Working Papers

FEDERAL RESERVE BANK OF BOSTON

No. 25-13

Misestimating House Values: Consequences for Household Finance

Stefano Corradin, José L. Fillat, and Carles Vergara-Alert

Abstract:
This study examines the effect of systematic household misestimation of home prices on financial decisions, including stockholdings, consumption, and asset allocation. Using exogenous variation in house values, mortgage debt, and homeowner misestimation identified through differences in local housing market characteristics, we find that a $60,000 increase in house overvaluation (approximately one standard deviation) results in a 1.1 to 1.9 percent decrease in risky stockholdings, a 1.5 to 4.3 percent increase in consumption, and a 1.3 to 2.5 percent increase in the share of risk-free assets over liquid wealth. The results highlight the need to better understand how housing wealth and beliefs about house values affect portfolio choice, spending, and overall household finance.

JEL Classifications: G11, D11, D91, R21, C61
Keywords: Household finance, portfolio choice, housing, misestimation

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The authors thank Antonio Davila for his research assistance. They thank Fernando Alvarez, Laurent Calvet, Joao Cocco, Pierre Collin-Dufresne, Marjorie Flavin, Tim Landvoigt, Claus Munk, Wayne Passmore, Joe Peek, Federico Perali, Eric Smith, Jacob Sagi, Chester Spatt, Richard Stanton, Suresh Sundaresan, Lars Svensson, Selale Tuzel, Stijn Van Nieuwerburgh, Nancy Wallace, and Scott Wang for their helpful comments.

This version: October 2025 **https://doi.org/10.29412/res.wp.2025.13**

1 Introduction

Housing represents the most important asset for most households. Therefore, house values play a key role in household decisionmaking, notably about stockholdings and consumption. However, households' estimates of their own house's value do not often align with market prices. Although the average house value misestimation across all homeowning households is close to zero ($7,600 of undervaluation on average in our sample), its standard deviation is large ($59,800). We find that 5 percent of homeowners undervalue their house by at least $87,500, while 5 percent overvalue their house by at least $53,000.

House value misestimation has been documented for more than half a century.[1] However, the literature on portfolio choice that incorporates housing typically assumes that households accurately observe house prices (see, for example, Flavin and Yamashita (2002), Campbell and Cocco (2003), Cocco (2005), Yao and Zhang (2005), Fischer and Stamos (2013), Corradin, Fillat, and Vergara-Alert (2014), Chetty, Sándor, and Szeidl (2017), and Chen, Michaux, and Roussanov (2020)).

In this paper, we study how house value misestimation affects households' portfolio and consumption decisions. We first develop a simple theoretical framework to show the implications of incorporating misestimation in the analysis of household choices in the presence of housing. We then use household-level data to estimate the effects of misestimation on portfolio and consumption decisions.

We measure house value misestimation as the difference between the owner's subjective valuation of their house and its market value, which is adjusted for home improvements.[2] We exploit a new mechanism based on homeowners who just purchased a house. Our key assumption is that the house's market value is known with certainty—and therefore misestimation is zero—only at the time of purchase. After purchase, the market value of the house follows a random process that the homeowner can estimate but does not accurately observe. Using this assumption, we create a novel measure of misestimation by comparing data on self-reported (subjective) housing values from the Panel Study of Income Dynamics (PSID) with market house prices constructed using Zip-code-level transaction-based house price indexes from the Federal Housing Finance Agency

[1] Kish and Lansing (1954) and Kain and Quigley (1972) find large discrepancies when they compare homeowners' reported house values with values obtained from professional appraisals. These two studies assume implicitly that appraisals are free of error. Robins and West (1977), who also assume that appraisals are unbiased estimates of house values, conclude that house values determined by homeowners and professional appraisals contain errors of 7 percent and 5 percent, respectively. Although there is consensus on the presence of measurement errors in house prices, there is no agreement on the sign and magnitude. Kish and Lansing (1954), Robins and West (1977), Ihlanfeldt and Martínez-Vázquez (1986), Goodman Jr. and Ittner (1992), Kiel and Zabel (1999), Agarwal (2007), and Benítez-Silva et al. (2015) document the overestimation of reported house values, which range from 3 percent to 16 percent. By contrast, the empirical analyses in Kain and Quigley (1972) and Follain and Malpezzi (1981) find that owners' self-reported house values underestimate house prices by about 2 percent.

[2] Throughout the paper, we use "misestimation" and "house value misestimation" interchangeably. This misestimation is directional: Positive misestimation corresponds to overvaluation, and negative misestimation corresponds to undervaluation. We do not consider misestimation in any other asset class.

(FHFA). Our novel measure shows that misestimation is a widespread and sizable phenomenon, with substantial variation across households and regions, but its average is close to zero.

To guide our empirical analysis of the effects of house value misestimation on portfolio and consumption decisions, we develop a stylized three-period model of portfolio choice that incorporates household misestimation of housing values, building on the framework established by Cocco (2005). Our model relates to an emerging literature that incorporates survey evidence on house price expectations (Kuchler, Piazzesi, and Stroebel (2023)) into models with housing as well as previous work that emphasizes the effect of expectations on housing demand (Landvoigt (2017)), mortgage-level choices (Bailey et al. (2019)), and home improvements (Choi, Hong, and Scheinkman (2014)).[3] Recent papers examine the role of house price expectations in shaping key housing decisions, including the rent-versus-buy choice Bailey et al. (2018), the timing of home sales Bottan and Perez-Truglia (2025), and characteristics of home purchases such as price and size Gargano, Giacoletti, and Jarnecic (2023).

In our model, households face risky home prices and can invest in risky stocks, in addition to risk-free assets. After buying a house via a mortgage, households have heterogeneous beliefs about the growth rate of house prices. We assume that households' beliefs about the expected growth rate of house prices follow a normal distribution in which the mean is the expected growth rate of market value house prices. These beliefs determine the level at which households estimate their future house values and therefore affect their portfolio and consumption decisions.

This modeling approach allows us to establish a causal relationship between the exogenous changes in house value misestimation—defined as the difference between the expected house value conditional on the household's belief about the mean price growth rate and the expected house value conditional on the market mean price growth rate—and household decisions that we employ in the empirical analysis later. The model provides two predictions. First, households overvaluing their home will perceive that their overall risk exposure is already high and, consequently, will prefer to reduce the stock share of liquid wealth with constant relative risk aversion preferences. Second, households will increase nonhousing consumption and hold more safe financial assets rather than expose themselves to additional stock market risk.

We then empirically investigate the relationship between households' house value misestimation and their portfolio and consumption choices. Using the PSID household-level data from 1984 to 2021, we find that a $60,000 increase in house overvaluation (approximately one standard deviation) results in a 1.1 to 1.9 percent decrease in risky stockholdings, a 1.5 to 4.3 percent increase in consumption, and a 1.3 to 2.5 percent increase in the share of risk-free assets over liquid wealth, holding house value and mortgage debt constant.

Our empirical approach builds on (Chetty, Sándor, and Szeidl 2017), who underscore the im-

[3]Building on macroeconomic general equilibrium frameworks, Burnside, Eichenbaum, and Rebelo (2016) and Kaplan, Mitman, and Violante (2020) incorporate house price expectations to study aggregate boom-and-bust dynamics in housing markets.

portance of separately identifying home equity and mortgage debt when analyzing the impact of housing on portfolio decisions. Following their methodology, we employ two distinct instruments: a measure of state-level housing supply elasticity for the subjective market value of the house, and the interaction of state-level average house prices at the year of purchase with national mortgage rates for the outstanding mortgage balance. While our analysis draws on a different data set and covers a longer period, we verify that–before incorporating house price misestimation–our baseline estimates are consistent with those of Chetty, Sándor, and Szeidl (2017) in both sign and magnitude. This alignment lends credibility to our empirical strategy.

Our empirical analysis extends the literature by explicitly accounting for the role of house value misestimation in portfolio decisions. Since misestimation itself may be endogenous, we employ an instrumental variable strategy to identify its effect. Therefore, we introduce two novel instruments that capture variation in households information sets based on locally available signals. The first instrument is the number of housing transactions at the Zip code level, assuming that while local transaction volume shapes information availability, it does not directly influence individual portfolio choices. As an alternative, we use the volume of local Google searches related to housing transactions, which proxies similarly for information exposure. Our results remain robust across both instruments.

Finally, a fundamental assumption in our empirical approach is that the only way to eliminate misestimation is to have the house on sale continuously on sale, and to receive periodic market offers from buyers. One could argue that online real estate databases such as Zillow, professional appraisals for refinancing or home equity extraction, and municipalities' real estate tax assessments should mitigate house price misestimation. However,these estimates of market valuation are not exempt from error and rarely coincide with actual transaction prices. In 2018, for instance, Zillow's website documented that 15.7 percent of the Zillow market estimates missed the subsequent transaction price by more than 20 percent, and 50 percent of the estimates missed the transaction price by more than 5 percent.[4,5]

The paper is structured as follows. In Section 2, we develop our measure of misestimation and documents its stylized facts. In Section 3, we describe the stylized model that guides our empirical approach, and we study its comparative statics. In Section 4, we develop our empirical strategy. Section 5 presents and discusses our empirical results. Section 6 concludes.

[4]Source: https://www.zillow.com/zestimate/#acc.

[5]Zillows automated valuation model (the "Zestimate") was not introduced until 2006 and, at launch, covered about 40 million U.S. homes; nationwide coverage expanded only gradually over the subsequent years. Consequently, online real estate databases such as Zillow were either absent or too thinly populated to affect the properties included in our sample.

2 House Value Misestimation

The main goal of our paper is to analyze the effects of house value misestimation on stockholdings, consumption, and housing decisions. We conduct our empirical analysis using several data sources. First and foremost, we use PSID data from 1984 to 2021 to obtain information at the household level on stockholdings, consumption, and housing decisions. The PSID comprises a panel of individuals and households that are followed over time. The most relevant variable is the self-reported value of each household's home. The survey data also provide socioeconomic characteristics of the households and granular geographic locations.[6] Specifically, we use data on family income; family size (number of family members); and the head of household's age, gender, education, and marital and employment status.

We estimate house value misestimation as the difference between the household's subjectively determined house value and the house's actual market value. Self-reported values in PSID are our measure of *subjective house values*. We use the FHFA House Price Index (HPI) at the five-digit Zip code level to construct a proxy for the house's *market value*. We estimate the market value of the property by applying the local HPI growth rate for the household's Zip code to the most recent purchase price of the house. Formally, misestimation $m_{i,t}$ for each household i at time t is defined as $m_{i,t} = HV^S_{i,t} - HV^M_{i,t}$, where $HV^S_{i,t}$ denotes the subjective value of the house i at time t that the owner reported in the PSID and $HV^M_{i,t}$ is the market value of the house. A positive value of $m_{i,t}$ indicates overvaluation, while a negative value indicates undervaluation. We make one key assumption to build our measure of house value misestimation: The house value that households report in the year of purchase corresponds to the true market value of the house. Hence, household i's house value misestimation is zero at the time of the housing transaction, or $HV^M_{i,t_0} = HV^S_{i,t_0}$. Thereafter, home improvements add to the market value of the house, which evolves following the price growth in the corresponding Zip code. Specifically, $HV^M_{i,t} = \left(HV^M_{i,t-1} + HI_{i,t-1}\right) \Delta \log(HPI_{zip^i,t})$, where $HI_{i,t-1}$ denotes the home improvements for household i at time $t-1$. This assumption allows us to use a repeat-sales index at a very granular level (that is, the Zip code level) as opposed to using a hedonic pricing model to account for the house's market price.

Table 1 reports descriptive statistics for the measure of house value misestimation. Panel A presents summary moments for the full sample. We observe that, on average, households modestly underestimate the value of their home by approximately $7,600, with a standard deviation of $59,800. The distribution exhibits substantial heterogeneity: The bottom 5 percent of households undervalue their property by more than $87,500, whereas the top 5 percent overvalue it by more than $53,000. Panel B examines the evolution of misestimation around household moves. The mean misestimation declines sharply as the move approaches, reaching zero in the year of the move (by

[6] We use the restricted Geospatial Data Tract Level, produced and distributed by the University of Michigan's Survey Research Center, Institute for Social Research. This panel data set contains the census tract info and Zip code location of each household. See Appendix OA-I for more details about the data construction.

Table 1: **House Value Misestimation Statistics.** Sample mean, standard deviation, 5th and 95th percentiles, and the number of observations for house value misestimation (Panel A). The data on subjective house values and house improvements come from the PSID. Data on market house values are derived using FHFA data at the five-digit Zip code level and PSID home prices at transaction times. Mean and standard deviation of house value misestimation for households that moved, by year, from two years before to two years after the move (Panel B). Period: 1984–2021.

Panel A. Descriptive statistics

	Mean	Std. Dev.	p5	p95	Obs.
House Value Misestimation ($\times\$100,000$), $m_{i,t}$	-0.076	0.598	-0.875	0.530	60,901
Subjective House Value ($\times\$100,000$), HV^S	1.750	1.796	0.146	5.000	60,901
Market House Value ($\times\$100,000$), HV^M	1.866	2.384	0.148	5.630	60,901
Home Improvements ($\times\$100,000$), HI	0.026	0.200	0.000	0.130	60,901
HI if ($HI > 0$)	0.412	0.688	0.100	1.400	38,651

Panel B. Misestimation around moves

Relative Year	Mean	Std. Dev.	Obs.
$t-2$	0.172	0.419	4,466
$t-1$	0.069	0.148	1,911
t	0.000	0.000	20,761
$t+1$	0.104	0.157	3,828
$t+2$	0.247	0.390	7,865

construction), and then rises in the following years. This pattern suggests that households largely eliminate valuation errors when relocating but gradually develop further misestimation thereafter, potentially reflecting limited information about the new housing market or changing neighborhood characteristics. Consistent with these patterns, Figure 1 illustrates the empirical distribution of misestimation, which is approximately symmetric but displays wide dispersion, indicating that both overvaluation and undervaluation are prevalent among homeowners.

We investigate whether the extent of misestimation is driven by key socioeconomic factors, including family income, household size, age, gender, educational attainment, marital status, and employment status. The results, presented in Table 2, indicate that, although there is some persistence (captured by the positive and significant sign of the coefficient $m_{i,t-1}$), none of these variables exhibits statistical significance in explaining variations in the level of misestimation.[7] Moreover, a variance decomposition analysis using socioeconomic variables reveals that family income (in logs), employment status, education, and family size explain 55.8 percent, 20.2 percent, 11.7 percent, and 9.2 percent of the explained variation, respectively. Therefore, four variables are needed to explain most of the variation attributed to socioeconomic factors, which together explain only 38.4 percent of the total variation in misestimation.

Overall, a key takeaway from our analysis is that house value misestimation is a widespread

[7] We report the descriptive statistics in Appendix Table A-1.

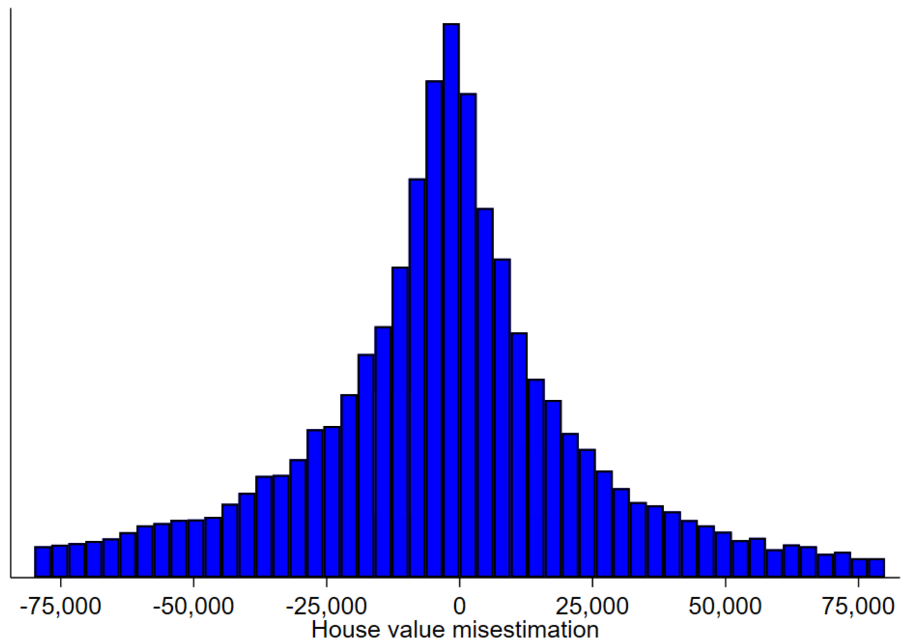

Figure 1: **Distribution Plot of House Value Misestimation.** This histogram shows the empirical distribution of house value misestimation for U.S. households from 1984 to 2021. House value misestimation is calculated as the difference between a household's self-reported house value in the PSID and the estimated market value of the house, which is derived using the FHFA HPI at the five-digit Zip code level. A positive misestimation value indicates overvaluation by the homeowner, while a negative value indicates undervaluation.

phenomenon with substantial variation across households. While self-reported house values tend to be slightly underestimated on average, both overestimation and underestimation are common, with a significant fraction of households exhibiting large misestimation errors. Our findings suggest that socioeconomic characteristics, such as family income, employment status, education, and household size, do not play a significant role in explaining the extent of misestimation. The persistence of misestimation over time, as indicated by the significance of lagged values, highlights the potential for systematic biases in the perceptions of property values at the household level. These results underscore the importance of considering misestimation in economic models of household financial behavior, as it may have far-reaching implications for stockholdings, consumption, and housing decisions.

Table 2: **Misestimation and Socioeconomic Indicators.** The dependent variable for all specifications is misestimation (in $100,000), $m_{i,t}$. We control for the logarithm of family income, number of family members, gender (male = 1), education (high school or more = 1), marital status (married = 1), and employment status (employed = 1) of the head of the household. Column (1) also controls for lagged misestimation, $m_{i,t-1}$. All our estimations use age of the head of the household, year, and five-digit Zip-code-level fixed effects. Robust t-statistics are shown in parentheses. ****, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level of confidence, respectively.

	(1) $m_{i,t}$	(2) $m_{i,t}$
$m_{i,t-1}$	0.423***	
	(0.0592)	
Family Income (log)	-0.0291*	-0.0185
	(0.0157)	(0.0198)
Family Size	-0.0052	-0.0100
	(0.0054)	(0.0081)
Gender	-0.0456	-0.0978**
	(0.0291)	(0.0401)
Education	-0.0174	-0.0213
	(0.0189)	(0.0255)
Married	0.00721	0.0270
	(0.0286)	(0.0365)
Employed	-0.0249	-0.0278
	(0.0176)	(0.0258)
Observations	28,101	28,269
R-squared	0.591	0.381
Zip Code FE	Yes	Yes
Year FE	Yes	Yes
Age FE	Yes	Yes

3 Model

3.1 Set-up

We build on a stylized model of housing and portfolio choice as in Cocco (2005) and Chetty, Sándor, and Szeidl (2017), introducing misestimation of house prices. Our model has three dates $t = 0, 1, 2$. A household endowed with house H_0, mortgage debt M_0, and liquid wealth L_0 makes financial investment decisions at $t = 0$ and $t = 1$, and consumption takes place at $t = 1$ and $t = 2$. The household's utility depends on adjustable consumption C_t and housing consumption H_0. The household faces three sources of uncertainty. First, home prices are risky. Second, after $t = 0$, the household holds heterogeneous beliefs about the growth rate of house prices. Third, the household can invest in a risky asset.

The household i maximizes lifetime expected utility:

$$\max_{\alpha_0,\alpha_1^i,C_1^i,C_2^i} \delta E_0\left[\frac{\left(C_1^{i,1-\beta}H_0^{\beta}\right)^{1-\gamma}}{1-\gamma}\right] + \delta^2 E_0\left[\frac{H_0^{\beta(1-\gamma)}}{(1-\gamma)} \times (\underbrace{W_2 - P_2 \times H_0}_{C_2^i})^{(1-\beta)(1-\gamma)}\right]$$
$$+\,\delta^3 E_0\left[\frac{(P_2 \times H_0 + S_2)^{1-\gamma}}{1-\gamma}\right]. \tag{1}$$

At $t = 0$, the household can invest in a risk-free financial asset with return $1 + R_f = \exp(r_f)$ and a risky asset (for example, stocks) with return $1+R_s = \exp(r)$, where r is normally distributed with mean μ_r and variance σ_r^2. The only choice variable at $t = 0$ is α_0, the share of liquid wealth invested in the risky asset. Let $R_w = \alpha_0 R_s + (1 - \alpha_0)R_f$ denote the household's financial return on liquid wealth, and assume that short-sales constraints restrict $\alpha \in [0, 1]$.

Home prices are $P_0 = 1$ and $P_1 = \exp(p_1)$, where p_1 is normal with mean μ_p^i and variance σ_p^2. The correlation between home price growth and stock returns is $\rho = \mathrm{corr}[p, r]$. As in Bailey et al. (2019), we assume that households beliefs about the expected growth rate of house prices follow a normal distribution with mean μ_p^m, the expected growth rate of market value house prices, and standard deviation σ_p^m:

$$\mu_p^i \sim N(\mu_m, \sigma_m). \tag{2}$$

We adopt the normal distribution for our parametric predictions based on the empirical evidence about the distribution of misestimation that we observe in Figure 1. This simple set-up allows us to measure house value misestimation. At $t = 0$, the homeowner has just bought the house H_0 at the price P_0. Immediately after, the homeowner draws their beliefs about the house value's appreciation from (2), deviating from the market value of house. When $\mu_p^i > \mu_m$ ($\mu_p^i < \mu_m$), homeowners overestimate (underestimate) house prices, leading to positive (negative) house value misestimation.

At $t = 1$, the household's budget constraint is

$$C_1^i + P_1 \times H_0 = (1 + \underbrace{R_w}_{\alpha_1^i R_s + (1-\alpha_1^i)R_f}) \times L_0 + Y_1 + P_1 \times H_0 - (1 + R_{MTG}) \times \frac{M_0}{2}, \tag{3}$$

where R_{MTG} is the mortgage rate; Y_1 is the labor income, which we assume is deterministic; and L_0 is the initial liquid wealth. We assume that the household repays half of the mortgage balance, which increases their home equity share. The share of the risky asset out of liquid wealth α_1^i and numeraire consumption C_1^i depends crucially on whether the homeowner is optimistic or pessimistic about housing return via μ_p^i.

At $t = 2$, we incorporate two components for the household's expected utility (see Equation 1). The first component depends on the numeraire consumption decision $C_2^i = W_2 - P_2 \times H_0$. For tractability, we assume that the household's belief μ_p^i realized between $t = 0$ and $t = 1$ does not change between $t = 1$ and $t = 2$. The second component, $P_2 \times H_0 + S_2$, depends on the total market value of assets and addresses the concern that the household cannot monetize the house at the end of $t = 2$ in our framework by introducing a bequest motive. Following Cocco (2005), we assume that the household bequeaths the house as well as any unconsumed savings, S_2, to their offspring, who derive constant relative risk aversion (CRRA) utility from the total market value of these assets.

It is worth emphasizing that our objective is not to construct a full life-cycle or general-equilibrium model. Our stylized three-period set-up serves only to isolate the mechanism through which belief-driven misestimation affects household portfolios and consumption. The models value lies in offering clean comparative statics that motivate our empirical tests.

3.2 Parameters

Before presenting the numerical results, we specify the parameter values for our model. For parameters related to life-cycle portfolio choices, we follow Chetty, Sándor, and Szeidl (2017), setting the risk-free rate at $R_f = 0.02$, the stock risk premium at 0.06, and the annual stock return volatility at $\sigma = 0.157$ per annum. The mortgage rate is set as R_{MTG} at 0.04. We assume that $\gamma = 10$. Regarding housing preferences, we set the relative preference parameter at $\beta = 0.3$. We set the parameter of expected housing return at $\mu_p = 0.016$ as a base parameter. We set the house price volatility σ_p at 0.062 and the belief dispersion σ_m at 0.01. Both Cocco (2005) and Yao and Zhang (2005) assume a zero correlation between housing and the stock market, $\rho = 0$.[8]

We set the time horizon of our model to 10 years to represent an investment horizon over which housing commitments are likely to be important. We set liquid wealth at $L_0 = \$44,000$, house value at $P_0 \times H_0 = \$150,000$, and mortgage at $M_0 = \$105,000$, implying an initial loan-to-value ratio of 70 percent. Finally, the present value of future labor income is approximately five times current financial wealth for households whose head is in their late 40s or early 50s; hence, we set $Y_1 = 5 \times L_0$, as in Chetty, Sándor, and Szeidl (2017).

3.3 Predictions

We next study how house value misestimation impacts investment in a risky asset and numeraire consumption. Figure 2 displays the distribution of house value misestimation based on the model at $t = 1$. We compute misestimation as the difference between the expected house value based on μ_p^i and the expected market value of the house based on μ_m:

$$m_1^i = E_1[P_2|\mu_p^i] - E_1[P_2|\mu_m], \tag{4}$$

[8]This assumption is also supported by Appendix Figure A-1.

which is consistent with our definition of empirical house value misestimation presented in Section 2. The first component, based on average belief μ_p^i, corresponds to the subjective value of the house that the owner reported in the PSID, while the second component, based on the expected market growth rate μ_m, corresponds to the market value of the house. The model distribution mimics closely the empirical distribution of misestimation that we observe in Figure 1. When $\mu_p^i > \mu_m$ ($\mu_p^i < \mu_m$), we find positive (negative) house value misestimation $m_1^i > 0$ ($m_1^i < 0$).

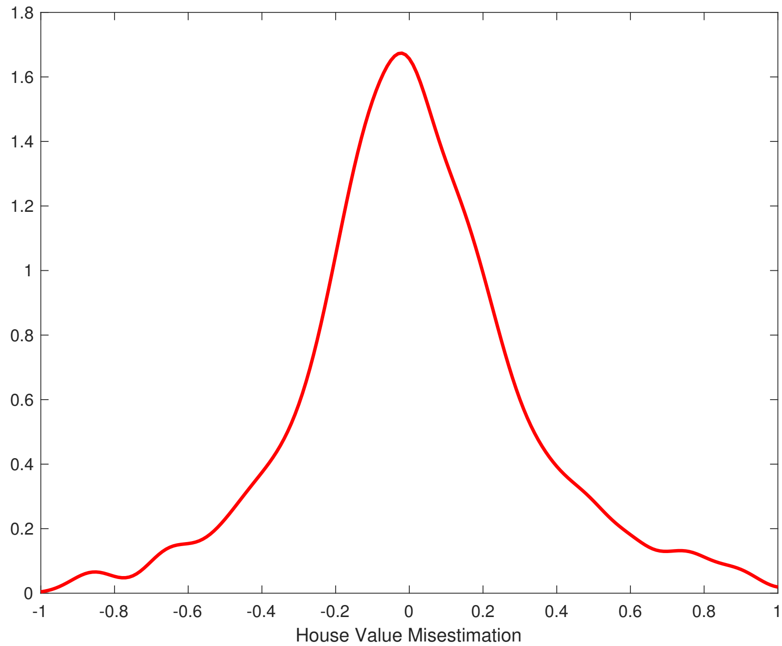

Figure 2: **Distribution Plot of House Value Misestimation Based on the Model.** This figure plots the histogram of the variable house value misestimation computed at $t = 1$. Misestimation m_1^i is computed as the difference between the expected house value based on μ_p^i and the expected value of market value based on μ_m.

It is important to distinguish between heterogeneity in true house price growth and heterogeneity in beliefs about house price growth. In our set-up, misestimation captures subjective deviations from the market-expected value, which are orthogonal to realized price shocks. While both affect perceived wealth, only misestimation generates cross-sectional variation in consumption and portfolio allocations that is independent of true wealth changes.

We first focus our analysis on the relationship between misestimation and investment in a risky asset. We solve the model numerically because closed-form solutions are not available.[9] Figure

[9]We use the same numerical techniques as those employed by Cocco (2005) and Chetty, Sándor, and Szeidl (2017) to solve the model. We use backward induction and compute continuation values over grids. We approximate the state and choice variables using equal-spaced grids and the probability density functions of shocks with Gaussian quadratures.

3 shows the numerical results of households' allocation to the risky asset as a function of house value misestimation. It shows that investment in the risky asset declines in misestimation m_i. An increase in the average belief μ_p^i increases the perceived net return on housing, leading to positive misestimation m_1^i, and induces the household to reduce their exposure to the stock market, therefore choosing a lower share in the risky asset α_1^i. As a result, the household increases their exposure to the the risk-free asset, $1-\alpha_1^i$, when misestimation increases, as is also shown in Figure 3. Prediction 1 summarizes this result:

Prediction 1: *At time* 1*, a household with a higher average belief* μ_p^i *overestimates the value of its house, resulting in a larger misestimation* m_1^i *and a lower allocation to the risky asset* α_1^i.

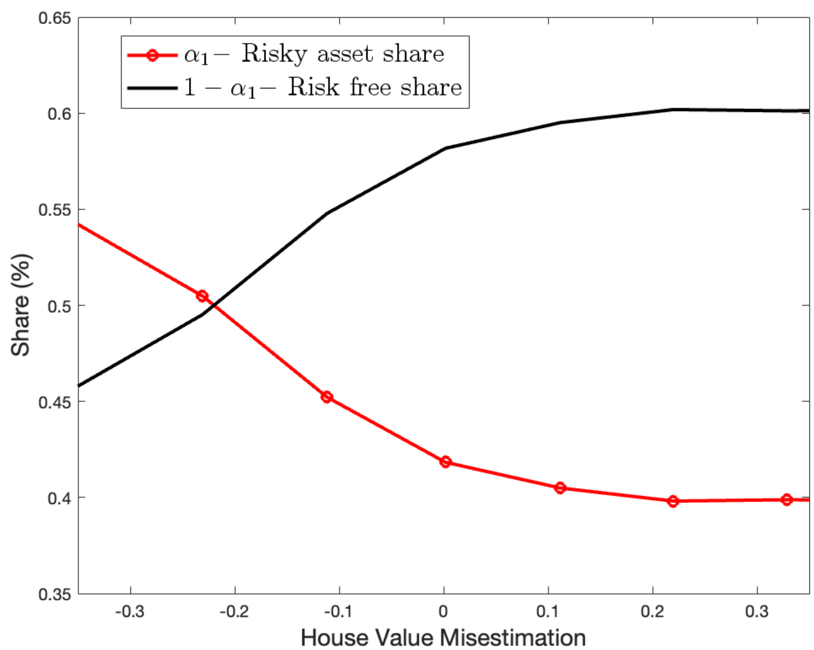

Figure 3: **Relationship between House Value Misestimation and Risky and Risk-free Asset Allocation.** This figure plots the household's optimal allocation to risky assets (for example, stocks) and risk-free assets as a function of house value misestimation, derived from the numerical solution of the model. House value misestimation is defined as the difference between the homeowners subjective valuation and the market value of the house.

Second, we focus on the relationship between misestimation and consumption. Figure 4 shows the numerical results of households' consumption as a function of house value misestimation. It shows that consumption C increases with misestimation m_i. As misestimation increases (that is, as households increasingly overvalue their homes), consumption rises. Overestimating homeowners perceive themselves as wealthier and therefore consume more, while underestimating households consume less. An increase in the average μ_p^i increases the perceived net return on housing, leading to positive misestimation m^i, which induces the household to consume more. Prediction 2 summarizes this result:

Prediction 2: *At time* 1*, a household with a higher average belief* μ_p^i *overestimates the value of its house, resulting in a larger misestimation* m_1^i *and a higher numeraire consumption* C_1^i.

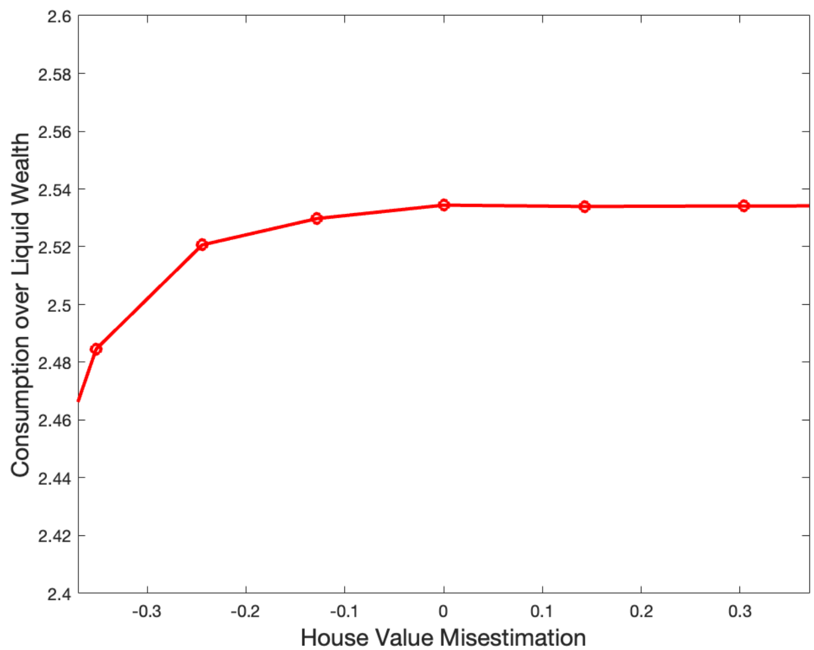

Figure 4: **Relationship between House Value Misestimation and Consumption.** This figure illustrates the model's predicted relationship between house value misestimation and nonhousing consumption, expressed as a share of liquid wealth.

In addition, our framework implies a third prediction concerning households allocation to risk-free assets. Because overestimating homeowners perceive themselves as already exposed to greater housing risk, they reallocate their liquid portfolios away from risky stocks toward safe assets.[10] This substitution effect implies that, as house value misestimation increases, households allocate a larger share of their liquid wealth to risk-free assets. We summarize this relationship in the following prediction:

Prediction 3: *At time* 1*, a household with a higher average belief* μ_p^i *overestimates the value of its house, resulting in a larger misestimation* m_1^i *and a greater allocation to risk-free assets* $(1-\alpha_1^i)$.

[10]This third implication follows directly from the households budget constraints and the previous two predictions. When overvaluing their home, households reduce the share of risky assets (Prediction 1) and increase consumption (Prediction 2), which jointly imply a higher residual allocation to risk-free assets.

4 Empirical Strategy

Following the theoretical predictions in Section 3, our objective is to empirically establish the causal effect of house value misestimation on households' choices, such as those related to stockholdings and stock market participation, investment in risk-free assets, and nonhousing consumption. We estimate the effects of misestimation on households' choices using the following linear specification:

$$Y_{it} = \beta_1 m_{it} + \beta_2 HV_{it} + \beta_3 MTG_{it} + \beta_4 X_{it} + \eta_t + \eta_{\text{state}} + \eta_{\text{age}} + \varepsilon_{it}, \tag{5}$$

where Y_{it} is the variable of interest for household i at time t, and m_{it} is house value misestimation as described in the preceding section. HV_{it} and MGT_{it} denote the reported house value and the mortgage debt, respectively. As in (Chetty, Sándor, and Szeidl 2017), we separate the reported house value from the mortgage debt because they serve distinct roles in household portfolio decisions and have different implications for risk exposure, liquidity, and wealth accumulation.[11] We also include a vector X_{it} of socioeconomic controls at the household-year level, including number of family members, family income (in logs), gender, education, and marital status.

All our specifications include time (η_t), state of residence (η_{state}), and age fixed (η_{age}) effects to control for aggregate common trends and unobserved geographical variation. Specifically, age fixed effects enable us to account for all unobservable characteristics and systematic differences across households of the same age cohort that might influence decisionmaking. This method ensures that our estimation isolates the variation in decisions attributable to house value misestimation, avoiding biases that might arise from omitted variables correlated with age. Thus, our estimates capture the impact of house value misestimation while controlling for potential confounders tied to cohort-specific behavioral patterns such as generational attitudes toward risk, financial literacy, or typical life-cycle patterns in asset allocation. Moreover, fixed effects offer the advantage of capturing nonlinearities and cohort-specific dynamics that a simple age control might overlook, leading to more robust and interpretable results. Additionally, by including year fixed effects, we account for time-varying factors that affect all households uniformly, such as macroeconomic trends, policy changes, or market shocks, while state fixed effects control for spatial heterogeneity such as differences in housing markets, state regulations, or local economic conditions. Together, these fixed effects create a robust framework that isolates the variation in household decisions attributable to house value misestimation, free from confounding influences linked to age, temporal dynamics, and geographic disparities.

Our empirical specification holds constant both the true market value of the house and the mortgage balance, thereby isolating misestimation as an independent driver of household financial choices. Therefore, the behavioral responses we document cannot be explained by variation in

[11] By analyzing mortgage debt separately, we isolate the net effect of housing on household wealth and portfolio decisions while accounting for the risks introduced by leverage.

actual house price growth alone.

It is imperative that we isolate exogenous variation in misestimation to address potential endogeneity concerns, measurement error in our misestimation variable, and reverse causality. We do so by using two novel instruments for our house value misestimation variable: differences across the number of housing transactions at the Zip code level and local Google Trends data on searches related to housing markets. In the following subsection 4.1, we develop these two instruments. In subsection 4.2, we justify the adoption of two well-established instruments for house values and mortgage debt to address potential endogeneity concerns related to the choice of house and mortgage size.

4.1 Instrumenting House Value Misestimation

The amount of housing-market-related information available to households can impact their ability to develop more accurate and reliable assessments of area property values. Based on this idea, we introduce two novel instrumental variables designed to isolate exogenous variation in misestimation. Both instruments are similar: We use a variable that correlates strongly with the accuracy of a household's house value estimation. We interact this variable with the sign of the household's previous misestimation (that is, whether the house was overvalued or undervalued) to capture the effect of information on the absolute value of misestimation. While the availability of housing-market-related information is relevant in determining misestimation, it is arguably exogenous to the household's portfolio and consumption decisions.

First, we use the number of housing *transactions* from CoreLogic data at the Zip code level, since the more liquid local house markets are, the more information households have on hand to infer the value of their house. Our key assumption is that the number of local transactions do not affect households' portfolio and consumption decisions. We calculate transaction rates per capita by Zip code. These rates form the basis of percentile bins (that is, 10 percent, 20 percent, up to 90 percent) for each year. The resulting categorical variable, *trans10bins*, stratifies Zip codes into deciles based on transaction volume, reflecting variations in local housing market dynamics. We interact this categorical variable with the sign of misestimation in the previous period, as more information can reduce the absolute value of misestimation. This instrumental variable enables us to capture exogenous variation in housing activity within Zip codes, providing a robust control for market shocks that affect household financial decisions. This instrument also mitigates the measurement error in the market value of the house. A higher volume of local transactions systematically lowers the idiosyncratic component of an individual house's market value. In sum, using the number of housing transactions at the Zip code level as an instrumental variable addresses critical endogeneity concerns by providing an exogenous source of variation in house value misestimation.

Second, we use an alternative instrument for robustness purposes. Consistent with the first approach, we employ the number of housing-transaction-related *searches* at the most granular level available from Google Trends. We construct a dictionary of keywords associated with households engaged in home-buying or -selling activities, like "homes for sale," "mortgage rates," "real estate agent near me," etc.[12] This dictionary serves as the basis for identifying relevant search queries in Google Trends, which we then use as an alternative measure of real estate market conditions. To create the instrumental variable, we first assign each Zip code to a decile based on search intensity observed in Google Trends, stratified by year and geographic region. We then interact this ranked search intensity measure with the sign of the previously observed household misestimation. This approach allows us to exploit both cross-sectional and temporal variation in real estate search activity as an exogenous source of identification while also accounting for potential nonlinearities in the relationship between search behavior and households' house value estimation.

To address potential concerns regarding the validity of our instruments, we conduct a series of robustness checks reported in Appendix A-III. We test whether our proxies for the local information environment (that is, the number of housing transactions and the number of housing-transaction-related searches) correlate with local economic fundamentals such as median household income. The results show no statistically significant relationship between either instrument and income levels across Zip codes, suggesting that the instruments are not driven by local growth expectations and thus satisfy the exclusion restriction. Appendix A-III also reports first-stage results confirming that both instruments correlate strongly with the informational precision of local housing prices, thereby supporting the relevance condition required for identification.

4.2 Instrumenting House Value and Mortgage Debt

Building upon Chetty, Sándor, and Szeidl (2017), we employ two separate sets of instrumental variables for house value and mortgage debt. As noted, we separate the reported house value from the mortgage debt because they serve distinct roles in household portfolio decisions and have differing implications for risk exposure, liquidity, and wealth accumulation.

To instrument the subjective house value, we interact a measure of state-level housing supply elasticity with FHFA national house prices. This approach isolates exogenous variation in house prices due to supply constraints, allowing us to estimate the causal effect of changes in property value on financial portfolios. For robustness, we employ two different measures of elasticity of housing supply. The most widely used measure of elasticity is the one developed in Saiz (2010), derived from land availability and regulation data. Alternatively, we use the measure proposed in Guren et al. (2020), which exploits the fact that local house-price sensitivity to regional prices differs across metropolitan statistical areas (MSAs). The latter study constructs the instrument by estimating the historical sensitivity of local house prices to regional housing cycles and by

[12] In Appendix OA-II, we provide the dictionary that we use to obtain the intensity of search by designated market area (DMA), which we map to Zip codes. DMAs are geographic regions in the United States defined by Nielsen Media Research to represent television and radio markets. These regions serve as reference units for Google Trends, which provides search data that can be segmented by such regions.

interacting the historical sensitivity with current shocks to regional house prices, akin to a Bartik-based instrument. The benefit of this instrument is that it helps predict local house prices by exploiting the fact that house prices in some cities are more sensitive to regional fluctuations compared with house prices in other cities in the same region.

To instrument mortgage debt, we use the year-of-purchase average house prices in the individual's state interacted with mortgage rates. By comparing individuals who purchased homes during different market conditions, we separate the effects of house value from mortgage debt while controlling for overall wealth changes.

These instruments help control for unobserved variation such as local labor market conditions and selection biases in housing purchase timing. By utilizing these instruments, we disentangle the separate effects of house value and mortgage debt on households' decisions.

4.3 Additional Empirical Challenges

Our empirical strategy addresses endogeneity concerns about potentially biased estimates of the effects of misestimation on households' choices. Variables of interest such as investment and consumption decisions, misestimation, house values, and mortgage debt could be subject to measurement error or present reverse causality.

In particular, our constructed measure of misestimation might be subject to measurement error that can lead to attenuation bias. By design, we utilize the household's reported house value, accepting this as the representation of their perceived property worth, including home improvements. Hence, the only source of measurement error in the misestimation variable is our proxy for the market value of the house. The source of measurement error is simply the existence of house-specific characteristics that are not captured in the corresponding household's Zip code HPI. A systematic relationship between house-specific characteristics and households' portfolio or consumption decisions could further bias our estimates.

Reverse causality also presents a significant challenge. The relationship between house value misestimation and household choices may be bidirectional. For instance, a household experiencing financial distress might adjust its perception of its house value or misreport mortgage debt, leading to simultaneity bias.

Our careful selection of instruments described earlier addresses both measurement error and simultaneity concerns in several critical ways. By using exogenous variation from housing transactions and search intensity, we address biases related to these challenges. Specifically, the Zip-code-level housing transaction rates provide an external proxy for market dynamics, which reduces the idiosyncratic noise inherent in individual house valuations. This directly addresses measurement error by anchoring perceived house values to observable and systematic market activity, thereby improving the accuracy of our misestimation variable. Moreover, the Google Trends–based search intensity captures local interest in housing market activity, further reinforcing the robustness of our identification strategy by introducing variation that is orthogonal to household-level financial choices.

We also address simultaneity through these instruments, as they are constructed based on external market activity and information flows that are unlikely to be directly influenced by individual household decisions. For instance, the interaction of transaction volume or search intensity with lagged misestimation ensures that the instruments capture external drivers of misestimation rather than endogenous household behaviors. By isolating these external sources of variation, our approach breaks the feedback loop between household decisions (for example, portfolio allocation or consumption) and perceived house values, effectively addressing reverse causality.

In sum, our instrumentation strategy not only controls for omitted variables that could otherwise confound the relationship between misestimation and household choices but also ensures that the variation used for identification is exogenous, robust, and interpretable. This dual mitigation of measurement error and simultaneity bias strengthens the credibility of our empirical results and provides a reliable foundation for causal inference.

Finally, a potential concern regarding heterogeneity in the effects of misestimation due to differences in household characteristics, such as income, education, or financial literacy, is resolved by our analysis presented previously in Table 2. We run a regression of misestimation on a comprehensive set of socioeconomic indicators, including income, family size, gender, education, employment status, and others. The results demonstrate that these indicators are not significantly related to misestimation, suggesting that misestimation is not systematically driven by observable household characteristics. This finding implies that the effects of misestimation are unlikely to vary meaningfully across these dimensions, reducing concerns about unobserved heterogeneity biasing our results. In the online appendix, we show additional robustness tables exploring the heterogeneous effects by interacting misestimation with the socioeconomic controls. The results indicate that the average treatment effect estimated in our analysis provides a reliable and unbiased measure of the impact of misestimation.

5 Results

This section presents the empirical analysis of house value misestimation on household financial decisions, including stockholdings, stock market participation, risk-free assets, and consumption.

The results, summarized in Tables 4 through 7, demonstrate that overestimation of house values significantly influences portfolio allocation, investment behavior, and consumption patterns. Specifically, a $50,000 increase in house overvaluation results (holding house value and mortgage debt constant), on average, in a 0.9 to 1.7 percent decrease in the share of risky stockholdings, a 1.3 to 3.3 percentage point reduction in stock market participation, a 2.3 to 4.4 percent increase in the share of consumption, and a 1.7 to 2.2 percent increase in the share of risk-free asset holdings over liquid wealth. These findings highlight the economic significance of house value misestimation in shaping household financial decisions.

5.1 Household Finance Data

The objective of this paper is to establish a theoretical and empirical relationship between misestimation and household finance decisions on stockholdings, consumption, and risk-free assets. We use the same PSID sample from 1985 to 2021 to obtain these variables at the household level over time, and Table 3 shows the relevant descriptive statistics. The measure of stockholdings includes direct stock ownership, IRAs, and annuity holdings. To compute households' liquid wealth, we calculate the risk-free assets at the household level. Risk-free assets comprise bonds, insurance (both net of debt), and checking and savings balances, minus the outstanding mortgage principal on the primary residence. We calculate consumption as the sum of the food used at home, food used away from home, and food delivered at home.[13] In line with the literature, we use household wealth to normalize portfolio choices. We calculate liquid wealth as the sum of the household's primary residence value, its second-house value (net of debt), business value (net of debt), bonds and insurance assets (net of debt), stockholdings (net of debt), checking and savings balances, and IRAs and annuities, less the mortgage principal on the primary residence.

The descriptive statistics of key variables presented in Table A-1 provide an overview of the main financial variables included in our analysis. The data set includes variables such as total and liquid wealth, mortgage amounts, stockholdings, consumption patterns, and risk-free asset allocations. The sample is restricted to households with liquid wealth exceeding $2,963.30, corresponding to the average monthly salary in the United States in 2000. The table reports the mean, standard deviation, 5th and 95th percentiles, and the total number of observations for each variable. It shows substantial variation in household wealth and financial behavior, highlighting the heterogeneity in stock market participation, consumption decisions, and portfolio allocation. For comparability across different survey waves, we focus exclusively on first mortgages.

Additionally, the online appendix OA-I contains a more detailed description of the data sources and data cleansing process. Appendix Table A-1 presents key socioeconomic indicators, including family income, household size, age, gender, education, marital status, and employment status, which serve as control variables in our empirical analysis.

5.2 House Value Misestimation and Stockholdings

Table 4 examines the relationship between house value misestimation and the proportion of household portfolios allocated to stocks. The results show a negative and statistically significant co-

[13]Before 1999, the consumption data that the PSID collected were very limited, primarily including only food and housing expenditures. For consistency with those earlier periods, we limit our consumption data to food consumption throughout the full sample.

Table 3: **Descriptive Statistics of Key Variables.** This table presents summary statistics for the primary variables in the analysis, including the sample mean, standard deviation, 5th and 95th percentiles, and the total number of observations. Housing market data are sourced from the FHFA, while data on house value misestimation, household socioeconomic characteristics, and financial decisions are obtained from the PSID. The sample is restricted to households with liquid wealth exceeding $\$2,963.30$, which corresponds to the average monthly salary in the United States in 2000.

	Mean	Std. Dev.	p5	p95	Obs.
Wealth:					
Total Wealth ($\times\$100,000$), TW	4.083	15.077	-0.085	15.100	36,226
Liquid Wealth ($\times\$100,000$), LW	0.284	11.570	-0.480	4.200	36,447
Household Choices:					
Mortgage ($\times\$100,000$), MTG	0.998	1.078	0.000	3.130	44,089
Stock Holdings over Liquid Wealth, SV/LW	0.254	0.365	0.000	0.980	17,857
Consumption over Liquid Wealth, C/LW	0.487	0.781	0.009	1.999	17,782
Risk-free Assets over Liquid Wealth, RFA/LW	0.876	0.737	0.006	1.818	18,889
Stock Participation, $SV > 0$	0.447	0.497	0.000	1.000	18,889
Participants' Stock Holdings, SV/LW	0.613	0.318	0.050	1.000	7,409

efficient for the misestimation variable across all specifications. Households that overvalue their homes allocate a smaller share of their liquid wealth to stocks, consistent with Prediction 1 of our theoretical model.

Our estimates show that a one-standard-deviation increase in house overvaluation (which represents an overvaluation of $59,800) results, on average, in a 1.14 to 1.86 percent decrease in the share of risky stockholdings, holding house value and mortgage debt constant.

This effect remains robust to controlling for house value, mortgage debt, and socioeconomic factors. Consistent with the model presented in Section 3, households that overvalue their house tend to hold a lower share of risky stocks due a substitution effect. Housing is a large risky asset, and a larger valuation overweights risky assets in the household's portfolio. The optimal response is to reduce their exposure to risky stockholdings, as the house is indivisible. The impact of mortgage values are also noteworthy and in line with the model findings. Households that are more levered (that is, have larger mortgages) also reduce their risky stockholdings, as leverage reduces their risk-taking capacity. Home equity has an impact on stockholdings comparable to that of overvaluation. (Chetty, Sándor, and Szeidl 2017) emphasize the need to control for leverage when evaluating the effects of house values on households' decisions. Consistent with their finding, we find that greater home equity also results in a crowding out of risky stockholdings, à la (Cocco 2005). While market house values have a negligible or negative effect, mortgage value has a very significant and negative impact on stockholdings. In robustness analysis, we find equivalent results with home equity instead of mortgage value. When we control for home equity, the impact of higher market house value is not significant or negative when the instruments based on (Guren et al. 2020) is used, exactly in line with (Chetty, Sándor, and Szeidl 2017).

The coefficient estimates of the instrumented misestimation are larger in magnitude than the ordinary least squares (OLS) estimates and remain significant. The Kleibergen–Paap Wald F-statistic confirms the strength of our instrumental variables, lending credibility to the causal interpretation of the estimates. We report the first-stage estimates in the Appendix. It is important to reiterate that the choice of instrument enables us to partly address endogeneity and measurement error concerns. Specifications in columns (4) and (7) instrument misestimation with the number of completed housing transactions at the Zip code level. Arguably, households living in a Zip code where more transactions are executed may have more information about the actual market value of the properties and therefore have a better estimate of the market value of housing in their Zip code (which is our measure HV^S). Similarly, specifications in columns (5) and (8) use as an instrument for misestimation the state-level number of Google searches containing words related to housing markets. The idea is that more frequent searches result in more informed responses about the household's house value. Both the number of transactions and the search intensity are plausibly uncorrelated with household-level portfolio allocation decisions.

The effects of other variables on stockholdings also align with economic intuition. Not all the estimates on the socioeconomic variables are statistically significant, but family income and education have an expected positive and significant impact on stockholdings.

To further assess the robustness of our findings, we re-estimate the baseline regressions under two alternative sample restrictions, reported in Table 5. Columns (1), (3), (5), and (7) limit the sample to properties with a ratio of land to total house value (which includes land and structure) above the top quartile, addressing concerns that our misestimation measure may partly reflect idiosyncratic characteristics of the building rather than beliefs about overall property value. Columns (2), (4), (6), and (8) restrict the sample to households with home equity above the top quartile. This second restriction mitigates concerns related to the interpretation of the reported house value. The concept of a house price is somewhat opaque in a search market, where there is a tradeoff between transaction price and time on the market: Sellers who can wait longer typically obtain higher prices, while those needing to sell quickly accept lower ones. Households may incorporate private information about their own urgency to sell into their self-reported valuation (HV^{S}), implying that HV^{S} could represent the expected price conditional on their individual sale horizon, whereas HV^{M} represents the expected market price for an average time on the market. Restricting the sample to high-home-equity households reduces the relevance of this concern, as these households are less likely to anticipate near-term sales or liquidity needs. Across both robustness checks, the estimated coefficients on house price misestimation remain negative and statistically significant, and their magnitude is broadly consistent with the baseline results. These findings confirm that the observed reduction in stockholdings associated with house overvaluation reflects belief-driven misestimation rather than noise from property characteristics or from heterogeneity in households intended time to sell.

We also explore the extensive margin of stockholdings in Table 6. The left-hand side of the regression specification is a dummy variable that takes the value of one if the household reports a positive value of stockholdings in a given year. We maintain simplicity by running a linear probability model, but results are robust to nonlinear specifications such as probit or logit.

Our findings indicate that households that overvalue their home are less likely to participate in the stock market. Specifically, we estimate that a one-standard-deviation increase in house overvaluation results (holding house value and mortgage debt constant), on average, in a 1.5 to 3.59 percentage point reduction in stock market participation. This result is both statistically and economically significant. The OLS results hold and are stronger when we instrument misestimation, market house values, and mortgages. These results related to the extensive margin of stockholdings do not map directly to the model. However the results are consistent with the intuition that overvaluation leads households to reduce their allocation to risky stocks, and with some of the households being on the margin, misestimation pushes them to leave the stock market altogether.

5.3 House Value Misestimation and Consumption

Previous research underscores limitations in PSID consumption measures (Li et al. 2007; Attanasio and Pistaferri 2014). These challenges remain central to interpreting consumption dynamics from PSID data. Nonetheless, we use the more reliable food-consumption measure (Hall and Mishkin 1982) to further exploit the predictions of household choices in our theoretical framework.

The results in Table 7 suggest that overvaluation has a positive wealth effect on consumption, a result that holds both in the OLS framework of column (2) and when misestimation is instrumented to extract the exogenous variation, in columns (4), (5), (7), and (8). We find that an increase of one standard deviation in overvaluation ($59,800) results in a 2.63 to 4.31 percentage point higher consumption relative to liquid wealth.

Our results are consistent with the literature quantifying the wealth effect of housing values. The literature has produced several empirical estimates of the marginal propensity to consume (MPC) out of housing wealth. (Poterba 1984) find an MPC ranging from 0.04 to 0.06, suggesting that a $1 increase in housing wealth leads to a $0.04 to $0.06 increase in consumption. (Case, Quigley, and Shiller 2005) estimate the MPC to be about 0.05 to 0.15, with higher estimates for the United States compared with other countries. (Carroll, Otsuka, and Slacalek 2011) estimate the MPC to be about 0.05 to 0.08, with higher estimates during housing booms. (Mian and Sufi 2011) find that the housing wealth effect was amplified during the 2007–2009 financial crisis, with (Dynan 2012) showing an MPC of about 0.05 to 0.10 during the crisis period. However, we focus primarily on the effects of misestimation of house values, and it is not straightforward to compare marginal propensities to consume found in the literature with our estimates. Yet, for the median household in our sample, whose consumption is 19 percent of their liquid wealth, a \$100,000 increase in overvaluation represents a 7.2 percentage point higher consumption ratio, that is, an increase from 18 to 26 percent of annual consumption over liquid wealth. For a median liquid wealth of \$40,000, consumption increases by \$2,880 over a year.

5.4 House Value Misestimation and Risk-free Assets

Table 8 analyzes the impact of house value misestimation on the share of risk-free assets over liquid wealth. A \$50,000 increase in house overvaluation results (holding house value and mortgage debt constant), on average, in a 1.7 to 2.2 percent increase in the share of risk-free asset holdings over liquid wealth.

Table 4: **Stockholdings and Misestimation.** This table shows the effects of house price misestimation (in $100,000) on a household's stockholdings. The dependent variable is the share of stock value as part of total liquid wealth if the liquid wealth is greater than $2,963.30. Columns (1) and (2) show the simple OLS results of the panel regressions without and with misestimation. Columns (3) through (5) use the (Saiz 2010) elasticity of supply interacted with house prices at the state level as an instrument for the subjective house values, while columns (6) through (8) use the (Guren et al. 2020) measure of elasticity of supply as an instrument for the subjective house values. Misestimation is instrumented with a measure of Zip code transactions in columns (4) and (7) and with the intensity of internet searches about housing markets in columns (5) and (8). Mortgage value is instrumented by the HPI index at the year of purchase interacted with long-term interest rates in all specifications. KPW denotes the Kleibergen–Paap Wald F-statistic coefficient, used to assess the strength of instrumental variables in the regression analysis. The $t-$ statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance of the coefficients at the 99 percent, 95 percent, and 90 percent levels of confidence. Standard errors are clustered at the year and Zip code levels.

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$m_{i,t}$		-0.019***		-0.031***	-0.021***		-0.022**	-0.021**
		(0.003)		(0.011)	(0.008)		(0.009)	(0.009)
HV^S	0.031***	0.032***	0.037*	0.054*	0.013	0.029**	0.006	0.002
	(0.001)	(0.001)	(0.019)	(0.031)	(0.020)	(0.013)	(0.012)	(0.013)
MTG	-0.025***	-0.025***	-0.066***	-0.056***	-0.053***	-0.082***	-0.070***	-0.079***
	(0.002)	(0.002)	(0.015)	(0.018)	(0.017)	(0.016)	(0.019)	(0.020)
Family Size	-0.016***	-0.015***	-0.013***	-0.016***	-0.012**	-0.016***	-0.017***	-0.013***
	(0.002)	(0.002)	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)
Family Income (log)	0.039***	0.036***	0.062***	0.026	0.088***	0.075***	0.101***	0.113***
	(0.004)	(0.004)	(0.024)	(0.043)	(0.027)	(0.019)	(0.021)	(0.022)
Gender	-0.017	-0.019*	-0.013	-0.015	-0.018	-0.010	-0.022	-0.009
	(0.011)	(0.011)	(0.014)	(0.018)	(0.018)	(0.015)	(0.019)	(0.019)
Education	0.075***	0.072***	0.086***	0.070***	0.090***	0.074***	0.082***	0.080***
	(0.005)	(0.005)	(0.012)	(0.020)	(0.015)	(0.010)	(0.011)	(0.012)
Married	0.007	0.007	-0.003	-0.016	-0.014	0.002	0.015	-0.008
	(0.010)	(0.010)	(0.012)	(0.015)	(0.015)	(0.014)	(0.017)	(0.017)
Observations	13,724	13,724	8,823	6,954	6,630	7,210	5,712	5,553
R-squared	0.151	0.155	0.073	0.079	0.064	0.041	0.022	-0.016
IV m_i_t	-	-	-	Transactions	Searches	-	Transactions	Searches
IV HV	-	-	Saiz	Saiz	Saiz	γ	γ	γ
IV MTG	-	-	Saiz	Saiz	Saiz	γ	γ	γ
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibeergen Paap			66.27	34.91	80	91.19	111.6	97.42
KPW			33.15	2.903	6.813	48.57	9.388	8.483
Cragg Donald			29.25	2.647	6.078	74.46	12.84	11.70
Anderson Rubin			9.820	2.285	2.607	13.88	2.994	3.405
Fuller Test			1	1	1	1	1	1
Fisrt Stage F			92.78	63.16	58.83	49.15	34.76	29.22
Hansen J			0	5.899	8.468	0	6.768	7.245

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: **Robustness of Misestimation Effects on Stockholdings: Land Share and Home Equity Restrictions.** This table reports the estimated effects of house price misestimation (in $100,000) on a households stockholdings under alternative sample restrictions. The dependent variable is the share of stock value as part of total liquid wealth for households with liquid wealth greater than $2,963.30. Columns (1), (3), (5), and (7) restrict the sample to properties with a land-to-total-house-value ratio above the top quartile, while columns (2), (4), (6), and (8) restrict it to households with home equity above the top quartile. Columns (1) and (2) present simple OLS estimates including misestimation. Columns (3) through (6) use the (Saiz 2010) elasticity of housing supply interacted with state-level house prices as an instrument for subjective house values, while columns (7) and (8) use the (Guren et al. 2020) elasticity measure. Misestimation is instrumented with the number of Zip-code-level housing transactions in columns (3), (4), (7) and (8) and with the intensity of internet searches related to housing markets in columns (5) and (6). Mortgage value is instrumented in all specifications by the interaction between the HPI index at the year of purchase and long-term interest rates. KPW denotes the KleibergenPaap Wald F-statistic, used to assess instrument strength. t–statistics are reported in parentheses. The symbols ***, **, and * indicate statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Standard errors are clustered at the year and Zip code levels.

Subsample (top quartile): VARIABLES	(1) Land/Value OLS	(2) Home eq. OLS	(3) Land/Value IV	(4) Home eq. IV	(5) Land/Value IV	(6) Home eq. IV	(7) Land/Value IV	(8) Home eq. IV
$m_{i,t}$	-0.022***	-0.020***	-0.048*	-0.041**	0.000	-0.023*	-0.074**	-0.017
	(0.006)	(0.004)	(0.026)	(0.018)	(0.022)	(0.013)	(0.030)	(0.012)
HV^S	0.036***	0.025**	0.109	0.110	-0.043	0.039	0.075**	-0.030
	(0.004)	(0.002)	(0.074)	(0.072)	(0.051)	(0.053)	(0.035)	(0.029)
MTG	-0.033***	-0.019***	-0.012	-0.102*	-0.118*	-0.064	-0.034	-0.039
	(0.006)	(0.004)	(0.058)	(0.056)	(0.059)	(0.045)	(0.035)	(0.042)
Observations	1,577	5,006	1,239	3,148	1,268	2,954	504	2,138
R-squared	0.196	0.130	-0.214	-0.123	-0.520	0.048	0.019	-0.069
IV m_i_t	-	-	Transactions	Transactions	Searches	Searches	Transactions	Transactions
IV HV	-	-	Saiz	Saiz	Saiz	Saiz	γ	γ
IV HE	-	-	Saiz	Saiz	Saiz	Saiz	γ	γ
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibeergen Paap			7.703	14.35	13.56	31.38	16.03	32.85
KPW			0.594	1.180	1.199	2.656	1.295	3.151
Cragg Donald			0.556	1.099	1.061	2.402	1.455	3.666
Anderson Rubin			1.395	1.367	1.564	1.802	1.488	1.575
Fuller Test			1	1	1	1	1	1
Fisrt Stage F			5.271	13.93	3.209	17.03	4.801	10.70
Hansen J			3.845	4.694	8.806	13.25	X	5.071

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: **Stock Market Participation and Misestimation.** This table shows the effects of house price misestimation (in $100,000) on a household's stock market participation. The dependent variable is the stock market participation. Columns (1) and (2) show the simple OLS results of the panel regressions without and with misestimation. Columns (3) through (5) us the (Saiz 2010) elasticity of supply interacted with house prices at the state level as an instrument for the subjective house values, while columns (6) through (8) use the (Guren et al. 2020) measure of elasticity of supply as an instrument for the subjective house values. Misestimation is instrumented with a measure of Zip code transactions in columns (4) and (7) and with the intensity of internet searches about housing markets in columns (5) and (8). Mortgage value is instrumented by the HPI index at the year of purchase interacted with long-term interest rates in all specifications. KPW denotes the Kleibergen–Paap Wald F-statistic coefficient, used to assess the strength of instrumental variables in the regression analysis. The $t-$ statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance of the coefficients at the 99 percent, 95 percent, and 90 percent levels of confidence. Standard errors are clustered at the year and Zip code levels.

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$m_{i,t}$		-0.025***		-0.060***	-0.038***		-0.036**	-0.033**
		(0.004)		(0.017)	(0.012)		(0.014)	(0.014)
HV^S	0.044***	0.045***	0.081**	0.115**	0.018	0.041**	0.009	-0.009
	(0.002)	(0.002)	(0.031)	(0.054)	(0.030)	(0.019)	(0.018)	(0.019)
MTG	-0.028***	-0.028***	-0.114***	-0.098***	-0.063**	-0.116***	-0.104***	-0.095***
	(0.004)	(0.004)	(0.024)	(0.028)	(0.026)	(0.023)	(0.028)	(0.028)
Family Size	-0.031***	-0.030***	-0.031***	-0.035***	-0.023***	-0.033***	-0.033***	-0.029***
	(0.004)	(0.004)	(0.006)	(0.008)	(0.007)	(0.005)	(0.006)	(0.007)
Family Income (log)	0.075***	0.071***	0.082**	0.004	0.132***	0.126***	0.159***	0.185***
	(0.006)	(0.006)	(0.037)	(0.071)	(0.041)	(0.028)	(0.032)	(0.033)
Gender	-0.024	-0.026	-0.017	-0.017	-0.006	-0.010	-0.025	-0.005
	(0.017)	(0.017)	(0.021)	(0.027)	(0.027)	(0.024)	(0.028)	(0.029)
Education	0.142***	0.139***	0.143***	0.105***	0.167***	0.150***	0.164***	0.166***
	(0.008)	(0.008)	(0.021)	(0.035)	(0.024)	(0.016)	(0.017)	(0.019)
Married	0.022	0.021	0.013	-0.005	-0.020	0.011	0.023	-0.012
	(0.015)	(0.015)	(0.019)	(0.023)	(0.023)	(0.021)	(0.025)	(0.026)
Observations	15,505	15,505	10,066	7,964	7,384	8,222	6,561	6,191
R-squared	0.169	0.171	0.067	0.035	0.082	0.050	0.027	-0.002
IV m_i_t	-	-	-	Transactions	Searches	-	Transactions	Searches
IV HV	-	-	Saiz	Saiz	Saiz	γ	γ	γ
IV MTG	-	-	Saiz	Saiz	Saiz	γ	γ	γ
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibeergen Paap			73.56	40.32	88.79	106.7	134	121.3
KPW			36.77	3.352	7.525	56.11	11.31	10.67
Cragg Donald			32.91	3.058	6.505	90.75	15.19	14.20
Anderson Rubin			11.90	3.332	2.536	13.88	3.507	3.259
Fuller Test			1	1	1	1	1	1
Fisrt Stage F			134.1	83.06	86.76	78.36	52.89	45.48
Hansen J			0	8.581	7.135	0	9.959	8.837

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: **Consumption and Misestimation.** This table shows the effects of house price misestimation on a household's allocation to nonhousing consumption. The dependent variable is food consumption (Cons) over liquid wealth (LW) if the liquid wealth is greater than $2,963.30. Columns (1) and (2) show the simple OLS results of the panel regressions without and with misestimation. Columns (3) through (5) use the (Saiz 2010) elasticity of supply interacted with house prices at the state level as an instrument for the subjective house values, while columns (6) through (8) use the (Guren et al. 2020) measure of elasticity of supply as an instrument for the subjective house values. Misestimation is instrumented with a measure of Zip code transactions in columns (4) and (7) and with the intensity of internet searches about housing markets in columns (5) and (8). Mortgage value is instrumented by the HPI index at the year of purchase interacted with long-term interest rates in all specifications. KPW denotes the Kleibergen–Paap Wald F-statistic coefficient, used to assess the strength of instrumental variables in the regression analysis. The $t-$ statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance of the coefficients at the 99 percent, 95 percent, and 90 percent levels of confidence. Standard errors are clustered at the year and Zip code levels.

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$m_{i,t}$		0.025***		0.072**	0.044**		0.041*	0.033
		(0.006)		(0.032)	(0.020)		(0.024)	(0.024)
HV^S	-0.054***	-0.055***	-0.068	-0.152	-0.057	-0.000	0.028	0.035
	(0.004)	(0.004)	(0.058)	(0.115)	(0.051)	(0.038)	(0.036)	(0.038)
MTG	0.041***	0.041***	0.162***	0.157***	0.162***	0.094**	0.080	0.100**
	(0.006)	(0.006)	(0.039)	(0.053)	(0.042)	(0.040)	(0.049)	(0.048)
Family Size	0.100***	0.100***	0.094***	0.106***	0.098***	0.091***	0.095***	0.101***
	(0.006)	(0.006)	(0.013)	(0.018)	(0.015)	(0.013)	(0.014)	(0.016)
Family Income (log)	-0.083***	-0.079***	-0.156**	-0.006	-0.152**	-0.183***	-0.215***	-0.242***
	(0.011)	(0.011)	(0.067)	(0.147)	(0.065)	(0.055)	(0.064)	(0.065)
Gender	0.110***	0.112***	0.148***	0.160***	0.128***	0.069**	0.046	0.033
	(0.028)	(0.028)	(0.032)	(0.038)	(0.034)	(0.033)	(0.035)	(0.038)
Education	-0.120***	-0.117***	-0.110***	-0.030	-0.119***	-0.129***	-0.138***	-0.155***
	(0.013)	(0.013)	(0.037)	(0.073)	(0.038)	(0.029)	(0.032)	(0.034)
Married	-0.019	-0.018	-0.018	-0.015	0.016	0.023	0.021	0.029
	(0.025)	(0.025)	(0.030)	(0.034)	(0.033)	(0.033)	(0.036)	(0.039)
Observations	14,992	14,992	9,693	7,645	7,345	7,930	6,318	6,157
R-squared	0.111	0.112	0.032	-0.008	0.034	0.020	0.004	-0.011
IV m_i_t	-	-	-	Transactions	Searches	-	Transactions	Searches
IV HV	-	-	Saiz	Saiz	Saiz	γ	γ	γ
IV MTG	-	-	Saiz	Saiz	Saiz	γ	γ	γ
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibeergen Paap			67.69	36.02	87.38	102.2	129.3	120
KPW			33.87	2.996	7.410	53.93	10.97	10.58
Cragg Donald			29.78	2.695	6.425	86.37	14.53	14.05
Anderson Rubin			12.09	3.213	3.127	2.862	2.552	1.715
Fuller Test			1	1	1	1	1	1
Fisrt Stage F			51.08	36.91	39.23	35.56	25.27	24.90
Hansen J			0	13.44	5.684	0	19.12	7.960

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: **Risk-free Assets and Misestimation.** This table shows the effects of house price misestimation on a household's allocation to risk-free assets. The dependent variable is risk-free assets (RFA) over liquid wealth (LW) if the liquid wealth is greater than $2,963.30. Columns (1) and (2) show the simple OLS results of the panel regressions without and with misestimation. Columns (3) through (5) us the (Saiz 2010) elasticity of supply interacted with house prices at the state level as an instrument for the subjective house values, while columns (6) through (8) use the (Guren et al. 2020) measure of elasticity of supply as an instrument for the subjective house values. Misestimation is instrumented with a measure of Zip code transactions in columns (4) and (7) and with the intensity of internet searches about housing markets in columns (5) and (8). Mortgage value is instrumented by the HPI index at the year of purchase interacted with long-term interest rates in all specifications. KPW denotes the Kleibergen–Paap Wald F-statistic coefficient, used to assess the strength of instrumental variables in the regression analysis. The $t-$ statistics are reported in parentheses. The symbols ***, **, and * denote the statistical significance of the coefficients at the 99 percent, 95 percent, and 90 percent levels of confidence. Standard errors are clustered at the year and Zip code levels.

VARIABLES	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV	(7) IV	(8) IV
$m_{i,t}$		0.030***		0.042***	0.025**		0.022*	0.022*
		(0.004)		(0.015)	(0.012)		(0.013)	(0.012)
HV^S	-0.047***	-0.048***	-0.035	-0.043	0.015	-0.021	-0.012	0.001
	(0.002)	(0.002)	(0.029)	(0.044)	(0.030)	(0.017)	(0.016)	(0.017)
MTG	0.038***	0.038***	0.071***	0.051**	0.032	0.084***	0.065***	0.060**
	(0.003)	(0.003)	(0.022)	(0.025)	(0.025)	(0.021)	(0.025)	(0.025)
Family Size	0.024***	0.024***	0.016***	0.019**	0.010	0.031***	0.037***	0.032***
	(0.004)	(0.004)	(0.006)	(0.008)	(0.007)	(0.005)	(0.006)	(0.006)
Family Income (log)	-0.032***	-0.027***	-0.074**	-0.047	-0.122***	-0.088***	-0.092***	-0.108***
	(0.006)	(0.006)	(0.034)	(0.058)	(0.039)	(0.026)	(0.027)	(0.029)
Gender	0.003	0.006	0.002	0.007	-0.006	0.010	0.014	-0.006
	(0.016)	(0.016)	(0.019)	(0.024)	(0.025)	(0.022)	(0.026)	(0.027)
Education	-0.104***	-0.100***	-0.127***	-0.108***	-0.147***	-0.119***	-0.119***	-0.121***
	(0.007)	(0.007)	(0.019)	(0.030)	(0.023)	(0.015)	(0.015)	(0.017)
Married	0.012	0.013	0.034**	0.046**	0.055***	-0.004	-0.019	0.004
	(0.014)	(0.014)	(0.017)	(0.020)	(0.021)	(0.019)	(0.022)	(0.023)
Observations	14,861	14,861	9,656	7,659	7,081	7,876	6,307	5,929
R-squared	0.169	0.173	0.071	0.089	0.020	0.037	0.043	0.020
IV m_i_t	-	-	-	Transactions	Searches	-	Transactions	Searches
IV HV	-	-	Saiz	Saiz	Saiz	γ	γ	γ
IV MTG	-	-	Saiz	Saiz	Saiz	γ	γ	γ
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AGE FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibeergen Paap			67.93	38.10	84.70	99.53	124	109.7
KPW			33.92	3.159	7.169	52.64	10.52	9.657
Cragg Donald			30.37	2.863	6.230	86.83	14.33	13.18
Anderson Rubin			5.797	2.007	2.130	7.827	1.519	1.895
Fuller Test			1	1	1	1	1	1
Fisrt Stage F			80.38	59.30	51.27	47.40	37.12	31.98
Hansen J			0	5.706	9.653	0	3.704	9.277

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6 Conclusions

This paper provides novel insights into the financial consequences of house value misestimation for households. Using a combination of theoretical modeling and empirical analysis, we establish that households systematically overestimate or underestimate the value of their house value, leading to significant shifts in portfolio allocation, consumption, and investment decisions.

We document a robust negative relationship between house overvaluation and the share of risky assets in household portfolios. Specifically, a one-standard-deviation increase in house overvaluation (which represents an overvaluation of $59,800) results, on average, in a decrease of 1.14 to 1.86 percent in the allocation to risky stockholdings, consistent with our theoretical model's predictions. This finding highlights a critical departure from standard portfolio choice models, which typically assume accurate perceptions of wealth.

Furthermore, we find that overvaluation is associated with increased nonhousing consumption. An increase of one standard deviation in overvaluation ($59,800) results in a 2.63 to 4.31 percentage point higher consumption relative to liquid wealth. This result underscores the role of housing wealth misestimation in the marginal propensity to consume, suggesting that households adjust their spending behavior in response to perceived (rather than actual) wealth gains. Additionally, households with higher perceived house values tend to reallocate financial assets away from stocks toward risk-free assets, reinforcing a conservative shift in portfolio composition.

From an identification perspective, our use of housing market liquidity and real estate search intensity as instrumental variables mitigates concerns about reverse causality and measurement error. The strength of our instruments, confirmed by statistical tests, bolsters the causal interpretation of our results.

These results have broad implications for financial theory and policy. First, they challenge the common assumption in portfolio choice models that households accurately observe their wealth. Second, they suggest that financial advisors and policymakers should account for biases in housing wealth perceptions when designing investment and retirement strategies. Third, given the widespread use of home equity as collateral, our findings imply that misestimation of house values could have significant implications for credit availability and macroeconomic stability.

Future research should explore the heterogeneity of these effects across demographic groups and different housing market conditions. Additionally, investigating how financial literacy or real-time market information mitigates the effects of misestimation on household decisionmaking presents an important avenue for further study. Our analysis suggests that policies aimed at improving the accuracy of homeowners selling-price expectationssuch as more frequent professional appraisals or enhanced financial educationmay help optimize household financial decisions and contribute to overall economic stability.

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Appendix

A-I Further Analysis of Misestimation

We investigate socioeconomic effects of misestimation through regression analyses. These models explore the relationships between misestimation and variables such as family income, family size, gender, education, marital status, employment, and tenure. We include fixed effects at the five-digit Zip code level, year, and age, and we also cluster standard errors at the Zip code, year, and age levels for robust inference.

We assess the determinants of changes in house value misestimation using six regression models. Model 1 examines the relationship between changes in misestimation, changes in house value, lagged misestimation, and other controls. Model 2 focuses on undervaluers (cases in which misestimation was less than zero), while Model 3 analyzes overvaluers (cases in which misestimation was greater than or equal to zero). Model 4 investigates changes in market house values as a determinant of misestimation for overvaluers, and Model 5 applies the same approach to undervaluers. Model 6 expands on the analysis of overvaluers with market value changes. Across all models, we apply fixed effects at the Zip code, year, and age levels, and we cluster standard errors at the same levels for statistical robustness.

Additional analyses includes ordinary least squares (OLS) and instrumental variable (IV) models to examine key financial behaviors. These models explore relationships such as stock value over liquid wealth, food consumption as a fraction of liquid wealth, stock participation and value for stockholders, risk-free assets over total wealth, and home improvements over market house value for stockholders. We trim extreme values at the 5th and 95th percentiles within each state.

To enhance model precision, we also incorporate several controls, including mortgage size, house value, and local socioeconomic factors such as family size, family income (log-transformed), gender, education, and marital status. Fixed effects for state, year, and age are included, and when Google Trends data are used as an instrumental variable, designated market area (DMA) codes are added as fixed effects too. We employe a range of IVs: elasticity data from Saiz, gamma variables from Guren, transaction bins from CoreLogic, and decile bins from Google Trends. These elements provide a robust framework for understanding the nuanced interactions between house value misestimation, financial variables, and socioeconomic trends.

Appendix Table A-1 provides an overview of the socioeconomic characteristics of the households included in our analysis, such as family income, household size, age, gender, education, marital status, and employment status, which serve as control variables in our empirical analysis. The sample is restricted to households with liquid wealth exceeding \$2,963.30, corresponding to the average monthly salary in the United States in 2000. The table reports the mean, standard deviation, 5th and 95th percentiles, and total number of observations for each variable.

House value misestimation may simply vary because homeowners learn and adjust the subjective

Table A-1: **Descriptive Statistics of Socioeconomic and Instrumental Variables.** This table presents summary statistics for the primary variables in the analysis, including the sample mean, standard deviation, 5th and 95th percentiles, and total number of observations. Housing market data are sourced from the Federal Housing Finance Agency (FHFA), while data on house value misestimation, household socioeconomic characteristics, and financial decisions are obtained from the Panel Study of Income Dynamics (PSID). The sample is restricted to households with liquid wealth exceeding $2963.30, which corresponds to the average monthly salary in the United States in the year 2000.

	Mean	Std. Dev.	p5	p95	Obs.
Socioeconomic Characteristics:					
Family Income (log)	10.885	0.959	9.278	12.223	60,373
Family Size	3.043	1.419	1.000	5.000	60,901
Age	43.950	14.347	25.000	72.000	60,893
Gender (Male=1)	0.872	0.334	0.000	1.000	60,900
Education (High School or More = 1)	0.396	0.489	0.000	1.000	59,128
Married (Married=1)	0.792	0.406	0.000	1.000	60,897
Employed (Employed=1)	0.840	0.367	0.000	1.000	60,876
Tenure	5.706	6.303	1.000	19.000	60,901
Instrument Variables:					
Elasticity FHFA, ε_{HPI}	238.453	170.215	54.785	585.030	38,848
Elasticity FHFA year of purchase, $\varepsilon_{HPI} \times HPI_{t_0}$	203.844	153.071	37.453	510.682	38,848
γ_{HPI}	132.957	91.916	39.300	305.415	30,111
$\gamma_{HPI} \times HPI_{t_0}$	112.242	80.656	32.221	268.431	30,111
Transaction 10 Bins	6.267	2.584	2.000	10.000	46,827
Google Trends Bins	5.452	2.619	1.000	10.000	25,437

valuation of their house in the direction of its market value or simply because market values move, with no changes in subjective valuations. The latter would be consistent with homeowners anchoring their house value at the purchase price, for example. Specifically, learning and anchoring could play a significant role in explaining the variation of misestimation within Zip codes across households. Table A-2 shows the results of OLS panel regressions of changes in house value misestimation at the household level for different subsamples on these potential determinants of misestimation dynamics. We control for lagged levels of misestimation, the current subjective value of the house (in logs), and the socioeconomic characteristics described in the previous table.

We find that changes in both the subjective and market valuations of a house have a significant impact on misestimation: Misestimation increases when the household increases the subjective value, and misestimation decreases when market values grow, all else equal. The coefficients for ΔHV^S and ΔHV^M are positive and negative, respectively, which confirms that the variation in misestimation is driven by variation in both subjective and market valuation growth rates. These results are not driven by the subsample of households that undervalue or by the subsample of households that overvalue, as shown in columns (2)–(3) and (5)–(6).

Table A-2: **The Determinants of Changes in House Value Misestimation.** This table shows analysis of the determinants of house value misestimation. The dependent variable for all specifications is the change in misestimation (in $100,000), Δm_{it}. The independent variables are the change in the subjective house value, ΔHV^S, and the change in the market house value, ΔHV^M. We control for lagged misestimation, $m_{i,t-1}$, and the house value in terms of HV^S (log). Our set of controls includes the logarithm of family income, education (high school or more = 1), employment status of the head of the household (employed = 1), and the number of family members. We also control for the age, gender (male = 1), marital status (married = 1), tenure, tenure squared, and the number of transactions in the household's Zip code. All our estimations use year and Zip-code-level fixed effects. Robust t-statistics are shown in parentheses. ***, **, and * indicate significance at the 1 percent, 5 percent, and 10 percent level of confidence, respectively. Standard errors are clustered at the year and Zip code level.

	(1) All Households	(2) Only Undervaluers	(3) Only Overvaluers	(4) All Households	(5) Only Undervaluers	(6) Only Overvaluers
ΔHV^S	0.574***	0.543***	0.584***			
	(0.0491)	(0.0345)	(0.0487)			
ΔHV^M				-0.357***	-0.502***	-0.219***
				(0.0621)	(0.0534)	(0.0484)
$m_{i,t-1}$	-0.126***	-0.102*	-0.208***	-0.273***	-0.170***	-0.423***
	(0.0271)	(0.0537)	(0.0315)	(0.0380)	(0.0331)	(0.0937)
HV^S(log)	-0.0608*	-0.0706*	-0.0341*	0.265***	0.284***	0.289***
	(0.0305)	(0.0371)	(0.0171)	(0.0356)	(0.0355)	(0.0438)
Observations	43,789	18,304	24,671	43,789	18,304	24,671
R-squared	0.493	0.417	0.613	0.234	0.364	0.273
ZIP FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Age FE	Yes	Yes	Yes	Yes	Yes	Yes

All our specifications in Table A-2 include lagged misestimation, $m_{i,t-1}$. The negative term indicates that a higher level of misestimation relates to smaller future increases of misestimation. Households tend to react, as a higher misestimation triggers a decline in future misestimation, everything else equal, suggesting that there is mean reversion in misestimation.

Overall, we find that both growth in the subjective house value (that is, actively updating the subjective valuation) and growth in the market value (that is, the subjective value being sticky) play a significant role in explaining the variation of misestimation within Zip codes across households.

A-II Correlation between Housing and Stock Returns

In this appendix, we justify our assumption of zero correlation between housing and stock returns used in our model. Figure A-1 illustrates the absence of a relationship between U.S. housing returns and U.S. stock returns over the period analyzed in our empirical study.

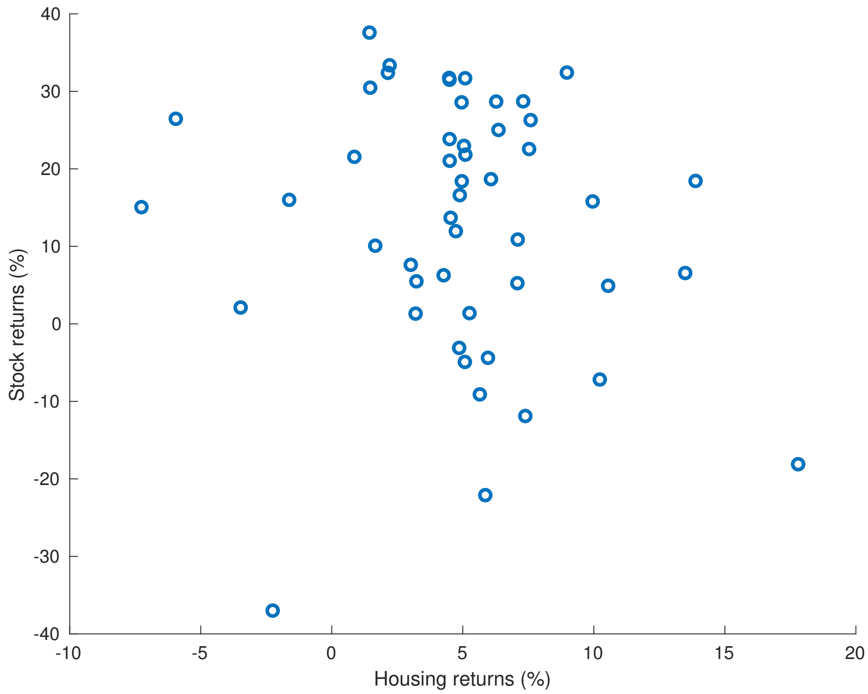

Figure A-1: **Historical U.S. Stock Returns versus U.S. Housing Returns.** This figure displays the scatter plot of U.S.stock returns and U.S. housing returns for the period 1984–2024.

A-III Assessing Instrument Validity: Housing Turnover and Google Search Intensity

In this appendix, we assess the empirical validity of the instruments used in our main analysis (that is, local housing market turnover and Google search intensity for housing-related terms), which proxy for the information environment surrounding housing markets. Two potential identification concerns merit discussion. First, both instruments may correlate with local growth expectations, potentially violating the exclusion restriction. Second, the relevance condition linking these variables to the precision of expectations was not sufficiently demonstrated.

A-III.1 Exclusion Restriction: Testing for Correlation with Local Economic Conditions

To examine whether our instruments capture variation in local economic expectations rather than purely informational conditions, we test their correlation with a key measure of local fundamentals: median family income at the Zip code level. If either instrument proxies for broader economic optimism (or local demand shocks), it should covary positively with local income levels. Conversely, if the instruments are valid, their correlation with income should be statistically indistinguishable from zero once we control for fixed effects and clustering.

We estimate the following specification:

$$\text{median\_family\_income}_{zt} = \alpha + \sum_{b=1}^{10} \beta_b \, \text{Bin}^{IV}_{b,zt} + \gamma_t + \delta_z + \varepsilon_{zt}, \tag{A-1}$$

where $\text{Bin}^{IV}_{b,zt}$ are decile indicators of either (i) the volume of housing transactions or (ii) the intensity of Google housing-related searches in Zip code z and year t. We include year and Zip code fixed effects and cluster standard errors at the year level. The results are reported in Table A-3.

Table A-3: **Correlation between Median Family Income and Housing Activity.** This table reports the coefficients, standard errors, and p-values from regressions of Zip-code-level median family income on decile indicators of (1) housing market turnover (column 1) and (2) Google search intensity for housing-related terms (column 2). Each specification includes Zip code and year fixed effects, with standard errors clustered at the year level.

	(1) Transactions IV	(2) Google Search IV
Decile 1	370.678	-486.053*
	(271.085)	(212.385)
Decile 2	358.437	-259.533
	(237.385)	(254.016)
Decile 3	56.897	34.116
	(163.495)	(229.737)
Decile 4	255.967	103.396
	(294.923)	(236.378)
Decile 5	217.271	104.608
	(259.056)	(144.750)
Decile 6	253.896	83.765
	(193.413)	(138.005)
Decile 7	283.437	249.341
	(329.017)	(187.468)
Decile 8	-172.712	256.908
	(196.064)	(219.437)
Decile 9	-285.240	355.926
	(202.419)	(251.499)
Decile 10	-126.024	-15.147
	(392.612)	(233.207)
Observations	10,487	13,335
Adjusted R^2	0.97	0.96

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As shown in Table A-3, the estimated coefficients are economically small and statistically insignificant across all deciles of both instruments. For the regression using housing transactions (column 1), none of the coefficients is significant at conventional levels (all p-values > 0.18), and the R^2 is high (0.97) due to the inclusion of fixed effects. Similarly, for the regression using Google search intensity (column 2), coefficients alternate in sign and remain far from statistical significance (all p-values > 0.07).

The lack of systematic relationship between median income and either instrument provides strong evidence that neither variable captures broader economic conditions or local growth expectations. In other words, Zip codes with higher turnover or greater housing search activity do not systematically exhibit higher income levels once we account for time and location effects. This supports the exogeneity of the instruments with respect to local fundamentals.

A-III.2 Relevance Condition: First-stage Results

The relevance of both instruments stems from their connection to the informativeness of local housing markets. In areas with higher transaction volumes, market prices incorporate more dispersed private information, thereby reducing the dispersion of price expectations. Similarly, a higher intensity of Google searches for housing-related terms reflects greater public attention and information gathering, enhancing the precision of beliefs.

To verify empirical relevance, we report the first-stage results of the IV regressions corresponding to Tables 4–8. While the set of first-stage regressions is identical across the analyses of stockholdings, stock market participation, consumption, and risk-free asset holdings—and thus the coefficients are expected to be the same—we report each specification separately due to slight differences in the number of observations across samples. The first-stage tables are organized as follows:

- Tables A-4 and A-5 report the first-stage estimates corresponding to specifications (3)-(5) and (6)-(8) from Table 4, respectively, which examine the effect of misestimation on stockholdings.
- Tables A-6 and A-7 report the first-stage estimates corresponding to specifications (3)-(5) and (6)-(8) from Table 6, respectively, which examine the effect of misestimation on stock market participation.
- Tables A-8 and A-9 report the first-stage estimates corresponding to specifications (3)-(5) and (6)-(8) from Table 7, respectively, which examine the effect of misestimation on consumption.
- Tables A-10 and A-11 report the first-stage estimates corresponding to specifications (3)-(5) and (6)-(8) from Table 8, respectively, which examine the effect of misestimation on risk-free asset holdings.

These results confirm the strength and relevance of the instruments used in the IV specifications throughout our analyses. Specifically, we instrument house value (HV), mortgage balances (MTG), and housing misestimation ($m_{i,t}$). For HV, we employ the Saiz (2010) measure of housing supply elasticity, denoted as *elast_FHFA*. The coefficient on this variable is negative and highly significant across all specifications (for example, 0.002 with $p < 0.01$ in Table A-4), indicating that house values are systematically lower in areas with more elastic housing supply. This finding is consistent with the notion that areas with more elastic housing supply experience less upward pressure on house prices in response to demand shocks, thereby supporting *elast_FHFA* as a valid instrument for HV.

To instrument for MTG, we use a variation of the Saiz measure that is interacted with the elasticity at the time of home purchase, *elast_FHFAYearPurchase*. This instrument also displays strong first-stage relevance, with positive and statistically significant coefficients across all mortgage regressions (for example, 0.003 with $p < 0.01$), suggesting that homebuyers in more elastic markets obtain higher mortgages, possibly due to greater affordability or looser credit conditions. These first-stage patterns are stable across alternative specifications and confirm the relevance of the instrument for mortgage balances.

We instrument for the misestimation variable $m_{i,t}$ using two proxies for belief formation: housing market transactions in the property's Zip code (*Transactions*) and local housing-related Google search activity (*Searches*). Both instruments are highly predictive of $m_{i,t}$ in the first-stage regressions. The coefficients for the 10 bins of levels of housing *Transactions* are positive and statistically significant for most bins, while the coefficients for the 10 bins of deciles on Google *Searches* are of similar magnitude and significance. These results imply that local housing market activity and online interest are strongly correlated with house value misestimation, consistent with mechanisms such as salience, attention, or extrapolative expectations.

Additional covariates, such as household income, education, and family size, behave as expected, reinforcing the robustness of the instrumented relationships. Together, these findings provide compelling evidence that the instruments are both statistically relevant and conceptually credible, validating their use in addressing endogeneity concerns in household asset holdings and belief formation.

Overall, in both specifications, the interaction of turnover (or search intensity) with the sign of prior mispricing strongly predicts the absolute forecast error, consistent with the models mechanism: Where information flows more freely, errors shrink more rapidly. The corresponding F-statistics for instrument relevance exceed the conventional threshold of 10, confirming the strength of the instruments (see Tables 4–8).

A-III.3 Assessing Instrument Validity: Conclusions

Taken together, these results mitigate concerns about the validity of the instruments. The absence of correlation between our instruments and local income suggests that they are not driven by local growth expectations. At the same time, the first-stage regressions confirm that both variables are strong predictors of the informational component of mispricing. While no instrument can be perfectly exogenous, these tests support the view that housing turnover and housing-related search intensity primarily capture information diffusion rather than local economic fundamentals, thereby satisfying both the relevance and exclusion conditions required for valid identification.

Specific. on Table 4:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
elast_FHFA	-0.002***	-0.003***	-0.002***	-0.003***	-0.001***	-0.002***	-0.003***	-0.001***
elast_FHFAyearpurchase	0.001***	0.003***	0.001***	0.003***	0.001***	0.001**	0.003***	0.001***
Bin_1			0.173*	0.024	0.466***	0.055	-0.063	0.675***
Bin_2			0.197**	0.048	0.553***	-0.079	-0.064	0.788***
Bin_3			0.195**	0.030	0.571***	0.227***	-0.031	0.613***
Bin_4			0.172**	-0.003	0.571***	0.235***	0.078*	0.529***
Bin_5			0.073	0.064	0.546***	0.259***	0.093*	0.550***
Bin_6			0.097	0.032	0.518***	0.135*	0.021	0.588***
Bin_7			0.186**	0.006	0.527***	-0.006	-0.023	0.492***
Bin_8			0.133*	0.049	0.641***	0.121	-0.029	0.506***
Bin_9			0.186**	-0.062	0.533***	0.271**	0.029	0.434***
Bin_10			0.107	-0.039	0.581***	0.315***	0.048	0.433***
Family Size	0.155***	0.066***	0.139***	0.068***	0.015	0.154***	0.074***	0.017
Family Income (log)	1.421***	0.592***	1.450***	0.559***	-0.163***	1.472***	0.568***	-0.179***
Gender	0.033	-0.082	0.085	-0.082	-0.095*	0.118	-0.063	-0.100*
Education	0.642***	0.231***	0.624***	0.198***	-0.088***	0.693***	0.241***	-0.100***
Married	-0.055	0.008	0.007	0.032	-0.046	-0.058	-0.012	-0.031
Constant	-13.185***	-5.455***	-13.579***	-5.161***	1.766***	-13.721***	-5.260***	1.918***
Observations	8,823	8,823	6,954	6,954	6,954	6,630	6,630	6,630
R-squared	0.430	0.390	0.423	0.385	0.306	0.422	0.385	0.314
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-4: First-stage Regressions for the Stockholdings and Misestimation Regressions (Part 1). First-stage regressions that correspond to specifications (3)–(5) in Table 4.

Specific. on Table 4:	(6) HV	(6) MTG	(7) HV	(7) MTG	(7) $m_{i,t}$	(8) HV	(8) MTG	(8) $m_{i,t}$
gammaHPI	0.004***	-0.001***	0.005***	-0.001***	-0.003***	0.005***	-0.001***	-0.003***
gamFHFAyearpurchase	-0.000	0.005***	-0.000	0.004***	0.003***	-0.000	0.004***	0.003***
Bin_1			0.051	-0.046	0.322***	0.110	-0.039	0.454***
Bin_2			0.183*	0.141**	0.441***	0.098	0.076	0.590***
Bin_3			0.170*	0.049	0.466***	0.263***	0.023	0.463***
Bin_4			0.158*	-0.025	0.401***	0.220***	0.031	0.426***
Bin_5			0.092	0.018	0.471***	0.135	0.021	0.443***
Bin_6			0.402***	0.019	0.421***	0.306***	0.015	0.532***
Bin_7			0.278***	0.004	0.468***	0.134*	-0.052	0.497***
Bin_8			0.300***	0.060	0.507***	0.231***	0.081*	0.471***
Bin_9			0.232***	-0.045	0.521***	0.348***	0.023	0.430***
Bin_10			0.108	-0.084	0.520***	0.212**	-0.102	0.482***
Family Size	0.099***	0.054***	0.078***	0.055***	0.015	0.098***	0.070***	0.014
Family Income (log)	1.374***	0.574***	1.449***	0.559***	-0.143***	1.448***	0.572***	-0.148***
Gender	0.154	0.086	0.094	0.025	-0.068	0.216*	0.077	-0.033
Education	0.498***	0.249***	0.499***	0.233***	-0.009	0.545***	0.255***	-0.020
Married	-0.164*	0.041	-0.054	0.133**	0.065	-0.189*	0.040	0.067
Constant	-14.128***	-6.075***	-14.902***	-5.926***	1.706***	-14.954***	-6.116***	1.725***
Observations	7,210	7,210	5,712	5,712	5,712	5,553	5,553	5,553
R-squared	0.408	0.367	0.416	0.361	0.309	0.408	0.360	0.309
IV	γ	γ	γ	γ	Transactions	γ	γ	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-5: First-stage Regressions for the Stockholdings and Misestimation Regressions (Part 2). First-stage regressions that correspond to specifications (6)–(8) in Table 4.

Specific. on Table 6:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
elast_FHFA	-0.003***	-0.003***	-0.002***	-0.003***	-0.001***	-0.002***	-0.003***	-0.001***
elast_FHFAyearpurchase	0.001***	0.003***	0.001***	0.003***	0.001***	0.001***	0.003***	0.001***
Bin1_1			0.151	0.026	0.472***	0.029	-0.048	0.705***
Bin1_2			0.171**	0.059	0.545***	-0.03	-0.034	0.803***
Bin1_3			0.231***	0.06	0.575***	0.195***	-0.024	0.616***
Bin1_4			0.149**	0.01	0.606***	0.231***	0.071*	0.525***
Bin1_5			0.071	0.057	0.524***	0.219***	0.074	0.550***
Bin1_6			0.131*	0.029	0.533***	0.146**	0.032	0.588***
Bin1_7			0.173**	0.009	0.525***	-0.059	-0.052	0.496***
Bin1_8			0.123*	0.045	0.632***	0.169**	0.001	0.498***
Bin1_9			0.170**	-0.056	0.511***	0.345***	0.051	0.413***
Bin1_10			0.084	-0.052	0.511***	0.309***	0.037	0.452***
Family Size	0.153***	0.062***	0.144***	0.070***	0.020*	0.160***	0.074***	0.02
Family Income (log)	1.382***	0.578***	1.415***	0.553***	-0.177***	1.445***	0.563***	-0.194***
Gender	0.048	-0.074	0.116	-0.062	-0.139**	0.134	-0.05	-0.130**
Education	0.667***	0.229***	0.656***	0.193***	-0.105***	0.733***	0.234***	-0.115***
Married	-0.096	0.001	-0.078	0.001	-0.04	-0.118	-0.028	-0.037
Constant	-12.720***	-5.297***	-13.183***	-5.093***	1.928***	-13.365***	-5.190***	2.106***
Observations	10,066	10,066	7,964	7,964	7,964	7,384	7,384	7,384
R-squared	0.427	0.394	0.422	0.387	0.303	0.413	0.386	0.313
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-6: First-stage Regressions for the Stock Market Participation and Misestimation Regressions (Part 1). First-stage regressions that correspond to specifications (3)–(5) in Table 6.

Specific. on Table 6:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
gammaHPI	0.005***	-0.002***	0.005***	-0.001***	-0.003***	0.005***	-0.001***	-0.003***
gamFHFAyearpurchase	-0.000	0.005***	-0.001	0.004***	0.003***	-0.001	0.004***	0.003***
Bin1_1			0.033	-0.038	0.320***	0.073	-0.069	0.443***
Bin1_2			0.122	0.121**	0.427***	0.095	0.055	0.573***
Bin1_3			0.177**	0.068	0.462***	0.251***	0.033	0.453***
Bin1_4			0.154*	-0.008	0.431***	0.197**	0.028	0.424***
Bin1_5			0.072	0.001	0.451***	0.092	0.032	0.443***
Bin1_6			0.389***	0.025	0.399***	0.301***	0.015	0.532***
Bin1_7			0.253***	-0.017	0.466***	0.078	-0.086*	0.497***
Bin1_8			0.266***	0.043	0.502***	0.264***	0.085*	0.480***
Bin1_9			0.217***	-0.037	0.477***	0.361***	0.015	0.427***
Bin1_10			0.111	-0.08	0.459***	0.191*	-0.110*	0.468***
Family Size	0.090***	0.052***	0.077***	0.057***	0.016	0.093***	0.069***	0.015
Family Income (log)	1.336***	0.551***	1.422***	0.535***	-0.144***	1.435***	0.554***	-0.151***
Gender	0.147	0.103*	0.098	0.05	-0.092*	0.205*	0.111*	-0.069
Education	0.538***	0.250***	0.529***	0.236***	-0.032	0.583***	0.262***	-0.041*
Married	-0.182**	0.027	-0.112	0.105*	0.049	-0.223**	0.012	0.06
Constant	-13.689***	-5.791***	-14.599***	-5.654***	1.747***	-14.795***	-5.924***	1.796***
Observations	8,222	8,222	6,561	6,561	6,561	6,191	6,191	6,191
R-squared	0.411	0.365	0.419	0.36	0.298	0.407	0.357	0.303
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-7: First-stage Regressions for the Stock Market Participation and Misestimation Regressions (Part 2). First-stage regressions that correspond to specifications (6)–(8) in Table 6.

Specific. on Table 7:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
elast_FHFA	-0.003***	-0.003***	-0.002***	-0.003***	-0.001***	-0.002***	-0.003***	-0.001***
elast_FHFAyearpurchase	0.001***	0.003***	0.001***	0.003***	0.001***	0.001***	0.003***	0.001***
Bin1_1			0.15	0.037	0.459***	0.029	-0.046	0.702***
Bin1_2			0.172**	0.057	0.545***	-0.045	-0.028	0.796***
Bin1_3			0.232***	0.062	0.576***	0.193***	-0.02	0.613***
Bin1_4			0.131*	0.011	0.605***	0.223***	0.073*	0.525***
Bin1_5			0.071	0.062	0.554***	0.229***	0.081*	0.546***
Bin1_6			0.130*	0.026	0.539***	0.152**	0.037	0.587***
Bin1_7			0.183***	0.025	0.531***	-0.057	-0.053	0.493***
Bin1_8			0.117	0.047	0.647***	0.168**	0.002	0.496***
Bin1_9			0.167**	-0.07	0.523***	0.344***	0.052	0.412***
Bin1_10			0.096	-0.051	0.544***	0.312***	0.041	0.455***
Family Size	0.156***	0.063***	0.148***	0.068***	0.019	0.160***	0.072***	0.02
Family Income (log)	1.386***	0.586***	1.422***	0.561***	-0.185***	1.449***	0.572***	-0.198***
Gender	0.055	-0.073	0.124	-0.062	-0.132**	0.126	-0.051	-0.127**
Education	0.685***	0.229***	0.674***	0.193***	-0.108***	0.737***	0.233***	-0.113***
Married	-0.111	-0.001	-0.097	0	-0.036	-0.124	-0.027	-0.038
Constant	-12.742***	-5.359***	-13.235***	-5.159***	2.006***	-13.410***	-5.271***	2.148***
Observations	9,693	9,693	7,645	7,645	7,645	7,345	7,345	7,345
R-squared	0.419	0.394	0.413	0.388	0.304	0.413	0.387	0.313
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-8: Firs-stage Regressions for the Consumption and Misestimation Regressions (Part 1). First-stage regressions that correspond to specifications (3)–(5) in Table 7.

Specific. on Table 7:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
gammaHPI	0.005***	-0.002***	0.005***	-0.001***	-0.003***	0.005***	-0.001***	-0.003***
gamFHFAyearpurchase	-0.000	0.005***	-0.001	0.004***	0.003***	-0.001	0.004***	0.003***
Bin1_1			0.034	-0.04	0.318***	0.079	-0.066	0.443***
Bin1_2			0.125	0.121**	0.428***	0.094	0.055	0.574***
Bin1_3			0.174*	0.071	0.464***	0.258***	0.033	0.455***
Bin1_4			0.146*	-0.009	0.432***	0.191**	0.038	0.422***
Bin1_5			0.076	-0.004	0.490***	0.101	0.038	0.439***
Bin1_6			0.388***	0.024	0.402***	0.294***	0.013	0.533***
Bin1_7			0.265***	-0.011	0.470***	0.081	-0.087*	0.491***
Bin1_8			0.274***	0.049	0.508***	0.261***	0.088**	0.478***
Bin1_9			0.220***	-0.05	0.487***	0.356***	0.013	0.428***
Bin1_10			0.128	-0.073	0.480***	0.197**	-0.113*	0.472***
Family Size	0.090***	0.052***	0.074***	0.056***	0.014	0.093***	0.067***	0.015
Family Income (log)	1.343***	0.555***	1.430***	0.540***	-0.151***	1.437***	0.559***	-0.153***
Gender	0.139	0.100*	0.095	0.05	-0.093*	0.195*	0.108	-0.067
Education	0.550***	0.252***	0.545***	0.239***	-0.036	0.586***	0.263***	-0.040*
Married	-0.180**	0.032	-0.108	0.112*	0.058	-0.221**	0.02	0.058
Constant	-13.752***	-5.844***	-14.668***	-5.699***	1.826***	-14.823***	-5.970***	1.815***
Observations	7,930	7,930	6,318	6,318	6,318	6,157	6,157	6,157
R-squared	0.403	0.362	0.411	0.358	0.301	0.407	0.357	0.303
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-9: First-stage Regressions for the Consumption and Misestimation Regressions (Part 2). First-stage regressions that correspond to specifications (6)–(8) in Table 7.

Specific. on Table 8:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
elast_FHFA	-0.003***	-0.003***	-0.002***	-0.003***	-0.001***	-0.002***	-0.003***	-0.001***
elast_FHFAyearpurchase	0.001***	0.003***	0.001***	0.003***	0.001***	0.001***	0.003***	0.001***
Bin10_1			0.191**	0.031	0.466***	0.051	-0.041	0.710***
Bin10_2			0.164**	0.055	0.548***	-0.034	-0.037	0.801***
Bin10_3			0.230***	0.063	0.564***	0.204***	-0.025	0.625***
Bin10_4			0.156**	0.006	0.606***	0.247***	0.072*	0.524***
Bin10_5			0.084	0.05	0.519***	0.227***	0.071	0.533***
Bin10_6			0.130*	0.023	0.540***	0.157**	0.029	0.603***
Bin10_7			0.170**	-0.004	0.534***	-0.067	-0.053	0.493***
Bin10_8			0.131*	0.055	0.640***	0.161*	-0.004	0.511***
Bin10_9			0.172**	-0.057	0.523***	0.351***	0.05	0.420***
Bin10_10			0.075	-0.054	0.508***	0.356***	0.047	0.439***
Family Size	0.157***	0.064***	0.150***	0.072***	0.022*	0.167***	0.077***	0.022*
Family Income (log)	1.381***	0.574***	1.413***	0.549***	-0.180***	1.443***	0.562***	-0.199***
Gender	0.037	-0.089*	0.108	-0.078	-0.149***	0.136	-0.062	-0.144**
Education	0.692***	0.228***	0.684***	0.195***	-0.106***	0.762***	0.229***	-0.119***
Married	-0.093	0	-0.085	-0.006	-0.04	-0.132	-0.038	-0.034
gammaHPI								
gamFHFAyearpurchase								
Constant	-12.712***	-5.271***	-13.149***	-5.066***	1.968***	-13.348***	-5.183***	2.168***
Observations	9,656	9,656	7,659	7,659	7,659	7,081	7,081	7,081
R-squared	0.43	0.395	0.425	0.388	0.304	0.416	0.387	0.315
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-10: First-stage Regressions for the Risk-free Asset Holdings and Misestimation Regressions (Part 1). First-stage regressions that correspond to specifications (3)-(5) in Table 8.

Specific. on Table 8:	(3) HV	(3) MTG	(4) HV	(4) MTG	(4) $m_{i,t}$	(5) HV	(5) MTG	(5) $m_{i,t}$
gammaHPI	0.005***	-0.002***	0.005***	-0.001***	-0.004***	0.005***	-0.001***	-0.004***
gamFHFAyearpurchase	-0.000	0.005***	-0.001	0.004***	0.003***	-0.001	0.004***	0.003***
Bin10_1			0.022	-0.05	0.326***	0.084	-0.061	0.443***
Bin10_2			0.113	0.120**	0.436***	0.083	0.02	0.578***
Bin10_3			0.180**	0.06	0.455***	0.263***	0.025	0.454***
Bin10_4			0.149*	-0.007	0.426***	0.198**	0.013	0.428***
Bin10_5			0.071	-0.012	0.439***	0.088	0.018	0.442***
Bin10_6			0.394***	0.015	0.395***	0.300***	0.007	0.546***
Bin10_7			0.265***	-0.025	0.464***	0.074	-0.083*	0.495***
Bin10_8			0.272***	0.039	0.509***	0.267***	0.085*	0.492***
Bin10_9			0.196***	-0.055	0.491***	0.374***	0.018	0.436***
Bin10_10			0.095	-0.081	0.465***	0.212**	-0.110*	0.454***
Family Size	0.089***	0.056***	0.079***	0.062***	0.021*	0.095***	0.075***	0.02
Family Income (log)	1.363***	0.557***	1.427***	0.532***	-0.146***	1.463***	0.559***	-0.150***
Gender	0.116	0.087	0.063	0.038	-0.077	0.194*	0.096	-0.054
Education	0.531***	0.225***	0.531***	0.219***	-0.026	0.579***	0.238***	-0.036
Married	-0.179**	0.013	-0.108	0.092	0.037	-0.239**	-0.002	0.049
Constant	-13.961***	-5.828***	-14.633***	-5.592***	1.750***	-15.100***	-5.953***	1.760***
Observations	7,876	7,876	6,307	6,307	6,307	5,929	5,929	5,929
R-squared	0.414	0.368	0.42	0.364	0.301	0.411	0.362	0.307
IV	Saiz	Saiz	Saiz	Saiz	Transactions	Saiz	Saiz	Searches
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Table A-11: First-stage Regressions for the Risk-free Asset Holdings and Misestimation Regressions (Part 2). First-stage regressions that correspond to specifications (6)–(8) in Table 8.

Online Appendix

OA-I Data Description

The Panel Study of Income Dynamics (PSID) is a longitudinal household-level survey that began in 1968, tracking households and their offspring over time. With over five decades of data collection, the PSID has recorded insights from more than 84,000 individuals, offering an invaluable resource for understanding household dynamics and economic trends across generations. Our study leverages the PSID to analyze the misestimation of household values, focusing on periods when households move. At the time of relocation, the market value of the property is known, providing a reliable baseline for subsequent analyses of value misestimation. Using the Federal Housing Finance Agencys (FHFA) House Price Index (HPI) at the five-digit Zip code level, the data set includes 20,769 observations of household moves and nearly 40,125 related observations of misestimation.

We took several key steps to create the database. First, individual-level data were processed by executing the IND2021ER .do file, which resulted in a data set containing 84,121 records and 2,605 variables. This file was saved in .dta format for further analysis. Family-level data, spanning 1968 to 2021, were processed next. This data set includes one record for every family interviewed since 1968, even if they participated in only a single wave of the survey. For each year, .do files were executed and the outputs saved as .dta files. Since all files were initially stored in a shared folder, scripts were adapted to facilitate their transfer and organization into a more manageable structure.

Geocode data covering census tracts, states, Zip codes, core-based statistical areas (CBSAs), and metropolitan statistical areas (MSAs) from 1968 to 2021 were also processed. This data set comprises 306,189 observations, and scripts were modified to unify these files into a cohesive format suitable for longitudinal analysis. Additionally, wealth data collected during selected years1984, 1989, 1994, 1999, 2001, 2003, 2005, and 2007were incorporated. The wealth files were processed by modifying file paths in the original scripts, resulting in a consolidated data set focused on wealth-related variables that are crucial for understanding economic trajectories.

Raw data from various external sources were integrated to enhance the dat aset. This included FHFA HPI data at the five-digit Zip code level, annual house price indexes adjusted to a 1990 benchmark, and Google Trends data, which were merged with DMA codes and Zip codes. Once compiled, the raw data underwent a rigorous process of standardization, cleaning, and merging. Variable names and formats were standardized across all years, and identifiers were added where necessary. Observations with excluded valuessuch as house prices labeled 9999998 or 9999999—were removed to ensure data accuracy. The data were reshaped from a wide format, where variables for different years are stored across columns, to a long format, where each observation represents a unique household-year combination. This process resulted in a comprehensive data set with 1,411,432 observations and 95 variables.

To create a unified data set, heads of households were extracted from the individual-level data and saved in temporary files. Zip code variables were integrated from the geocode files by matching FamilyID and year. These were merged with family- and individual-level data sets, producing a consolidated data set with 32,824 unique head-of-household observations across all years and 1,661 variables. The wealth data sets were similarly integrated. Variables from the selected years were cleaned, renamed, and merged with the family-level data in a one-to-one relationship, enabling robust longitudinal analyses that consolidate wealth variables with family identifiers.

The 05 Merge process involved multiple steps to integrate and enrich the data set with key variables. First, the HPI Zip code data from FHFA were prepared by creating a two-year growth variable for HPI growth, calculated using the following formula:

$$\text{Two-Year HPI Growth (\%)} = \left[\left(1 + \frac{\text{Previous Year HPI}}{100}\right) \cdot \left(1 + \frac{\text{Current Year HPI}}{100}\right) - 1\right] \cdot 100$$

This same formula was applied to create a two-year growth variable for state-level HPI. Subsequently, Zip-code-level HPI data were merged in a many-to-one relationship, resulting in 1,411,432 observations and 90 variables, while state-level HPI data brought the data set to 95 variables. Additional integrations included elasticity data (Saiz) by Zip code (106 variables), FHFA index data by year (107 variables), and CBSA crosswalk and gamma data (Guren) by Zip code and CBSA (111 variables). CoreLogic ZIP code liquidity data were merged by year and Zip code, expanding the data set to 112 variables, while Google Trends data added further detail, culminating in 116 variables. The process also computed elasticity using the state HPI index (Saiz) and created a variable for elasticity and year of purchase, assigning elasticity values to movers, thereby enriching the data set for comprehensive longitudinal analysis.

To refine the data set and prepare it for analysis, we first removed observations from 1968, dropping 32,824 entries, then removed records with missing Zip codes, eliminating an additional 161,926 observations. Key control variables were then created or renamed for regression purposes, including family income (log-transformed), gender (coded as 1 for male), education (coded as 1 for college-educated individuals), marital status (coded as 1 for married individuals), and employment (coded as 1 for individuals employed full- or part-time). Variables for tracking household movement and the year of purchase were introduced, along with a calculation for the gamma HPI (Guren) using the FHFA-5 index, with adjustments made for movers and carried forward within families.

To estimate the market value of houses over time, we implemented a stepwise procedure to address missing values and account for annual appreciation rates. The variable HI, representing home improvements, was initialized to zero for observations with missing values:

$$\text{HI} = 0, \quad \text{if HI is missing.}$$

Next, we calculated the adjusted house value, HV_M_HI, which incorporates both the baseline house value (HV) and any home improvements (HI). For households that moved (move = 1), the value of HV_M_HI was set equal to HV:

$$\text{HV\_M\_HI} = \text{HV}, \quad \text{if move} = 1.$$

For households that did not move (move = 0), we estimated HV_M_HI iteratively using prior-year data. The value was updated by applying annual appreciation rates from the housing price index (HPI), specifically HPI_FHFA5 for years before 1999 and HPI_FHFA5_2years for years after 1997. The updates were computed as follows:

1. For years before 1999:

$$\text{HV\_M\_HI}_t = \text{HV\_M\_HI}_{t-1} \times \left(1 + \frac{\text{HPI\_FHFA5}}{100}\right) + \text{HI}, \quad \text{if HV\_M\_HI is missing.}$$

2. For years after 1997:

$$\text{HV\_M\_HI}_t = \text{HV\_M\_HI}_{t-1} \times \left(1 + \frac{\text{HPI\_FHFA5\_2years}}{100}\right) + \text{HI}, \quad \text{if HV\_M\_HI is missing.}$$

These steps ensure that the adjusted house value reflects both home improvements and cumulative appreciation while accommodating differences in appreciation rates over time. The iterative approach accounts for the temporal dependency of house values, ensuring consistency in the panel data set.

Financial variables were also meticulously prepared. Stock value was calculated as the sum of publicly traded stockholdings, mutual funds, or investment trusts. Checking and savings accounts combined balances across checking, savings, and money market accounts. Other assets encompassed life insurance cash values, valuable collections, or rights in trusts or estates. Cash assets included certificates of deposit, government bonds, and treasury bills, while debt was defined as the sum of all credit card, student loan, medical bill, legal bill, and family loan liabilities. Liquid wealth was defined as the total of stock value, checking and savings accounts, other assets, and cash, minus debt (excluding IRAs). Risk-free assets were defined as the sum of checking and savings accounts, other assets, and cash. Total wealth aggregated the values of various asset types, including farm or business ownership, real estate (other than the main home), vehicles, and private annuities, net of debt and inclusive of home equity.

Additional variables were created to measure misestimation as the difference between subjective house value and market house value (inclusive of home improvements). Consumption variables were calculated as the sum of expenditures on food at home, food delivery, and dining out. Indicators for stock participation (coded as 1 for stockholders) and stock value for stockholders were introduced. The data set was further enriched with lags, changes, and logarithmic transformations of key variables such as misestimation, subjective house value, market house value, mortgage, and food consumption.

To prepare the IVs, we defined the panel structure by specifying the unique family identifier (`family_id`) and the temporal variable (`year`).

This step ensures that subsequent calculations respect the panel structure of the data, treating observations as part of a time series within families.

Next, we constructed an IV to address potential endogeneity in the model. The variable `IV` is derived from `trans_10_bins`, which represents decile bins for a specific variable, and the sign of the lagged misestimation variable (`misper_100k`). The calculation was conducted separately for years before and after 1998:

$$\mathrm{IV}_t = \begin{cases} \text{trans\_10\_bins} \times \text{sign}(l1.\text{misper\_100k}), & \text{if year} < 1998, \\ \text{trans\_10\_bins} \times \text{sign}(l2.\text{misper\_100k}), & \text{if year} \geq 1998. \end{cases} \tag{OA-1}$$

Additionally, we generated dummy variables representing each decile bin (`Bin10_1` through `Bin10_10`). These were interacted with the lagged sign of `misper_100k` to create expressions as follows:

$$\text{Bin10}_i = \begin{cases} \text{trans\_10\_bins}_i \times \text{sign}(l1.\text{misper\_100k}), & \text{if year} < 1998, \\ \text{trans\_10\_bins}_i \times \text{sign}(l2.\text{misper\_100k}), & \text{if year} \geq 1998, \end{cases} \tag{OA-2}$$

for $i = 1, \ldots, 10$.

To assess the relationship between observed trends and the misestimation variable, we incorporated Google Trends data. Using decile bins for Google Trends (`google_trends_bins`), we generated interaction terms between these bins and the second lag of `misper_100k`:

$$\text{google\_bins}_i = \text{google\_trends\_bins}_i \times \text{sign}(l2.\text{misper\_100k}), \tag{OA-3}$$

for $i = 1, \ldots, 10$.

These transformations facilitated the exploration of nuanced interactions between misestimations, decile bins, and external trends in a structured panel data framework.

The process refined the data set by addressing missing or extreme values and developing models to explore the determinants and effects of house value misestimation. The initial step involved removing all observations with missing misestimation values, resulting in a data set of 60,194 observations (4.4 percent of the original data set). Additionally, observations with negative stock values (13 entries) were dropped. To address outliers, key variables such as misestimation, house value, and mortgage were winsorized at the 1st and 99th percentiles within each year. Descriptive statistics for these variables are summarized in the accompanying table.

OA-II Google Trends

Google Trends is a public-web that analyzes the popularity of a query across regions and over time. It has historical search data back to 2004. It provides a normalized index of search volume data so one can explore trends. The data are presented on a scale of zero to 100, representing the relative search interest of a given query compared with the highest point over the selected region and time frame. Using Google Trends, we compare multiple (up to five) queries to understand consumer behavior over time and across regions.

We created a dictionary of possible queries that individuals could have searched in Google. For this, we ask ChatGPT, "What 25 words are the most searched in Google and other search engines when people are trying to buy or sell a house?" The following list comprises the answers that ChatGPT provided: "Real estate near me," "Real estate for sale," "New homes," "Real estate listings," "Apartments for rent," "Houses for rent," "Houses for sale near me," "Houses for sale," "Land for sale near me," "Land for sale," "For sale by owner," "Realtor near me," "Vacation rentals," "Condos for sale," "New construction homes near me," "Selling a house," "Cost of selling a house," "How to sell my house," "Taxes on selling a house," "Capital gains on selling a house," "How much does it cost to sell a house," "Realtor," "Real estate agent," "Real estate agent near me," and "Top real estate agents." Additionally, to complete the dictionary, we asked ChatGPT, 'Top 25 searches in Google when a person is trying to sell or buy a house in the USA since 2004." The results comprised two lists, one for buying and another for selling, which we added to the dictionary: "Homes for sale,""Mortgage calculator," "Home buying tips," "First-time homebuyer programs," "Best neighborhoods to buy a house," "Home affordability calculator," "Mortgage rates," "Home inspection checklist," "Home buying process," "Down payment assistance programs," "Homebuyer grants," "Closing costs for buyers," "Types of mortgages," "Home appraisal process," "Home warranty," "Property taxes by Zip code," "Home insurance quotes," "Buying a house with bad credit," "Buying a foreclosure," "Home inspection tips," "Homebuyer seminars," "Buying a house checklist," "Real estate market trends," "house value estimator," "Home staging tips," "Selling a house by owner (FSBO)," "Home selling process," "Best time to sell a house," "Selling a house with a real estate agent," "Home selling tips," "Pricing my house to sell," "Closing costs for sellers," "Disclosure requirements when selling a house," and "Selling a house with tenants." Moreover, we added "Zillow" because of its significance over time. In the end, our dictionary consisted of 54 different queries.

As Google Trends only allows the user to compare five queries, we selected the "Houses for sale" search as a reference query. We split the dictionary into 14 lists of four queries per list.

For each list, we added up the reference query. We computed the values of the group in the United States from 2005 to 2021, but only even years. We calculated the yearly average for each query because the data obtained are on a monthly basis. We then calculated the interest by designated market area (DMA) per year per query. There are 210 DMAs in the United States.

The interest per region result was normalized by scaling it based on yearly values in the yearly database. We added each list to a new data frame. We replace infinity and NaN values with zeros to prevent errors during further analysis. We finished with 1,890 observations.

We cleaned the database by removing columns in which all values are zero, leaving us with 30 queries. This indicates that, from the dictionary proposed, 24 searches were not very popular when compared with the rest. We then calculated the mean per row, that is, the mean per year and region.

Finally, to create the IV, we grouped the data by year and calculated the quantiles (10) for the mean column within each year. We assigned each row to a bin based on its mean value relative to the quantiles.

From the remaining queries, we grouped each DMA region by year and then divided it in deciles and assigned a number to each decile per year. We added a bins column to the data frame, indicating the bin assignment for each year and region.