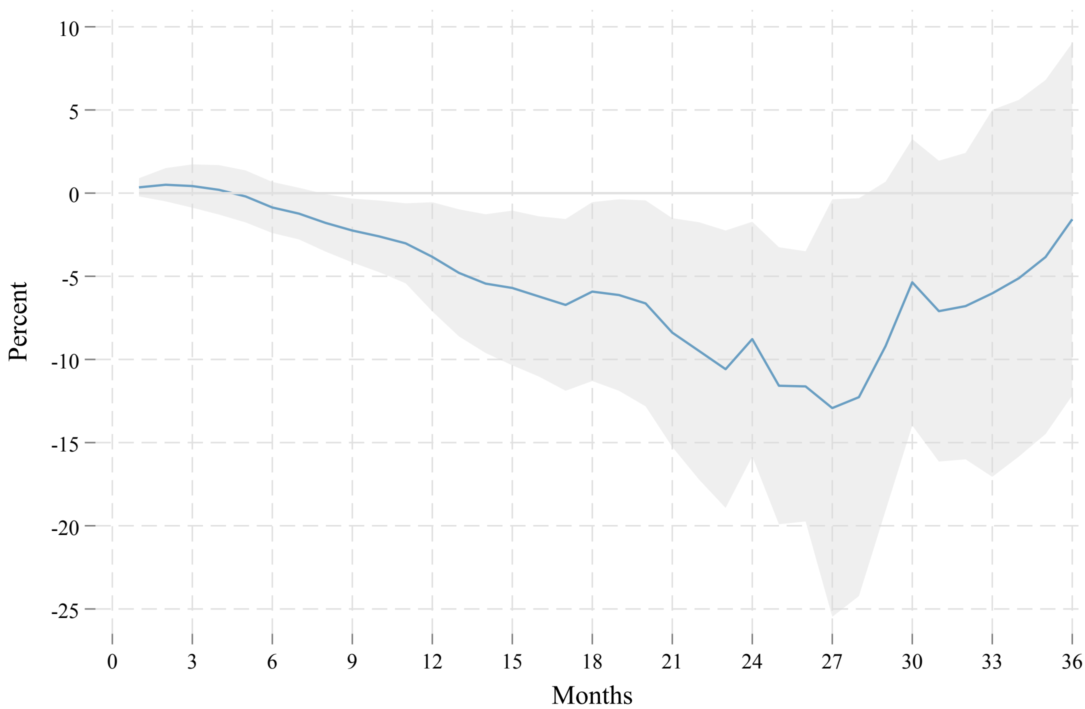
The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes interacted with CBSA-level shares of high origination CLTVs for the month prior to the shock instrumented by the mortgage rate-specific monetary policy shock. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t + h$ and the annual change in purchase shares for time $t - 1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis
$^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$.

Table A7: First-time buyer share of home purchases regressions by supply elasticity

| | Higher supply elasticity | | | Lower supply elasticity | | |
|---|---|---|---|---|---|---|
| | (1)<br>$h = 1$ | (2)<br>$h = 2$ | (3)<br>$h = 3$ | (4)<br>$h = 1$ | (5)<br>$h = 2$ | (6)<br>$h = 3$ |
| $\Delta$ Mortgage rate | $0.0430^{**}$ | $0.0473^{***}$ | 0.0129 | $0.0295^{*}$ | $0.0168^{*}$ | $0.0395^{***}$ |
| | (0.0170) | (0.0138) | (0.0169) | (0.0154) | (0.0089) | (0.0129) |
| Observations | 951 | 951 | 931 | 917 | 917 | 897 |
| K-P Fstat | 17.45 | 28.51 | 16.31 | 15.31 | 24.50 | 13.82 |
| Number of transactions | 1116771 | 1123939 | 1104245 | 1761729 | 1775027 | 1739654 |

The table provides estimates for changes in first-time buyer shares of home purchases in response to mortgage rate changes instrumented by the mortgage rate-specific monetary policy shock by above and below median CBSA-level housing supply elasticity. The left-hand side of the IV regression is the change between the annual differences in purchase shares for time $t + h$ and the annual change in purchase shares for time $t - 1$. Controls include lagged values of national offered mortgage rates, local unemployment rates, and monthly changes in annual differences of first-time buyer purchase shares from the previous twelve months, the three previous monetary policy shocks, and the previous month's average effective Federal Funds Rate (EFFR) and CBOE Volatility Index (VIX). The data sample excludes CBSA-month date observations where any of the previous twenty-five months contains fewer than 150 observed transactions, and runs from December 2012 through December 2019. Driscoll-Kraay standard errors reported in parenthesis
$^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$.

Figure A3: House Price IRF




*Notes*: The figure plots the local projection IRF estimated coefficients of regressing log price growth in response to a 1 p.p. mortgage rate increase instrumented by the mortgage rate-specific monetary policy shock at the CBSA-month date level. 90% confidence bands using Driscoll-Kraay standard errors are reported. Controls include 12 months of lags of monthly log price changes and the local unemployment rate, the three previous shocks, lags for the month prior to the shock for the effective federal funds rate and month-average VIX level, and CBSA fixed effects. The data sample spans December 2012 through December 2023.

Table A8: Calibration of Income Process Parameters

| **Parameter** | **Value** | **Description** |
|---|---|---|
| $\rho^p$ | 0.959 | Persistence |
| $p_z$ | 0.407 | Probability of receiving persistent shock |
| $\mu_{\eta 1}$ | -0.85 | Mean of $\eta_1$ |
| $\mu_{\eta 2}$ | | Mean of $\eta_2$ |
| $\sigma_{\eta 1}$ | 0.364 | Std dev of $\eta_1$ |
| $\sigma_{\eta 2}$ | 0.069 | Std dev of $\eta_1$ |
| $p_\epsilon$ | 0.353 | Probability of receiving transitory shock |
| $\mu_{\epsilon 1}$ | 0.271 | Mean of $\epsilon_1$ |
| $\mu_{\epsilon 2}$ | | Mean of $\epsilon_2$ |
| $\sigma_{\epsilon 1}$ | 0.35 | Std dev of $\epsilon_1$ |
| $\sigma_{\epsilon 2}$ | 0.037 | Std dev of $\epsilon_2$ |
| $\sigma_\beta$ | 0.196 | Individual heterogeneity in earnings |

Notes: Benchmark parameter values used in the income calibration. Largely taken from Guvenen et al. (2021).

Table A9: Moments matched in income calibration

| **Parameter** | Model | GKOS data |
|---|---|---|
| St. dev. of 5-year income growth for median income earner | 0.76 | 0.76 |
| Skewness of 5-year income growth for median income earner | -0.67 | -0.65 |

Notes: GKOS moments are taken from the averaging across ages for the median recent earnings values for the data used to produce Figures C9 and C10. Data are obtained from the supplementary file from Guvenen et al. (2021).

# Appendix B

# Appendices to Chapter 2

Table B1: Hedonic regressions

| | Seller gap | |
|---|---|---|
| | (1) | (2) |
| Black seller | -0.0432*** | |
| | (0.0009) | |
| Black-only seller | | -0.0494*** |
| | | (0.0010) |
| Observations | 3616122 | 3616122 |
| $R^2$ | 0.903 | 0.903 |

*Notes*: Regressions include control for building square footage and lot area, age, heating and cooling systems, pools, garages, and categorical dummies for number of bedrooms and bathrooms. Census tract × year-quarter of sale date fixed effects are included as well. We exclude transactions with sale values less than $10,000 and above the 99th percentile of sales values. Reported standard errors are clustered at the tract level. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table B2: Seller and property characteristics: Any delinquency

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Black seller | -0.0032*** | -0.0029*** | -0.0029*** | | | |
| | (0.0003) | (0.0003) | (0.0003) | | | |
| Black-only seller | | | | -0.0032*** | -0.0029*** | -0.0029*** |
| | | | | (0.0003) | (0.0003) | (0.0003) |
| Delinquent 30d+ | | -0.0046*** | -0.0046*** | | -0.0046*** | -0.0046*** |
| | | (0.0002) | (0.0002) | | (0.0002) | (0.0002) |
| Roof | | | 0.0031*** | | | 0.0031*** |
| | | | (0.0005) | | | (0.0005) |
| Replacement | | | 0.0028*** | | | 0.0028*** |
| | | | (0.0004) | | | (0.0004) |
| Remodel | | | 0.0114*** | | | 0.0114*** |
| | | | (0.0008) | | | (0.0008) |
| Observations | 593895 | 593895 | 593895 | 593895 | 593895 | 593895 |
| $R^2$ | 0.723 | 0.723 | 0.723 | 0.723 | 0.723 | 0.723 |

*Notes*: This table presents the estimates of the racial gap in annualized returns when we control for seller's mortgage delinquency status and property renovations. Sellers are identified as delinquent if they have any delinquency in the year prior to selling their home. All regressions follow the same specification in Equation 2.1. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. The first three columns show the estimates for Black sellers, while the last three columns show the estimates for Black-only sellers. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table B3: Seller and property characteristics: Last month 90 day+ delinquency

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Black seller | -0.0032*** | -0.0029*** | -0.0029*** | | | |
| | (0.0003) | (0.0003) | (0.0003) | | | |
| Black-only seller | | | | -0.0032*** | -0.0029*** | -0.0029*** |
| | | | | (0.0003) | (0.0003) | (0.0003) |
| delqlast90 | | -0.0098*** | -0.0098*** | | -0.0098*** | -0.0098*** |
| | | (0.0003) | (0.0003) | | (0.0003) | (0.0003) |
| Roof | | | 0.0030*** | | | 0.0030*** |
| | | | (0.0005) | | | (0.0005) |
| Replacement | | | 0.0028*** | | | 0.0028*** |
| | | | (0.0004) | | | (0.0004) |
| Remodel | | | 0.0114*** | | | 0.0114*** |
| | | | (0.0008) | | | (0.0008) |
| Observations | 593895 | 593895 | 593895 | 593895 | 593895 | 593895 |
| $R^2$ | 0.723 | 0.723 | 0.724 | 0.723 | 0.723 | 0.724 |

*Notes*: This table presents the estimates of the racial gap in annualized returns when we control for seller's mortgage delinquency status and property renovations. Sellers are identified as delinquent if they have a 90 day or longer delinquency in the month prior to selling their home. All regressions follow the same specification in Equation 2.1. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. The first three columns show the estimates for Black sellers, while the last three columns show the estimates for Black-only sellers. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table B4: Seller and property characteristics: Last month any delinquency

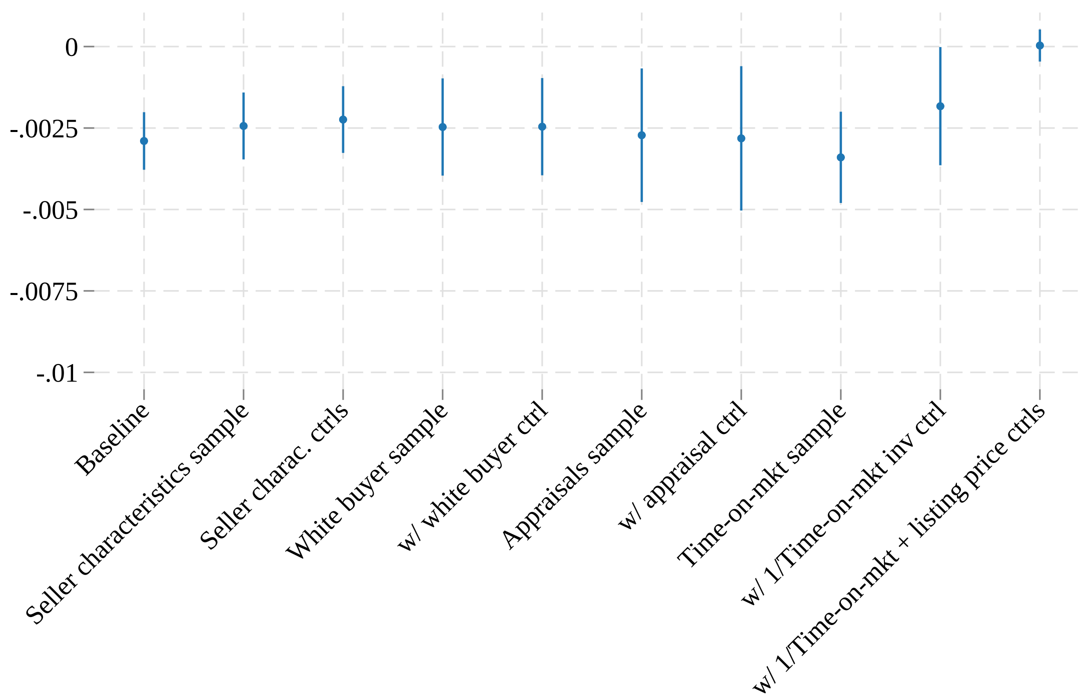
| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Black seller | -0.0032*** | -0.0029*** | -0.0029*** | | | |
| | (0.0003) | (0.0003) | (0.0003) | | | |
| Black-only seller | | | | -0.0032*** | -0.0029*** | -0.0029*** |
| | | | | (0.0003) | (0.0003) | (0.0003) |
| delqlast | | -0.0073*** | -0.0073*** | | -0.0073*** | -0.0073*** |
| | | (0.0003) | (0.0003) | | (0.0003) | (0.0003) |
| Roof | | | 0.0031*** | | | 0.0031*** |
| | | | (0.0005) | | | (0.0005) |
| Replacement | | | 0.0028*** | | | 0.0028*** |
| | | | (0.0004) | | | (0.0004) |
| Remodel | | | 0.0114*** | | | 0.0114*** |
| | | | (0.0008) | | | (0.0008) |
| Observations | 593895 | 593895 | 593895 | 593895 | 593895 | 593895 |
| $R^2$ | 0.723 | 0.723 | 0.724 | 0.723 | 0.723 | 0.724 |

*Notes*: This table presents the estimates of the racial gap in annualized returns when we control for seller's mortgage delinquency status and property renovations. Sellers are identified as delinquent if they have any delinquency in the month prior to selling their home. All regressions follow the same specification in Equation 2.1. All regressions include the Census tract-level annualized mean house price growth rate between the purchase year and sale year, as well as the Census tract by sale year-quarter fixed effects. The first three columns show the estimates for Black sellers, while the last three columns show the estimates for Black-only sellers. Standard errors are clustered at the Census tract levels. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table B5: Listings characteristics mean unconditional gaps

| | Black vs. non-black sellers | | |
|---|---|---|---|
| | listing_price_chg | ln_sale_listing_gap | days_on_mkt |
| 0 | .0022365 | -.0242126 | 66.4779 |
| 1 | -.0030063 | -.0259817 | 69.65689 |
| | **Black-only vs. non-black-only sellers** | | |
| | listing_price_chg | ln_sale_listing_gap | days_on_mkt |
| 0 | .0021992 | -.024188 | 66.45347 |
| 1 | -.0028762 | -.0272893 | 71.28378 |

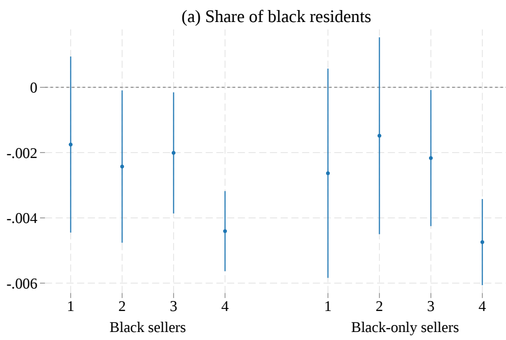
Figure B1: Regressions with additional short-sale restriction



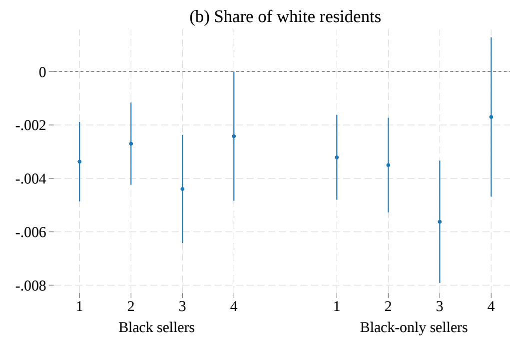

*Notes*: This figure presents the annualized housing returns gap with a variety of controls. The specification of the first plot corresponds to that in Table 2.1, the specification of the second and third plots correspond to those in Table 2.2, the specification of the fourth and fifth plots correspond to those in Table 2.3, the specification in the sixth and seventh plots correspond to those in Figure 2.1, and the specification in the eighth, ninth, and tenth plots correspond to those in Table 2.7. Standard errors are clustered at the tract level with 95% confidence intervals displayed.

Figure B2: Annualized housing return gaps by socioeconomic characteristics

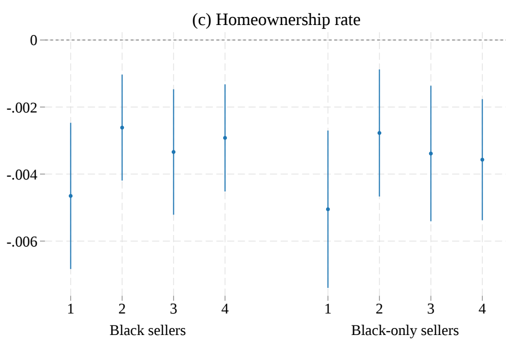
(a) Share of Black residents



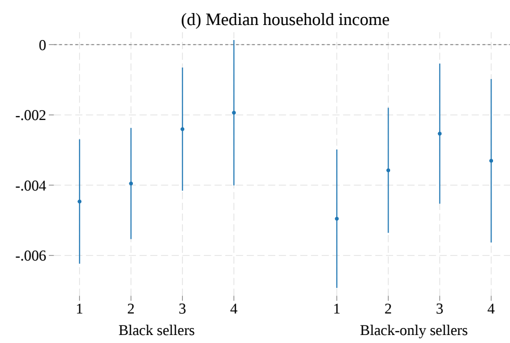

(b) Share of White residents



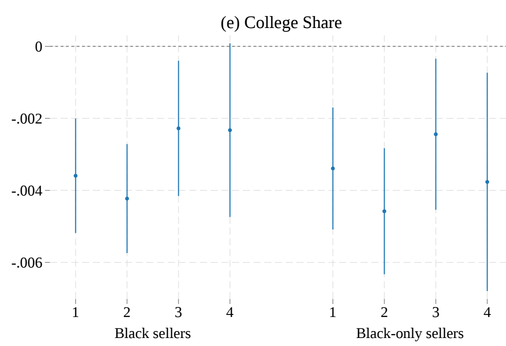

(c) Homeownership rate




(d) Median household income




(e) Share of college educated




*Notes*: This Figure presents the annualized housing returns in Census tracts with different sociodemographic characteristics. Census tracts are grouped into quartiles based on their characteristics indicated by the title for each panel. All regressions include Census tract-level annualized mean house price index growth between purchase year and sale year and Census tract × year-quarter fixed effects. Standard errors are clustered at the tract level. * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table B6: Summary statistics

| | (1) | | | |
|---|---|---|---|---|
| | mean | sd | p50 | count |
| seller_black | .0271065 | .1623937 | 0 | 1151718 |
| seller_black_only | .021388 | .1446742 | 0 | 1151718 |
| seller_white_only | .8115546 | .3910676 | 1 | 1151718 |
| seller_white | .9381494 | .2408841 | 1 | 1150256 |
| years_bw_sales | 6.343741 | 3.717371 | 5.252055 | 1151718 |
| ln_sell_diff | .2038178 | .2319206 | .177334 | 1151718 |
| sell_diff_ann | .0431859 | .0518457 | .0339154 | 1151718 |
| sr_val_transfer | 361007.4 | 277474.2 | 285000 | 1151718 |
| delq | .0679296 | .2516252 | 0 | 813872 |
| delq90 | .0233747 | .1510905 | 0 | 813872 |
| roof | .0153323 | .122871 | 0 | 930973 |
| replacement | .0180703 | .1332059 | 0 | 930973 |
| remodel | .0081377 | .0898416 | 0 | 930973 |
| days_on_mkt | 56.90062 | 90.19312 | 28 | 366303 |
| first_price | 366341.2 | 282645.3 | 285000 | 366303 |
| last_price | 364817.5 | 280171.9 | 285000 | 366303 |
| implied_appr_val | 423251.6 | 383832.1 | 333355.1 | 239872 |

# Appendix C

# Appendices to Chapter 3

Table C1: Mortgage rate expectations vs mortgage rates – National aggregate data

| | Shr. expecting $r^m \uparrow$ | | Shr. expecting $r^m \downarrow$ | | Net Shr. | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $r^m$ | -0.0601*** | | 0.0690*** | | -0.1291*** | |
| | (0.0148) | | (0.0090) | | (0.0220) | |
| L.$r^m$ | | -0.0591*** | | 0.0674*** | | -0.1265*** |
| | | (0.0146) | | (0.0090) | | (0.0218) |
| Prev. 6-month avg. $r^m$ | 1.1400*** | 1.0798*** | -0.5127*** | -0.4413*** | 1.6528*** | 1.5211*** |
| | (0.1694) | (0.1656) | (0.1053) | (0.1039) | (0.2538) | (0.2495) |
| Constant | 0.7581*** | 0.7538*** | -0.2011*** | -0.1941*** | 0.9592*** | 0.9479*** |
| | (0.0689) | (0.0681) | (0.0418) | (0.0417) | (0.1023) | (0.1017) |
| Observations | 171 | 170 | 171 | 170 | 171 | 170 |

The table presents estimated coefficients of regressing the share of homeowners' mortgage rate expectattions on mortgage rates and 6-month rolling averages of monthly mortgage changes. The data sample spans January 2011 through March 2025. Data are obtained from the Fannie Mae National Housing Survey. Newey-West standard errors with 12 lags reported in parenthesis

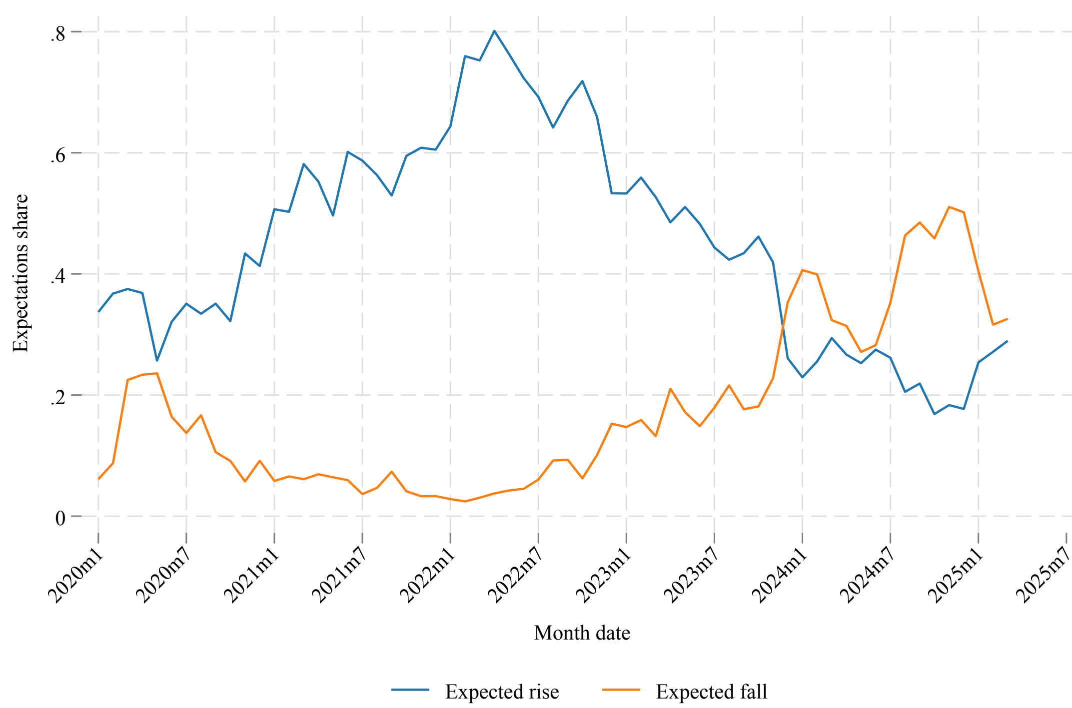
$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table C2: House price expectations vs mortgage rate expectations – National data

| | Share expecting price ↑ | | | | Share expecting price ↓ | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Shr. $E[r^m]\uparrow$ | 1.533*** | | 1.461*** | | -0.927*** | | -0.876*** | |
| | (0.373) | | (0.370) | | (0.314) | | (0.314) | |
| Shr. $E[r^m]\downarrow$ | | -2.888*** | | -2.788*** | | 2.373*** | | 2.317*** |
| | | (0.894) | | (0.878) | | (0.624) | | (0.619) |
| $r^m$ | 0.093*** | -0.071** | | | -0.039 | 0.050** | | |
| | (0.033) | (0.030) | | | (0.027) | (0.021) | | |
| L.$r^m$ | | | 0.088*** | -0.065** | | | -0.035 | 0.047** |
| | | | (0.033) | (0.029) | | | (0.028) | (0.020) |
| Shr. $E[r^m]\uparrow \times r^m$ | -0.235*** | | | | 0.140** | | | |
| | (0.076) | | | | (0.064) | | | |
| Shr. $E[r^m]\downarrow \times r^m$ | | 0.444*** | | | | -0.326*** | | |
| | | (0.145) | | | | (0.101) | | |
| Shr. $E[r^m]\uparrow \times$ L.$r^m$ | | | -0.217*** | | | | 0.127** | |
| | | | (0.075) | | | | (0.064) | |
| Shr. $E[r^m]\downarrow \times$ L.$r^m$ | | | | 0.421*** | | | | -0.315*** |
| | | | | (0.140) | | | | (0.099) |
| 6-month roll-avg. $r^m$ | -0.150 | 0.111 | -0.233 | 0.055 | 0.371** | 0.328** | 0.440*** | 0.361*** |
| | (0.210) | (0.200) | (0.197) | (0.185) | (0.177) | (0.142) | (0.167) | (0.131) |
| Constant | -0.241 | 0.794*** | -0.221 | 0.771*** | 0.475*** | -0.139 | 0.461*** | -0.128 |
| | (0.181) | (0.131) | (0.183) | (0.124) | (0.152) | (0.091) | (0.155) | (0.087) |
| Observations | 171 | 171 | 170 | 170 | 171 | 171 | 170 | 170 |
| $R^2$ | 0.438 | 0.298 | 0.422 | 0.292 | 0.489 | 0.528 | 0.481 | 0.525 |

The table contains estimated coefficients regressing the share of homeowners expecting house price increases or decreases in one-year on mortgage rate levels, the share expecting mortgage rate increases or decreases, and their interaction at the national-level. The data sample spans January 2011 through March 2025. Data are obtained from the Fannie Mae National Housing Survey.
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Figure C1: House price expectation shares




The figure plots the time series of the national share of homeowners expecting a house price increase in one year and expecting a house price decrease in one year. The data sample spans January 2020 through March 2025. Data are obtained from the Fannie Mae National Housing Survey.

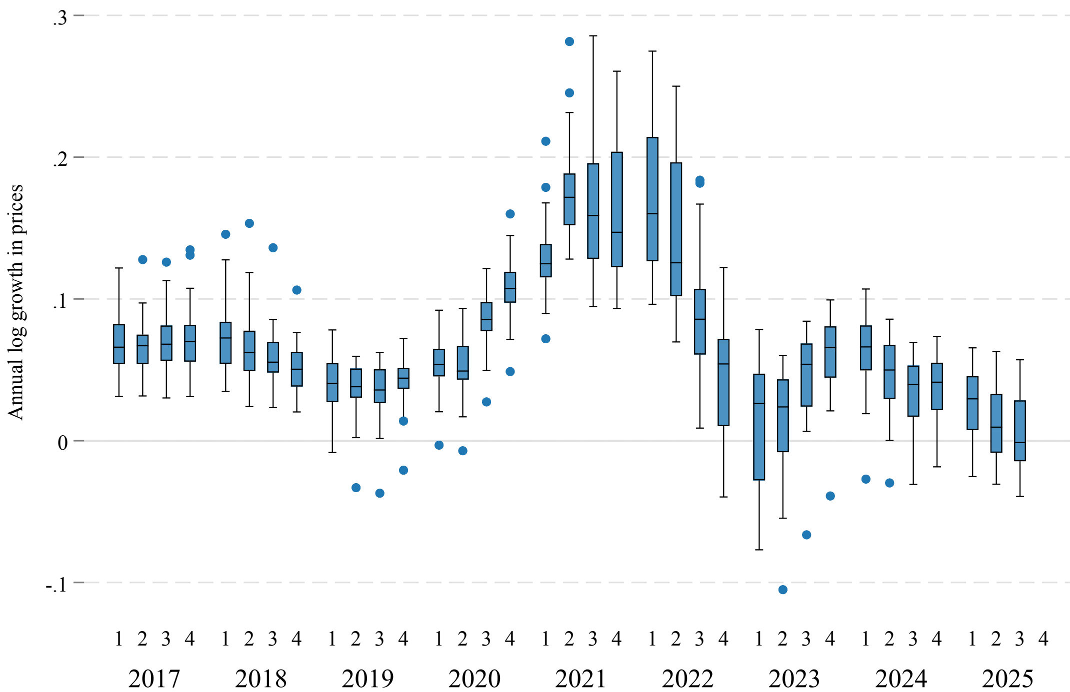
Table C3: Good time to sell vs expectations – SoC Micro data, reasons

| | Price reasons | | Rate reasons | | Affordability reasons | | Other reasons | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $r^m$ | 0.2230*** | 0.1228** | -0.6121*** | -0.5207*** | -0.2840*** | -0.2745*** | 0.0293 | 0.0285 |
| | (0.0546) | (0.0501) | (0.0521) | (0.0501) | (0.0388) | (0.0346) | (0.0253) | (0.0212) |
| E[hp] ↑=1 | 1.4687*** | | -0.5167*** | | 0.2542** | | 0.3417*** | |
| | (0.1294) | | (0.1769) | | (0.1227) | | (0.1116) | |
| E[hp] ↑=1 × $r^m$ | -0.1735*** | | 0.1649*** | | 0.0217 | | -0.0109 | |
| | (0.0217) | | (0.0435) | | (0.0245) | | (0.0207) | |
| E[hp] ↓=1 | | -0.5162*** | | -0.6106* | | -1.0316*** | | -0.1618 |
| | | (0.1605) | | (0.3532) | | (0.1838) | | (0.2104) |
| E[hp] ↓=1 × $r^m$ | | 0.0644** | | -0.0310 | | 0.0450 | | -0.0408 |
| | | (0.0297) | | (0.0880) | | (0.0378) | | (0.0427) |
| 6-mon. roll. avg. $r^m$ | 2.3228*** | 2.4127*** | -0.1434 | -0.1400 | 0.3630 | 0.4744 | 0.9367*** | 1.0233*** |
| | (0.5244) | (0.5527) | (0.5201) | (0.5225) | (0.4704) | (0.4778) | (0.2619) | (0.2705) |
| Constant | -2.2545*** | -1.4546*** | -0.1651 | -0.4062* | -0.8274*** | -0.6382*** | -2.7728*** | -2.5999*** |
| | (0.2946) | (0.2568) | (0.2212) | (0.2148) | (0.1776) | (0.1524) | (0.1334) | (0.1051) |
| Observations | 68868 | 68868 | 68868 | 68868 | 68868 | 68868 | 68868 | 68868 |

The table presents estimated coefficients of a logistic regression estimating the effect that mortgage rates, 6-month rolling averages of monthly mortgage changes, the binary measure of homeowners expecting house price increases or decreases in one year and their interaction with mortgage rates on binary indicators of homeowner reasons for believing it is a good time to sell a home. The data sample spans January 2011 through October 2024. Data are obtained from the University of Michigan Survey of Consumers. Clustered standard errors at the month date level reported in parenthesis

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Figure C2: House price growth: Log yr-on-yr growth



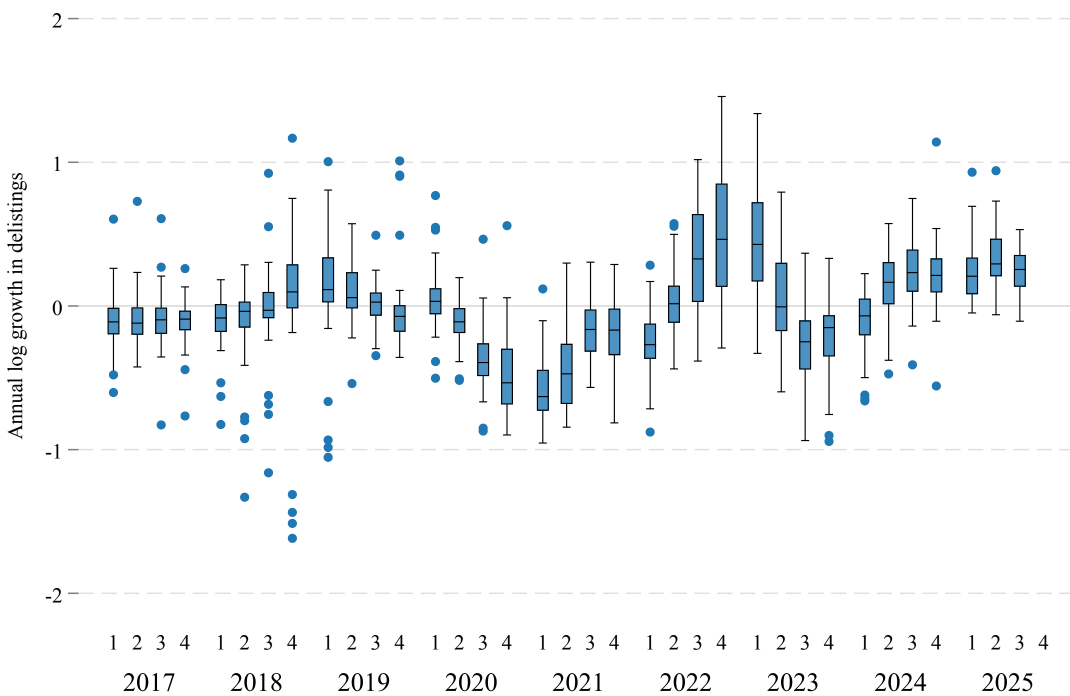

The figure plots the distribution of CBSA-quarter date year-on-year house price log growth from 2017Q1 through 2025Q3. Data originate from Freddie Mac.

Table C4: Delistings vs House price + mortg. rate exp. – National data

| | $\Delta^{12}\ln(delist/active)$ | | | $\Delta^{12}\ln(delist/new)$ | | | $\Delta^{12}\ln(delist)$ | | | $\Delta^{12}\ln(delist/sold)$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Shr. $E[r^m]\uparrow$ | 0.43*** | | | 0.43*** | | | 0.28 | | | 0.74** | | |
| | (0.16) | | | (0.16) | | | (0.24) | | | (0.32) | | |
| Shr. $E[r^m]\downarrow$ | | -0.55** | | | -0.71 | | | -0.24 | | | -0.94* | |
| | | (0.27) | | | (0.51) | | | (0.40) | | | (0.53) | |
| Shr. E$[r^m]$ net | | | 0.26** | | | 0.35* | | | 0.15 | | | 0.45** |
| | | | (0.10) | | | (0.20) | | | (0.16) | | | (0.21) |
| $r^m$ | 0.04** | 0.06*** | 0.05*** | 0.04** | 0.12*** | 0.11*** | 0.09*** | 0.09*** | 0.09*** | 0.13*** | 0.16*** | 0.14*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) |
| E[hp]↑ | -0.87*** | -0.78*** | -0.85*** | -0.87*** | -1.18** | -1.28** | -0.54 | -0.45 | -0.51 | -1.38** | -1.22** | -1.33** |
| | (0.28) | (0.29) | (0.28) | (0.28) | (0.55) | (0.54) | (0.41) | (0.42) | (0.42) | (0.55) | (0.57) | (0.55) |
| Constant | -0.04 | 0.14 | 0.03 | -0.04 | 0.01 | -0.13 | -0.38 | -0.27 | -0.33 | -0.41 | -0.12 | -0.30 |
| | (0.18) | (0.18) | (0.17) | (0.18) | (0.33) | (0.33) | (0.27) | (0.26) | (0.26) | (0.36) | (0.35) | (0.34) |
| Observations | 99 | 99 | 99 | 99 | 99 | 99 | 99 | 99 | 99 | 99 | 99 | 99 |
| $R^2$ | 0.470 | 0.407 | 0.454 | 0.470 | 0.445 | 0.472 | 0.464 | 0.439 | 0.454 | 0.568 | 0.524 | 0.556 |

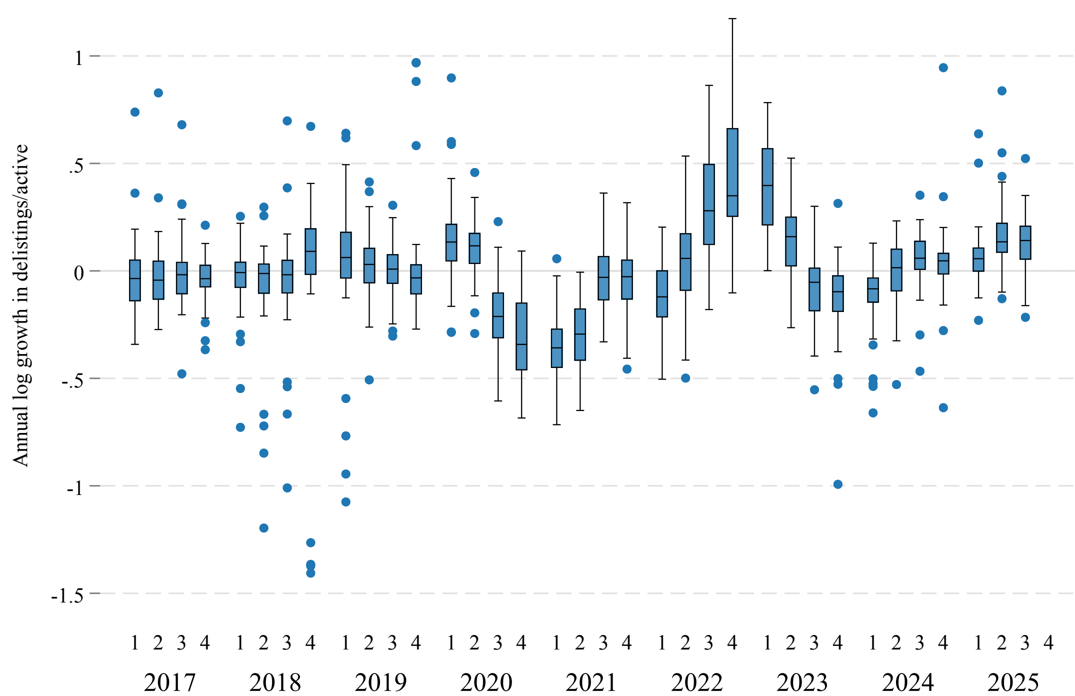
The table presents estimated coefficients from regressing various national delistings annual log growth measures on mortgage rates and national homeowner expectation shares of mortgage rate increases, mortgage rate decreases, and house price increases. Delistings growth measures include the delistings-to-active listings ratio, the delistings-to-new listings ratio, delistings, and the delistings-to-sold ratio. The data sample spans January 2017 through September 2025. Data originate from Redfin, a national real estate brokerage. Newey-West standard errors with 12 lags reported in parenthesis
$^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Figure C3: Delistings: Log yr-on-yr growth




The figure plots the distribution of metropolitan-quarter date log year-on-year growth delistings from 2017Q1 through 2025Q3. Data originate from Redfin, a national real estate brokerage.

Figure C4: Delistings vs active listings: Log yr-on-yr growth




The figure plots the distribution of metropolitan-quarter date log year-on-year growth delistings-to-active ratios from 2017Q1 through 2025Q3. Data originate from Redfin, a national real estate brokerage.