The Impact of Assumption Financing on Housing Prices and Supply

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July 2024

Abstract

Assumable mortgages allow buyers to retain existing loan terms, preserving lower mortgage rates despite rising rates. Analyzing a novel dataset of properties financed with assumable mortgages across 14 US regions, we find that the assumable feature raises average property prices by over $20k, representing a 5% premium. This premium captures more than 80% of the assumption option's market value and influenced by several regional factors. We present evidence of the lock-in effect, where rising interest rates reduce housing supply and household mobility. We further demonstrate that mortgage assumption alleviates this lock-in effect, thereby enhancing both housing supply and mobility.

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The structure and design of the mortgage market wield significant influence over housing prices and supply dynamics (Campbell, Clara, & Cocco, 2021). The two dominant mortgage types—adjustable-rate mortgages (ARMs) and fixed-rate mortgages (FRMs)—offer distinct advantages and drawbacks for both housing and macroeconomic stability. ARMs are advantageous in stabilizing the economy and facilitating the transmission of monetary policy via the household channel (Campbell et al., 2021). However, they carry inherent risks and can introduce instability into the housing market, affecting both demand and pricing structures. Conversely, FRMs provide homeowners with a substantial degree of certainty regarding their financial obligations, shielding them from market interest rate volatility. Nevertheless, this stability can induce a lock-in effect, particularly when mortgage rates experience significant increases.[1]

Given the inherent trade-offs of these standard mortgage financing methods, economists are increasingly exploring alternative mortgage financing options and their implications (Guren, Krishnamurthy, & McQuade, 2021; Brueckner, Calem, & Nakamura, 2016; Gathergood & Weber, 2017). One such alternative is the assumable mortgage, which allows buyers to take over the seller's loan, including the advantageous terms agreed upon at origination. Assumable mortgages have gained prominence since significant deregulation in 2009 (Adelino, Schoar, & Severino, 2023), now constituting 23% of active mortgages as of 2024.[2]

Although assumable mortgages have existed for over 90 years, they have only recently gained widespread public attention. Historically, their lack of prominence can be attributed to the prolonged trend of decreasing interest rates since the early 1980s, which rendered the assumption feature out of the money and diminished the appeal of it. However, the recent surge in mortgage rates has sparked renewed interest in assumable mortgages. From January 2021 to October 2023, the average 30-year mortgage rate skyrocketed from 2.65% to 7.79%, prompting the public to recognize the significant potential for interest savings through assumption financing.[3] The growth in assumable mortgages coupled with the recent increase in interest rates presents a valuable opportunity to analyze the impact of assumption financing on housing prices and supply.

To examine the impact of assumption financing on housing transactions, we construct a novel dataset using property-level data from two sources. First, we obtain assumption financing data from the Roam website,[4] which identifies properties financed with assumable mortgages (hereafter, assumable properties) across 14 regions, including Atlanta, Austin, Colorado Springs, Dallas, Denver, Fort-Worth, Houston, Lake-

[1] The lock-in effect occurs when current market rates surpass the fixed rates of existing mortgages, discouraging homeowners from moving or refinancing, thus restricting housing supply and household mobility

[2] https://www.nytimes.com/2024/05/09/business/low-rate-assumable-mortgage.html

[3] https://edition.cnn.com/2024/05/31/economy/low-rate-assumable-mortgages-explained/index.html

[4] See https://www.withroam.com/.

land, Miami, Orlando, Phoenix, Saint Petersburg, San Antonio, and Tampa. Second, we collect property transaction data from the RedFin website,[5] which provides rich details on housing characteristics and the transaction history for a large number of listed U.S. properties. By combining these two data sources, we overcome the empirical constraints in prior research and are able to compare transactions involving properties financed with and without assumable mortgages. Furthermore, with detailed information on the assumable mortgage rate for each of the assumable properties, we can quantify the value of mortgage assumption and gauge its impact on transaction prices.

We begin our analysis by comparing transactions of assumable properties with those of similar non-assumable properties. Our findings reveal that, on average, assumable properties sell for over $20k more and at a faster pace—approximately one week sooner—compared to non-assumable properties. These disparities persist even after employing a hedonic regression model to isolate the effects of observable property characteristics on transactions.

Next, we quantify the mortgage assumption value (MAV) and examine the extent to which it is capitalized into the property price. Our analysis indicates that more than 80% of this value translates into a price premium, highlighting that savings from assumable mortgages primarily benefit the seller. This share is higher in markets characterized by strong seller bargaining power, fewer financial constraints for buyers, a larger working-age population, and higher rental costs.

In the second set of tests, we delve into the economic implications of assumption financing by examining its impact on lock-in effect. We begin by demonstrating that the growth of mortgage rates indeed impedes the expansion of new listings and hamper household mobility, creating a lock-in effect. Next, we show that assumption financing can alleviate this lock-in effect. Our analysis reveals that counties with greater access to assumption financing experience a less pronounced negative impact of increasing interest rates on housing supply and household mobility.

Our paper builds on the study by LaCour-Little, Lin, & Yu (2020), which investigated the effects of assumption financing on housing prices amidst rising interest rates through simulations. We enhance their model by incorporating refinancing options and maturity adjustments to more accurately value mortgage assumptions. Additionally, we construct a novel dataset to provide empirical evidence on the real-world effects of assumption financing on housing transactions. Our research also highlights the role of assumption financing in mitigating the lock-in effect, offering vital policy insights for housing markets facing supply

[5] See https://www.redfin.com/.

constraints.

The contribution of our study is threefold. Firstly, it represents the first large-scale empirical investigation into the impact of assumption financing on housing prices and quantifies how this impact is reflected in sale prices. Unlike previous studies that primarily focused on initial price premiums or discounts associated with assumable mortgages, our research delves into unraveling the intrinsic value of the assumable feature itself. Our novel dataset allows us to explore the real-life effects of assumption financing, filling gaps in existing literature where prior research often relied on simulation methods (LaCour-Little et al., 2020) or limited empirical tests to narrowly-defined markets (Sirmans, Smith, & Sirmans, 1983). Furthermore, our study innovates by examining the impact of assumable mortgages in the post-COVID period—a period characterized by a significant increase in interest rates following historically low levels—an environment not previously explored in existing literature.

Secondly, our study contributes to the literature examining the impact of credit supply on house prices (Favara & Imbs, 2015; Justiniano, Primiceri, & Tambalotti, 2019; Mian & Sufi, 2022; Adelino, Schoar, & Severino, 2012). We add to this literature by highlighting a positive correlation between the availability of assumption financing, representing an affordable mortgage credit option, particularly in periods of rising interest rates, and house prices.

Thirdly, our paper adds to the literature on household mobility and the lock-in effect (Ferreira, Gyourko, & Tracy, 2010; Brown & Matsa, 2020). We present empirical evidence showing that a rapid increase in mortgage rates triggers a lock-in effect, evidenced by reduced new listings and household mobility. However, we find that such effects are mitigated in regions with greater access to assumption financing. This study represents the first empirical documentation of the beneficial impact of affordable mortgage credit in mitigating the lock-in effect. This discovery carries practical implications, as the availability of assumable mortgages can significantly alleviate constraints on housing supply and household mobility caused by the lock-in effect. Policymakers may therefore consider promoting awareness of assumable mortgages as a strategy to counteract declines in housing market fluidity.

The remainder of the paper is organized as follows. Section 1 offers background information on assumable mortgages and reviews relevant literature. Section 2 details the sample construction and descriptive statistics. Section 3 investigates the impact of assumption financing on property transactions. Section 4 quantifies the value of mortgage assumption. Section 5 investigates the factors affecting its translation into the price premium. Section 6 explores the influence of assumption financing on mitigating the lock-in effect.

Finally, Section 7 summarizes our findings and presents conclusions.

1. Background and Prior Literature

An assumable mortgage is a home financing arrangement that allows the buyer, who will be the new owner-occupant, to take over the existing mortgage and its terms from the current owner. Government-backed mortgages, such as those insured by the Federal Housing Administration (FHA), or backed by the Veterans Administration (VA) and the United States Department of Agriculture (USDA), are generally assumable. As of 2024, approximately 12.2 million loans, or 23% of active mortgages, are assumable,[6] with FHA mortgages being the most prevalent type, accounting for roughly 60% of the market share of the assumable mortgages.[7]

The major distinction between assumable mortgages and conventional ones lies in the loan assumption feature. Conventional loans operate on a "due-on-sale" basis, whereas assumable mortgages allow homeowners to transfer the terms of their existing mortgage, including the historical loan rate, to new buyers. Although assumable mortgages were first introduced by the FHA in 1934, they have largely been overlooked for decades due to two main reasons.

First, assumption loans accounted for a small market share before 2008 due to low FHA mortgage limits. For instance, the FHA mortgage limit for a one-unit single-family property was much lower than the median sales price before 1980.[8] These strict FHA mortgage limits at the time prevented FHA loans, and hence assumable mortgages, from gaining significant market share.

Second, from the mid-1980s onward, a long-term trend of decreasing interest rates further diminished interest in assumption financing. The sustained low-interest rate environment over the past decades made the built-in assumable feature less attractive, especially considering the insurance premiums associated with these mortgages.

While assumable mortgages attracted brief attention in the late 1970s and early 1980s due to a spike in interest rates, and several studies, including a seminal paper on the value of the assumable feature (Sirmans

[6] https://www.nytimes.com/2024/05/09/business/low-rate-assumable-mortgage.html

[7] The U.S. Department of Housing and Urban Development reports that FHA mortgages accounted for approximately 14% of the market share in the first quarter of 2024. For more details, see https://www.hud.gov/sites/dfiles/Housing/images/FHASFMarketShare2024Q1.pdf

[8] The median sales price for a one-unit single-family property was $62,750 in 1979 (https://fred.stlouisfed.org/series/MSPUS). The FHA mortgage limit was 65% of the conforming loan limit= 0.65 * 67,500= $43,875 (https://www.fhfa.gov/sites/default/files/2023-03/loanlimitshistory07.pdf).

et al., 1983), were conducted during that period, major regulatory changes since then cast doubt on whether the findings from those studies still apply today. These changes include the imposed requirement of creditworthiness reviews of buyers,[9] interest rate deregulation in the early 1980s,[10] and significant increases in FHA loan limits as part of an array of policy responses to the financial crisis of 2008-2009 (LaCour-Little et al., 2020). This underscores the need for more contemporary research in this area.

Furthermore, understanding the impact of assumption financing in the current market is increasingly crucial due to its prevalence. Following the 2008-2009 financial crisis, the suspension of subprime mortgage products backed by Wall Street capital and the increase in loan limits substantially boosted the market share of assumable mortgages.[11] As depicted in Figure 1, assumable mortgages financed less than 10% of properties on average before the 2008 GFC. However, following the crisis, this proportion surged to roughly 40% in 2011, and has since stabilized at around 20% in recent years, indicating a significant supply of properties backed by assumable mortgages in the housing market.

Meanwhile, the decades-long low-interest rate environment, coupled with a recent spike in interest rates following the 2020 COVID pandemic, has rendered most existing assumable mortgages in the money with below-market interest rates. This offers homebuyers opportunities to achieve significant savings on their mortgage payments.[12] As shown in Figure 1, the 30-year fixed-rate mortgage remained consistently low throughout the last decade but spiked from 2.96% in 2021 to 6.81% in 2023, the likes of which have not been seen since the 1970s.

Given the allure of interest-saving potential, assumable mortgages have once again captured the attention of homebuyers. Figure 2 illustrates a notable increase in public interest, evident in Google search data for the term "Assumable mortgage." In contrast, searches for "Conventional mortgage" show no comparable

[9] Prior to December 1, 1986, FHA mortgages had minimal requirements for assumability unless the seller requested a release from liability. This leniency led to the rise of "straw buyers", who purchased properties on behalf of less creditworthy individuals, increasing the default probability. To curb such behaviour, assumability restrictions were forced afterwards. Specifically, to carry on the existing assumable mortgages, the new borrowers must pass the creditworthiness review launched by the lender (https://www.hud.gov/sites/documents/41551C4HSGH.PDF). Additionally, buyers need to pay the seller's home equity — the difference between the final selling price and the remaining loan balance—at the time of the transaction.

[10] Prior to 1983, FHA and VA imposed interest rate ceilings that often made their mortgage rates lower than market rates. Borrowers were prohibited from paying the interest rate differential as points. Consequently, sellers covered this cost by charging higher home prices to recoup the interest rate differential. See Zerbst & Brueggeman (1977), Colwell, Guntermann, & Sirmans (1979). After the removal of these ceilings in 1983, the price discount between conventional and assumable mortgages disappeared. (Asabere & Huffman, 1997)

[11] During the Global Financial Crisis (GFC), the suspension of subprime mortgage products backed by Wall Street capital prompted a surge in FHA lending activity, filling the gap left by the faltering private mortgage market. See https://www.americanprogress.org/article/the-federal-housing-administration-saved-the-housing-market/

[12] For instance, a real estate agent in the Phoenix area secured a home with a 2.375% assumable mortgage interest rate in October 2023, amid market mortgage rates exceeding 7%, resulting in monthly savings of over $1000 on the mortgage. (https://www.businessinsider.com/how-to-get-lowest-best-mortgage-rate-payment-assumable-mortgage-2023-12)

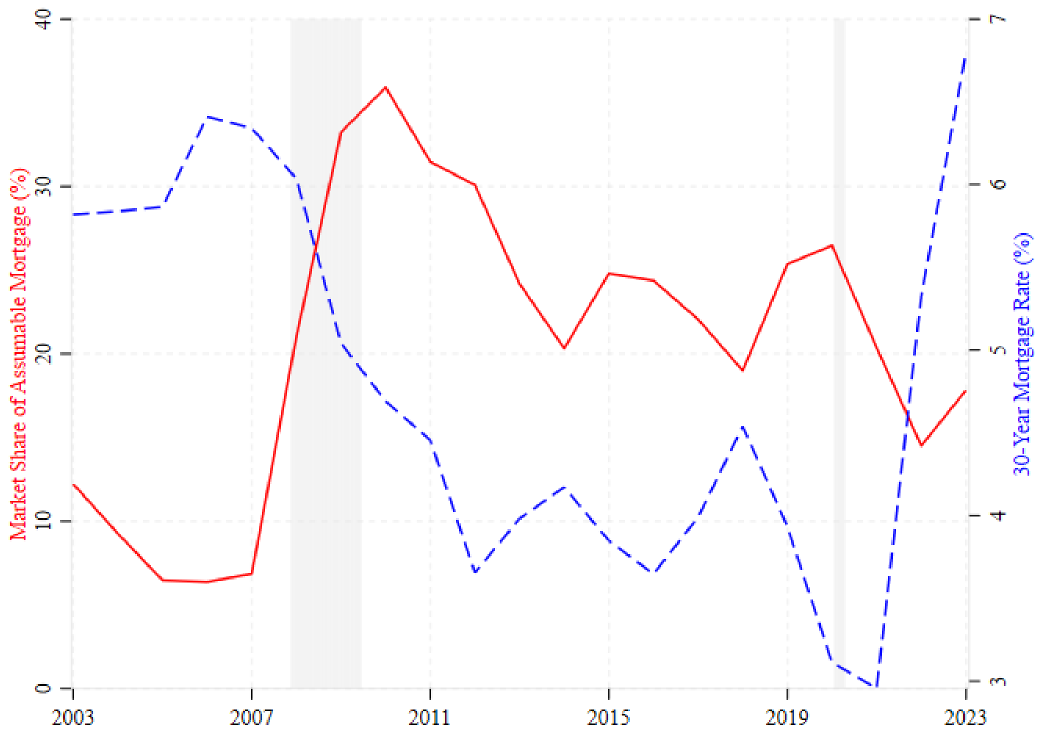

Figure 1: Market share of assumable mortgages and 30-Year average mortgage Rate (2003-2023)

The solid line represents the market share of assumable mortgages, calculated as the sum of houses sold with FHA and VA financing divided by total houses sold each year, based on data from the HMDA databases. The dashed line shows the historical 30-year average mortgage rate in percentage. Source: https://fred.stlouisfed.org/series/MORTGAGE30US.

upward trend.[13] In addition, the fact that the Federal Housing Administration (FHA) and Department of Veterans Affairs (VA) processed more than double the number of assumption cases in 2023 compared to the previous year also underscores the growing household awareness and adoption of this affordable financing option.[14] This surge reflects the increasing recognition of assumable mortgages as a viable strategy for securing favorable mortgage terms, especially in a high-interest rate environment.

1a. Mortgage assumption and house price

Shortly after the introduction of assumable mortgages, researchers identified a correlation between this financing method and housing price fluctuations. Early studies attributed these fluctuations to mortgage discount points charged by lenders. Since the FHA set a lower ceiling rate for its loans compared to con-

[13] Alternatively, we also explore Google search interest for the terms "Mortgage" and "Mortgage loan." Google Trends data indicates that the interest in these terms has remained quite stable over time, further highlighting the distinct upward trend in search interest specifically for "Assumable mortgage."

[14] https://www.newsnationnow.com/business/your-money/assumable-mortgage-how-to/

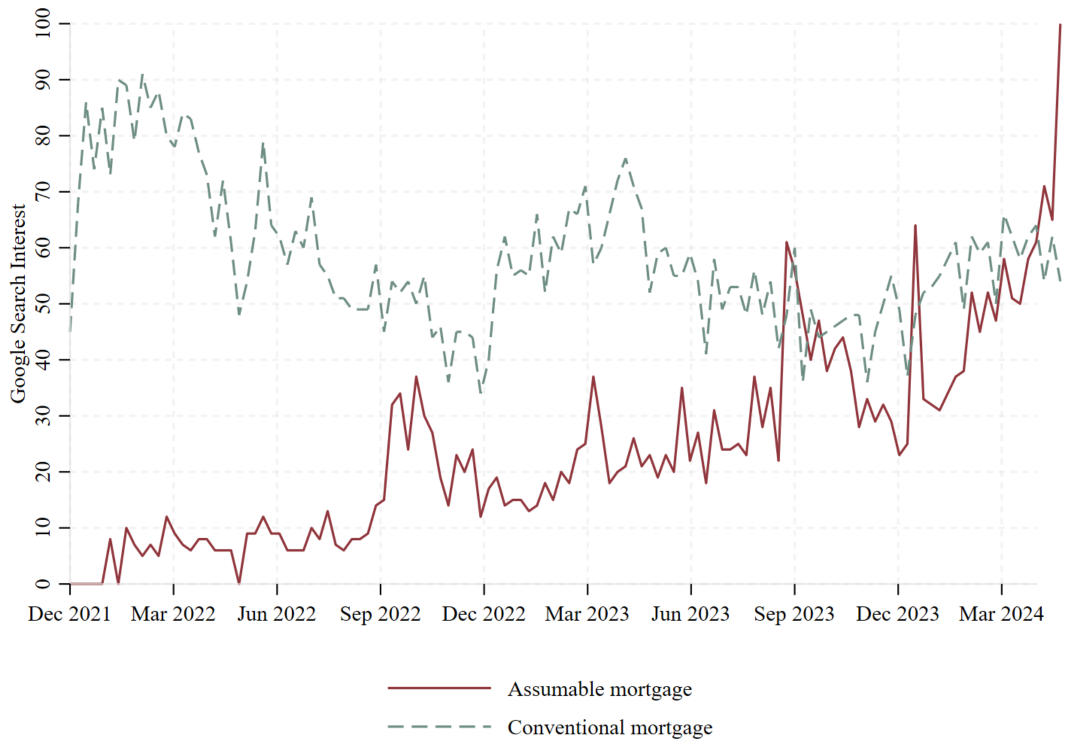

Figure 2: Google search in assumable mortgage and conventional mortgage

This graph compares Google search interest in the terms "Assumable mortgage" and "Conventional mortgage" from December 2021 to May 2024. The y-axis represents the ratio of search volume relative to the peak search volume within the specified period, where a value of 100 denotes peak popularity, 50 indicates half the peak popularity, and 0 signifies insufficient data. Data is sourced from Google Trends (https://trends.google.com/trends). The solid red line represents interest in "Assumable mortgage," while the dashed teal line represents interest in "Conventional mortgage."

ventional loans, lenders imposed discount points on FHA home-sellers to offset the rate disparity. Sellers typically passed these costs to FHA home-buyers through increased housing prices. Using a sample from Columbus, Ohio, Zerbst & Brueggeman (1977) found that buyers with FHA or VA mortgages paid higher percentages of asking prices, with almost half of the discount points' value transferred from sellers to buyers. Colwell et al. (1979) further revealed that up to 77% of discount points were incorporated into final selling prices based on sellers' expectations of buyers' financing methods. However, after the removal of interest rate ceilings in 1983, the price discount between conventional and assumable mortgages disappeared (Asabere & Huffman, 1997).[15]

Another strand of literature examines how the incentives for assumable mortgage home-buyers influence price changes. This body of research argues that higher insurance premiums required by assumable mort-

[15] https://www.upi.com/Archives/1983/12/01/FHA-mortgages-freed-from-interest-ceilings/5585439102800/

gages may incentivize buyers to bid at lower prices (Asabere & Huffman, 2008). Assumable mortgages, initially introduced to improve credit supply for those with higher loan-to-value (LVR) and payment-to-income ratios (PTI)[16], have a higher default probability compared to conventional mortgages. Assumable mortgage borrowers are often credit-constrained, though temporarily (Goodman Jr & Nichols, 1997), and typically have lower credit scores than conventional mortgage borrowers (Pennington-Cross & Nichols, 2000). Additionally, the monthly repayment and downpayment requirements influence buyers' decisions to adopt an assumable mortgage (Hendershott, LaFayette, & Haurin, 1997). To offset heightened risk, assumable loans incur higher insurance premiums and origination fees, prompting borrowers to submit lower bids to alleviate these costs (Asabere & Huffman, 2008). If sellers accept early bids to minimize opportunity costs, it can result in lower sales prices for properties financed with assumable mortgages. Analysing of 9,000 home transactions in San Antonio, Texas, Asabere & Huffman (2008) find supportive evidence on this argument, showing that financing costs associated with assumable mortgages are reflected in final sales prices.

However, the aforementioned studies mainly focus on the price premiums or discounts generated when assumable mortgages are initiated, offering limited insight into the intrinsic value of the assumable feature itself. This value, reflected in the mortgage rate differences when a buyer assumes the seller's mortgage, allows eligible new buyers to finance their properties at the original rates specified in the mortgage contract, resulting in significant interest savings and potentially influencing the sale price of the house.

The seminal paper by Sirmans et al. (1983) investigates this assumable feature's value. Using a sample of homes sold in a major county of the Atlanta metropolitan area in 1980, they find that homes financed with assumable loans commanded higher prices on average compared to those with conventional mortgages, attributing approximately one-third of the assumable value to the selling price. Similarly, Sunderman, Canaday, & Colwell (1990) confirms the presence of premiums linked to assumption finance and associates these premiums with the loan-to-price ratio.

More recently, LaCour-Little et al. (2020) use simulations to examine the impact of incorporating assumption financing into housing prices as interest rates rise. They show that assumption value might offset price declines resulting from increasing rates and that the effects are influenced by buyer-seller negotiations. While the assumable feature is particularly valuable when market rates are higher than assuming mortgage rates, Allen & Springer (1998) argue it also holds value for above-market loan assumptions. Buyers opting

[16] Asabere & Huffman (2008) show PTIs are 31% for assumable loans versus 28% for conventional loans

to assume higher-rate existing mortgages over current conventional rates are driven by non-interest factors like ease of qualification and reduced transaction costs, which are reflected in increased housing prices.

Building on LaCour-Little et al. (2020), our study utilizes real-world transaction data to empirically examine the impact of assumption financing on housing prices. As highlighted in their paper: "*The ideal data set would identify transactions with, and without, assumable FHA financing and record actual sales prices realized and whether the available assumption option was utilized and details on the credit profile of the buyer assuming the debt*." Leveraging our unique dataset on assumption financing, we are able to quantify its value and examine the degree to which this value is reflected in prices, as well as factors contributing to variations in this relationship.

1b. Mortgage assumption and lock-in effect

Understanding the value of assumption financing can also help address the lock-in effect on housing supply in a rising interest rate environment. The sharp increase in mortgage rates has led to a decrease in properties being sold and a decline in new listings. As shown in Figure 3, the total properties sold (red line) have decreased by roughly 30% in the two years following the interest rate shock. The number of new listings (green line) also fell by about two million after a decade of stable supply.

This decrease is likely because homeowners are discouraged from selling due to the inability to finance new properties at the historically low rates of their current mortgages. Since the interest rate has nearly tripled from 2.65% in January 2021 to 7.79% in October 2023, financing a similar property now requires a monthly payment 1.78 times higher. For instance, a buyer who financed a $450,000 property at a 2.65% rate in 2021 would pay $1,450 monthly. At the current 7.79% rate, the same property would cost $2,589 per month.

This increased financial burden leads homeowners to delay selling to avoid higher interest payments on new homes, reducing housing supply. The second part of our study explores the impact of assumable mortgages on this lock-in effect. We hypothesize that assumable mortgages can alleviate this lock-in effect by allowing new buyers to take over the existing mortgage terms.

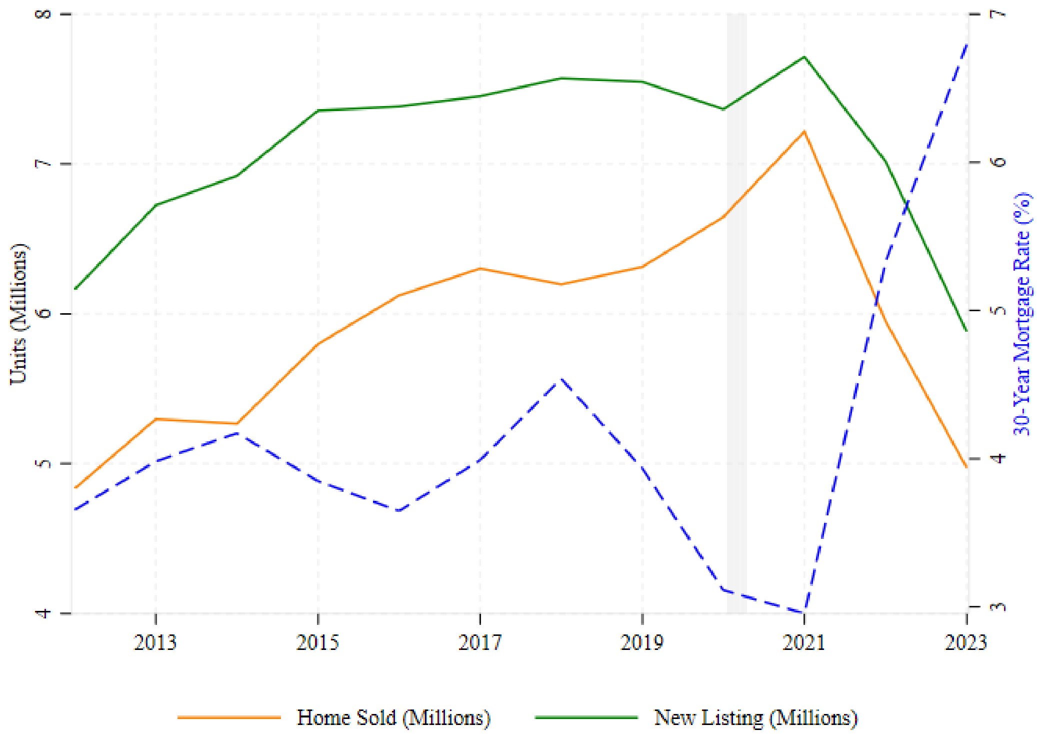

Figure 3: Time-series changes in new listings and home sales (2012-2023)

The green solid line shows the total units of new listings in millions, while the orange solid line represents the total units of homes sold in millions. Data is sourced from the RedFin website. The dashed line illustrates the 30-year average mortgage rate percentage over the same period.

2. Data and Descriptive Statistics

The property data for this study comes from two platforms: Roam and RedFin. Roam, launched in September 2023, focuses on identifying U.S. properties with assumable mortgages and facilitating the loan assumption process. RedFin, a technology-driven real estate platform, offers extensive property listings across the U.S. Appendix A provides examples of the information available from both platforms.

To construct our dataset, we manually collected information from Roam, which identifies properties with assumption financing in 14 metropolitan areas: Atlanta, Austin, Colorado Springs, Dallas, Denver, Fort-Worth, Houston, Lakeland, Miami, Orlando, Phoenix, Saint Petersburg, San Antonio, and Tampa. Like other real estate websites, Roam provides information about property characteristics such as address, size, year built, and sale conditions including asking price. Most importantly, Roam reports the assumable mortgage rate and required down payment for assuming the mortgage, which is essential for computing the property-specific benefit associated with assumption financing.

We then integrated this data with information from RedFin, which offers additional property details not available on Roam. These details include days on market, parking availability, fireplace presence, views, heating and cooling systems, basement and attic status, renovation history, roofing material, and historical transaction data, including prior sale dates and prices.

Next, we gather data on listings with non-assumable mortgages to compare with properties financed with assumable mortgages. Properties listed on RedFin but not on Roam are categorized as non-assumable. Although Roam may not cover all properties eligible for assumption financing, a property's absence from Roam suggests that the seller or real estate agent may be unaware of or indifferent to the value of assuming the existing mortgage. Without proper acknowledgment and promotion, the benefits of assumable mortgages are less likely to add value to these properties. Therefore, we classify them with other non-assumable properties. To sharpen the identification of non-assumable properties, we exclude properties whose description on the RedFin website contains any of the following words or phrases: "FHA," "VA," "Assume," "Assuming mortgage," "Assumable mortgage," "Assuming loan," "Assumable loan," "Assuming rate," or "Assumable rate" in their properties description. Appendix B provides the detailed identification procedures.

2a. Sample construction

To obtain the sale prices of properties financed with assumable mortgages, we first identify properties delisted from Roam between October 7, 2023, and March 11, 2024.[17] We then cross-check these properties' transaction records on RedFin to confirm their sale status. Through this verification process, we exclude 2,383 properties delisted from Roam but not documented on RedFin, and 8,675 properties delisted from Roam but still listed on RedFin.[18] This yields a dataset of 5,210 recently sold properties eligible for assumption financing. For conciseness, we refer to these properties as "assumable properties", and all other properties as "non-assumable properties".

Next, we combine this dataset of assumable properties with another dataset containing details of non-assumable properties from RedFin. We filter each property to retain only the most recent transaction and require at least one additional prior transaction record. Properties in ZIP codes with fewer than five properties in our sample are excluded. This process results in a final pre-matched sample of 39,228 properties,

[17] As of October 7, 2023, Roam recorded 6,119 properties with assumption financing, about 13.5% of all listed properties on RedFin across the 14 regions covered by Roam. Cross-verification based on property addresses on the RedFin website confirms that more than 99% of these assumable properties are listed accurately.

[18] These are properties whose status is listed by RedFin as "For Sale–Active," "For Sale–New," "For Sale–Back On Market," "List," "Relist," or "Sale price Change".

including 1,397 assumable and 37,831 non-assumable properties. Details on the sample construction process can be found in Appendix C.

Panel A of Table D.2 in Appendix C shows that, on average, assumable properties in our sample tend to be smaller in size and less expensive compared to non-assumable properties. Therefore, to better quantify the impact of assumption financing on house prices, we undertake a matching procedure that pairs each assumable property with a non-assumable property exhibiting similar attributes. This matching process progresses in two stages. First, we identify all non-assumable properties in the same ZIP code as each assumable property, acknowledging the importance of location in housing transactions. Second, we perform a propensity score matching (PSM) for properties within the same ZIP code area. This matching procedure considers various factors including the number of bedrooms and bathrooms, property size, construction year, and amenities such as parking, fireplace, view, heating and cooling systems, basement, or attic. Additionally, the PSM takes into account the property's renovation history, as well as the date and price of the preceding transaction, to mitigate the potential influence of omitted property characteristics on house prices.[19] The matching process produces 1,212 paired property observations, involving 606 assumable properties and their respective non-assumable counterparts. Additional details can be found in Appendix D. As depicted in Panel B of Table D.2, the characteristics of assumable properties do not significantly differ from their non-assumable counterparts after matching.

2b. Descriptive statistics

Panel A of Table 1 presents summary statistics of major variables used in our sample regressions. A detailed definition of property characteristic variable is provided in Appendix E. On average, properties in our sample have a sale price of $414,000 and spend 55 days on the market. They typically encompass approximately 2,500 square feet, with an average of 3.5 bedrooms and 2.5 bathrooms. Parking facilities are available in nearly all properties (97.7%), and the majority have heating (94.2%) and cooling systems (85%). Around half of the homes feature at least one fireplace, and approximately 6% have undergone renovation.

As a preliminary analysis, Panel B of Table 1 compares the sale prices and days on market of assumable properties with those of their non-assumable counterparts. We observe that, on average, assumable proper-

[19]While we require the controlled property to be at the same ZIP code as the treated property, the unobservable characteristics of distinct streets or blocks within the same ZIP code area might contribute to variations in sale prices. Factors like security level, proximity to schools or public transportation, and exposure to potential hazards such as floods or wildfires could affect property values. Although these traits may not be directly observable, they are likely reflected in the home's historical price.

Table 1: Descriptive statistics

Panel A: Summary statistics

	Mean	SD	P10	P25	Median	P75	P90
Sale price	414	208	248	300	377	470	600
Days on market	55.3	49.0	12.0	24.0	40.0	72.5	117.0
Assumable	0.50	0.50	0	0	0.5	1	1
Age	23	23	2	4	18	38	51
Bedrooms	3.5	0.9	3.0	3.0	3.0	4.0	5.0
Bathrooms	2.5	0.7	2.0	2.0	2.0	3.0	3.5
House size	2,046	785	1,210	1,486	1,877	2,490	3,112
Parking space	0.98	0.15	1	1	1	1	1
Fireplace	0.51	0.50	0	0	1	1	1
Has view	0.11	0.32	0	0	0	0	1
Renovation	0.06	0.23	0	0	0	0	0
Heating	0.94	0.23	1	1	1	1	1
Cooling	0.85	0.36	0	1	1	1	1
Basement	0.13	0.33	0	0	0	0	1
Attic	0.02	0.14	0	0	0	0	0
Roof type	5.33	2.54	3	3	4	8	8

Panel B: Univariate test

	Assumable=1	Assumable=0	Diff	Diff%	T-Value	P-Value
Sale price	424.3	403.6	20.7*	5.12%	1.73	0.08
Days on market	54.0	58.0	−4.0*	−6.90%	−1.76	0.08

Panel A provides summary statistics for the primary variables utilized in our baseline regression analysis. Our sample comprises a total of 1,212 observations, evenly split between 606 assumable properties and 606 non-assumable counterparts. Continuous variables are subject to winsorization at the top and bottom 1% levels. Sale prices are in thousands of dollars, and house sizes are in square feet. Panel B compares the average sales price (in thousands) and number of days on market for properties that can be financed with assumable mortgages (i.e., Assumable = 1) and those that cannot (i.e., Assumable = 0). The variable Diff% represents the percentage difference between assumable and non-assumable properties, scaled by the values of non-assumable properties. Significance levels are indicated by *, **, and ***, representing 10%, 5%, and 1% significance levels, respectively. The definition of the variables is reported in Appendix E.

ties are sold for nearly $21k more than their non-assumable counterparts, representing a premium of about 5.12% over the price of the non-assumable homes. Additionally, assumable properties tend to sell more quickly than their non-assumable counterparts. Specifically, while the average non-assumable property remains on the market for 58 days before being sold, the average assumable property is listed for only 54 days, approximately four days sooner than its non-assumable counterpart. These preliminary findings underscore the value proposition of assumable mortgages for buyers. By assuming existing mortgages, buyers can potentially secure lower interest rates for the remaining loan term, especially beneficial during periods of high interest rates as observed during our study period. This advantage likely contributes to the higher sale prices and quicker sale times observed for assumable properties compared to non-assumable ones.

3. Impact of Assumption Financing on Property Transactions

Next, we conduct an Ordinary Least Squares (OLS) regression analysis in the matched sample to analyze how the assumable mortgage feature impacts house prices and days on the market, while controlling for property characteristics.

$$Y_i \quad = \quad \beta A_i + \mathbf{X}_i \gamma'_x + \delta_{z(i)} + \delta_{t(i)} + \varepsilon_i, \tag{1}$$

In the above model, Y represents the log value of one of two housing transaction variables: sales price or days on the market. The primary explanatory variable of interest is A_i, which equals one if property i is an assumable property and zero otherwise. We incorporate a large set of control variables, denoted as $\mathbf{X}_i$, to adjust for the effect of property characteristics on housing transactions (Adelino et al., 2023). These controls comprise the property's age, number of bedrooms, number of bathrooms, and size, as well as indicators for the availability of parking, fireplace, view, heating, cooling, basement, attic, roof type, and renovation status. The baseline regression model (1) additionally incorporates ZIP code fixed effects, denoted as δ_z for ZIP code z, and time-of-listing fixed effects $\delta_{t(i)}$, where $t(i)$ indicates the year-month when the property was initially listed on RedFin for the current sale. These controls aid in reducing bias stemming from unobservable factors that may vary over time or across locations, potentially confounding the relationship between assumable status and property transactions. Continuous variables are winsorized at the 1st and 99th percentiles, and standard errors are clustered at the ZIP code level.

In our baseline regression, the coefficient of interest, denoted as β, captures the variance in property transactions (such as final selling price or selling speed) attributed to the assumption financing option. Given our anticipation that the interest-saving associated with the assumable feature would enhance the attractiveness of assumable properties, we predict a positive (or negative) β when the explanatory transaction variable is price (or days on market).

The results of the baseline regression (1) are reported in Table 2. In Column (1), we observe that assumable properties are associated with higher prices compared to their non-assumable counterparts, with statistically and economically significant differences. Controlling for other housing characteristics, assumable properties are estimated to sell for approximately $\exp(0.066) - 1 = 6.8\%$ more than comparable non-assumable properties. Given the average sale price of a non-assumable property ($403,600, as shown in

Table 2: Impact of assumption financing on housing transactions—baseline regression

	Log sale price			Log days on market		
	(1)	(2)	(3)	(4)	(5)	(6)
Assumable	0.066∗∗∗	0.069∗∗∗	0.076∗∗∗	−0.113∗∗	−0.129∗∗	−0.092∗∗∗
	(0.00)	(0.00)	(0.00)	(0.03)	(0.01)	(0.00)
Log age	−0.012	−0.050∗∗∗	−0.049∗∗∗	−0.033	0.019	0.044∗∗
	(0.21)	(0.00)	(0.00)	(0.14)	(0.58)	(0.01)
Log bedrooms	0.105	0.364∗∗∗	0.393∗∗∗	−0.241	−0.194	−0.085
	(0.33)	(0.00)	(0.00)	(0.22)	(0.44)	(0.46)
Log bathrooms	0.472∗∗∗	0.332∗∗∗	0.334∗∗∗	0.238	0.154	0.370∗∗∗
	(0.00)	(0.00)	(0.00)	(0.21)	(0.46)	(0.00)
Log house size	0.275∗∗	0.176∗	0.163	0.103	0.141	−0.105∗∗
	(0.02)	(0.09)	(0.11)	(0.49)	(0.39)	(0.01)
Parking space	0.234∗∗∗	0.122	0.131	0.170	0.007	0.163
	(0.01)	(0.17)	(0.16)	(0.33)	(0.98)	(0.24)
Fireplace	0.042	0.093∗∗∗	0.096∗∗∗	−0.109∗	−0.050	−0.021
	(0.10)	(0.00)	(0.00)	(0.05)	(0.56)	(0.67)
Has view	0.157∗∗∗	0.025	0.027	−0.000	0.072	0.057
	(0.00)	(0.36)	(0.34)	(1.00)	(0.45)	(0.32)
Renovation	−0.025	−0.005	−0.007	−0.089	−0.092	−0.040
	(0.53)	(0.87)	(0.83)	(0.39)	(0.47)	(0.59)
Heating	−0.110∗	−0.008	0.001	−0.202	−0.051	−0.037
	(0.06)	(0.89)	(0.99)	(0.11)	(0.81)	(0.73)
Cooling	0.077	−0.035	−0.045	0.052	0.084	−0.095
	(0.17)	(0.47)	(0.36)	(0.62)	(0.67)	(0.36)
Basement	0.176∗∗∗	0.046	0.037	−0.129	0.087	−0.127∗
	(0.00)	(0.17)	(0.28)	(0.10)	(0.51)	(0.08)
Attic	−0.051	0.010	0.008	0.191	0.303	0.080
	(0.16)	(0.84)	(0.87)	(0.31)	(0.15)	(0.37)
Constant	9.790∗∗∗	10.539∗∗∗	10.569∗∗∗	3.160∗∗∗	2.691∗∗∗	4.043∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Roof type	✓	✓	✓	✓	✓	✓
ZIP code FE		✓	✓		✓	✓
Year-Month FE			✓			✓
Observations	1,212	1,212	1,212	1,212	1,212	1,212
R^2	0.448	0.817	0.823	0.035	0.350	0.814

This table presents the results from the baseline regression (1). Columns (1) to (3) show the impact of assumption financing on housing prices, measured by the log of the sale price, where the sale price represents the final selling price of the property in dollars. Columns (4) to (6) display the effect of assumption financing on selling speed, measured by the log of days on market. House sizes are measured in square feets. The analysis includes ZIP code and year-month fixed effects, with standard errors clustered at the ZIP code level to account for intra-ZIP code correlation, ensuring robust statistical inference. P-values are shown in parentheses, with *, **, and *** indicating significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Appendix E.

Panel B of Table 1), this translates to a premium of over $20,000 for an assumable property. Furthermore, in Column (4), we find that properties with an assumable feature tend to sell more quickly. The days on the market for assumable properties are estimated to be $1-\exp(-0.11) = 10.4\%$ lower than their non-assumable counterparts. This suggests that assumable properties are sold approximately six days sooner compared to the average non-assumable property, which typically spends 58 days on the market (as indicated in Panel B of Table 1).

In columns (2) and (5), we extend our control by incorporating ZIP-code-fixed effects to accommodate time-invariant observable location-specific characteristics. In columns (3) and (6), we repeat the regressions by including both ZIP-code-fixed effects and time-fixed effects. This additional adjustment allows us to further capture the variation in explanatory transaction variables induced by time trends. The reported findings consistently demonstrate a positive impact of assumption financing on the attractiveness of properties, evident in both a higher selling price and a faster selling speed. Overall, the baseline regressions provide supportive evidence for the argument that assumption financing adds value to properties.

To mitigate the concern that our findings are confounded by other observable property characteristics (Adelino et al., 2023), we also estimate a two-stage regression model:

$$Y_i = \mathbf{X}_i \gamma'_x + \delta_{z(i)} + \delta_{t(i)} + \omega_i \tag{2}$$

$$\omega_i = \beta A_i + \varepsilon_i, \tag{3}$$

In the first stage, we estimate the hedonic regression model (2). Introduced by Rosen (1974), the hedonic regression method is widely employed in real estate literature to break down property values into the sum of their estimated quality attributes.[20] The residuals from the first stage regressions, denoted as ω_i, capture variation in transaction characteristics not explained by variations in observable property traits X_i, or by property location and time fixed effects. In the second stage, Equation (3) decomposes the hedonic regression residuals ω_i into two components. The first component, denoted as βA_i, accounts for variation in ω_i related to whether or not the property is assumable. The second component, denoted as ε_i, captures the variation in ω_i unrelated to the assumption feature.

We follow Adelino et al. (2023) and Ganduri, Xiao, & Xiao (2023) and estimate the hedonic regression (2) separately for each Core-Based Statistical Area (CBSA),[21] using all transactions observed for that

[20] Rosen (1974) explains that a class of differentiated products, such as residential properties, can be entirely described by a vector of objectively measured quality traits $\mathbf{X} = (x_1, \ldots, x_k)$. For observed sale prices Y, the specific values of characteristics linked to each property, $\gamma_1 x_1, \ldots, \gamma_k x_k$, establish a set of implicit or "hedonic" prices. Hedonic regressions estimate the coefficients $\gamma_1, \ldots, \gamma_k$ by regressing the property transaction characteristic Y against property quality attributes $x_1, \ldots, x_k$.

[21] To ensure robust estimation based on sufficiently large samples, we conduct regression (2) by CBSA rather than by ZIP code.

CBSA. The control set $\mathbf{X}_i$ in the hedonic regressions remains consistent with that of the baseline regression (1). Additionally, for each CBSA, we include both ZIP code fixed effects ($\delta_{z(i)}$) and time fixed effects ($\delta_{t(i)}$) in (2).

In the second stage (3), we regress the residuals from the first stage, ω_i, on the assumption financing dummy A_i. We estimate (2)–(3) separately for the log sale price (Y_i=log(Sale price$_i$)) and the log days on market (Y_i=log(Days on market$_i$)). The associated β estimates are reported in Table 3. Consistent with the baseline results in Table 2, our findings show that assumable properties command higher prices and sell in shorter periods in this robust setting.

Table 3: Impact of assumption financing on housing transactions—Robustness test

	(1) Log sale price^H	(2) Log days on market^H
Assumable	0.042***	−0.092***
	(0.00)	(0.00)
Constant	−0.031***	0.007
	(0.00)	(0.60)
ZIP code FE	✓	✓
Year-Month FE	✓	✓
Observations	1,209	1,209
R^2	0.408	0.485

This table presents the second-stage regression results of Equation (3). The first-stage regressions are conducted for each Core-Based Statistical Area (CBSA) using all transactions with complete control variable data. The second stage regresses the residuals of the transaction variables (Log sale price and Log days on market) from the first stage on the Assumable dummy. ZIP code and year-month fixed effects are included in the analysis, and standard errors are clustered at the ZIP code level to account for intra-ZIP code correlation and ensure robust statistical inference. p-values in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively. The variable definitions are provided in Appendix E.

In summary, the findings presented in Tables 2 and 3 support the notion that the assumable feature enhances a property's appeal, as indicated by the higher selling price and shorter time on the market.

4. Quantifying the Mortgage Assumption Value

Having established that the presence of an assumption financing option is associated with more favorable outcomes for home sellers, we proceed to compute the value of this option and quantify the extent to which the option's value is reflected in the sales price. To achieve this, we calculate the Mortgage Assumption Value (MAV), which represents the present value of future savings from assuming an existing lower-interest-

This approach aligns with that of Adelino et al. (2023).

rate mortgage compared to obtaining the same mortgage at market interest rates. Our benchmark MAV measure for property i at time t is constructed as the difference between the remaining balance on the existing mortgage and the current market value of paying off this balance:

$$\mathrm{MAV}_{it} = \sum_{k=1}^{T_i - t} \frac{\mathrm{Pmt}_i}{(1 + r_{t_i^o})^k} - \sum_{k=1}^{T_i - t} \frac{\mathrm{Pmt}_i}{(1 + r_t)^k}, \tag{4}$$

The first term, $\sum_{k=1}^{T_i-t} \frac{\mathrm{Pmt}_i}{(1+r_{t_i^o})^k}$, represents the remaining mortgage balance, calculated as the sum of the discounted monthly mortgage payments Pmt_i on the existing mortgage until its maturity at T_i. Here, the discount rate is the assumable T_i-year mortgage rate $r_{t_i^o}^{T_i}$ which was set when the existing mortgage originated at time t_i^o. The second term, $\sum_{k=1}^{T_i-t} \frac{\mathrm{Pmt}_i}{(1+r_t)^k}$, reflects the present value of the outstanding mortgage payments, discounted at the current mortgage rate r_t.

The MAV measure in Equation (4), proposed by Adelino et al. (2023), improves the method by Sirmans et al. (1983), who estimated the MAV as

$$\frac{(1 + r_t) - (1 + r_{t_i^o})}{(1 + r_t)}. \tag{5}$$

Unlike expression (5), the benchmark MAV measure in (4) considers the remaining mortgage period (i.e., $T_i - t$), reflecting that a longer remaining term allows buyers to benefit from interest savings for a longer time, thus increasing potential savings. Appendix F provides a detailed explanation and example of the MAV calculation.

Table 4 presents the summary statistics of MAV estimated based on Equation (4). The average MAV for the sample of assumable properties is \$95,636. This indicates that households able to assume the existing mortgage can potentially save nearly \$100,000 in interest costs compared to financing with the market mortgage rate. This amount represents 23.1% of the sale price and 35.4% of the outstanding loan balance. Furthermore, the outstanding loan balance accounts for 65.6% of the final selling price, suggesting that buyers can finance approximately two-thirds of the property's value at the lower assumable mortgage rate if they manage to provide a 34.4% down payment.

In our preliminary analysis, we quantify the portion of MAV incorporated into the final selling price by employing the method of Sirmans et al. (1983). As detailed in Appendix G, we find that an increase of \$1,000 in MAV is associated with a \$295 rise in the final selling price of the property. Given that the average

Table 4: Summary statistics of MAV

	Mean	SD	P10	P25	Median	P75	P90
MAV	95.7	38.7	54.1	68.0	88.8	116.6	143.1
MAV/Sale price	0.265	0.122	0.138	0.190	0.244	0.311	0.415
MAV/Unpaid loan balance	0.354	0.052	0.276	0.329	0.375	0.389	0.399
Unpaid loan balance%	65.6	11.7	52.1	56.5	64.4	73.6	81.9

This table provides the summary statistics of mortgage assumption value (MAV) for the 606 assumable properties. MAV, Sale price, and Unpaid loan balance are expressed in thousands. MAV/Sale price indicates the proportion of MAV relative to the final selling price of the non-assumable counterpart. The Unpaid loan balance% represents the proportion of the unpaid loan balance relative to the final selling price of the assumable property. The definitions of these variables are provided in Appendix E.

MAV is \$95,708, this translates to an average increase of \$28,234 in the final selling price of assumable properties compared to similar non-assumable properties.[22] This result aligns with the price differences observed in Panel B of Table 1.

To further explore this relationship, we estimate the price difference for each pair of matched properties, investigating the extent to which these differences can be explained by MAV. The price difference, hereafter referred to as the price premium, is calculated as the difference between an assumable property and a similar non-assumable one. This within-group comparison allows for a more precise quantification of MAV's impact on price, as properties in each pair share similar characteristics and are located within the same ZIP code area. Consequently, the price premium reflects the additional amount that homebuyers are willing to pay for the assumable mortgage feature. As MAV estimate the intrinsic value of the assumable feature at the transaction point, the coefficient of MAV could then capture the proportion of MAV that is priced.

To test, we regress the price premium% on MAV%:

$$\text{Price premium}_i \quad = \quad \beta \text{MAV}_i + \gamma_S \text{Sale}_i + \mathbf{X}_i \gamma_x^{'} + \delta_{z(i)} + \varepsilon_i \tag{6}$$

In this regression, we control for the transaction-specific characteristics of the property by incorporating the dollar value of the final selling price. Additionally, housing characteristics ($\mathbf{X}_i$) as outlined in Table 2 are included, along with ZIP code fixed effects ($\delta_{z(i)}$). The results of regression (6), under several alternative specifications, are presented in Table 5.

In Column (1), we measure the price premium as a fraction of the sales price. To mitigate the impact of scaling factors on both dependent and independent variables, we include the reciprocal of the sale price (i.e.,

[22] The marginal effect at the average MAV is computed as \$95,708 $\times$ 0.295 = \$28,234.

Table 5: Price premium and MAV

	(1) Price premium/Sale price (%)	(2) Price premium	(3) Sale price^{Res}
MAV/Sale price (%)	0.886**		
	(0.05)		
MAV		0.890**	0.829***
		(0.04)	(0.00)
1/Sale price	−0.206***		
	(0.00)		
Sale price		0.469***	0.252***
		(0.00)	(0.00)
Log age	−0.021	−8.556	12.788
	(0.43)	(0.36)	(0.16)
Log bedrooms	0.226	89.532	93.573*
	(0.12)	(0.10)	(0.07)
Log bathrooms	−0.382***	−121.154***	−169.936***
	(0.00)	(0.00)	(0.00)
Log house size	0.488***	157.060***	−376.950***
	(0.00)	(0.00)	(0.00)
Parking space	0.074	20.505	62.438**
	(0.77)	(0.78)	(0.01)
Fireplace	−0.032	−15.388	−65.260***
	(0.57)	(0.45)	(0.00)
Hasview	−0.128*	−63.961**	−104.793***
	(0.07)	(0.03)	(0.00)
Renovation	0.002	−3.636	−63.282***
	(0.98)	(0.89)	(0.00)
Heating	0.272	92.769	175.028**
	(0.28)	(0.32)	(0.02)
Cooling	−0.313	−86.223	−112.444*
	(0.17)	(0.30)	(0.07)
Basement	−0.142*	−45.107	35.533
	(0.06)	(0.13)	(0.22)
Attic	0.063	8.192	34.817
	(0.57)	(0.83)	(0.42)
Constant	−3.173***	−1424.964***	2601.536***
	(0.00)	(0.00)	(0.00)
Roof type	✓	✓	✓
ZIP code FE	✓	✓	✓
Observations	606	606	604
R^2	0.849	0.874	0.941

This table reports the results for regression (6). MAV, Price premium, Sale price, and Sale price^{Res} are in thousands of dollars. Price premium % is calculated as the Price premium divided by the Sale price, and MAV % is the MAV scaled by the Sale price. ZIP code fixed effects are included, and standard errors are clustered at the ZIP code level. p-values are in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E.

1/Sale price) as a control. This approach is similar to methodologies commonly employed in investment-Q sensitivity literature, where the reciprocal value of assets is controlled, as both the dependent variable (capital expenditure) and the main independent variable (Tobin's Q) are scaled by assets (Chen, Goldstein, & Jiang, 2007; Jiang, Kim, & Pang, 2011).

Our analysis reveals that a 1% increase in the proportion of MAV on sales, attributed to fluctuations in the policy rate, leads to an 88.6% transfer of this increment into the price premium. This finding underscores the mutual awareness of both buyers and sellers regarding the value associated with the assumable feature, with sellers primarily benefiting.[23]

In Column (2), we present the outcomes of directly regressing the dollar value of the price differential on MAV. Moving to Column (3), we adopt an alternative approach to gauge the price premium. Specifically, the alternative metric for the price premium, denoted as Sale price^{Res}, is computed based on the residual value derived from the Hedonic regression incorporating observable housing characteristics. Since the assumable feature was not factored into the initial stage of the Hedonic regression when estimating the residual, Sale price^{Res} can be interpreted as an indication of the extra price attributed to the assumable feature. The results align with the previous findings.[24]

4a. Refinancing option

In our baseline MAV estimation model (4), we assume households retain their mortgages until maturity. However, households may refinance if interest rates decrease during the mortgage term. Consequently, the advantages of the assumable mortgage feature might diminish when the market interest rate falls to the assumable mortgage rate. In (7), we account for this by assuming refinancing occurs when the market rate drops to the assumable mortgage rate $r_{t_i^o}$ at time τ_i. This implies that households adopting assumption financing will enjoy interest savings solely between time t and time τ_i. After τ_i, this advantage vanishes, as

[23]We offer two explanations for our discovery that a significant portion of the value of the option to assume benefits the seller more than the buyer. Firstly, sellers tend to prioritize the cash sale price, while buyers, especially those reliant on income rather than wealth, are more concerned with manageable monthly mortgage payments. Therefore, buyers may be willing to pay a higher sale price for an assumable property that can be amortized over the next 30 years in exchange for lower monthly payments. For instance, consider a scenario where a buyer purchases an assumable property with an assumable rate of 2.5% while the market rate is 7.5%. The property has a fair value of $450k, with a loan balance of 90%. Even if the seller included 60% of the MAV in the final selling price above the fair value, the buyer would still benefit from monthly interest savings of approximately $470, representing a roughly 15% reduction in mortgage interest payments. Secondly, buyers may derive unquantifiable non-financial benefits from obtaining a low-interest-rate loan in a high-interest-rate environment. Alternatively, behavioral biases might lead them to overestimate the savings gained from mortgage assumption. For example, buyers might calculate MAV based on the property's listed price, overlooking that this price might already incorporates a significant portion of the interest-saving benefits.

[24]Including the downpayment percentage as additional controls in the regressions does not alter our conclusions.

it would be rational for both sets of borrowers to refinance at the lower market interest rate.[25]

$$\text{MAV}_{it} = \sum_{k=1}^{T_i-t} \frac{\text{Pmt}_i}{(1+r_{t_i^o})^k} - \sum_{k=1}^{\tau_i-t} \frac{\text{Pmt}_i}{(1+r_t)^k} - \frac{1}{(1+r_t)^{\tau_i}} \sum_{k=1}^{T_i-\tau_i} \frac{\text{Pmt}_i}{(1+r_{\tau_i})^k}, \tag{7}$$

The first term, $\sum_{k=1}^{T_i-t} \frac{\text{Pmt}i}{(1+rt_i^o)^k}$, represents the remaining mortgage balance at transaction time t. The remaining terms capture the present value of the outstanding mortgage payments considering refinancing. The first part, $\sum_{k=1}^{\tau_i-t} \frac{\text{Pmt}i}{(1+r_t)^k}$, records the present value of mortgage payments before the refinancing time τ_i. The second part, $\frac{1}{(1+r_t)^{\tau_i}} \sum_{k=1}^{T_i-\tau_i} \frac{\text{Pmt}_i}{(1+r_{\tau_i})^k}$, represents the present value of the mortgage's terminal value. The terminal value refers to the mortgage's market value after refinancing occurs at time τ_i, when the market interest rate r_{τ_i} drops to the assumable mortgage rate $r_{t_i^o}$.

4b. Maturity-adjusted mortgage rates

As outlined in our baseline MAV estimation model in equation (4), households have the option to either assume the existing assumable mortgage rate $r_{t_i^o}^{T_i}$ or finance the outstanding payments with a new loan at the prevailing market mortgage rate r_t, where r_t denotes the rate for a T_i-year mortgage. While equation (4) takes into account the remaining loan terms when assessing the assumable feature, it does not adjust the interest rate accordingly. Instead, the market rate r_t is set as the standard 30-year market mortgage rate. [26] In this section, we modify (4) by adjusting the market interest rate based on the remaining time-to-maturity of the assumable mortgage. Specifically, as modeled in (8), the market rate for a $T_i-(t-t_i^o)$-year mortgage is applied to the new loan, where $T_i-(t-t_i^o)$ represents the remaining time-to-maturity of the existing mortgage.

$$\text{MAV}_{it} = \sum_{k=1}^{T_i-t} \frac{\text{Pmt}_i}{(1+r_{t_i^o}^{T_i})^k} - \sum_{k=1}^{T_i-t} \frac{\text{Pmt}_i}{(1+r_t^{T_i-(t-t_i^o)})^k}, \tag{8}$$

[25]It's worth noting that it might not be optimal for households to refinance immediately when the interest rates drop below the assumable mortgage rate, considering factors such as prepayment penalties and refinancing costs (Campbell, 2006). As a result, the MAV estimated by this method may be more conservative compared to the actual value of the assumption feature.

[26]We assume an initial loan term T_i of 30 years, which aligns with common practice in the U.S. market. This assumption is further supported by the observation that the average remaining loan term for the sample assumable mortgages is approximately 27 years, suggesting that the initial term of these mortgages was likely 30 years.

4c. Prepayment option and maturity-adjusted mortgage rates

Finally, we incorporate both the refinancing option and the maturity-adjusted mortgage rates into the MAV estimation:

$$\mathrm{MAV}_{it} = \sum_{k=1}^{T_i-t} \frac{\mathrm{Pmt}_i}{(1+r_{t_i^o}^{T_i})^k} - \sum_{k=1}^{\tau_i-t} \frac{\mathrm{Pmt}_i}{(1+r_t^{\tau_i})^k} - \frac{1}{(1+r_t^{\tau_i})^{\tau_i}} \sum_{k=1}^{T_i-\tau_i} \frac{\mathrm{Pmt}_i}{(1+r_{\tau_i}^{T_i-\tau_i})^k}, \tag{9}$$

Here, the first term, $\sum_{k=1}^{T_i-t} \frac{\mathrm{Pmt}_i}{(1+r_{t_i^o}^{T_i})^k}$, reflects the present value of the remaining mortgage balance if a household successfully assumes the existing assumable mortgage, allowing for the potential of refinancing if applicable. The subsequent terms in Equation (9) capture the current market value of paying off the remaining balance with maturity-adjusted mortgage rates $r_t^{\tau_i}$, while also considering the option of refinancing.

4d. Empirical results on alternative model specifications

To incorporate the refinancing option as modeled in Equation (7), we would need to estimate the refinancing time for each property. This is defined as the shortest period required for the market interest rate to decrease by $r_t - r_{t_i^o}^{T_i}$. We employ an autoregressive integrated moving average (ARIMA) model that allow us to forecast the prospective monthly fluctuations in 30-year mortgage rates and pinpoint the earliest instance when the rate drops by $r_t - r_{t_i^o}^{T_i}$. Specifically, we use an ARIMA(2,1,1) model, featuring two autoregressive terms, one difference term, and one moving average term, to make our predictions. To validate our forecasting model, we ascertain that the residuals conform to a white noise distribution and that the process is both stationary and invertible (Box & Jenkins, 1970). The Portmanteau test fails to reject the null hypothesis that the residuals are white noise, while the stability condition of the ARIMA estimates affirms that the process satisfies the conditions of stationarity and invertibility.

We then proceed with rate changes forecasting using historical data of 30-year mortgage rates from 1971 to 2023. We start from 1971 as it marks the earliest availability of mortgage rate data.[27] The shortest periods estimated accordingly are then utilized as the predicted time until the next refinancing event, denoted as $\tau_i - t$.[28] This methodology facilitates a more accurate valuation of the assumable feature by factoring in potential refinancing behavior in response to interest rate fluctuations.

[27] Data source: https://fred.stlouisfed.org/series/MORTGAGE30US

[28] In cases where $\tau_i - t$ exceeds $T_i - t$, the remaining mortgage payments Pmt_i will be discounted over the period $T_i - t$, just as in (4).

To account for the change in maturities of the new mortgage as specified in (8), we derive the maturity-adjusted mortgage rate for each new loan contingent on the remaining time-to-maturity of the extant assumable mortgage. The adjusted mortgage rate is computed as r_t - ($y_t(30)$ - $y_t^i(ttm)$), where r_t represents the market interest rate utilized in the main equation (1) for estimating the present value of the new loan. In this context, $y_t(30)$ denotes the 30-year Treasury yield, and $y_t^i(ttm)$ denotes the yield of a Treasury security with a maturity equivalent to the remaining time-to-maturity of the assumable mortgage. This adjustment presupposes that assumable mortgages were initially issued with a 30-year term and posits alignment between the mortgage rate yield curve and the Treasury rate yield curve.

Finally, we integrate both the refinancing option and the maturity-adjusted mortgage rate into MAV estimation, as detailed in (9). In this model, the maturity-adjusted mortgage rate serves as the rate for discounting new mortgages, with the refinancing period $\tau_i - t$ being accounted when discounting.

Panel A of Table 6 presents the summary statistics for MAVs calculated using the adjusted models. The statistics reveal that MAVs derived from these diverse model specifications exhibit similar mean and distributional characteristics when compared to those computed using the baseline MAV estimation model outlined in Equation (4). We then reanalyze the regressions in Table 5 employing these modified MAVs. The results are reported in Panel B of Table 6. Our findings consistently underscore a substantial increase in property prices attributable to MAV. In Appendix H, we extend our analysis to consider the prospect of households refinancing multiple times throughout the remaining lifespan of the mortgage. Specifically, we allow households securing property financing at market interest rates to pursue refinancing whenever the rate experiences a 1% decline. Even under these augmented conditions, our results remain statistically and economically robust.

Table 6: Price premium and modified MAV

Panel A: Summary statistics of alternative MAV measures

	Mean	SD	P10	P25	Median	P75	P90
MAV estimated based on Equation (7)	95.576	38.747	53.773	67.830	88.529	116.550	143.141
MAV estimated based on Equation (8)	96.382	38.975	54.276	68.565	88.927	117.454	144.377
MAV estimated based on Equation (9)	96.249	38.990	54.149	68.429	88.629	117.454	144.377

Panel B: Regression results

	MAV estimated based on (7)			MAV estimated based on (8)			MAV estimated based on (9)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MAV / Price	0.890**			0.934**			0.938**		
	(0.05)			(0.05)			(0.05)		
MAV		0.895**	0.814***		0.886**	0.835***		0.891**	0.815***
		(0.03)	(0.00)		(0.04)	(0.00)		(0.03)	(0.00)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
ZIP code FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	606	606	604	606	606	604	606	606	604
R^2	0.835	0.863	0.938	0.884	0.874	0.942	0.835	0.863	0.938

Panel A provides the summary statistics of mortgage assumption value (MAV) for the 606 assumable properties estimated based on Equations (7)-(9). MAVs are in thousands of dollars. Equation (7) incorporates the refinancing option in MAV estimation.Equation (8) accounts for changes in maturities of the new mortgage in MAV estimation. Equation (9) integrates both the refinancing option and the maturity-adjusted mortgage rate in MAV estimation. Panel B presents the results corresponding to Table 5 using alternative MAV estimations as outlined in Equations (7) through (9). Specifically, Columns (1) to (3) report the results incorporating the refinancing option in MAV estimation as modelled in (7). Columns (4) to (6) present the findings accounting for the change in maturities of the new mortgage in MAV estimation, as specified in (8). Columns (7) to (9) display the results that integrate both the refinancing option and the maturity-adjusted mortgage rate in MAV estimation. Dependent variables for Columns (1), (4), and (7) are price premium over sales in percentage. Dependent variables for Columns (2), (5), and (8) are the dollar value of the price premium. Dependent variables for Columns (3), (6), and (9) are Sale price^{Res}. MAV, Price premium, Sale price, and Sale price^{Res} are in thousands of dollars. ZIP code fixed effects are included, and standard errors are clustered at the ZIP code level to account for intra-ZIP code correlation and ensure robust statistical inference. P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Appendix E.

5. Cross-Sectional Tests

As shown in Table 5, the sensitivity of the price premium to MAV, denoted as "MAV-β," is less than one. This indicates that the savings derived from assumable mortgages are distributed between sellers and buyers, with sellers primarily benefiting. We further investigate the factors influencing the portion of MAV captured by the seller.

5a. Buyer versus Seller Markets

One potential determinant is the disparity in bargaining power between buyers and sellers (LaCour-Little et al., 2020; Bian, Lin, & Liu, 2018). In markets where sellers possess greater bargaining power, they can demand a higher price for the assumption feature, leading to a larger portion of MAV being capitalized into the final sale price. Consequently, we hypothesize that properties in such markets will exhibit a higher MAV-β.

To test this hypothesis, we proceed in three steps. First, we estimate county-specific MAV-β using the following regression model:

$$\text{Price premium}_{i,c} = \sum \beta_c \text{MAV}_{i,c} * \eta_c + \mathbf{X}_i \gamma_x^{'} + \gamma_p + \varepsilon_i \tag{10}$$

where the Price premium$_{i,c}$ represents the price difference between assumable property i located in county c and its corresponding non-assumable counterpart. η_i is the county indicator. MAV$_{i,c}$ is the market assumable value of property i located in county c and the MAV-β, β_c, captures the average portion of MAV being incorporated into the price for county c. The control set X_i are the same as those used in Column(2) of Table 5.[29]

In the second step, we categorize assumable properties based on the sellers' bargaining power in their respective counties. Counties where sellers hold greater bargaining power are termed "seller markets," while those where sellers hold less power are termed "buyer markets." We then categorize properties into the buyer market and seller market based on the median values of two proxies: Δ Median sale price and Δ Housing inventory.

The first proxy, Δ Median sale price, measures the yearly growth of the median sale price in the local

[29] In this model, we do not control for the time-fixed effects as MAV is estimated based on mortgage rate differences, which are inherently time-dependent.

housing market. A stronger growth in median sale price suggests intense competition among buyers for listed properties, thereby granting sellers greater bargaining leverage. Consequently, a higher Δ Median sale price indicates a seller market, whereas a lower value suggests a buyer market.

The second proxy, Δ Housing Inventory, measures the growth of housing inventory in the local market. This metric compares the supply (listings) and demand (delisted properties) in the local housing market. A greater increase in inventory suggests that housing supply is growing faster than demand, weakening sellers' negotiating positions. Therefore, a higher Δ Housing inventory indicates a buyer market, while a lower value signifies a seller market.

In our final step, we compare the MAV-β between buyer and seller markets as categorized earlier. The results are depicted in Figure 4. The first column (a, e) displays results where the MAV in (10) is estimated based on Equation (4), the second column (b, f) presents results where the MAV in (10) is estimated based on Equation (7), the third column (c, g) displays results where the MAV in (10) is estimated based on Equation (8), and the fourth column (d, h) displays results where the MAV in (10) is estimated based on Equation (9). The red dot indicates the average MAV-β within each group, with 95% confidence intervals. In line with our hypothesis, we observe a greater portion of MAV being incorporated in prices in seller markets. For instance, when employing Δ Median sale price as the proxy, (a) demonstrates that 92% of the assumption value is integrated into the price in seller markets, nearly twice the amount observed in buyer markets. Likewise, utilizing Δ Housing inventory as the proxy, (e) reveals that 90% of the assumption value is translated into the price premium when sellers possess greater bargaining power, as opposed to only half in a buyer's market.

5b. Buyers' financial constraint

Financial constraints among buyers can be another factor impacting the portion of MAV captured by sellers. While interest savings from assumption financing are appealing, buyers must first cover the seller's equity (i.e., downpayment) - the difference between the final selling price and the remaining mortgage balance – before taking over the assumable mortgage. High downpayment requirements necessitate substantial cash or additional loans, and imply a smaller interest-saving benefits to be enjoyed by buyers. This could diminish the appeal of assumable properties and reduce the MAV reflected in the price premium (Fuster & Zafar, 2016).

To test this, we categorized assumable properties into two groups based on their downpayment require-

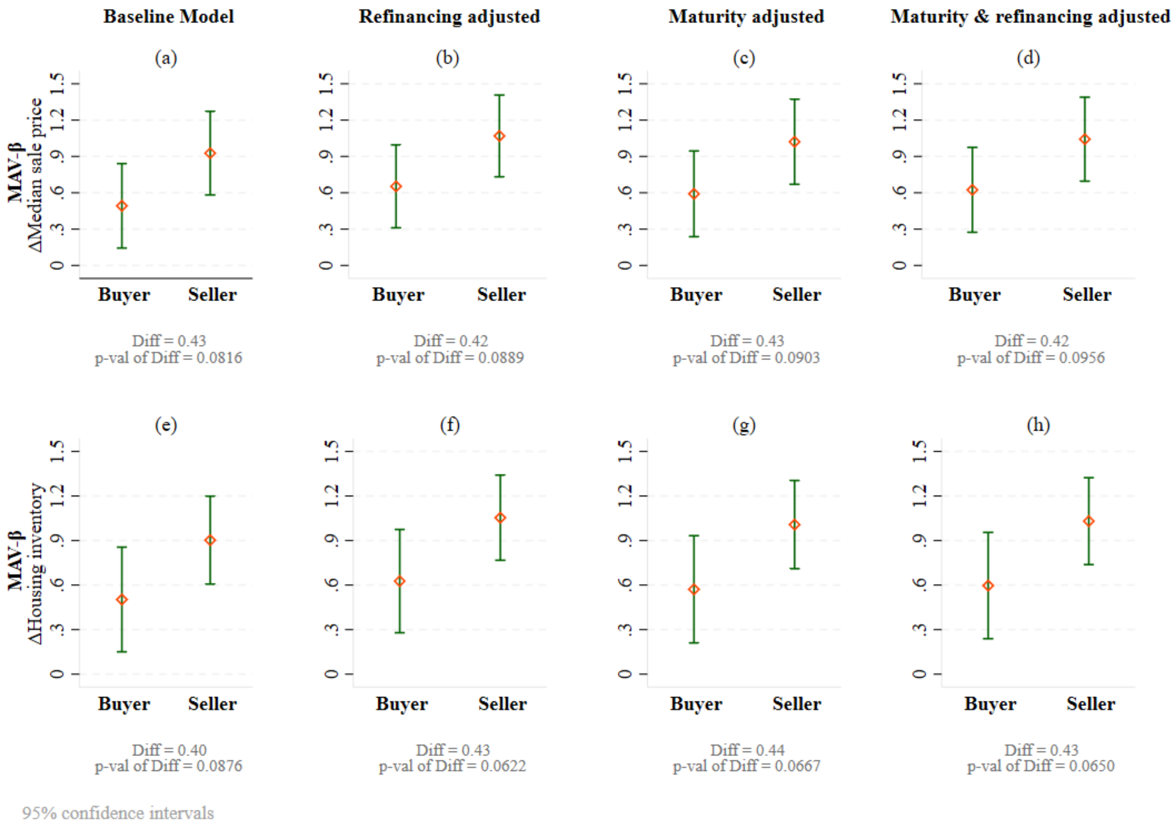

Figure 4: The impact of bargaining power on MAV-price incorporation

The graph compares the portion of MAV being incorporated into price premiums among buyers and sellers market. The graphs in the first row (a-d) use Δ Median sale price to measure negotiation power between sellers and buyers. Δ Median sale price records the yearly growth of median sale price in the local housing market. The second row of graphs (e-h) employs Δ Housing inventory as the measure of negotiation power. Δ Housing inventory captures the growth of housing inventory in the local housing market, estimated as the difference between new listings and delisted properties. Properties with an above-median value of Δ Median sale price or a below-median value of Δ Housing inventory are considered to be in the seller market. Conversely, properties a below-median value of Δ Median sale price or with an above-median value of Δ Housing inventory are considered to be in the buyer market. The first column (a, e) displays results where the MAV in (10) is estimated based on Equation (4), the second column (b, f) presents results where the MAV in (10) is estimated based on Equation (7), the third column (c, g) displays results where the MAV in (10) is estimated based on Equation (8), and the fourth column (d, h) displays results where the MAV in (10) is estimated based on Equation (9). The red dot represents the average value of MAV-β in each group, with the range based on 95% confidence intervals.

ments. This requirement is calculated as the difference between the final selling price and the remaining mortgage balance, scaled by the average income of local borrowers from the HMDA database. Normalizing the downpayment by local income helps us understand how buyers' ability to meet the downpayment influences MAV capitalization. Properties in Florida were excluded due to their unique buyer demographics, which include a significant portion of wealthy buyers from higher-cost markets and financially secure retirees, making them less likely to be constrained by high downpayment requirements.[30]

[30] https://www.miamiherald.com/money/cash-offers-on-florida-homes/

Properties with an above-median downpayment requirement were classified as the high downpayment group, while those with a below-median requirement were classified as the low downpayment group. Given that a high downpayment requirement induces greater financial burden to buyers, we expect a less pronounced incorporation of MAV into price premiums among such properties.

In line with our hypothesis, the graph presented on the first row of Figure 5 suggests that capitalization is more evident among the low downpayment group compared to the high downpayment group. As shown in (a), 98% of MAV can be integrated into the price premium among the low downpayment group, while only 53% can be incorporated into the price among the high downpayment group.

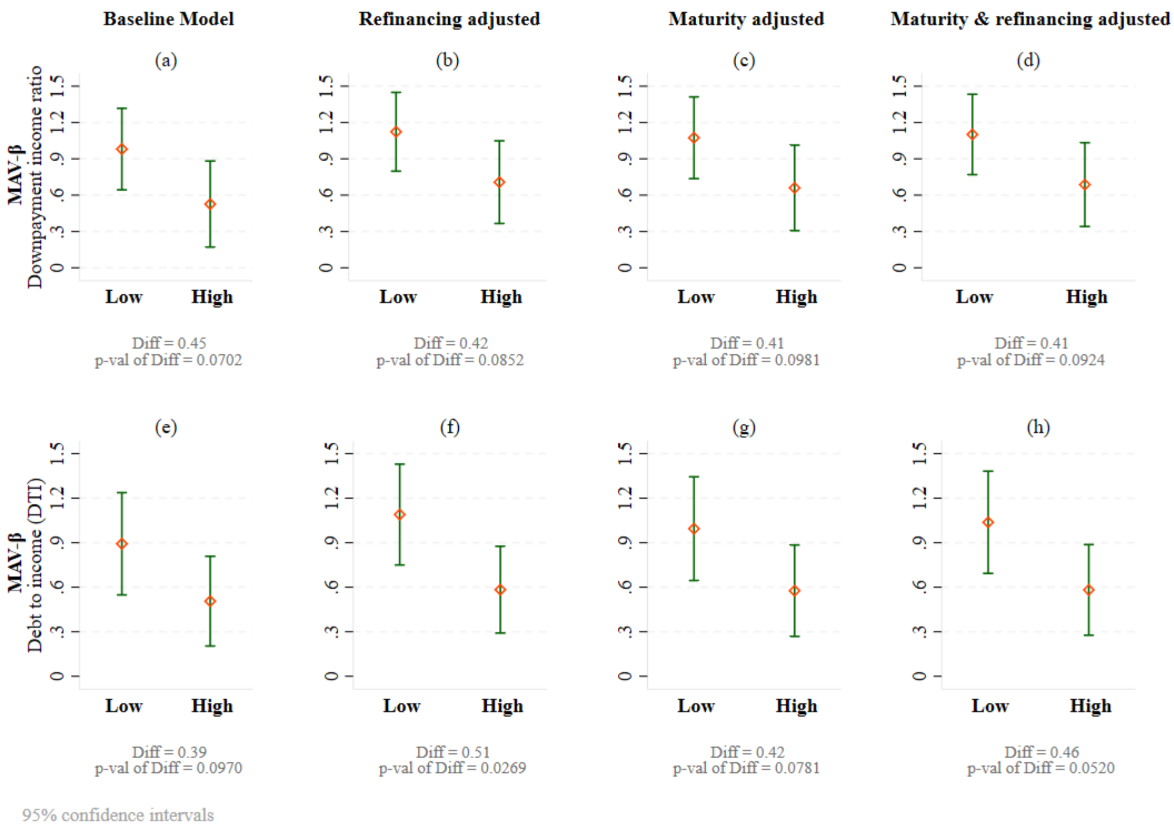

Figure 5: The impact of buyers' financial constraints on MAV-price incorporation

The graph explores how MAV contributes to price premiums, showing variations across different levels of buyers' constraints. The first row (a-d) depicts variations among properties with different downpayment requirements, scaled by the average income of borrowers in the local region to reflect downpayment challenges. The second row (e-h) illustrates variation among groups with different Debt-to-Income (DTI) ratios, using 45% as a high DTI threshold. Buyers in regions with an above-median value of DTI or downpayment are considered to face greater constraints. The first column (a, e) displays results where the MAV in (10) is estimated based on Equation (4), the second column (b, f) presents results where the MAV in (10) is estimated based on Equation (7), the third column (c, g) displays results where the MAV in (10) is estimated based on Equation (8), and the fourth column (d, h) displays results where the MAV in (10) is estimated based on Equation (9). The red dot represents the average value of MAV-β in each group, with the range based on 95% confidence intervals.

While homebuyers can secure additional loans to finance a substantial downpayment, this is challenging for borrowers with a high Debt-to-Income (DTI) ratio. A high DTI limits buyers' ability to raise sufficient funds, reducing their willingness to pay for the mortgage assumption feature and hindering the full incorporation of MAV into the price premium.

To test this, we estimate the percentage of borrowers with a high DTI in each region with borrowers information obtained from HMDA database. as this is the maximum ratio that allows buyers to qualify for an affordable interest rate on a second loan.[31] We employ 45% as the high DTI threshold. Similar trends are observed when using thresholds of 40% or 50%. Regions with above-median DTI are classified as high-constraint areas, while those with below-median DTI are classified as low-constraint areas. We predict that higher financial constraints will negatively impact the capitalization of MAV into the price premium, resulting in less MAV incorporation in high-constraint areas.

The graph presented on the second row of Figure 5 provides supporting evidence for the aforementioned argument. For example, graph (e) shows that about 89% of MAV is incorporated into the price premium in low-constraint areas, compared to only 51% in high-constraint areas, highlighting the impact of buyers' financial constraints on MAV capitalization.

5c. Share of working age population

Next, we explore whether demographics contribute to the variability in MAV-price premium sensitivity, focusing on aging, a crucial factor in local housing prices (Takáts, 2012). People typically buy homes during their working years and sell them as they grow older. Therefore, the age distribution in a locality can influence the bargaining power of buyers and sellers, affecting MAV-price premium sensitivity.

To examine this, we analyze the impact of the working-age population percentage on MAV incorporation into price premiums. We define the working age as 25 to 65 years. By scaling the number of working-age individuals by the total population in the area, we classify areas with above-median proportions of working-age individuals as high work-age groups and those with below-median proportions as low work-age groups. Figure 6 shows that counties with lower proportions of working-age population exhibit around 50% MAV-price premium sensitivity, whereas this figure roughly doubles in areas with higher proportions of working-age population.

[31] https://www.urban.org/urban-wire/could-rarely-used-government-backed-loan-feature-help-level-playing-field-todays-high

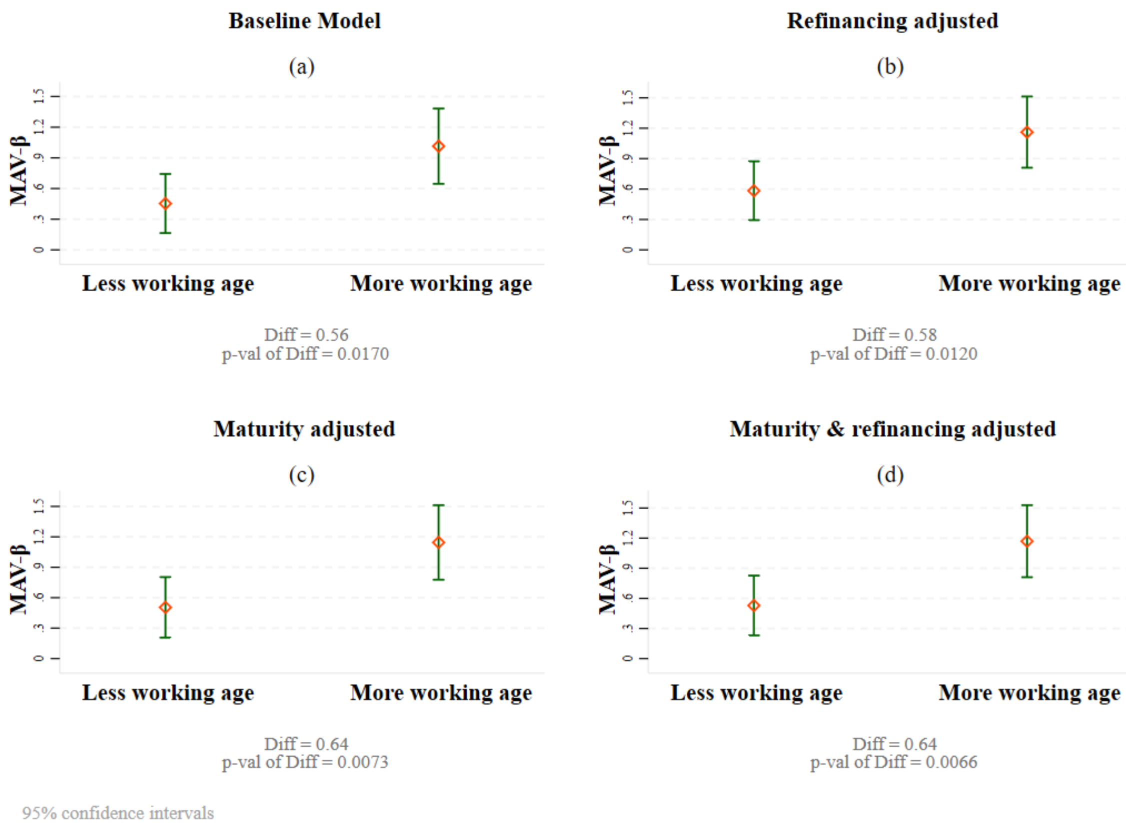

Figure 6: The impact of Working Age Population on MAV-price incorporation

The graph investigates the integration of MAV into price premiums across different proportions of the working-age population. Working-age proportion is calculated by dividing the total number of individuals aged 25 to 65 by the total population in the local area. Areas with above-median proportions are categorized as high work-age group, while those below-median are low work-age group. (a) presents results where MAV is estimated based on Equation (4). (b) shows results where MAV is estimated using Equation (7). (c) displays MAV estimations based on Equation (8). (d) presents results where MAV is estimated using Equation (9). The red dot represents the average value of MAV-β in each group, with the range based on 95% confidence intervals.

5d. Rental expenses

Households may choose to postpone their home-buying decisions and opt for renting especially when market properties are less affordable. As a result, local rental expenditures can influence the incorporation of MAV into property prices. In areas with lower rental costs, households are more likely to delay purchasing, reducing demand for listed properties, including those with assumable mortgages. Consequently, a smaller portion of MAV is expected to be reflected in the final selling prices of assumable properties in these regions.

To test this hypothesis, we collected county-level rental expense data from HUD.[32] We categorized areas where the median rent for 3-bedroom properties exceeded the sample median as having higher rental

[32] https://www.huduser.gov/portal/datasets/50per.html

expenses, and those below the median as having lower rental expenses.[33] Consistent with our expectations, Figure 7 demonstrates that the lower rental expenses group exhibits a smaller MAV-β.

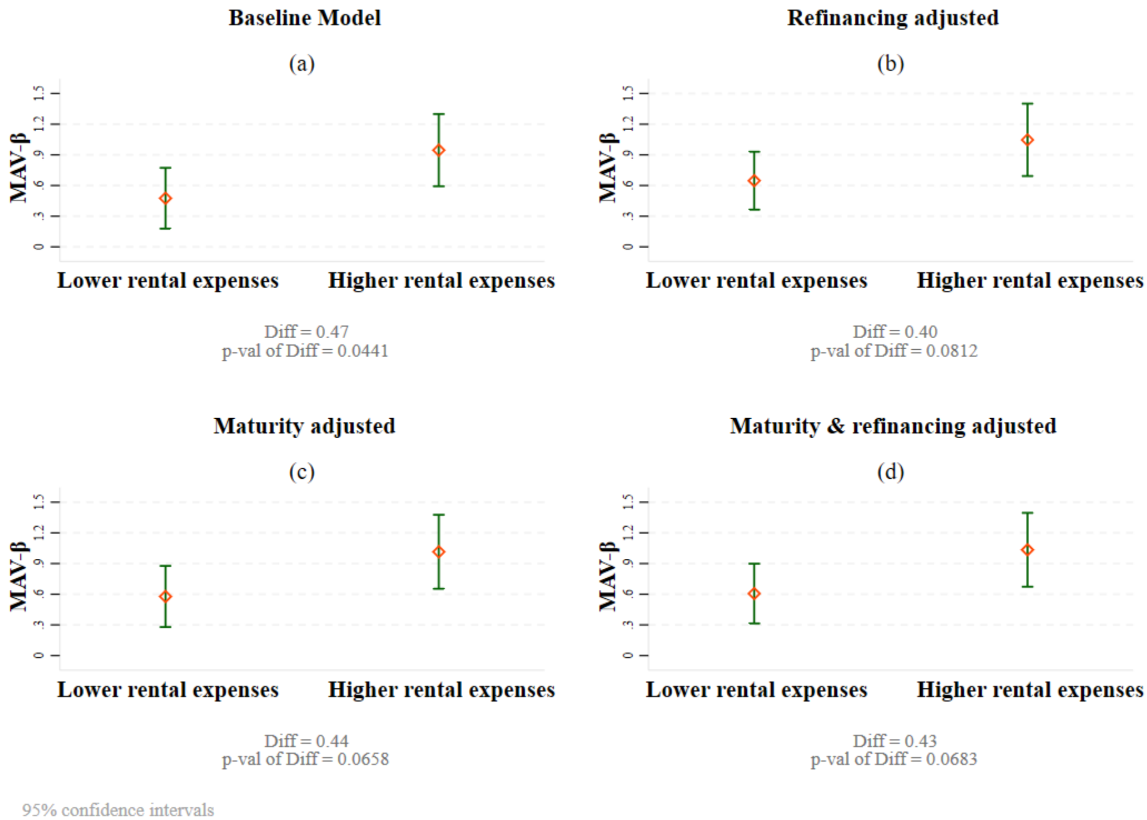

Figure 7: The impact of rental expenses on MAV-price incorporation

The graph investigates the integration of MAV into price premiums across areas with different rental expenses. The county level rental expenses data is obtained from HUD (`https://www.huduser.gov/portal/datasets/50per.html`). Areas with above-median rental expenses of 3-bedroom properties are categorized as higher rental expenses group, while those below-median are lower rental expenses group. (a) presents results where MAV is estimated based on Equation (4). (b) shows results where MAV is estimated using Equation (7). (c) displays MAV estimations based on Equation (8). (d) presents results where MAV is estimated using Equation (9). The red dot represents the average value of MAV-β in each group, with the range based on 95% confidence intervals.

In Appendix I, we construct a composite index to better capture the local characteristics influencing the sensitivity of MAV-price premiums. This index integrates all four dimensions discussed earlier. The combined index reveals a disparity of approximately 0.70 in MAV-β between the high and low groups, a difference of more than 1.5 times greater than the average differences observed when examining each dimension individually.

[33] Similar results were obtained when using the rental prices of 1-bedroom, 2-bedroom, and 4-bedroom properties for classification.

6. Do Assumable Mortgages Mitigate Lock-in Effect?

The rise in interest rates presents a challenge to the housing market known as the lock-in effect. This occurs when homeowners hesitate to sell their properties due to fears of not securing new mortgages at rates as favorable as their existing ones. This reluctance reduces housing supply, driving up the prices of listed properties and imposing a dual burden of higher mortgage rates and elevated purchase prices on new homebuyers.

This effect is currently unfolding in the U.S. housing market. According to the National Association of Realtors (NAR), the volume of previously owned homes sold in 2023 declined to its lowest point since 1995, with only 4.09 million transactions. Concurrently, the median home price surged to a record high of $389,800.[34] Given that assumable mortgages allow new buyers to benefit from historically low rates, it's natural to ask whether these mortgages mitigate the lock-in effect.

To explore this, we need a panel dataset tracking housing transactions across regions with varying levels of assumption financing availability. We create this dataset by merging regional housing transaction data from Redfin[35] with assumable mortgage issuance data from the HMDA database.[36] Redfin data allows us to construct lock-in effect outcome variables, while HMDA data lets us estimate assumption financing availability for each region. Since the smallest unit in the HMDA database is the county, our panel dataset for this set of test operates at the county level. We also integrate 30-year fixed-rate mortgage rates from FRED[37] to examine how housing supply and household mobility change when mortgage rates fluctuate. Our analysis covers the period from 2012 (the earliest year for which Redfin provides regional housing transaction data) to 2022 (the latest year for which regional assumable mortgage issuance data is available from the HMDA database).

6a. New listings

To measure the lock-in effect, the first measure we employed is the log growth rate in new listings, denoted as $\Delta\log(\text{Listings}_{ct})$, where c indicates the county and t indicates the year of observation. To analyze the impact of assumption financing on the lock-in effect, we explore whether changes in new listings in response to interest rate fluctuations are less pronounced in areas with higher prevalence of assumption financing.

[34] https://www.nar.realtor/newsroom/existing-home-sales-slid-1-0-in-december
[35] https://www.redfin.com/news/data-center/
[36] https://ffiec.cfpb.gov/data-browser/data/2022?category=states
[37] https://fred.stlouisfed.org/series/MORTGAGE30US

Appendix Figure J.1 visualizes the availability of assumption financing at the county level, indicating the fraction of properties with assumption financing. For each county c and year t, this fraction is calculated as the ratio of the dollar amount of assumable mortgages originated in county c over the five-year period prior to year t, to the total number of mortgages originated in that county over the same period.[38] The figure shows a substantial variation across counties in the fraction of assumable mortgages, ranging from 0.4% in Pitkin County, Colorado, to 84% in Long County, Georgia. This wide range in the prevalence of assumption financing makes investigating its impact on mortgage market outcomes particularly meaningful.

To quantify this impact, we define an indicator for high assumption availability, A_{ct}^{high}, as one if the fraction of properties with assumption financing in county c exceeds the median fraction across counties, and zero otherwise. We then regress $\Delta\log(\text{Listings}_{ct})$ on changes in mortgage rates (Δr_t) and its interaction with A_{ct}^{high} to determine if the sensitivity of new listings to changes in mortgage rates varies across regions with different assumption financing availability:

$$\Delta\log(\text{Listings}_{ct}) \quad = \quad \beta_1 \Delta r_t + \beta_2 A_{ct}^{high} \times \Delta r_t + \beta_3 A_{ct}^{high} + \mathbf{Z}_{ct}\gamma_z' + \delta_c + \varepsilon_{ct}. \tag{11}$$

The vector $\mathbf{Z}_{ct}$ of conditioning variables comprises changes in local house prices, income, and unemployment rates. Additionally, it includes a "COVID" indicator, set to one for the years 2020 to 2022. This indicator accounts for any unforeseen effects stemming from the COVID-19 pandemic, ensuring the robustness of our findings against potential distortions caused by anomalous fluctuations in the housing market during the pandemic period. County fixed effects δ_c are controlled to account for unobservable county-level factors that remain constant over time.

The regression results are presented in columns (1)–(2) of Table 7. Column (1) presents the model without acconuting for assumption availability ($\beta_2 = \beta_3 = 0$). It indicates that, holding other factors constant, a one-percentage increase in mortgage rates leads to a 1.2% decrease in new listings growth. This supports the notion that rising interest rates contribute to a lock-in effect, evident in the decline of new listings growth in the housing market. Column (2) refines the analysis by lifting the restriction on β_2 and β_3. It reports a positive and significant coefficient of 1.6% for the interaction term $A_{ct}^{high} \times \Delta r_t$, consistent with the argument that assumption financing can mitigate the lock-in effect stemming from a sharp increase

[38] Due to the lack of time-series data on the fraction of outstanding government-insured mortgages, we use this five-year window as a proxy. A longer window would reduce the number of observations for estimating regression (11). As a robustness check, we also compute A_{ct}^{high} using a three-year window. The resulting estimates, reported in Table J.1, confirm those based on the benchmark five-year window reported in Table 7.

in mortgage rates. Specifically, the results implies that assumption financing help counties with greater availability nearly offsets the negative response of new listings to interest rate increases ($\beta_2 + \beta_3$).

Table 7: Lock-in effect

	(1) Δ Log listings	(2) Δ Log listings	(3) Δ Movers	(4) Δ Movers
Δ r$_m$	−0.012∗∗∗ (0.00)	−0.020∗∗∗ (0.00)	−0.007∗∗ (0.03)	−0.015∗∗∗ (0.00)
$A^{high} \times \Delta$ r$_m$		0.016∗∗∗ (0.00)		0.017∗∗∗ (0.00)
A^{high}		0.009 (0.61)		0.014 (0.29)
Δ Log county house price	0.069∗∗∗ (0.00)	0.069∗∗∗ (0.00)	0.004 (0.76)	0.006 (0.56)
Δ Log county income	−0.097∗∗ (0.02)	−0.097∗∗ (0.02)	5.478∗∗∗ (0.00)	5.079∗∗∗ (0.00)
Δ County unemployment	−0.006∗∗∗ (0.00)	−0.006∗∗∗ (0.00)	−0.007∗∗∗ (0.00)	−0.008∗∗∗ (0.00)
COVID period	−0.097∗∗∗ (0.00)	−0.097∗∗∗ (0.00)	−0.039∗∗∗ (0.00)	−0.049∗∗∗ (0.00)
Constant	0.184∗∗∗ (0.00)	0.179∗∗∗ (0.00)	0.062∗∗∗ (0.00)	0.050∗∗∗ (0.00)
County FE	✓	✓	✓	✓
Observations	25,471	25,471	25,471	25,471
R^2	0.132	0.132	0.670	0.667

This table examines the impact of assumption financing on the lock-in effect. Columns (1) and (2) analyze how assumption financing influences the effects of interest rate hikes on housing listings, while Columns (3) and (4) investigate its impact on the effects of interest rate increases on household mobility. County fixed effects are included, and standard errors are clustered at the county level. County house prices and income are in dollars, and county unemployment rates are in percentages. Δr_m and Δ Movers are expressed in percentages. P-values are shown in parentheses, with *, **, and *** indicating significance levels of 10%, 5%, and 1%, respectively. Variable definitions are provided in Appendix E.

6b. Household mobility

The second measure we employed to capture the lock-in effect in the local housing market is the household mobility of county c in year t, denoted as ΔMovers_{ct}. Household mobility is calculated as the change in the number of movers within the county, scaled by its population at the beginning of the year. To ensure the reliability of our findings, we focus our analysis on movers aged 25 years and older, as they are more likely to make independent relocation decisions. County-level migration data is sourced from the American Community Survey (ACS) that conducted by the U.S. Census Bureau, which collects information on respondents' prior places of residence and estimates annual migration volumes.

To evaluate the effectiveness of assumption financing in mitigating the decline in household mobility induced by the lock-in effect, similar to (11), we regress ΔMovers_{ct} on Δr_t and its interaction with A_{ct}^{high}, controlling the same vector of conditioning variables $\mathbf{Z}_{ct}$:

$$\Delta\text{Movers}_{ct} = \beta_1 \Delta r_t + \beta_2 A_{ct}^{high} \times \Delta r_t + \beta_3 A_{ct}^{high} + \mathbf{Z}_{ct}\gamma_z^{'} + \delta_c + \varepsilon_{ct} \tag{12}$$

The results are presented in Column (3) and Column (4) of Table 7. Column (3) indicates that a one-percentage increase in mortgage rates is associated with a 0.7% decrease in household mobility, all else being equal. In Column (4), we observe that assumption financing can mitigate this negative impact on household mobility, as evidenced by a significant positive coefficient of 1.7% for the interaction term $A_{ct}^{high} \times \Delta r_t$. When considering the value of -1.5% for β_1, the results suggest that assumption financing can offset the adverse effects of interest rate increases on household mobility in areas with higher availability, potentially avoiding a 1.5% decline in mobility. In summary, the findings presented in Table 7 lend support to the argument that assumable mortgages can alleviate the adverse impacts of a positive interest rate shock on lock-in effect.

6c. Difference-in-differences analysis

To establish a causal relationship between assumption financing availability and the lock-in effect, we next conducted the Difference-in-Differences (DID) analysis. To test, we compare the impact of the interest rate spike starting from 2021 on the lock-in effect in areas with higher assumption financing availability versus those with lower availability. The model is specified as follows:

$$\begin{aligned} \Delta L_{ct} = {} & \beta_1 \Delta r_t + \beta_2 \text{Post} + \beta_3 \text{Post} \times \Delta r_t + \beta_4 \text{Treat} + \beta_5 \text{Treat} \times \Delta r_t + \beta_6 \text{Treat} \times \text{Post} \\ & + \beta_7 \text{Treat} \times \text{Post} \times \Delta r_t + \mathbf{Z}_{ct}\gamma_z^{'} + \varepsilon_{ct} \end{aligned} \tag{13}$$

In this model, ΔL_{ct} represents one of two lock-in effect outcomes: $\Delta\,\text{Listing}_{ct}$ or $\Delta\,\text{Movers}_{ct}$. The "Post" variable indicates the period after the interest rate spike (i.e., 2021 and 2022), while "Treat" identifies counties with higher assumption financing availability. Counties are categorized into treatment and control groups based on their assumption financing availability, with treatment counties having above-median availability and control counties below-median. The composition of these groups remains constant throughout the sample period, and county fixed effects are excluded to avoid collinearity with the Treat dummy. The triple interaction term Treat $\times$ Post $\times$ Δr_t is the key variable, capturing the differential change in the lock-in effect for counties with higher assumption financing availability compared to those with lower availability, before and after the interest rate shock.

To enhance the comparability between treatment and control counties, we matched each treatment county with a neighboring county based on the growth in local house price, local income, and unemployment rate.[39] To verify the parallel trend assumption, which posits that outcome variables follow similar trends prior to the treatment event (Roberts & Whited, 2013),we compared the pre-event trends in our outcome variables Δ Listing$_{ct}$ and Δ Movers$_{ct}$ (Li & Zhan, 2019). Statistical tests of the mean differences in these outcome variables, presented in Panel B of Table 8, indicate that the matched sample meets the parallel trend assumption. Specifically, the outcome variables exhibit similar growth patterns one period and two periods before the event.

After verifying the parallel trend assumption, we conducted the difference-in-difference (DID) analysis using our matched sample. The results from Equation (14) are detailed in Columns (1) and (3) of Table 8. To address concerns about multicollinearity between the Post variable and the COVID period indicator, we excluded the latter from the control set in Columns (2) and (4). Panel A of Table 8 indicates that after the interest rate hike, mortgage rate increase negatively impacts the growth of new listings and mobility ($\beta_1 + \beta_3$), exacerbating the lock-in effect. However, the significant and positive coefficients of the triple interaction term demonstrate that the availability of assumption financing mitigates this negative impact. Overall, the DID analysis suggests a causal impact of assumption financing availability in alleviating the lock-in effect.

7. Concluding Remarks

Following the sharp increase in interest rates post-COVID-19, housing affordability concerns have escalated among households and policymakers. Higher rates not only burden households with increased mortgage payments but also constrain housing supply growth due to the lock-in effect. This study investigates assumable mortgages—an increasingly popular and affordable financing option—and their impact on the housing market.

Using a novel dataset on assumable mortgage rates and down payments across 14 U.S. regions, we

[39] Neighboring counties are identified using the county adjacency file available at https://www.census.gov/programs-surveys/geography/library/reference/county-adjacency-file.html

Table 8: Lock-in effect: Difference in difference (DID) tests

Panel A: DID results

	(1) Δ Log listings	(2) Δ Log listings	(3) Δ Movers	(4) Δ Movers
Δ r$_m$	0.026*	0.037***	−0.015**	−0.006
	(0.05)	(0.00)	(0.03)	(0.37)
Post	0.035	−0.063***	0.035	−0.045**
	(0.42)	(0.00)	(0.37)	(0.02)
Δ r$_m$ × Post	−0.060***	−0.065***	0.004	−0.000
	(0.00)	(0.00)	(0.71)	(0.97)
Treat	0.054***	0.053***	−0.022**	−0.023***
	(0.00)	(0.00)	(0.01)	(0.01)
Δ r$_m$ × Treat	−0.057***	−0.055***	−0.006	−0.005
	(0.01)	(0.01)	(0.66)	(0.74)
Post × Treat	0.048	0.055	−0.041	−0.035
	(0.15)	(0.10)	(0.22)	(0.28)
Δ r$_m$ × Treat × Post	0.058**	0.054**	0.047**	0.044**
	(0.02)	(0.03)	(0.03)	(0.04)
Δ Log county house price	0.048*	0.048*	−0.011	−0.011
	(0.07)	(0.08)	(0.50)	(0.48)
Δ Log county income	−0.101*	−0.096*	4.829***	4.833***
	(0.07)	(0.08)	(0.00)	(0.00)
Δ County unemployment	−0.000	−0.012***	−0.005	−0.014***
	(0.94)	(0.00)	(0.36)	(0.00)
COVID period	−0.080**		−0.065**	
	(0.01)		(0.01)	
Constant	0.158***	0.147***	0.064***	0.055***
	(0.00)	(0.00)	(0.00)	(0.00)
Observations	12,852	12,852	12,852	12,852
R^2	0.010	0.010	0.613	0.613

Panel B: Pre-event trends in Δ Log listings and Δ Movers for treated and matched counties

		Change from T-3 to T-2	Diff (p-value)	Change from T-2 to T-1	Diff (p-value)
Δ Log listings	Treated	-0.171	0.065 (0.37)	-0.244	-0.032 (0.50)
	Matched	-0.236		-0.212	
Δ Movers	Treated	-0.165	-0.052 (0.58)	-0.129	-0.012 (0.83)
	Matched	-0.113		-0.116	

Panel A presents the results of the Difference-in-Differences (DID) test. The variable "Treat" indicates counties with above-median assumption financing availability, while "Post" marks the period after the interest rate spike (i.e., 2021 and 2022). County house prices and income are in dollars, and county unemployment rates are in percentages. Δr_m and Δ Movers are expressed in percentages. Standard errors are clustered at the county level. p-values in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E. Panel B compares the pre-event trends in Δ Log listings and Δ Movers between treated and matched counties.

analyze how assumption financing influences housing transactions and housing supply. Our findings show that assumption financing enhances property attractiveness, leading to higher selling prices and shorter days-on-market. This is primarily driven by the interest-saving benefits of assumable features, particularly in times of rising interest rates. Over 80% of this benefit is reflected in property price premiums, with stronger effects seen where sellers have greater bargaining power, buyers face fewer financial constraints, and there is a larger working-age population and higher rental expenses.

We propose two explanations for our finding that a large fraction of the value of the option to assume accrues to the seller rather than the buyer. First, sellers may focus on the cash sale price, while buyers, especially those relying on income rather than wealth, are more concerned with manageable monthly mortgage payments. Consequently, buyers may be willing to pay a higher sale price for an assumable property that can be amortized over the next 30 years in exchange for lower monthly payments. Second, buyers might derive unmeasured non-financial benefits from obtaining a low-interest-rate loan in a high-interest-rate environment, or they may, due to behavioral biases, overestimate the savings afforded by mortgage assumption.

Additionally, we find that assumable mortgages can alleviate declines in housing supply and mobility caused by the lock-in effect. By allowing new home purchases at historically lower rates, assumable mortgages stimulate housing market activity and mitigate the adverse labor market effects associated with reduced mobility during periods of rising interest rates. Appendix J.3 demonstrates that increasing the market share of assumable mortgages to around 35% significantly improves housing supply and household mobility following rising interest rates. For instance, with a 2% increase in mortgage rates (from 4% to 6%), the reduction in housing listings could be controlled to less than 5% if the market share of assumable mortgages can be elevated to 25-35%. Although household mobility is less responsive as it requires stronger incentives for relocation than for listing a home, substantial improvements can still be achieved if the market share of assumable mortgages can be raised to 35-45% in local regions.

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ONLINE APPENDIX

A. Information Provided in Roam and RedFin Website

Figure A.1 provides an example of information reported on the Roam website. Besides housing features, Roam website provides detailed information on the requested downpayment for taking over the existing assumable mortgage, the assumable mortgage rate (i.e., Roam Rate) and the monthly payment (i.e., Principal & Interest).

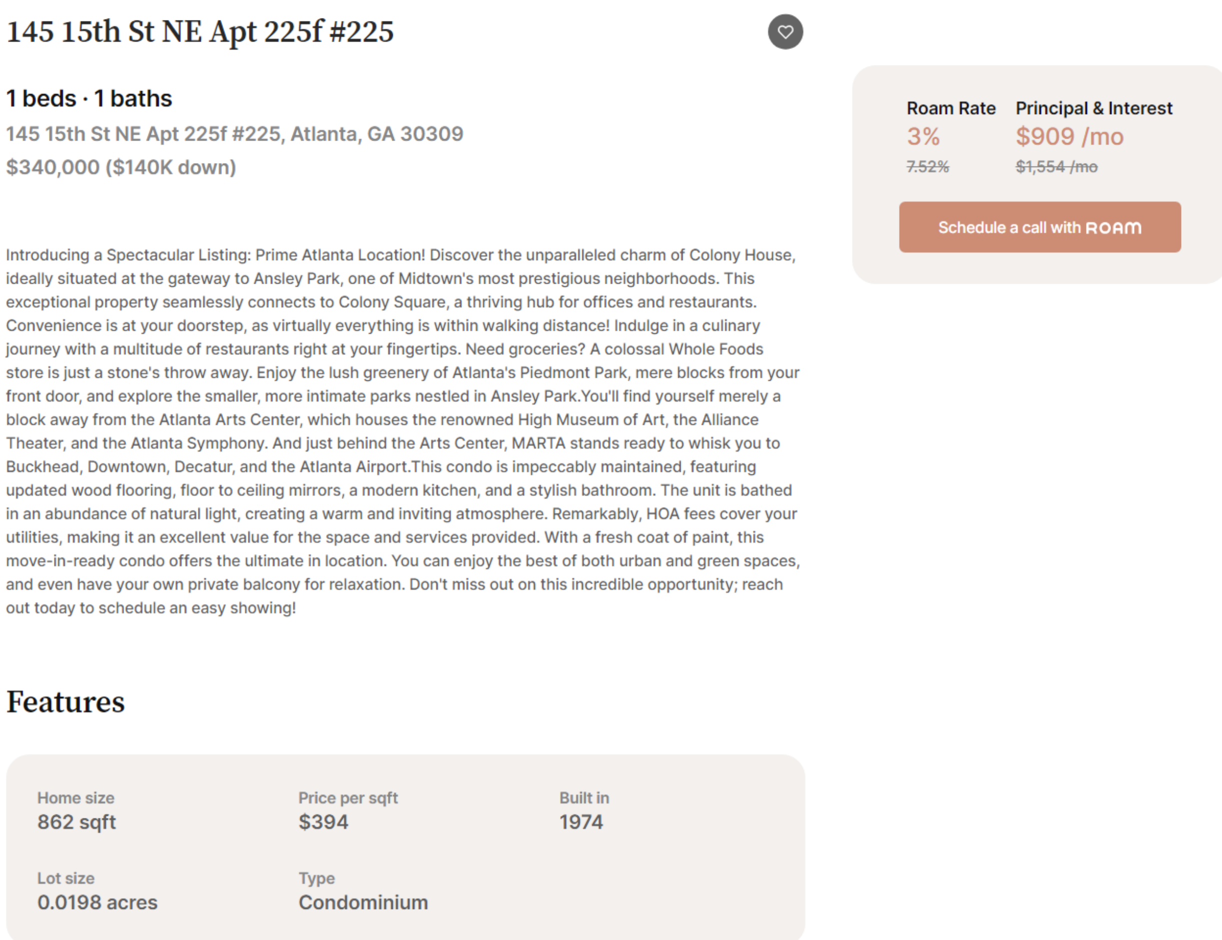


Figure A.1: Information provided in Roam website

source: https://www.withroam.com/listing/145-15TH-ST-NE-APT-225F-225-Atlanta-GA-30309/21675

Figure B.1 provides an example of information reported on the RedFin website of the same property. RedFin provides detailed information on the properties, including the listing days, the size of the property, the Parking space information, the age of the properties and some interior and exterior characteristics of the property. These information was used to construct control variables in our regressions. RedFin also provides historical transaction information on some of the properties.

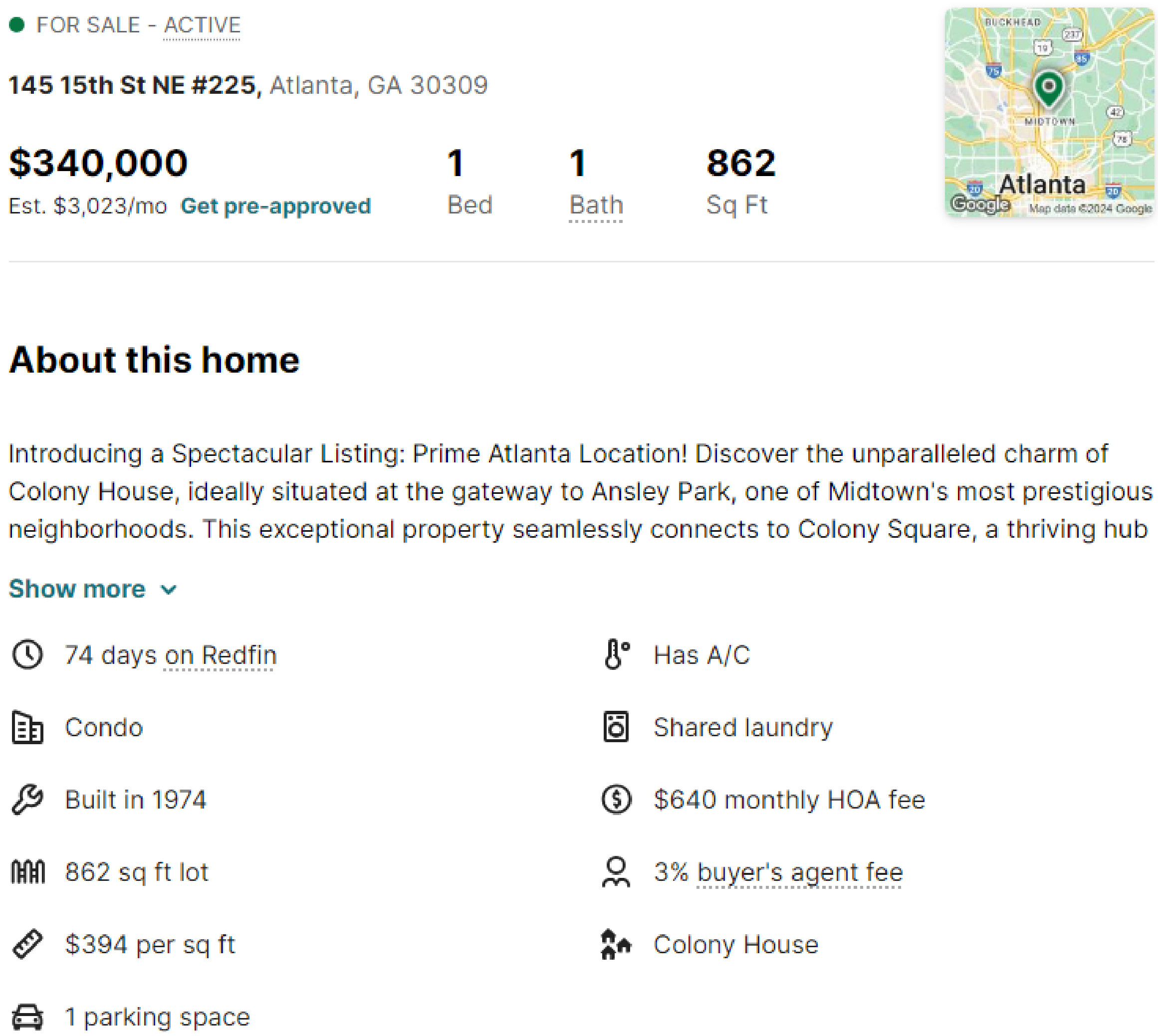


Figure A.2: Information provided in RedFin website

source: https://www.redfin.com/GA/Atlanta/145-15th-St-NE-30309/unit-225/home/24680990

Property details for 145 15th St NE #225

Parking

Parking Information

- # of Total Parking: 1
- Parking Features: Drive Under Main Level

Interior

Virtual Tour

- Virtual Tour2 Unbranded(External Link)

Bedroom Information

- Bedroom Features: Master on Main
- # of Main Level Bedrooms: 1

Interior Features

- Interior Features: Entrance Foyer, High Ceilings 9 ft Main, High Speed Internet
- Common Walls: 2+ Common Walls
- Appliances: Dishwasher, Disposal, Electric Range
- Flooring: Carpet, Hardwood

Bathroom Information

- Master Bathroom Features: Tub/Shower Combo
- # of Main Level Bathrooms: 1
- # of Full Bathrooms: 1

Room Information

- LaundryFeatures: Common Area
- Kitchen Features: Cabinets White,Stone Counters
- Dining Room Features: Open Concept
- Room Type: Other

Exterior

Property Information

- Levels: One
- Construction Materials: Other
- Exterior Features: Balcony
- Roof: Concrete
- Property Condition: Resale
- Ownership: Condominium

Lot Information

- TaxLegalDescription: 225

Utilities

Utility Information

- Cooling: Central Air
- Heating: Central, Electric, Forced Air
- Water Source: Public
- Electric: 110 Volts
- Sewer: Public Sewer
- Utilities: Cable Available, Electricity Available, Phone Available, Sewer Available, Water Available

Figure A.2: Information provided in RedFin website (continued)

Sale and tax history for 145 15th St NE #225

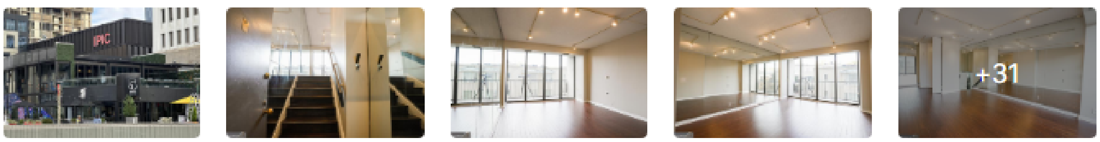
Sale History Tax History

Today

Nov 8, 2023 Date	Listed (Active) FMLS #7299425	$340,000 Price

Nov, 2023

Nov 3, 2023 Date	Listed (New) GAMLS #10222073	$340,000 Price



Listing provided courtesy of Georgia MLS (GAMLS) GAMLS IDX

Introducing a Spectacular Listing: Prime Atlanta Location! Discover the unparalleled charm of Colony House, ideally situated at the gateway to Ansley Park, one of Midtown's most prestigious neighborhoods. This exceptional property seamlessly connects to Colony

Show more

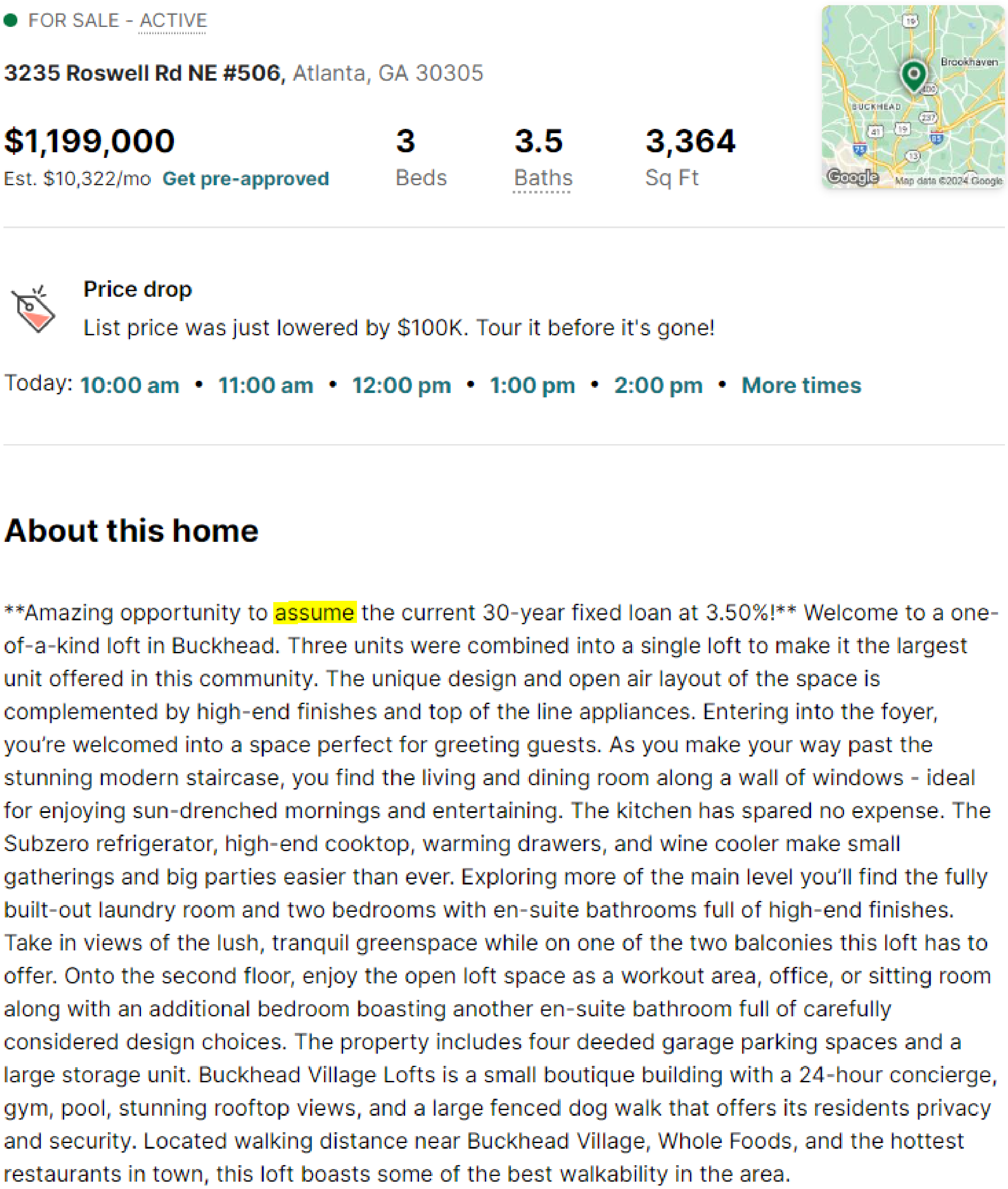
Sep, 2020

Sep 10, 2020 Date	Sold (MLS) (Sold) GAMLS #8828936	$219,900 Price
Aug 6, 2020 Date	Pending (Under Contract) GAMLS #8828936	— Price
Jul 27, 2020 Date	Listed (New) GAMLS #8828936	$219,900 Price

Figure A.2: Information provided in RedFin website (continued)

B. Example of Identifying Assumable Property in RedFin

This section provides an example of how we identify assumable properties on RedFin. We exclude properties listed on RedFin but not on the Roam website if they are assumable. To identify these, we filter out properties whose descriptions on RedFin contain any of the following terms: "FHA," "VA," "Assume," "Assuming mortgage," "Assumable mortgage," "Assuming loan," "Assumable loan," "Assuming rate," or "Assumable rate." For instance, the property at 3235 Roswell Rd NE #506, Atlanta, GA 30305, is listed on RedFin but not on Roam. Since its description includes the keyword "assume," (highlighted) it is excluded from the non-assumable properties group.



FOR SALE - ACTIVE

3235 Roswell Rd NE #506, Atlanta, GA 30305

$1,199,000
Est. $10,322/mo **Get pre-approved**

3	**3.5**	**3,364**
Beds	Baths	Sq Ft

Price drop
List price was just lowered by $100K. Tour it before it's gone!

Today: **10:00 am** • **11:00 am** • **12:00 pm** • **1:00 pm** • **2:00 pm** • **More times**

About this home

Amazing opportunity to assume the current 30-year fixed loan at 3.50%! Welcome to a one-of-a-kind loft in Buckhead. Three units were combined into a single loft to make it the largest unit offered in this community. The unique design and open air layout of the space is complemented by high-end finishes and top of the line appliances. Entering into the foyer, you're welcomed into a space perfect for greeting guests. As you make your way past the stunning modern staircase, you find the living and dining room along a wall of windows - ideal for enjoying sun-drenched mornings and entertaining. The kitchen has spared no expense. The Subzero refrigerator, high-end cooktop, warming drawers, and wine cooler make small gatherings and big parties easier than ever. Exploring more of the main level you'll find the fully built-out laundry room and two bedrooms with en-suite bathrooms full of high-end finishes. Take in views of the lush, tranquil greenspace while on one of the two balconies this loft has to offer. Onto the second floor, enjoy the open loft space as a workout area, office, or sitting room along with an additional bedroom boasting another en-suite bathroom full of carefully considered design choices. The property includes four deeded garage parking spaces and a large storage unit. Buckhead Village Lofts is a small boutique building with a 24-hour concierge, gym, pool, stunning rooftop views, and a large fenced dog walk that offers its residents privacy and security. Located walking distance near Buckhead Village, Whole Foods, and the hottest restaurants in town, this loft boasts some of the best walkability in the area.

Figure B.1: Example of identifying an assumable property in RedFin

C. Sample Construction

This table details the sample construction process. Our sample originates from 185,010 properties listed in RedFin across 14 metropolitan areas: Atlanta, Austin, Colorado Springs, Dallas, Denver, Fort-Worth, Houston, Lakeland, Miami, Orlando, Phoenix, Saint Petersburg, San Antonio, and Tampa. It includes both assumable and non-assumable properties. The table shows the reduction in observations at each data cleaning step and reports the remaining observations for the entire sample used in hedonic regression, as well as the matched sample used in our baseline regression analysis.

Table C.1: Sample construction

	Deleted Observations	Remaining observations
Transactions from RedFin		**185,010**
Missing CBSA code	6,320	
Missing Historical transactions information	125,408	
Missing other controls in (1)	13,457	
Properties in ZIP codes with fewer than five properties	597	
Whole sample for Hedonic regressions		**39,228**
Observations drop during propensity score matching	38,016	
Matched Sample		**1,212**

This table outlines the sample construction process. It specifies the drop in observations at each data cleaning step and reports the remaining observations for the entire sample for hedonic regression, as well as the matched sample used for our baseline regression analysis.

D. Property Matching

To match each assumable property with a similar non-assumable one from the same ZIP code area, we conduct propensity score matching (PSM) on our raw sample. Specifically, we first perform a logit regression to assign a propensity score to each property based on characteristics such as the number of bedrooms and bathrooms, property size, construction year, and amenities like parking, fireplace, view, heating and cooling systems, basement, or attic. Additionally, the PSM considers the property's renovation history, as well as the date and price of the preceding transaction, to control for any potentially omitted property characteristics influencing house prices. We note that while we match properties in the same ZIP code area, unobservable differences at the street or block level may contribute to variations in sale prices. Factors like security level, proximity to schools or public transportation, and exposure to hazards such as floods or wildfires could affect property values, although indirectly. However, these traits are likely reflected, to some extent, in the home's historical price. Therefore, including the historical price of the property in the matching process could at least partially account for these unobservable yet important housing qualities.

To ensure the robustness of the PSM, we exclude ZIP codes with fewer than five properties. The significant coefficients of the logit regression presented in Table D.1 indicate significant variations in housing characteristics among the assumable properties and non-assumable ones. For instance, non-assumable properties tend to be larger and less expensive compared to assumable ones, suggesting an imbalance in the raw sample. This imbalance is further evidenced in Panel A of Table D.2, where we compare the mean values of housing characteristics for assumable and non-assumable properties before matching.

With the propensity scores estimated from the logit regression, we then match each of the assumable properties with a non-assumable one using a nearest neighbourhood matching strategy within a 0.03 caliper radius without replacement. The matching process yields 1,212 matched property observations, comprising 606 assumable properties and their corresponding non-assumable counterparts.

Panel B of Table D.2 presents the housing characteristics of assumable and non-assumable properties after matching. It indicates that, in the matched sample, the housing characteristics of assumable properties no longer significantly differ from those of non-assumable properties.

Table D.1: Logit regression for estimating propensity score

	Dependent variable: Assumable	
	Coefficient	p-value
Bedrooms	0.331∗∗∗	0.00
Bathrooms	0.031	0.73
House size	−0.221∗∗	0.02
Age	−0.010∗∗∗	0.00
Last selling price	−2.692∗∗∗	0.00
Year from last sold	0.016	0.13
Parking	0.917∗∗∗	0.00
Fireplace	0.053	0.65
Has view	−0.199	0.13
Renovation	−0.194	0.30
Heating	0.236	0.29
Cooling	−0.508∗∗∗	0.00
Basement	−0.000	1.00
Attic	−0.046	0.87
Constant	−5.772∗∗∗	0.00
Roof type	✓	
Postcode FE	✓	
Year FE	✓	
Observations	35,037	
Pseudo R^2	0.104	

This table presents the results of the logit regression used to estimate the propensity score for matching. House size is measured in thousands of square feet, while the last selling price is denoted in millions. The regression is conducted on the entire sample, consisting of 39,228 observations. The reduction in observations is attributed to the inclusion of fixed effects. p-values in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E.

Table D.2: Propensity score matching—summary statistics

Panel A : Pre-match sample					
	Assumable=1	Assumable=0	Diff	t-stat	p-val
Bedrooms	3.528	3.372	0.155∗∗∗	3.66	0.00
Bathrooms	2.471	2.539	−0.067∗	−1.77	0.08
House size	2.053	2.195	−0.142∗∗∗	−3.25	0.00
Build year	1999	1995	3.900∗∗∗	3.90	0.00
Last selling price	0.326	0.487	−0.161∗∗∗	−8.99	0.00
Year from last sold	2.479	1.765	0.714∗∗∗	5.30	0.00
Parking space	0.972	0.941	0.032∗∗∗	3.42	0.00
Fireplace	0.523	0.495	0.028	1.41	0.16
Has view	0.118	0.208	−0.090∗∗∗	−5.63	0.00
Renovation	0.055	0.082	−0.027∗∗∗	−2.47	0.01
Heating	0.936	0.870	0.065∗∗∗	4.94	0.00
Cooling	0.844	0.825	0.0187	1.25	0.21
Basement	0.129	0.116	0.0131	1.03	0.30
Attic	0.021	0.025	−0.004	−0.60	0.55
Roof type: Composition	0.489	0.356	0.133∗∗∗	7.01	0.00
Roof type: Concrete	0.009	0.014	−0.005	−1.00	0.32
Roof type: Metal	0.015	0.047	−0.032∗∗∗	−3.85	0.00
Roof type: Others	0.114	0.133	−0.020	−1.47	0.14
Roof type: Shingle	0.302	0.232	0.070∗∗∗	4.18	0.00
Roof type: Tile	0.044	0.097	−0.053∗∗∗	−4.52	0.00
Roof type: Wood	0.006	0.004	0.002	0.79	0.43
Panel B : Post-match sample					
	Assumable=1	Assumable=0	Diff	t-stat	p-val
Bedrooms	3.528	3.500	0.028	0.54	0.59
Bathrooms	2.476	2.458	0.017	0.41	0.68
House size	2.069	2.025	0.044	0.98	0.33
Build year	2000	2000	−0.700	−0.59	0.56
Last selling price	0.327	0.335	−0.008	−0.77	0.44
Year from last sold	2.477	2.319	0.158	0.89	0.38
Parking space	0.975	0.979	−0.003	−0.38	0.70
Fireplace	0.526	0.502	0.025	0.86	0.39
Has view	0.119	0.106	0.013	0.73	0.47
Renovation	0.056	0.059	−0.003	−0.25	0.81
Heating	0.937	0.947	−0.010	−0.74	0.46
Cooling	0.845	0.855	−0.010	−0.48	0.63
Basement	0.127	0.122	0.005	0.26	0.79
Attic	0.021	0.018	0.003	0.41	0.68
Roof type: Composition	0.485	0.472	0.013	0.46	0.65
Roof type: Concrete	0.010	0.008	0.002	0.30	0.76
Roof type: Metal	0.017	0.010	0.007	1.01	0.31
Roof type: Others	0.117	0.119	−0.002	−0.09	0.93
Roof type: Shingle	0.300	0.314	−0.013	−0.50	0.62
Roof type: Tile	0.045	0.056	−0.012	−0.92	0.36
Roof type: Wood	0.007	0.002	0.005	1.34	0.18

The table compares the housing characteristics between assumable and non-assumable properties before and after propensity score matching. House size is measured in thousands of square feet, while the last selling price is denoted in millions. The pre-match sample is the whole dataset used for the hedonic regression, consisting of 39,228 properties, including 1,397 assumable and 37,831 non-assumable properties. The post-matched sample comprises 1,212 properties, with 606 assumable properties and 606 non-assumable properties.

E. Variable Definitions

Variables	Definition
Sale price	The sale price data is primarily obtained from the historical sold price section on the RedFin website. If this data is unavailable, the latest recorded listing prices are used instead. In cases where both are missing, the ask price (advertising price) displayed on the Roam website is used.
Days on market	The days on market is recorded as the difference between the latest listing or relisting date and the date when the property is sold, under contract, or pending, whichever occurs first.
Assumable	Indicator of properties eligible for financing through assumable mortgages.
Age	The age of the properties, calculated as the difference between the year the properties are sold and their year of construction.
Bedrooms	The number of bedrooms in the property.
Bathrooms	The number of bathrooms in the property.
House size	The total square feet of the property.
Parking space	A dummy variable that equals one if the property includes at least one parking space, and zero otherwise.
Fireplace	A dummy variable that equals one if the property includes at least one fireplace, and zero otherwise.
Has view	A dummy variable that equals one if the property mentions having views on the RedFin website, and zero otherwise.
Renovation	A dummy variable that equals one if the property reports renovations on the RedFin website, and zero otherwise.
Heating	A dummy variable that equals one if heating options are reported in RedFin and zero otherwise.
Cooling	A dummy variable that equals one if cooling options are reported in RedFin and zero otherwise.
Basement	A dummy variable that equals one if the property reports basement in RedFin and zero otherwise.
Attic	A dummy variable that equals one if the property reports attic in the RedFin website and zero otherwise.
Roof type	Seven dummies based on roof materials (i.e., stone, wood).
MAV	The mortgage assumable value, representing the present value of future savings from assuming an existing lower-interest-rate mortgage compared to obtaining the same mortgage at market interest rate.
Log sale price^H	The residual value of Log sale price predicted in the hedonic regression model.
Log days on market^H	The residual value of Log days on market predicted in the hedonic regression model.
Price premium	The difference in the final selling price between the assumable property and its matched non-assumable counterpart.
1/Sale price	The inverse value of sales price.
Sale price^{Res}	The residual value of sale price predicted in the hedonic regression model.
Δ r_m	The annual variation in mortgage rates, computed as the difference between the 30-year average mortgage rate at the year's end and its value at the begining of the year.
Δ Log listings	The log growth rate in new listings.

Variables	Definition
Δ Movers	The annual change in the number of movers aged 25 and above, normalized by the size of the local population.
A^{high}	A dummy variable that takes the value of one if the county's accumulated 5-year assumable issuance fraction surpasses the median fraction across counties in a given year, and zero otherwise.
Δ Log county house price	The log growth rate in county median house price.
Δ Log county income	The log growth rate in county disposable income.
Δ County unemployment	The yearly change in the county unemployment rate.
COVID period	An indicator denoting the post-COVID period, set to one for observations from the year 2020 onward, and zero otherwise.

F. Estimation of MAV

This section illustrates the process for estimating MAV for the property located at 145 15th St NE Apt #225, Atlanta, GA 30309. Utilizing the data provided by Roam (Figure A.1), we first determine the remaining loan period ($T_i - t$) of the assumable mortgage using the following equation:

$$\text{Bal}_i = \sum_{k=1}^{T_i - t} \frac{\text{Pmt}_i}{(1 + r_{t_i^o})^k} \tag{F.1}$$

In this context, Bal_i represents the outstanding loan balance, calculated as the difference between the advertised price ($340,000) and the down payment amount ($140,000), which equals $200,000. The monthly payment (Pmt) is reported as "Principal & Interest" on the Roam website, amounting to $909 per month. The discount rate (rt_i^o) is the monthly assumable rate, set at 0.25% (i.e., 3%/12). Using this information and Equation F.1, the remaining loan period ($T_i - t$) is calculated to be approximately 320 months.

Having established the remaining loan period, we then estimate the present value of the remaining mortgage payments using the formula $\sum_{k=1}^{T_i - t} \frac{\text{Pmt}_i}{(1+r_t)^k}$, where r_t represents the current market interest rate. According to Roam, the current market rate is 0.63% per month (i.e., 7.52%/12)[40]. Employing this rate, the present value of the remaining mortgage payments is calculated to be $125,386. Thus, the MAV for the property is then calculated as the difference between the unpaid loan balance ($200,000) and the present value of the remaining mortgage payments ($125,386), yielding an MAV of $74,614.

[40] 7.52% is the interest rate of a conventional mortgage as suggested on the Roam website on November 9, 2023

G. MAV and Sales Price

To preliminarily assess the incorporation of MAV into the final selling price, we employ the methodology outlined by Sirmans et al. (1983). Specifically, we conduct a regression analysis where the dependent variable is the dollar value of the final selling price, regressed on the MAV as follows:

$$\text{Sale price}_i \quad = \quad \beta \text{MAV}_i + \gamma_{\text{DP}} \text{DP}_i + \mathbf{X}_i \gamma_x' + \delta_{z(i)} + \varepsilon_i \tag{G.1}$$

Here, Sale price$_i$ denotes the selling price of property i, MAV$_i$ represents the mortgage assumption value, DP$_i$ is the downpayment as a fraction of the sale price, $\mathbf{X}_i$ encompasses housing characteristics as detailed in Table 2 and $\delta_z(i)$ represents ZIP code fixed effects. For non-assumable properties, MAV is set to zero and the downpayment percentage is fixed at 20%, a standard requirement for conventional mortgages.[41]

The results, displayed in Table G.1, indicate a significant positive relationship between MAV and the final selling price. Specifically, a $1,000 increase in MAV is associated with a $295 increase in the selling price (Column 2). Given the average MAV of $95,708, this implies that assumable properties sell for approximately $28k more than non-assumable properties with comparable attributes.[42] This observation is consistent with the price differential reported in Panel B of Table 1. To mitigate potential multicollinearity issues between the downpayment percentage and MAV, we exclude the downpayment variable in Column (2). The findings remain statistically and economically robust.

[41] Most conventional mortgages require a downpayment of 20% in the U.S. housing market.

[42] The marginal effect at the average MAV is calculated as $95,708 $\times$ 0.295 = $28,234.

Table G.1: Sale price and MAV

	(1) Sale price	(2) Sale price
MAV	0.331∗∗∗	0.295∗∗∗
	(0.00)	(0.00)
Downpayment percentage	−43.272	
	(0.52)	
Log age	−19.208∗∗∗	−19.400∗∗∗
	(0.00)	(0.00)
Log bedrooms	108.672	107.761
	(0.11)	(0.12)
Log bathrooms	174.034∗∗∗	174.491∗∗∗
	(0.00)	(0.00)
Log house size	70.393	70.414
	(0.12)	(0.11)
Parking space	19.600	18.070
	(0.49)	(0.52)
Fireplace	44.812∗∗∗	44.401∗∗∗
	(0.00)	(0.00)
Hasview	9.945	9.556
	(0.59)	(0.60)
Renovation	−5.734	−6.063
	(0.75)	(0.73)
Heating	1.085	−0.825
	(0.98)	(0.98)
Cooling	5.391	7.059
	(0.86)	(0.82)
Basement	6.212	6.146
	(0.56)	(0.57)
Attic	−0.602	−0.981
	(0.98)	(0.96)
Constant	−495.490∗	−501.602∗∗
	(0.05)	(0.05)
Roof type	✓	✓
ZIP code FE	✓	✓
Observations	1,212	1,212
R^2	0.752	0.752

This table reports the results for regression (G.1). MAV, Sale price, Price premium, and Sale price^{Res} are expressed in thousands. ZIP code fixed effects are included in the analysis, and standard errors are clustered at the ZIP code level to account for intra-ZIP code correlation and ensure robust statistical inference. p-values in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E.

H. Multiple-refinancing Option

In this section, we further release the refinancing constraint, allowing households to refinance multiple times during the mortgage's remaining lifespan. Specifically, we assume households refinance at market rates whenever there is a 1% interest rate drop. Below is an example of how MAV can be estimated in such cases, assuming the household refinances twice before the mortgage matures:

$$\text{MAV}_{it} = \sum_{k=1}^{T_i-t} \frac{\text{Pmt}_i}{(1+r_{t_i^o}^{T_i})^k} - \left[\sum_{k=1}^{\tau_{i,1}-t} \frac{\text{Pmt}_i}{(1+r_t)^k} + \frac{1}{(1+r_t)^{\tau_{i,1}-t}} \left(\sum_{k=1}^{\tau_{i,2}-\tau_{i,1}} \frac{\text{Pmt}_i}{(1+r_{\tau_{i,1}})^k} + \frac{1}{(1+r_{\tau_{i,1}})^{\tau_{i,2}-\tau_{i,1}}} \sum_{k=1}^{T_i-\tau_{i,2}} \frac{\text{Pmt}_i}{(1+r_{\tau_{i,2}})^k} \right) \right]$$

Here, $\tau_{i,1}$ and $\tau_{i,2}$ represent the two refinancing times. The interest rate $r_{\tau_{i,1}}$ at $\tau_{i,1}$ equals $r_t - 1\%$, and $r_{\tau_{i,2}}$ at $\tau_{i,2}$ equals $r_t - 2\%$. Columns (1) to (3) of Table H.1 reports the results corresponding to Columns (1) to (3) in Table 6 using this alternative MAV estimations. In Columns (4) to (6), we further account for the maturity-adjusted mortgage rate when estimating the MAV with the multiple-refinancing option. The results remain statistically and economically similar.

Table H.1: Price premium and MAV: modified MAVs with multiple-refinancing option

	Corresponding to (1) to (3) in Table 6			Corresponding to (7) to (9) in Table 6		
	(1)	(2)	(3)	(4)	(5)	(6)
MAV / Price (%)	0.897*			0.943*		
	(0.05)			(0.05)		
MAV		0.897**	0.838***		0.893**	0.840***
		(0.04)	(0.00)		(0.04)	(0.00)
Controls	✓	✓	✓	✓	✓	✓
ZIP code FE	✓	✓	✓	✓	✓	✓
Observations	606	606	604	606	606	604
R^2	0.849	0.874	0.941	0.836	0.874	0.941

This table presents the results corresponding to Table 6 using alternative MAV estimations accounting for multiple-refinancing option. Specifically, Columns (1) to (3) reports the results corresponding to Columns (1) to (3) in Table 6. Columns (4) to (6) reports the results corresponding to Columns (7) to (9) in Table 6. The dependent variables for Columns (1) and (4) are Price premium%. The dependent variables for Columns (2) and (5) are the dollar value of the Price premium. The dependent variables for Columns (3) and (6) are Sale price^{Res}. MAV, Price premium, Sale price, and Sale price^{Res} are expressed in thousands. ZIP code fixed effects are included in the analysis, and standard errors are clustered at the ZIP code level to account for intra-ZIP code correlation and ensure robust statistical inference. P-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Appendix E.

I. Cross-sectional Test: Combined Index

Given that MAV-β is sensitive to sellers' bargaining power, buyers' financial constraints, local age distribution and rental expenses, we construct a composite index to capture all these dimensions. To achieve this, we first normalize Δ Median sale price, Δ Housing inventory, rental expenses, the proportion of high DTI, and the proportion of working-age population by percentile.[43] This normalization scales each variable from 1 to 100. For Δ Median sale price, rental expenses and the proportion of working-age population, 1 signifies the lowest value, and 100 denotes the highest value. Conversely, for Δ Housing inventory and the proportion of high DTI, 100 indicates the lowest value, and 1 represents the highest value. This ensures higher values correspond to greater MAV-β. Subsequently, we create the combined index using equal weighting:

$$I_c = 0.5(SBP_c^{INV} + SBP_c^{SALE}) + BFC_c + Age_c + Rent_c \tag{I.1}$$

In this equation, I_c is the combined index of county c. SBP_c^{INV} and SBP_c^{SALE} denote the normalized values of two indicators of sellers' bargaining power—namely, ΔMedian Sale Sale price and Δ Housing inventory. We take the average value of the two measures to ensure equal weighting across the three dimensions. BFC_c corresponds to the normalized value of the proportion of DTI in county c, reflecting the dimension of buyers' financial constraints. Additionally, Age_c represents the normalized value of the proportion of the working-age population, and $Rent_c$ indicates the normalized value of rental expenses.

We then split our sample based on the median value of I_c and report MAV-β for these groups in Figure I.1. As predicted, counties exhibiting a high combined index are associated with a greater value of MAV-β. In addition, the combined index is more effective in capturing the local characteristics contributing to variations in MAV-price premium sensitivity. While each dimension individually explains MAV-β differences from 0.39 to 0.64, the combined index shows a 0.8 MAV-β disparity between high and low index groups—more than 1.5 times greater than the average differences explained by individual dimensions.

[43] We exclude the Downpayment variable from this analysis as its effect does not apply uniformly across all regions (e.g., Florida).

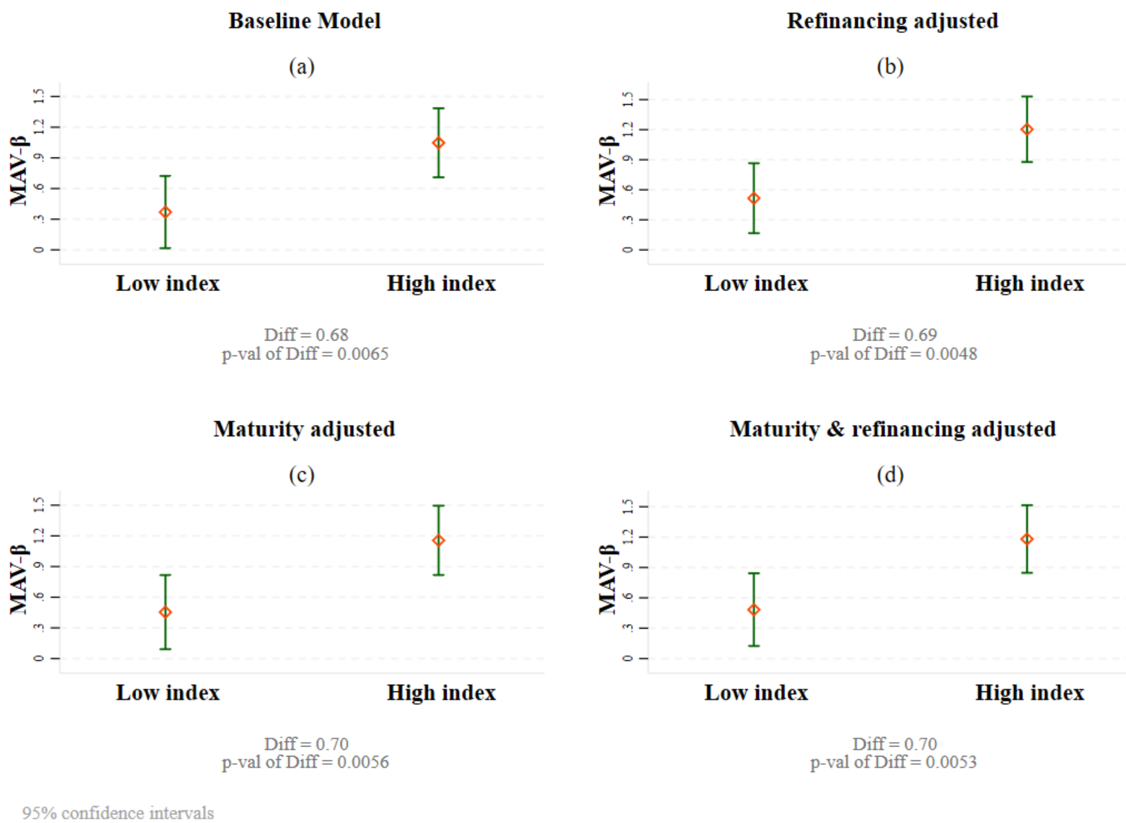


Figure I.1: Combined index

The graph present MAV-β among high and low combined index group. High index groups are areas with above-median combined indices, while low index groups are those with below-median indices. (a) present results where MAV is estimated based on Equation (4). (b) shows results where MAV is estimated based on Equation (7). (c) displays MAV estimations based on Equation (8). (d) presents results where MAV is estimated based on Equation (9). The red dot represents the average value of MAV-β in each group, with the range based on 95% confidence intervals.

J. Additional Figures and Tables for Section 6

This appendix provides the geographic distribution of mortgage assumption availability and the robustness test results from Table 7.

J.1. Availability of assumption financing

Figure J.1 displays the fraction of assumable mortgages in each U.S. county in 2022. This fraction is calculated as the ratio of the dollar amount of assumable mortgages originated in a county from 2018 to 2022 to the total number of mortgages originated in that county over the same period. Lighter colors or smaller fraction indicate lower availability of assumption financing, while darker colors or larger fraction indicate higher availability.

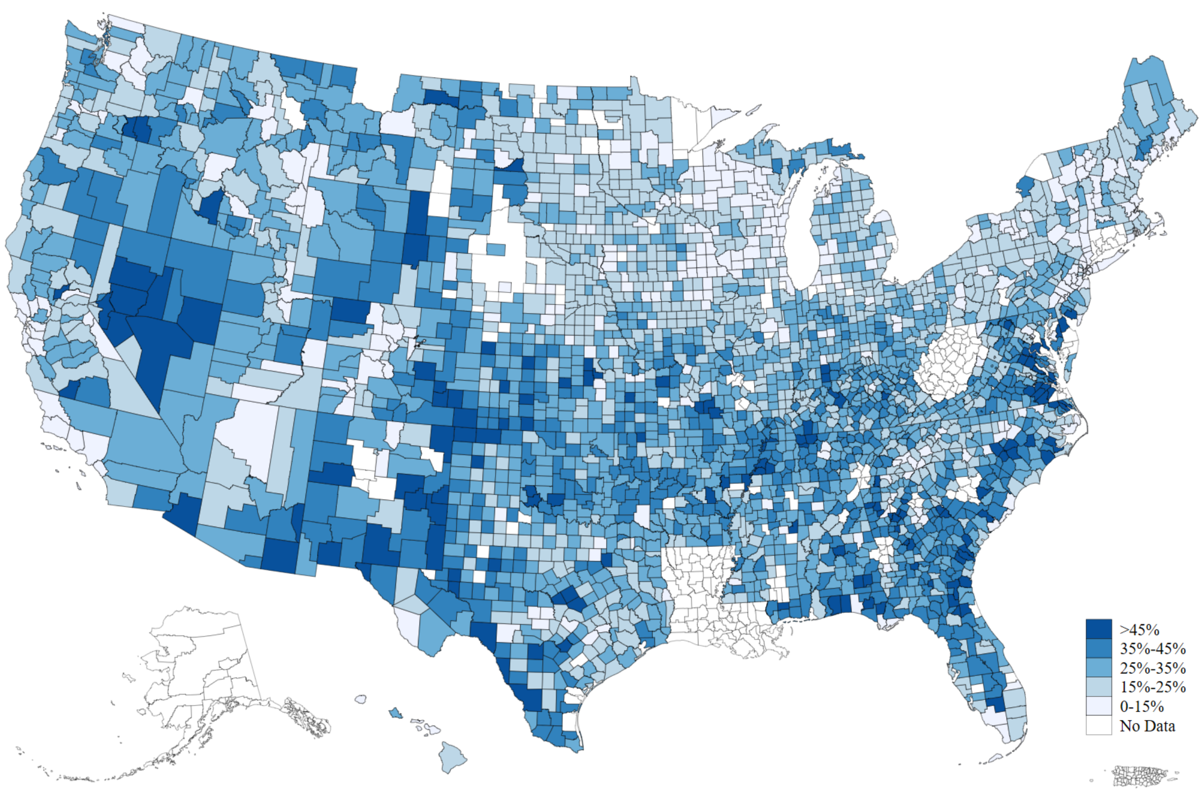


Figure J.1: Fraction of assumable mortgages by county

This map shows the assumption financing availability for each U.S. county in 2022. The availability is calculated as the ratio of the dollar amount of assumable mortgages originated in a county from 2018 to 2022 to the total number of mortgages originated in that county over the same period. The loan issuance data are from the HDMA.

J.2. Alternative measure and model specification

Table J.1 repeats our tests in Table 7 using an alternative measure of assumption financing availability. Instead of a five-year window, A_{ct}^{high} is redefined as one if the fraction of properties with assumption financing in county c—calculated as the ratio of the dollar amount of assumable mortgages originated over the three years prior to year t to the total number of mortgages originated in that county over the same period—exceeds the median value of that ratio across counties in year t, and zero otherwise.

Table J.1: Lock-in effect: alternative measure

	(1) Δ Log listings	(2) Δ Movers
Δ r$_m$	−0.021∗∗∗	−0.013∗∗∗
	(0.00)	(0.00)
$A^{high} \times \Delta$ r$_m$	0.019∗∗∗	0.014∗∗
	(0.00)	(0.01)
A^{high}	0.045∗∗∗	0.008
	(0.01)	(0.52)
Δ Log county house price	0.069∗∗∗	0.007
	(0.00)	(0.56)
Δ Log county income	−0.097∗∗	5.079∗∗∗
	(0.02)	(0.00)
Δ County unemployment	−0.006∗∗∗	−0.008∗∗∗
	(0.00)	(0.00)
COVID period	−0.097∗∗∗	−0.049∗∗∗
	(0.00)	(0.00)
Constant	0.161∗∗∗	0.053∗∗∗
	(0.00)	(0.00)
County FE	✓	✓
Observations	25,471	25,494
R^2	0.133	0.631

This table reports the impact of assumption financing on the lock-in effect with alternative measure of A^{high}. Specifically, A^{high} is the indicator of high assumption financing availability that takes the value of one if the county c has an above-median estimated share of assumable properties in a given year t, and zero otherwise. The share of assumable properties is calculated by dividing the accumulated 3-year assumable issuance volume by the accumulated 3-year issuance volume of total loans in the local region Columns (1) depict the influence of assumption financing in mitigating the effects of interest rate hikes on housing listings. Columns (2) present the impact of assumption financing in alleviating the effects of interest rate increases on household mobility. County fixed effects are included, and standard errors are clustered at the county level. County house prices and income are in dollars, and county unemployment rates are in percentages. Δr_m and Δ Movers are expressed in percentages. p-values in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E.

Next, in Table J.2, we demonstrate that the findings from Table 7 remain consistent with an alternative model specification. Instead of regressing changes in the lock-in effect outcome variables on interest rate changes, Table J.2 presents results where we regress the level of the outcome variables on the interest rate level and its interaction with A^{high}: rates is mitigated in regions with higher assumption financing:

$$\text{Lock}_{ct+1} \quad = \quad \beta_1 r_t + \beta_2 A^{high}_{ct} \times r_t + \beta_3 A^{high}_{ct} + \mathbf{U}_{ct}\gamma'_u + \delta_c + \varepsilon_{ct}. \tag{J.1}$$

Here, Lock_{ct+1} represents either log new listings or the portion of movers in the local regions. The vector $\mathbf{U}ct$ of conditioning variables includes the log of local house prices, income, and unemployment rates, as well as the "COVID period" indicator.

Table J.2: Lock-in effect: alternative model specification

	(1) Log listing	(2) Log listing	(3) Movers%	(4) Movers%
r_m	−0.041∗∗∗	−0.068∗∗∗	−0.041∗∗∗	−0.050∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)
$A^{high} \times r_m$		0.055∗∗∗		0.020∗∗
		(0.00)		(0.02)
A^{high}		−0.177∗∗∗		0.017
		(0.00)		(0.67)
Log county house price	0.351∗∗∗	0.350∗∗∗	0.011	0.011
	(0.00)	(0.00)	(0.55)	(0.57)
Log county income	−0.223∗∗∗	−0.222∗∗∗	5.077∗∗∗	5.078∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)
County unemployment	−0.115∗∗∗	−0.115∗∗∗	−0.058∗∗∗	−0.057∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)
COVID Period	0.572∗∗∗	0.573∗∗∗	0.085∗∗∗	0.086∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	3.455∗∗∗	3.546∗∗∗	−34.452∗∗∗	−34.467∗∗∗
	(0.00)	(0.00)	(0.00)	(0.00)
County FE	✓	✓	✓	✓
N	28,833	28,833	28,833	28,833
R^2	0.895	0.895	0.929	0.929

This table reports the impact of assumption financing on the lock-in effect in an alternative model specification. Columns (1) depict the influence of assumption financing in mitigating the effects of interest rate hikes on housing listings. Columns (2) present the impact of assumption financing in alleviating the effects of interest rate increases on household mobility. County fixed effects are included in the analysis, and standard errors are clustered at the county level. County house prices and income are in dollars, and county unemployment rates are in percentages. r_m and Movers are expressed in percentages. p-values in parentheses. *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. The definition of the variables is reported in Appendix E.

In line with Table 7, the negative β_1 across all columns in Table J.2 indicate that high interest rates worsen the lock-in effect in the local housing market. However, the positive and significant coefficients of the interaction term, $A^{high} \times r_m$, in Columns (2) and (4) suggest that assumption financing can alleviate these effects.

J.3. Policy implications

To quantify the impact of mortgage rate increases on housing supply and household mobility under different financing assumptions, we calibrate a reduced-form model based on Equation (J.1):

$$\text{Lock}_{ct+1} \quad = \quad \beta_1 r_t + \sum_{j=1}^{4} \left(\beta_{2j} A_{ct}^{\text{Group}_j} \times r_t + \beta_{3j} A_{ct}^{\text{Group}_j} \right) + \mathbf{U}_{ct} \gamma_u' + \delta_c + \varepsilon_{ct}. \tag{J.2}$$

In this context, $A_{ct}^{\text{Group}_j}$ serves as an indicator for county c, categorizing it into one of four groups based on the proportion of assumable mortgages available in the local region. The first group includes counties where the fraction of assumable mortgages is less than 15%. The second group covers counties with a fraction between 15% and 25%. The third group consists of counties where the fraction ranges from 25% to 35%, while the fourth group includes those with a fraction between 35% and 45%.

Table J.3: Calibration results

Panel A									
		Log listing				Movers%			
		$<15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$<15\%$	$15-25\%$	$25-35\%$	$35-45\%$
r_m	4%	4.93	5.05	5.26	5.33	7.16	7.34	7.46	7.48
	5%	4.82	5.01	5.24	5.35	7.12	7.30	7.41	7.49
	6%	4.71	4.97	5.22	5.37	7.07	7.25	7.37	7.49
	7%	4.59	4.93	5.20	5.39	7.03	7.21	7.33	7.49
Panel B									
		%Δ Listing				%Δ Movers			
		$<15\%$	$15-25\%$	$25-35\%$	$35-45\%$	$<15\%$	$15-25\%$	$25-35\%$	$35-45\%$
Δr_m	1%	−11.3%	−4.0%	−1.9%	2.2%	−0.62%	−0.58%	−0.55%	0.05%
	2%	−22.6%	−8.0%	−3.8%	4.4%	−1.24%	−1.16%	−1.10%	0.09%
	3%	−33.8%	−12.0%	−5.8%	6.5%	−1.86%	−1.73%	−1.66%	0.14%

Panel A displays the Log listing and Movers% conditional on various r_m and assumption financing availability, calibrated according to Equation J.2. Panel B computes the corresponding changes in these outcomes in response to different annual increases in mortgage rates.

We then estimate the corresponding Log listing and Mover% for interest rates of 4%, 5%, 6%, and 7%. The results are presented in Panel A of Table J.3. Using these estimates, we calculate the percentage changes in listings and movers for interest rate increases of 1%, 2%, and 3% across areas with different assumption financing availability in a given year. These results are shown in Panel B of Table J.3. For better visualization, we also illustrate these changes in Figure J.2.

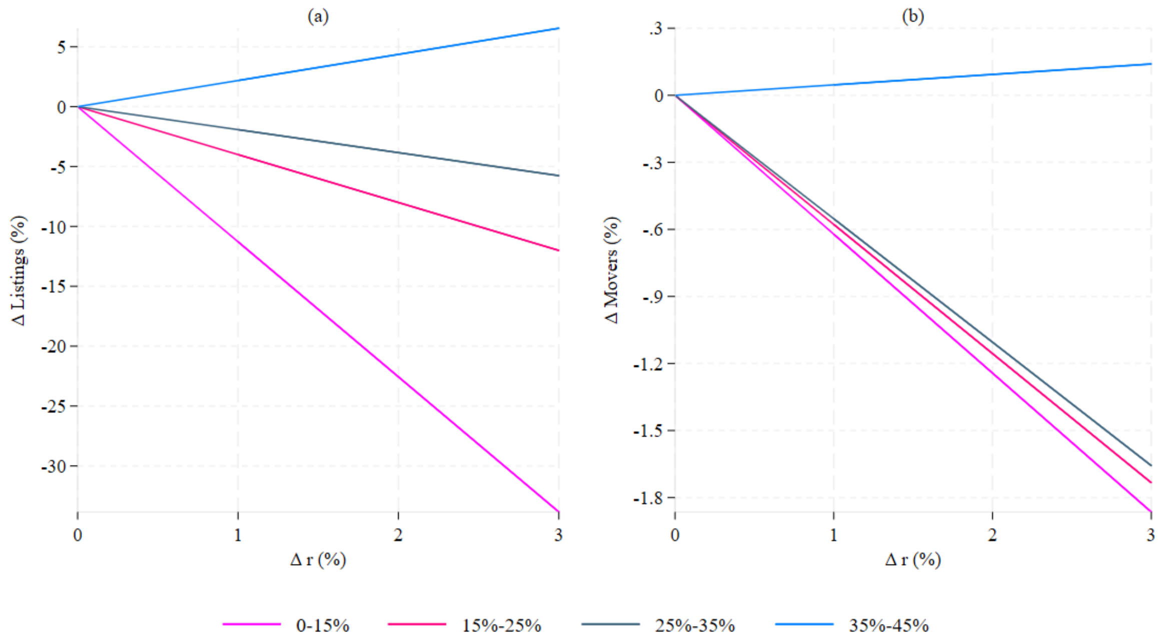


Figure J.2: Lock-in effect: calibration output

The graph presents the corresponding changes in Listing and Movers% conditional on various r_m and assumption financing availability, calibrated according to Equation J.2.

The calibrated results reinforce our earlier findings that the impact of rising interest rates on housing supply and household mobility can be moderated by the availability of assumable financing. Specifically, we observe the most significant declines in supply and mobility in counties where assumable mortgages constitute less than 15% of the total. Conversely, counties with more than 35% of assumable mortgages are able to fully mitigate these negative effects.

Increasing the local market share of assumable mortgages to between 25% and 35% can significantly offset the negative impact of rising interest rates on housing supply. For instance, if the interest rate increases by 2% within a year, counties where assumable mortgages make up less than 15% of the market are expected to see housing listings drop by over 20%—a trend consistent with the observed 19% decline in US housing transactions from 2022 to 2023.[44]

However, if policymakers can boost the market share of assumable mortgages to 25-35%, the reduction in housing listings could be controlled to less than 5%. While household mobility remains more resistant

[44] https://apnews.com/article/housing-home-sales-real-estate-home-prices-d5e85d54ac0c7abd90bb8217e8057875

to change as it requires stronger incentives for relocation than for listing a home, it can also see significant improvement if the market share of assumable mortgages is increased to 35-45% in local regions.