Spatial Extrapolation in the Housing Market

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Abstract

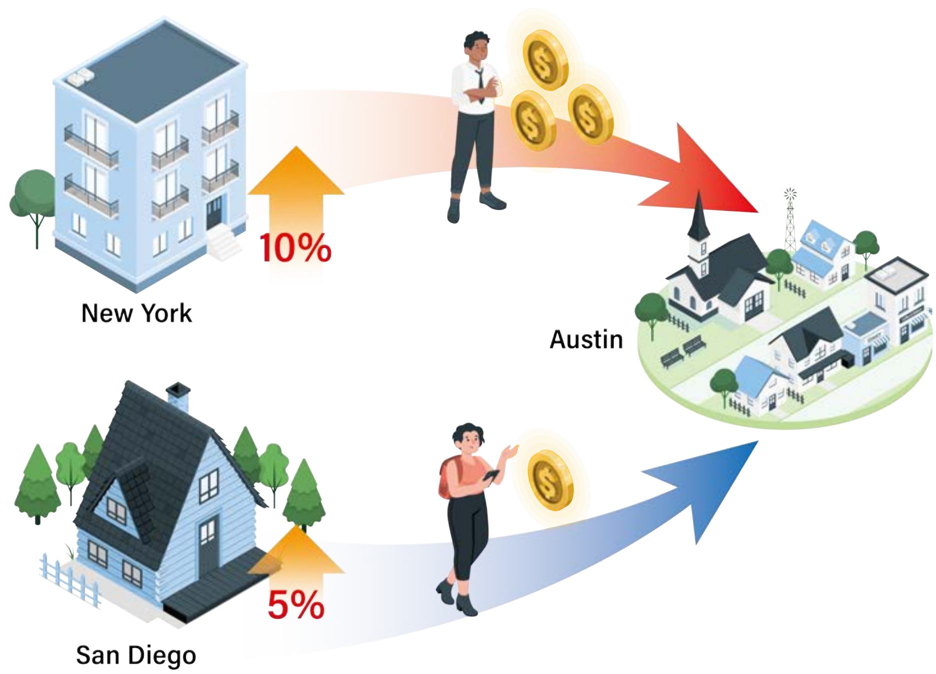
This paper introduces "spatial extrapolation," a concept that refers to how economic expectations for one region are formed by extrapolating from the economic outcomes of another geographic area. We demonstrate this unique form of extrapolation by analyzing the purchasing behavior of out-of-town (OOT) homebuyers. Using data from approximately 3 million OOT housing transactions in the U.S. between 2002 and 2017, we find that a 50% increase in five-year hometown house prices leads OOT buyers to pay 2% more for OOT properties. The higher the hometown house price growth, the lower the realized returns and purchase discounts obtained by OOT buyers. To rule out the wealth effect, the paper designs two strategies. First, we classify renters, migrants, and second-home (SH) buyers to control the wealth increase from hometown properties. Second, we estimate geographic heterogeneity in extrapolative beliefs. We find that OOT buyers from higher extrapolation hometowns increase their purchase prices more after the hometown house price growth. Overall, our research highlights the potential spillover effects of extrapolation into other asset markets and provides evidence that extrapolative expectations have broader effects than previously recognized.

I. Introduction

An extrapolative belief framework posits that individuals' future expectations of a given quantity are positively influenced by its *own* recent past values, with more weight given to the more recent past. For instance, investors' return expectations are positively correlated with past stock returns (Greenwood and Shleifer, 2014). Similarly, individuals draw from past relevant experiences to shape their beliefs (Malmendier and Nagel, 2016). In the context of housing markets, Kuchler and Zafar (2019) find that people who previously experienced higher *local* house price growth tended to expect higher *national* house price growth in the future. These findings highlight that people form their economic expectations based on past observations.

In this paper, we introduce a new form of extrapolation known as "spatial extrapolation." This refers to the process where an individual forms expectations about economic outcomes *in one region* by extrapolating from their experiences *in another geographic location*. We demonstrate this unique form of extrapolation by examining the scenario where homebuyers purchase new properties in towns different from their previous living regions. We show that when two buyers purchase *the same out-of-town (OOT) property*, the spatial extrapolative belief will make the buyer with the higher house price growth *in her previous living area ("hometown")* pay a higher price than the other buyer without the same hometown experience. We have illustrated this phenomenon in Figure 1.

Figure 1. The Case of Two OOT Homebuyers



The Higher the Hometown House Price Growth, the Higher the OOT Purchase Prices In Figure 1, we provide an example of two OOT homebuyers interested in buying similar properties in Austin. The buyer from New York has observed a 10% increase in house prices in her hometown zip code over the past five years, while the buyer from San Diego has only seen a modest 5% increase in the hometown house price. Due to the extrapolative beliefs formed from their hometown experiences, the New Yorker would expect a higher future house price in Austin than the San Diego buyer. This difference in spatial extrapolative beliefs makes the New York buyer willing to pay more than the San Diego buyer for the same property.

An OOT homebuyer is defined as someone who reports a mailing address that is different from the newly purchased property and is at least 60 miles away. Our approach to identifying OOT buyers is similar to the one used by Chinco and Mayer (2016), who identify second-home buyers from another Metropolitan Statistical Area (MSA). Second, we require that the reported mailing address be at least 60 miles away from the purchased property's address. This 60-mile threshold is based on a study by Knyazeva, Knyazeva, and Masulis (2013), which considers the 60-mile radius to be the threshold for identifying non-local independent directors. Our results remain robust for other distance thresholds from 120 to 800 miles, as shown in Appendix A.1.

Our research indicates that spatial extrapolation drives purchase price differences among OOT buyers. We analyzed around 3 million OOT housing transactions in the United States from 2002 to 2017. The results show that OOT buyers, who have seen a 50% increase in their hometown's house price growth over the past five years, tend to pay about two percentage points more for OOT properties than those buyers without the same price growth experience. This difference in purchase price remains even after accounting for factors such as market timing fixed effects and time-varying characteristics of the hometown or property. Figure 2 presents the estimated non-linear and positive relationship between OOT purchase prices and hometown house price growth.

However, a higher initial purchase price for an OOT property does not lead to a higher subsequent sale price. Instead, they would sell the property at a slightly lower price. By calculating the realized returns from the repeat sale transactions, we find that OOT buyers with a 100% increase in the past five-year hometown house price will obtain 1.2% lower returns from their OOT properties. The finding contradicts the rational explanation that those OOT buyers pay a high price because hometown house price growth could provide valuable information on the future OOT housing market that helps them maximize profitability from selling the OOT property at a high price.

OOT Buyers Overpay after Hometown House Price Growth OOT buyers tend to overpay for OOT properties after experiencing substantial hometown house price growth. We corroborate the overpayment by first controlling for the characteristics of the purchased OOT properties. It shows that for OOT properties with similar characteristics, the buyers who have experienced higher hometown house price growth are willing to pay even higher prices.

Second, analyzing OOT buyers' purchase discounts[1] further confirms the overpayment. In particular, we find a significantly negative relationship between the past hometown house price growth and the purchase discount. OOT buyers with high hometown house price growth tend to receive low purchase discounts for similar properties. In other words, OOT buyers would pay higher transaction prices relative to the list prices after the high hometown house price growth. The results imply that after the high hometown house price growth, OOT buyers are less likely to negotiate aggressively with home sellers and are more willing to accept higher transaction prices.

There could be a concern that counties with high past house price growth could be fundamentally different from other counties. The hometown characteristics could be correlated with both past hometown house price growth and OOT buyers' purchase prices.

To rule out the time-varying hometown characteristics driving our results, we consider more rigorous constraints by adding the hometown county interacted with year fixed effects. Exploiting the OOT purchase price variation within the same hometown county and year, we find very robust high payment after the hometown house price growth.

More strikingly, we find a large geographic variation in overpayments across hometown and OOT housing markets in Figure 4. Following a 100% increase in hometown house prices, OOT buyers from Alabama, Nebraska, and North Carolina tend to have the strongest response by increasing their OOT purchase prices the most. On the other hand, OOT buyers from several middle states in the U.S. tend to pay lower average purchase prices for OOT properties than buyers from other states.

We document the heterogeneity in OOT overpayments by county characteristics as well. For example, after the hometown house price growth, OOT buyers from *low-income hometown zip codes* who purchase new properties *in low-income OOT zip codes* tend to make the largest increase in purchase prices relative to other buyers. Among buyers *from hometowns with the same income level*, those who

[1] Purchase discount = list price / transaction price - 1

purchase properties in higher-income OOT markets tend to increase their purchase prices less than those who purchase properties in lower-income OOT housing markets. Within the same income level of *OOT zip codes*, the buyers from lower-income hometowns tend to increase their purchase prices more than those from higher-income hometowns. The findings challenge the wealth effect explanation, which predicts a larger purchase price increase by high-income buyers following the hometown house price growth.

Two Strategies to Exclude Wealth Effect and Validate Belief Effect To validate the extrapolative belief channel, our main challenge lies in distinguishing the belief impact from other factors that may also affect OOT homebuyers's house payments. For instance, OOT buyers who have observed a significant increase in house prices in their hometowns may have also experienced an increase in housing wealth (known as the "wealth effect"). This housing wealth increase may enable OOT homebuyers to afford more expensive properties, which leads to higher purchase prices. Although controlling for property characteristics can partly address this issue, we implement more rigorous identification strategies to rule out the wealth effect and other potential channels.

First, we examine the purchase price differences among three types of homebuyers: renters, migrant homeowners, and second-home (SH) buyers. Our second strategy exploits the house price belief data from the American Community Survey (ACS). With the belief data, we estimate the heterogeneity in the extrapolation level across geographic locations and link it back to OOT buyers' housing transaction behavior.

Strategy 1: Renter, Migrant, and Second-home Buyer In the first strategy, we trace back to OOT buyers' hometown properties through the mailing addresses recorded in deed transactions. Using the hometown property ownership information, we categorize OOT buyers into three groups: renters who have not previously owned any properties in their hometowns, migrant homeowners who sell their purchased hometown properties within two years of the OOT transaction, and second-home (SH) buyers who keep their hometown properties for at least two years after the OOT transaction. Because renters are less susceptible to wealth increase from the house price increase, and we control for the purchase and approximate sale price of migrant homeowners and SH buyers, we are able to identify the extrapolation effect while removing the wealth effect.

The results show that renters, relative to the migrants and second-home (SH) buyers, have a smaller but significant purchase price sensitivity to past hometown house price growth. Given a 50% increase in hometown house prices over the past five years, renters are willing to pay an average of 1.3 percentage points more for new OOT properties. As renters do not own properties in their hometowns, their willingness to pay more is less likely driven by increased housing wealth.

For migrants and second-home (SH) buyers, we exclude the effect of the wealth increase by controlling for their hometown property purchase and potential sale prices. Our findings indicate that, after controlling for the wealth increase, migrants and SH buyers pay approximately 1.85 and 2.55 percentage points more, respectively, in response to a 50% increase in hometown house prices.

Malmendier and Nagel (2016) suggest that individuals with a shorter window of experience (e.g., lifetime history) are more influenced by recent experiences than those with longer experiences, as recent experiences account for a greater share of their accumulated life history. Our findings corroborate the extrapolation channel: the longer a buyer has lived in her hometown, the less she is influenced by recent five-year hometown house price growth when buying an OOT property.

Strategy 2: Extrapolative House Price Belief In the second strategy, the results indicate that OOT buyers' extrapolative beliefs extending beyond geographical borders indeed influence their house transaction prices. We start by exploring the ACS data, which present household beliefs about their own home values. Specifically, the survey participants were asked to estimate the selling price of their property at the time of the survey, as shown in Figure A.12. By controlling for the actual county house price index, demographics, property, and county characteristics, our results show that individuals who experience one standard deviation (41%) increase in local housing prices anticipate a 4.5% higher property value. Overall, households extrapolate from past local house price changes when forming their house price belief.

Why do people extrapolate? Why do people from different areas extrapolate differently? Although this paper does not explore what determines the extrapolation, it shows some novel findings about household demographics and extrapolation levels. Given the same local house price increase in the past, young people (i.e., people under 40) increase the expected house price and extrapolate more than old people (i.e., people over 60). This finding aligns with the research done by Malmendier and Nagel (2016). Besides, we find that single men extrapolate the most, followed by single women. Married men and women extrapolate the least and do not significantly differ from each other in extrapolation. Among racial groups, Asians do not exhibit extrapolative beliefs. Black and American Indian households show a stronger extrapolation tendency than White households. The higher the education of members of a household, the lower the extrapolation level. Households without a bachelor's degree extrapolate the most. Additionally, households holding a bachelor's degree extrapolate less than no-degree households but more than those holding a master's or doctorate degree. Each year and based on income level, we sort households into five income quintile groups. Households in a higher income group extrapolate less than those in the lower income group.

OOT Buyers Act on Extrapolative House Price Beliefs We investigate whether OOT buyers *act on* their extrapolative beliefs formed from hometown house price growth. First, we estimate the extrapolation level of households in each county using the ACS data. For each county, we regress households' expected house values on past five-year house price growth associated with the same control variables as previous. We refer to the coefficient on a county's past five-year house price growth as its "extrapolation beta." A higher belief sensitivity to the past house price growth (i.e., extrapolation beta) indicates a greater tendency for households in the county to extrapolate when forming house price beliefs. Then, we link the estimated *hometown-county* extrapolation beta to OOT buyers' house transactions. Our analysis implies that OOT buyers from hometowns with high levels of extrapolation are likely to pay more than those from low extrapolation areas, given the same increase in the past hometown house prices.

Inspired by Guren, McKay, Nakamura, and Steinsson (2021); Palmer (2015), we construct a belief sensitivity instrumental variable (IV) called "extrapolative price." The extrapolative price of hometown MSA m in state s consists of two components as in the following equation.

$$z_{m,s,t} = \underbrace{\widehat{\beta}_{m,s}}_{\text{Extrapolation level relative to other MSAs in the state}} \times \underbrace{\text{State } \Delta HPI_{s,[t-6,t-1]}}_{\text{state-level house price change}}$$

To explain the IV approach intuitively, suppose that two OOT buyers come from the same hometown state but two different MSAs. When forming house price beliefs, the households in one MSA highly rely on and extrapolate from the past house price experience (high extrapolation MSA), while the households in the other MAS extrapolate less from the past house price growth (low extrapolation MSA). Given the same past state-level house price growth, the OOT buyer from the high extrapolation MSA will have a higher expected house price ("extrapolative price") than the other buyer from the low extrapolation MSA. This strategy exploits the exogenous variation in the house price belief sensitivity to the same house price change *across different MSAs within the same state*.

To estimate the extrapolation heterogeneity across MSAs, we use the individual-level house price belief data from the ACS dataset. We regress the households' expected house values on the past five-year *state-level* house price growth. In the specification, we control for the concurrent county house price index, the property characteristics, individual demographic characteristics, county characteristics, and the time and county fixed effects. More importantly, we interact the MSA dummy variables with the past five-year *state-level* house price growth and estimate the coefficient, $\widehat{\beta}_{m,s}$, for each MSA in a state. The estimated $\widehat{\beta}_{m,s}$ only captures, given the same true county house price and other economic fundamentals that will affect house price belief, how households in different MSAs adjust their own house price belief differently by extrapolating from the same state house price growth differently. As we control for other wealth-increase factors that influence household house price beliefs, the estimated $\widehat{\beta}_{m,s}$ provides an exogenous variation in house price extrapolation tendency across MSAs independent of the wealth change.

Our instrumental variable satisfies the relevant condition and exclusion restriction criteria. Essentially, our sensitivity IV should only capture the extrapolative component of future house price beliefs formed from past hometown-state house price experiences. The IV should not capture any component related to wealth increases caused by past house price growth. The estimated sensitivity of house price belief to past hometown-state price growth ensures that sensitivity IV is exogenous to wealth increase, hence providing the exogenous variation in extrapolative house price beliefs that are orthogonal to wealth increases. Since state- and zip-level house price growth are highly correlated, the relevant condition can be easily satisfied, which is also verified in our first-stage regression.

Contribution and Literature Our paper is the first to document and explore spatial extrapolation across geographical locations. Our findings indicate that individuals make extrapolations beyond location boundaries, and these extrapolations influence their economic beliefs in one region based on their experiences in another. Our study provides a valuable contribution to the extrapolative belief literature by exploring a novel form of extrapolation: spatial extrapolation. The beginning of research on extrapolation belief dates back to the early 1990s (Cutler, Poterba, and Summers, 1990; De Long, Shleifer, Summers, and Waldmann, 1990; Frankel and Froot, 1990; Hong and Stein, 1999). Some recent survey evidence of investors' beliefs draws researchers' attention back to the extrapolation belief (Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014). For example, Greenwood and Shleifer (2014) indicate that investors over-extrapolate past returns, which leads to low returns afterward. These survey data on investors' beliefs provoke a new round of research on extrapolation belief (Barberis, Greenwood, Jin, and Shleifer, 2015; Glaeser and Nathanson, 2017; Cassella and Gulen, 2018; Da, Huang, and Jin, 2021; DeFusco, Nathanson, and Zwick, 2022; Liao, Peng, and Zhu, 2022; Jin and Sui, 2022). For example, a return extrapolation model by Barberis, Greenwood, Jin, and Shleifer (2018) explains many behaviors we observe in bubbles, such as large price increases and trading volume.

The paper contributes to the experience effect literature as well. This strand of research starts from Malmendier and Nagel (2011), where they find that individual experiences of macroeconomic shocks affect financial risk-taking. Following it, many papers find that personal life experiences could have an important role in shaping people's future expectations. For example, individuals' inflation expectations are influenced by the inflation experienced during their lifetime (Malmendier and Nagel, 2016) and price changes of goods in their personal grocery bundles (D'Acunto, Malmendier, Ospina, and Weber, 2021). Personal experience also influences a household's future expectations of housing markets. With Facebook data, Bailey, Cao, Kuchler, and Stroebel (2018) show that the house experiences of an individual's friends influence her expectation of local housing markets and change her probability of owning a house and house payment amount. Kuchler and Zafar (2019) documents a positive relationship between past price changes experienced by households and their expectation of future national house price changes.

Scarce research has studied how belief plays a role in the housing market, and our paper literally contributes to it. Armona, Fuster, and Zafar (2019) use a unique "information experiment" where individuals receive information about past house price changes. They find that individuals extrapolate from information about the recent past house price changes when forming price forecasts. Using the Michigan Survey data, De Stefani (2021) shows that consumers' house price expectations depend upon the recent history of house price developments in their city of residence. Glaeser and Nathanson (2017) builds a theoretical extrapolative model for house prices, which leads the prices to display three features present in the data but usually missing from rational expectations models: momentum at one-year horizons, mean reversion at five-year horizons, and excess longer-term volatility relative to fundamentals. Some other literature also explores the extrapolation in housing markets (Case, Shiller, and Thompson, 2012; Fuster, Perez-Truglia, Wiederholt, and Zafar, 2022).

The paper is not limited to providing innovative insight regarding spatial extrapolative belief. More importantly, our paper contributes to understanding whether and how much households turn belief into action. There remains a debating puzzle regarding the transition from investors' beliefs to their actions. According to Giglio, Maggiori, Stroebel, and Utkus (2021a), changes in beliefs do not predict when investors will trade, but they do influence the direction and magnitude of trades when they occur. Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu (2023) find a link between individuals' reported ESG investment motives and their actual investment behaviors, with the highest ESG portfolio holdings among individuals who report ethics-driven investment motives. However, Chaudhry (2022) finds a limited passthrough of beliefs to asset demand, leading to a far smaller causal effect of subjective growth expectations on asset prices than standard models suggest. Other literature also explores the relationship between the beliefs of investors and their financial decisions (Merkle and Weber, 2014; Drerup, Enke, and Von Gaudecker, 2017; Bailey, Dávila, Kuchler, and Stroebel, 2019; Ameriks, Kézdi, Lee, and Shapiro, 2020; Andonov, Rauh, et al., 2020; Dahlquist and Ibert, 2021; Giglio, Maggiori, Stroebel, and Utkus, 2021b; Beutel and Weber, 2022; D'Acunto, Weber, and Yin, 2022; Meeuwis, Parker, Schoar, and Simester, 2022). As real estate asset takes up a high proportion of household wealth, this paper explores whether households act on their extrapolative beliefs. It finds that OOT homebuyers' extrapolative beliefs, formed from past house price experiences in their hometowns, lead to irrational purchase behavior of *OOT* properties.

Lastly, our research paper contributes to the study of out-of-town (OOT) buyers in housing markets, building on the works such as (Badarinza and Ramadorai, 2018; Favilukis and Van Nieuwerburgh, 2021; Cvijanović and Spaenjers, 2021). We offer a novel perspective by exploring the belief channel, particularly the extrapolative belief, behind the high payments made by OOT homebuyers. As far as we know, our paper is the first to explain the high payment of OOT homebuyers from the perspective of extrapolative belief. In contrast, Chinco and Mayer (2016) finds that OOT buyers push up and create mispricing in local house prices without digging into the mechanism behind their purchase behavior. In detail, Chinco and Mayer (2016) uses deed records of OOT homebuyers and finds that a one percentage point increase in the fraction of sales by OOT buyers in a given month is associated with a 1.7% increase in the implied-to-actual-rent ratio (IAR) appreciation rate, a proxy for mispricing, over the next year in OOT MSA. However, our paper significantly differs from theirs in that we conduct a micro-level analysis of OOT buyer behavior and provide a creative mechanism that explains why they are willing to pay high prices for OOT properties, leading to an increase in local house prices. Besides, Favilukis and Van Nieuwerburgh (2021) develop a model that quantifies the welfare effects of out-of-town (OOT) home buyers. They find house prices rise by 6.5% in the city center when OOT buyers represent 10% of housing demand in the city center, assuming that OOT buyers do not rent out their properties. Gorback and Keys (2020); Li, Shen, and Zhang (2020); Sakong (2021) explore the capital flow impacts of Chinese foreigners on local house prices and rents.

The remainder of this paper is organized as follows: Section II describes data and the construction of measurements. Section III discusses the estimation approach. Section IV shows the empirical results. Section V concludes the paper.

II. Data and Measurement

A. House Purchase Price of Out-of-town (OOT) Buyers

In this paper, we leverage CoreLogic deed transaction data to obtain data on out-of-town (OOT) homebuyers' house transactions. CoreLogic is a premier U.S. real estate data provider, and its data has been extensively used in literature (Favilukis and Van Nieuwerburgh, 2021; Goldsmith-Pinkham and Shue, 2023). This database encompasses more than 3100 counties in the U.S., representing over 99% of the population[2]. From CoreLogic, we are able to collect detailed deed transaction information, such as transaction date, property address, buyer and seller information, and sales prices. CoreLogic deed transaction data dates back as far as the early 1990s. However, for the purposes of this research, our sample spans from 1997 to 2017, as we are only able to measure zip-level house returns from 2002.

We clean the deed transaction data through the following steps. First, we drop the non-arm's length transaction records listed as the intrafamily transfer and exclude mortgage refinancing deed events. Second, we keep only transactions between individuals. In other words, we exclude the transactions where either the sellers or buyers are non-individuals, such as developers, companies, or governments. Similarly, we exclude foreclosure transactions. Some deed transactions have missing or unusually low transaction prices (e.g., $1 or $5). The low or missing sales prices could be due to data imputing errors or intrafamily transfer events. Hence, I restrict the sample to the deed transactions with sales prices greater than (including) $5,000, one percentile cutoff of housing transaction prices in our sample. However, raising the threshold to $10,000 by following Baldauf, Favilukis, Garlappi, and Zheng (2022) gives similar and robust results.

[2]As per the data description provided by CoreLogic: https://www.corelogic.com/wp-content/uploads/sites/4/downloadable-docs/capital-markets-data-sources.pdf

B. Hometown House Price Growth Experience

To measure an OOT buyer's return experience in her hometown, we use the zip-level Federal Housing Finance Agency (FHFA) house price index and appreciation. We also use the Zillow Home Value Index (ZHVI) and get very similar results. We construct the measurement for hometown house price growth experience, $Hometown\ \Delta HPI_{h,[t-6,t-1]}$, which is defined as the change of house price index (HPI) in hometown zip code h in the past five years until the OOT property transaction year t-1.

$$Hometown\ \Delta HPI_{h,[t-6,t-1]} = \frac{\mathrm{HPI}_{h,t-1}}{\mathrm{HPI}_{h,t-6}} - 1$$

We will explain how we define "hometown" for OOT buyers in the following section. In the robustness tests, we examine other year horizons of measuring return experience from one to ten years.

C. Identify Out-of-town (OOT) Homebuyers

We define an out-of-town (OOT) buyer as one who purchases a house over 60 miles from the place she lived in before the OOT transaction. The hometown of an OOT buyer, defined as the zip code or county she lived in previously, is inferred from the mailing address contained in the deeds of OOT properties.

To explain our detailed procedure for identifying OOT buyers, first, we use the mailing address. We specifically use the mailing zip code, contained in a deed transaction record, to determine whether a buyer comes from another area and also measure the distance between OOT and hometown properties. Homebuyers usually are required to write the mailing address to receive tax documents. For this reason, it is unlikely for a buyer to write a random and incorrect address where they have never lived deliberately. Chinco and Mayer (2016) applies a similar methodology to find second-home buyers from another MSA.

However, compared to Chinco and Mayer (2016), we use the distance between hometown and OOT properties to refine our OOT buyer measurement. We calculate the distance between the OOT property and the mailing address zip code through the NBER zip distance dataset. It may be unreasonable to consider one as an OOT buyer if she moves from a nearby neighborhood, say from Mountain View to Palo Alto, even though the zip codes for the two districts are different. Therefore, we require that an OOT buyer report a mailing address more than 60 miles from the OOT property address. We choose 60 miles as the threshold by following Knyazeva et al. (2013), which defines non-local independent directors as those employed outside 60 miles of a focal firm. Our results are still robust by implementing other distance thresholds from 120 to 800 miles.

It is important to acknowledge that our method of identifying out-of-town (OOT) buyers is not perfect. The main issue is that some buyers list OOT property addresses as their mailing addresses, which makes it difficult to determine certain types of OOT buyers. For example, we may not include international buyers since they typically do not write foreign addresses in the deed records. Additionally, it may be challenging to identify OOT buyers who sell their current home and permanently relocate to a new city where they purchase an OOT property, such as for job relocation. However, we still try to account for this situation by defining "migrators" as OOT buyers who sell their hometown property within two years of purchasing the OOT property. By tracing the hometown properties of OOT buyers, we can further categorize them as renters, migrators, or second-home buyers (explained in Section II.G.1). Finally, although unlikely, some OOT buyers tend not to report true mailing addresses, potentially impacting our estimates. However, since the reasons for hiding their address may vary, it's unclear how ignoring this type of homebuyer would affect our results.

D. County and Property Characteristics

We obtain the time-varying county-level characteristics from three main sources: U.S. Census Bureau Population and Housing Unit Estimates, Small Area Income and Poverty Estimates (SAIPE), and U.S. Bureau of Labor Statistics Local Area Unemployment (LAU) statistics Datasets. For every U.S. county between 2000 and 2017, we collect data on the county's total population, median age, gender ratio, and other demographic characteristics from the Population and Housing Unit Estimates dataset. We retrieve median income data from the SAIPE dataset and employment data such as labor force ratio and employment ratio from the LAU dataset.

To obtain time-varying property characteristics, we link deeds data and property listing data from CoreLogic by following Goldsmith-Pinkham and Shue (2023). The property listing data comes from Multiple Listing Service (MLS) systems and provides information on when the property is listed for sale, the listing price, and the closing price. Additionally, the data offers the most up-to-date characteristics of the property when it is sold, such as the square footage, total number of rooms, number of bedrooms, presence of a pool, waterfront location, and more. The MLS data also records public remarks about the listed property. We adopt the approach suggested in Goldsmith-Pinkham and Shue (2023) and determine whether a property has undergone renovation or upgrade by checking whether a public remark contains any of the keywords "RENOV," "REMODEL," "UPDATE," and "RESTORE." To match property characteristics and deeds data, we use the county fips code and property parcel number. To ensure that the property characteristics are the most current at the time of the transaction, we require that the final transaction date documented in a deed fall within day t - 90 and t + 365 of the close date t recorded in the MLS data.

E. Purchase List Price and Purchase Discount

To determine the purchase discount that OOT homebuyers receive, we need to link the listing data and deed transaction data. This process is similar to merging the house characteristics to deed transaction records as explained in Section II.D. We follow the method used by Goldsmith-Pinkham and Shue (2023).

Sellers may change the list prices of their properties over time after the initial listing. To accurately measure the purchase discount (or premium) obtained by the OOT homebuyers, we need to ensure that the list price is the most current one at the time of purchase. To achieve this, we require that the final transaction date documented in a deed falls within 90 days before to 365 days after the close date recorded in the MLS data.

Then, we choose the list price that is closest to the deed transaction date. This ensures that the matched list prices reflect the prices at which the OOT homebuyers start negotiating with sellers. This method helps us to obtain a better measurement of the purchase discount obtained by OOT homebuyers. With the matched list price, we define the purchase discount as the following

$$\text{Purchase Discount} = \frac{\text{Purchase List Price} - \text{Transaction Price}}{\text{Transaction Price}} \times 100$$

F. Measuring Realized Returns of OOT Properties

We measure the realized house returns by identifying two-way transactions given a house. The annualized return obtained by OOT buyer i with the purchase date b of OOT property and sale date s is expressed as the form in the following.

$$Realized\ Ret_{is} = \left(\frac{P_{is}}{P_{ib}}\right)^{\frac{1}{s-b}} - 1$$

where P_{ib} denotes the purchase price of an OOT property in year b and P_{is} represents its sale price in year s.

We require a valid realized return to satisfy the following criteria. First, the sale transaction after the OOT property purchase transaction must be an arm's length transaction. Specifically, we do not consider a realized return valid if the sale transaction is an intrafamily transfer. Second, we use a fuzzy matching algorithm to filter out two-way transactions where the buyer names in the purchase transaction differ greatly from the seller names in the sale transaction. To perform this comparison, we utilize the Python Record Linkage Toolkit [3]. Specifically, we use the Levenshtein algorithm with a matching threshold value of 0.75 to match two first and last buyer names in the purchase transaction and two first and last seller names in the sale transaction. Only if the names in the purchase and the consecutive sale transactions are closely matched through the algorithm, we treat a realized return as valid. Goldsmith-Pinkham and Shue (2023) use a tolerance of 0.7 with a function "matchit" in Stata to compare the names. However, we believe our fuzzy matching algorithm with the tolerance value would give us a more accurate realized return. Third, we require that the gap between the OOT property purchase date and the sale date is more than (including) 180 days. Baldauf et al. (2022) use a holding period of 183 days to filter out invalid two-way transactions. Goldsmith-Pinkham and Shue (2023) require a minimum holding length of three months to consider the returns valid. Our selection of 180 days as the minimum length required for a valid return could be supported by the previous literature.

G. Tracing Hometown Properties of OOT Buyers

We locate the homes of out-of-town (OOT) buyers in their hometowns by using the mailing addresses listed in their deed transactions. Since we are unable to obtain the parcel number of an OOT buyer's hometown property from her OOT property deed, we use fuzzy matching to locate her hometown house based on the first and last names of the two homeowners, mailing zip codes, street names, and street numbers found in her OOT deed. To perform this matching, we utilize the same Python Record Linkage Toolkit described in Section II.F. Our fuzzy matching process consists of two steps. First, we use the exact matching method to match the OOT mailing address to properties in the hometown. We only search for the hometown property within the mailing zip code provided in the OOT deed record. The final matched hometown house must be located within the zip code specified in the mailing address of

[3] For information on the toolkit, please visit: `https://recordlinkage.readthedocs.io/en/latest/index.html`

the OOT deed. Second, we compare the first and last names of the two homeowners, the street name, and the street number of the property with the mailing information from the OOT property deed. We use the Levenshtein distance algorithm to perform a fuzzy match on property owner names with a threshold value of 0.85. We use the Damerau-Levenshtein distance to match the property street names with the same threshold value. We group the matching criteria into three categories: first name match, last name match, and street information match. In the final matched hometown houses, we require that at least two matching criteria are met. Therefore, we require that either the first and last names are matched, the first name and street information are matched, the last name and the street are matched, or all three criteria are matched.

G.1. Identify Renters, Migrators, and Second-home OOT Buyers

With the hometown property information, we can categorize OOT buyers into three groups: renters, migrators, and second-home (SH) buyers. Renters are those with no matching deed record, suggesting they were renting their residence when they purchased OOT properties. Migrators and SH buyers, on the other hand, are linked to deeds based on their mailing addresses, indicating ownership of properties in their hometowns. Migrators are defined as those who sell their hometown properties within two years of their OOT property purchase. In contrast, SH buyers maintain ownership of their hometown properties for at least two years after purchasing OOT properties.

G.2. Hometown House Values and Living Length

In our subsequent analysis of migrators and second-home (SH) buyers, we figure out when and by how much they purchased their hometown properties. With the purchase prices of hometown properties, we could control OOT buyers' wealth and, to some extent, mitigate any wealth effects that could be correlated with the experience effects in our analysis. In terms of OOT buyers' living length in hometowns, we measure the years they have lived in the hometown properties listed in OOT deeds until their OOT property purchases.

However, our measurement of living length is only the minimum length OOT buyers live in their hometowns. Two reasons could lead to our underestimation of the living length. First, we do not take into account other properties purchased before the hometown property listed in the mailing address from OOT deeds. For example, if an OOT buyer has owned multiple houses in her hometown, we can only trace back to her hometown property listed in the mailing address in her OOT deed. If she purchased other properties before the listed hometown property, we would underestimate her living length in her hometown. Second, if an OOT buyer was a renter in the hometown before she became a property owner, her actual living length in the hometown would be longer than our measurement. With that being said, the potential measurement error could only result in a downward bias of our estimation because we could only treat the return-experienced OOT buyers (treated group) as those less or no-experienced OOT buyers (control group).

H. House Price Beliefs from American Community Survey

The American Community Survey (ACS) conducted by the U.S. Census Bureau provides the house price belief of households in the U.S. We collect the belief data from the Integrated Public Use Microdata Series (IPUMS). U.S. Census Bureau surveys approximately 3.5 million households annually and asks interviewees' beliefs regarding their house prices as well as demographic, socioeconomic, and housing information. Figure A.12 shows the survey question for eliciting households' house price beliefs. Specifically, the interviewees are asked to estimate the selling price of their current property, which helps us measure their house price beliefs. Additionally, we collect information about households' age, gender, marital status, education, race, employment status, and family income, along with the total number of rooms and bedrooms in the home and the year it was built, as these factors are highly correlated with the house price belief. Controlling for a rich set of characteristics could help us separate the extrapolative price belief from the rational belief of households.

To ensure the accuracy of our analysis, we thoroughly clean our ACS sample by limiting it to only include house owners living in 1-family homes and removing households with ages less than 20. We also eliminate observations with an expected house price of less than $15,000, which is the 1st percentile of the entire sample. The procedure ensures that our results are reliable and provide valuable insights into the extrapolative belief of households.

I. Description of Data

In Appendix, Figures A.2 and A.3 present the geographical distributions of out-of-town (OOT) counties and states where the OOT housing transactions in my sample occur from 2002 to 2017. The figure implies that OOT transactions are more prevalent in states such as Florida, California, Texas, and Illinois, while less common in the central regions of the United States. Florid attracts OOT homebuyers the most with around 24% OOT transactions in my sample occurring in Florida. With such significant differences in OOT property purchases across various regions, it is essential to consider location-related factors when analyzing OOT transactions.

Figure A.1 presents the proportion of housing transactions conducted by OOT homebuyers annually from 1997 to 2017. The percentage of OOT transactions rose steadily throughout the 90s and peaked in 2005. After a slight dip during the 2008 financial crisis, it quickly picked up again. On average, OOT transactions account for approximately 6% per year in our sample.

Table 1 reports the summary statistics of the main variables and house characteristics variables used in the analysis. The summary statistics table for our main sample of OOT transactions in Panel A suggests that the median purchase price of OOT buyers is around $181,000 with a mean value of around $275,000. The average hometown return experienced by OOT buyers over the past five years is 23% with a standard deviation of 35%. Panel B shows the county-level characteristics of OOT buyers' hometowns. The characteristics include population, median age, median income, income growth, and labor force ratio. Panel C of Table 1 shows the summary statistics of our realized return sample. OOT buyers who have sold their OOT properties have an annualized realized return of 8% on average. The mean and median values of purchase prices in the return sample are very close to the statistics in our main sample shown in Panel A. On average, OOT buyers hold their OOT properties for six years with a median of five years.

III. Empirical Approach

This section describes the regression methodology I mainly implement and shows the results of out-of-town (OOT) buyers extrapolating from hometown price experiences when buying houses out of town.

A. Main Specification

Our primary analysis starts from a linear regression that accounts for the difference in final transaction prices among OOT buyers with different past hometown house price growth experiences. The specification takes the form below.

$$\text{Log(Purchase Price)}_{o,h,i,t} = \alpha + \beta \,\text{Hometown } \Delta HPI_{h,[t-6,t-1]} + \delta_o \times \psi_t + \gamma_h + \epsilon_{o,h,i,t} \tag{1}$$

In Equation 1, the outcome variable *Log(Purchase Price)*$_{o,h,i,t}$ is the log of the purchase price of property located in OOT o and made by individual i coming from hometown h at time t. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the house price changes in the hometown h over the past five years. $\delta_o \times \psi_t$ includes the interaction of OOT zip code and transaction year-month fixed effects that absorb any time-varying effects of the OOT housing markets. γ_h is the hometown fixed effects which will absorb any effects from the time-invariant county or personal characteristics associated with OOT buyers' purchase prices, such as wealth strata and education of OOT buyers. The main interest of the coefficient, β, reflects how much an OOT buyer would additionally pay, given a 100% increase in the past five-year house return in her hometown. The coefficient will capture the effect of out-of-town buyers' extrapolation from hometown price experiences in finalizing transaction prices.

An OOT buyer paying more for a house may be due to the economic condition and growth of OOT counties, such as income growth and labor force ratio. To mitigate effects from the confounding factors that could affect purchase prices, we control for the time-varying OOT county characteristics, including the hometown house price index, the log of the county population, county median age, the log of median income, median income growth, and labor force ratio. The hometown house price index is the zip-level ZHVI in the hometown in one year before the transaction year. Similar to the hedonic model, we add property characteristics as control variables to absorb transaction price differences caused by the unobserved house quality that may be correlated with hometown house price growth experiences.

A.1. Realized Return

We examine OOT buyers' realized returns with the following specification.

$$\begin{aligned}\text{Realized Ret}_{o,h,i,t} = \alpha + \beta\,\text{Hometown}\;\Delta HPI_{h,[t-6,t-1]} \\ + \delta_{\text{o}} \times \psi_{\text{Sale YM}} + \delta_{\text{o}} \times \psi_{\text{Buy YM}} \\ + \psi_{\text{Sale YM}} \times \psi_{\text{Buy YM}} + \gamma_h + \epsilon_{o,h,i,t}\end{aligned} \tag{2}$$

where *Realized Ret*$_{o,h,i,t}$ is the annualized realized return obtained by OOT buyer i who is from hometown h and buys a property in OOT o at time t. We discuss the details of measuring valid realized returns for OOT buyers in Section II.F. Similarly, *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the past five-year house price changes in hometown h. We add several fixed effects in the specification. $\delta_o \times \psi_{\text{Sale YM}}$ and $\delta_o \times \psi_{\text{Buy YM}}$ are the OOT zip code interacted with sale year-month and purchase year-month fixed effects, respectively. We add the interaction of purchase and sale year-month fixed effects, $\psi_{\text{Sale YM}} \times \psi_{\text{Buy YM}}$ to control for overall effects from market timing. γ_h is the hometown fixed effects similar to Equation 1.

B. Extrapolative Belief of House Price

To validate the extrapolative belief channel that drives the purchase price differences among OOT buyers, we implement the following specification.

$$\begin{aligned} \text{Log(Expected House Price)}_{c,i,p,t} = \alpha + \ & \beta_1 \text{ County } \Delta HPI_{c,[t-6,t-1]} \\ & + \beta_2 \text{ Log(County HPI)}_{c,t} + \beta_3 X_{p,t} + \beta_4 H_{i,t} + \beta_5 K_{c,t} \\ & + \delta_{\text{c}} + \psi_t + \epsilon_{o,h,i,t} \end{aligned} \tag{3}$$

where *Log(Expected House Price)*$_{c,i,p,t}$ is the log of the expected house price of individual i living in house p in county c at year t. County $\Delta HPI_{c,[t-6,t-1]}$ is the past five-year county return measured from year $t-6$ to $t-1$ for a survey year t. The reason we add a one-year lag for measuring the return experience is that the U.S. Census Bureau usually requires the interviewees to submit their survey responses in the first half of a survey year (e.g., April or May). To most accurately capture the house returns experienced by households, we measure the past five-year house price growth ending in one year before households submit their survey response. The main coefficient of interest, β_1, reflects how much households extrapolate from the past five-year house price growth when forming their house value beliefs.

We control for the concurrent ZHVI house price index, *Log(County HPI)*$_{c,t}$, in county c and year t. Households expect a higher house price possibly because the current local market house price is at a high level. To exclude the effects that the true market price drives a rational belief, we control for the current market price in local housing markets as the proxy for the rational price for which households could sell their houses. In addition, we control for time-varying property, demographic, and county characteristics. $X_{p,t}$ denotes the property characteristics, including the total room number, bedroom number, and the log of house age. $H_{i,t}$ denotes the individual characteristics, including age, squared age, marriage status, education, race, employment status, and family income. $K_{c,t}$ represents the county characteristics, including the log of the county population, county median age, the log of median income, median income growth, labor force ratio, and labor force ratio growth. Controlling for the characteristics could help us mitigate omitted variable bias that may correlate with the past county house price growth and the expected house price of households.

C. Sensitivity Instrumental Variable (IV) Approach

Inspired by Guren et al. (2021); Palmer (2015), we develop an empirical approach called the belief sensitivity instrument. Our strategy combines house price belief and housing transaction data to obtain the exogenous variation in extrapolative house price belief across locations that is orthogonal to wealth changes. The strategy exploits the differences in the sensitivity of house price beliefs to past five-year house price growth across Metropolitan Statistical Areas (MSAs) within the same state.

To explain this approach simply, let's say that two groups of people live in the same state but in two MSAs. People in different MSAs have different sensitivity of house price beliefs to the same *state-level* house price growth. In other words, they extrapolate from the same house price growth differently. By exploiting the heterogeneity in extrapolation extent across MSAs within the same state, we can estimate the differences in extrapolative house price beliefs formed from the same state price growth. This estimated extrapolative house price belief is our sensitivity instrumental variable (IV).

The detailed steps are in the following. First, we estimate the sensitivity differences of own house value belief to *state-level* house price growth across MSAs using a specification similar to Specification 3.

$$\begin{aligned} \text{Log(Expected House Price)}_{c,m,s,p,t} = \alpha + {} & \beta_{m,s}\, \gamma_{m,s} \times \text{State } \Delta HPI_{s,[t-6,t-1]} \\ & + \psi \text{ State } \Delta HPI_{s,[t-6,t-1]} + \gamma_{m,s} \\ & + \lambda \text{ Log(County HPI)}_{c,t} + \theta\, X_{p,t} + \kappa\, H_{i,t} + \nu\, K_{c,t} \\ & + \delta_{\mathrm{c}} + \psi_t + \epsilon_{c,m,s,p,t} \end{aligned} \tag{4}$$

The dependent variable, *Log(Expected House Price)*$_{c,m,s,p,t}$, is the log of the expected house price of an individual in county c, MSA m, state s, house p, and at time t. $\gamma_{m,s}$ represents the MSA dummy variables. *State* $\Delta HPI_{s,[t-6,t-1]}$ is the state-level house price growth in the past five years. As we interact the MSA dummy variable with state-level house price growth in the past five years, the estimated $\widehat{\beta}_{m,s}$ captures the differences in the sensitivity of house price belief to state house price growth. Same as Specification 3, we control for the concurrent level of county house prices, *Log(County HPI)*$_{c,t}$, the property characteristics, $X_{p,t}$, individual demographic characteristics, $H_{i,t}$, county characteristics, $K_{c,t}$, and the time and county fixed effects.

Second, we construct our belief sensitivity IV through the following equation.

$$z_{m,s,t} = \widehat{\beta}_{m,s} \text{ State } \Delta HPI_{s,[t-6,t-1]}$$

The belief sensitivity IV, $z_{m,s,t}$, measures the difference across MSAs in the expected house price formed by extrapolating from state-level house price growth. Intuitively, given the same state-level house price growth, individuals from an MSA with a high level of extrapolation have a higher expected house price in the future. Likewise, given the same level of extrapolation, individuals experiencing a higher state-level house price growth have a higher expected house price due to the extrapolative belief.

Third, we use the estimated $z_{m,s,t}$ to instrument for the past five-year hometown-zip house price growth, *Hometown* $\Delta HPI_{h,[t-6,t-1]}$, in Specification 1. In detail, based on hometown geographic information, we link the sensitivity IV back to OOT housing transaction data. Then, we use the 2SLS method to estimate Specification 1 and examine how much individuals react to the extrapolative house price beliefs in their new OOT property purchase prices.

Two key assumptions must be satisfied for our sensitivity IV to be valid. The first assumption is the exclusion restriction. It means that, given a set of controls, there should be no other confounding factors that are correlated with both hometown-zip house price growth and property purchase prices that are influenced by extrapolative belief. Essentially, our sensitivity IV should only capture the extrapolative component of future house price beliefs that are formed from past hometown house price experiences. The IV should not capture any component related to wealth increases caused by past house price growth. Although hometown-state and zip house price growth are correlated, implying a correlation between state house price growth and potential wealth increase, the estimated sensitivity of house price belief to past price growth is exogenous to wealth increase. In other words, the differences in extrapolation level, $\widehat{\beta}_{m,s}$, are orthogonal to wealth increases, hence providing an exogenous variation in extrapolative house price beliefs across geographic locations.

The second assumption is that the IV needs to satisfy the "relevant condition," which means that the estimated hometown extrapolative price, $z_{m,s,t}$, needs to be correlated with hometown-zip past house price growth. Since state- and zip-level house price growth are highly correlated, this assumption can be easily satisfied. We also verify this assumption through our first-stage regression.

IV. Empirical Results

A. Baseline Results

We begin by examining how the past five-year hometown house price growth experience affects the purchase prices of out-of-town (OOT) homebuyers. Our sample is restricted to transactions made by OOT buyers from 2002 to 2017 across the U.S. The OOT buyers are defined as those who purchase properties more than 60 miles away from their reported mailing addresses in deeds. Section II.C discusses the detailed identification of OOT buyers. We use an extrapolation horizon of 5 years but show very similar results with other extrapolation horizons in Appendix A.1.

Table 2 shows that higher past five-year hometown house price experiences are associated with higher purchase prices for OOT properties made by OOT buyers. After controlling for time-invariant characteristics of hometown and property zip area and overall market trend through fixed effects (i.e., transaction year-month fixed effects), Column 1 presents clear evidence of the positive correlation. The result in Column 2 is particularly noteworthy, as it indicates that the past house price growth in the *property zip code area* significantly explains the transaction prices paid by OOT buyers. This is evidenced by the reduction in the coefficient on hometown house return from 0.14 to 0.07. It suggests that the characteristics of property and hometown housing markets are very correlated and could significantly impact how much OOT buyers are willing to pay for new properties in the OOT market. The significant coefficient on the past five-year house price growth in OOT zip is consistent with prior literature that homebuyers tend to overreact to the past long-run price growth in housing markets (Case et al., 2012; Armona et al., 2019). Column 3 adds the log of the property-zip house price index from one year before the transaction as an additional control variable. It helps account for situations where homebuyers may pay a high price when the house prices in OOT markets are at a peak.

Our preferred specification is presented in Column 4, where we add hometown zip code fixed effects and the interaction of property zip code and transaction year-month fixed effects. The interaction fixed effects allow us to control for the time-varying characteristics of OOT housing markets, which will significantly influence property transaction prices. With the interaction fixed effects, we are comparing the buyers' purchase prices for properties in the same OOT zip-code area in the same transaction month. The coefficient of 0.038 on the hometown's past house price growth suggests that one standard deviation (35%) increase in the past five-year hometown house price growth would make OOT buyers pay 1.3

percentage points more than OOT buyers without such return experience. Given the median property transaction price of around \$200,000 in our sample, 1.3 percentage points imply approximately \$2,600 overpayment for a median OOT homebuyer.

A.1. Decreasing Purchase Price Sensitivity as Experience Horizon Increaes

Our findings are not limited to the five years of house price growth experience horizon. The horizons from 1 to 10 years show a very robust and positive correlation between hometown past house price experiences and new property transaction prices in OOT markets. Panel A in Figure 3 shows the sensitivity of OOT buyers' purchase price to cumulative hometown house price growth experience within varying years of the horizon. The sensitivity is the estimated β through our preferred specification in Column 5 of Table 2. The figure clearly shows a robust price sensitivity towards hometown house price growth experiences, measured by horizons ranging from one to ten years. Additionally, it is noteworthy that the purchase price sensitivity gradually decreases as the experience horizon increases, with a higher sensitivity towards more recent ones. This gradual decrease in sensitivity with increasing return horizon aligns with the extrapolation framework (Barberis, 2018) and confirms our extrapolative belief channel's validity in explaining the purchase behavior of OOT buyers. As presented in Appendix A.4, the results are robust when measuring the price growth experience *in individual years*.

A.2. Time-series Variation in Purchase Price Sensitivity

The observed positive relation between OOT purchase price and hometown house price growth is not driven by certain years. In Appendix, Figure A.5 shows the *time-series variation* in the sensitivity of OOT buyers' property purchase prices to the hometown house price growth *across different transaction years*. Most years except from 2008 to 2010 show a robust and positive effect of hometown house price growth on OOT purchase prices.

The insignificance of the hometown house price growth effect indicates that the pattern is not solely driven by the increased wealth resulting from the hometown house price growth. If higher hometown house price growth made OOT buyers wealthier and able to afford more expensive properties, we would observe higher purchase prices from them even during the 2008-2010 period. However, the lower purchase price they are willing to pay suggests their pessimistic views on future house prices, considering the rapid increase in hometown house prices around the 2008 financial crisis. In other words, the beliefs of OOT buyers play an essential role in the observed variation in OOT purchase price sensitivity to past hometown house price growth.

B. Low Realized House Returns after High Hometown House Price Growth

People may worry that OOT buyers pay higher prices for OOT properties after the hometown house price growth possibly because they rationally interpret national and local market trends through their hometown housing market lens. Essentially, their hometown markets could offer insights into OOT housing trends. Information contained in the past hometown house price growth may provide OOT buyers with valuable market signals for their OOT transactions. Leveraging the past hometown housing market information could be a rational behavior, which helps OOT buyers maximize their market profitability in the end. To investigate this possibility, we examine the two-way transactions of OOT properties made by OOT buyers. Section II.F provides a detailed methodology for measuring realized returns.

Panel B of Table 2 shows that OOT buyers would sell the OOT properties at slightly lower prices and realize lower returns from buying and selling OO properties. First, Columns 1 and 2 examine the sale prices of OOT properties through the baseline specifications same as the one implemented in Panel A. Column 2 suggests that given two OOT buyers from the same hometown zip code selling OOT properties in the same zip code and year-month, the buyer experiencing a higher five-year hometown house price growth would sell the OOT properties at a slightly lower price. However, the hometown effect on the sale price is small compared to the effect on the OOT purchase price.

In Columns 3 and 4, we examine the realized return from OOT properties, which is calculated through the two-way transactions made by OOT buyers. Column 3 controls for the *time-invariant characteristics* of the hometown and property zip code areas and the *time-varying characteristics* of the property zip code area through the fixed effects. In Column 4, we add the interaction fixed effects of purchase and sale transaction year-months. This purchase and sale year-month interaction fixed effects will explain all the effects associated with the overall market timing and property holding length. The significant coefficient of -0.012 indicates that a 100% increase in hometown house price growth over the past five years will result in OOT buyers earning 1.2 percentage points lower returns annually.

Overall, we find significantly lower OOT property returns realized by the OOT buyers after higher hometown house price growth. The low returns are mostly driven by the high purchase price paid by

OOT buyers. The low returns on the other side could also suggest that the OOT buyers overpay for OOT properties after the hometown house price growth. The findings indicate that the past hometown house price growth does not inform about future OOT housing markets. It seems unlikely that OOT buyers are rationally using information from their hometown housing markets to make informed and profitable decisions in the OOT housing market. Instead, our results suggest that the extrapolation belief formed from their hometown housing markets plays a significant role in driving their purchase decisions in the OOT housing market.

C. OOT Buyers Overpay after Hometown House Price Growth

In this section, we present empirical evidence that Out-of-town (OOT) buyers tend to overpay for OOT properties after experiencing substantial growth in house prices in their hometown. We corroborate the overpayment by controlling for the characteristics of the purchased OOT properties and examining the purchase discounts associated with OOT transactions.

C.1. Property Characteristics cannot Explain High OOT Payment

To rule out the effect of wealth increase that makes OOT buyers affordable for more expensive houses, we control for a range of property characteristics. The characteristics include the property age, square footage, bedroom, bathroom numbers, and whether a property has a garage, pool, cooling system, fireplace, basement, or waterfront. We also determine whether a property has been upgraded or is a new construction. The variable construction of property characteristics is discussed in Section II.D.

Table 3 suggests that controlling for purchased property characteristics, OOT buyers show very robust and significant extrapolation from their hometown house price growth experiences. In this table, we restrict the sample to the OOT transactions for which we have successfully matched property characteristics. The coefficient in Column 1 is estimated through our main baseline specification in Table 2 but using the sample with property characteristics matched. It suggests that a 50% increase in the hometown house price growth over the past five years would be associated with around one percentage point increase in the purchase prices. Accounting for the property's characteristics in Column 2 slightly reduces the coefficient from 0.022 to 0.018, but it remains robust and significant. Column 3 adds two dummy variables indicating whether a property was upgraded before and whether it is a new construction. Compared to Column 1, the coefficient of Column 3 on hometown house price growth does not change much.

Overall, Table 3 suggests that the purchased property characteristics cannot explain much of the high purchase prices made by OOT buyers. Therefore, this result rules out the possibility that the wealth increase leads to OOT buyers with high house price growth experience paying more for more expensive properties. Instead, it shows that buyers who have experienced high house price growth in their hometowns are willing to pay even higher prices for properties with very similar characteristics. Therefore, it can be concluded that OOT buyers tend to overpay for properties with the same quality after experiencing an increase in hometown house prices.

C.2. Low Purchase Discounts after High Hometown House Price Growth

Table 4 reveals that OOT homebuyers are more likely to select OOT properties with higher list prices if they have experienced a significant increase in their hometown house price growth over the past five years. However, the high hometown house price growth results in OOT buyers paying even higher transaction prices relative to the list prices. Consequently, the analysis suggests that OOT buyers who have experienced a high hometown house price growth would obtain a low purchase discount[4].

It is possible that OOT homebuyers are willing to pay a higher price because the extrapolation from hometown house price growth leads to their optimistic belief toward future OOT house prices. This optimism may make them reluctant to negotiate aggressively with home sellers, resulting in smaller purchase discounts for OOT homebuyers. In this section, we will examine the list price of purchased properties and the purchase discount of OOT homebuyers. The detailed process of obtaining the list prices and purchase discounts has been described in Section II.E.

Suppose two home buyers from the same zip code in their hometown purchase properties in the same OOT zip code area and transaction month. Column 1 of Table 4 demonstrates that the buyer whose hometown house price has increased by 100% over the past five years would buy a house listed at a 1.8% higher price than the other buyer who did not experience a similar increase. Column 2 of Table 4 controls for the purchased-property characteristics. It suggests that if two similar properties were available, the OOT buyer with a 100% increase in the hometown house price would opt for the home with a 1.5% higher list price than the other buyer who did not experience a similar increase.

However, the buyer experiencing a higher hometown house price growth would pay an even higher

[4] Purchase Discount = (Purchase List Price - Transaction Price) / Transaction Price $\times$ 100.

transaction price relative to the list price. Through the list and transaction prices, Columns 3 and 4 of Table 4 analyze the purchase discounts obtained by OOT buyers. Column 3 shows that the buyer with a higher hometown house price growth would obtain a significantly lower discount on the purchase price. Column 4 observes a very robust result with the purchased house characteristics controlled. Column 4 suggests that, given the two OOT buyers purchase similar properties, the buyer with a 100% hometown house price increase in the past five years would obtain a lower purchase discount by approximately 23 basis points.

Panel B of Figure 3 shows the purchase discounts over cumulative hometown house price growth experience horizons from 1 to 10 years. The figure shows consistently lower purchase discounts after the hometown house price growth across all years of experience horizons. Consistent with Panel A, OOT buyers respond to the recent experience more strongly. The purchase discounts obtained by OOT buyers are lower when the hometown house price growth experience is more recent. Overall, the consistently high transaction prices scaled by the list prices and decreasing hometown house price growth effect by horizons challenge the possibility that the wealth increase drives our results.

Table 4 suggests that when OOT buyers experience high house price growth in their hometown, they tend to buy the properties with a higher list price from among similar houses. However, it does not explain why those buyers end up having high transaction prices. Analyzing the purchase discounts shows that buyers with high hometown house price growth tend to receive low purchase discounts for similar properties. In other words, OOT buyers would pay even higher transaction prices relative to the list prices after the high hometown house price growth. It possibly suggests that the spatial extrapolative belief formed from the past hometown house price growth makes those buyers less aggressive in negotiating final transaction prices with home sellers. Although it would be interesting to explore how spatial extrapolative belief influences a buyer's negotiation, this paper will not delve deeper into it due to its scope.

D. Heterogeneity in Hometown and OOT County Characteristics

There could be a concern that the counties experiencing high house price growth in the past could be fundamentally different from those without a similar high price growth. Specifically, where OOT buyers come from (i.e., hometown) could determine where they purchase new OOT properties and their subsequent transaction prices. The heterogeneity in OOT buyers' hometown characteristics could be correlated with both high past house price growth and high OOT property purchase prices. For example, OOT buyers experiencing a high hometown house price growth could come from a high-income-level hometown area or experience a high-income growth as well. The high-income level and growth could make the OOT buyers pay higher prices for OOT properties. Although the hometown zip code fixed effects in our specification could mitigate the endogenous issue to an extent, it may not fully eliminate other confounding factors associated with time-varying hometown characteristics.

D.1. Geographic Heterogeneity in Purchase Price Changes

Figure 4 presents the hometown- and OOT-state heterogeneity in OOT purchase price changes for a 100% increase in the hometown-zip house price over the past five years. Panel A of Figure 4 shows how buyers from different hometown states would change their OOT purchase prices given the past hometown house price growth. Panel B demonstrates the variation in purchase price changes made by OOT buyers *across OOT states* where the property transactions occurred. The purchase price changes for a 100% increase in the hometown house price are estimated using the main baseline Specification 1, wherein hometown- or OOT-state dummy variables are interacted with the past hometown house price growth.

In Figure 4, Panel A shows that OOT buyers have varying purchase price responses across different hometown states. When faced with a 100% growth in hometown house prices, OOT buyers from Alabama, Nebraska, and North Carolina tend to have the strongest response by increasing their OOT purchase prices the most. On the other hand, OOT buyers from several middle states in the US tend to pay lower average purchase prices for OOT properties than those from other states. For instance, even though people from Texas have relatively higher wealth levels than people from other states, they are less likely to increase their OOT purchase prices after experiencing a growth in hometown house prices.

Panel B in Figure 4 demonstrates the difference across OOT housing markets in the purchase price changes made by OOT buyers following a 100% increase in the hometown-zip house price over the past five years. Unlike Panel A, Panel B reveals that the middle part of the U.S. experienced more significant price increases. However, when hometown house prices increase, some states, such as South Carolina, Arkansas, and West Virginia, are likely to experience lower average purchase prices made by OOT buyers. It may suggest that OOT buyers would be less willing to purchase properties in those OOT states when their hometown housing markets experience house price growth.

In Appendix Figure A.6, we show a similar figure for the county-level geographic heterogeneity in purchase price response by OOT buyers.

D.2. Control for Time-varying Hometown Characteristics

To rule out the time-varying hometown characteristics driving our results, we consider a more constrained specification by adding the hometown-county-year fixed effects. By exploiting only the OOT purchase price variation *within the same hometown county and year*, we exclude the possibility of other unobserved county characteristics driving our results.

Panel A of Table 5 shows that our results are not driven by time-varying hometown county characteristics. In Column 1, we add the interaction of hometown county and transaction year fixed effects. By doing that, we only compare the purchase prices made by OOT buyers from the same hometown county buying OOT properties in the same year. The result shows that, given two OOT buyers from the same hometown county and buying properties in the same year, the buyer with a higher price growth experience will pay a significantly higher price for OOT property. In Column 2, we control for, Log(Hometown HPI)$_{h,t-1}$, the log of the hometown ZHVI house price index one year before the OOT transaction. After experiencing a high house price growth in the hometown, an OOT buyer could become richer through the increased house value. To mitigate the wealth effect, we add the hometown house price index as a proxy for how much an OOT buyer could sell her hometown property right before the OOT purchase transaction. The house price index constructed by Zillow represents the typical home value in a local housing market at a specific time. The effect of past hometown house price growth on OOT property purchase prices is still significant and positive.

In Column 3 of Table 5, we add the interaction of property and hometown county fixed effects to eliminate confounding factors related to the relationship between OOT and hometown counties. For example, homebuyers in two counties may have a close relationship, and the social network could influence information or belief transmission and hence the transaction prices (Bailey et al., 2018). However, our results reveal that the bond between two counties does not drive our results. Comparing two buyers from the same hometown county and buying properties in the same property counties, the one with high price growth experience still pays more than the other without the same experience.

D.3. Zip-code Income Level and Growth and OOT Purchase Price Response

Figure 5 shows, following a 100% increase in the past five-year hometown house price growth, the purchase price response by OOT buyers from hometown zip codes in three income terciles and buying properties in OOT zip codes in three income terciles. We sort OOT buyers into one of three income tercile groups based on the income levels of hometown or OOT zip codes. Then, we analyze the differences in OOT purchase price changes by interacting the income dummy variables with the hometown-zip house price change variable, $Hometown\ \Delta HPI_{h,[t-6,t-1]}$.

Panel A presents the OOT purchase price changes by income terciles of the hometown and OOT zip codes, separately. The figure shows that OOT buyers from low-income hometown zip codes are most responsive to the past hometown house price growth and increase their OOT purchase prices the most. In contrast, OOT buyers from high-income hometown zip codes would not significantly respond to the hometown house price growth in their OOT purchase prices.

When analyzing the difference in the OOT buyers' purchase price changes by income levels of *OOT zip codes*, we find a very similar pattern. Following a 100% increase in the hometown house price growth, the OOT buyers' purchase prices will increase the most at the low-income OOT housing markets and will increase the least at the high-income OOT markets.

In Panel B, we examine the purchase price response by hometown-OOT-income pairs. The figure suggests that OOT buyers coming from low-income hometown zip codes and buying properties at low-income OOT zip codes tend to increase their purchase price the most after the hometown house price increase. Within the same income tercile of *hometown zip codes*, OOT buyers exhibit decreasing purchase price sensitivity to hometown house price growth as the OOT-zip income level increases. Within the same income tercile of *OOT zip codes*, the buyers from hometowns in a lower income tercile tend to increase their purchase prices more than those from higher-income hometowns. More strikingly, OOT buyers coming from high-income hometown zip codes and buying properties in high-income OOT zip codes will pay significantly low purchase prices after the hometown house price growth.

Figure 5 reveals the heterogeneity in purchase price response across different income levels of hometown and OOT zip codes. In contrast to the wealth effect, which predicts a larger purchase price increase by high-income buyers than by low-income buyers, we find that OOT buyers from low-income hometown zip codes and buying properties at low-income OOT zip codes tend to increase their OOT purchase prices the most.

In Panel B of Table 5, we include the hometown-zip income levels and growth as additional control variables. The effect of hometown house price growth on OOT purchase prices remains robust after including the income variables. Column 1 shows the baseline regression result using the sample with non-missing income level data, while Column 2 controls for the hometown-zip income level. Comparing Columns 1 and 2 suggests that the hometown-zip income does not change the coefficient on hometown house price growth much. Similarly, Column 3 shows the baseline regression result using the sample with non-missing income growth data, while Column 4 controls for the hometown-zip income growth over the past five years. The results are very similar. Panel B of Table 5 suggests that either hometown income level or growth can explain our findings.

Overall, Table 5 suggests that experiencing high hometown house price growth will make OOT buyers significantly pay more than other OOT buyers without the same experience, a finding not driven by the fundamental economic characteristics of counties or the possible bond among them.

D.4. Heterogeneity by Other Local Economic Characteristics

We further show the heterogeneity in purchase price responses across the groups formed by other local economic characteristics including labor force participation rate (LFR), unemployment rate (UR), house price index (HPI), and social connectedness index (SCI).

In the Appendix, Figure A.8 shows how hometown- and OOT-county labor force participation rates (LFR) correlate with the purchase price responses by OOT buyers. Panel A assigns the OOT buyers into one of three groups based on the LFR of the hometown or OOT counties. It shows that OOT buyers from low LFR hometown counties tend to be more responsive in purchase prices than those from high LFR hometown counties, following the same 100% increase in the past hometown house price growth. However, we do not observe a linear relationship between buyers's purchase prices and the LFR of OOT counties. Panel B shows that the largest increase in the purchase price occurs for the buyers coming from low-LFR hometowns and buying properties at high-LFR hometowns (i.e., low-to-high-LFR buyers). Other groups of buyers, such as low-to-low-LFR and medium-to-low-LFR buyers also have large responses in OOT purchase prices after the hometown house price growth.

Similarly, Panel A of Figure A.9 in the Appendix appears to suggest that OOT buyers from low unemployment rate (UR) hometown counties tend to increase their purchase prices less than those from high UR hometown counties, following the same 100% increase in the past hometown house price growth. There is not much difference in purchase price changes across buyers buying properties in different UR terciles of OOT counties. Panel B shows that the largest increase in the purchase price occurs for the buyers coming from high-UR hometowns and buying properties at medium-UR hometowns (i.e., high-to-medium-UR buyers). OOT buyers from low-UR hometowns seem to increase purchase prices relatively less than buyers in other groups of hometown-OOT-UR pairs.

Table A.2) shows the results of our regression analysis that includes the hometown UR, the five-year growth in UR, LFR, and the growth in LFR as control variables in the baseline specifications. Our analysis reveals that when we control for the levels and growth of economic fundamentals, we find a consistent and significant increase in payment after the hometown house price increase.

Figure A.10 analyzes the changes in purchase prices based on the house price index (HPI) for hometown and out-of-town (OOT) zip codes. Panel A shows that when hometown house prices have increased by 100% in the last five years, OOT buyers from low-HPI hometown zip codes tend to increase their purchase prices more than buyers from high-HPI hometown zip codes. Panel B reveals that buyers from high-HPI hometowns who are purchasing properties in high-HPI OOT markets (i.e., high-to-high-HPI buyers) do not significantly increase their purchase prices following a 100% increase in hometown house prices. Among buyers from the same low-HPI tercile of hometown zip codes, those going to OOT zip codes with higher HPIs tend to increase their purchase prices more than those going to lower-HPI markets. These findings challenge the explanation of the wealth effect.

In Figure A.11, we investigate the correlation between the OOT purchase prices and social connectedness between hometown and out-of-town (OOT) zip codes. We use the social connectedness index (SCI) developed by Meta (Facebook) Company to measure the connection between hometown and OOT housing markets. We then classify OOT buyers into five quintile groups based on SCI between hometown and OOT zip codes. A higher SCI indicates a stronger connection between the two zip codes.

Our findings show that there is not a significant difference in purchase price responses for buyers with SCI Quintiles 1 to 4, following a 100% increase in the hometown house price growth. However, buyers in the SCI Quintile 5 group tend to react differently from buyers in other groups. The result suggests that when there is a strong connection between hometown and OOT zip codes, the OOT buyers tend to respond more strongly by increasing their purchase prices even further than otherwise, following the same hometown house price growth.

The figure indicates that information asymmetry is less likely to be the reason behind the positive relationship between OOT purchase prices and hometown house price growth. If information asymmetry caused high OOT payments, we should have observed higher payments when the connection between hometown and OOT housing markets is weak. However, we observed the opposite. It is possible that when two counties are very similar and hence have a strong connection, buyers tend to rely more on their hometown house price growth experience to form the OOT house price beliefs, which influence the final transaction prices more.

E. Separate Wealth Effect through Three Types of Buyers

The high past hometown house price growth may increase OOT buyers' wealth through hometown property holdings. People could have a concern that the increase in wealth may explain why OOT buyers are willing to pay a premium for properties over those who have not experienced high hometown house price growth. This section will separate the extrapolation effect from the wealth effect.

E.1. Purchase Price Differences among Renter, Migrator, and Second-home Buyer

To isolate the wealth effect, we first investigate OOT buyers' property holdings in their hometowns, identified through the mailing addresses provided on their OOT deeds. Based on the ownership status of hometown properties and the timing of any sale of such properties, we categorize OOT buyers into three distinct groups: renters, migrators, and second-home (SH) buyers.

Renters are those with no matching deed record in their hometown, suggesting they were renting their residence when they purchased OOT properties. Migrators and SH buyers, on the other hand, are successfully linked to deeds based on their mailing addresses, indicating their ownership of properties in their hometowns. In our analysis, migrators are defined as those who sell their hometown properties within two years of their OOT property purchase. In contrast, SH buyers maintain ownership of their hometown properties for at least two years after purchasing OOT properties. The detailed methodologies for identifying the ownership of hometown properties for OOT buyers and their categorization are explained in Sections II.G and II.G.1.

Table 6 illustrates how the three types of OOT buyers respond to the same hometown house price growth differently in OOT purchase prices. With our baseline specification, Columns 1, 2, and 3 examine the OOT property purchase price response to past five-year hometown house price growth separately for each type of renter, migrator, and SH buyer, respectively. Column 4 puts all three types of OOT buyers together and analyzes how they respond differently to the hometown house price experience when paying for OOT properties.

Table 6 shows that renters have the smallest but significant sensitivity to the past hometown house price growth, while Migrators have a larger sensitivity and SH homebuyers have the largest sensitivity. Column 4 suggests that a renter who has experienced a 50% increase in hometown house price over the past five years, on average, pays a premium of 1.25 percentage points[5] more than renters without the price increase. The interaction terms in Column 4 suggest that the Migrators and SH buyers who experienced a similar hometown house price increase of 50% pay premiums of 1.85 and 2.55 percentage points, respectively[6].

Figure 6 plots the linear combination of the estimated coefficients in Column 4 of Table 6. It visually presents that renters would pay a higher purchase price after the hometown house price growth.

Table A.3 in the Appendix reveals that the characteristics of purchased OOT properties cannot explain our findings. Both with and without controlling for the characteristics, there is a very robust higher payment driven by the hometown house price growth.

This difference in purchase price reaction among renters, migrators, and SH buyers could largely be attributed to the wealth effect. As we assume that the renters without owning properties are less likely to experience wealth increase from hometown house price growth, those estimated interaction coefficients could help us disentangle the extrapolative belief effect from the wealth effect. Overall, even after considering the wealth effect, we continue to observe a significant influence of past hometown house price growth on the purchase prices of OOT properties.

E.2. Control for Wealth Increase from Hometown Properties

Given our ability to link OOT buyers to their hometown properties, we can efficiently account for the impact of wealth by considering the purchase price and the approximate sale price of their hometown properties. Furthermore, we can gain a more precise insight into OOT buyers' exposure to hometown house price growth experiences by calculating their residence length, determined by the deed mailing addresses. The methodology for measuring and cleaning the residence length is discussed in Section II.G.2.

To focus on the impact of the past five-year hometown house price growth on OOT buyers' purchasing

[5] $0.025 \times 0.5 = 0.0125$

[6] $(0.025 + 0.012) \times 0.5 = 0.0185$ for migrators and analogous calculation for SH buyers

behavior, we restrict the sample to OOT buyers residing in their hometowns for a minimum of five years. This criterion ensures that the OOT buyers in our sample have truly experienced at least five years of house price growth in their hometowns.

In Table 7, we introduce the variables of residence length, the logarithm of the purchase price of hometown properties, and the logarithm of the hometown house price index one year prior to the OOT property purchase. The purchase prices of hometown properties indicate the OOT buyers' wealth level, and our findings highlight a positive correlation between property purchase prices in hometowns and OOTs. It suggests that wealthier OOT buyers are more likely to purchase higher-priced properties. Moreover, the zip-level house price index in the hometown approximates the potential sale price of an OOT buyer's hometown property if the buyer decides to sell it before buying an OOT property. Therefore, by accounting for the purchase price and the projected sale price of a hometown property, we can control for any wealth increase tied to the hometown property. Column 2 of Table 7 suggests that OOT buyers, having experienced a 50% increase in hometown house price growth, tend to overpay by approximately 1.65 percentage points compared to those without such an experience.

Research in the experience effect finds that individuals with shorter experience duration are more influenced by recent experiences than those with longer experiences (Malmendier and Nagel, 2016; Malmendier, 2021a,b). To verify the extrapolative belief channel driving the overpayment of experienced OOT buyers, we examine the purchase behavior of OOT buyers with varying residence lengths. As shown in Column 3 of Table 7, we categorize OOT buyers based on the length of their hometown residence and create dummy variables for different groups. For instance, the dummy variable "Living Years [7, 8]" equals one if an OOT buyer has been living in the hometown house for seven to eight years at the time of the OOT property purchase; otherwise zero. Similar definitions are applied to other residence length dummy variables. We then examine the interaction of these groups with the five-year hometown house price growth. The reference group is OOT buyers with five to six years of residence.

The results align with the experience effect framework: as the length of residence increases, the influence of recent five-year hometown house price growth on OOT property transaction prices diminishes. For example, Column 3 of Table 7 indicates that OOT buyers who have resided in their hometown for five to six years are more likely to overpay by 3.1 percentage points if they encounter a 50% increase in their hometown house prices compared to those without such experiences. A comparison of the coefficients on interaction terms suggests that, as residence length increases, the impact of recent five-year hometown house price growth on OOT property transaction prices diminishes.

Figure 7 visually presents these findings, displaying the linear combination of coefficients on hometown house price growth, Hometown $\Delta HPI_{h,[t-6,t-1]}$, and the interaction terms of residence length and hometown house price growth. The combination values indicate the degree of overpayment by an OOT buyer in a specific residence-length group who has experienced a 100% (1 unit) increase in hometown house price growth over the past five years compared to those who have not. The figure suggests that the past five-year hometown house price growth significantly influences the OOT property purchase prices of buyers who have lived in their hometowns for ten years or less. For those residing for more than ten years, their OOT property purchase price is less affected by their hometown house price growth experiences.

Importantly, Figure 7 reveals that as the residence length of an OOT buyer in the hometown increases, the influence of the most recent five-year hometown house price growth on the purchase price of her OOT property diminishes. This finding aligns with the experience effect framework (Malmendier, 2021a,b), lending credence to our extrapolative belief explanation.

In conclusion, our results suggest that controlling for the wealth effect, OOT buyers extrapolate from their past hometown house price growth when purchasing OOT properties. More recent hometown house price growth experiences are more influential for OOT buyers with shorter residence durations (i.e., less experience) in hometowns.

F. Extrapolaitve Belief from House Price Growth

In this section, we use the American Community Survey to gauge household expectations of their property values, investigating whether their expectations are influenced by previous house price growth experiences. We subsequently assess the extent of this extrapolation at a county level, establishing a connection to the purchasing behavior of Out-of-town (OOT) buyers. Specifically, we explore whether OOT buyers originating from areas characterized by high extrapolation levels are more sensitive to past hometown house price growth when purchasing OOT properties.

F.1. Individuals Extrapolate from Past House Price Growth

Do households extrapolate from their past house price growth experiences when forming house price beliefs? Even though some previous literature has documented the extrapolative belief and experience effect among households, we first validate the finding through American Community Survey (ACS) data.

We elicit the households' beliefs of their house values from ACS data. U.S. Census Bureau, which runs the survey program, asks interviewees how much they think their house would be sold for if it is sold at the interview time, as shown in Figure A.12. We get households' price beliefs from their survey answers as the dependent variable. Then, we control for the concurrent ZHVI house price index as the rational estimate benchmark for local house prices. In addition, we control for property, demographic, socioeconomic, and county characteristics as those characteristics are highly correlated with their house price beliefs and house price growth experience. In detail, we include age, gender, marital status, education, race, employment status, and family income, along with the total number of rooms and bedrooms in the house and the year it was built. The county characteristics included are the same as Table 5. We add household county and year fixed effects to control for invariant county characteristics and time trends.

Table 8 shows the past five-year house price growth experiences have a significant and positive impact on the expected house values of households, controlling for a set of characteristics. Specifically, Column 1 adds the year and county fixed effects to absorb any time-invariant characteristics that could also impact their expected house values through channels other than extrapolation. Column 2 adds the time-varying county characteristics, same as Table 5. Columns 3 and 4 add the house and demographic characteristics, respectively. We have discussed the detailed characteristics variables in Section III.B.

We focus on the results of Column 4 as it is our preferred specification. The results suggest that, on average, households experiencing a one standard deviation (41%) increase in the past local house price growth would expect a higher house value by approximately 4.5 percentage points. We use the equal sampling weight in our analysis. We observe similar and robust results with different sampling weights, as shown in Table A.4 in the Appendix.

We analyze how house price beliefs are affected by experiences in different price growth experience horizons. Over varying price growth horizons measured in years, Figure 8 illustrates the varying sensitivity of belief to past house price growth (extrapolation beta β_1). The figure implies that the sensitivity decreases as the experience horizon increases. This pattern is consistent with the recency attribute of experience effect (Malmendier, 2021a,b) and the decaying weight on past house price growth from extrapolation framework (Barberis et al., 2018).

F.2. Demographic Heterogeneity in Extrapolative Belief

One feature of the experience effect is that young households, relative to old households, are more influenced by their recent experiences and update their expectation more strongly (Malmendier and Nagel, 2016). To get more evidence to support the extrapolative belief channel, we interact the county house price growth with age groups of households with a specification similar to Column 4 of Table 8. Following Malmendier and Nagel (2016), we classify households into three age groups: less than 40 years old, between 40 to 60 years old, and over 60 years old. The base group is the youngest households with ages less than 40 years old.

Panel A of Figure 9 confirms our extrapolation belief explanation. The figure shows that young individuals, relative to the old, are more sensitive to and extrapolate more from past price growth when forming house price beliefs. As age increases, the level of extrapolation (i.e., the belief sensitivity to past house price growth) decreases. Panel B shows that single men extrapolate the most, followed by single women. Married men and women extrapolate the least and do not significantly differ from each other in extrapolation. Panel C suggests that among racial groups, Asians do not exhibit extrapolative beliefs. Black and American Indian households show a stronger extrapolation tendency than White households. Panel D reveals that the higher the education of members of a household, the lower the extrapolation level. Households without a bachelor's degree extrapolate the most. Additionally, households holding a bachelor's degree extrapolate less than no-degree households but more than those holding a master's or doctorate degree. In Panel E, we sort households into five income quintile groups each year based on income level. Households in a higher income group extrapolate less than those in the lower income group.

Why do people extrapolate? Why do people from different areas extrapolate differently? Although this paper does not explore what determines the extrapolation, Figure 9 shows that extrapolation beliefs vary by the demographics of households. It would be interesting to dig into the factors that determine demographic heterogeneity in extrapolation.

F.3. OOT Buyers from High Extrapolation Hometown More Responsive to Price Growth

In the previous section, we have established that past house price growth experiences shape households' expectations of property values. In the current section, we further investigate whether OOT buyers act upon their extrapolative beliefs by analyzing the purchase prices of OOT buyers from areas with varying degrees of extrapolation.

First, for each county in ACS, we run the same specification 3 as Table 8, omitting year and county fixed effects. Then, we collect the beta coefficient, $\beta_{c,1}$, on the past five-year county house price growth. A high beta coefficient suggests a high level of extrapolation among individuals within that county. We refer to these beta coefficients as "Extrapolation Betas."

Second, we integrate these extrapolation betas into our OOT housing transaction data by using the hometown county FIPS codes. We then divide the OOT transactions into quintile groups based on hometown "extrapolation beta," with the first and fifth quintiles representing the lowest and highest levels of hometown extrapolation, respectively. In our regression analyses, we use a similar specification as in Table 2, but interact the quintile group dummies of hometown extrapolation beta with the past hometown-zip house price growth. The quintile 1 group serves as the reference group.

Figure 10 reveals that, for a given increase in hometown house price over the past five years, OOT buyers from hometowns characterized by high extrapolation levels tend to pay more than those from hometowns with low extrapolation. OOT buyers from hometowns in the lowest two extrapolation beta quintile groups do not significantly more, given one unit increase in the past five-year house price. As the hometown extrapolation beta increases, people become more sensitive to the past hometown price growth in their property purchase prices. The coefficient on the highest extrapolation beta group (i.e., quintile 5) is around 0.07, which suggests that one standard deviation (35%) increase in the house price in the sample will make individuals from the highest extrapolation group of hometowns pay approximately 2.5 percentage points.

In summary, Figure 10 suggests that, when buying properties in OOT markets, OOT buyers act on their extrapolative beliefs formed from hometown price experiences. The buyers from high-extrapolation areas are more likely to extrapolate and pay more than those from low-extrapolation areas.

F.4. IV Estimation of Extrapolation Effect

In this part, we reestimate the extrapolation effect on house purchase prices through our sensitivity instrumental variable (IV) and the 2SLS method. Basically, we create our sensitivity IV by multiplying the estimated hometown MSA differences in extrapolation level $\widehat{\beta}_m$ and past five-year state house price growth $z_{m,s,t} = \widehat{\beta}_m \times$ State $\Delta HPI_{s,[t-6,t-1]}$. We have discussed in detail our sensitivity IV in Section III.B.

First, we examine whether our sensitivity IV satisfies the relevant condition by running the first-stage regression. Column 1 in Table 9 suggests a significantly positive correlation between our sensitivity IV and the hometown zip house price growth in the past five years.

Next, we use the sensitivity IV to instrument for the past five-year hometown-zip house price growth and rerun the same regressions as in Tables 2 and 6. Column 2 in Table 9 suggests that experiencing high hometown house price growth leads to significantly high purchase prices of new properties. One standard deviation (35%) increase in the past five-year house price growth leads to approximately two percentage points higher purchase prices of new OOT properties.

Column 3 in Table 9 explores how the three types of homebuyers react to hometown house price growth differently by interacting the dummy variables of three homebuyer types with hometown house price growth. The result is similar to Column 2. More interestingly, the tiny and insignificant coefficients on the two interaction terms suggest that migrants and second-home buyers do not react differently from renters, given the same past hometown house price growth. Considering that our sensitivity IV should only capture the extrapolative component from past hometown house price experiences NOT any component related to wealth increases caused by past house price growth, Column 3 seems to confirm that our sensitivity IV is orthogonal to wealth increase. Using the exogenous variation in extrapolation sensitivity to past house price growth, Column 3 implies that all three types of homebuyers have similar and significant responses to past hometown price growth when paying new OOT properties.

Overall, Table 9 uses the sensitivity IV, which is orthogonal to wealth increase, with 2SLS estimation and shows a robust extrapolation effect on purchase prices of new OOT properties.

V. Conclusion

People form their economic expectations by extrapolating from past experiences with the target itself or other related economic outcomes. Our paper is the first to uncover that homebuyers extrapolate across geographical locations. We demonstrate this spatial extrapolation by exploiting the scenario where homebuyers purchase new properties in towns different from their previous living regions. Our findings show that when two buyers purchase the same *out-of-town* house, the buyer who has experienced high house price growth *in their hometowns* tends to pay a higher price than the other buyer without the same hometown experiences.

The research examines approximately 3 million housing transactions conducted by OOT buyers in the United States from 2002 to 2017. Our findings show that OOT buyers who experienced 50% increase in hometown house price growth over the past five years tend to pay about two percentage points more for OOT properties than those without such experiences. This overpayment persists even after accounting for the *OOT* house market timing fixed effects and time-varying *hometown* county or property characteristics. Analyzing OOT buyers' realized returns reveals that those who have experienced an increase in the past five-year hometown house prices earn lower realized returns than other OOT buyers.

We develop two empirical identification strategies to rule out the wealth effect and other potential channels. First, we perform a series of by-homebuyer-type analyses to examine the purchase price differences among three types of homebuyers: renters, migrators, and second-home (SH) buyers. Second, we construct a sensitivity instrumental variable (IV) using the house price belief from American Community Survey data. We exploit exogenous variation in the sensitivity of house price beliefs to past five-year *state-level* house price growth across Metropolitan Statistical Areas (MSAs) within the same state. All the results show that OOT buyers extrapolate across geographic locations and pay higher prices for new OOT properties after experiencing high house price growth in hometowns.

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Figure 2. OOT Property Purchase Prices as Function of Hometown House Price Changes

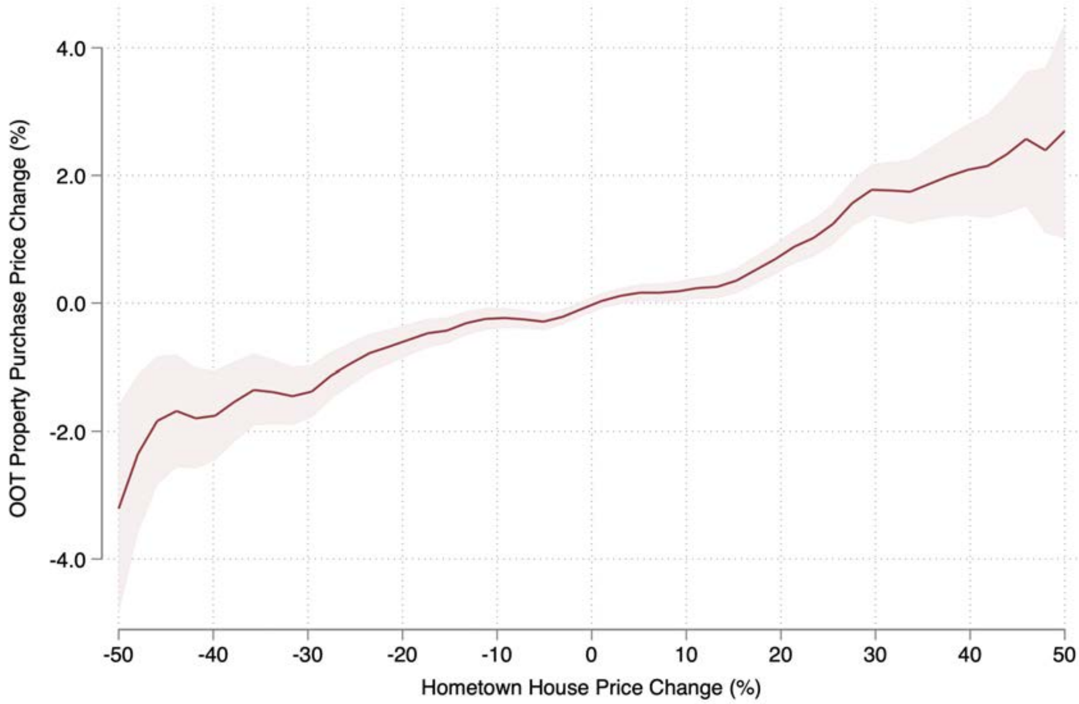


Figure 2 shows a non-linear relationship between purchase price changes and hometown house price changes experienced by OOT homebuyers over the past five years. The non-linear relationship is estimated using the local linear regression with the epanechnikov kernel. To create this plot, we first obtain the normalized log of OOT property purchase prices, which are the residuals from regressing the log of the OOT purchase prices on Property Zip $\times$ Transaction Year-Month (YM) fixed effects (FE) and Hometown Zip FE, similar to Column 5 on Table 2. Then, we obtain the normalized hometown house price growth over the past five years by running the same regression but replacing the dependent variable with $Hometown\ \Delta HPI_{h,[t-6,t-1]}$ and collecting the residuals. The shaded area in the plot represents the 95% confidence interval.

Figure 3. Sensitivity to Hometown House Price Growth over Experience Horizons

Panel A: Purchase Price

Panel B: Purchase Discount

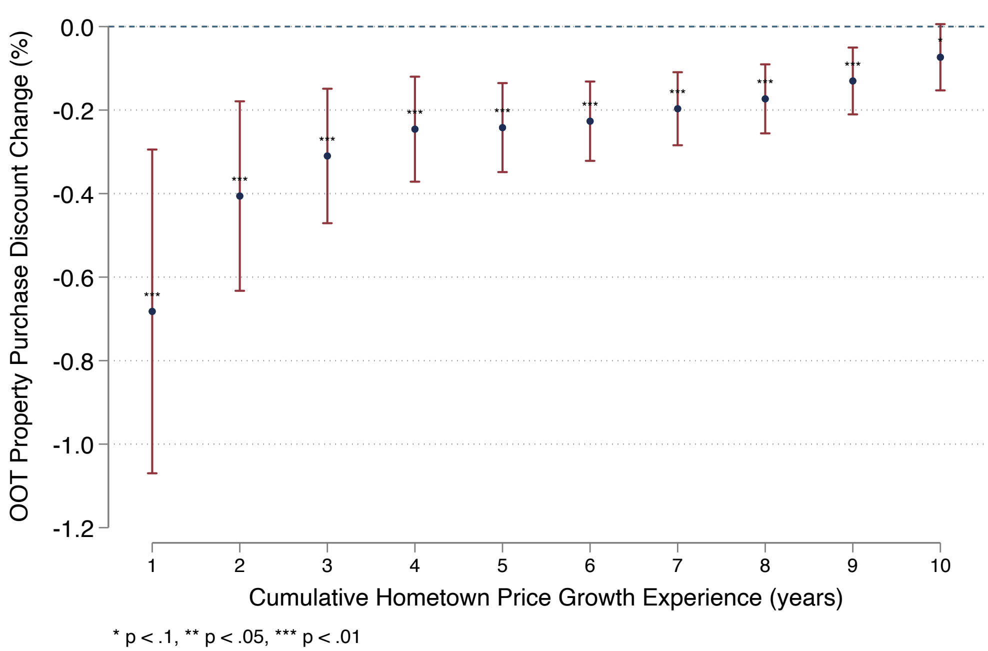
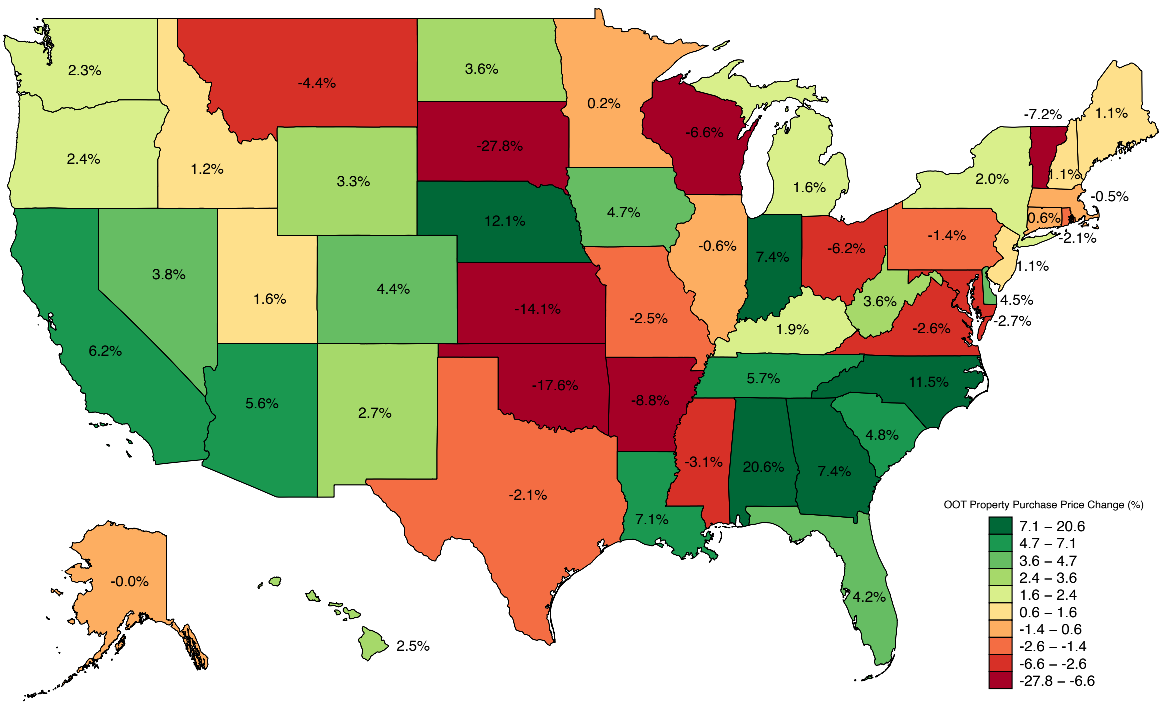


Figure 3 presents the effects of a 100% increase in the hometown house price within the experience horizons from 1 to 10 years on OOT buyers' purchase prices and purchase discounts. Panel A presents the effect on OOT purchase prices, while Panel B shows the effect on purchase discounts. *Purchase Discount* is measured as (*Purchase List Price* - *Transaction Price*) / *Transaction Price* $\times$ 100. The y-axis in the two panels shows the estimated changes in purchase prices or purchase discounts following a 100% increase in hometown house prices, i.e., sensitivity to hometown house price growth. We estimate the sensitivity using Specification 1. In this specification, we regress the log of OOT purchase prices or purchase discounts on the cumulative changes in hometown house prices within the indicated horizon. The hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects are included in the specification. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 4. Geographic Heterogeneity in OOT Purchase Price Changes for a 100% Hometown Zip House Price Increase

Panel A: OOT Purchase Price Changes by Hometown States



Panel B: OOT Purchase Price Changes by OOT States

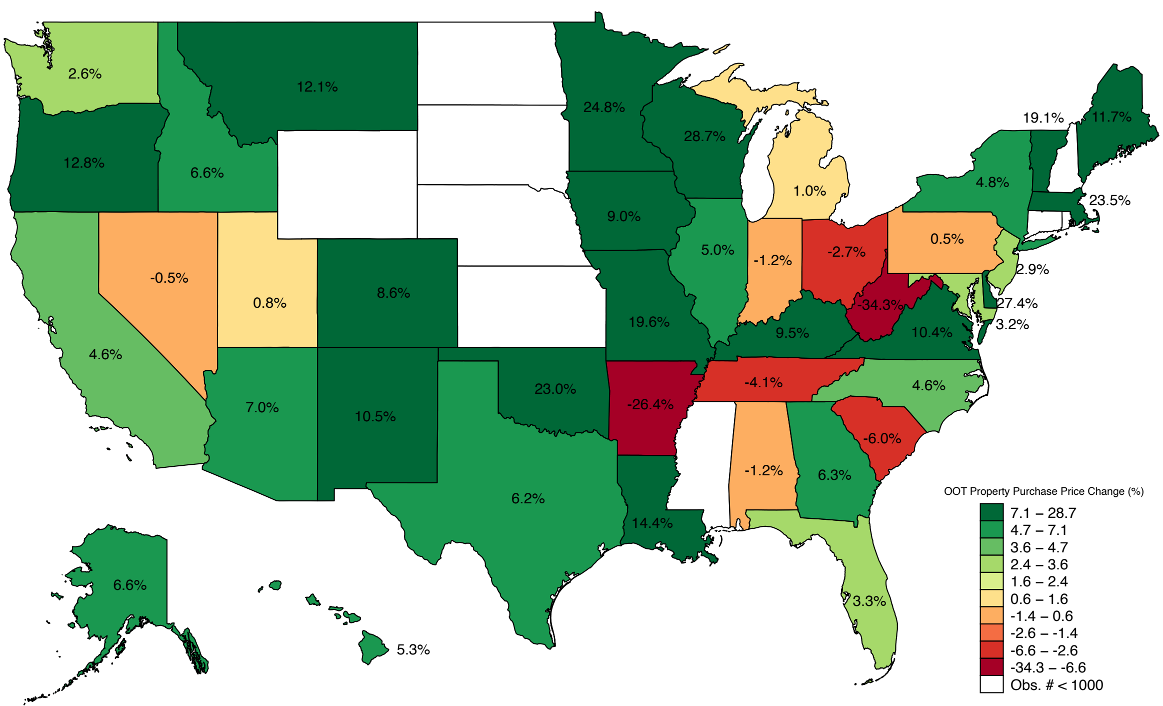
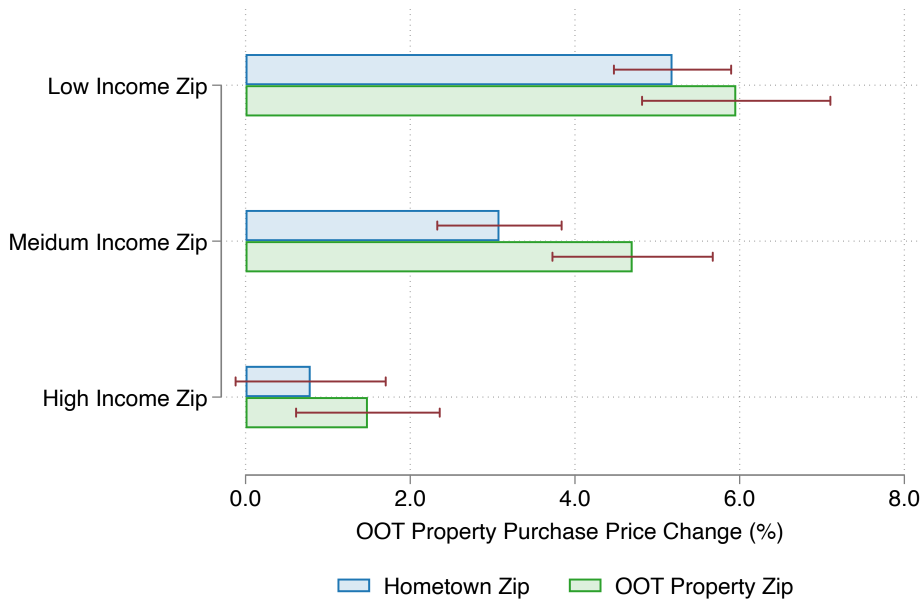


Figure 4 presents the hometown- and OOT-state heterogeneity in OOT purchase price changes following a 100% increase in the hometown-zip house price over the past five years. Panel A shows the differences *across hometown states* in the OOT purchase price changes following the hometown house price growth. Panel B demonstrates the heterogeneity in purchase price changes *across OOT states* where OOT buyers made the transactions. The purchase price changes for a 100% increase in the hometown house price are estimated using the main baseline Specification 1, wherein hometown- or OOT-state dummy variables are interacted with the hometown-zip house price change variable, *Hometown* $\Delta HPI_{h,[t-6,t-1]}$.

Figure 5. OOT Purchase Price Changes by Hometown- and OOT-Zip Income Level

Panel A: By Income Terciles of Hometown and OOT Property Zip



Panel B: By Hometown-OOT-Property-Zip Income Pairs

Figure 5 illustrates the effect of a 100% increase in hometown house prices on the OOT purchase prices by buyers in different income terciles of hometown- and OOT-zip codes. Panel A presents the purchase price changes by the income terciles of hometown and OOT property zip codes, separately. Panel B presents the purchase price changes by hometown-OOT-zip income pairs. In the specification, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 6. OOT Purchase Price Changes by Renters, Migrants, and Second-home (SH) Buyers

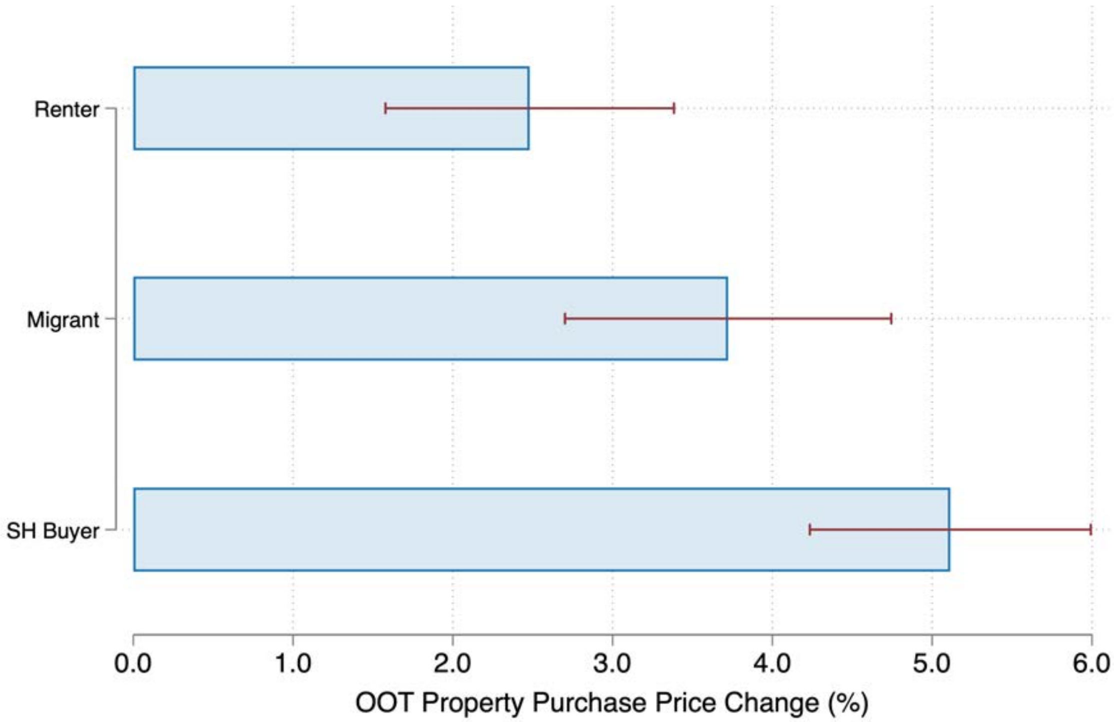


Figure 6 presents the OOT purchase price changes for renters, migrant homeowners, and second-home (SH) buyers, following a 100% increase in the hometown house price over the last five years. The bar values (i.e., purchase price changes) are estimated by linearly combining the coefficients on the interaction terms of the buyer-type dummies with the hometown-zip house price change, *Hometown* $\Delta HPI_{h,[t-6,t-1]}$, and the coefficient on *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ in Column 3 of Table 6. The detailed methodologies for identifying the three types of OOT buyers are described in Section II.G.1. Standard errors are clustered by hometown zip code.

Figure 7. OOT Purchase Price Changes by Living Length in the Hometown

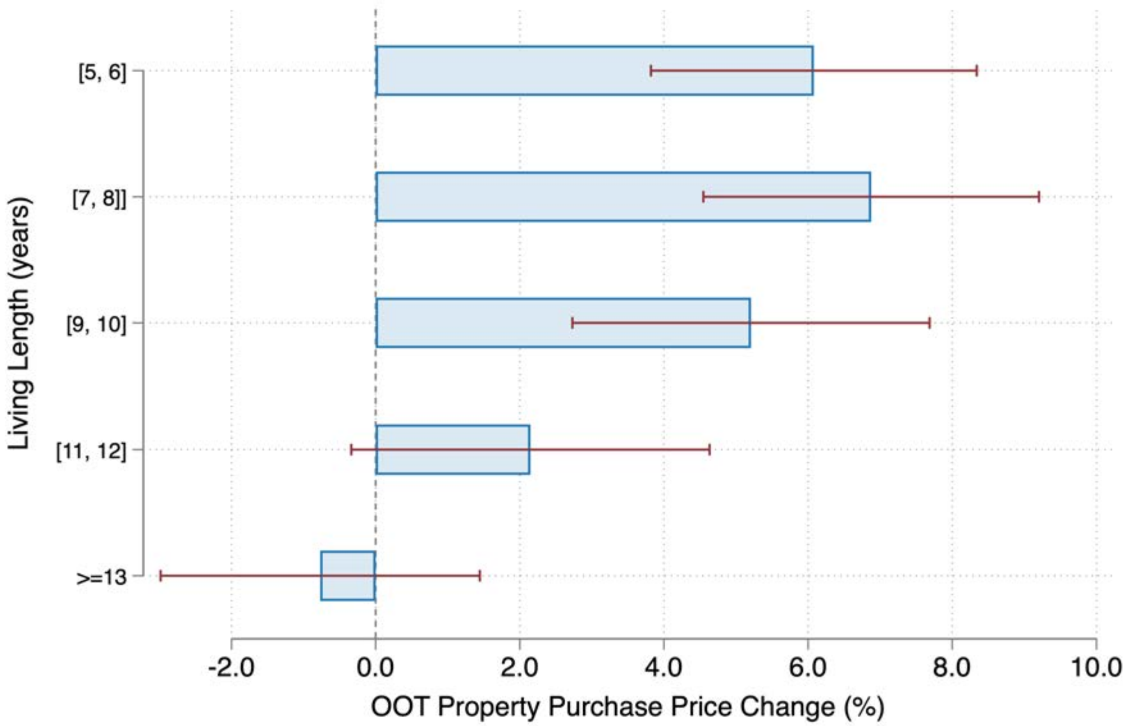


Figure 7 presents the effect of a 100% increase in hometown house price on OOT purchase price by migrant homeowners and second-home (SH) buyers, *controlling for the wealth increase from the hometown property and living length in the hometown property*. The bar values (i.e., purchase price changes) are estimated by the linear combination of coefficients on the hometown house price change, *Hometown* $\Delta HPI_{h,[t-6,t-1]}$, and the interaction terms of residence length and *Hometown* $\Delta HPI_{h,[t-6,t-1]}$. The estimated coefficients can be calculated from Column 3 of Table 7. Standard errors are clustered by hometown zip.

Figure 8. Changes in Expected House Values by Price Growth Experience Horizons

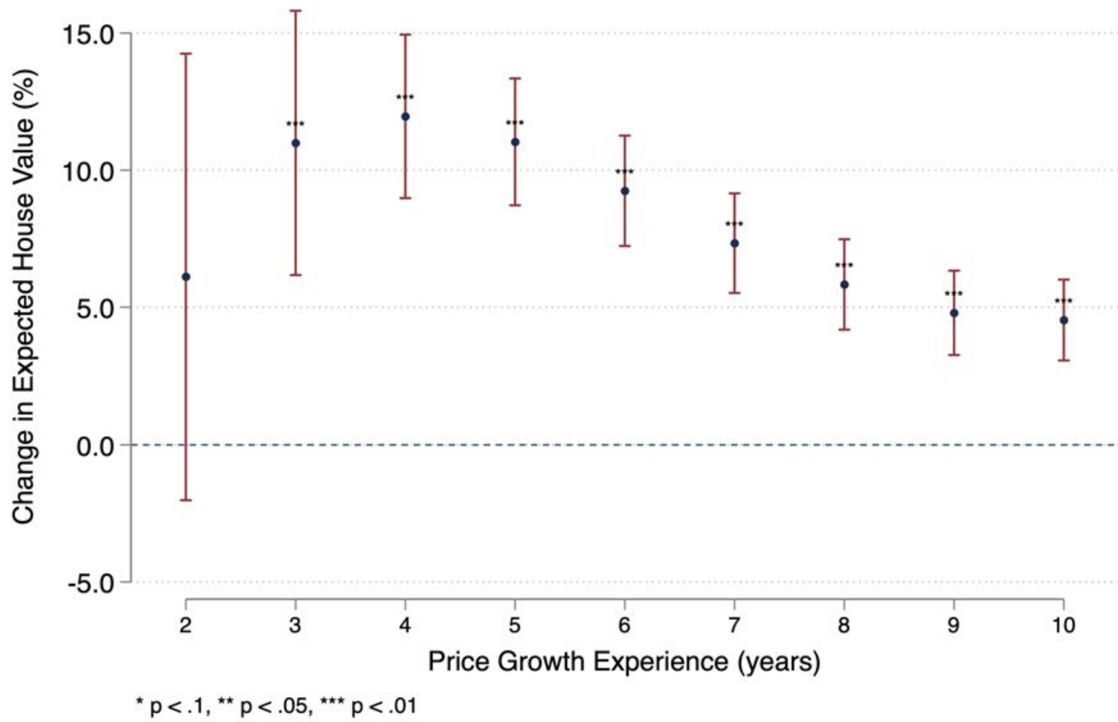
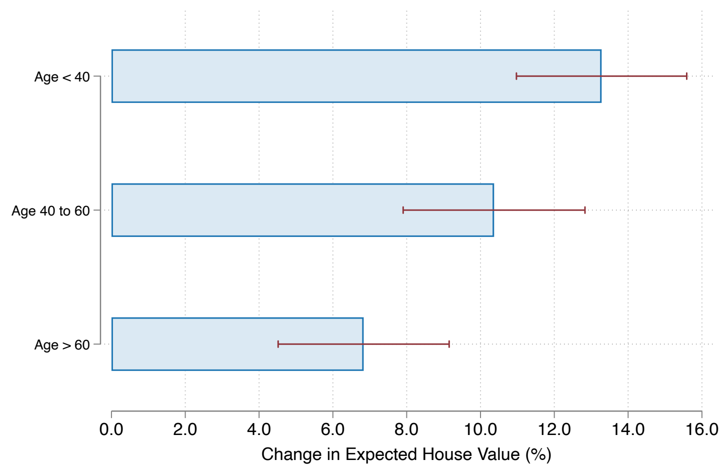


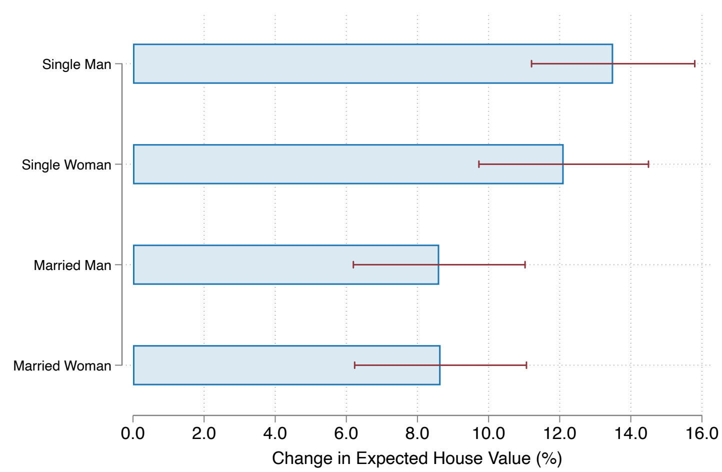
Figure 8 presents the changes in expected house values of households, following a 100% increase in the county house price over the last five years. The expected house value changes correspond to the extrapolation beta estimated through Specification 3 and reflect how much households extrapolate from the past county house price growth when forming house price beliefs. Standard errors are clustered by county FIPS codes. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 9. Extrapolation Heterogeneity by Demographics

Panal A: Age



Panal B: Gender and Marital Status



Panal C: Race

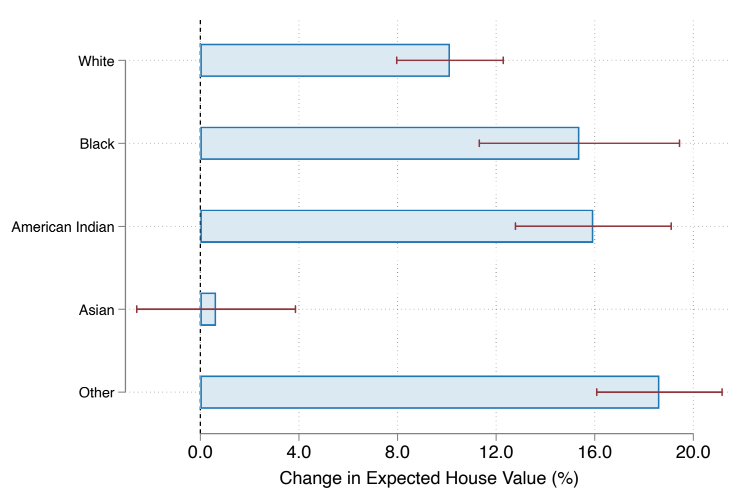
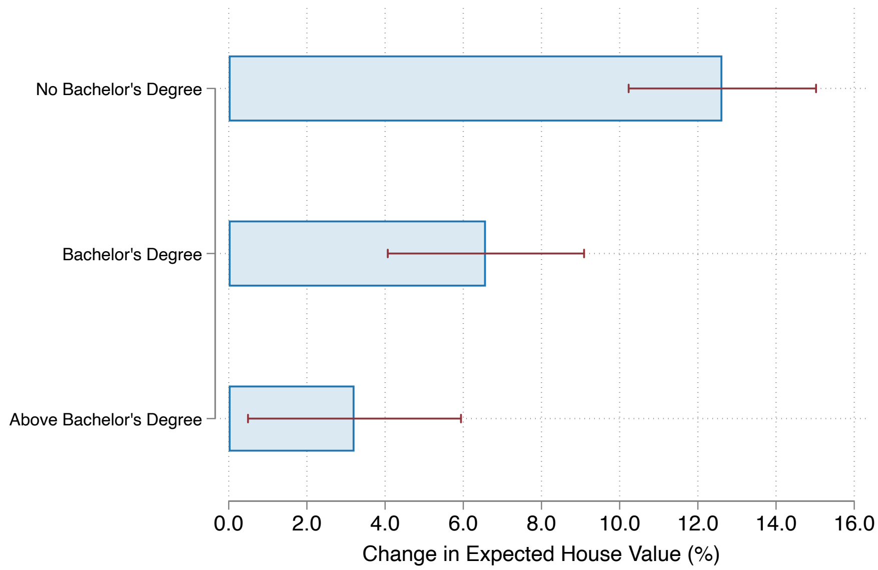


Figure 9. Extrapolation Heterogeneity by Demographics

Panal D: Education



Panal E: Income

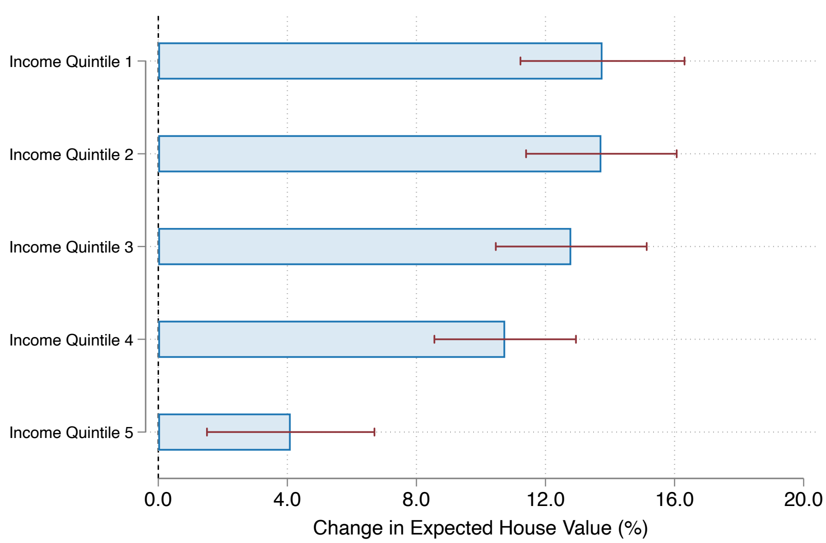


Figure 9 presents the changes in expected house values of households across different demographic groups, following a 100% increase in the county house price over the last five years. The demographic groups are indicated in panel titles. To obtain the results, we first assign the households into groups based on specific demographic characteristics. Then, we estimate Specification 3 and interact the county house price growth, *County* $\Delta HPI_{c,[t-6,t-1]}$, with the demographic group dummy variables. The bar values (i.e., purchase price changes) are estimated by the linear combination of the coefficients on the county house price change, *County* $\Delta HPI_{c,[t-6,t-1]}$, and the coefficients on the interaction terms of the demographic group dummies and *County* $\Delta HPI_{c,[t-6,t-1]}$. Standard errors are clustered by county FIPS codes.

Figure 10. Changes in OOT Purchase Prices by Hometown Extrapolation Beta Quintiles

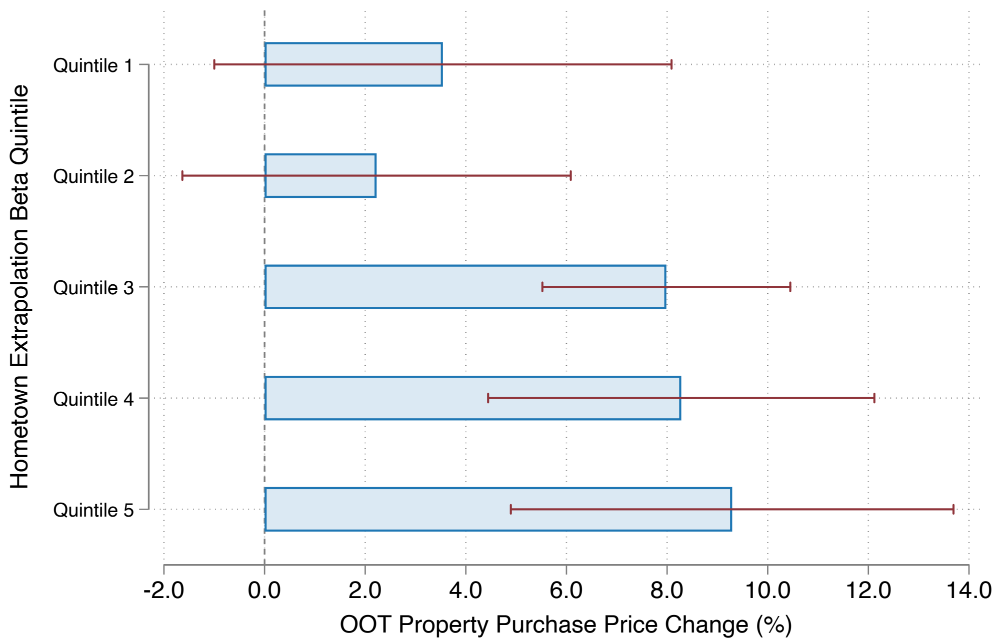


Figure 10 presents the effect of a 100% increase in the hometown house price on the OOT purchase price changes by buyers from hometowns with different extrapolation levels (i.e., extrapolation beta). First, we estimate the extrapolation beta for each county using Specification 3. The extrapolation beta represents the extent people in a county extrapolate from the past county-level house price growth when forming house price beliefs. Then, we link the extrapolation beta to the hometown counties of OOT buyers. Finally, we sort OOT buyers into five quintile groups based on the hometown extrapolation beta, with a higher quintile representing a higher hometown extrapolation level. We estimate the OOT purchase price changes by interacting hometown extrapolation beta quintile dummy variables with *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ using Specification 1. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 1.Summary Statistics

Panel A: Main Sample of OOT Transactions

	N	Mean	SD	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Transaction Price	2,644,929	275,809	675,531	43,000	105,600	181,000	315,000	752,500
Hometown $\Delta HPI_{h,[t-6,t-1]}$	2,644,929	0.23	0.35	-0.25	-0.02	0.18	0.43	0.89
OOT-Hometown Distance (in 100 miles)	2,644,918	7.29	6.79	0.72	1.58	5.71	10.69	21.49

Panel B: Hometown County Characteristics

	N	Mean	SD	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
County Population	2,424,626	1,480,074	2,269,013	59,023	278,227	722,068	1,491,967	9,705,913
County Median Age	2,424,626	37	4	32	35	37	39	44
County Median Income	2,424,612	58,826	15,894	38,817	47,128	55,247	68,167	89,954
County Median Income Growth	2,351,841	0.03	0.04	-0.04	0.00	0.02	0.05	0.10
County Labor Force Ratio	2,416,713	0.51	0.04	0.44	0.49	0.52	0.54	0.57
County Labor Force Ratio Growth	2,343,295	-0.00	0.02	-0.03	-0.01	-0.00	0.01	0.02

Panel C: Realized Return Sample of OOT Properties

	N	Mean	SD	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Annualized Return	387,276	0.08	0.14	-0.08	-0.00	0.04	0.12	0.30
Purchase Price	387,276	266,302	344,123	45,000	105,000	178,000	310,000	735,000
Sale Price	387,276	328,917	481,810	62,000	137,000	222,000	370,000	875,000
Holding Length	387,276	6	4	1	3	5	9	14

Panel D: American Community Survey Sample

	N	Mean	SD	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Expected House Value	10,441,966	342,955	384,644	65,000	150,000	250,000	400,000	875,000
ZHVI House Price Index	10,441,966	266,195	159,965	108,347	150,653	213,921	334,523	580,272
Five-year County Return	10,441,041	0.17	0.41	-0.36	-0.09	0.10	0.36	1.01
Rooms	10,441,966	7	2	4	6	7	8	11
Bedrooms	10,441,966	4	1	3	4	4	5	6
House Age	10,441,966	37	22	5	19	37	55	73
Household Age	10,441,966	52	17	24	39	52	63	80
Male	10,441,966	0.48	0.50	0	0	0	1	1
Married	10,441,966	0.66	0.47	0	0	1	1	1
Attend College or Above	10,441,966	0.37	0.48	0	0	0	1	1
Black	10,441,966	0.08	0.27	0	0	0	0	1
Employed	10,441,966	0.63	0.48	0	0	1	1	1
Family Income	10,441,966	104,681	97,225	16,700	46,490	80,080	129,000	277,000

Table 1 reports the summary statistics of the main variables in the analysis.

Table 2. OOT Purchase and Sale Prices and Realized Returns after Hometown House Price Growth

Panel A: Purchase Price

	Log(Purchase Price)			
	(1)	(2)	(3)	(4)
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.140***	0.071***	0.057***	0.038***
	(0.005)	(0.005)	(0.005)	(0.003)
Property Zip $\Delta HPI_{o,[t-6,t-1]}$		0.394***	0.202***	
		(0.003)	(0.005)	
Log(Property Zip HPI)$_{o,t-1}$			0.517***	
			(0.008)	
Adjusted R^2	0.478	0.485	0.488	0.538
Observations	2,644,929	2,644,929	2,644,929	2,644,929
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip FE	Yes	Yes	Yes	
Year-Month (YM) FE	Yes	Yes	Yes	
Property Zip × YM FE				Yes

Panel B: Sale Price and Realized Return

	Log(Sale Price)		Realized Return	
	(1)	(2)	(3)	(4)
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.006	-0.009**	-0.013***	-0.012***
	(0.005)	(0.005)	(0.002)	(0.002)
Adjusted R^2	0.479	0.512	0.491	0.532
Observations	387,276	387,276	387,276	387,276
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip FE	Yes	Yes	Yes	
Sale YM FE	Yes	Yes	Yes	
Property Zip × Sale YM FE		Yes	Yes	Yes
Property Zip × Buy YM FE			Yes	Yes
Buy YM × Sale YM FE				Yes

Panel A in Table 2 presents the effect of past five-year hometown house price growth on OOT buyers' property purchase prices in OOT markets. Panel B presents the effect on the sale prices and realized returns of OOT properties. The outcome variable in Panel A is the log of the purchase price of the OOT property. In Panel B, the outcome variable in Columns 1 and 2 is the log of the sale price of the OOT property, while the outcome variable in Columns 3 and 4 is the realized return calculated from the purchase and sale prices of the OOT property. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h over the past five years. *Property-Zip* $\Delta HPI_{o,[t-6,t-1]}$ is the zip-level house price changes in the OOT zip o over the past five years. *Log(Property-Zip HPI)*$_{o,t-1}$ is the zip-level house price index in the property zip o one year before the purchase (i.e., t-1). We include different combinations of fixed effects indicated at the bottom of the table. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. OOT Purchase Prices Controlling for Property Characteristics

	Log(Purchase Price)		
	(1)	(2)	(3)
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.022***	0.018***	0.018***
	(0.004)	(0.002)	(0.002)
Log(House Age)		-0.071***	-0.089***
		(0.001)	(0.001)
Garage		0.170***	0.168***
		(0.002)	(0.002)
Pool		0.088***	0.087***
		(0.001)	(0.001)
Cooling		0.035***	0.030***
		(0.002)	(0.002)
Fireplace		0.086***	0.086***
		(0.001)	(0.001)
Basement		0.030***	0.029***
		(0.003)	(0.003)
Waterfront		0.273***	0.272***
		(0.002)	(0.002)
Bathrooms		0.077***	0.076***
		(0.002)	(0.002)
Log(Sq Ft)		0.774***	0.772***
		(0.009)	(0.009)
Bedrooms		0.030***	0.029***
		(0.002)	(0.002)
Upgraded			0.080***
			(0.001)
New Construction			-0.069***
			(0.002)
Adjusted R^2	0.559	0.819	0.820
Observations	1,185,475	1,185,475	1,185,475
Hometown Zip FE	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes

Table 3 presents the effect of the hometown-zip house price growth on the OOT purchase prices, controlling for property characteristics. For a more detailed description of property characteristics, please refer to Section II.D. The outcome variable is the log of the purchase price. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. All columns include the hometown zip code and the property zip interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Purchase List Price and Discount

	Log(Purchase List Price)		Purchase Discount	
	(1)	(2)	(3)	(4)
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.018***	0.015***	-0.242***	-0.225***
	(0.004)	(0.002)	(0.058)	(0.057)
Adjusted R^2	0.561	0.832	0.184	0.189
Observations	1,139,157	1,139,157	1,139,157	1,139,157
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes	Yes
House Charac.		Yes		Yes

Table 4 presents the effect of the hometown-zip house price growth on the selected properties' list prices and the final purchase discounts received by OOT buyers. The detailed procedure of obtaining the list prices and purchase discounts has been described in Section II.E. Columns 1 and 2 present the effect on the list prices of the purchased OOT properties. Columns 3 and 4 present the effect on the purchase discounts received by OOT buyers in the transactions. *Purchase Discount* is measured as (*Purchase List Price - Transaction Price*) / *Transaction Price* × 100. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. All columns include the hometown zip code and the property zip interacted with transaction year-month fixed effects. Columns 2 and 4 control for purchased property characteristics the same as the characteristics applied in Column 3 in Table 3. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5. OOT Purchase Prices Controlling for Hometown County Characteristics

Panel A: With Hometown County × Year Fixed Effects

	Log(Purchase Price)		
	(1)	(2)	(3)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.067***	0.053***	0.059***
	(0.007)	(0.008)	(0.008)
Log(Hometown HPI)$_{h,t-1}$		0.047***	0.046***
		(0.011)	(0.012)
Adjusted R^2	0.558	0.558	0.571
Observations	2,627,903	2,627,903	2,627,903
Hometown Zip FE	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes
Hometown County × Year FE	Yes	Yes	Yes
Property × Hometown Counties FE			Yes

Panel B: Control for Hometown-Zip Income Level and Growth

	Log(Purchase Price)			
	(1)	(2)	(3)	(4)
	Sample with income		Sample with income growth	
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.035***	0.033***	0.023***	0.020***
	(0.003)	(0.003)	(0.004)	(0.004)
Hometown Zip Income		0.001***		
		(0.000)		
Hometown Zip Income $\text{Growth}_{h,[t-6,t-1]}$				0.016***
				(0.006)
Adjusted R^2	0.545	0.545	0.543	0.543
Observations	2,388,271	2,388,271	1,503,637	1,503,637
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes	Yes

Panel A of Table 5 presents the effect of hometown house price growth on the OOT purchase prices with the hometown county times transaction year fixed effects. The outcome variable is the log of the OOT purchase prices. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. *Log(Hometown HPI)*$_{h,t-1}$ is the zip-level house price index in hometown h in year t-1. All columns add the hometown zip code and the property zip interacted with transaction year-month fixed effects, and *the hometown county times transaction year fixed effects*. Column 3 includes the OOT-Hometown counties fixed effects. Panel B of Table 5 controls for the hometown-zip income level and growth over the past five years. The income data comes from the adjusted gross income from IRS Statistics of Income (SOI) data. Columns 1 and 3 of Panel B show the baseline regression results using the sample with non-missing income level and growth data, respectively. Columns 2 and 4 show the effect of hometown house price growth on the OOT purchase prices, controlling for the hometown-zip income level and growth, respectively. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6. Renters, Migrants, and Second-home (SH) Buyers

	Log(Purchase Price)			
	(1) Renter	(2) Migrator	(3) SH Buyer	(4) All Sample
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.028***	0.040***	0.044***	0.025***
	(0.005)	(0.011)	(0.005)	(0.003)
Migrator $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$				0.014***
				(0.004)
SH Buyer $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$				0.027***
				(0.003)
Migrator				0.084***
				(0.002)
Second-home Buyer				-0.027***
				(0.001)
Adjusted R^2	0.570	0.547	0.553	0.552
Observations	1,094,174	214,993	1,148,793	2,901,467
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip $\times$ YM FE	Yes	Yes	Yes	Yes

Table 6 presents the effect of hometown house price growth on the purchase prices made by the three types of OOT buyers. The identification for the three types of OOT buyers (i.e., renters, migrants, second-home (SH) buyers) is described in Sections II.G and II.G.1. The outcome variable is the log of the OOT purchase price. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. Columns 1, 2, and 3 examine the effect of hometown house price growth separately for each buyer type, which is indicated in the column title. Column 4 puts all three types of OOT buyers together and analyzes their different OOT purchase price responses to the same hometown house price growth. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7. Controlling for Housing Wealth Increase and Living Length

	Log(Purchase Price)		
	(1)	(2)	(3)
Hometown $\Delta HPI_{h,[t-6,t-1]}$	0.039***	0.033***	0.061***
	(0.008)	(0.009)	(0.011)
Log(Hometown House Purchase Price)	0.139***	0.189***	0.191***
	(0.002)	(0.003)	(0.003)
Log(Hometown HPI)$_{h,t-1}$		0.060***	0.062***
		(0.015)	(0.015)
Living Years		0.012***	0.013***
		(0.000)	(0.000)
Living Years [7, 8] $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$			0.008
			(0.008)
Living Years [9, 10] $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$			-0.009
			(0.010)
Living Years [11, 12] $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$			-0.039***
			(0.011)
Living Years $\geqslant$ 13 $\times$ Hometown $\Delta HPI_{h,[t-6,t-1]}$			-0.068***
			(0.009)
Adjusted R^2	0.554	0.558	0.559
Observations	502,331	502,331	502,331
Hometown Zip FE	Yes	Yes	Yes
Property Zip $\times$ YM FE	Yes	Yes	Yes

Table 7 presents the effect of hometown house price growth on migrants and second-home (SH) OOT buyers' purchase prices, controlling for the wealth increase from hometown properties and the living length. We restrict the sample to OOT buyers residing in their hometown properties for a minimum of five years to make sure they have experienced the five-year house price growth when making OOT transactions. We then assign OOT buyers based into five groups on the length of their residence and create five group dummy variables. For instance, the dummy variable, *Living Years [7, 8]*, equals one if an OOT buyer has lived in her hometown property for seven to eight years when buying the OOT property, and otherwise zero. Similar definitions are applied to other residence length dummy variables. *Hometown* $\Delta HPI_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. All columns include the hometown zip code and the property zip interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8. Extrapolative House Price Belief of U.S. Households

	Log(Expected House Value)			
	(1)	(2)	(3)	(4)
County $\Delta HPI_{c,[t-6,t-1]}$	0.093***	0.108***	0.100***	0.101***
	(0.015)	(0.014)	(0.012)	(0.012)
Log(County HPI)$_{c,t}$	0.643***	0.563***	0.554***	0.552***
	(0.034)	(0.035)	(0.030)	(0.029)
Adjusted R^2	0.387	0.387	0.525	0.581
Observations	10,442,382	10,442,382	10,442,382	10,442,382
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
County Charac.		Yes	Yes	Yes
House Charac.			Yes	Yes
Demographic Charac.				Yes

Table 8 presents the effect of county house price growth on the expected house values of U.S. households in the American Community Survey data. The dependent variable is the log of the expected own-house value of households. *County* $\Delta HPI_{c,[t-6,t-1]}$ is the county-level house price changes in the past five years. *Log(County HPI)*$_{i,t}$ is the log of the county house price index in a survey year. We include age, gender, marital status, education, race, employment status, and family income, along with the total number of rooms and bedrooms in the house and the year it was built. The county characteristics included are the same as Table 5. Columns 1 to 4 have different fixed effects and characteristics controlled, as indicated at the bottom of the Table. The construction of the characteristic variables is discussed in Section III.B. Standard errors are clustered by county FIPS codes. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9. Belief Sensitivity IV Estimation

	Hometown $\Delta HPI_{h,[t-6,t-1]}$	Log(Purchase Price)			
	(1) First Stage	(2) OLS	(3) IV-2SLS	(4) OLS	(5) IV-2SLS
Extrapolative Price	3.747***				
	(0.084)				
Hometown $\Delta HPI_{h,[t-6,t-1]}$		0.035***	0.057***	0.021***	0.059***
		(0.004)	(0.010)	(0.005)	(0.011)
Migrator × Hometown $\Delta HPI_{h,[t-6,t-1]}$				0.013**	0.004
				(0.005)	(0.010)
SH Buyer × Hometown $\Delta HPI_{h,[t-6,t-1]}$				0.025***	0.005
				(0.003)	(0.007)
Migrator				0.086***	0.087***
				(0.003)	(0.003)
Second-home Buyer				-0.036***	-0.031***
				(0.002)	(0.002)
Adjusted R^2	0.866	0.564	-0.263	0.565	-0.259
Observations	1,513,657	1,382,705	1,382,705	1,382,705	1,382,705
Hometown Zip FE	Yes	Yes	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes	Yes	Yes

Table 9 presents the effect of hometown house price growth on OOT purchase prices using our belief sensitivity instrumental variable (IV). Basically, we construct the belief sensitivity IV by multiplying the estimated hometown-MSA heterogeneity in the house price belief sensitivity to past state house price growth, $\widehat{\beta}_m$, and the past five-year state-level house price growth. The belief sensitivity IV $z_{m,s,t} = \widehat{\beta}_m \times State\ Ret_{s,[t-6,t-1]}$. We discuss in detail the IV construction in Section III.B. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix

Figure A.1. Percentage of Out-of-town (OOT) Transactions

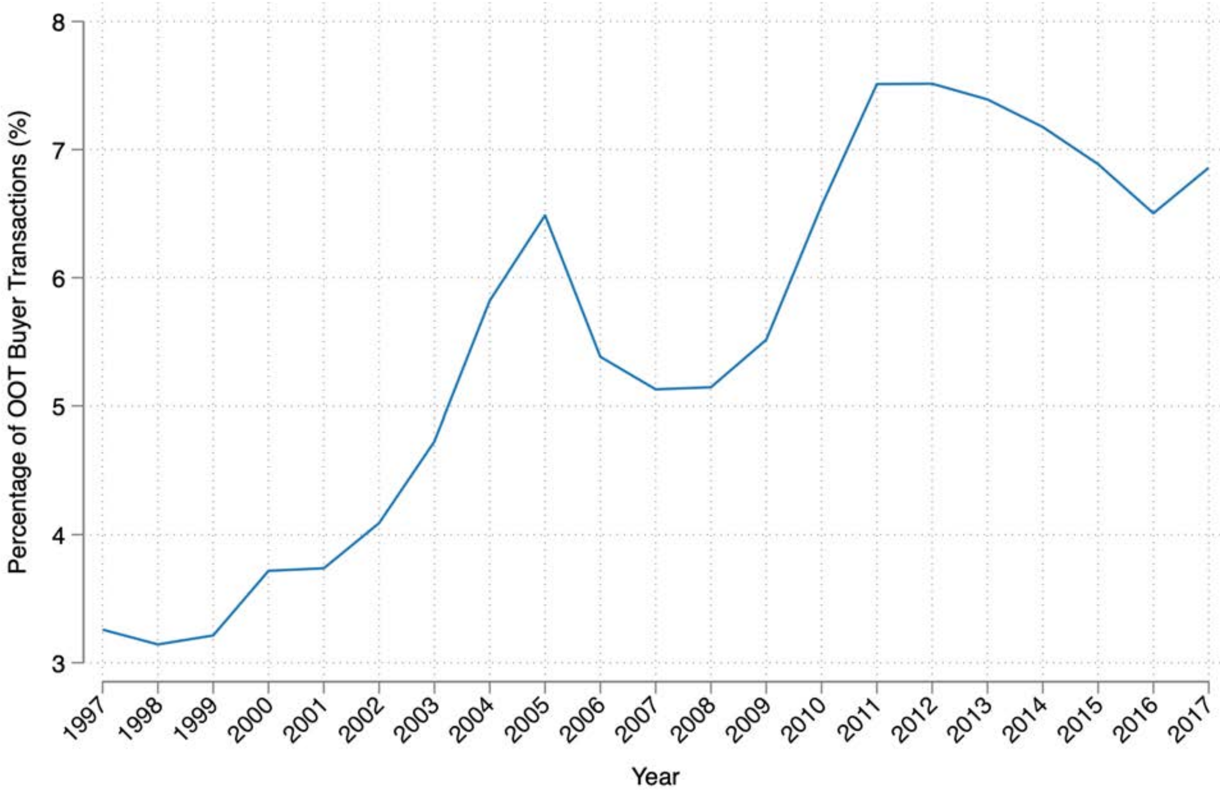
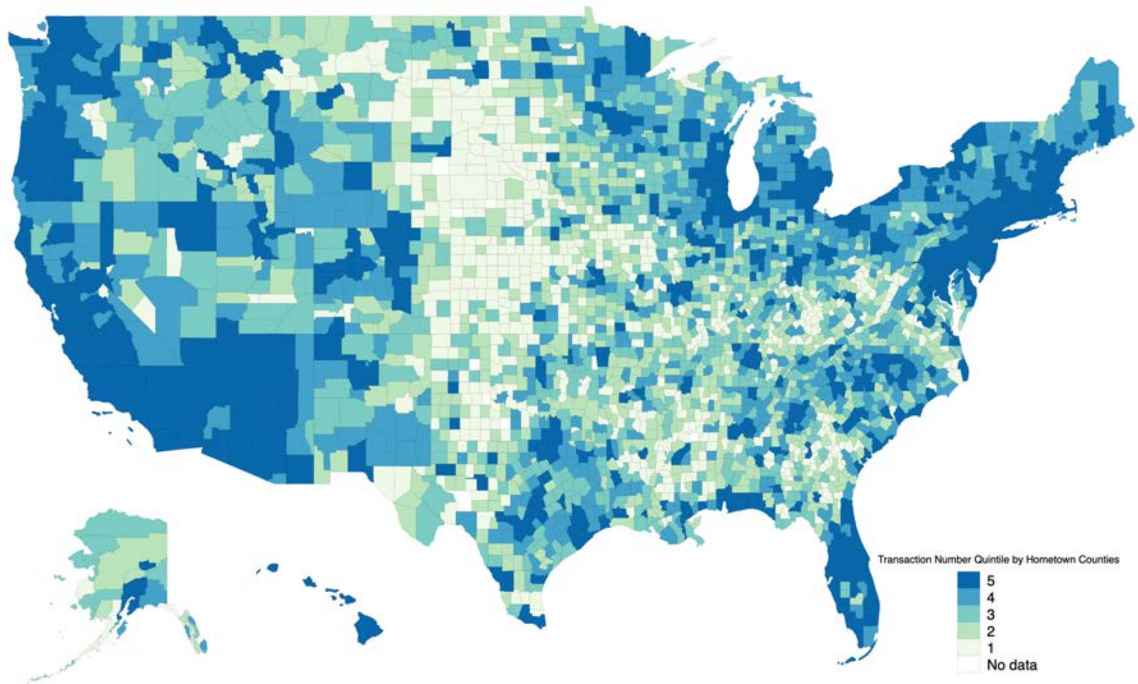


Figure A.1 presents the percentage of housing transactions made by out-of-town (OOT) homebuyers each year from 1997 to 2017. The identification of OOT buyers is discussed in Section II.C.

Figure A.2. Percentages of Transactions by Hometown States

Panel A: County level



Panel B: State level

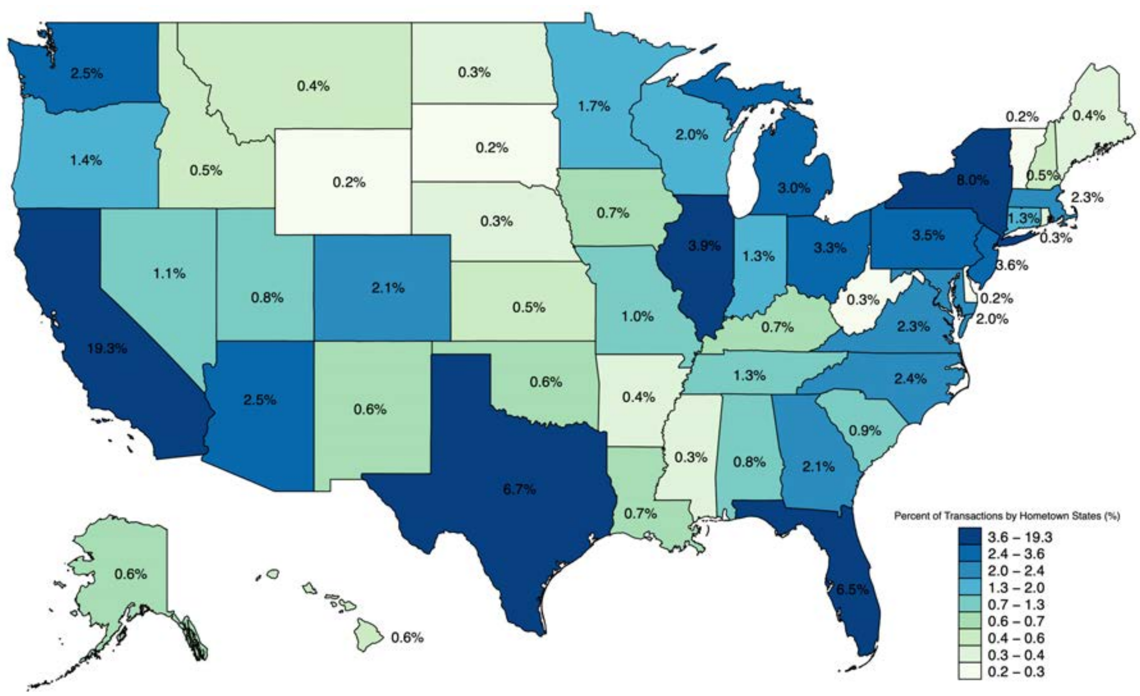
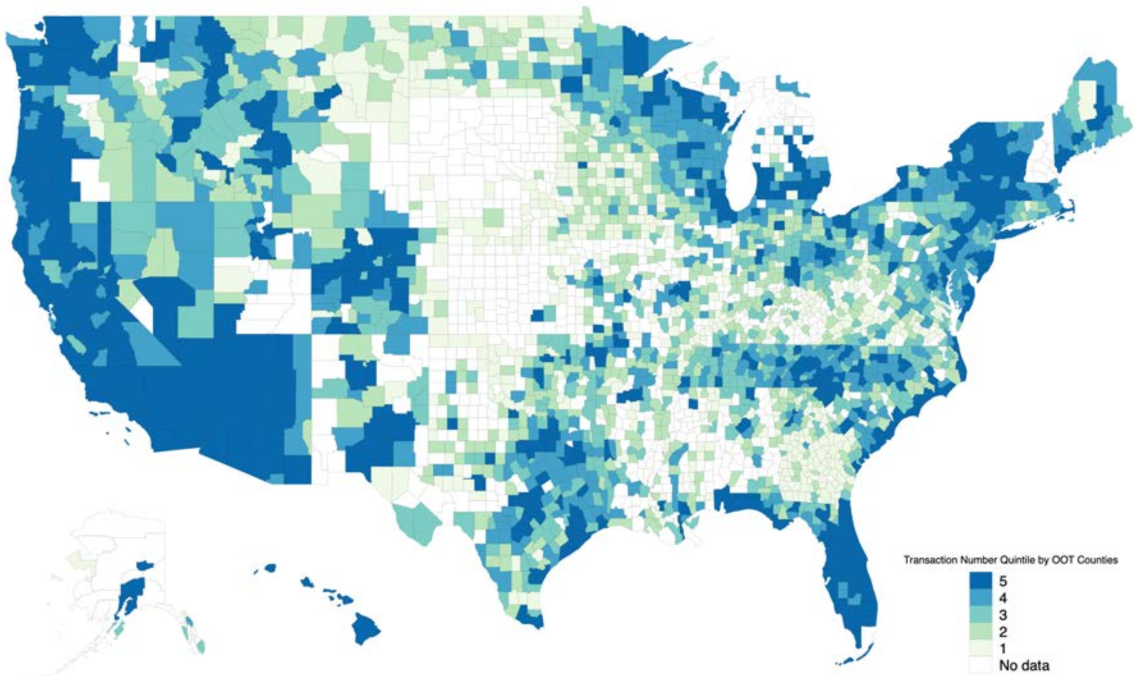


Figure A.2 presents the geographical distributions of OOT transaction numbers by the hometown counties and states of OOT buyers in our sample. OOT buyers are those who report mailing addresses (i.e., hometowns) over 60 miles away from the purchased OOT property addresses. Panel A shows the county-level geographical distribution of OOT transactions, where each color category in the legend represents a quintile. Panel B shows the state-level geographical distribution of OOT transactions, where the legend shows the percentage of transactions made by OOT buyers from a hometown state over the total OOT transactions of the nation from 2002 to 2017.

Figure A.3. Percentages of Transactions by Out-of-town (OOT) States

Panel A: County level



Panel B: State level

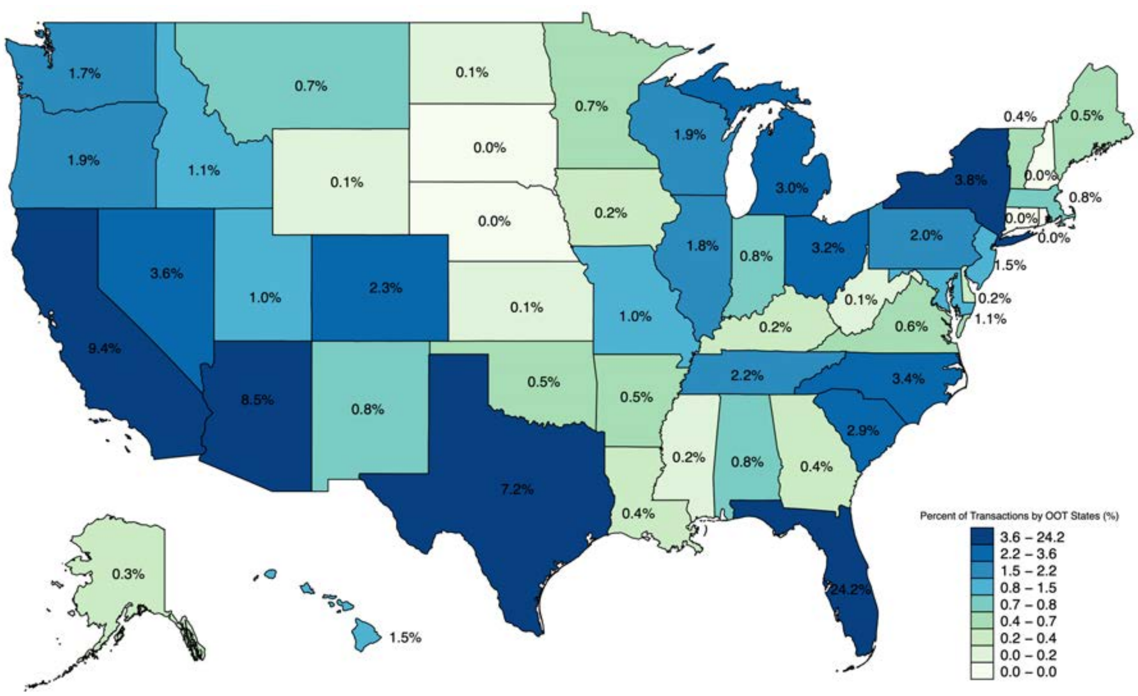


Figure A.3 presents the geographical distributions of OOT transaction numbers by the OOT counties and states where OOT transactions occurred in our sample. OOT buyers are those who report mailing addresses (i.e., hometowns) over 60 miles away from the purchased OOT property addresses. Panel A shows the county-level geographical distribution of OOT transactions, where each color category in the legend represents a quintile. Panel B shows the state-level geographical distribution of OOT transactions, where the legend shows the percentage of transactions that occurred in a state over the total OOT transactions of the nation from 2002 to 2017.

Figure A.4. Hometown Extrapolation by Individual Experience Horizons

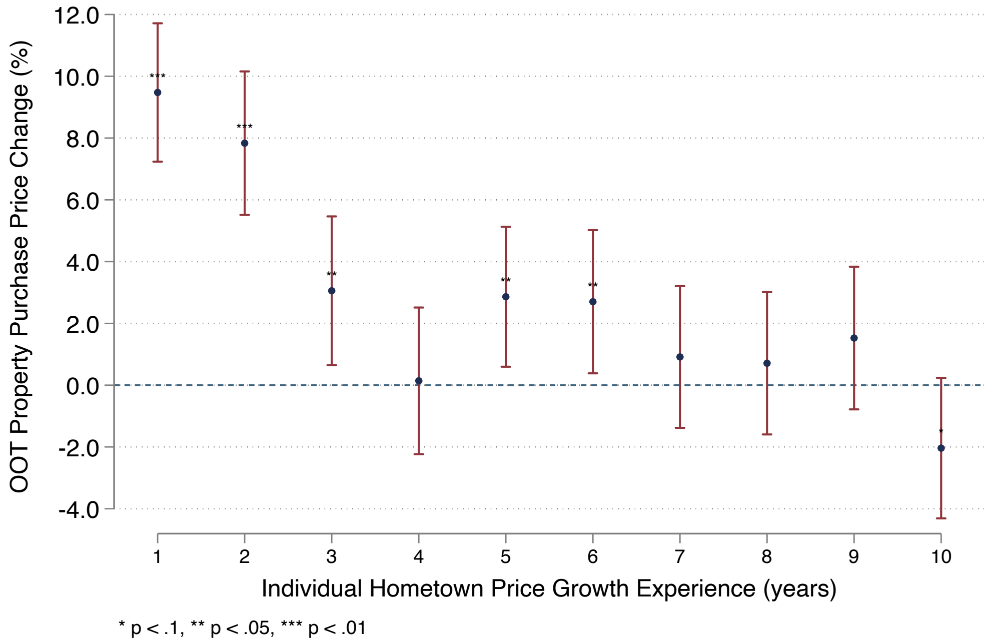
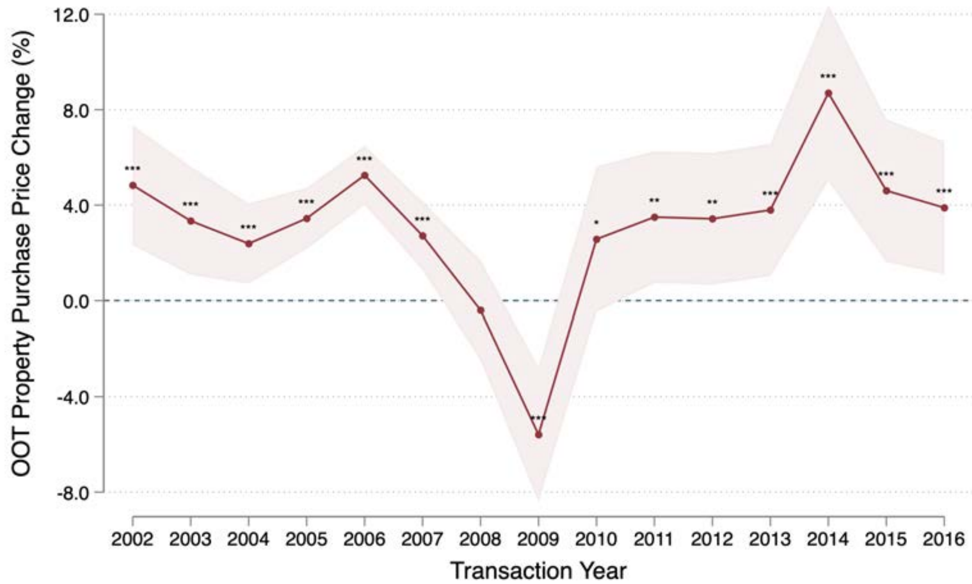


Figure A.4 presents how OOT buyers' purchase prices change, following a 100% increase in hometown house prices in an *individual year* in the past before buying the OOT property. The y-axis shows the estimated sensitivity of purchase prices to the past hometown house price changes. The sensitivity is estimated through Specification 1, in which we regress the log of OOT purchase prices on the changes in hometown house prices in a specific year of horizons. In the specification, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.5. Hometown Extrapolation over Transaction Year

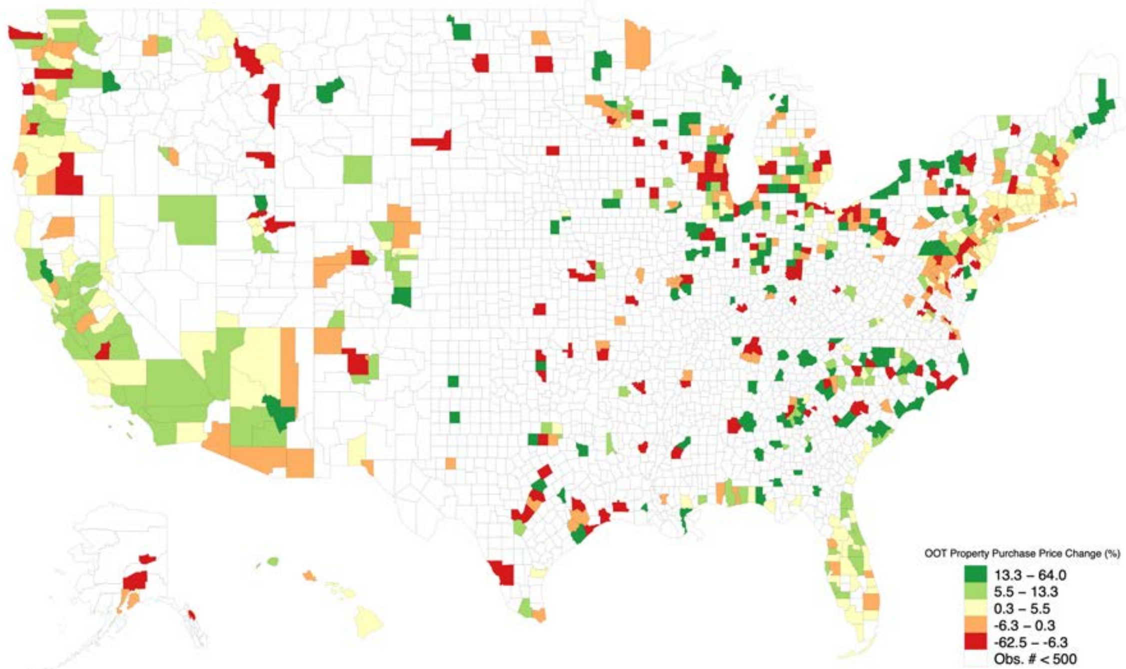


* p < .1, ** p < .05, *** p < .01

Figure A.5 examines the effect of past five-year hometown house price growth on OOT buyers' property purchase prices in different transaction years. The value of each dot shows that, *in a specific transaction year*, how OOT buyers with 100% increase in hometown house price over the past five years would pay additionally relative to other OOT buyers without hometown house price change. To create the plot, we perform a similar regression to Column 5 in Table 2, but interact Hometown $\Delta HPI_{h,[t-6,t-1]} with 15 dummy variables for transaction years from 2002 to 2016, respectively. Then, we collect the coefficients on the inter$
$\Delta HPI_{h,[t-6,t-1]} and each of the interaction term coefficients. Finally, we perform linear combination tests on the linearly combined coeff$
$** denotes statistical significance at the 10\%, 5\%, and 1\% level, respectively.$

Figure A.6. Geographic Heterogeneity in OOT Purchase Price Changes for a 100% Hometown Zip House Price Increase

Panel A: OOT Purchase Price Changes by Hometown Counties



Panel B: OOT Purchase Price Changes by OOT Counties

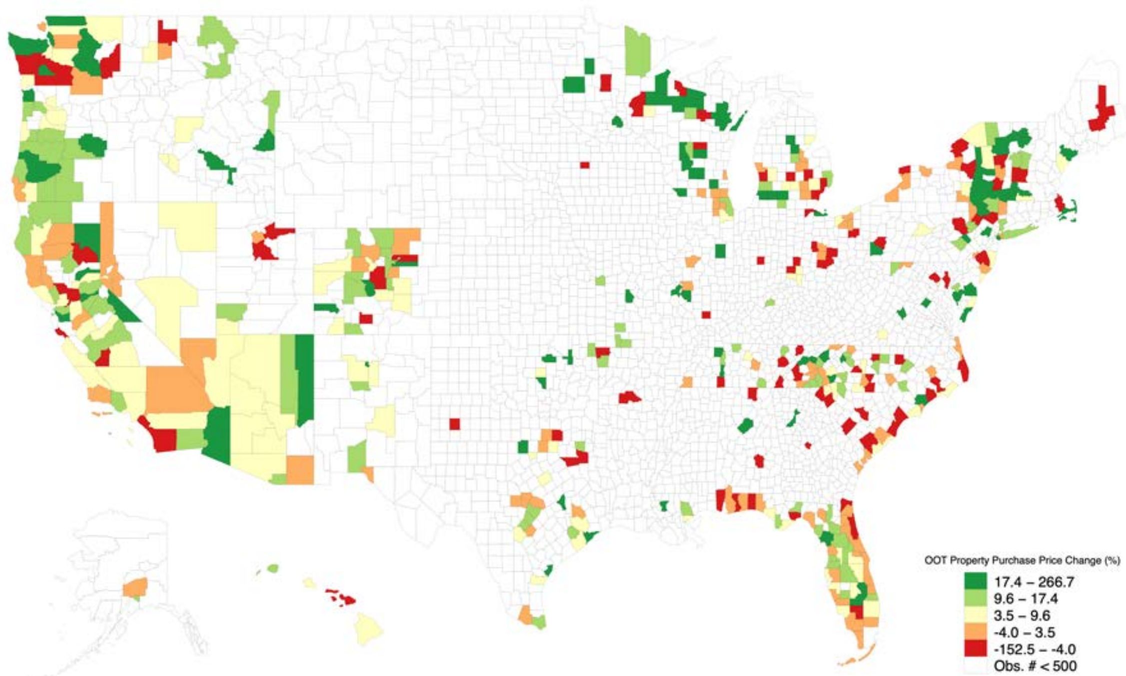
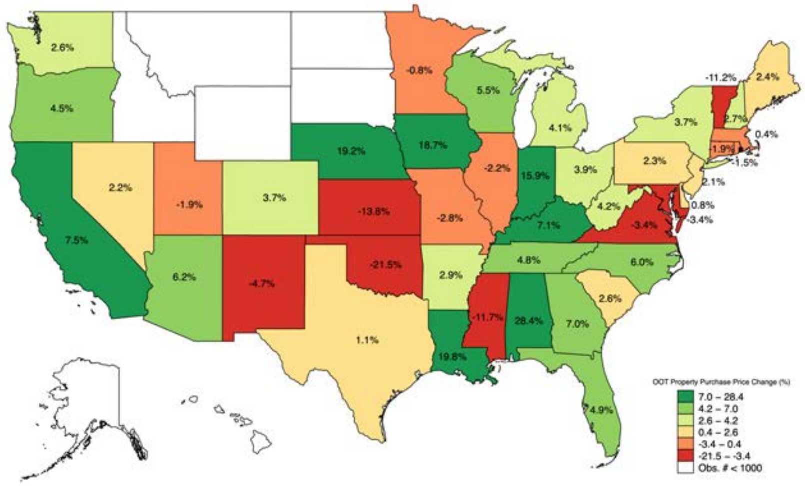


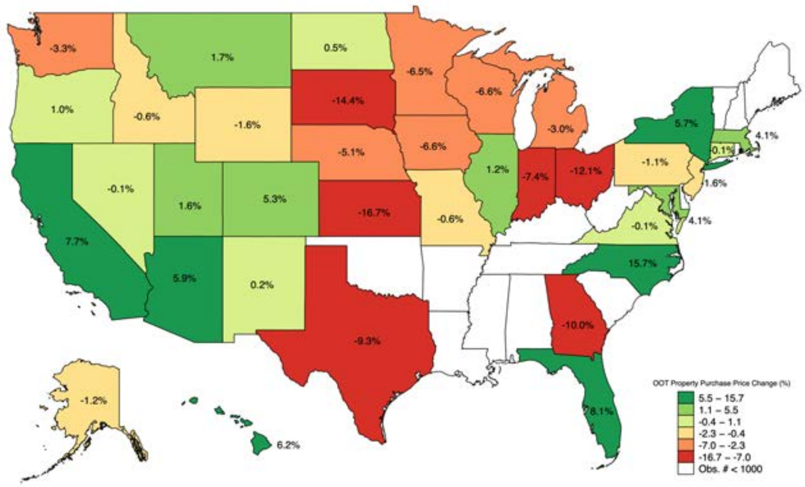
Figure A.6 presents the hometown- and OOT-county heterogeneity in OOT purchase price changes for a 100% increase in the hometown-zip house price over the past five years. Panel A of Figure A.6 shows how buyers from different hometown counties would change their OOT purchase prices given the past hometown house price growth. Panel B demonstrates the variation in purchase price changes made by OOT buyers *across OOT counties* where the property transactions occurred. The purchase price changes for a 100% increase in the hometown house price are estimated using the main baseline Specification 1, wherein hometown- or OOT-county dummy variables are interacted with the hometown-zip house price change variable, $\textit{Hometown Ret}_{h,[t-6,t-1]}$.

Figure A.7. Hometown Heterogeneity in Purchase Price Changes at Florida, Arizona, and California for a 100% Hometown Zip House Price Increase

Panel A: Purchase Transactions in Florida



Panel B: Purchase Transactions in Arizona



Panel C: Purchase Transactions in California

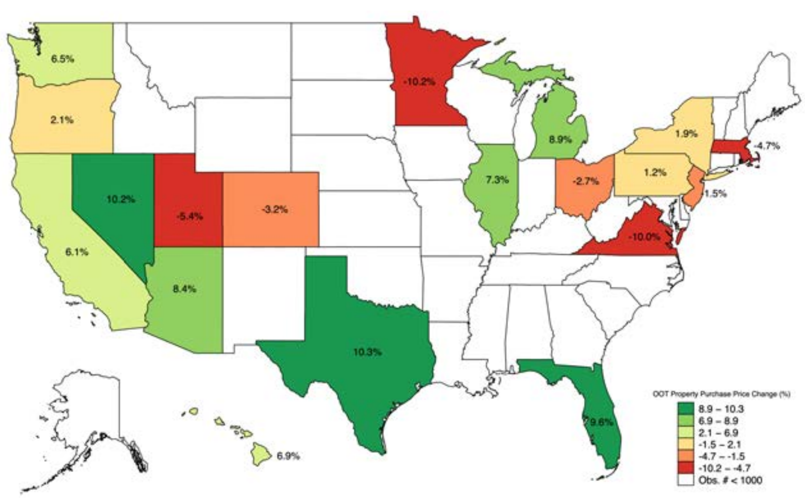
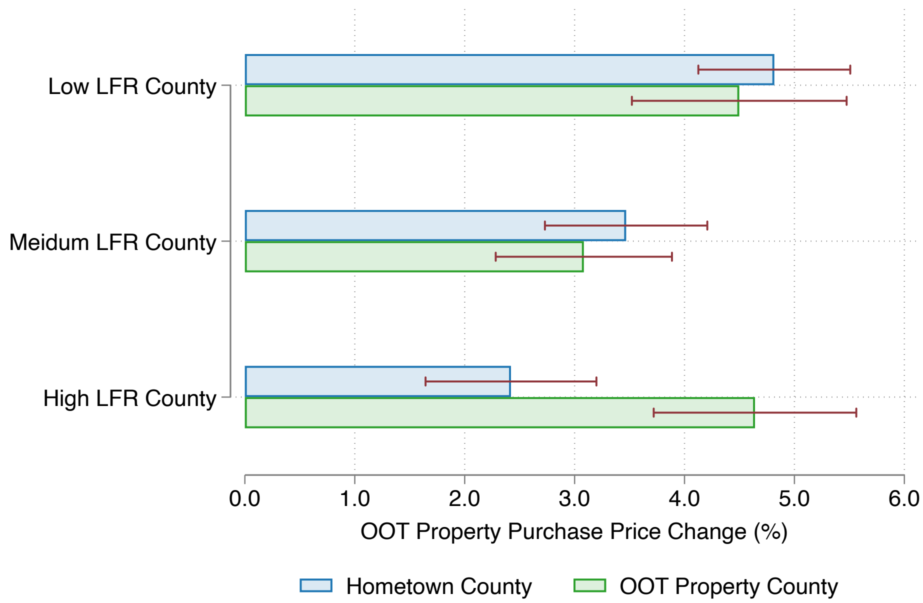


Figure A.7 presents the hometown-state heterogeneity in the purchase price changes for properties in Florida, Arizona, and California, given a 100% increase in the hometown zip house price over the past five years. Panel A shows the increases in purchase prices for OOT properties *in Florida* by buyers from different hometown states. Panels B and C show the increases in purchase prices for OOT properties *in Arizona* and *California*. We select the three states because they have the highest number of transactions made by OOT buyers. The coefficients are estimated through baseline Specification 1 and by interacting the hometown-OOT-state-pair dummy variables with the hometown-zip house price change variable, $Hometown\ Ret_{h,[t-6,t-1]}$.

Figure A.8. Hometown Extrapolation by County Labor Force Participation Rate (LFR)

Panel A: By Labor Force Participation Rate (LFR) Terciles of Hometown and OOT Property Counties

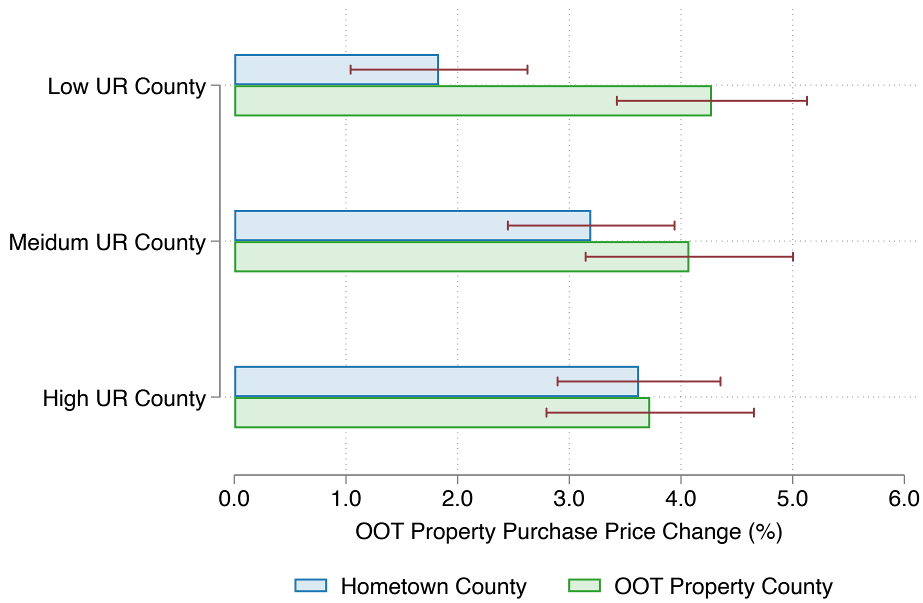


Panel B: By LFR Terciles of Hometown-OOT-Property-County Pairs

Figure A.8 illustrates the impact of a 100% increase in hometown house prices on the purchase prices of OOT properties by buyers coming from hometown counties and buying properties in OOT counties with different labor force participation rates (LFR). Panel A presents the results of purchase price sensitivity to the hometown house price growth by the labor force participation rate (LFR) terciles of hometown and OOT property zip codes. Panel B presents the purchase price sensitivity by LFR terciles of hometown-OOT-county pairs. In the specification for estimating the sensitivity coefficients, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.9. Hometown Extrapolation by County Unemployment Rate (UR)

Panel A: By Unemployment Rate (UR) Terciles of Hometown and OOT Property Counties



Panel B: By UR Terciles of Hometown-OOT-Property-County Pairs

Figure A.9 illustrates the impact of a 100% increase in hometown house prices on the purchase prices of OOT properties by buyers coming from hometown counties and buying properties in OOT counties with different unemployment rates (UR). Panel A presents the results of purchase price sensitivity to the hometown house price growth by the unemployment rate (UR) terciles of hometown and OOT property zip codes. Panel B presents the purchase price sensitivity by UR terciles of hometown-OOT-county pairs. In the specification for estimating the sensitivity coefficients, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.10. Hometown Extrapolation by Zip-level House Price Index (HPI)

Panel A: By Hometown and OOT Property Zip HPI

Panel B: By Hometown-OOT-Property-Zip HPI Pairs

Figure A.10 illustrates the impact of a 100% increase in hometown house prices on the purchase prices of OOT properties by buyers from hometown zip codes with different house price index (HPI) levels and buying properties at OOT zip codes of different house price index (HPI) levels. Panel A presents the results of purchase price changes by the HPI-level terciles of hometown and OOT property zip codes. Panel B presents the purchase price changes by hometown-OOT-zip HPI pairs. In the specification, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.11. Hometown Extrapolation by Facebook Social Connectedness Index (SCI)

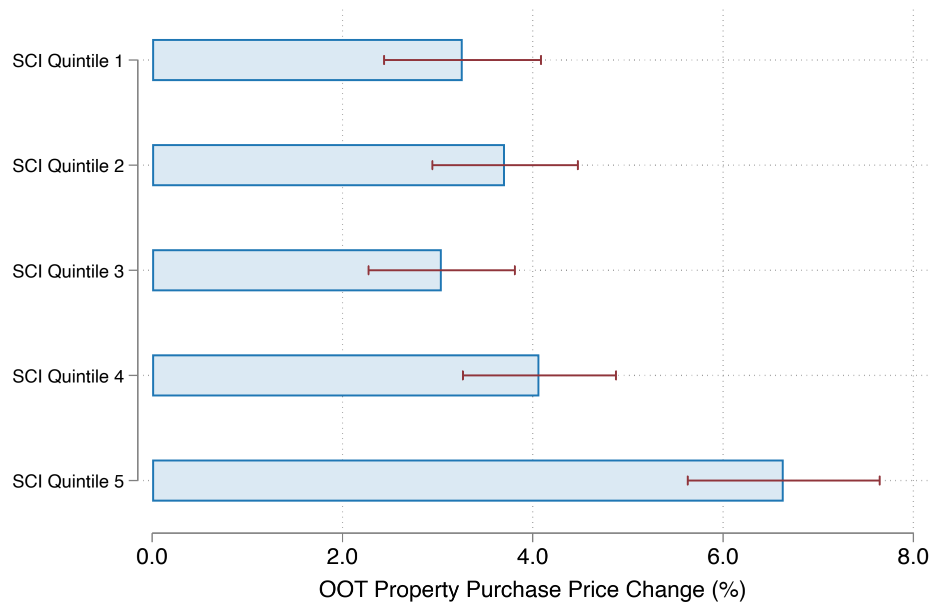


Figure A.11 illustrates the impact of a 100% increase in hometown house prices on the purchase prices of OOT properties by buyers with different levels of social connectedness index (SCI) between hometown and OOT zip codes. The SCI measurement is created by Meta (i.e., Facebook) and is publicly available at `https://dataforgood.facebook.com/dfg/tools/social-connectedness-index`. In the specification for estimating the sensitivity coefficients, we include the hometown zip code fixed effects and the property zip code interacted with transaction year-month fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.12. Expected House Price Questionnaire from American Community Survey

2016 ACS top

Questionnaire form **view entire document:** text **image**

16. About how much do you think this house and lot, apartment, or mobile home (and lot, if owned) would sell for if it were for sale?

Amount - *Dollars*

$________________.00

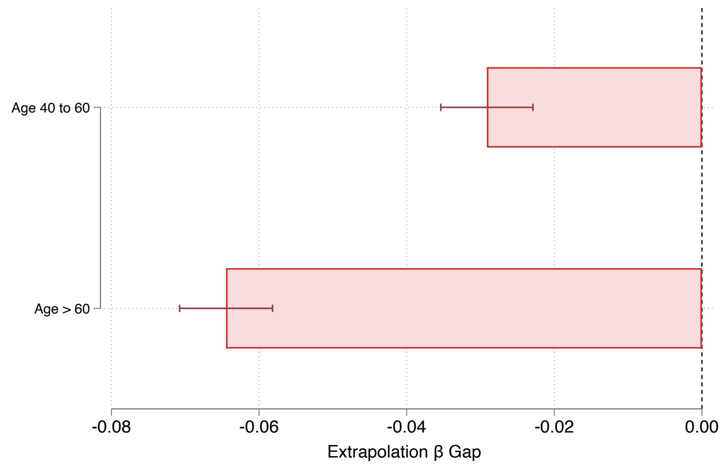
Questionnaire instructions **view entire document:** text **image**

16. Enter your best estimate of the value of the property; that is, how much you think the property would sell for if it were on the market. If this is a house, include the value of the house, the land it is on, and any other structures on the same property. If the house is owned but the land is rented, estimate the combined value of the house and the land. If this is a condominium unit, estimate the value for the condominium, including your share of the common elements. If this is a mobile home, include the value of the mobile home **and the value of the land only if you own the land.**

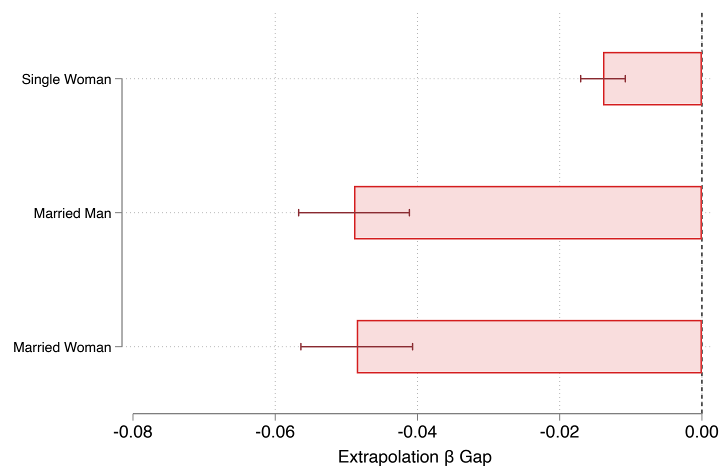
Figure A.12 shows the questionnaire from the American Community Survey that elicits households' belief of their house values.

Figure A.13. Extrapolation β Gap by Age, Gender, and Marital Status

Panel A: Age



Panel B: Gender and Marital Status



Panel C: Race

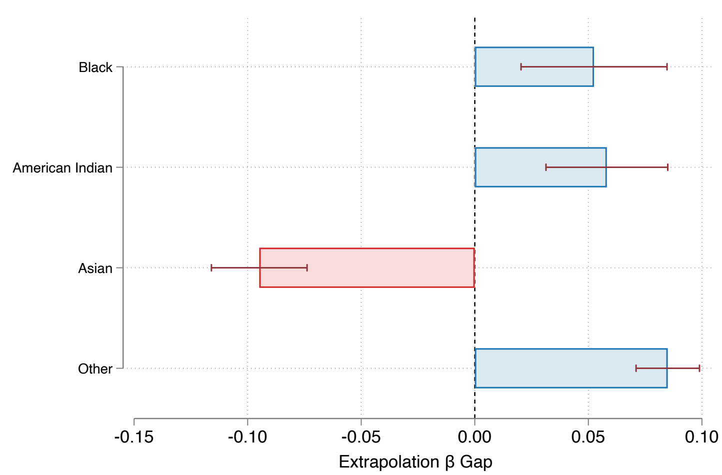
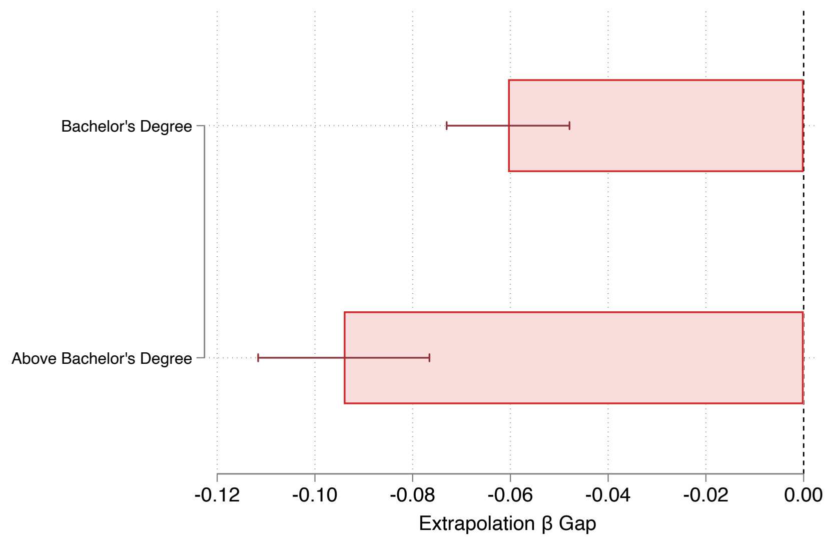


Figure A.13. Extrapolation β Gap by Race and Education

Panel D: Education



Panel E: Income

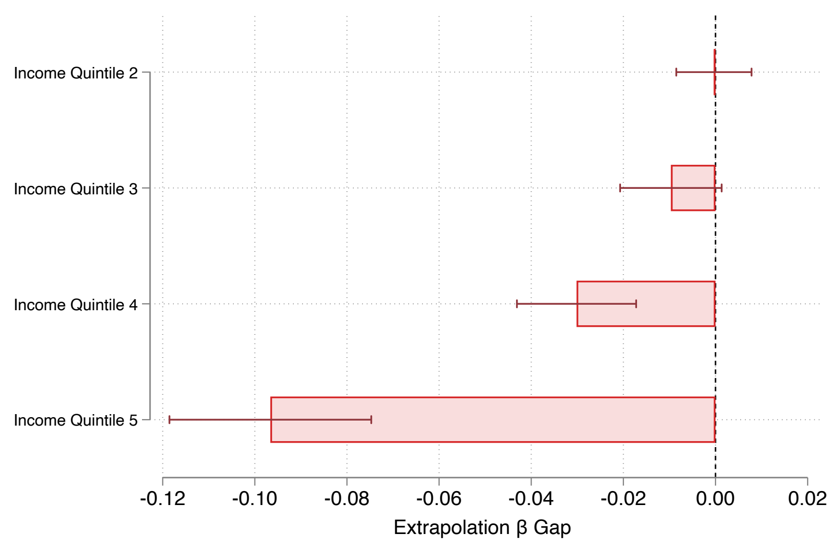


Figure A.13 presents the difference in changes in expected house values of households in different demographic groups, following a 100% increase in county house prices over the last five years. The demographic groups are indicated in panel titles. To get the results, we first assign the households into groups based on specific demographic characteristics. Then, we estimate Specification 3 but interact the county house price growth with the demographic group dummy variables. The bar values (i.e., purchase price changes) correspond to the coefficients (in percentage) on the interaction terms of demographic group dummies and house price growth $\textit{Hometown Ret}_{h,[t-6,t-1]}$. Standard errors are clustered by hometown zip code.

Table A.1. Out-of-town (OOT) Homebuyers Defined by Different Distances

	Log(Purchase Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
	100 Miles	120 Miles	200 Miles	400 Miles	600 Miles	800 Miles
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.035***	0.033***	0.030***	0.025***	0.029***	0.029***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Adjusted R^2	0.549	0.552	0.559	0.566	0.571	0.577
Observations	2,430,474	2,265,765	1,905,683	1,484,082	1,257,258	1,065,946
Hometown Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Property-Zip $\times$ YM FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A.1 examines the extrapolation effect of out-of-town (OOT) buyers defined by different distances. The distance is indicated in the column titles. All columns include the hometown zip code and the OOT zip interacted with transaction year-month fixed effects. Standard errors are clustered by OOT zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2. Hometown Extrapolation Controlling for Hometown Unemployment Rate and Labor Force Participation Rate

	Log(Purchase Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Sample with unemployment rate (UR)			Sample with labor force rate (LFR)		
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.037***	0.026***	0.033***	0.038***	0.037***	0.037***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Hometown UR		-0.614***				
		(0.064)				
Hometown $UR_{h,[t-6,t-1]}$			-0.008***			
			(0.002)			
Hometown LFR					0.168***	
					(0.026)	
Hometown $LFR_{h,[t-6,t-1]}$						0.042***
						(0.013)
Adjusted R^2	0.550	0.550	0.550	0.551	0.551	0.551
Observations	2,864,606	2,864,606	2,864,606	2,847,105	2,847,105	2,847,105
Hometown Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel A of Table A.2 presents how the purchase prices of OOT properties change when hometown house price growth experience changes, controlling for the hometown unemployment rate (*Hometown UR*), unemployment rate growth over the past five years (*Hometown* $\Delta UR_{h,[t-6,t-1]}$), hometown labor force participation rate (*Hometown LFR*), labor force rate growth over the past five years (*Hometown* $\Delta LFR_{h,[t-6,t-1]}$). The outcome variable is the log of the purchase price. *Hometown* $Ret_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. Columns 1 and 4 show the baseline regression results using the sample with non-missing unemployment rate and labor force rate data, respectively. Columns 2 and 3 control for hometown unemployment rate, and unemployment rate growth over the past five years, respectively. Columns 5 and 6 control for hometown labor force rate, and labor force rate growth over the past five years, respectively. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3. Purchase Prices of Renters, Migrants, and Second-home (SH) Buyers

	Log(Purchase Price)	
	(1)	(2)
	Sample with matched house characteristics	robu$_r eg4$
Hometown Ret$_{h,[t-6,t-1]}$	0.012***	0.011***
	(0.004)	(0.003)
Migrator × Hometown Ret$_{h,[t-6,t-1]}$	0.001	-0.010***
	(0.005)	(0.003)
SH Buyer × Hometown Ret$_{h,[t-6,t-1]}$	0.019***	0.018***
	(0.004)	(0.002)
Migrator	0.077***	0.016***
	(0.002)	(0.002)
Second-home Buyer	-0.032***	-0.010***
	(0.002)	(0.001)
Adjusted R^2	0.560	0.820
Observations	1,185,475	1,185,475
Hometown Zip FE	Yes	Yes
Property Zip × YM FE	Yes	Yes
House Charac.		Yes

Table A.3 examines three types of out-of-town (OOT) buyers' purchase prices and their hometown house price growth experiences in the past five years. The identification for the three types of OOT buyers (i.e., renters, migrants, second-home (SH) buyers) is described in Sections II.G and II.G.1. The outcome variable is the log of the purchase price. *Hometown Ret*$_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. Columns 1, 2, and 3 examine the OOT property purchase price response to the past five-year hometown house price growth separately for each buyer type, which is indicated in the column title. Column 4 puts all three types of OOT buyers together and analyzes how they respond differently to the hometown house price experience in their purchase prices. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4. Extrapolation of Household in American Community Survey

	Log(Expected House Value)		
	(1)	(2)	(3)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.110***	0.110***	0.118***
	(0.012)	(0.014)	(0.014)
Log(County HPI)$_{i,t}$	0.554***	0.561***	0.557***
	(0.030)	(0.034)	(0.035)
Adjusted R^2	0.581	0.587	0.584
Observations	10,441,966	5,209,629	10,441,966
Sample Weight	Equal	Household	Individual
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County Charac.	Yes	Yes	Yes
House Charac.	Yes	Yes	Yes
Demographic Charac.	Yes	Yes	Yes

Table A.4 examines the effect of county house returns over the past five years on households' house value belief using American Community Survey data. The dependent variable is the log of the expected house value of households. County $\text{Ret}_{i,[t-6,t-1]}$ is the zip-level house price changes in the county in the past five years. Log(County HPI)$_{i,t}$ is the log of the county house price index in a survey year. We include age, gender, marital status, education, race, employment status, and family income, along with the total number of rooms and bedrooms in the house and the year it was built. The county characteristics included are the same as Table 5. Columns 1 to 3 use different sampling weights in regression analysis. All columns include the house, demographic, and county characteristics. The construction of the characteristic variables is discussed in Section III.B. We also include the county code and survey year fixed effects. Standard errors are clustered by county FIPS code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.