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 U.S. housing transactions by OOT homebuyers between 2002 and 2017, we find that a 50% increase in five-year hometown house prices leads OOT buyers to pay an additional 2% for new OOT properties. We design two identification strategies to rule out the wealth effect and other channels. First, we analyze the purchase price differences among renters, migrants, and second-home (SH) buyers. Second, by exploiting the belief data, we estimate the heterogeneity in the extrapolation level across geographic locations and link it back to OOT buyers' housing transaction behavior. Overall, our research demonstrates the potential spillover effects of extrapolation into other asset markets and provides evidence that extrapolative expectations have broader effects than previously recognized.

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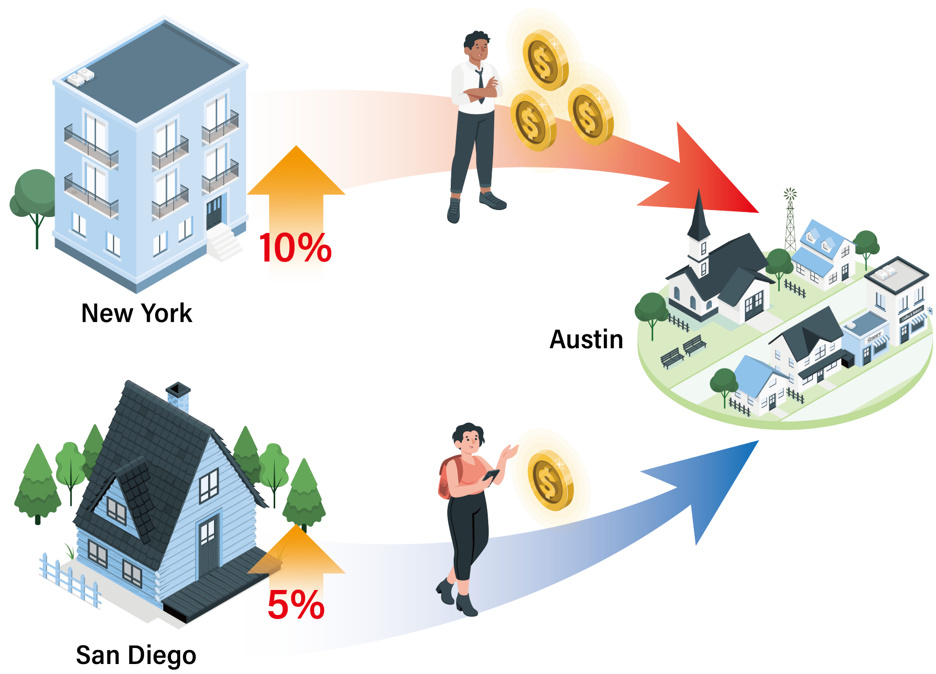
I. Introduction

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' expectations of returns 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) found that people who previously experienced higher *local* house price growth tended to expect higher *national* house price increases in the future. These findings highlight that people form their economic expectations based on past experiences.

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 high 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



In Figure 1, we provide an example of two OOT homebuyers interested in buying houses in Austin. The buyer from New York has observed a 10% increase in house prices in her hometown over the last five years, while the buyer from San Diego has only seen a modest 5% increase in house prices in her hometown. Due to the extrapolative beliefs formed from their hometown experiences, the New Yorker expects 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. Homeowners need to keep their mailing addresses up to date with the government to ensure they receive important documents. Based on this, we assume that a homebuyer must have lived at the reported mailing address until purchasing a new OOT property. 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 housing transactions conducted by OOT buyers 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 properties in other towns compared to those who have not experienced such price growth. This difference in purchase price remains even after accounting for factors like 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 price changes and hometown house price changes.

However, a higher initial purchase price for an OOT property does not lead to a higher sale price. Instead, the OOT buyer with high hometown house price growth would sell the property at a slightly but significantly lower price than other OOT buyers with the same hometown experience. By calculating the realized returns from the repeat sale transactions, we find that OOT buyers with a 100% increase in the past five years see 1.2% lower realized returns from their OOT properties. This challenges the rational explanation that those OOT buyers pay a high price because the growth of hometown house price could provide valuable information on the future OOT housing markets that helps them maximize profitability by selling the property at a high price.

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, analyzing OOT buyers' purchase discounts[1] further shows it is NOT purely OOTs buying more luxury houses or other wealth-increase factors that drive the observed higher payment. In particular, we find a significantly negative relationship between the past hometown house price growth and the purchase discount. After experiencing higher hometown house price growth, OOT buyers tend to choose properties with higher list prices *from among similar houses*. Comparing the list and final transaction prices, we find that buyers with a higher hometown house price growth tend to have a lower purchase discount for similar properties. What this implies is that the spatial extrapolative house price belief makes those OOT buyers less aggressive in negotiating final transaction prices with home sellers, partially explaining their high house payments.

To identify the spatial extrapolation effect, we develop two empirical identification strategies. 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.

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

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

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.

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.5. 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.

Next, 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.

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

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

[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

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.

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 $Hometown\ Ret_{h,[t-6,t-1]}$ 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.

$$\text{Hometown Ret}_{h,[t-6,t-1]} = \frac{\text{HPI}_{h,t-1}}{\text{HPI}_{h,t-6}} - 1$$

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.

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

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

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

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 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.5 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

Figure A.2 presents 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.

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

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 Ret*$_{h,[t-6,t-1]}$ 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.

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

where *Realized OOT 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 Ret*$_{h,[t-6,t-1]}$ 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.

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

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 Ret*$_{c,[t-6,t-1]}$ 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.

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

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 Ret*$_{s,[t-6,t-1]}$ 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.

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

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 Ret*$_{h,[t-6,t-1]}$, 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.

Table 2 shows that higher past five-year hometown house price experiences are associated with higher purchase prices of new properties made by OOT buyers. Column 1 presents clear evidence of the positive correlation. In Column 2, 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), the coefficient decreases from approximately 0.21 to 0.14. It suggests that the heterogeneity in property and hometown locations and market timing could significantly impact how much OOT buyers are willing to pay for new properties. The result in Column 3 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. This 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 4 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 shown in Column 5, 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 factors related to the time-varying OOT housing market, which could significantly influence property transaction prices. The coefficient of 0.038 on hometown past return 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.

The horizons from 1 to 10 years of measuring hometown house price experience 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 hometown house price experiences over varying experience year horizons. 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 return experiences, measured by horizons ranging from one to ten years. Additionally, it is noteworthy that the sensitivity towards past hometown return experiences gradually decreases as the return 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.

The observed positive relation between OOT purchase price and hometown house price growth is not driven by certain years. In Appendix, Figure A.4 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 robust and persistent effects of hometown house price growth on OOT purchase prices.

A.1. Heterogeneity in 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. The heterogeneity in OOT buyers' hometown characteristics could drive both high past house returns and high new property purchase prices. The hometown zip code fixed effects in our specification could mitigate the endogenous issue to an extent, but it may not fully get rid of the effects from confounding factors related to time-varying hometown characteristics.

To rule out the time-varying hometown characteristics driving our results, we first control for a set of hometown characteristics at the county-year level. We have discussed the construction of the county characteristics in Section II.D. Next, we consider more rigorous constraints by adding hometown-county-year fixed effects. By doing that, we exclude the possibility of county characteristics influencing our results and only explore the OOT purchase price variation within the same hometown county and year.

Table 5 shows that our results are not driven by heterogeneity in time-varying hometown county characteristics. In Column 1, we control the hometown county characteristics, including the log of the county population, county median age, median income, median income growth, labor force ratio, and labor force ratio growth. The coefficient on the past five-year hometown return is still significantly positive. In Column 2, we control for, Log(Hometown HPI)$_{h,t-1}$, the hometown house price index one year before the OOT transaction. After experiencing a high house return 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 returns on new property purchase prices is still significant and positive.

Column 3 adds the interaction of hometown county and transaction year-month fixed effects. 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 significantly more than the other without the same experience.

In Column 4, 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.

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

A.2. Controlling for Property Characteristics

To rule out the effect of wealth increase that makes OOT buyers affordable for more expensive houses, we control for a set 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 extrapolate from their hometown house price growth experiences. In this part, we restrict the sample to the OOT transactions for which we have matched listing data on property characteristics. The coefficient in Column 1, which corresponds to our main specification in Table 2 but is estimated using the sample with property characteristics matched, suggests that a 50% increase in the hometown house returns over the past five years would be associated with one percentage point increase in the purchase prices. Accounting for the property's characteristics in Column 2 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. The coefficient on hometown house returns does not change much.

Overall, Table 3 rules out the possibility that OOT buyers with high price growth experience paying more for new properties is driven by the wealth increase, which makes OOT buyers affordable to more expensive houses.

A.3. Purchase List Price and Discount

Table 4 indicates that experiencing a high increase in hometown house prices over the past five years will make OOT homebuyers choose houses with higher list prices. The results also suggest that a higher increase in hometown house prices will lead to a lower purchase discount obtained by OOT homebuyers, even when controlling for house characteristics.

If OOT homebuyers would like to pay a higher price because the hometown house price growth extrapolation leads to the optimistic OOT house price belief, the optimistic belief could make the OOT buyers less aggressive when negotiating final transaction prices with home sellers. In the end, the spatial extrapolative house price belief will lead to smaller purchase discounts for OOT homebuyers. In this section, we 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 month. In Table 4, Column 1 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 house characteristics applied in Column 3 of Table 3. This suggests that if two similar houses 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.

Through the list and transaction prices, Columns 3 and 4 of Table 4 examine the purchase discount obtained by OOT buyers. Again, we compare two OOT buyers from the same hometown zip code buying houses in the same OOT property zip code area and transaction year and month. Column 3 shows that the buyer with a higher hometown house price growth would obtain a significantly lower discount on the purchase price. Controlling for the purchased house characteristics, we observe a very robust result. 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 23 basis points than the other buyer without the house price increase.

According to the results presented in Table 4, it seems that when OOT buyers experience high house price growth in their hometown, they tend to choose a house with a higher list price from among similar houses. However, this does not explain why those buyers end up paying a high purchase price in the end. The purchase discount obtained by those OOT buyers shows that buyers with high hometown house price growth tend to receive a low purchase discount for similar properties. It could suggest that the spatial extrapolative house price belief formed from past hometown house price growth makes those buyers less aggressive in negotiating final transaction prices with home sellers, partially explaining their high house payments. 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.

B. Realized House Returns

OOT buyers who have experienced high returns in their hometown markets tend to pay more, 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 hometown house price changes could provide OOT buyers with valuable market signals for their OOT transactions. If so, leveraging housing market information from past hometown house returns could be a rational behavior, which helps OOT buyers maximize their market profitability in the end.

To investigate this possibility, we calculated the realized returns of OOT properties through two-way transactions made by OOT buyers. Section II.F provides a detailed methodology for measuring realized returns. Table **??** presents the annualized realized returns obtained by OOT buyers. Column 1 indicates that, on average, OOT buyers experiencing a 50% increase in hometown house returns over the past five years tend to yield five percentage points lower returns, accounting for time-invariant hometown and property zip area characteristics. However, after adjusting for property market timing effects in Column 2, the coefficient for past hometown house returns becomes a bit more negative. It suggests that OOT buyers who have experienced high hometown returns often choose an advantageous time to sell their OOT properties. However, when selling at the same time in the same market, those with high hometown returns seem to struggle more in selecting the right time to purchase. Column 3 supports the finding.

In Column 3, we account for property purchase timing in a market by adding the interaction of OOT zip code and year-month of purchase (OOT Zip $\times$ Buy YM) fixed effects. The coefficient for hometown returns in Column 3 becomes less negative but remains significant. This negative return gap holds up when controlling for the holding length of OOT properties in Column 4. In Column 5, we add the interaction of the year-month of purchase transaction and the year-month of sale transaction fixed effects. The significant coefficient of -0.012 indicates that a 100% increase in hometown house returns over the past five years will result in OOT buyers earning 1.2 percentage points lower returns annually.

Overall, we find significantly negative realized returns earned by the OOT buyers experiencing high hometown house price growth. It implies that the past hometown housing returns do not inform about OOT housing markets. It appears less likely that OOT buyers are rationally leveraging information from their hometown housing markets to maximize profitability in OOT housing markets. The bad purchase timing selected by OOT buyers with high past hometown house price experiences explains much their negative realized returns. It may convince us that the extrapolative belief plays a significant role in driving their property purchase decisions and high transaction prices.

C. Separate Wealth Effect through Three Types of Buyers

The high past property returns in hometowns 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 effect of hometown return extrapolation from the wealth effect.

C.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 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 paying OOT properties. 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 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[4] 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[5].

Figure 4 plots the estimated coefficients in Column 4 of Table 6 and visually presents how the three types of OOT buyers react to the same hometown house price increase differently.

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 returns on the purchase prices of OOT properties.

C.2. Hometown House Values and Living Length

Given our ability to associate Out-of-Town (OOT) buyers with their hometown properties, we can efficiently account for the impact of wealth by considering the purchase price and the approximate sale price of these properties. Furthermore, we can gain a more precise insight into OOT buyers' exposure to hometown return 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

[4] $0.025 \times 0.5 = 0.0125$

[5] $(0.025 + 0.012) \times 0.5 = 0.0185$ for migrators and analogous calculation for SH buyers

II.G.2.

To focus on the impact of five-year hometown house returns on OOT buyers' purchasing 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 property returns 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 returns, 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 returns. 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 returns 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 returns on OOT property transaction prices diminishes.

Figure 5 visually presents these findings, displaying the linear combination of coefficients on hometown returns, Hometown $\text{Ret}_{h,[t-6,t-1]}$, and the interaction terms of residence length and hometown return. 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 returns over the past five years compared to those who have not. The figure suggests that the past five-year hometown house returns significantly influence 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 return experiences.

Importantly, Figure 5 reveals that as the residence length of an OOT buyer in the hometown increases, the influence of the most recent five-year hometown returns 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 returns when purchasing OOT properties. More recent hometown return experiences are more influential for OOT buyers with shorter residence durations (i.e., less experience) in hometowns.

D. 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 return 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 returns when purchasing OOT properties.

D.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.5. 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 return 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 return 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.3 in the Appendix.

We analyze how house price beliefs are affected by experiences in different return experience horizons. Over varying return horizons measured in years, Figure 6 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 returns from extrapolation framework (Barberis et al., 2018).

D.2. Young People Extrapolate More than The Old

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.

Figure 7 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. Specifically, the coefficient of 0.14 for individuals younger than 40 implies that they would expect approximately 5.7 percentage points[6] higher house value given one standard deviation (41%) increase in the county house price over the past five years. In contrast, individuals over 60 years old would only expect a house price of 3.2 percentage points higher given the same house price increase.[7]

Figure 7 shows that young individuals are more susceptible to recent return experiences, and their extrapolative expectations update more strongly than old individuals, which is consistent with the experience effect framework.

D.3. OOT Buyers from High Extrapolation Hometown Pay More

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 returns. A

[6] $0.14 \times 0.41 \approx 0.057$

[7] $0.079 \times 0.41 \approx 0.032$

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 returns. The quintile 1 group serves as the reference group.

Figure 8 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 8 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.

D.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 $z_{m,s,t} = \widehat{\beta}_m \text{ State Ret}_{s,[t-6,t-1]}$. 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 returns. 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

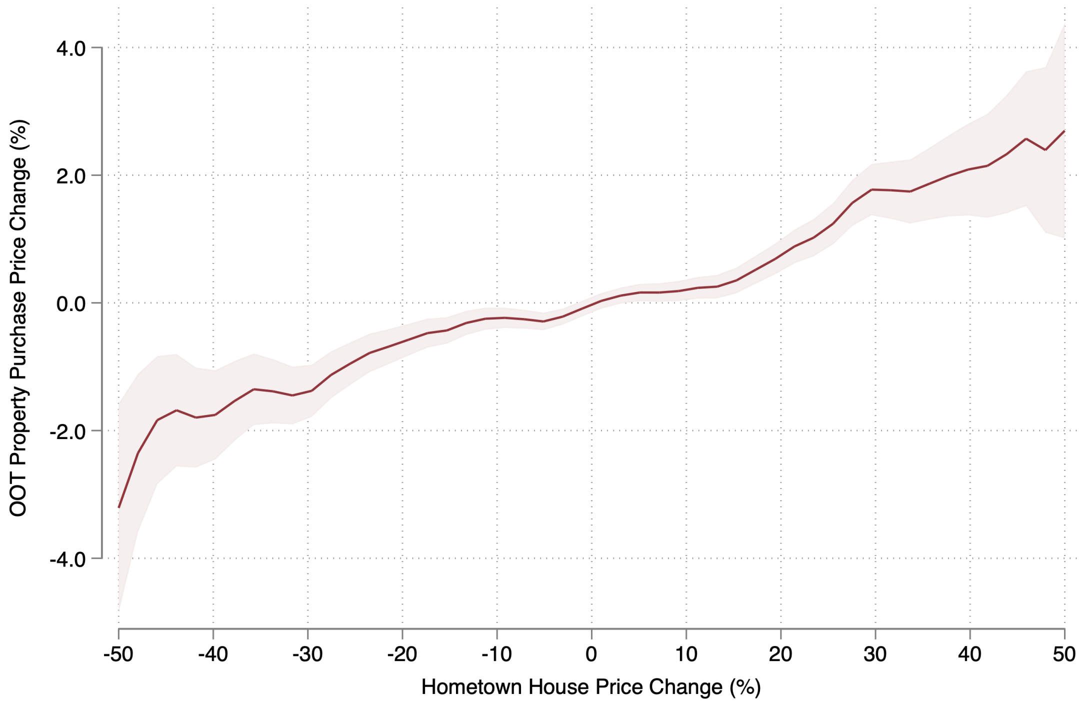


Figure 2 shows a non-linear relation between purchase price changes and hometown house price changes experienced by OOT homebuyers over the past five years, estimated using a local linear regression with the epanechnikov kernel. To create this plot, we first obtain the normalized log of the new property purchase prices, which are the residuals from regressing the original log of the 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 changes over the past five years by running the same regression but replacing the dependent variable with $Hometown\ Ret_{h,[t-6,t-1]}$ and collecting the residuals. The shaded area in the plot represents the 95% confidence interval.

Figure 3. Hometown Extrapolation by Experience Horizons

Panel A: Purchase Price

Panel B: Purchase Discount

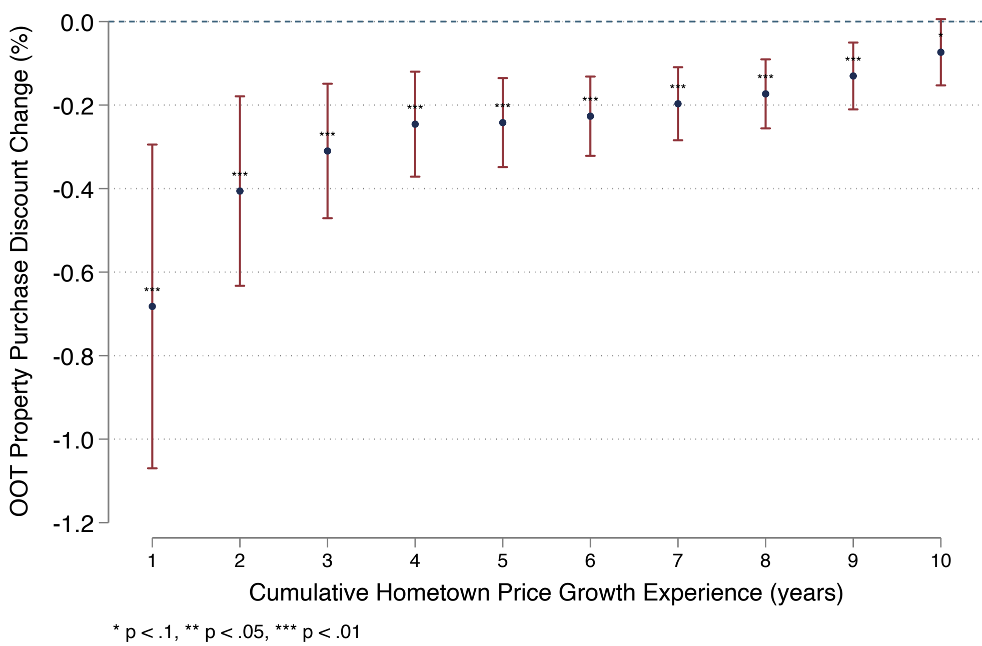


Figure 3 presents how OOT buyers' purchase prices and purchase discounts change, following a 100% increase in the hometown house prices in cumulative years of different horizons. Panel A presents the results for purchase prices, while Panel B is for purchase discounts. *Purchase Discount* is measured as (*Purchase List Price - Transaction Price*) / *Transaction Price* × 100. The y-axis of both panels shows the estimated sensitivity of purchase prices or purchase discounts to the past hometown house price changes. The sensitivity is estimated through Specification 1, in which we regress the log of OOT purchase prices or purchase discounts on the cumulative changes in hometown house prices within the indicated horizon. 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 4. Changes in OOT Purchase Prices by Renters, Migrants, and Second-home (SH) Buyers

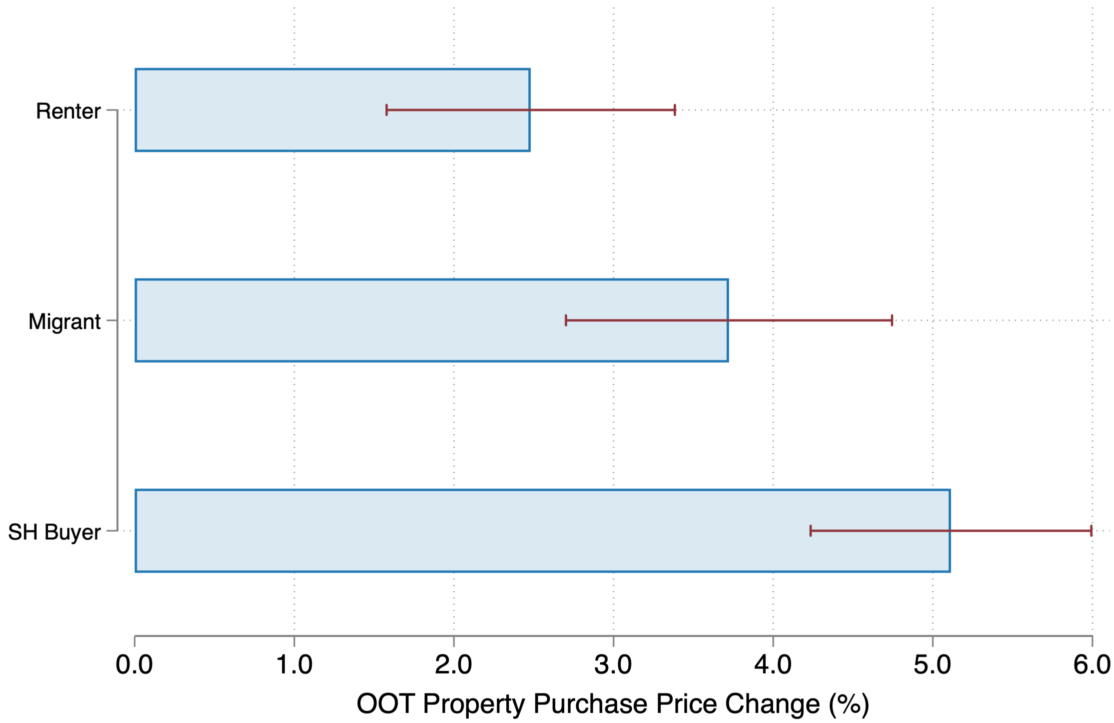


Figure 4 presents the changes in purchase prices of OOT properties for renters, migrant homeowners, and second-home (SH) buyers, following a 100% increase in hometown house prices over the last five years. The bar values (i.e., purchase price changes) are estimated by linearly combining the coefficients on the interaction terms of the buyer-type dummies with the hometown house price change, $Hometown\ Ret_{h,[t-6,t-1]}$, and the coefficient on $Hometown\ Ret_{h,[t-6,t-1]}$ 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 5. Changes in OOT Purchase Prices by Hometown Residence Length

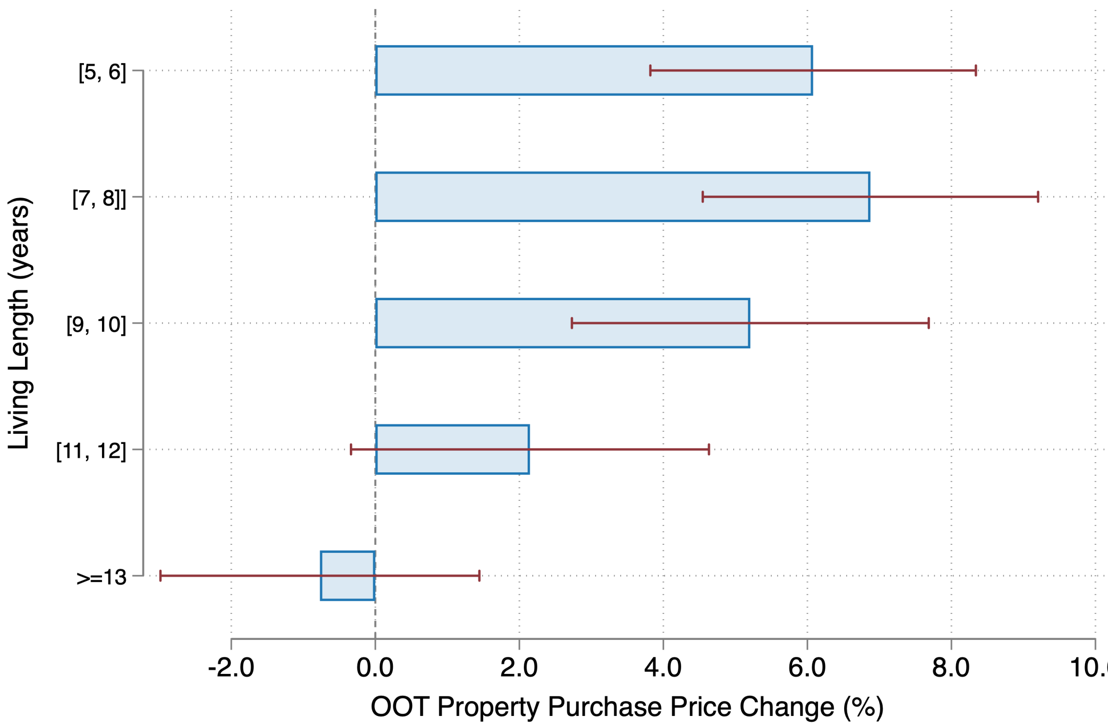


Figure 5 presents the changes in purchase prices of OOT properties for migrant homeowners and second-home (SH) buyers with different living lengths in hometown properties, following a 100% increase in hometown house prices over the last five years. The purchase price changes are estimated by *controlling for housing wealth increase and living length*. The bar values (i.e., purchase price changes) correspond to the linear combination of coefficients on hometown house price change, $\textit{Hometown Ret}_{h,[t-6,t-1]}$, and the interaction terms of residence length and $\textit{Hometown Ret}_{h,[t-6,t-1]}$. The estimated coefficients can be calculated from Column 3 of Table 7. Standard errors are clustered by hometown zip.

Figure 6. Changes in Expected House Values by Price Growth Experience Horizons

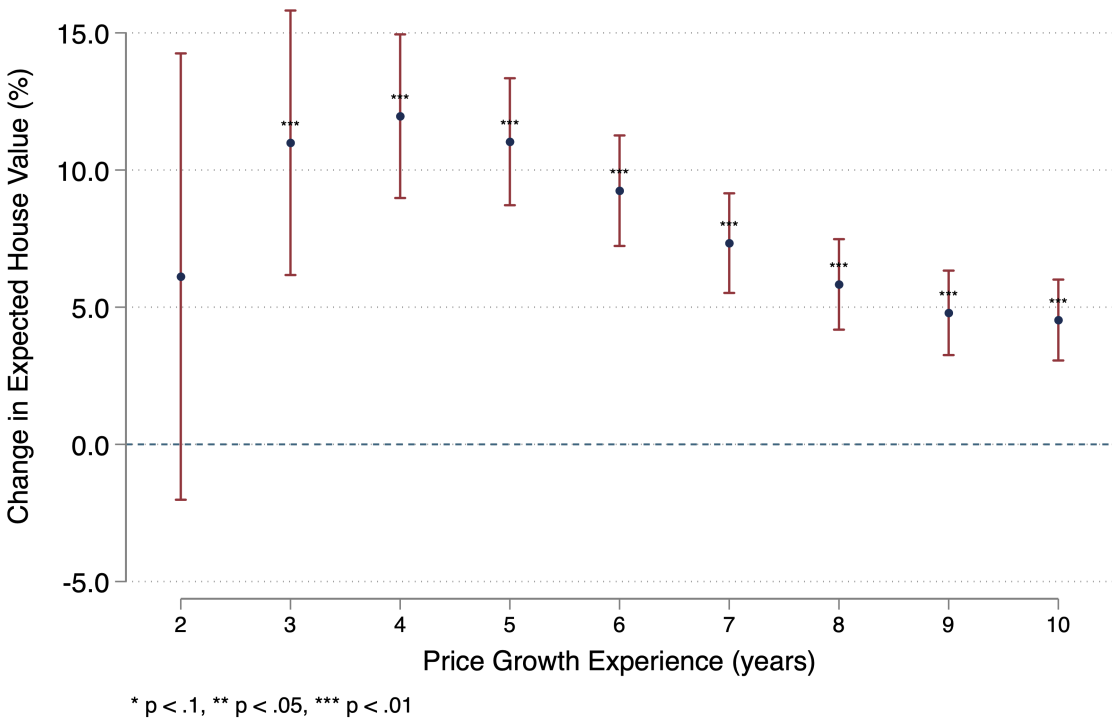
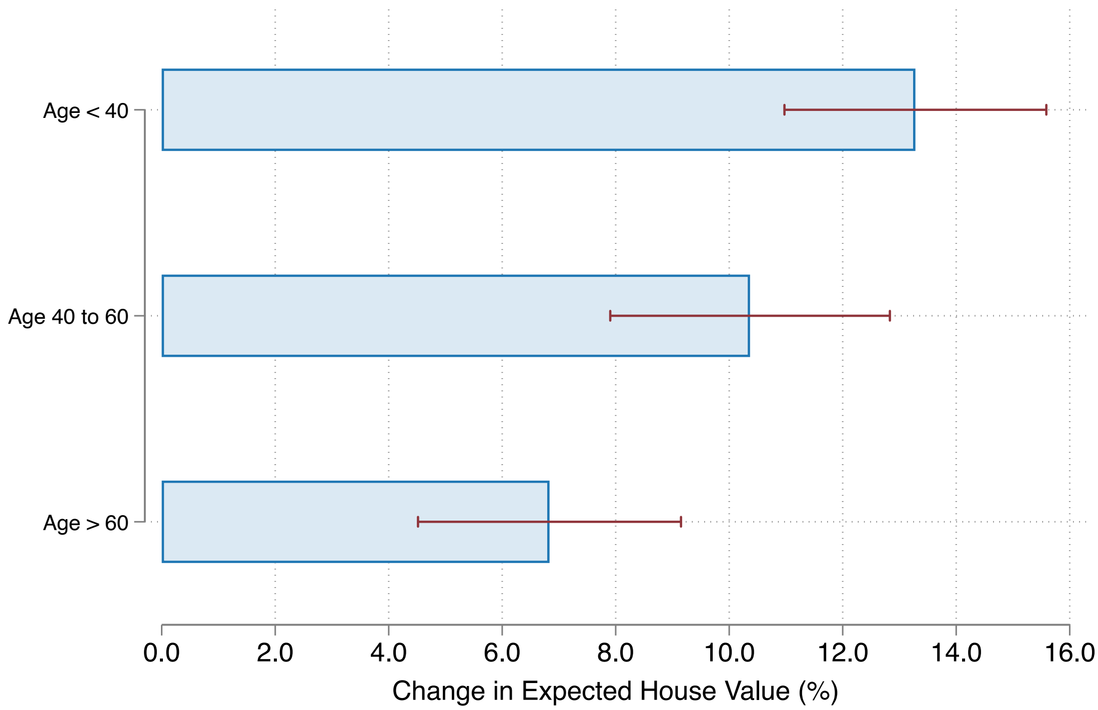


Figure 6 presents the changes in expected house values of households, following a 100% increase in county house prices over the last five years. The expected house value changes correspond to the extrapolation beta estimated through Specification 3 and reflect how much households extrapolate from the past county house price growth when forming expected house values. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 7. Extrapolation Heterogeneity by Demographics

Panal A: Age



Panel B: Gender

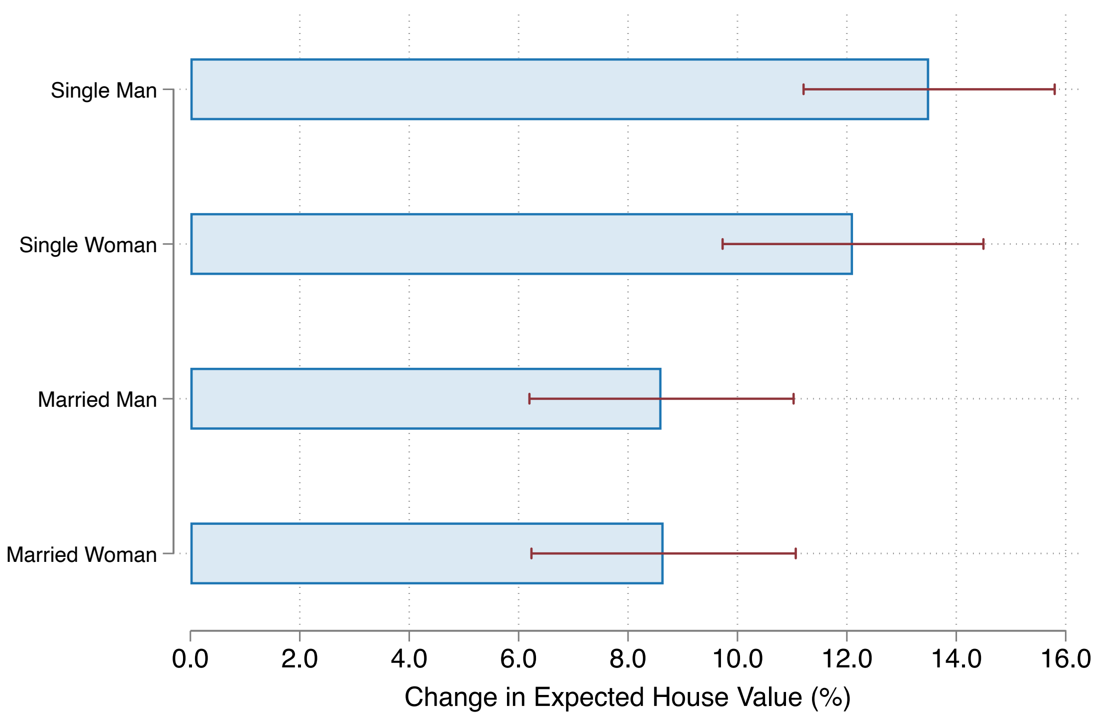
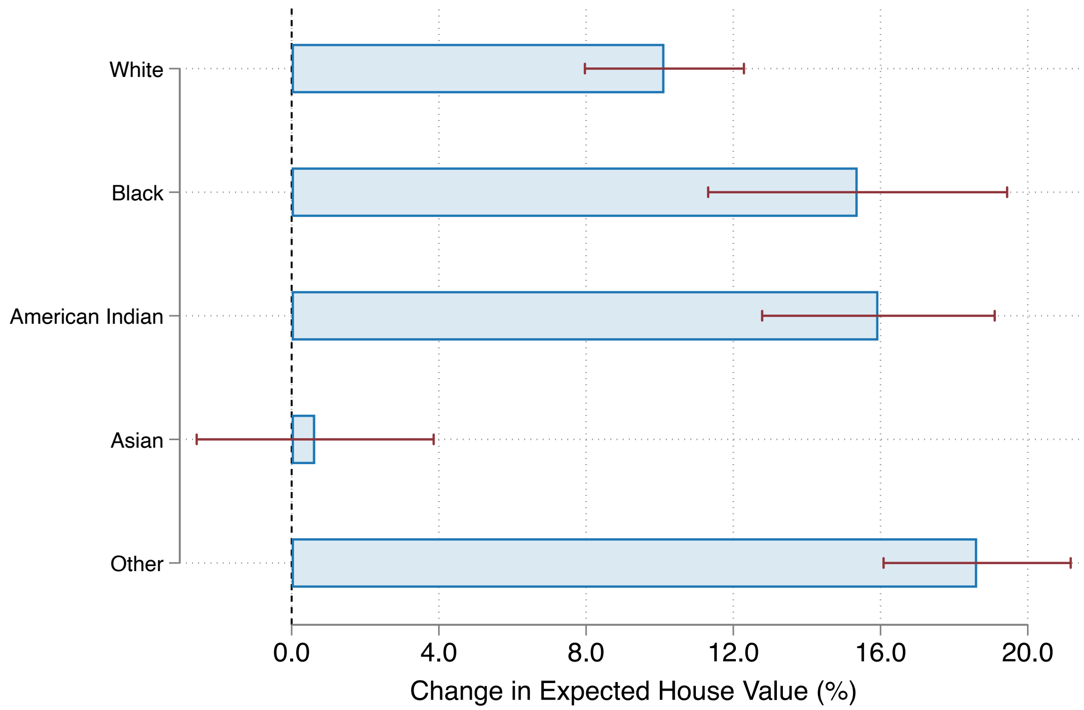


Figure 7. Extrapolation Heterogeneity by Demographics

Panal C: Race



Panal D: Education

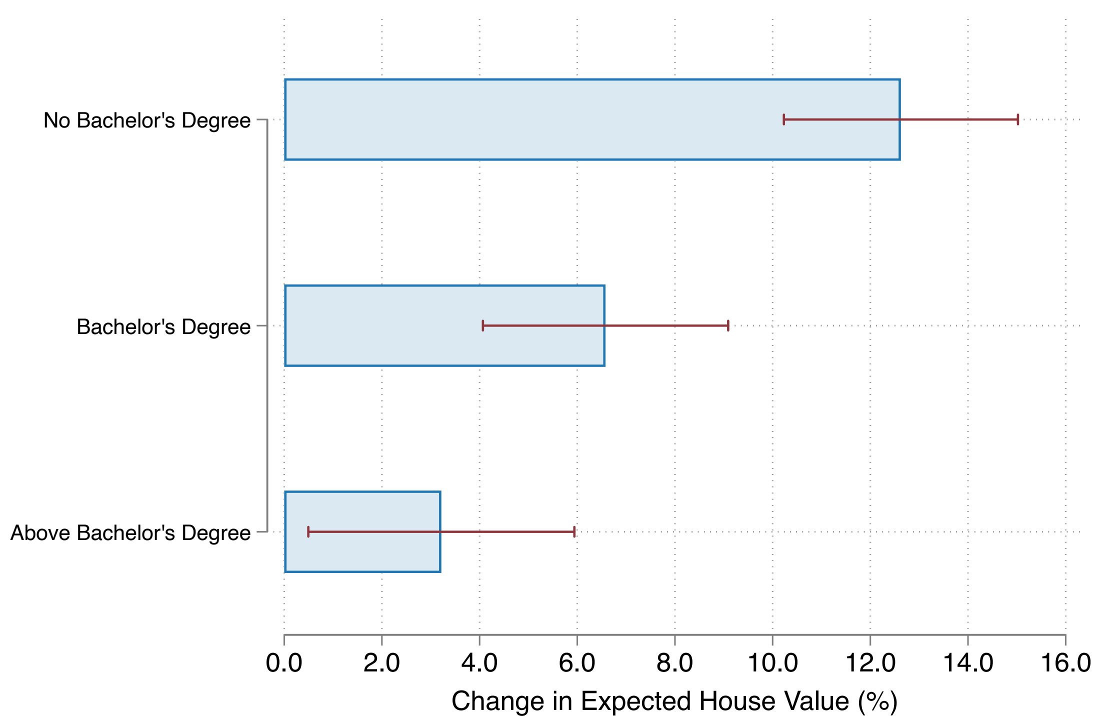


Figure 7. Extrapolation Heterogeneity by Demographics

Panal E: Income

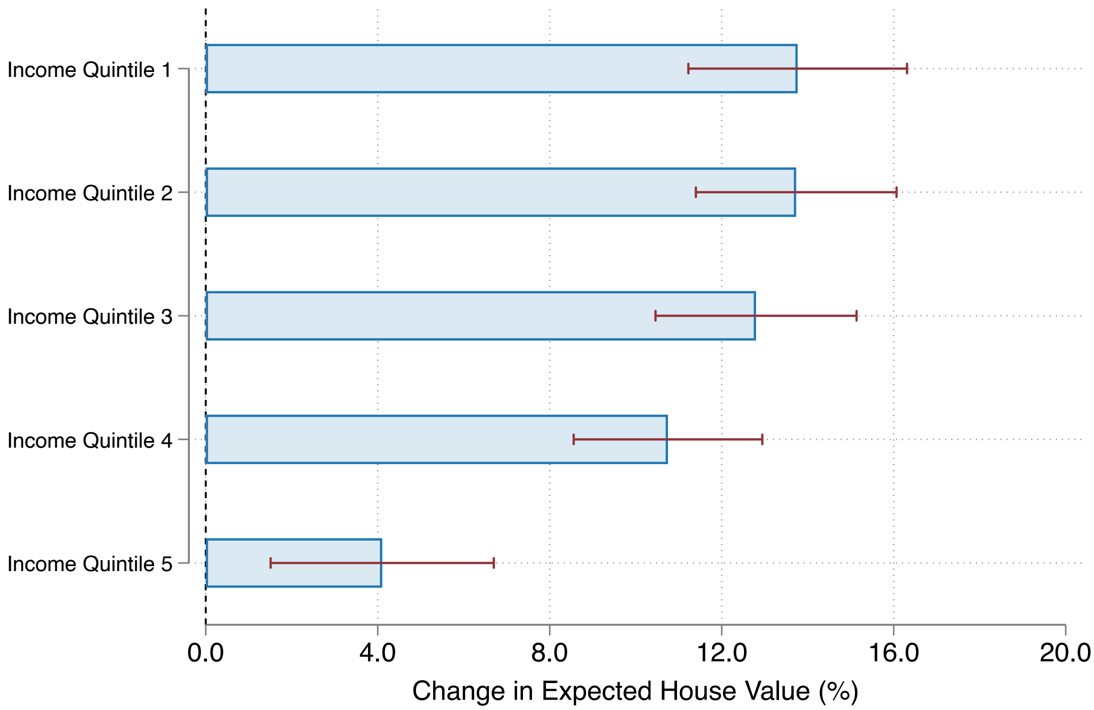


Figure 7 presents the changes in expected house values of households of different demographic groups following a 100% increase in county house prices over the last five years. The demographic groups are indicated in panel titles. To get the results, we first assign the households into groups based on 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 linear combination (in percentage) of the coefficient on hometown house price change, $Hometown\ Ret_{h,[t-6,t-1]}$, and coefficients on the interaction terms of the demographic group dummies and house price growth. Standard errors are clustered by hometown zip code.

Figure 8. Changes in OOT Purchase Prices by Hometown Extrapolation Beta Quintiles

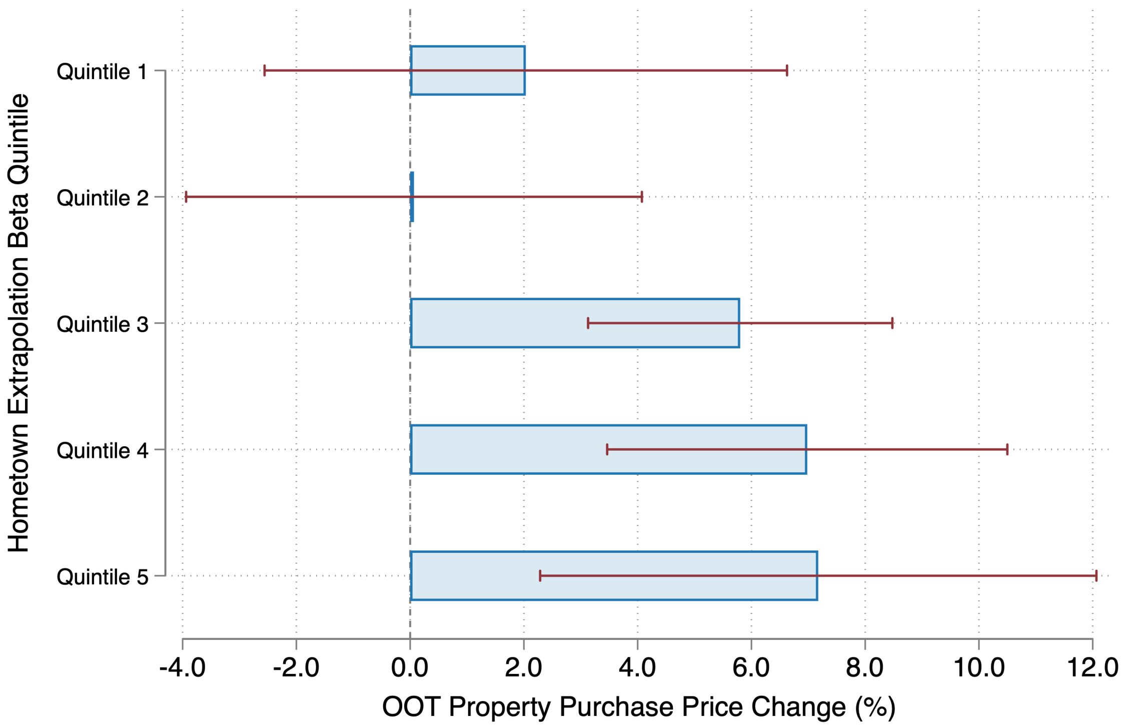


Figure 8 presents the changes in purchase prices of OOT properties by buyers from hometowns with different extrapolation levels (i.e., extrapolation beta), following a 100% increase in hometown house prices over the last five years. First, we estimate the extrapolation beta for each county using Specification 3. The extrapolation beta represents how much people in a county extrapolate from past county-level house price changes when forming expected own house values. Then, we link the extrapolation beta to the hometown counties of OOT buyers. Finally, we sort households according to their hometown extrapolation beta and perform the baseline analysis 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 Ret_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. Purchase Price of Out-of-town (OOT) House and Hometown House Price Growth Experience

Panel A: Purchase Price

	Log(Purchase Price)			
	(1)	(2)	(3)	(4)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.140***	0.071***	0.057***	0.038***
	(0.005)	(0.005)	(0.005)	(0.003)
Property Zip $\text{Ret}_{o,[t-6,t-1]}$		0.394***	0.202***	
		(0.003)	(0.005)	
Log(Property Zip $\text{HPI})_{o,t-1}$			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	Yes
Year-Month (YM) FE	Yes	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 $\text{Ret}_{h,[t-6,t-1]}$	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	Yes
Sale YM FE	Yes	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 examines 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* $\textit{Ret}_{h,[t-6,t-1]}$ is the zip-level house price changes in the hometown h in the past five years. *Property-Zip* $\textit{Ret}_{o,[t-6,t-1]}$ is the zip-level house price changes in the OOT zip o over the past five years. *Log(Property-Zip* $\textit{HPI})_{o,t-1}$ 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. Hometown Extrapolation Controlling for Property Characteristics

	Log(Purchase Price)		
	(1)	(2)	(3)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	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 how the purchase prices of OOT properties change when hometown house price growth experience changes, 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* $Ret_{h,[t-6,t-1]}$ 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 Ret$_{h,[t-6,t-1]}$	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 $\times$ YM FE	Yes	Yes	Yes	Yes
House Charac.		Yes		Yes

Table 4 examines how OOT buyers' hometown house price growth experiences affect the list prices of their purchased properties and the purchase discounts received. The detailed process of obtaining the list prices and purchase discounts has been described in Section II.E. Columns 1 and 2 show how the list prices of the purchased OOT property change as the hometown house price growth changes. Columns 3 and 4 show the results for the purchase discounts received by OOT homebuyers in the transactions. *Purchase Discount* is measured as (*Purchase List Price - Transaction Price*) / *Transaction Price* $\times$ 100. *Hometown Ret*$_{h,[t-6,t-1]}$ 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 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. Hometown Extrapolation Controlling for Hometown County Characteristics

	Log(Purchase Price)			
	(1)	(2)	(3)	(4)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.029***	0.020***	0.053***	0.059***
	(0.003)	(0.004)	(0.008)	(0.008)
Log(Hometown $\text{Population})_{h,t}$	-0.012	-0.012		
	(0.017)	(0.017)		
Hometown Median $\text{Age}_{h,t}$	-0.001	-0.001		
	(0.001)	(0.001)		
Log(Hometown Median $\text{Income})_{h,t}$	0.017	-0.023		
	(0.019)	(0.021)		
Hometown Median Income $\text{Growth}_{h,[t-1,t]}$	-0.025	-0.003		
	(0.018)	(0.019)		
Hometown Labor Force $\text{Ratio}_{h,t}$	0.287***	0.284***		
	(0.052)	(0.052)		
Hometown Labor Force $\text{Growth}_{h,[t-1,t]}$	-0.052	-0.047		
	(0.041)	(0.041)		
Log(Hometown $\text{HPI})_{h,t-1}$		0.030***	0.047***	0.046***
		(0.007)	(0.011)	(0.012)
Adjusted R^2	0.549	0.549	0.558	0.571
Observations	2,339,662	2,339,662	2,627,903	2,627,903
Hometown Zip FE	Yes	Yes	Yes	Yes
Property Zip × YM FE	Yes	Yes	Yes	Yes
Hometown County × Year FE			Yes	Yes
Property × Hometown Counties FE				Yes

Table 5 presents how the purchase prices of OOT properties change when hometown house price growth experience changes, controlling for home county characteristics. For a more detailed description of county characteristics, please refer to Section II.D. 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. *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. Column 3 adds the hometown county times transaction year-month fixed effects. Column 4 includes the Property-Hometown counties fixed effects. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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

	Log(Purchase Price)			
	(1) Renter	(2) Migrator	(3) SH Buyer	(4) All Sample
Hometown $\text{Ret}_{h,[t-6,t-1]}$	0.028***	0.040***	0.044***	0.025***
	(0.005)	(0.011)	(0.005)	(0.003)
Migrator × Hometown $\text{Ret}_{h,[t-6,t-1]}$				0.014***
				(0.004)
SH Buyer × Hometown $\text{Ret}_{h,[t-6,t-1]}$				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 × YM FE	Yes	Yes	Yes	Yes

Table 6 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 7. Hometown Extrapolation Controlling for Housing Wealth Increase and Living Length

	Log(Purchase Price)		
	(1)	(2)	(3)
Hometown $\text{Ret}_{h,[t-6,t-1]}$	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 $\text{HPI})_{h,t-1}$		0.060***	0.062***
		(0.015)	(0.015)
Living Years		0.012***	0.013***
		(0.000)	(0.000)
Living Years [7, 8] $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$			0.008
			(0.008)
Living Years [9, 10] $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$			-0.009
			(0.010)
Living Years [11, 12] $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$			-0.039***
			(0.011)
Living Years $\geqslant$ 13 $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$			-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 experienced hometown house price growth on the migrants and second-home (SH) OOT buyers' purchase prices. We restrict the sample to OOT buyers residing in hometowns for a minimum of five years. We then categorize OOT buyers based on the length of their residence and create dummy variables for different groups. For instance, the dummy variable, *Living Years [7, 8]*, equals one if an OOT buyer has lived in the hometown house for seven to eight years at the time of the OOT property purchase, and otherwise zero. Similar definitions are applied to other residence length dummy variables. *Hometown* $Ret_{h,[t-6,t-1]}$ 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 $\text{Ret}_{h,[t-6,t-1]}$	0.093***	0.108***	0.100***	0.101***
	(0.015)	(0.014)	(0.012)	(0.012)
Log(County HPI)$_{i,t}$	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 own house values of U.S. households in the American Community Survey data. The dependent variable is the log of the expected house value of households. *County Ret*$_{i,[t-6,t-1]}$ 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 code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9. Belief Sensitivity IV Estimation

	Hometown $\text{Ret}_{h,[t-6,t-1]}$	Log(Purchase Price)			
	(1) First Stage	(2) OLS	(3) IV-2SLS	(4) OLS	(5) IV-2SLS
Extrapolative Price	3.747***				
	(0.084)				
Hometown $\text{Ret}_{h,[t-6,t-1]}$		0.035***	0.057***	0.021***	0.059***
		(0.004)	(0.010)	(0.005)	(0.011)
Migrator $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$				0.013**	0.004
				(0.005)	(0.010)
SH Buyer $\times$ Hometown $\text{Ret}_{h,[t-6,t-1]}$				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 $\times$ YM FE	Yes	Yes	Yes	Yes	Yes

Table 9 reestimates the extrapolation effect on OOT house purchase prices through our belief sensitivity instrumental variable (IV). Basically, we construct the belief sensitivity IV by multiplying the estimated hometown-MSA differences in the house price belief sensitivity to past state house price growth, $\widehat{\beta}_m$, and past five-year state house price growth, $z_{m,s,t} = \widehat{\beta}_m \, State\ Ret_{s,[t-6,t-1]}$. 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

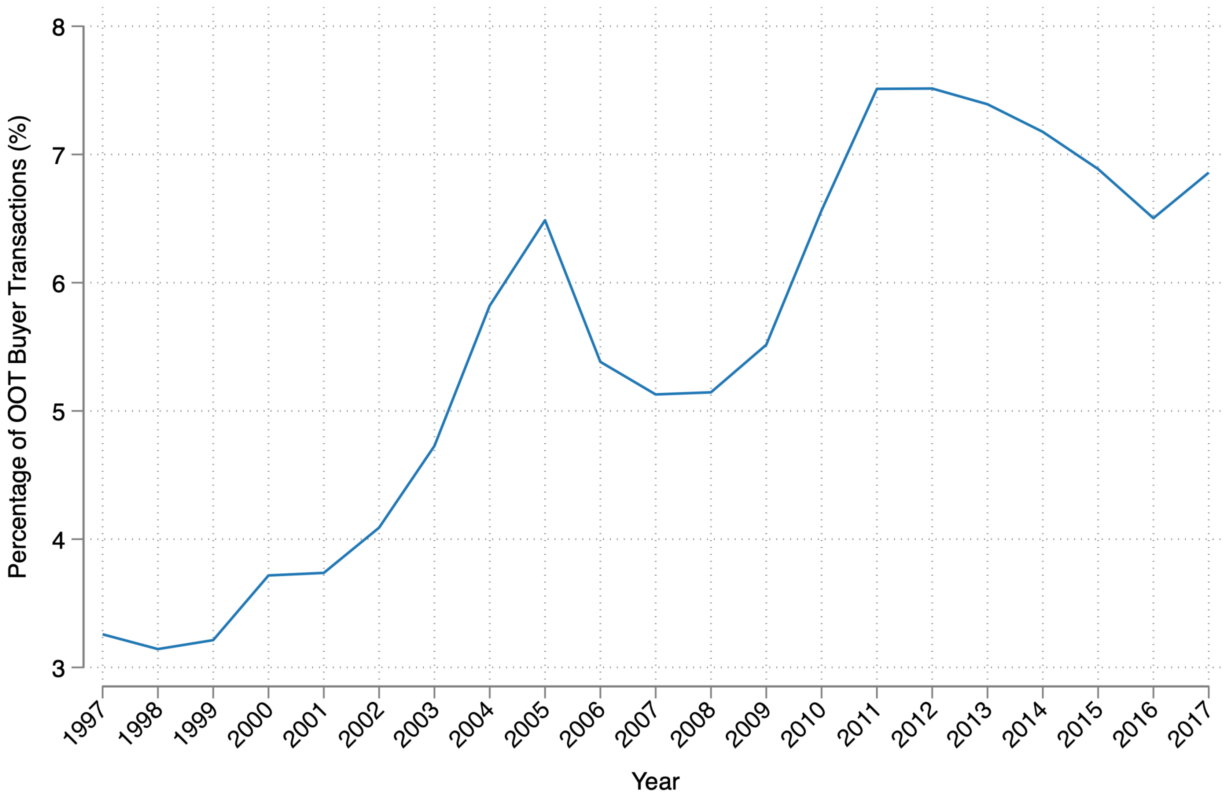
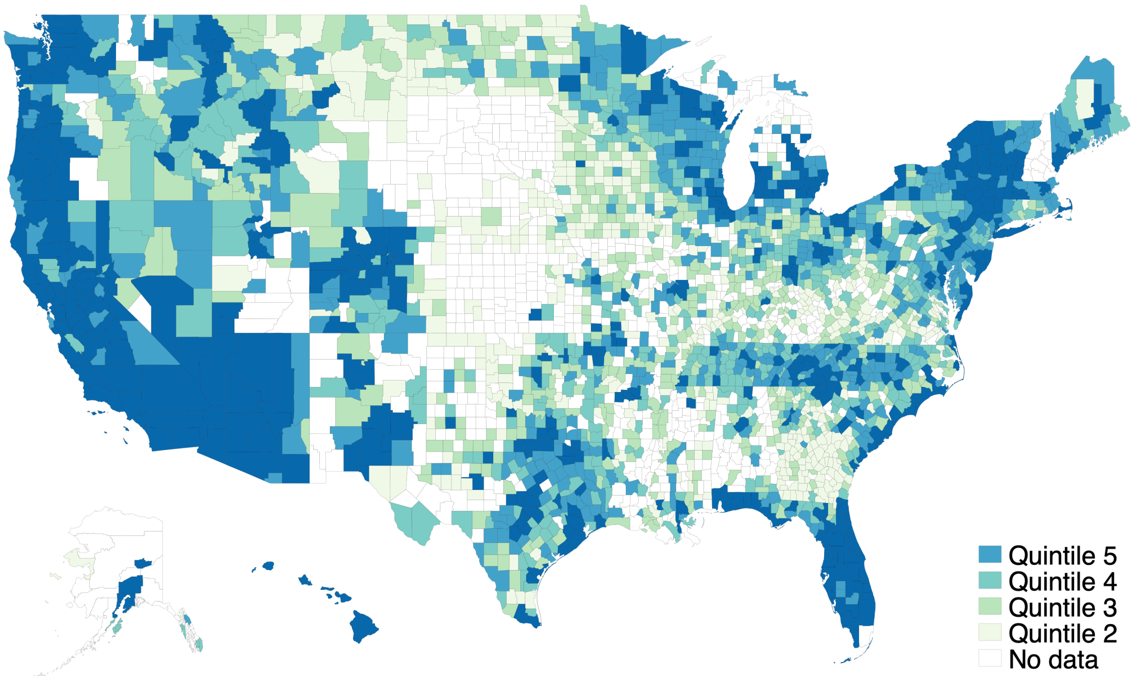


Figure A.1 presents the percentage of housing transactions made by out-of-town (OOT) homebuyers each year from 1997 to 2017. The identification of OOT buyers is discussed in Section II.C.

Figure A.2. Geographical Distributions of Out-of-town (OOT) Buyers

Panel A: County level



Panel B: State level

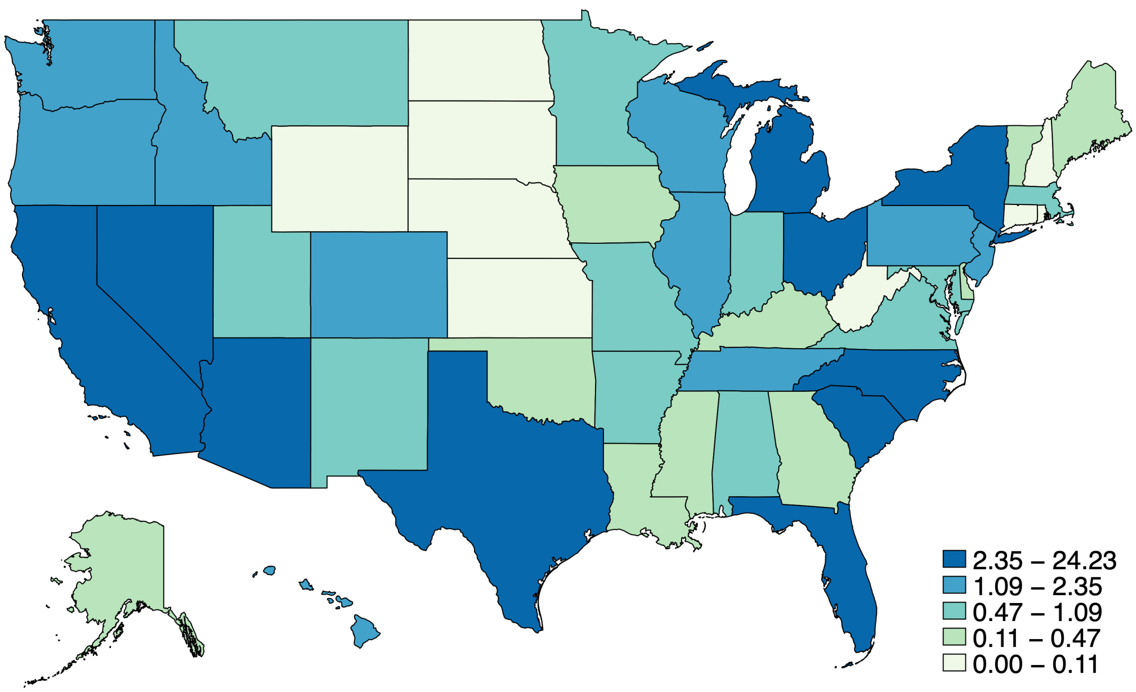


Figure A.2 presents the geographical distributions of the counties and states where OOT buyers purchased the properties from 2002 to 2017. OOT buyers are those who report mailing addresses (i.e., hometowns) over 60 miles away from the purchased OOT property addresses. Panel 1 shows the county-level geographical distribution of OOT transactions, where each color category in the legend represents a quintile. Panel 2 shows the state-level geographical distribution of OOT transactions, where the legend shows the percentage of transactions in a state over the total OOT transactions of the nation from 2002 to 2017.

Figure A.3. Hometown Extrapolation by Individual Experience Horizons

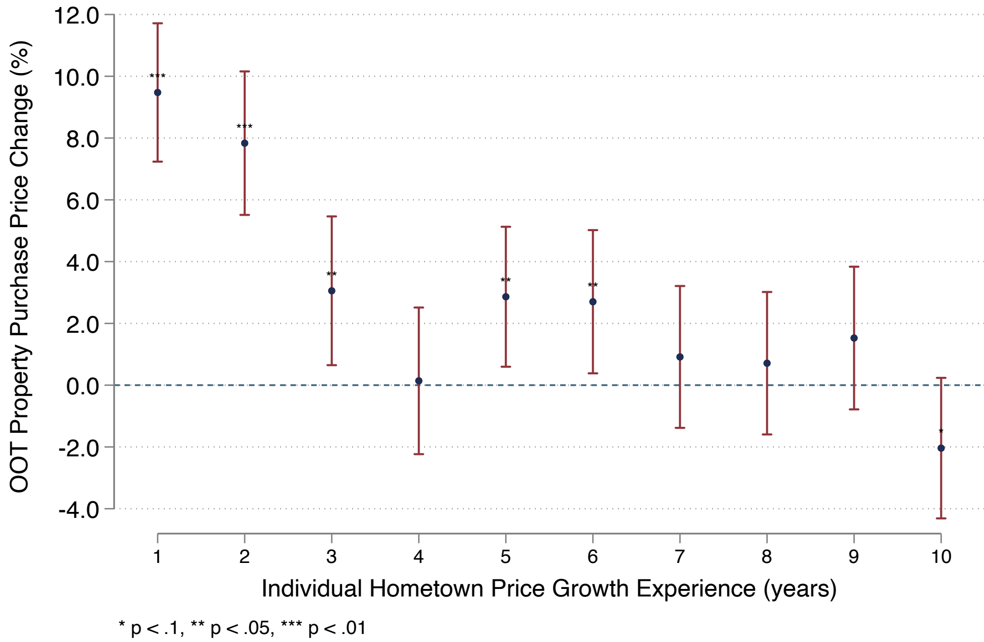


Figure A.3 presents how OOT buyers' purchase prices change, following a 100% increase in hometown house prices in an *individual year* in the past before buying the OOT property. The y-axis shows the estimated sensitivity of purchase prices to the past hometown house price changes. The sensitivity is 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.4. Hometown Extrapolation over Property Transaction Year

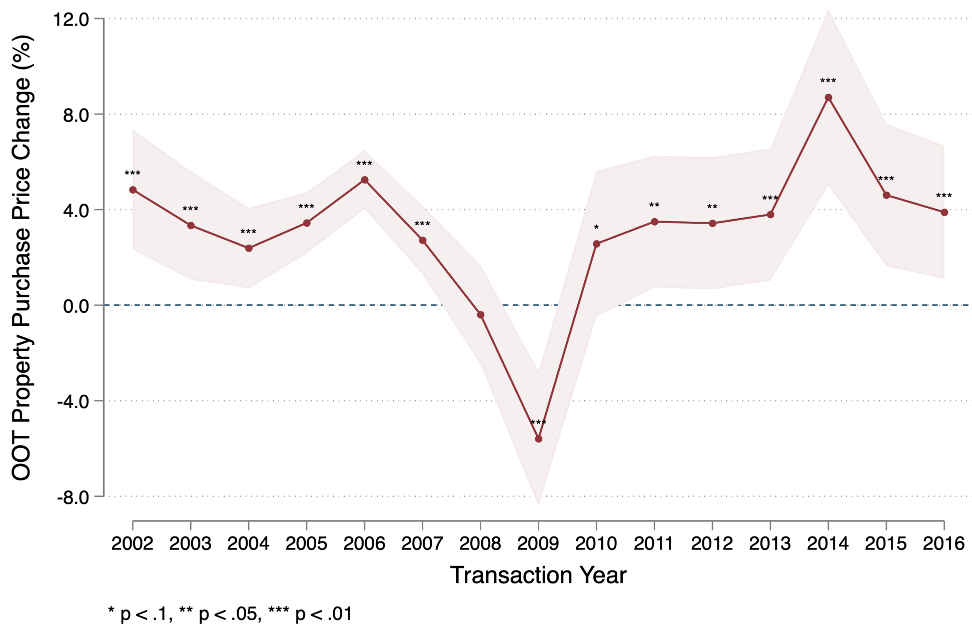


Figure A.4 examines the effect of past five-year hometown house price growth on OOT buyers' property purchase prices in different transaction years. The value of each dot shows that, *in a specific transaction year*, how OOT buyers with 100% increase in hometown house price over the past five years would 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 $HometownRet_{h,[t-6,t-1]}$ with 15 dummy variables for transaction years from 2002 to 2016, respectively. Then, we collect the coefficients on the interaction terms and separately combine the coefficient on $HometownRet_{h,[t-6,t-1]}$ and each of the interaction term coefficients. Finally, we perform linear combination tests on the linearly combined coefficients. Standard errors are clustered by hometown zip code. *,**, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A.5. 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

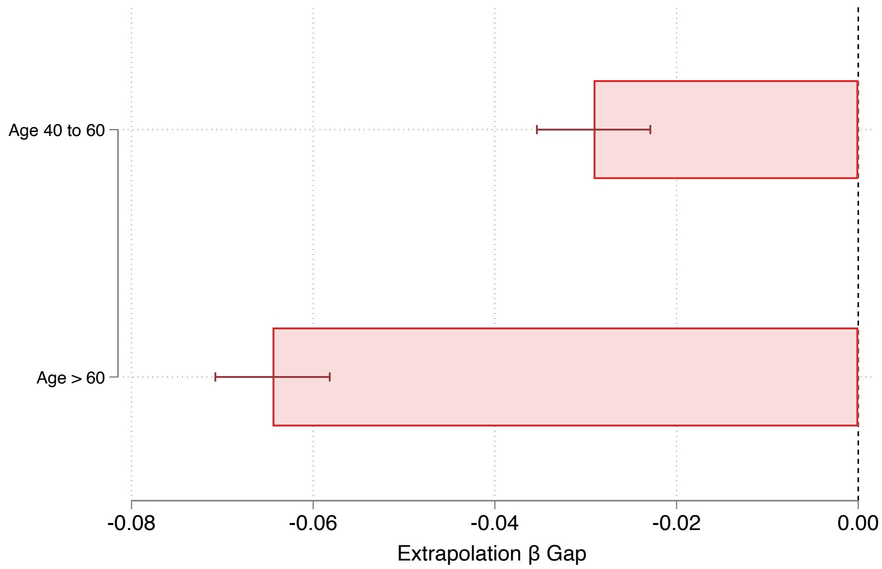
Questionnaire instructions **view entire document:** text **image**

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

Figure A.6. Extrapolation β Gap by Age, Gender, and Marital Status

Panel A: Age



Panel B: Gender and Marital Status

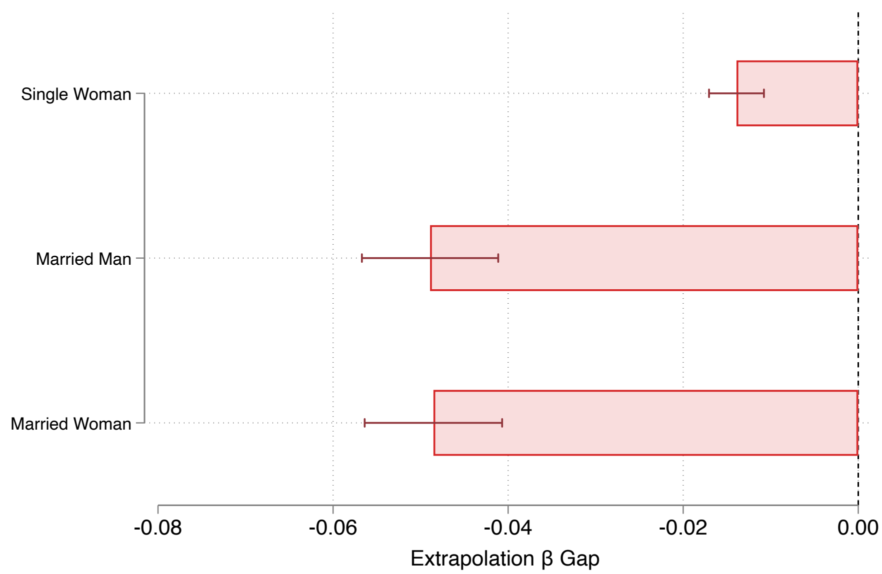
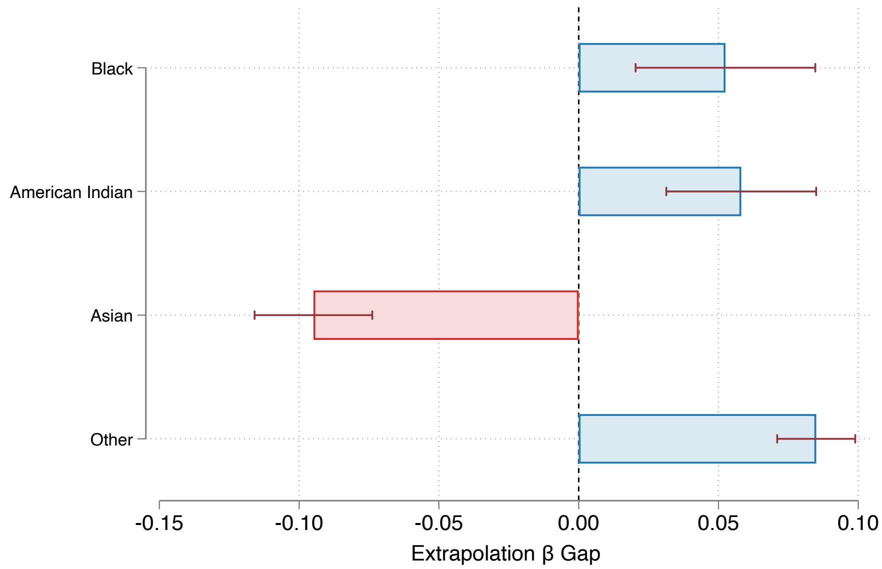


Figure A.6 presents the difference in changes in expected house values of households in different demographic groups, following a 100% increase in county house prices over the last five years. The demographic groups are indicated in panel titles. To get the results, we first assign the households into 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 $Hometown\ Ret_{h,[t-6,t-1]}$. Standard errors are clustered by hometown zip code.

Figure A.7. Extrapolation β Gap by Race and Education

Panel A: Race



Panel B: Education

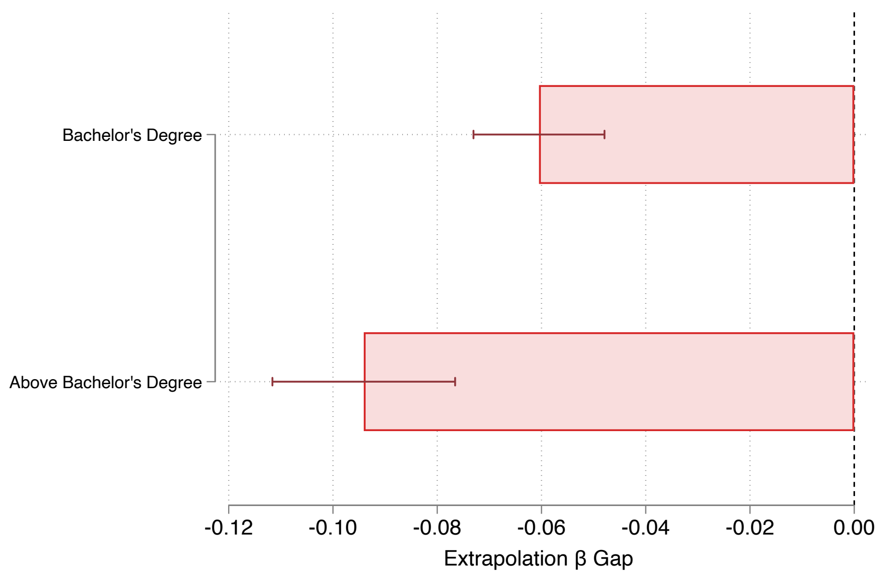


Figure A.6 presents the difference in changes in expected house values of households in different demographic groups, following a 100% increase in county house prices over the last five years. The demographic groups are indicated in panel titles. To get the results, we first assign the households into 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 $Hometown\ Ret_{h,[t-6,t-1]}$. Standard errors are clustered by hometown zip code.

Figure A.8. Extrapolation β Gap by Income

Panel A: Income

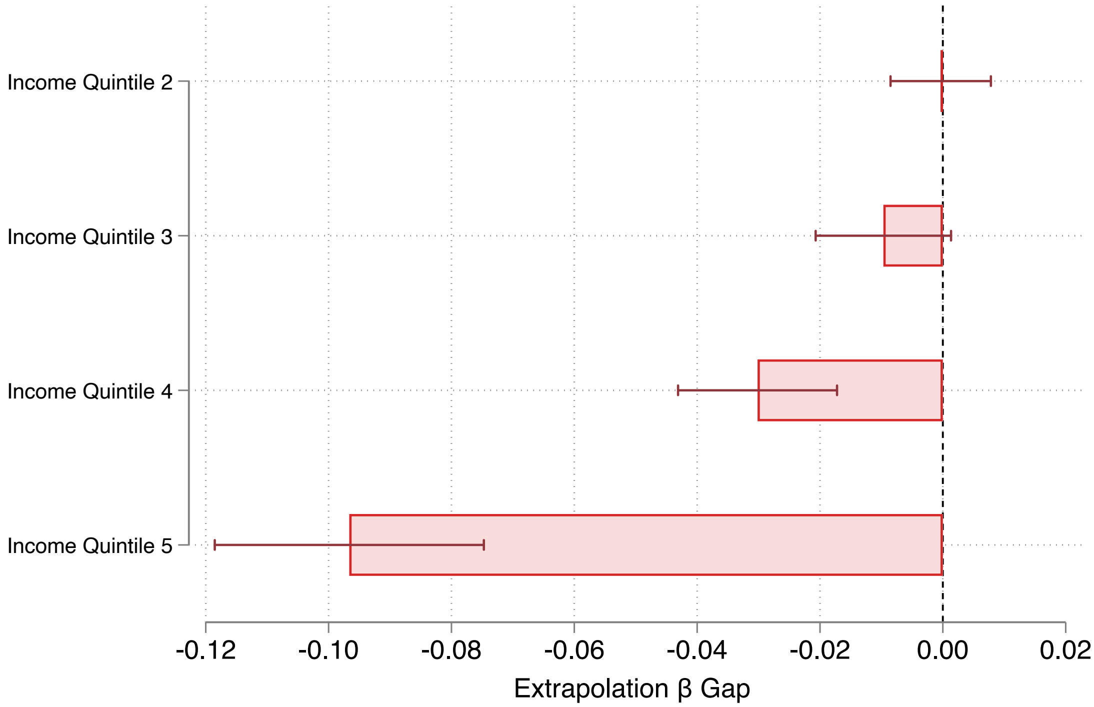


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Table A.1. Out-of-town (OOT) Homebuyers Defined by Different Distances

	Log(Purchase Price)					
	(1) 100 Miles	(2) 120 Miles	(3) 200 Miles	(4) 400 Miles	(5) 600 Miles	(6) 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 × 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. Purchase Prices of Renters, Migrants, and Second-home (SH) Buyers

	Log(Purchase Price)	
	(1)	(2)
	Sample with matched house characteristics	robu$_r eg$4
Hometown Ret$_{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.2 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.3. 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.3 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.