Homeownership as Rental Risk Insurance

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Abstract

Why do households choose to own rather than rent, even when ownership requires large upfront costs and long-term commitments? This paper proposes that homeownership serves as insurance against rental-price risk. Using panel data we document that rental risk rises with age. To quantify the implications of this risk, we develop a life-cycle model in which heterogeneous households choose between renting and owning under income, rent, and house price shocks, subject to borrowing constraints, moving costs, and bequest motives. Because of rental risk, homeownership rate falls by 0.7 percentage points-indicating that the desire to self-insure against uninsurable rent shocks accounts for a significant share of observed ownership. The mechanism operates primarily through the extensive margin: higher rental volatility encourages transitions into ownership, especially for middle-aged households near the down payment threshold. These findings highlight a previously underappreciated motive for homeownership and suggest that volatility in rental markets can have first-order effects on tenure decisions and welfare.

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1 Introduction

Housing tenure decisions are inherently tied to risk. For homeowners, the key risk lies in home equity volatility driven by local housing market fluctuations. A fall in house prices can significantly erode wealth-especially for those whose portfolios are heavily concentrated in real estate. Liquidity constraints and high transaction costs can exacerbate the impact of such shocks. This perspective has been widely studied in models of portfolio choice and housing investment (Cocco, 2005; Davis and Van Nieuwerburgh, 2014; Rust, 1987).

Why do households choose to own rather than rent, despite the substantial upfront costs and long-term commitments that ownership entails? Traditional explanations emphasize housing investment, tax incentives, or mobility frictions. In this paper, we propose a new answer: *homeownership provides insurance against rental-price risk*.

Renters face distinctive and persistent uncertainties-rising rents due to inflation, limited control over lease renewals, and housing instability. In contrast, the vast majority of U.S. mortgages (92%) are fixed-rate contracts, allowing households to lock in monthly payments for decades. Once the mortgage is repaid, housing services become virtually costless. These differences imply that renting exposes households to long-term consumption volatility, while owning offers a hedge against housing cost risk. We argue that this rental risk creates a powerful, yet underappreciated, motive for homeownership.

Research Question. To what extent does rental risk shape housing tenure decisions in the United States? Specifically, how much of observed homeownership can be attributed to its role as a hedge against rental-price uncertainty?

We approach this question in three steps. First, we document new empirical facts about rental risk over the life cycle using twenty years of PSID panel data (2001-2021). We estimate residual variance in rent and house prices by age, controlling for observables via hedonic regressions. The evidence reveals that rental risk increases with age, particularly after age 60 (Figure 1). This growing exposure-uninsured for renters but avoidable for owners-motivates our central mechanism.

Second, we build a life-cycle model in which heterogeneous agents choose between renting and owning, facing income shocks, stochastic rent and house price processes, borrowing constraints, moving costs, and a bequest motive. The model is estimated using the Method of Simulated Moments (MSM) to match life-cycle patterns of tenure, assets, and housing wealth. It replicates the observed age profiles of homeownership (Figure 4), and captures cross-sectional heterogeneity in exposure to housing risk (Tables 3–4–6).

Third, we perform a counterfactual experiment that eliminates rental-price risk. We find that homeownership rates fall by **0.5 percentage points**, implying 0.5% increase in welfare, implying that a meaningful share of U.S. homeownership is driven by the desire to self-insure against rental volatility. This magnitude is comparable to the effects of mortgage interest deductions and relaxed credit constraints found in previous work (Sinai and Souleles, 2005; Favilukis et al., 2017; Banks et al., 2015). The effect operates chiefly through the extensive margin: households near the down-payment threshold are more likely to purchase in order to reduce future risk exposure.

Related Literature. This paper contributes to several strands of literature. First, we build on life-cycle models of housing tenure and portfolio choice under uncertainty (Cocco, 2005; Halket and Vasudev, 2014; Ejarque, 2014). Second, we complement work on the non-financial benefits of homeownership-such as social stability, commitment, and political engagement (Glaeser and Shapiro, 2002; Sinai and Souleles, 2013; Painter, 2000). Third, we contribute to research on consumption risk-sharing and household behavior under incomplete markets and frictions in asset ownership (Blundell et al., 2008; Rampini and Viswanathan, 2016; Chang, 2019). To our knowledge, this is among the first papers to formally quantify the role of rental price risk in driving tenure decisions over the life cycle using a structural model matched to long-run panel data.

2 Data

Our empirical analysis draws on the Panel Study of Income Dynamics (PSID), a nationally representative panel survey of U.S. families since 1968. We focus on the 2001-2021 period, during which the PSID consistently reports household-level outcomes for income, assets, demographics and especially housing. We restrict to household heads aged 27-80 and separate renters and homeowners. The panel structure allows us to trace the evolution of idiosyncratic housing price shocks over the life cycle and to link those empirical moments directly to our structural model.

To isolate the unobserved component of housing payments, we estimate hedonic regressions of log unit real rent [1] and log unit house price on a rich set of observables. For renters, we define the *unit rental price* as the total annual rent divided by the number of rooms, and estimate

$$\ln(\text{unit rent}_{i,t}) = \alpha_0 + \sum_k \alpha_k X^{(k)}_{i,t} + \gamma_t + u^{(q)}_{i,t},$$

where $\{X^{(k)}_{i,t}\}$ includes log household income, net wealth[2], age, education, race, presence of children, a mover indicator, and housing-type dummies, and γ_t are year fixed effects. An analogous specification is estimated for owner-occupied unit prices. The regression residuals, $u^{(q)}_{i,t}$ and $u^{(p)}_{i,t}$, capture the idiosyncratic rental and price shocks that are not explained by observed household or housing characteristics.

2.1 Life-Cycle Patterns of Rental and Price Risk

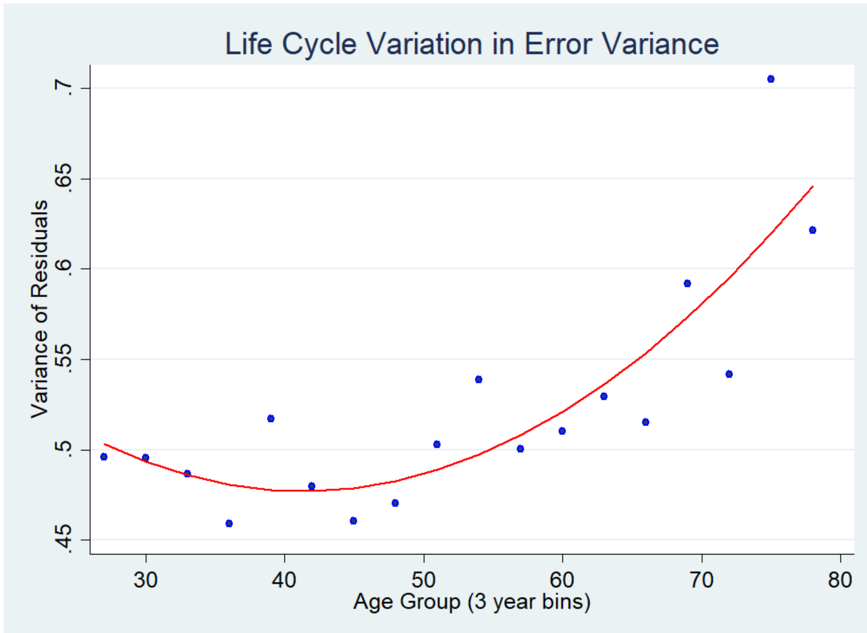
We summarize housing risk at each age by the variance of the corresponding residual,

$$\sigma^2_q(a) \;=\; Var\big(u^{(q)}_{i,t} \mid \text{age} = a\big), \quad \sigma^2_p(a) \;=\; Var\big(u^{(p)}_{i,t} \mid \text{age} = a\big).$$

Households are binned into three-year age groups, and within each bin we compute the sample variance of the regression residuals. Figure 1 plots the resulting profile of rental risk, revealing a steady rise in $\sigma^2_q(a)$ over the life cycle, with particularly large increases after age sixty. Figure 2 reports the parallel exercise for house-price risk, which also increases with age but at a markedly flatter rate.

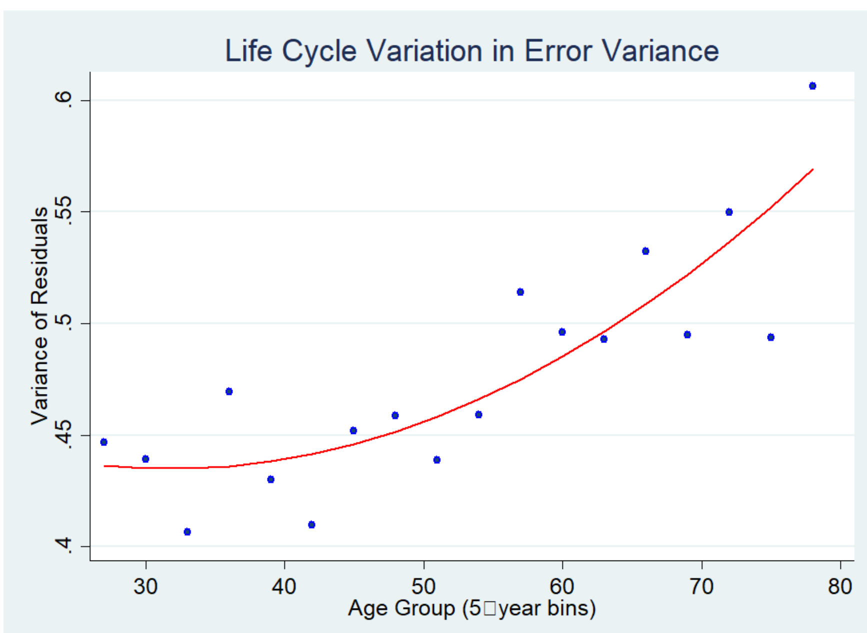
[1] All nominal amounts are converted into 2010 dollars
[2] an inverse-hyperbolic-sine transformation

Figure 1: Residual Variance of Unit Rent by Age Group (PSID).



Residuals of pooled regressions with individual and year fixed effects, clustering at the person level. We save the squared residuals from each regression, collapse them into three-year age bins.

Figure 2: Residual Variance of Unit House Price by Age Group (PSID).

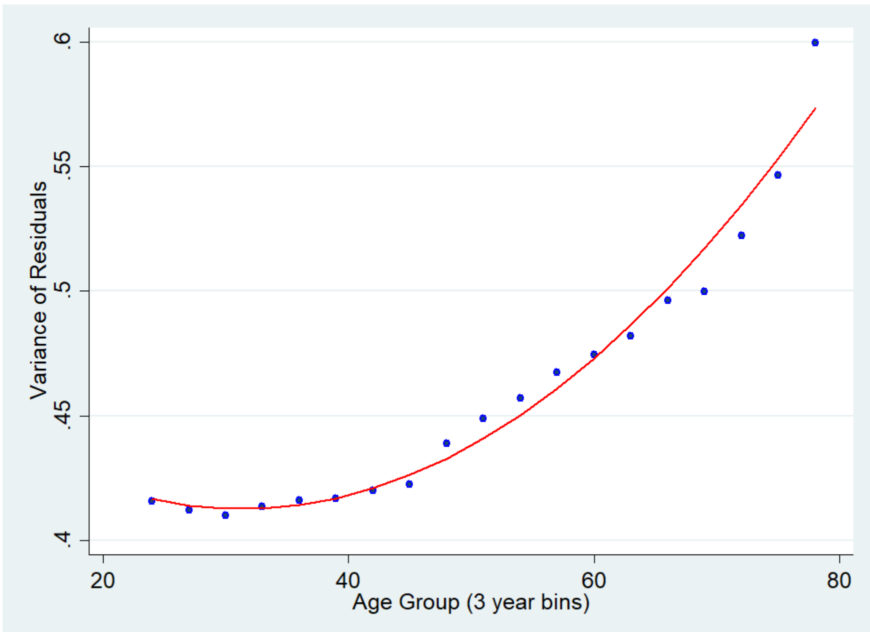


These life-cycle patterns underscore that housing cost uncertainty is nontrivial at all ages and rises as households grow older, motivating our models incorporation of age-dependent risk parameters.

2.2 Geographic and Mobility Robustness

Since the PSID does not report granular location, we replicate the rental-risk exercise in the American Community Survey (ACS), which includes metropolitan-area identifiers. Using ACS cross-sections from 2001-2021, we deflate all nominal values into 2010 dollars by merging in the CPI series and then estimate the same hedonic specification with fixed effects for metropolitan statistical areas. The resulting age profile of rental risk (Figure 3) closely matches the PSID pattern, confirming that the observed increase in rental uncertainty is not driven by unobserved geographic heterogeneity.

Figure 3: Residual Variance of Unit Rent by Age Group (ACS, with MSA Controls).



We further split the PSID sample into movers and stayers. Persistently high residual variance among non-movers indicates that rental risk stems from stochastic price changes rather than relocation risk alone.

Taken together, these results demonstrate that both rental and ownership costs carry non-trivial risks and is robust across data sources and subsamples.

3 Quantitative Model

In this section, we develop a partial-equilibrium life-cycle framework in which heterogeneous households choose between renting and owning in the presence of stochastic income, rental, and house-price processes. Households also face borrowing constraints, moving costs, and hold bequest motives. By introducing idiosyncratic rental-price risk that increases with age, the model captures how owning can serve as insurance against unpredictable rent shocks. We solve the households dynamic programming problem , estimate exogenous shock processes to PSID data by GMM, and estimate the remaining structural parameters by maximum likelihood on tenure-choice transition probabilities. The full computational algorithm is described in appendix A.

3.1 Environment

Households live for $T = 18$ discrete periods [3]. In each period $t = 1, \ldots, T$, a household must decide (i) whether to rent or own next period, $o_{t+1} \in \{0, 1\}$, (ii) how many units of housing services to consume, $h_{t+1} \in \mathcal{H}$[4], (iii) how much to hold in financial assets, $a_{t+1} \in \mathcal{A}$, and (iv) how much to consume c_t.

At the start of period t, before making those choices, the household observes its state

$$\underbrace{(s_t = (s_{y,t},\, s_{q,t},\, s_{p,t})),}_{\text{exogenous shocks}} \quad \underbrace{a_t}_{\substack{\text{financial assets} \\ \text{(can be negative)}}} \quad , \quad \underbrace{h_t}_{\substack{\text{housing services} \\ \text{(room units)}}} \quad , \quad \underbrace{o_t \in \{0,1\}}_{\text{tenure status}}.$$

where $s_t = (s_{y,t},\, s_{q,t},\, s_{p,t})$ are three exogenous Markov states corresponding to log-income, log-unit-rent, and log-unit-house-price, respectively; a_t is financial asset holdings (which may be positive or negative, subject to constraints); h_t is the current stock of housing services; and o_t is the current tenure indicator (0 if renting, 1 if owning). When choosing $(o_{t+1},\, h_{t+1},\, a_{t+1})$, the household must satisfy the budget constraint corresponding to its tenure transition (renting vs. owning) and the downpayment requirement $\phi \in [0, 1]$ if $o_{t+1} = 1$. If housing size is adjusted ($h_{t+1} \neq h_t$), the household incurs a moving cost fraction $\zeta \in [0, 1]$ of the current rental or sale value. Financial assets earn net interest $r > 0$. Owners also receive net-sale proceeds of any existing housing stock $p_t\, h_t(1 - \delta)$, where $\delta \in [0, 1]$ is the housing depreciation rate.

[3]corresponding to ages 27 through 81 in three-year increments
[4]with room as unit of housing

To simplify notation we write

$$y_t = y(s_{y,t}), \quad q_t = q(s_{q,t}), \quad p_t = p(s_{p,t}),$$

3.2 Preferences

In period t, a household with state $(y_t, q_t, p_t, c_t, h_{t+1}, o_{t+1})$ derives flow utility from non-durable consumption c and housing flow h according to a CES aggregator with ownershipspecific taste shifters:

$$u(c,h,o) = \frac{\left[\alpha\, c^{\nu} + \psi_o\,(1-\alpha)\, h^{\nu}\right]^{\frac{1-\gamma}{\nu}}}{1-\gamma}.$$

Here, $\alpha \in (0,1)$ governs the share of non-durable consumption in the CES composite, while $\nu > 0$ controls the intratemporal elasticity of substitution between consumption and housing services-approaching a Cobb-Douglas form as $\nu \to 0$. The parameter $\gamma > 0$ is the coefficient of relative risk aversion. Finally, ψ_o captures the ownership-specific taste for housing services, with $\psi_1 = 1$ and $\psi_0 \in [0,1]$ lower for renters.

At the end of period T (age 81), households die and receive warm-glow bequest utility from net worth (financial assets or housing equity if an owner). Formally, the terminal value function is

$$V_{T+1}(s,a,h,o) = \theta_B \frac{\left[a + o\, p(s_p)\, h\right]^{1-\gamma}}{1-\gamma}$$

where $\theta_B > 0$ scales the bequest motive. If $o = 0$, the terminal bequest is purely financial a; if $o = 1$, it's housing equity.

3.3 Budget Constraints and Tenure Transitions

After observing (s_t, a_t, h_t, o_t) at the start of period t, the household chooses $(o_{t+1}, h_{t+1}, a_{t+1})$. Current consumption c_t is pinned down by one of four mutually exclusive (o_t, o_{t+1}) cases:

1. Renter → Renter ($o_t = 0 \to o_{t+1} = 0$).

$$c_t + q_t\, h_{t+1} + \underbrace{\zeta\,[q_t\, h_t]}_{\substack{\text{moving cost if} \\ h_{t+1} \neq h_t}} + a_{t+1} = y_t + (1+r)\, a_t,$$

subject to borrowing constraint $a_{t+1} \geq 0$.

2. Owner → Owner ($o_t = 1 \to o_{t+1} = 1$).

$$c_t \; + \; p_t \, h_{t+1} \; + \; \underbrace{\zeta \left[p_t \, h_t \right]}_{\substack{\text{moving cost if} \\ h_{t+1} \neq h_t}} \; + a_{t+1} \; = \; y_t \; + \; (1 + r) \, a_t \; + \; p_t \, h_t \, (1 - \delta),$$

with down payment constraint

$$a_{t+1} \; \geq \; -\, (1 - \phi) \, p_t \, h_{t+1}$$

3. Renter → Owner ($o_t = 0 \to o_{t+1} = 1$).

$$c_t \; + \; p_t \, h_{t+1} \; + \; \underbrace{\zeta \left[q_t \, h_t \right]}_{\substack{\text{moving cost if} \\ h_{t+1} \neq h_t}} \; + a_{t+1} \; = \; y_t \; + \; (1 + r) \, a_t,$$

with down payment constraint

$$a_{t+1} \; \geq \; -\, (1 - \phi) \, p_t \, h_{t+1}$$

4. Owner → Renter ($o_t = 1 \to o_{t+1} = 0$).

$$c_t \; + \; q_t \, h_{t+1} \; + \; \underbrace{\zeta \left[p_t \, h_t \right]}_{\substack{\text{moving cost if} \\ h_{t+1} \neq h_t}} \; + a_{t+1} \; = \; y_t \; + \; (1 + r) \, a_t \; + \; p_t \, h_t \, (1 - \delta),$$

subject to $a_{t+1} \geq 0$.

3.4 Recursive Formulation

To simplify notation, denote by

$$W_t\big(s_t, a_t, h_t, o_t; \, o_{t+1}\big)$$

the auxiliary value function corresponding to the choice $o_{t+1} \in \{0, 1\}$. Specifically,

$$W_t\big(s_t, a_t, h_t, o_t; \, o_{t+1}\big) \; = \; \max_{h_{t+1} \in \mathcal{H}, \, a_{t+1} \in \mathcal{A}} \Big\{ u\big(c_t, \, h_{t+1}, \, o_{t+1}\big) \; + \; \beta \, \mathbb{E}_t \big[V_{t+1}(s_{t+1}, \, a_{t+1}, \, h_{t+1}, \, o_{t+1}) \big] \Big\},$$

subject to the appropriate budget and collateral constraints for the tenure transition ($o_t \to o_{t+1}$).

Given these auxiliary value functions, the households period$t$ Bellman equation is simply

$$V_t\big(s_t, a_t, h_t, o_t\big) \;=\; \max_{o_{t+1}\in\{0,1\}} \; W_t\big(s_t, a_t, h_t, o_t;\, o_{t+1}\big).$$

At $t = T+1$, the terminal condition is

$$V_{T+1}(s, a, h, o) \;=\; \theta_B \,\frac{\big[a \;+\; o\,p\,h\big]^{1-\gamma}}{1-\gamma},$$

and no further choice of $o_{t+1}, h_{t+1}, a_{t+1}$ is made. This completes the recursive formulation.

3.5 Taking Taste Shock

Once the auxiliary values $W_t(\cdot,\, o_{t+1} = 0)$ and $W_t(\cdot,\, o_{t+1} = 1)$ are computed, we introduce an additive taste shock [5] $\varepsilon_{t+1}(o')$ to each tenure choice $o' \in \{0, 1\}$. Concretely, at state (s_t, a_t, h_t, o_t), the households decision problem becomes

$$\max_{o_{t+1}\in\{0,1\}} \Big\{ W_t(s_t, a_t, h_t, o_t;\, o_{t+1}) \;+\; \varepsilon_{t+1}(o_{t+1}) \Big\},$$

where each $\varepsilon_{t+1}(o')$ is i.i.d. Taking expectations over the εs yields the value function:

$$V_t(s_t, a_t, h_t, o_t) \;=\; \underbrace{\mathbb{E}\Big[\max_{o'\in\{0,1\}} \big\{ W_t(\ldots; o') + \varepsilon(o') \big\}\Big]}_{\text{expected maximum}} \;=\; \xi\,\Big[\,\gamma_{\text{const}} \;+\; \ln\!\big(e^{W_t(\ldots,0)/\xi} \;+\; e^{W_t(\ldots,1)/\xi}\big)\Big],$$

where $\gamma_{\text{const}} \approx 0.5772$ is the Euler-Mascheroni constant. Equivalently, one may write

$$V_t(s_t, a_t, h_t, o_t) \;=\; \xi\,\ln\!\big(e^{W_t(s_t,a_t,h_t,o_t;0)/\xi} \;+\; e^{W_t(s_t,a_t,h_t,o_t;1)/\xi}\big) \;+\; \xi\,\gamma_{\text{const}}.$$

From this expression, the conditional probability of choosing ownership next period ($o_{t+1} = 1$) is

$$\Pr\big(o_{t+1} = 1 \mid s_t, a_t, h_t, o_t\big) \;=\; \frac{\exp\big(W_t(s_t, a_t, h_t, o_t;\, 1)/\xi\big)}{\exp\big(W_t(s_t, a_t, h_t, o_t;\, 0)/\xi\big) \;+\; \exp\big(W_t(s_t, a_t, h_t, o_t;\, 1)/\xi\big)}.$$

Similarly, $\Pr(o_{t+1} = 0)$ is the complement.

[5] Type-I extreme-value with scale parameter $\xi > 0$

4 Estimation and Calibration

We adopt a two-step approach to identify the parameters of the model. In the first step, we externally calibrate the stochastic processes governing income, rent, and house prices to replicate the empirical age profiles of second moments observed in the PSID. In the second step, we estimate the remaining structural parameters-governing preferences, housing utility, borrowing constraints, and mobility costs-using maximum likelihood based on observed tenure transitions. Technical details of both the GMM procedure and the likelihood implementation are provided in Appendix A and B.

4.1 Calibration of Stochastic Processes

We begin by targeting the age-specific residual variances of three key variables: permanent income (y_t), unit rental prices (q_t), and unit house prices (p_t). These residuals are obtained from hedonic regressions in the PSID after controlling for observable characteristics (see Section B). We discretize each process using a Rouwenhorst method and estimate process parameters by GMM to match the empirical variance profiles $\{\widehat{\sigma}^2_{y,t}, \widehat{\sigma}^2_{q,t}, \widehat{\sigma}^2_{p,t}\}_{t=1}^{18}$.

For income, we adopt a persistent-transitory structure in line with Blundell et al. (2008), **?**, and Michaud and St. Amour (2023). The best fit is achieved with an extremely persistent AR(1) component ($\rho_y \approx 0.999$) and a moderate transitory shock. This mirrors findings in consumption-smoothing studies that attribute much of life-cycle income risk to low-frequency shocks.

For both rental and house prices, we estimate AR(1) processes with innovations representing idiosyncratic location-specific variation. The resulting persistence values are modest ($\rho_q \approx 0.26$, $\rho_P \approx 0.26$), consistent with transitory fluctuations around a city-level price trend. These patterns echo the empirical dynamics studied in Sinai and Souleles (2005) and Davis and Van Nieuwerburgh (2014), who find that rents and prices can fluctuate significantly at the micro level, even in stable aggregate environments.

Table 1 reports the calibrated parameters. Figure 13 confirms that the model reproduces the empirical variance profiles well.

4.2 Estimation of Structural Parameters

With the stochastic processes fixed, we estimate the remaining structural parameters governing preferences, constraints, and costs using a maximum likelihood approach. The

Table 1: Externally Calibrated Parameters

Variable	Value	Description
T	18	Nr of periods
r	0.061	Risk-free rate
Housing		
ϕ	0.20	Loan-to-value ratio
δ	0.12	Housing depreciation rate
ζ	0.08	Moving cost
ψ_1	1.00	Ownership utility weight
α	0.80	Consumption weight
Prices		
		Income
ρ_y	0.999	Persistence corr
σ_y^p	0.601	St dev of persistent
σ_y^t	0.259	St dev of transitory
		Rental Price
ρ_q	0.261	Correlation
σ_q	0.705	St dev
μ_q	-2.442	Initial log rental-price
		House Price
ρ_P	0.258	Correlation
σ_P	0.665	St dev
μ_P	0.014	Initial log house-price

likelihood function is constructed from observed tenure transitions in the PSID panel from 2001-2021, spanning individuals aged 27-80. We include household-specific state variables-financial assets, income, housing stock, and tenure-and compute the conditional choice probabilities implied by the model using a logit structure derived from value function differences under a small taste shock.

Table 2 presents the estimated parameters. The estimated discount factor $\beta \approx 0.83$ implies an effective annual subjective discount rate of approximately 3%, aligning with values used in structural life-cycle models such as Cocco (2005), Halket and Vasudev (2014), and Favilukis et al. (2017). The curvature of utility, captured by γ, is estimated at 2.17, consistent with moderate risk aversion in models of housing and savings decisions.

A key parameter is the renters housing utility shifter $\psi_0 \approx 0.18$, which implies that renters value housing services substantially less than owners on the margin. This is crucial for generating observed differences in housing consumption across tenures, consistent with the housing lock-in channel emphasized by Davis and Van Nieuwerburgh (2014) and

Sinai and Souleles (2013). The moving cost estimates are economically significant and asymmetric: entry into ownership entails a fixed cost of roughly 11% of annual income, while exits from ownership (i.e., selling) are far cheaper. This asymmetry helps generate persistence in tenure choices and reinforces the insurance value of ownership.

Finally, borrowing limits are estimated to allow moderate leverage-households can borrow up to approximately 80% of housing value when purchasing. This is consistent with empirical mortgage constraints observed in U.S. housing data.

Table 2: Structural Parameter Estimates

Parameter	Estimate	Interpretation
β	0.8291	Discount factor (annual 0.94)
ν	1.4241	Intratemporal CES parameter
γ	2.1070	CRRA over the composite good
ψ_0	0.1769	Renters taste for housing (relative to owners)
θ_B	2.7709	Bequest-motive scaling

Notes: Estimates obtained by maximizing the log-likelihood of PSID tenure-choice transitions (2001-2021).

Together, the externally calibrated processes and structurally estimated parameters yield a model that closely replicates life-cycle patterns of tenure, asset accumulation, and housing consumption. In the next sections, we examine the models implications in counterfactual environments and assess the welfare and distributional impact of rental risk.

4.3 Model Fit

We now evaluate the empirical validity of the estimated model by comparing its implications to a range of moments observed in the PSID and ACS. Our validation strategy emphasizes both average patterns and distributional features of tenure choice, as well as dynamic margins such as transition rates. While the model is estimated using individual-level tenure transitions and residual variance profiles, the moments below are not directly targeted and serve as out-of-sample tests of the models ability to replicate key features of the U.S. housing market.

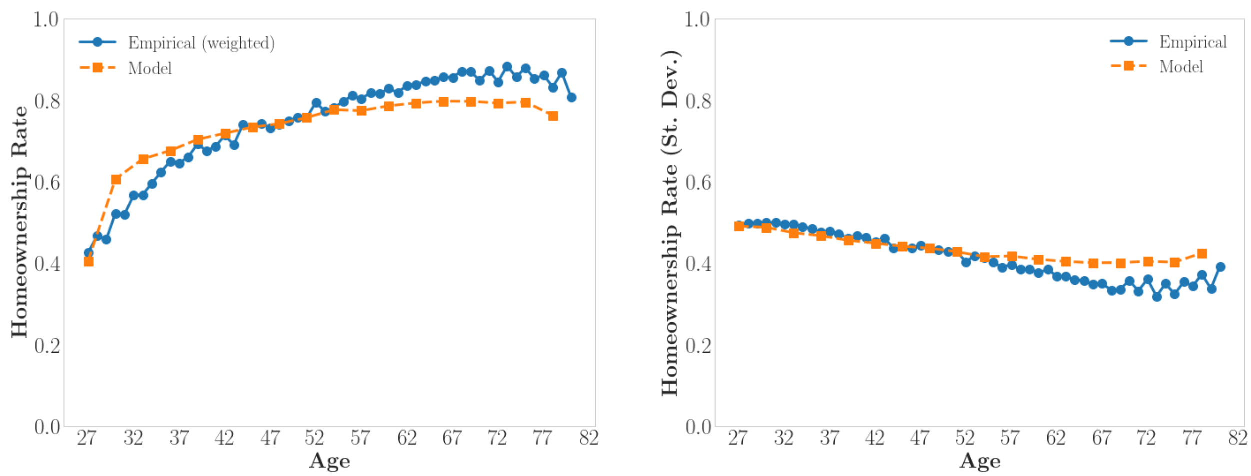
4.3.1 Life-Cycle Patterns in Homeownership and Dispersion

Figure 4 compares model-generated homeownership profiles to empirical patterns in the PSID and ACS. Panel (a) shows the average homeownership rate by age, while panel (b) plots the cross-sectional standard deviation in ownership rates by age-an indicator of heterogeneity in tenure outcomes.

The model replicates the upward-sloping average ownership path remarkably well: young households start with low ownership rates due to liquidity constraints, but as wealth accumulates and income stabilizes, more households transition into ownership. The model slightly underpredicts ownership at older ages, likely due to the omission of reverse mortgage markets or downsizing frictions. This overall pattern is consistent with the canonical findings of Cocco (2005), Halket and Vasudev (2014), and Li et al. (2016).

Panel (b) demonstrates that the model also reproduces the decline in tenure dispersion with age. Younger cohorts exhibit greater variance in ownership outcomes, reflecting differential timing in transitions due to asset, income, and taste heterogeneity. As households age, tenure becomes more stable-most have either committed to ownership or remain long-term renters. The model captures this narrowing of the distribution, which serves as a key validation of the underlying idiosyncratic process calibration.

Figure 4: Life-Cycle Homeownership: Data vs. Model



(a) Mean Homeownership Rate by Age (b) Std. Dev. of Homeownership by Age

4.3.2 Tenure Transition Rates: Renters vs. Owners

To assess the models ability to capture dynamic behavior, we examine tenure transitions-specifically, the probability of switching from owning to renting and vice versa over a three-year horizon. These moments capture both financial fragility (e.g., forced sales) and upward mobility (e.g., renter-to-owner transitions).

Figure 5 presents the comparison. Panel (a) shows the $P(\text{own} \to \text{rent})$ rate. The model overpredicts downward transitions at young ages, though qualitatively it captures the declining hazard over the life cycle. In the PSID, such transitions are relatively rare, reflecting both adjustment costs and selection: younger buyers tend to be financially stable, having cleared both down payment and underwriting thresholds. One possible interpretation is that the model may lack frictions like foreclosure stigma or credit penalties that make ownership exits costly. Panel (b) shows renter-to-owner transitions. The model

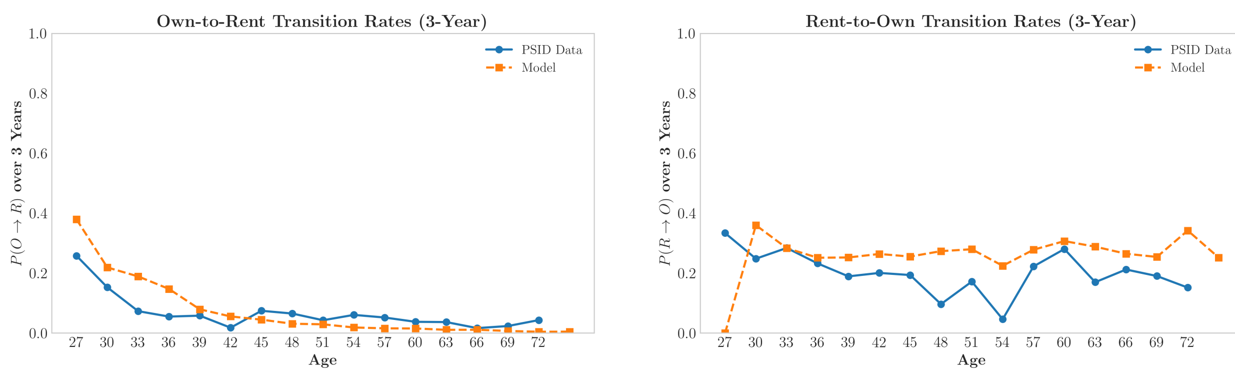
Table 3: Homeownership rates by age group

Age group	Data	Full model	No rental risk
27-45	0.612	0.643	0.650
46-63	0.788	0.772	0.760
64-81	0.858	0.790	0.772
Overall	0.731	0.727	0.720

again matches the overall shape but overstates the transition probability, especially for older renters. This partly reflects the models assumption that credit access is uniform conditional on assets and income, whereas in reality older renters may face unobservable barriers such as poor credit scores, medical risks, or landlord discrimination **??**,**??**.

Despite these deviations, the overall transition patterns demonstrate the models ability to generate non-trivial churn in tenure status and validate the importance of liquidity, risk, and taste shocks in driving life-cycle transitions.

Figure 5: Tenure Transitions: 3-Year Ownership Switching Rates



(a) Own-to-Rent Transition Rate

(b) Rent-to-Own Transition Rate

4.4 Joint Distribution by Asset Quantile

Table 4 evaluates the models ability to match joint distributions of tenure, assets, and consumption. Specifically, we compare model-simulated and PSID moments by asset quintile: mean financial assets, homeownership rate, and average consumption (all normalized by average income).

The model closely matches the empirical asset gradient in homeownership. Among the lowest quintile, ownership rates remain below 50%, while among the top quintile, nearly all households own-a pattern replicated in both data and simulation. Importantly, the model also reproduces the gradual increase in average consumption across the wealth distribution, reinforcing that the estimated preferences and constraints yield realistic consumption-savings behavior.

Table 4: Moments by Asset Quantile: Data vs. Model at age 50

Quantile	**Data**			**Model**		
	$\overline{a+ph}$	$\Pr(o=1)$	$\bar{h}$	$\overline{a+ph}$	$\Pr(o=1)$	$\bar{h}$
1st	-0.44	0.24	4.45	3.00	0.84	5.81
2nd	0.70	0.55	5.20	6.64	0.77	8.38
3rd	2.79	0.91	6.22	10.01	0.72	6.00
4th	6.82	0.95	6.61	14.17	0.79	9.92
5th	29.92	0.97	7.98	27.14	0.67	11.11

Notes: Moments are computed from a crosssection of PSID observations at age 50 and a simulated crosssection. $\overline{a+ph}$ is mean home equity; $\Pr(o=1)$ is homeownership rate; $\bar{h}$ is mean housing.

4.5 Process Moments: Residual Moments of Price and Income Risk

As a final validation, Table 5 compares the unconditional means, standard deviations, and correlations of the log residuals of income, rent, and house prices in the PSID and model simulation. These are the empirical moments targeted in our GMM estimation of exogenous stochastic processes (Section 4.1).

Table 5: Price Processes : Data vs. Model

Variable	**Mean**		**Std Dev**		$\textbf{Corr}_{\text{Data}}$			$\textbf{Corr}_{\text{Model}}$		
	Data	**Model**	**Data**	**Model**	Income	Rent	HP	Income	Rent	HP
Income	1.414	1.178	2.065	0.721						
Rent	0.107	1.110	0.097	0.081	0.082			0.003		
House Price	1.231	1.257	1.180	0.870		0.084			0.002	

Notes: Means and standard deviations refer to age-bin unconditional aggregates of $\ln y$, $\ln q$, and $\ln p$. Correlations are pairwise sample correlations across age bins. Data uses PSID residual variances; Model uses simulated series under the estimated AR(1)/persistent-transitory processes.

The model replicates the high persistence of income shocks and their relatively low cross-sectional variance-features that are built into the persistent-transitory structure calibrated from the PSID and are well documented in the literature (e.g., Blundell et al., 2008). The relatively modest volatility of income reflects the smoothing effects of long-term labor contracts and stable wage profiles over the life cycle.

For rents and house prices, the model reasonably matches the higher short-run volatility of rents, which in the data reflect transitory fluctuations in local housing demand and supply-e.g., lease renewals, turnover, or temporary supply shocks. In the model, this is captured via the lower persistence of the rental-rate process. However, the model likely underpredicts some of the lumpiness in rent variation seen in the data, since it abstracts from institutional features like lease rigidity and regional rent control laws.

The weakest fit arises in the correlations between income and prices/rents. In the model, these correlations are mechanically low because the stochastic processes for income, rent, and price are estimated independently, and the model does not include a common macro or regional component that might jointly affect all three variables. In the data, by contrast, local demand shocks likely induce stronger positive co-movement between income and housing costs. This is an area where adding a regional business cycle component, as in Sinai and Souleles (2013) or Favilukis et al. (2017), could improve the models realism.

Overall, the table confirms that while the model captures key moments of individual-level variation and persistence, it abstracts from correlated shocks across markets-an intentional simplification that allows us to isolate the household-level mechanism of interest: the insurance value of homeownership under rental risk.

These features are crucial for capturing the insurance value of ownership: house prices co-move more strongly with local economic fundamentals, while rents contain a larger transitory component. This aligns with findings in Sinai and Souleles (2005), who highlight the role of owner-occupied housing in hedging long-run local cost of living.

Table 6: Homeownership rates by asset quintile: Data vs. Full model vs. No rental risk.

Asset quintile	**Data**	**Full model**	**No rental risk**
Overall	0.731	0.727	0.722
Q1	0.538	0.725	0.720
Q2	0.405	0.730	0.724
Q3	0.582	0.724	0.720
Q4	0.736	0.724	0.722
Q5	0.900	0.732	0.726

In Table 6 the fit is strongest for homeownership rates across wealth and age groups. The model reproduces the steep homeownership gradient with respect to asset holdings-capturing both the low ownership rates among the bottom quintile and the near-universal ownership among the top. This reflects the models liquidity constraint mechanism and the non-convexity induced by the down payment requirement, consistent with mechanisms emphasized by Cocco (2005) and Li et al. (2016).

Asset holdings are somewhat under-predicted for high-wealth households. This is not uncommon in structural models with limited asset return heterogeneity. Because the model lacks a bequest motive with heterogeneity or access to high-return assets beyond housing, very wealthy households cannot replicate observed tail behavior in financial wealth accumulation. However, the model still captures the overall upward trajectory of wealth and its divergence across tenure groups.

The biggest miss appears in the dispersion of consumption. The model implies lower cross-sectional variance in consumption than the data, especially within rental households. This likely stems from the stylized utility function and the omission of household composition shocks, credit score differences, or income uncertainty beyond what is captured by AR(1) plus transitory shocks. Still, the models general pattern-that renters exhibit more volatile consumption paths and lower average consumption-is in line with both empirical patterns and theoretical priors.

In short, Table 6 reveals that the model captures the key margins that matter for tenure and asset choice-particularly wealth gradients and age profiles-while modestly underperforming in areas like tail wealth and consumption dispersion where additional heterogeneity (e.g., in returns or preferences) could enhance realism.

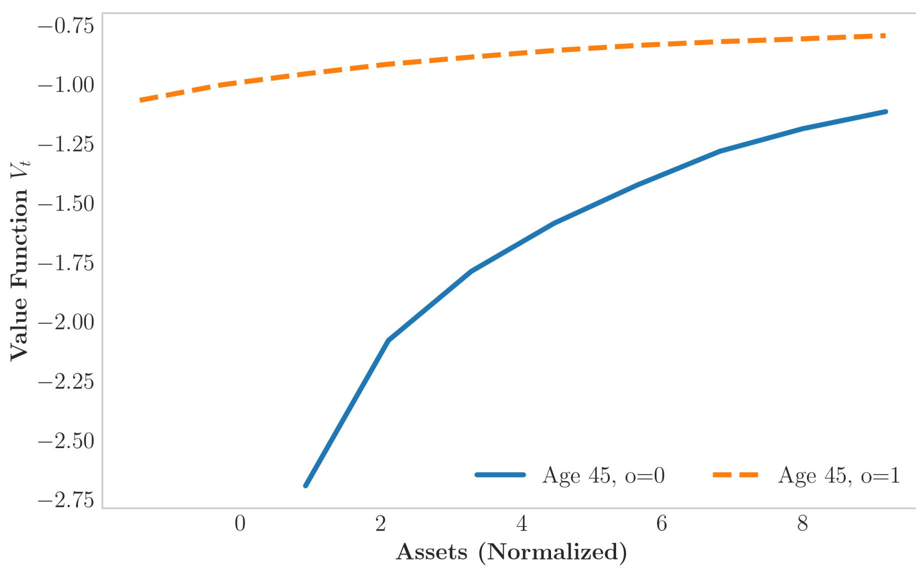
4.6 Main Mechanism: Policy Functions and Tenure Behavior

To better understand the economic forces that shape tenure choice over the life cycle, we analyze the households optimal policies as functions of financial resources and current ownership status. This section examines value functions, housing and saving policies, and the probability of transitioning into homeownership, all evaluated at a representative middle age (age 45). The goal is to unpack the mechanism through which rental risk and wealth interact to generate observed heterogeneity in homeownership and asset accumulation.

1. Value Functions and the Tenure Margin

Figure 6 plots the value function $V_t(a, o)$ at age 45 as a function of normalized assets a_t, separately for renters ($o = 0$) and owners ($o = 1$). Several features emerge. First, owners consistently enjoy higher lifetime utility than renters at every wealth level. This reflects both the absence of rental volatility and the fixed-payment structure of ownership, which eliminates exposure to future rent inflation. Second, the value function is strictly increasing and concave in wealth, capturing precautionary saving motives under income and housing shocks. The steep gradient at low asset levels indicates that marginal utility of wealth is particularly high for constrained renters, reinforcing the role of liquidity as a precondition for entering ownership.

Figure 6: Value Function V_t at Age 45 by Ownership Status



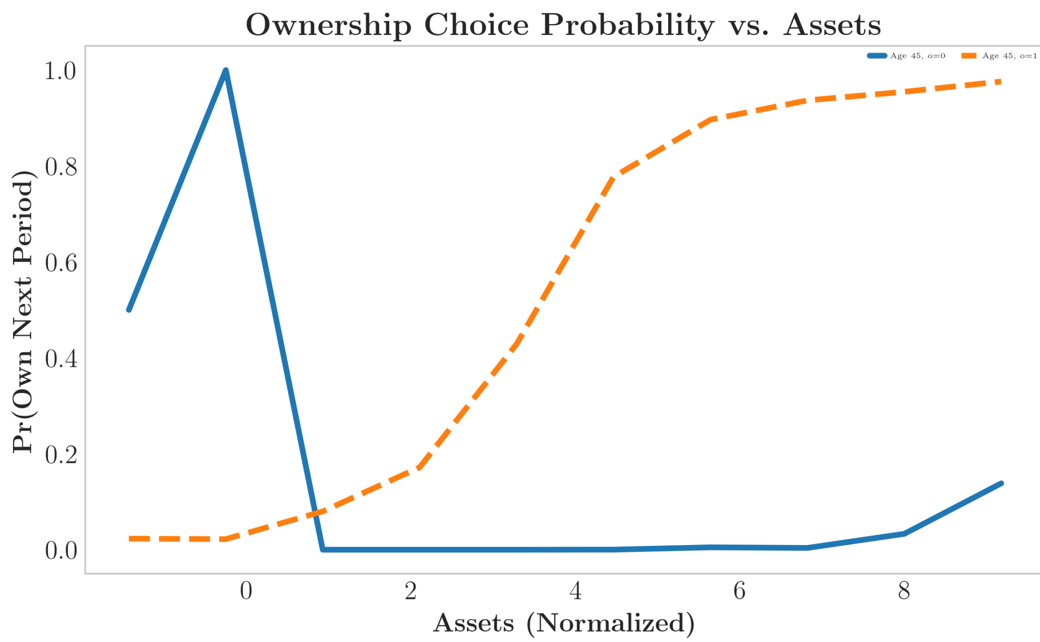
Note: Owners have consistently higher continuation values than renters.

2. Tenure Choice: Endogenous Transition into Ownership

Figure 7 shows the probability of choosing ownership in the next period as a function of assets, for renters and owners separately. For current renters, the probability of becoming an owner is non-monotonic in wealth. At very low wealth, renters are too constrained to afford the down payment or moving cost; at intermediate levels, the probability spikes as these barriers are overcome. At higher wealth levels, however, some households optimally continue renting due to preference shocks or temporary price realizations, reflecting the stochastic component in choice.

For current owners, the probability of remaining an owner increases monotonically in assets. Wealthier owners face fewer incentives to revert to renting, both because of sunk costs already incurred and because homeownership becomes increasingly valuable as a hedge against long-term housing expenditure risk.

Figure 7: Tenure Policy: Probability of Choosing Ownership at $t + 1$ by Asset Level at Age 45



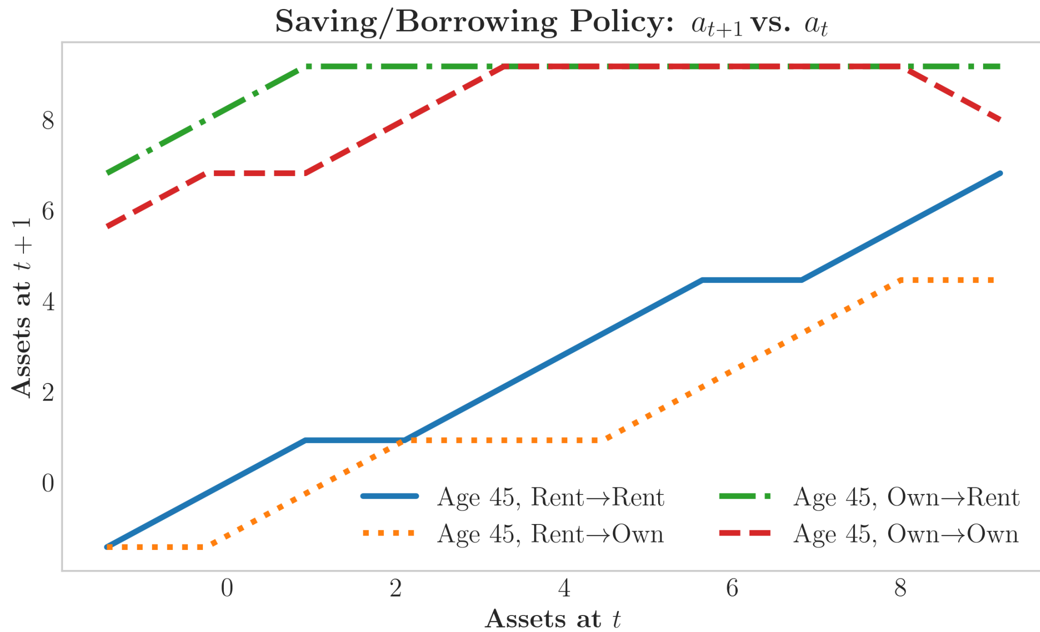
3. Saving and Borrowing Behavior

Figure 8 displays the asset accumulation policy $a_{t+1}(a_t)$ by current ownership and transition status. A few insights stand out. First, renters accumulate assets slowly over time, with low marginal savings early on due to tight budget constraints and the priority placed on consumption smoothing. Those who transition to ownership (dotted orange line) engage in modest asset accumulation and plateau around the down payment threshold, consistent with observed savings for a home behavior.

Current owners, in contrast, exhibit both higher absolute savings and lower marginal propensity to consume. Notably, those who stay owners (dashed red line) build wealth more aggressively than those who revert to renting, suggesting a reinforcing dynamic where ownership enables and incentivizes further accumulation, consistent with wealth-lock-in mechanisms.

4. Housing Consumption and the Role of Liquidity

Figure 8: Saving/Borrowing Policy: a_{t+1} vs. a_t at Age 45.



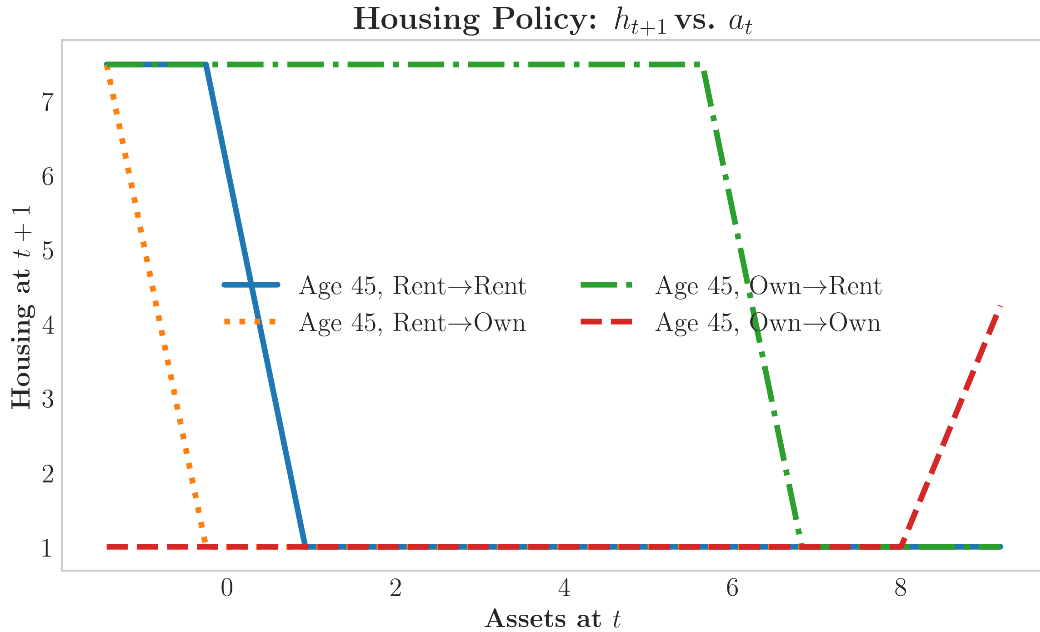
Note: Households transitioning to ownership tend to save up to but not beyond the down payment threshold.

Figure 9 illustrates the housing-service decision $h_{t+1}(a_t)$ conditional on next-period tenure. The differences are striking. Households that remain renters (solid blue line) or transition into renting tend to choose large housing units when wealth is low-a result of temporary high-valuation shocks given low savings-but sharply reduce housing consumption as financial constraints bind. Renters that switch to ownership (dotted orange) opt for smaller, more affordable homes, reflecting the indivisibility of purchasing relative to renting.

In contrast, existing owners who remain owners (dashed red) maintain or increase housing size as assets rise, while those who switch to renting (green dash-dot) reduce housing sharply. This asymmetry highlights how tenure type alters both the feasibility and desirability of housing consumption-ownership encourages smoother, more durable housing demand, while renting remains more elastic and volatile.

Taken together, these four policy dimensions confirm that the demand for ownership in this model arises endogenously from the interaction between risk exposure, borrowing constraints, and precautionary savings. Rental risk increases the relative value of ownership, especially for households near the down payment threshold, while existing owners gain from smoother housing consumption and accelerated wealth accumulation. The

Figure 9: Housing Policy: h_{t+1} vs. a_t at Age 45



Note: Ownership leads to more stable and upward-trending housing paths, while renters exhibit more volatility.

nonlinearities and asymmetries across these policies play a key role in generating the heterogeneous life-cycle profiles observed in the model and in the data.

5 Quantifying the Insurance Value of Homeownership

5.1 Main Counterfactual: Eliminating Rental-Rate Risk

To evaluate the quantitative contribution of rental-rate uncertainty to observed homeownership behavior, we conduct a counterfactual experiment that eliminates idiosyncratic rent shocks after the initial period of the life cycle. Specifically, we consider a scenario in which households observe a single draw of rental productivity q_1 at age 27 and then face no further rental volatility thereafter ($\sigma_q = 0$ for $t \geq 2$), while keeping all other sources of risk unchanged.

Figure 10 plots the resulting life-cycle homeownership rates in the baseline (with $\sigma_q = \widehat{\sigma}_q > 0$) and in the no-rental-risk counterfactual. Under the baseline, households purchase homes earlier in life and accumulate housing assets more aggressively. This reflects the role of homeownership as a hedge against rent inflation and displacement risk. In the absence of rental risk, households delay purchases, and average homeownership rates-particularly between ages 27 and 36 decline up to 5 %. For older agents rental risk adds from 1 to 4% for each age group. This attenuation highlights the insurance function of ownership: when rent is stable and predictable, renting becomes a more viable long-run strategy.

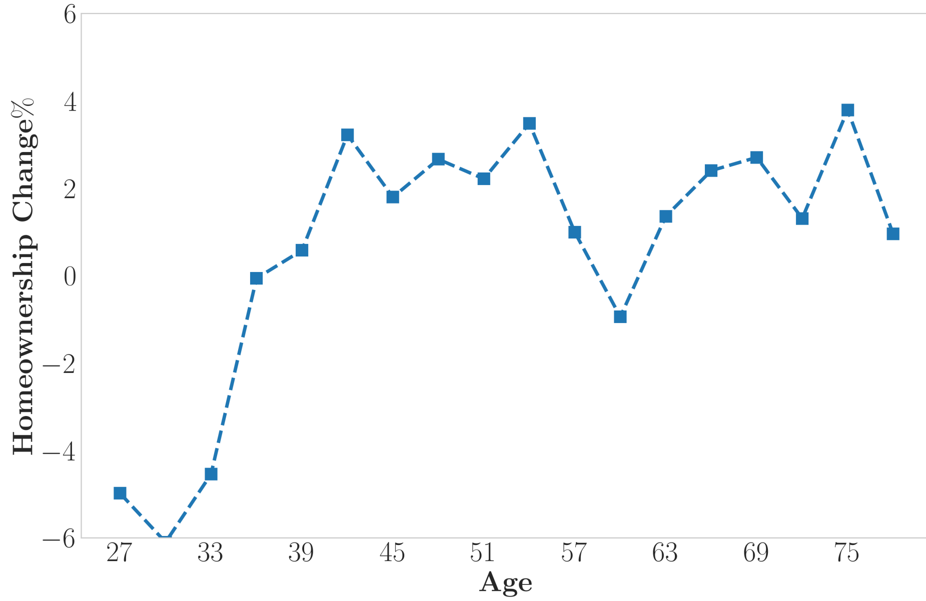
Table 6 further decomposes this effect across the wealth distribution. It shows that rental risk plays a disproportionately large role for middle-income households who are marginal buyersthose on the cusp of entering homeownership. The lowest and highest quintiles show more muted responses: the poorest remain liquidity constrained, while the wealthiest own regardless of rental conditions.

To assess the relative contribution of different types of housing market risk to homeownership behavior and household welfare, we consider four model variants in which we selectively shut down rental-rate and house-price shocks. The results are summarized in Table 8, which reports (i) the overall homeownership rate at age 50 and (ii) the associated average consumption-equivalent variation (c_{eq}) relative to the baseline model.

The full model, calibrated to match PSID-based volatility estimates for rents and house prices, delivers an average homeownership rate of 72.7%remarkably close to the empirical value of 72.9%. This serves as a validation of the models ability to replicate key life-cycle moments.

Turning to counterfactuals, we find that eliminating rental risk alone reduces the home-

Figure 10: Counterfactual: No Rental-Rate Risk.



Note: Eliminating rental-price shocks leads to later home purchases and lower overall homeownership.

ownership rate to 72.0%, a drop of 0.7 percentage points. While numerically modest, this change represents a deliberate decision to delay or forego home purchases due to the diminished insurance value of ownership. This result is consistent with prior findings (e.g., Figure 10) and highlights that rental volatilitythough typically absent from standard modelscan significantly influence marginal ownership decisions.

In Table 7, we conduct a channel decomposition to uncover the mechanisms behind the 0.7 pp decline in homeownership when rental risk is eliminated. First, the *insurance-value channel* captures the change in the curvature of the value function: holding savings, consumption and housing rules fixed, removing rental volatility would *increase* homeownership by approximately 2.7 pp. Second, the *precautionary-savings channel* of re-optimizing the saving rule under certainty: without rental risk, households reduce their buffer-stock savings, lowering homeownership by about 2.5 pp. Third, the *housing-adjustment channel* isolates changes in the optimal housing policy; homeownership falls by another 1.1 pp. The effects are also unequally distributed in life cycle with the strongest contribution for 36 to 48 years old for pre insurance and precautionary and for over 51 for housing channel. This decomposition demonstrates that rental-rate risk influences homeownership through multiple opposing forces, and that a small aggregate response conceals substantial offsetting behavioral adjustments.

Table 7: Homeownership Rate: Channel Decomposition

	Insurance	Precautionary	Housing Channel	Total
No Rental Risk	2.7	-2.5	-1.1	-0.9
No HP Risk	2.5	26.3	-14.8	14.1
Neither	6.1	26.2	-7.5	24.8

Note: Table presents % change in homeownership rate from different channels

More surprisingly, removing house-price risk instead leads to a sharp increase in homeownership, rising to 82.9%. This pattern reflects two mechanisms. First, when house prices are stable, households perceive ownership as less risky and more attractive. Second, since home equity becomes less volatile, agents face fewer downside tail risks from buying early. However, this shift comes with substantial welfare costs: the consumption-equivalent variation in this scenario is *9.26% lower* than in the baseline. That is, even though more households become homeowners when house-price risk is removed, their expected lifetime utility decreases. This counterintuitive result underscores the importance of precautionary behavior and endogenous selection: reducing price risk encourages over-ownership by households for whom renting may have been optimal under uncertainty. Higher homeownership is driven mostly by saving decision (precautionary saving channel), with insurance playing third order role, and housing channel partially offsetting it (Table 7).

In contrast, shutting down both sources of risk simultaneously further boosts homeownership to 90.7%, but again results in a welfare loss of 7.59%. This case represents an environment with perfect housing predictability, where households uniformly prefer ownership. Yet the welfare drop reveals that full certainty removes the incentive for precautionary saving and undermines the value of selection mechanisms that operate under risk.

Taken together, these results suggest a nuanced interpretation. While rental risk drives early transitions into ownership as a form of insurance, house-price risk serves a disciplining function: it prevents marginal households from over-committing to ownership. In that sense, the presence of housing market uncertainty plays a dual roleboth as a burden (for renters) and as a selection filter (for buyers). Models that ignore one or both dimensions risk mischaracterizing both the level and welfare implications of homeownership in the economy.

Table 8: Homeownership Rates vs Housing Market Risks

	Data	Baseline	No Rental Risk	No HP Risk	Neither
Homeownership	72.9	72.7	72.0	82.9	90.7
Cons Equiv			0.51	-9.26	-7.59

Note: The second row reports changes in household welfare in consumption-equivalent units (percent).

5.2 Marginal Propensity of Housing Demand

To better understand the mechanism through which rental volatility affects homeownership, we compute the marginal propensity of housing demand with respect to σ_q:

$$\frac{d\,\mathbb{E}[H]}{d\sigma_q} = \underbrace{\mathbb{E}[h \mid o=1] \cdot \frac{d\ \Pr(o=1)}{d\sigma_q}}_{\text{Extensive Margin}} + \underbrace{\Pr(o=1) \cdot \frac{d\,\mathbb{E}[h \mid o=1]}{d\sigma_q}}_{\text{Intensive Margin}}.$$

Figure 11 shows how total housing demand (averaged across the population and life cycle) responds to changes in σ_q, decomposed into extensive and intensive margins.

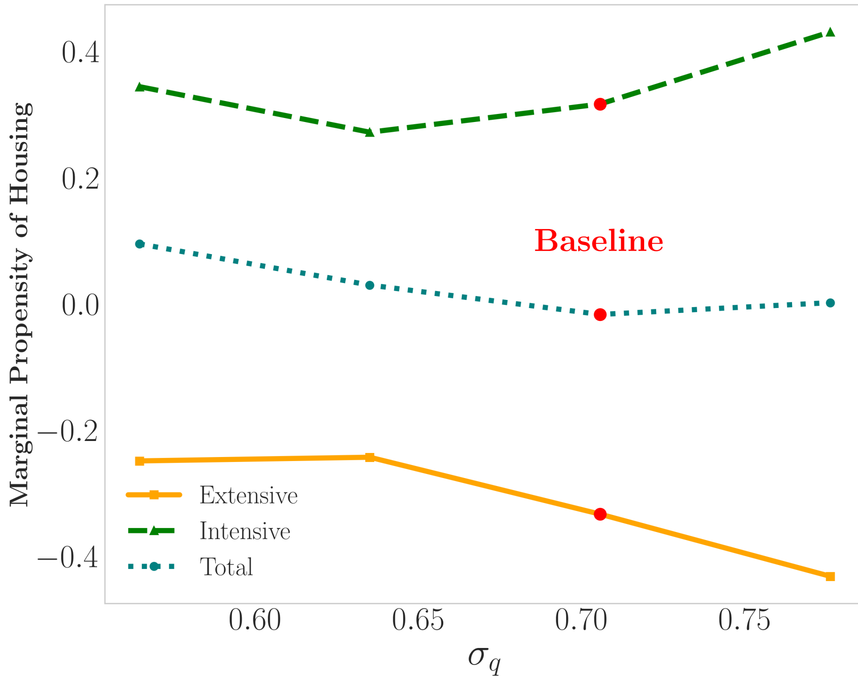
The extensive marginthe probability of owning a homeincreases robustly with rental risk, while the intensive marginhow much housing an owner choosesresponds more weakly. At the baseline σ_q, the extensive margin dominates: a 10% increase in rental volatility leads to a 34 percentage point rise in the ownership rate, while average house size among owners barely changes. This pattern is consistent with our insurance interpretation: higher rent uncertainty incentivizes the transition into ownership more than it alters post-purchase housing consumption.

5.3 Welfare Sensitivity to Rental-Rate Risk

Finally, we quantify how household welfare varies with the level of rental volatility σ_q. We compute the sensitivity of consumption-equivalent variation c_{eq} with respect to σ_q, defined as the uniform increase in consumption across all periods that would leave agents indifferent between a baseline and counterfactual level of volatility.

Figure 12 plots $d\,c_{\text{eq}}/d\sigma_q$ as a function of σ_q. The curve is distinctly non-monotonic: at low levels of volatility, marginal increases in σ_q improve welfare slightly, as they raise the perceived value of insurance and prompt earlier homeownership. However, beyond a threshold ($\sigma_q \gtrsim 0.7$), further increases in volatility impose steep welfare losses, reflecting

Figure 11: Marginal Propensity of Housing

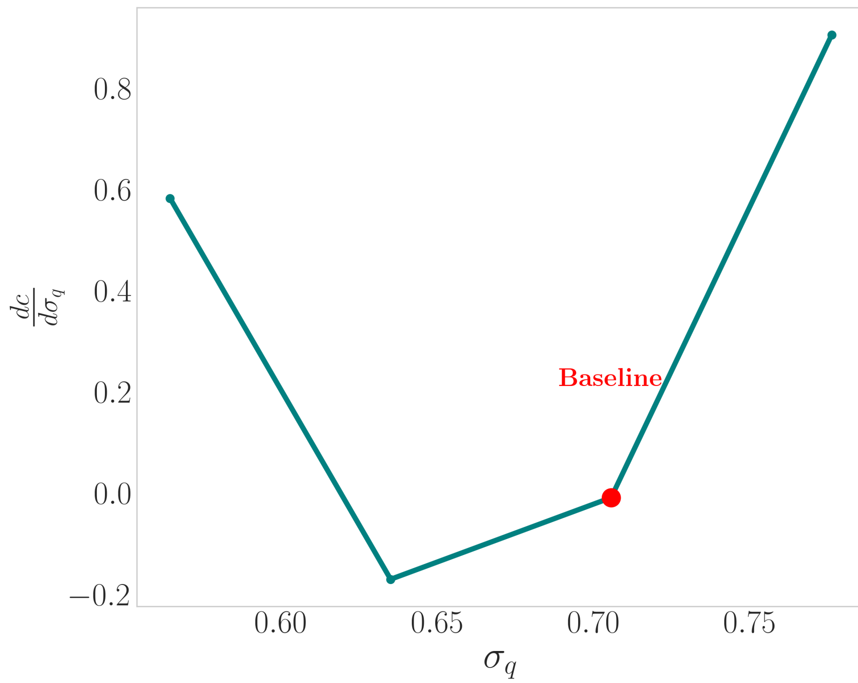


Note: Total housing demand responds to changes in rental volatility primarily through the extensive margin.

the sharply rising cost of rental risk and the inability of some households to insure fully due to liquidity constraints or borrowing limits.

This finding aligns with economic intuition: modest rental risk can spur welfare-improving tenure transitions, but excessive volatility imposes large utility costs, especially on renters who remain exposed. Thus, in addition to affecting observed tenure choices, rental volatility plays a first-order role in shaping ex-ante welfare.

Figure 12: Welfare Sensitivity to Rental Volatility



Note: Moderate rental volatility increases the value of insurance, but high volatility leads to sharp welfare losses.

6 Conclusion

This paper aims at a new explanation for why households choose to own rather than rent: homeownership provides insurance against rental-price risk. While the traditional focus in housing economics has been on price risk and wealth accumulation for owners, we show that volatility in rental costslargely uninsurable and persistentcan meaningfully shape tenure decisions. Using PSID panel data, we document that residual rental risk rises with age. We then embed this empirical fact into a structural life-cycle model and estimate it using methods for dynamic discrete choice models. The model replicates key patterns in tenure, however can be improved on assets, and housing wealth over the life cycle.

Our central counterfactual experiment demonstrates that eliminating rental risk reduces homeownership by approximately 0.5 percentage points, a magnitude comparable to widely studied policy levers like mortgage interest deductions. The mechanism operates primarily through the extensive margin: increased rent volatility leads middle-aged households near the down payment threshold to transition into ownership earlier in life. This result highlights a previously underexplored insurance motive for homeownership and underscores the importance of incorporating rental risk into models of household behavior.

Future Work. Several extensions could enrich the analysis and sharpen its empirical relevance. First, incorporating location-specific identifiers in the PSID would allow us to measure spatial variation in rental and house price risk more precisely. This would improve the accuracy of estimated stochastic processes and allow for geographically differentiated policy simulations. Second, introducing time-varying price trends and inflation dynamics into the model would enable a richer analysis of long-run expectations and their impact on tenure choices. Currently, our model assumes stationary processes for rents and prices; relaxing this assumption could reveal how beliefs about future housing markets shape ownership incentives.

Appendix

A Equilibrium

In our partial-equilibrium framework, prices of housing services (q_t) and houses (p_t) evolve exogenously according to the Markov processes calibrated in Section 4.1. Given the parameters and the discrete state space: exogenous shock states $s_t = (s_{y,t}, s_{q,t}, s_{p,t}) \in \mathcal{S}$, assets $a_t \in \mathcal{A}$, housing $h_t \in \mathcal{H}$, tenure $o_t \in \{0, 1\}$, an equilibrium is a triple

$$\Big(\{V_t\}_{t=1}^{T+1},\ \{\pi_t^a, \pi_t^h, \pi_t^o\}_{t=1}^{T},\ \mu\Big),$$

where:

1. **Value and policy functions.** For each period t, the value function $V_t(s, a, h, o)$ and associated policy functions

   $$a_{t+1} = \pi_t^a(s, a, h, o), \quad h_{t+1} = \pi_t^h(s, a, h, o), \quad \Pr(o_{t+1} = 1 \mid s, a, h, o) = \pi_t^o(s, a, h, o)$$

   satisfy the Bellman recursion detailed in Section 3.

2. **Stationary distribution.** Let

   $$P\big((s, a, h, o) \to (s', a', h', o')\big)$$

   denote the transition kernel induced by the exogenous shock law and policy rules. The cross-sectional distribution μ over the joint state space solves

   $$\mu(s', a', h', o') = \sum_{s,a,h,o} \mu(s, a, h, o)\ P\big((s, a, h, o) \to (s', a', h', o')\big),$$

   subject to $\sum_{s,a,h,o} \mu(s, a, h, o) = 1$.

Since this is a partial-equilibrium model, we do not solve for endogenous equilibrium prices. Future extensions could endogenize aggregate market-clearing conditions and policy within this framework.

A Toy Model

We consider a simple two-period deterministic model to capture the trade-offs between renting and owning a home. The agent lives for two periods, $t = 1, 2$, and consumes a single non-durable good c_t in each period. In addition, the agent chooses whether to rent or own a house.

Housing is modeled as an indivisible durable good. If the agent chooses to own, they consume housing services $h = 1$; if they rent, $h = 0$. Ownership requires purchasing the house in period 1 at price p, while renting entails paying a fixed rent R in each period. Labor income y is received only in the first period, and the interest rate is normalized to zero for simplicity.

The agent can save from period 1 to period 2 in the form of non-negative assets $a_1 \geq 0$, which carry over to period 2. Any remaining assets at the end of life, $a_2 \geq 0$, enter utility as a bequest. Preferences are given by:

$$U = \ln(c_1) + \beta \ln(c_2) + \beta\phi \ln(a_2) + \begin{cases} u_h & \text{if } h = 1 \text{ (own)}, \\ u_r & \text{if } h = 0 \text{ (rent)}, \end{cases}$$

where $\beta > 0$ is the discount factor, $\phi \geq 0$ governs the strength of the bequest motive, and $u_h > u_r$ captures the non-pecuniary utility benefit of owning relative to renting.

Letting a_1 denote savings from period 1 and a_2 the bequest, budget constraints depend on the housing choice. For a renter, constraints are:

$$c_1 = y - R - a_1 > 0, \quad c_2 = a_1 - R - a_2 > 0, \quad a_2 > 0.$$

For an owner, they purchase the house at price p and face:

$$c_1 = y - p - a_1 > 0, \quad c_2 = a_1 - a_2 > 0, \quad a_2 > 0.$$

Case 1: Renting

Budget Constraints When renting in both periods, the flow-of-funds are

$$c_1 + a_1 + R = y, \qquad \text{(period 1)} \qquad (1)$$

$$c_2 + a_2 + R = a_1, \qquad \text{(period 2)} \qquad (2)$$

Equivalently,

$$c_1 = y - R - a_1, \quad c_2 = a_1 - R - a_2.$$

Optimality Conditions Substitute into utility (omitting u_r) and maximize

$$\max_{a_1, a_2 > 0} \ln(y - R - a_1) + \beta \ln(a_1 - R - a_2) + \beta\phi \ln(a_2).$$

The FOCs are

$$-\frac{1}{y-R-a_1}+\frac{\beta}{a_1-R-a_2}=0, \tag{3}$$

$$-\frac{\beta}{a_1-R-a_2}+\frac{\beta\phi}{a_2}=0. \tag{4}$$

From (4):

$$\frac{1}{a_1-R-a_2}=\frac{\phi}{a_2} \implies a_2=\frac{\phi}{1+\phi}\,(a_1-R).$$

Substitute (A) into (3):

$$\frac{1}{y-R-a_1}=\frac{\beta}{a_1-R-a_2}=\frac{\beta}{\frac{1}{1+\phi}(a_1-R)}=\frac{\beta(1+\phi)}{a_1-R}.$$

Cross-multiplying gives

$$a_1-R=\beta(1+\phi)\,(y-R-a_1) \implies a_1^{\text{rent}}=\frac{\beta(1+\phi)\,y-(1+\beta\phi)R}{1+\beta(1+\phi)}.$$

Then from (A),

$$a_2^{\text{rent}}=\frac{\phi}{1+\phi}\big(a_1^{\text{rent}}-R\big).$$

Finally,

$$c_1^{\text{rent}}=y-R-a_1^{\text{rent}}, \tag{5}$$

$$c_2^{\text{rent}}=a_1^{\text{rent}}-R-a_2^{\text{rent}}. \tag{6}$$

Value Function Plugging into utility,

$$V^{\text{rent}}(y,R)=\ln\big(c_1^{\text{rent}}\big)+\beta\ln\big(c_2^{\text{rent}}\big)+\beta\phi\ln\big(a_2^{\text{rent}}\big)+u_r.$$

Case 2: Owning

Budget Constraints When owning from period 1, we have

$$c_1+a_1+p=y, \qquad \text{(period 1)} \tag{7}$$

$$c_2+a_2=a_1, \qquad \text{(period 2)} \tag{8}$$

Equivalently,

$$c_1=y-p-a_1, \quad c_2=a_1-a_2.$$

Optimality Conditions Maximize (omitting u_h):

$$\max_{a_1,a_2>0} \ln(y-p-a_1)+\beta\ln(a_1-a_2)+\beta\phi\ln(a_2).$$

FOCs:

$$-\frac{1}{y-p-a_1}+\frac{\beta}{a_1-a_2}=0, \tag{9}$$

$$-\frac{\beta}{a_1-a_2}+\frac{\beta\phi}{a_2}=0. \tag{10}$$

From (10):

$$a_2=\frac{\phi}{1+\phi}a_1.$$

Substitute into (9):

$$\frac{1}{y-p-a_1}=\frac{\beta(1+\phi)}{a_1} \implies a_1^{\text{own}}=\frac{\beta(1+\phi)\,(y-p)}{1+\beta(1+\phi)}.$$

Then

$$a_2^{\text{own}}=\frac{\phi}{1+\phi}a_1^{\text{own}}.$$

And

$$c_1^{\text{own}}=y-p-a_1^{\text{own}}, \tag{11}$$

$$c_2^{\text{own}}=a_1^{\text{own}}-a_2^{\text{own}}. \tag{12}$$

Value Function

$$V^{\text{own}}(y,p)=\ln\big(c_1^{\text{own}}\big)+\beta\ln\big(c_2^{\text{own}}\big)+\beta\phi\ln\big(a_2^{\text{own}}\big)+u_h.$$

Decision and Comparative Statics The agent chooses $h=1$ if

$$V^{\text{own}}(y,p)>V^{\text{rent}}(y,R).$$

We now derive how key variables respond to R and p.

(i) Rent R: From (A),

$$a_1^{\text{rent}}=\frac{\beta(1+\phi)\,y-(1+\beta\phi)R}{1+\beta(1+\phi)}, \quad \frac{\partial a_1^{\text{rent}}}{\partial R}=-\frac{1+\beta\phi}{1+\beta(1+\phi)}<0.$$

Then

$$c_1^{\text{rent}}=y-R-a_1^{\text{rent}}, \quad \frac{\partial c_1^{\text{rent}}}{\partial R}=-1-\frac{\partial a_1^{\text{rent}}}{\partial R}<0.$$

Since V^{rent} decreases in both c_1^{rent} and c_2^{rent}, higher R lowers V^{rent}, making owning more attractive.

(ii) Price p: From (A),

$$a_1^{\text{own}} = \frac{\beta(1+\phi)(y-p)}{1+\beta(1+\phi)}, \quad \frac{\partial a_1^{\text{own}}}{\partial p} = -\frac{\beta(1+\phi)}{1+\beta(1+\phi)} < 0.$$

Then

$$c_1^{\text{own}} = y - p - a_1^{\text{own}}, \quad \frac{\partial c_1^{\text{own}}}{\partial p} = -1 - \frac{\partial a_1^{\text{own}}}{\partial p} < 0.$$

Thus higher p lowers V^{own}, making renting more attractive.

In both cases, a rise in the cost of an option lowers consumption in period 1 for that option and reduces its value, so consumption and the ownership choice move together.

A Algorithm

Timing within Period t.

1. At the start of period t, the household observes $(s_t,\ a_t,\ h_t,\ o_t)$.
2. Based on that state, the household chooses

$$o_{t+1} \in \{0,1\}, \quad h_{t+1} \in \mathcal{H}, \quad a_{t+1} \in \mathcal{A},$$

   and current consumption c_t is determined by the corresponding budget constraint.
3. The household obtains period utility $u(c_t,\ h_{t+1},\ o_{t+1})$.
4. Exogenous shocks $(s_{y,t+1},\ s_{q,t+1},\ s_{p,t+1})$ are drawn according to $\Pi_y,\ \Pi_q,\ \Pi_P$. The model then proceeds to period $t+1$.

A.1 Computation.

Solving the life-cycle model requires computing value functions, policy functions, and simulating tenure-choice paths. The key steps are:

1. *Discretize State Space.* We construct finite grids for each exogenous Markov state s_y, s_q, s_p (via Rouwenhorst), for asset holdings $a \in \mathcal{A}$, and for housing services $h \in \mathcal{H}$. Tenure $o \in \{0,1\}$ is discrete.

2. *Backward Induction on t.* At $t = T+1$, set

$$V_{T+1}(s,a,h,o) = \theta_B \frac{\left[a + o\, p(s_p)\, h\right]^{1-\gamma}}{1-\gamma}.$$

For $t = T, \ldots, 1$, and each grid node $(s_t,\ a_t,\ h_t,\ o_t)$:

Table 9: Grids

Variable	Value	Description
n_a	10	Number of asset grid points
n_h	5	Number of housing grid points
ξ	0.01	Taste shock scale
n_y^p	2	nr of persistent income states
n_y^t	3	nr of transitory income states
n_q	5	nr of rentalrate states
n_P	5	nr of housingprice states

1. *Compute Auxiliary Values.* For each candidate tenure next period $o_{t+1} \in \{0,1\}$, solve

$$W_t(s_t, a_t, h_t, o_t;\, o_{t+1}) = \max_{h_{t+1}\in\mathcal{H},\, a_{t+1}\in\mathcal{A}} \Big\{ u(c_t,\, h_{t+1},\, o_{t+1}) + \beta\, \mathbb{E}_t\big[V_{t+1}(s_{t+1}, a_{t+1}, h_{t+1}, o_{t+1})\big] \Big\},$$

   subject to the appropriate budget/collateral constraint for the transition $(o_t \to o_{t+1})$. This entails looping over all feasible (h_{t+1}, a_{t+1}) on the grids $\mathcal{H} \times \mathcal{A}$.

2. *Aggregate via Taste Shocks.* Having $W_t(\cdot;0)$ and $W_t(\cdot;1)$, compute

$$V_t(s_t, a_t, h_t, o_t) = \xi\Big[\gamma_{\text{const}} + \ln\big(e^{W_t(\ldots,0)/\xi} + e^{W_t(\ldots,1)/\xi}\big)\Big].$$

3. *Policy Functions and Simulation.* Once all V_t are known, extract policy rules

$$o^*_{t+1}(s_t, a_t, h_t, o_t),\; h^*_{t+1}(\cdot),\; a^*_{t+1}(\cdot)$$

by selecting the o_{t+1} that maximizes $W_t + \varepsilon$(taste shock). We then simulate N_{sim} life-cycle trajectories by drawing $(s_{i,t})$ from Π_y, Π_q, Π_P and applying the policy functions to obtain $\{o_{i,t}, h_{i,t}, a_{i,t}\}$.

A.2 Parametrization

We split parameters into exogenous (set or calibrated externally) and structural (estimated via likelihood).

Exogenous/Calibrated Parameters:

- $\{\Pi_y,\, \Pi_q,\, \Pi_P\}$: Transition matrices for log-income, log-unit-rent, log-unit-house-price. Estimated by GMM matching PSID age-bin residual variances (Section 4).
- r: Net interest rate on financial assets. Set to 3% per annum, reflecting average mortgage yields.
- δ: Housing depreciation rate. Set to 2% per period (three-year interval).
- ϕ: Downpayment fraction. Calibrated to 20% to match typical loan-to-value requirements.

- ζ: Moving cost fraction. Calibrated to 5% of current housing expenditure.
- $\psi_1 = 1$: Owners housing taste shifter (normalization).
- ξ: Taste-shock scale. Initially set to match the overall homeownership rate; re-estimated alongside structural parameters.

Structural Parameters to Estimate:

$$\Theta_{\text{struct}} = \{\beta,\ \nu,\ \gamma,\ \psi_0,\ \theta_B\},$$

where

- $\beta \in (0, 1)$: Subjective discount factor.
- $\nu > 0$: Intratemporal CES parameter (elasticity of substitution between c and h).
- $\gamma > 0$: CRRA coefficient over the CES composite.
- $\psi_0 \in [0, 1]$: Renters housing taste shifter.
- $\theta_B > 0$: Bequest-motive scaling parameter.

B Estimation Strategy

Maximum Likelihood Estimation. We fit Θ_{struct} by maximizing the simulated likelihood of observed PSID tenure transitions $\{o_{i,t}\}$. Specifically:

1. *Solve and Simulate.* For each candidate Θ_{struct}, solve the model as described above, then simulate a panel of N_{sim} households over T periods. Record, at each simulated state $(s_{i,t},\ a_{i,t},\ h_{i,t},\ o_{i,t})$, the choice probability

$$\pi_{i,t}(\Theta) = \Pr\big(o_{i,t+1} = 1 \mid s_{i,t}, a_{i,t}, h_{i,t}, o_{i,t}\big) = \frac{\exp\big(W_t(s_{i,t}, a_{i,t}, h_{i,t}, o_{i,t};\ 1)/\xi\big)}{\sum_{o' \in \{0,1\}} \exp\big(W_t(s_{i,t}, a_{i,t}, h_{i,t}, o_{i,t};\ o')/\xi\big)}.$$

2. *Construct Log-Likelihood.* Using the actual PSID tenure choices $\{o_{i,t}^{\text{PSID}}\}$, form

$$\mathcal{L}(\Theta) = \sum_{i=1}^{N_{\text{PSID}}} \sum_{t=1}^{T-1} \Big[\, o_{i,t+1}^{\text{PSID}} \ln \pi_{i,t}(\Theta) \ +\ (1 - o_{i,t+1}^{\text{PSID}}) \ln\big(1 - \pi_{i,t}(\Theta)\big)\Big].$$

3. *Optimization.* We re-parameterize

$$x \ =\ \Big(\log \tfrac{\beta}{1-\beta},\ \log \nu,\ \log \gamma,\ \log \tfrac{\alpha}{1-\alpha},\ \log \tfrac{\psi_0}{1-\psi_0},\ \log \theta_B,\ \log \xi\Big),$$

so that $x \in \mathbb{R}^7$ maps bijectively to Θ_{struct}. We then maximize $\mathcal{L}(\Theta(x))$ via the Nelder-Mead algorithm. Standard errors are obtained from the inverse Hessian at the optimum.

GMM for Exogenous Processes. Before likelihood estimation, we separately estimate $\{\Pi_y, \Pi_q, \Pi_P\}$ by matching PSID age-bin residual variances to their theoretical AR(1)/PT profiles (Section **??**) via a two-step GMM. Details appear in Section 4.

Identification. Tenure-choice patterns across age, asset levels, and observed covariates identify $\{\beta, \nu, \gamma, \alpha, \psi_0, \theta_B, \xi\}$. In particular, the intertemporal trade-off β and curvature γ are pinned down by how households smooth consumption versus housing demand, while the CES elasticity ν (conditional on weight α) determine substitution between c and h. The renter taste shifter ψ_0 is identified by the renter-owner gap in housing consumption, and θ_B by late-life asset accumulation.

All simulations in paper has been conducted on sample of 10 000 agents.

B Data Work

We begin by constructing age-bin residual variances for three series-log income, log unit house price, and log unit rental price-using PSID data from 2001-2021. These residuals serve as inputs for our GMM procedure that fit AR(1) and persistent-transitory processes. All code below is implemented in Stata, with final datasets saved for Python estimation.

1. ACS CPI Adjustment (`0000.real2010variables.do`). We start with the ACS cross-section (`usa_00009.dta`), merging in a pre-computed CPI series (`cpi2010.dta`) by year. For each nominal variable X, we compute

$$X_{2010} \;=\; X \times \frac{100}{\text{CPI}_{\text{year}}},$$

to express all values in constant 2010 dollars. We generate:

`mortamt1_2010`, `owncost_2010`, `rent_2010`, `hhincome_2010`, `valueh_2010`, `incwage_2010`,

along with control variables {`incss_2010`, `incearn_2010`, `costelec_2010`, `costgas_2010`, `costwatr_2010`, `cost`
The resulting dataset is saved as `usa_00009_2010.dta`.

2. PSID Housing-Price Residuals (`var_rooms_p0419.do`). From `PSID_panel_2010.dta`, restrict to heads of household aged $27 \le \texttt{age} \le 80$, homeowners ($\texttt{own\_} = 1$), valid house values $1 \le \texttt{hp\_2010} \le 9{,}999{,}997$, and primary family members ($\texttt{rela\_} = 10$). Define:

$$\ln hp_{i,t} \;=\; \ln\!\left(\frac{\texttt{hp\_2010}}{\texttt{rooms\_}}\right), \quad \ln hhincome_{i,t} \;=\; \ln(\texttt{tota\_y\_2010}), \quad \ln \text{wealth}_{i,t} \;=\; \left(\texttt{wealth\_2010} - \texttt{he\_2010}\right).$$

We estimate the pooled regression

$$\ln hp_{i,t} = \beta_0 + \beta_1 \ln hhincome_{i,t} + \beta_2\, \texttt{moved\_}_{i,t} + \sum_k \beta_k\, \mathbb{I}(\text{race}_k) + \sum_j \beta_j\, \mathbb{I}(\text{house\_type}_j) + \beta_x \ln \text{wealth}_{i,t} + \beta_t\, \mathbb{I}(\text{time}_t)$$

including individual and time fixed effects (clustered by id). We save the residuals $\widehat{\varepsilon}_{i,t}^{(p)}$ as p=resid, then collapse $\{\widehat{\varepsilon}_{i,t}^{(p)}\}^2$ into three-year age bins $q = 1, \ldots, 18$:

$$\widehat{\sigma}_{p,q}^2 = \frac{1}{N_q} \sum_{\substack{i,t: \\ \text{age}(i,t) \in \text{bin } q}} \left(\widehat{\varepsilon}_{i,t}^{(p)}\right)^2.$$

These age-bin variances are saved in PSID_imputed_final_hp.dta.

3. PSID Rental-Price Residuals (var_rooms_q0419.do). Restrict to renters (own_ $=$ 5), ages $27 \leq \texttt{age} \leq 80$, valid rent $1 \leq \texttt{rent\_2010} \leq 99{,}996$, and rela_ $=$ 10. Define:

$$\ln rent_{i,t} = \ln\left(12 \times \frac{\texttt{rent\_2010}}{\texttt{rooms\_}}\right), \quad \ln hhincome_{i,t} = \ln(\texttt{tota\_y\_2010}), \quad \ln \text{wealth}_{i,t} = (\texttt{wealth\_2010}).$$

We run a similar pooled regression with person and time fixed effects, save residuals $\widehat{\varepsilon}_{i,t}^{(q)}$, and collapse $\{\widehat{\varepsilon}_{i,t}^{(q)}\}^2$ into age-bin variances $\widehat{\sigma}_{q,q}^2$. The results appear in PSID_imputed_final.dta.

4. PSID Income Residuals (02.wage_residual_PSID.do). Restrict to working heads (jobstat_r $=$ 1), ages $27 \leq \texttt{age} \leq 80$, and positive income $\texttt{y\_r\_2010} > 0$. Define:

$$\ln wage_{i,t} = \ln(\texttt{y\_r\_2010}), \quad \texttt{exp}_{i,t} = \texttt{age}_{i,t} - \texttt{educ\_years\_r}_{i,t} - 6, \quad \texttt{age2} = (\texttt{age}_{i,t})^2, \quad \texttt{exp2} = (\texttt{exp}_{i,t})^2.$$

We estimate via reghdfe:

$$\ln wage_{i,t} = \beta_0 + \beta_1\, \texttt{age}_{i,t} + \beta_2\, \texttt{age2}_{i,t} + \beta_3\, \texttt{exp}_{i,t} + \sum_\ell \beta_\ell\, \mathbb{I}(\text{controls}) + \alpha_i + \tau_t + \xi_{i,t}.$$

We demean residuals $\widehat{\xi}_{i,t}$ by adding back the unconditional mean of fitted $\ln wage$, then collapse $\{\widehat{\xi}_{i,t}\}^2$ into age-bin variances $\widehat{\sigma}_{y,q}^2$. These are saved in PSID_resid_wage.dta.

A GMM Estimation of Age-Bin Variance Profiles

Having extracted age-bin residual variances

$$\left\{\widehat{\sigma}_{y,q}^2\right\}_{q=1}^{18}, \quad \left\{\widehat{\sigma}_{p,q}^2\right\}_{q=1}^{18}, \quad \left\{\widehat{\sigma}_{q,q}^2\right\}_{q=1}^{18},$$

we match each series to its theoretical counterpart under AR(1) or persistent-transitory processes. All estimation is implemented in Python (see `analysis.py`).

1. Rents and House Prices: AR(1) in Logs. For $X_t \in \{p_t, q_t\}$, assume:

$$\ln X_t = \rho_X \ln X_{t-1} + \eta_t, \qquad \eta_t \sim \mathcal{N}(0, \sigma^2_{\eta_X}).$$

Under this specification, starting from $\ln X_0 = 0$, the variance of $\ln X_t$ at age bin t is

$$m_X(t; \rho_X, \sigma_{\eta_X}) = \sigma^2_{\eta_X} \sum_{j=0}^{t-1} \rho_X^{2j}, \quad t = 1, \dots, 18.$$

Let $\widehat{\boldsymbol{\varepsilon}}^2_X = [\widehat{\sigma}^2_{X,1}, \dots, \widehat{\sigma}^2_{X,18}]'$. We minimize the GMM criterion

$$J_X(\rho_X, \sigma_{\eta_X}) = \left[\widehat{\boldsymbol{\varepsilon}}^2_X - \mathbf{m}_X(\rho_X, \sigma_{\eta_X})\right]' W_X \left[\widehat{\boldsymbol{\varepsilon}}^2_X - \mathbf{m}_X(\rho_X, \sigma_{\eta_X})\right],$$

using a two-step diagonal weighting matrix W_X. We parametrize $\rho_X = 1/(1 + e^{-x_2})$ and $\sigma_{\eta_X} = e^{x_1}$ to enforce $\rho_X \in (0, 1)$, $\sigma_{\eta_X} > 0$. Optimization uses a standard nonlinear solver until convergence.

2. Income: Persistent-Transitory in Logs. For $\ln y_t$, suppose:

$$\ln y_t = P_t + \varepsilon_t, \quad P_t = \rho_y P_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, \sigma^2_{\eta_y}), \quad \varepsilon_t \sim \mathcal{N}(0, \sigma^2_{\varepsilon_y}).$$

Starting from $P_0 = 0$, the theoretical variance at bin t is

$$m_y(t; \rho_y, \sigma_{\eta_y}, \sigma_{\varepsilon_y}) = \sigma^2_{\varepsilon_y} + \sigma^2_{\eta_y} \sum_{j=0}^{t-1} \rho_y^{2j}, \quad t = 1, \dots, 18.$$

Let $\widehat{\boldsymbol{\varepsilon}}^2_y = [\widehat{\sigma}^2_{y,1}, \dots, \widehat{\sigma}^2_{y,18}]'$. We minimize

$$J_y(\rho_y, \sigma_{\eta_y}, \sigma_{\varepsilon_y}) = \left[\widehat{\boldsymbol{\varepsilon}}^2_y - \mathbf{m}_y(\rho_y, \sigma_{\eta_y}, \sigma_{\varepsilon_y})\right]' W_y \left[\widehat{\boldsymbol{\varepsilon}}^2_y - \mathbf{m}_y(\rho_y, \sigma_{\eta_y}, \sigma_{\varepsilon_y})\right],$$

with a two-step diagonal weighting matrix W_y. We parametrize $\rho_y = 1/(1 + e^{-x_2})$, $\sigma_{\eta_y} = e^{x_1}$, $\sigma_{\varepsilon_y} = e^{x_3}$, ensuring positivity.

3. Python Implementation. We load the merged PSID residual dataset (ages 27-80) and compute weighted variances by age bin for `y_resid`, `p_resid`, `q_resid`, yielding Python arrays `eps2_y`, `eps2_p`, `eps2_q` of length 18. We then instantiate our `GMMEstimator` class:

- `moment_ar(x, eps2)` returns $2 - \sigma^2_\eta \sum_{j=0}^{t-1} \rho^{2j}$. We parametrize $\rho = 1/(1 + e^{-x_2})$, $\sigma_\eta = e^{x_1}$.
- `moment_pt(x, eps2)` returns $2 - \left[\sigma^2_\varepsilon + \sigma^2_\eta \sum_{j=0}^{t-1} \rho^{2j}\right]$. We parametrize $\rho = 1/(1 + e^{-x_2})$, $\sigma_\eta = e^{x_1}$, $\sigma_\varepsilon = e^{x_3}$.

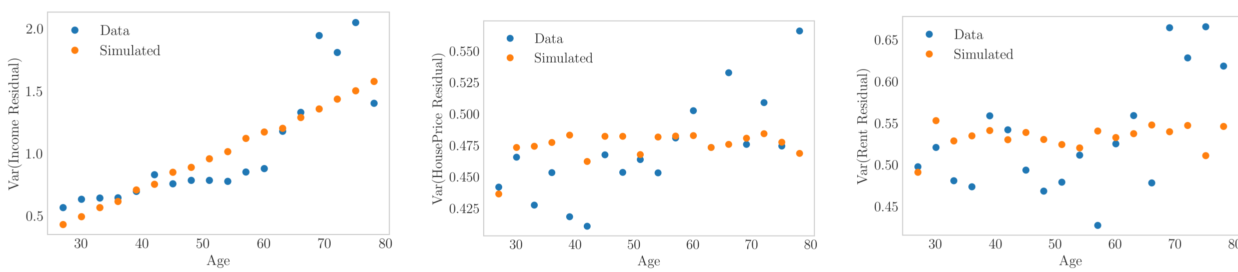
After optimizing each criterion, we apply `transform_ar(x)` or `transform_pt(x)` to recover $(\rho_X, \sigma_{\eta_X})$ or $(\rho_y, \sigma_{\eta_y}, \sigma_{\varepsilon_y})$.

4. Calibrated Values. The resulting GMM estimates (18 age bins) are:

$$\boxed{\begin{array}{lll} \rho_q = 0.261123, & & \sigma_{\eta_q} = 0.705475, \\ \rho_p = 0.258047, & & \sigma_{\eta_p} = 0.664769, \\ \rho_y = 0.999000, & \sigma_{\eta_y} = 0.259332, & \sigma_{\varepsilon_y} = 0.600596. \end{array}}$$

Figure 13 plots $\widehat{\sigma}^2_{y,t}$, $\widehat{\sigma}^2_{p,t}$, and $\widehat{\sigma}^2_{q,t}$ against age, revealing (i) a slow upward trend in income variance early in life and slight leveling in later bins; (ii) a monotonic rise in rental-price variance; and (iii) a similar but somewhat less pronounced rise in house-price variance.

Figure 13: Residual-Variance vs Simulation



(a) Income (b) House-Price (c) Rent

Table 2 presents the maximum-likelihood estimates of the seven structural parameters. These complement the externally calibrated exogenous parameters in Table 1.

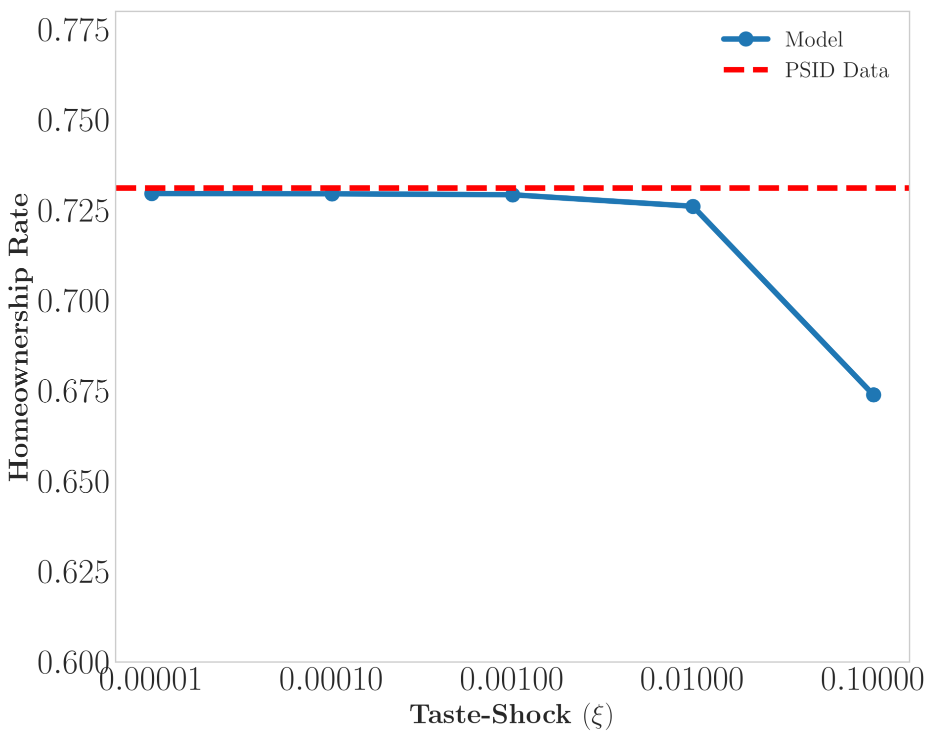
B Robustness to Taste-Shock Scale ξ

To assess the robustness of our results to assumptions about taste heterogeneity, we examine how the average homeownership rate responds to changes in the scale of the idiosyncratic taste shock ξ. Economically, ξ governs the influence of deterministic value differences versus unobserved utility draws in tenure choice: a small ξ implies nearly deterministic behavior (agents follow the policy function closely), while a large ξ introduces substantial randomness in choices.

We re-solve the model and simulate life-cycle tenure outcomes for a range of ξ values, spaced logarithmically from 10^{-5} to 10^{-1}. Figure 14 plots the resulting average homeownership rates in the model (solid blue) against the empirical PSID benchmark (dashed red). The results are reassuring: for $\xi \leq 0.01$, the models predictions are essentially flat and stable, indicating that tenure outcomes are primarily driven by underlying fundamentals rather than noise.

Only when ξ becomes implausibly large ($\xi = 0.1$) do we observe a marked decline in homeownership, driven by excessive random switching. Our calibrated value of $\widehat{\xi} = 0.01$ lies well within the flat region, implying that the model achieves realistic fit without relying on artificially high behavioral noise. This reinforces that homeownership in the model is primarily a result of economic selectionassets, prices, and riskrather than exogenous idiosyncratic taste.

Figure 14: Sensitivity of Average Homeownership to Taste-Shock Scale ξ.



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