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OPTIMAL PORTFOLIO CHOICE WITH PREDICTABILITY IN HOUSE PRICES AND TRANSACTION COSTS

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Optimal Portfolio Choice with Predictability in House Prices and Transaction Costs*

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Abstract

We develop and solve a model of optimal portfolio choice with transaction costs and predictability in house prices. We model house prices using a process with a time-varying expected growth rate. Housing adjustments are infrequent and characterized by both the wealth-to-housing ratio and the expected growth in house prices. We find that the housing portfolio share immediately after moving to a more valuable house is higher during periods of high expected growth in house prices. We also find that the share of wealth invested in risky assets is lower during periods of high expected growth in house prices. Finally, the decrease in risky portfolio holdings for households moving to a more valuable house is greater in high-growth periods. These findings are robust to tests using household-level data from the Panel Study of Income Dynamics (PSID) and Survey of Income and Program Participation (SIPP) surveys. The coefficients obtained using model-simulated data are consistent with those obtained in the empirical tests.

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1 Introduction

Housing plays an important role in the portfolio choices of households because it accounts for an important fraction of their wealth. Housing possesses three specific characteristics that make portfolio allocation decisions nontrivial. First, it is a durable consumption good and an investment asset. Second, moving to a new house involves high transaction costs; therefore, homeowners would find it optimal to rebalance their housing position less frequently than other investment assets. Third, house prices present a certain degree of predictability. In this paper, we generalize a well-known portfolio choice problem introduced by Grossman and Laroque (1990) (GL henceforth) to account for these three specific characteristics of housing. We first present empirical evidence of the predictability of house prices. Using data on aggregate housing prices for the U.S., we estimate a housing pricing process where its expected growth rate switches among high-, medium-, and low-growth regimes. Our estimates indicate that house prices in the U.S. have most frequently been in a medium-growth regime, with essentially flat real house prices. Conversely, real house prices grew 9.42% on average in periods of high expected growth and declined 16.19% in periods of low expected growth. We also estimate the model at the U.S. state level using the repeat sales indexes constructed by the Federal Housing Finance Agency (FHFA). The results demonstrate that there are important differences in expected growth rates and timing across U.S. states.

We introduce these regime-switching house pricing processes in a partial equilibrium model that solves for the housing consumption and portfolio choices of an agent. In the model, the agent incurs a transaction cost when selling the house that she currently owns to buy a new one. The existence of transaction costs makes housing consumption lumpy. Our model delivers qualitative and quantitative implications for the optimal consumption and portfolio decisions subject to transaction costs. We test such implications using household level data on wealth, housing values, and asset holdings available from the Panel Study of Income Dynamics (PSID) and the U.S. Census Bureau's Survey of Income and Program Participation (SIPP). We construct an indicator that captures the existence of periods of high expected growth in house prices at the U.S. state level. This indicator is based on the smoothed probabilities of being in a high-growth regime. In the empirical tests, we employ this indicator to determine whether housing return predictability affects housing and non-housing portfolio holdings across households. Moreover, we create a large panel of model simulated data for households with heterogeneity in transaction costs, locations across the U.S., and the initial ratio of total wealth to housing wealth (i.e., the wealth-to-housing ratio). We use these model-generated data to run tests similar to those that we empirically estimate using PSID and SIPP data.

Our main findings can be summarized in three sets of contributions. First, we demonstrate the effects of transaction costs and house price predictability on the portfolio holdings of housing assets. As in the GL model, an agent only moves to a more valuable house when her wealth-to-housing ratio reaches an optimal upper boundary.[1] Similarly, an agent only moves to a less valuable house when her wealth-to-housing ratio reaches an optimal lower boundary. In contrast to GL, these boundaries are time varying and depend on the dynamics of the expected growth rate of house prices. As a result, in our model, two state variables determine the agent's decisions: (i) the wealth-to-housing ratio and (ii) the time-varying expected growth rate of house prices. The intuition behind these state variables is as follows. Agents only move to a more valuable house when they are too wealthy for the house in which they live. Conversely, they move to a less valuable house when their current house is too large for their declining wealth; in this case, the agents decide to substitute housing for non-housing consumption and non-housing assets. This mechanism is richer when expectations about future house price growth change over time. In periods of high expected growth in house prices, waiting to move to a more valuable house makes the potential new house more expensive over time. This consideration is why a lower wealth-to-housing ratio is required to purchase a more valuable house in periods of high expected growth in house prices.[2]

Second, we reveal the implications of transaction costs and house price predictability for housing adjustments. We find a lower adjustment in the wealth-to-housing ratio for households that move to a more valuable house during periods of high expected growth in house prices compared to households moving in other periods. The housing portfolio share immediately after moving is higher for households moving during periods of high expected growth in house prices. Empirically, the decline in the wealth-to-housing ratio before and after moving is 61.2% lower for households moving during periods of high expected growth in house prices.

Third, we reveal the implications of housing transaction costs and house price predictability

[1] We use "more valuable house" throughout the paper to denote that the value of the house is higher in terms of price per square meter times the size of the house.

[2] The opposite argument is at work during periods of low expected growth in house prices: the wealth-to-housing ratio that determines the lower bound during a regime of high price growth is significantly lower than the ratio that determines the lower bound during a regime of lower house price growth.

for the portfolio choices of non-housing assets. We find that the share of wealth invested in risky assets is lower during periods of high expected growth in house prices. Specifically, in a regime of high expected growth, a $\$100,000$ increase in home equity increases the risky share of liquid wealth by 13.4%, whereas a $\$100,000$ increase in home equity in any regime of lower growth increases the risky share of liquid wealth by 24.8%. Additionally, conditional on moving, the change in risky asset holdings relative to total wealth is higher in periods of high expected growth in house prices than in any regime of lower growth. The average decrease in risky stock holdings relative to liquid wealth is approximately 5.2% for households that purchase more valuable houses in periods of high expected growth.

Finally, through simulations, we replicate the same tests that we run on the PSID and SIPP data. Our simulation results suggest that the model explains the important features that we find in the data. Specifically, we demonstrate that the calibrated model captures the empirical results in terms of sign and magnitude.

Related Literature

Our paper follows the literature studying investment decision problems under fixed adjustment costs.[3] The model in Grossman and Laroque (1990) is a milestone in this literature. There are two lines of research related to our study that depart from this seminal paper. First, the empirical aspect of our analysis is connected to the literature on (S,s) models, which empirically investigates the inaction region and tests the GL model, such as Eberly (1994), Attanasio (2000), Martin (2003), and Bertola, Guiso, and Pistaferri (2005).

Second, our model and its primary implications are related to papers that focus on particular implications of portfolio choice in the presence of housing, such as Flavin and Yamashita (2002), Damgaard, Fuglsbjerg, and Munk (2003), Cocco (2005), Yao and Zhang (2005), Flavin and Nakagawa (2008), Van Hemert (2008), Stokey (2009b), and Fischer and Stamos (2013). In general, this stream of the literature assumes that house prices evolve stochastically following a random walk process. Damgaard, Fuglsbjerg, and Munk (2003) also generalize the GL setting by allowing for both perishable and durable goods, the price of which follows a geometric Brownian motion. This theoretical study focuses on understanding the relationship between perishable and durable

[3] See Stokey (2009a) for a review of stochastic control problems in the presence of fixed adjustment costs.

consumption and the impact of specific joint dynamics of durable good and stock prices on portfolio choices. Cocco (2005) finds that investment in housing plays a crucial role in explaining the patterns of PSID cross-sectional variation in the composition of wealth and level of stock holding. Because housing investments are risky, younger and poorer homeowners have limited financial wealth to invest in stocks. Yao and Zhang (2005) investigate households' asset allocation and housing decisions in a life-cycle model. This model predicts that housing investment has a negative effect on stock market participation, as in Cocco (2005). Chetty and Szeidl (2011) distinguish between home equity wealth and mortgage debt, as they have opposite signed effects on portfolio choice. They find that increases in mortgage debt reduce stock holding significantly, whereas increases in home equity wealth raise stock holding. In addition, they provide evidence that higher housing investment substantially reduces the amount that households invest in risky stocks.[4] Fischer and Stamos (2013) also study the decisions of households that face time-varying expected growth rates in house prices and show that homeownership rates, as well as the sizes of housing and mortgages, increase during good periods of housing market cycles. However, their results do not point to a statistically significant impact of the regime of housing market cycles on stock holding.[5]

2 Predictability in Housing Markets

This section presents evidence supporting the time variation in expected house price growth rates for the U.S. at the national and state levels. We estimate a regime switching mechanism, as in Hamilton (1990), to identify time-varying first moments. In Appendix A, we demonstrate that the predictability of housing prices is robust to the approach whereby price-rent ratios predict

[4]Our paper is also related to the sizable literature that incorporates stock return predictability into portfolio choice models. Lynch and Balduzzi (2000) examine the re-balancing behavior of an agent in the presence of stock return predictability when transaction costs are non-zero. Brennan, Schwartz, and Lagnado (1997), Barberis (2000), Kim and Omberg (1996), and Campbell and Viceira (1999) analyze the impact of myopic versus dynamic decision-making when stock returns are predictable, but they refrain from considering the impact of transaction costs. Instead, in this paper, we analyze the impact of housing, as a consumption and investment good, on portfolio choices in the presence of transaction costs on housing and housing return predictability.

[5]Our work differs from Fischer and Stamos (2013) in at least three dimensions. First, we estimate an indicator to capture the periods of high expected growth in house prices at the U.S. state level. This indicator allows us to empirically quantify the effect of house price predictability on portfolio choice decisions. Second, Fischer and Stamos (2013) do not find that the regime of the housing market affects the share of wealth invested in the stock market using PSID data. However, we provide evidence showing that the share of wealth invested in risky assets is lower during periods of high expected growth in house prices. Third, our model is parsimonious and provides testable implications that can be compared to the GL model and Damgaard, Fuglsbjerg, and Munk (2003).

future returns on housing and how these two measures of predictability are empirically related.[6] In particular, we consider a house price process of the form:

$$\frac{dP}{P} = \mu_i dt + \sigma_p dZ, \tag{1}$$

where P denotes the house price level, μ_i is the expected growth rate when regime i is realized, and σ_p is the standard deviation of the growth rate, which we do not consider to be regime dependent. The dynamics of the underlying regime i follow a homogeneous first-order Markov chain. Let us assume that the expected growth in house prices, μ_i, may only take three values: high (μ_h), medium (μ_m), or low (μ_l).

Column (1) of Table 1 reports the parameter estimates of equation (1) using the U.S. house price data constructed in Shiller (2005). The sample period is $1925-2010$, and the data frequency is annual.[7] We also report estimates using quarterly data from the Federal Housing Finance Agency (FHFA) for the U.S. in aggregate and U.S. states. We adjust all of the data for core inflation, which measures inflation in the personal consumption expenditure basket less food and energy. For the long time series of U.S. aggregate data, we estimate an average real annual growth rate of -16.19%,-0.15%, and 9.42% during regimes of low, medium, and high expected growth in house prices, respectively. We reject the null hypothesis that the expected growth rate is identical across regimes.[8] The conditional probability of remaining in the regime of medium growth in house prices, λ_{mm}, is 96.86% at the aggregate U.S. level. This result implies that the economy is typically in a regime of medium growth in house prices.

The probability of a shift from the medium- to high-growth regime, λ_{mh}, is only 3.13%. Finally, this estimation exercise demonstrates that the conditional probability of switching from a high- to medium-growth regime, λ_{hm}, is 12.09%, whereas the conditional probability of switching from the

[6] We find strong linkages between the rent-price ratio and the estimated probabilities of being in a high-growth regime for housing prices. This result is relevant because the dividend-price ratio has been traditionally used as a predictor variable for stock returns.

[7] The Case-Shiller House Price Index (HPI) time series dates back to 1890 but is more reliable after 1925.

[8] Tests for the number of regimes are typically difficult to implement because the variables in models with multiple regimes do not follow standard distributions. Under the null hypothesis of a single regime in the simple two-regime model, the parameters of the other regime are not identified, and thus, there are unidentified nuisance parameters. The presence of unidentified parameters means that conventional likelihood ratio tests are not asymptotically χ^2 distributed. We report a test for linearity in all output, which is based on the likelihood-ratio statistic between the estimated model and derived linear model. Then, we report the approximate upper bound for the significance level of the LR statistic as derived by Davtes (1977). For an example of this procedure, see Garcia and Perron (1996).

high- to low-growth regime, λ_{hl}, is 9.45%. This result implies that periods of high growth in house prices are not very persistent.

[TABLE 1 HERE]

Figure 1 depicts the time series of real annual housing returns and the smoothed probability of being in regimes of high and low expected growth in house prices. The figure illustrates that the probability of being in a high-growth regime is greater than 50% on only two occasions. Those two occasions correspond to World War II and the most recent housing market boom. Regarding the latter, the probability of being in high-growth regime began to grow in 1996 and remained at its maximum value from 2000 to 2005. The value of this probability was extraordinarily high and persistent during this recent period. The high value of the smoothed probability of being in a regime of low expected growth in house prices illustrates that a period of downward correction in aggregate housing prices followed this housing market boom.

[FIGURE 1 HERE]

We use quarterly state-level FHFA house price indexes beginning in the first quarter of 1983.[9] Estimates using the FHFA aggregate index result in lower annualized growth rates than those estimated with the Case-Shiller index (see Column (2)). Both indexes are constructed using the same basic repeated sales methodology but use different data sources and implement the mechanics of the repeat-valuations framework in distinct ways.[10] Overall, FHFA HPI measures the aggregate price appreciation of a broad middle segment of the U.S. stock of single-family homes.

To account for the geographic heterogeneity in housing markets, we further analyze house prices at the state level.[11] Table 1 reports the parameter estimates for five of the most populated U.S. states (Columns (3)-(7)). During the most recent housing market boom, not all U.S. states

[9] House price indexes at the state level are extremely noisy for a number of states before the mid-80s, with sharp appreciation periods immediately followed by sharp depreciation periods. The noise in the first part of the sample makes the regime estimation challenging. The series become more stable for most states after the mid-80s. The same issue is also documented by Del Negro and Otrok (2007) who argue that recent movements in house prices at U.S. state level were mainly due to expansionary monetary policy.

[10] The FHFA HPI is a good estimate of the typical price appreciation of single-family houses, whereas the Case-Shiller HPI is a good estimate of the capital appreciation that would result from owning a representative sample of U.S. homes.

[11] Other levels of aggregation (i.e., metropolitan statistical area) are available, but we find that the state-level data is sufficiently disaggregated to establish our empirical conclusions.

experienced similar house price patterns to the U.S. aggregate. For example, house prices rose by 100% in California and then fell by 60%, whereas they barely moved in Texas. Part of this cross-sectional variation may stem from institutional differences across states, but that aspect is beyond the scope of this paper. Appendix A reports these results for all U.S. states. There is the substantial heterogeneity in house price processes across U.S. states. For some states, such as California, Florida, and New York, the high-growth regime displays quarterly mean real growth rates of 2.75%, 3.05%, and 2.54%, respectively, whereas for other states, such as Illinois and Texas, the high-growth regimes are characterized by modest growth in house prices with quarterly mean real growth rates of 1.13% and 0.45%, respectively.

Historically, regimes of high growth in house prices did not occur simultaneously across the different U.S. states. The recent period of boom-and-bust in house prices is an exception. Panels A and B of Figure 2 depict the smoothed probability of being in a regime of high or low growth, respectively.[12] This figure illustrates the pronounced cyclicality in the quarterly house price growth rates. Periods of high growth in house prices occur and present a long duration in some U.S. states. For example, the expected duration of a high-growth regime is 6.12 years for California, 5.75 years for Florida, 5.50 years for New York, and 4.20 years for Illinois. These expected durations are lower than that of the U.S. aggregate, 8.75 years, implying that several U.S. states have much longer cycles. For example, Texas has less pronounced cycles, and the spread between its high and low growth rates is not substantial. It has experienced relatively modest growth, with the expected duration of the high-growth regime being 17.25 years.[13]

[FIGURE 2 HERE]

Overall, the housing returns for the U.S. states are well captured by a three-regime switching model, and the mean growth rate in each regime is accurately portrayed. To understand the main implications of house price predictability for portfolio decisions, we first examine a model with infrequent housing adjustments in the presence of predictability. Then, we develop relevant qual-

[12] Note that the probability of being in a regime of medium growth in house prices is high when both the probability of being in the regimes of high growth (Panel A) and low growth (Panel B) are low.

[13] Figure 2 suggests that episodes of high growth were driven by a small group of outlier states in the first part of the sample, and therefore, these episodes were not synchronized. However, the effects of the recent period of high growth in house prices ($1999-2006$) are synchronized across several U.S. states. This period is identified as a regime of high growth in house prices for the U.S. aggregate using the short time series from the FHFA HPI or the long time series from the Case-Shiller HPI.

itative implications that we test using data featuring extensive information on housing purchases, portfolio holdings, and measures of housing return predictability at the state level.

3 The Model

We examine the consumption and portfolio choice of an agent in a continuous time economy with a risk-free asset, a risky asset, and two consumption goods: a perishable and a durable good, housing, with uncertain and persistent price evolution. Transactions in the housing market are costly. The infinitely lived agent has non-separable Cobb-Douglas preferences over housing and non-housing goods. She derives utility over a trivial flow of services generated by the house. This specification can be generalized as long as preferences are homothetic. Davis and Ortalo-Magne (2011) present evidence from the Decennial Census of Housing indicating that expenditure shares on housing are constant over time. The period utility function can be expressed as:

$$u(C, H) = \frac{1}{1-\gamma}(C^{\beta} H^{1-\beta})^{1-\gamma}, \tag{2}$$

where H is the service flow from the house (in square footage) and C represents non-housing consumption. $1 - \beta$ measures the preference for housing relative to non-housing consumption goods, and γ is the coefficient of relative risk aversion. The period-by-period budget constraint requires that the agent spends her income on the consumption of non-housing goods, changing the house size, and investing in risky and risk-free assets for the following period.

The housing stock depreciates at a physical depreciation rate δ. If the agent does not buy or sell any housing assets, the dynamics of the housing stock follows the process:

$$dH = -\delta H dt, \tag{3}$$

for a given initial condition $H_0 = \bar{H}$. We assume that the square foot price of the house, P, follows a geometric Brownian motion with time-varying drift:

$$dP = P\ \mu_i dt + P\ \sigma_P(\rho_{PS} dZ_1 + \sqrt{1 - \rho_{PS}^2} dZ_2), \tag{4}$$

where μ_i is the time-varying drift and ρ_{PS} is the correlation coefficient between the house price, P, and value of the risky financial asset, S, defined below.

Following Section 2, we assume that house price growth is predictable in the sense that μ_i follows an n-regime Markov chain and i takes values in the set $1, ..., n$. The generator matrix of the Markov chain is $\Lambda = [\lambda_{jk}]$ for $j, k \in \{1, ..., n\}$. Thus, the probability of moving from regime j to k within the time Δt is approximately $\lambda_{jk}\Delta t$. We solve the model for the general case of n regimes, but we focus on the three-regime case in the numerical section of the paper. We assume that the agent knows with certainty the economy's regime; thus, μ_i is observable by the agent at time t.

Let W define the agent's wealth in units of non-housing consumption. Wealth is composed of investments in financial assets (riskless and risky financial assets) and the value of current housing stock:

$$W = B + \Theta + HP, \tag{5}$$

where B is the wealth held in the riskless asset and Θ is the amount invested in the risky asset. The price of the risky asset, S, follows a geometric Brownian motion:[14]

$$dS = S\ \alpha_S dt + S\ \sigma_S dZ_1. \tag{6}$$

Given the process for risky asset prices, the housing stock's law of motion, and house price dynamics, wealth evolves according to the following process in regime i (for $i = 1, ..., n$):

$$\begin{aligned} dW = {} & [r(W - HP) + \Theta(\alpha_S - r) + (\mu_i - \delta)HP - C]dt \\ & + (\Theta\sigma_S + HP\rho_{PS}\sigma_P)dZ_1 + HP\sigma_P\sqrt{1 - \rho_{PS}^2}dZ_2. \end{aligned} \tag{7}$$

The homeowner can sell the house at any time τ_A. The agent incurs a transaction cost that is proportional to the value of the house that she is selling. As the quantity of housing changes discretely at the stopping time τ_A, the notation $H(\tau_A^-)$ is used to distinguish the amount of housing

[14] A large number of studies find that aggregate stock market returns are also predictable. We also estimate the parameters of equation (1) using annual values for the S&P500 index. We obtain a mean of the nominal annual growth rate of -19.90% during the low-growth regimes and 12.72% during the high-growth regimes. We are unable to reject the null hypothesis that the expected growth is identical across regimes for stock prices due to the noise around the estimates. The relatively stronger results for predictability in housing prices leads us to consider a model with predictability in housing prices and not in stock prices.

immediately prior to the sale from the quantity of housing immediately after the sale, $H(\tau_A)$. At the instant the house is sold, the homeowner's wealth is $W(\tau_A) = W(\tau_A^-) - \epsilon P(\tau_A)H(\tau_A^-)$, where $\epsilon P(\tau_A)H(\tau_A^-)$ is the transaction cost. The homeowner first decides whether it is optimal to instantaneously sell the house by comparing the value function associated with her problem conditional on selling a house (action) with the value function conditional on not selling (inaction).

In addition to voluntary housing adjustments, we incorporate moves that are required for exogenous reasons. Marital status changes that involve relocating to a new house and changes in family size are two possible interpretations of the exogenous moves. Following Stokey (2009b), we assume that this shock follows a Poisson distribution with a constant arrival rate κ. Let the stopping time τ_X define the arrival of the next exogenous relocation shock. The homeowner's next housing adjustment occurs at the minimum of the time of the exogenous relocation shock, and the time the agent chooses the next adjustment in the case the exogenous shock has not occurred, $\tau = \tau_A \wedge \tau_X$.

The value function of this problem, $V(W(0), P(0), H(0), i)$, satisfies the following Bellman equation in which the consumer chooses the optimal consumption of non-housing and housing, asset allocation, and optimal stopping time for buying a new house:

$$V(W(0), P(0), H(0), i) = \sup_{C,\Theta,H(\tau),\tau} E\left[\int_0^\tau e^{-\rho t} u(C, H)dt + e^{-\rho\tau} V(W(\tau), P(\tau), H(\tau), i)\right], \qquad (8)$$

for $i = 1, ..., n$ and $W(\tau) = W(\tau^-) - \epsilon P(\tau)H(\tau^-)$. We can use the homogeneity properties of the value function to reduce the problem with four state variables (W, P, H, i) to one with two state variables, $z = W/(PH)$, and i, as

$$V(W, P, H, i) = H^{1-\gamma} P^{\beta(1-\gamma)}\ V\left(\frac{W}{PH}, 1, 1, i\right) = H^{1-\gamma} P^{\beta(1-\gamma)} v\left(z, i\right). \qquad (9)$$

Furthermore, let $\hat{c}$ and $\hat{\theta}$ denote the scaled controls $\hat{c} = C/(PH)$ and $\hat{\theta} = \Theta/(PH)$. We refer to the ratio z as the wealth-to-housing ratio.

A solution consists of a value function $v(z, i)$ defined on the state space, where bounds $\underline{z}_i$ and $\overline{z}_i$ define an inaction region, z_i^* is the optimal regime-dependent return point, and a consumption policy $\hat{c}^*(z, i)$ and portfolio policy $\hat{\theta}^*(z, i)$ defined on $(\underline{z}_i, \overline{z}_i)$. The function $v(z, i)$ satisfies the Hamilton-

Jacobi-Bellman equation on the inaction region. Value matching and smooth pasting conditions hold at the two bounds, and an optimality condition holds at the return point. Compared to Grossman and Laroque (1990) and Damgaard, Fuglsbjerg, and Munk (2003), the novel feature exploited here is the Markov chain process governing the dynamics of the expected growth rate of house prices. Therefore, the model features optimal rules that reflect the ability of the agent to invest in a different regime of house price growth in the future. The agent must determine the optimal rule in each regime while accounting for the optimal rule in the other. Thus, the model generates richer rules than the standard one-regime models. Finally, the model accounts for the expected net loss from the exogenous moving shock. The following proposition indicates the properties of the optimal housing and portfolio choices derived from our model. Appendix B.1 provides further details on the derivation of the model.

Proposition 1 *The solution of the optimal portfolio choice problem defined above presents the following properties:*

1. $v(z,i)$ *satisfies*

$$(\widetilde{\rho}_i+\kappa)v(z,i) = \sup_{\hat{c},\hat{\theta}}\Bigg\{u(\hat{c})+\mathcal{D}v(z,i)+\sum_{j\neq i}\lambda_{ij}(v(z,j)-v(z,i)) \\ +\kappa M_i\frac{(z-\epsilon)^{(1-\gamma)}}{1-\gamma}\Bigg\} \quad \textit{for} \quad z\in(\underline{z}_i,\overline{z}_i), \tag{10}$$

where

$$\mathcal{D}v(z,i) =((z-1)(r+\delta-\mu_i+\sigma_P^2(1+\beta(\gamma-1))) \\ +\hat{\theta}(\alpha_S-r-(1+\beta(\gamma-1))\rho_{PS}\ \sigma_S\sigma_P)-\hat{c})v_z(z,i) \\ +\frac{1}{2}((z-1)^2\sigma_P^2-2(z-1)\hat{\theta}\ \rho_{PS}\ \sigma_P\sigma_S+\hat{\theta}^2\sigma_S^2)v_{zz}(z,i), \tag{11}$$

$$v(z,i)=M_i\frac{(z-\epsilon)^{(1-\gamma)}}{1-\gamma} \quad \textit{for} \quad z\notin(\underline{z}_i,\overline{z}_i), \tag{12}$$

$\widetilde{\rho}_i=0.5(-2\rho-2(\gamma-1)(\mu_i-\delta+\beta(\gamma-1)(1+\beta(\gamma-1))\sigma_P^2)$ *and* M_i *is defined as*

$$M_i=(1-\gamma)\sup_{z\geq\epsilon}z^{\gamma-1}v(z,i) \quad \textit{for} \quad i=1,...,n. \tag{13}$$

2. The return point z_i^* attains the maximum in

$$v(z^*, i) = M_i \frac{z_i^{*(1-\gamma)}}{1-\gamma} \quad for \quad i = 1, ..., n. \tag{14}$$

3. Value matching and smooth pasting conditions hold at the two thresholds $(\underline{z}_i, \overline{z}_i)$

$$v(\hat{z}, i) = M_i \frac{(\hat{z}_i - \epsilon)^{(1-\gamma)}}{1-\gamma}, \tag{15}$$

$$v_z(\hat{z}, i) = M_i (\hat{z}_i - \epsilon)^{-\gamma}, \tag{16}$$

for $\hat{z}_i = \underline{z}_i, \overline{z}_i$ and $i = 1, ..., n$.

4. Given a wealth-to-housing ratio z, where $v(z, i) > M_i \frac{(z-\epsilon)^{1-\gamma}}{1-\gamma}$, the agent chooses a optimal consumption $\hat{c}^*(z, i)$ and portfolio $\hat{\theta}^*(z, i)$ and $\hat{b}^*(z, i)$

$$\hat{c}^*(z, i) = \left(\frac{v_z(z, i)}{\beta} \right)^{1/(\beta(1-\gamma)-1)}, \tag{17}$$

$$\hat{\theta}^*(z, i) = -\omega \frac{v_z(z, i)}{v_{zz}(z, i)} + \frac{\rho_{PS}\sigma_P}{\sigma_S}(z-1), \tag{18}$$

$$\hat{b}^*(z, i) = 1 - (1 + \hat{\theta}^*(z, i))/z, \tag{19}$$

for $i = 1, ..., n$, and the constant ω is defined as $\omega = \left[\alpha_S - r + (1 - \beta(1-\gamma))\rho_{PS}\sigma_P\right]/\sigma_S^2$.

Figure 3 provides intuition regarding these equilibrium results in a simple set up with two regimes: a regime of high expected growth in house prices and a regime of low expected growth. Consider that an agent has a total wealth-to-housing ratio equal to 2.5 at the initial time $t = 0$. Assume that $t = 0$ belongs to a time interval in which the expected growth in house prices is high. The agent must pay a transaction cost every time she adjusts her housing consumption; therefore, she does not move to a more valuable house until she has accumulated a sufficient amount of wealth to compensate for this transaction cost. When the wealth-to-housing ratio, $W/(PH)$ in the figure, reaches the upper bound, the agent sells her house and purchases a more valuable one to reset her wealth-to-housing ratio to its optimal level. In Figure 3, this event corresponds to point 1 at time $t = \tau_1$. As a result, the ratio $W/(PH)$ returns to the optimal level z_h^*, which corresponds to point 1^*. Now assume that the economy moves towards a regime of low growth in house prices shortly after τ_1. Note that both the upper and lower bounds in this period of low expected house price growth are higher than their respective bounds in the period of high growth. The wealth-to-housing ratio evolves over time until it reaches the upper bound again (point 2) at time $t = \tau_2$. Therefore, the agent purchases a more valuable house (point 2^*). At time $t = \tau_3$, there is a shift to the regime of high expected growth in house prices (point 3). As a result, the upper bound shifts down and the agent moves to a more valuable house (point 3^*). The example continues with symmetrical situations in which the agent moves to a smaller house when her ratio reaches the lower bound (points 4, 5, and 6).

[FIGURE 3 HERE]

Predictability in housing returns implies that the wealth-to-housing ratio determines not only the optimal timing for re-balancing wealth composition but also the time-varying expected growth rate of house prices.[15] The time-varying expected growth rate of house prices causes a shift in the location of the bound where it is optimal to pay the transaction costs for re-sizing housing holdings.

4 Numerical Results and Model Predictions

There is no closed-form solution to the portfolio choice problem described in Section 3. Consequently, we implement an iterative algorithm based on Grossman and Laroque (1990) to derive the numerical solution to this problem. A detailed description of this algorithm can be found in Appendix B.2. We use the numerical results of the model to both provide economic intuition and introduce the main predictions of the model.

Table 2 reports the parameters that we use to calibrate the model. We assume a coefficient of relative risk aversion γ of 10 to approximately match the stock holdings relative to financial wealth observed in the PSID and SIPP data. We set the rate of time preference ρ at 2.5%. The parameter $1 - \beta$ measures the degree to which the agent values housing consumption relative to numeraire consumption. This parameter is set at 0.3, which is consistent with the average share of household housing expenditure in the U.S. We assume that the risk-free rate is equal to 1.5% annually. Using

[15] In Grossman and Laroque (1990), the only state variable is the wealth-to-housing ratio.

U.S. data over the 1889 – 2005 period, Kocherlakota (1996) reports an average real return on a market index of 7.7% and a standard deviation of 16.55%.

[TABLE 2 HERE]

Academics and practitioners agree that it is difficult to obtain an accurate estimate of the standard deviation of house prices at the individual house level. For example, using the standard deviation of house price indexes as a proxy for the standard deviation of the price of an individual house leads to low estimates due to the inertia of the indexes (i.e., see the low values of σ_P in Table 1.)[16] To obtain the numerical results from our model, we use the annual standard deviation of house prices obtained in Section 2 (see Table 1) as the systematic standard deviation of house prices, $\sigma_{P,1} = \rho_{PS}\sigma_P$, and we set the idiosyncratic standard deviation of house prices, $\sigma_{P,2} = \sqrt{1-\rho_{PS}^2}\sigma_P$, at 5% as a baseline value. Therefore, we consider the standard deviation of individual house prices, σ_P, as the combination of a systematic component, $\sigma_{P,1}$, and an idiosyncratic component, $\sigma_{P,2}$.[17] Then, we convert the quarterly parameters in Table 1 to annual parameters by multiplying the expected growth parameters by four and using the matrix exponential function for the transition probabilities.

Furthermore, we assume that the housing transaction cost is 10% of the unit's value as a baseline parameter. This figure includes commissions, legal fees, the time cost of searching, and the direct cost of moving the consumer's possessions. For simplicity, we set the physical annual depreciation rate of housing, δ, at 0%. We set the hazard rate κ for exogenous moves at 3%.[18] A higher hazard rate has the same effects as a higher transaction cost: it increases the overall cost of housing and makes voluntary adjustments less attractive.

In the reminder of this Section, we introduce the predictions of the model and the numerical results regarding housing portfolio choices (Subsection 4.1), the size of housing adjustments (Subsection 4.2), and the predictions of non-housing portfolio choices (Subsection 4.3). In Section

[16]Stanton and Wallace (2011) emphasize that indices generate downwardly biased estimates of the idiosyncratic volatility of prices around the index and thus systematically undervalue embedded default options in mortgage products.

[17]Campbell and Cocco (2003) estimate a standard deviation parameter for house prices of 16.2%, whereas Cocco (2005) estimates a standard deviation parameter for house prices of 11.5%. Yao and Zhang (2005) set the standard deviation at 10%.

[18]Cocco (2005) sets the hazard rate at 5.44% to roughly match the frequency of total (endogenous and exogenous) housing transactions observed in the PSID data.

6 we use household-level data from the PSID and SIPP to empirically test each of these model predictions.

4.1 Housing Portfolio Holdings. Model Predictions

The regime-switching mechanism together with transaction costs generates rich portfolio rules regarding the agents' house holdings. As in Grossman and Laroque (1990), the existence of transaction costs makes the wealth-to-housing ratio that determines the lower bound of the inaction region of housing transactions, $\underline{z}_i$, significantly different, and lower than the wealth-to-housing ratio that determines its upper bound, $\overline{z}_i$, for a given regime i, that is, $\underline{z}_i < \overline{z}_i$. However, the model with both predictability in house prices and transaction costs predicts that this inaction region of housing transactions is time varying. The following hypothesis formalizes this prediction:

Hypothesis 1. The wealth-to-housing ratio that determines the upper bound during a regime of high price growth is significantly lower than the ratio that determines the upper bound during a regime of lower house price growth. Analogously, the wealth-to-housing ratio that determines the lower bound during a regime of high price growth is significantly lower than the ratio that determines the lower bound during a regime of lower house price growth.

Figure 4 supports this hypothesis using numerical results that we obtain from the model when we use the parameter values in Table 2 and the parameters for the U.S. aggregate house price process of Column (2) of Table 1. This figure displays the difference between the value function, $v(z(t), i)$, and the value of adjusting house holdings, $(z(t) - \epsilon)^{1-\gamma} M_i/(1-\gamma)$, against the value of the wealth-to-housing ratio, $z(t)$. If this difference is positive, then the agent does not move to a more or less valuable house. As in Grossman and Laroque (1990), the agent only moves when this difference is zero, that is, when the value function from not moving given by $v(z(t), i)$ is equal to the value from moving given by $(z(t) - \epsilon)^{1-\gamma} M_i/(1-\gamma)$.[19] However, Figure 4 illustrates that, in our model, the upper and lower boundaries are not static. Instead, they depend on the regime of expected growth in house prices, i. Panels A, B, and C present the results for regimes of high,

[19] This is equivalent to saying that the values of the upper bounds $\overline{z}_i$ and the lower bounds $\underline{z}_i$ are determined by the value matching conditions in equation (15) for each regime i, by which the agent is indifferent between not moving and moving. Additionally, the smooth pasting conditions in (16) assure that $v(z(t), i)$ is differentiable on the threshold that triggers the agent to move. Figure 4 illustrates that this implies that $v(z(t), i)$ is less concave than $(z(t) - \epsilon)^{1-\gamma} M_i/(1-\gamma)$ at these points. However, $v(z(t), i)$ must become more concave than $(z(t) - \epsilon)^{1-\gamma} M_i/(1-\gamma)$ somewhere between $\underline{z}_i$ and $\overline{z}_i$.

medium, and low growth in house prices, respectively. Specifically, the upper (lower) bound that corresponds to the regime of high growth in house prices is lower than the upper (lower) bounds of the medium- and low-growth regimes. This finding is one of the main contributions of this paper.

[FIGURE 4 HERE]

Table 3 reports the numerical results that we obtain from the model when we use the parameter values in Table 2 and the parameters for the U.S. aggregate house price process shown in Column (2) of Table 1. These numerical results also support Hypothesis 1. We find that the agent buys a more valuable house when her wealth-to-housing ratio falls below $\underline{z}_h = 0.452$, $\underline{z}_m = 1.569$, and $\underline{z}_l = 2.530$, in the high-, medium- and low-growth regimes, respectively. However, she moves to a smaller house when her wealth-to-housing ratio exceeds $\overline{z}_h = 4.827$, $\overline{z}_m = 7.954$, and $\overline{z}_l = 26.104$ (see Column (1) in Table 3). The optimal wealth-to-housing ratio under transaction costs, z^*, is higher than the constant ratios of 0.628, 2.956 and 7.329 that would be chosen under no transaction costs, z^{nt}, (see Column (2)). Transaction costs make housing less attractive as an investment and, consequently, we should expect higher wealth-to-housing ratios when we consider transaction costs.

[TABLE 3 HERE]

The dynamics of the wealth-to-housing ratio are not the only drivers of housing transactions. They can also be initiated by a change in the expected growth rate of house prices. A transaction occurs when the regime switches from high to medium (low) and the agent's wealth-to-housing ratio $z(t)$ falls within the region $[\underline{z}_h = 0.452, \underline{z}_m = 1.569]$ ($[\underline{z}_h = 0.452, \underline{z}_l = 2.530]$). In this case, the lower bound increases from $\underline{z}_h$ to $\underline{z}_m$ (or to $\underline{z}_l$). As result, $z(t) \leqslant \underline{z}_m$ (or $z(t) \leqslant \underline{z}_l$) and, consequently, it is optimal for the agent to sell the current house and reduce her housing holdings.

Finally, we calibrate our model at the U.S. state level using parameters for the house price processes of California, Florida, New York, Illinois, and Texas reported in Columns (3) – (7) of Table 1. The results of this calibration exercise are shown in Panel B of Table 3. We find that accounting for different levels of house price predictability across U.S. states is crucial to capture the housing holdings across U.S. households. For example, California, Florida and New York are characterized by low values of the bounds and narrow inaction regions in high-growth regimes compared to states with lower expected house price growth in each respective regime.[20]

[20]These narrow inaction regions can be associated with the 2000 – 2006 period in which house prices grew at a

4.2 Size of Housing Adjustments. Model Predictions

The predictability of house prices impacts the probability of moving to a new house and the size of the housing adjustment. Column (3) of Table 3 presents the expected tenure or length of time between house purchases. When we use the parameters for the U.S. aggregate house price process in Column (2) of Table 1, we find that the expected length of stay in a house of a given size is lower in a high-growth regime than a the medium-growth regime. This result is equivalent to saying that the probability of making a housing purchase is higher in a high-growth regime than in the medium one after having made a housing purchase. Interestingly, we find a more frequent adjustment in a low-growth regime that features a wider inaction region. This finding seems counterintuitive, but a similar result is obtained in Grossman and Laroque (1990). If the housing stock depreciates rapidly, there will be very frequent purchases. In our framework, instead, the large expected decline in house price growth in the low-growth regime, μ_l, makes the expected growth of the wealth-to-housing ratio larger, increasing the probability of reaching the upper boundary. To illustrate this effect, Column (5) reports the expected growth rate of the wealth-to-housing ratio at the optimal return point. Similar to the U.S. as a whole, some states such as California, Florida, and Texas feature more frequent adjustments in low-growth regimes with very wide inaction regions.

To assess the impact of housing return predictability, we solve the model setting the cross terms of the generator matrix to zero, $\lambda_{kj} = 0$, and selecting the expected growth rate of the medium-growth regime. We refer to this framework as DFM because the effect of predictability in house prices is not considered, as in Damgaard, Fuglsbjerg, and Munk (2003). Two main results arise from the calibration under the DFM framework (see Panel A of Table 3). First, the inaction region is narrower in DFM. Second, the expected duration between moves is higher in DFM, increasing from approximately 22 to 28 years. Because the Markov-switching mechanism means that moves are not always a result of the wealth-to-housing ratio reaching the bounds, but result from a regime shift that leaves the agent's wealth-to-housing ratio outside the inaction region of the new regime. Finally, the expected length of stay is significantly lower than that found in a GL framework because the agent can substitute numeraire consumption for housing consumption. As a result, the optimal fraction of wealth placed in housing is lower than in the case where there is no numeraire

high rate. Conversely, based on the estimated smoothed probabilities (see Figure 2), the very large inaction region of California and Florida in the low-growth regime is due to the dramatic downturn during the $2007 - 2011$ period.

consumption.

Regarding the size of housing adjustments, Column (4) illustrates that the size of an upward adjustment in the wealth-to-housing ratio is higher in the low-growth regime (13.126) than in the regimes of medium (4.340) and high (2.645) growth in house prices. This result means that, conditional on moving to a different house, households move to more valuable houses in regimes of high growth than in regimes of lower growth. The following hypothesis describes this effect:

Hypothesis 2. Conditional on moving, the relative size of an upward adjustment is lower in a regime of high growth in house prices than in any lower growth regime.

Conditional on moving, the size of an upward adjustment in a high-growth regime is substantially lower in such states as California, Florida and New York because the increase in house value is larger in these states, for a given level of total wealth. In terms of the analysis of the model predictions, we focus on the upward adjustment because the sample of households that downsize their houses is small both in the PSID and SIPP datasets.[21] In the empirical Section 6.2, we use household level data to test whether the probability of increasing housing holdings is higher in periods of high growth in house prices than in periods of lower growth.[22]

4.3 Non-Housing Portfolio Holdings. Model Predictions

In this subsection we explore the non-housing portfolio rules generated by the regime-switching mechanism and the existence of transaction costs. The upper panel of Figure 5 plots the fraction of wealth invested in risky assets against wealth for the three regimes of the expected growth rate of house prices, $\Theta^*(z(t),i)/W(t)$, for any regime i. Each curve is drawn only for the realizations of $z(t)$ within the housing transaction inaction region. As in Grossman and Laroque (1990) and Damgaard, Fuglsbjerg, and Munk (2003), the share of wealth that the agent holds in risky assets reflects the fact that the agent is more risk tolerant when her wealth-to-housing ratio, $z(t)$, is close to the bounds, and more risk averse in the middle of the inaction region. Closer to the

[21] The previous literature demonstrates that the probability of upgrading to a more valuable house increases with the wealth-to-housing ratio (see Martin (2003)).

[22] Although, the model predicts a lower expected tenure or higher probability of increasing housing holdings in a low-growth regime for some states, we cannot test this hypothesis because our dataset does not include a sufficient number of years of low-growth regimes for these states. Therefore, we test whether the transition from a medium- to high-growth regime makes the upward adjustment more likely. We also test whether, conditional on moving, households buy more valuable houses relative to their wealth in periods of high growth in house prices.

boundaries of the inaction region, the monetary loss associated with the potential transaction costs is compensated by a change to the optimal wealth-to-housing ratio. Therefore, the agent is less risk averse leading to higher fractions of wealth invested in risky assets. The relatively high risk aversion coefficient that we use to obtain our numerical results, $\gamma = 10$, leads to an equilibrium in which the agent allocates a small fraction of her wealth to the risky asset.

[FIGURE 5 HERE]

Column (6) of Table 3 reports the relative risk aversion associated with the indirect utility of total wealth, $-(W(t)V_{WW})/V_W) = -(z(t)v_{zz})/v_z$. In a regime of high growth in house prices, the agent is more risk averse after a housing purchase. In this case, the loss of utility associated with the transaction is large due to the higher fraction of wealth optimally invested in housing and the relative risk aversion rises from 10 to 11.4 for the U.S. Moreover, in our model, the regime-dependent coefficient of relative risk aversion reflects the possibility of regime switches in the future. Therefore, the agent must determine the portfolio rule in each regime, while accounting for the possibility of a future shift in the expected growth rate of housing prices. The upper panel of Figure 5 also plots the fraction of wealth invested in risky assets against wealth in the DFM case. In the medium-growth regime, the policy function has a different shape approaching the lower and upper boundaries where the high-medium and medium-low-growth regime inaction regions overlap. The agent is more risk averse leading to lower stock holdings than in DFM. Where the inaction regions overlap, it is not optimal to readjust housing when a regime switch occurs. However, this is not the case for non-housing portfolio holdings. A negative jump in stock holdings occurs during a switch from a medium-to-high or medium-to-low regime.

Column (7) of Table 3 presents the average holding of risky asset after a home purchase, which is denoted by $E(\Theta/W)/E(\tau)$ to emphasize that this parameter is the average of Θ/W over the cycles. Transaction costs make the agent more risk averse. As a result, the averages are lower than the shares chosen by an agent facing no transaction costs (see Column (8)). There is a substantial decrease in average stock holdings when introducing transaction costs in the high growth regime, falling from 18.2% to 17.4%.

In a high-growth regime in house prices, the average stock holdings is 17.4% for U.S., lower than the 20.4% and 23.9% in medium- and low-growth regimes, respectively. Then, the average risky holdings in a high-growth regime are substantially lower than in a medium- or low-growth regime for such states as California and Florida for which the annual expected growth rate in house prices in a high-growth regime is approximately 12%. Furthermore, the model predicts a decrease in stock holdings when an upward housing adjustment is triggered. Conditional on moving, the change in risky asset holdings relative to wealth, $\Delta(\Theta/W)$, is larger in a high-growth regime (see Column (9)), when housing is quite attractive for investment purposes.

These predictions on risky stock holdings are summarized by the following hypotheses:

Hypothesis 3.1. Risky asset holdings relative to wealth are lower in a regime of high house price growth than in any regime of lower house price growth on average.

Hypothesis 3.2. Conditional on moving, the change in risky asset holdings relative to wealth is larger in a regime of high growth in house prices than in any lower growth regime.

Finally, we analyze the consumption of non-housing goods and the portfolio holdings of risk-free assets. Columns (10) and (11) represent the average numeraire consumption rate just after a housing trade and the optimal consumption rate without transaction costs, respectively. In general, the propensity to consume non-housing goods is increasing in $z(t)$. This propensity only differs as the agent approaches the boundaries. Increases in $z(t)$ yield increasingly smaller increases in the consumption rate when the agent approaches the upper boundary, whereas decreases in $z(t)$ generate increasingly large declines in the consumption rate when the agent approaches the lower boundary as illustrated in Figure 6. Regarding the risk-free portfolio holdings, the lower panel in Figure 5 plots the fraction of wealth invested in the risk-free asset, $B^*(z(t), i)/W(t)$. The agent is only a net borrower in a high-growth regime under the parameters in this numerical example. The agent finances housing holdings with a net short position in the financial market and therefore her home equity share is lower than one. Her borrowing (net saving) decreases (increases) with her ratio $z(t)$.

[FIGURE 6 HERE]

5 Data

We use survey data at the household level to test the theoretical predictions of the model. We obtain the data from two surveys, the PSID from 1984 to 2007, and the SIPP of the U.S. Census Bureau from 1997 to 2005. Both surveys have data on asset holdings and housing wealth.

In the analyses using PSID data, we calculate financial wealth as the sum of an individual's house value, their second house value (net of debt), business value (net of debt), other assets (net of debt), stock holdings (net of debt), checking and savings balances, IRAs and annuities less the mortgage principal on the primary residence.[23],[24] We divide these variables into two groups: those that are considered risky assets and those that are considered safe assets. The risky assets comprise stock holdings, IRAs and annuity holdings. The safe asset includes other assets (net of debt), checking balances, and savings balances, less the principal on the primary residence. The variables regarding financial wealth are net of debt, with the sole exception of the primary residence value in both the PSID and SIPP.

In the analyses using SIPP data, we calculate risky assets as the sum of equity in stocks and mutual funds, equity in IRAs, and equity in 401k and thrifts. The safe assets are interest-earning assets in banks and other institutions less the outstanding mortgage balance. The value of financial wealth is calculated by adding the risky asset value to safe asset value, business equity, the property value of the primary residence, housing equity in the second residence and other assets. In both the PSID and SIPP data-sets, the measure of house value is given by homeowners' estimate of home value. Home value is problematic in that there might be a large amount of measurement error in the figure quoted. However, we argue that whereas most homeowners only have a general idea of the value of their home, owners who are near to the bound or have recently bought a house have more precise knowledge of the value of their home.

We also include human capital as part of each household's total wealth. Following Jagannathan and Wang (1996), we estimate the human capital of each household as capitalized wage income, that is, as the present value of a growing annuity.[25] We assume that for each household, the wage

[23]Other assets include bonds and insurance.

[24]For comparability across different survey waves, we exclusively focus on first mortgages.

[25]As Palacios-Huerta (2003) acknowledges, measuring human capital as capitalized wage income has several limitations. First, it does not account for the capital gains in the stock of human capital. Second, this simple measure assumes that the labor supply is exogenous. Third, it ignores the worker's skill premium and experience. Fourth, it does not net out the effect of physical capital on labor income and human capital returns. Fifth, this measure does

remains constant at the current real level until age 65, and then the wage ends, as in Heaton and Lucas (2000) and Eberly (1994). Appendix C contains additional details regarding the specific variables that we use from the PSID and SIPP surveys and the methodological approach to account for human capital.

Table 4 presents the descriptive statistics for the main variables that we use in the empirical analysis. We present statistics for the full sample and for the selection of households that moved to a more or less valuable house (second and third pairs of columns, respectively.) We present the means and standard deviations of the relevant variables. The most important variable in the model is the wealth-to-housing ratio, z.[26] Stock holdings are approximately 10.2% of financial wealth, and safe assets without debt holdings represent 10.9% of financial wealth, or 14.1% for households that buy a more valuable house. We report statistics on stock holdings without retirement assets (IRA, 401k). We define the dummy m_{BIG} (m_{SMALL}) to identify households selling the current house to buy a more (less) valuable house in the same U.S. census region.

[TABLE 4 HERE]

We also report summary statistics for variables that aid us in distinguishing between changes in housing that occur for reasons that are exogenous to the model and changes in housing that occur because individuals have a total wealth-to-housing ratio that is close to the boundary. To account for moves that are required for exogenous reasons, we use variables that capture changes in the household around each home purchase. Consequently, we control for changes in family size, marital status, and employment status in our empirical specification.[27]

Our model does not explicitly study the portfolio choices of renters. We focus our study on understanding the portfolio decisions of homeowners. In our model, as in Stokey (2009b), renting would be equivalent to holding zero equity in a house. Table 5 provides information on the percentage of movers by current ownership status (owner, renter, or occupied) across all households in the PSID and SIPP surveys. The four columns represent the percentage of households that moved

not account for regional differences. We have run different robustness checks on these five limitations for all of the results that we present. We find that the results obtained using the measure of human capital in Jagannathan and Wang (1996) are robust.

[26] Although we present statistics for the wealth-to-housing ratio without and with human capital, we use the measure with human capital in the remainder of the paper.

[27] Both the PSID and SIPP provide data on family size, marital status, and employment status at the household level.

to a new address in the same U.S. macro-region, moved to a new address in the same U.S. state, and moved to a new address and were not previously homeowners.

We can easily identify the households moving to a different house in the PSID because it explicitly reports whether there has been a move since the previous interview. The SIPP does not report house moves explicitly; thus, we must identify them by tracking the households' address identifiers. Table 5 reports that the percentage of owners who move is much lower than the percentage of renters who move. This finding is consistent with the fact that renters face lower transaction costs than homeowners. The percentage of movers to a different U.S. census region or U.S. state is very low among owners. Finally, new homeowners represent 5.47% (3.79%) of the total homeowners in the SIPP (PSID).

[TABLE 5 HERE]

6 Empirical Results

In this section, we use the household survey data described in Section 5 to test the model's predictions that we stated in Section 4. Moreover, we replicate the same tests using model-simulated data to address the concern that the model is non-linear due to the Markov switching mechanism, whereas the reduced-form regressions estimated in the this section are mostly linear. To generate model-simulated data, we consider the empirical distribution of the cross-section of wealth-to-housing ratios, z_t, observable in the SIPP in 1996.[28] For simplicity, we limit our exercise to simulating the choices of households from the five U.S. states for which we present house price parameters in Section 2 and optimal policies in Section 4. They represent approximately 36% of the U.S. population, but they are representative of the geographic heterogeneity in U.S. housing markets. Overall, we generate 50 years of quarterly data for $2,721$ individual households. For each simulated database, we perform regressions similar to those run on the PSID and SIPP data. We repeatedly simulate panel data $5,000$ times to produce a sampling distribution for the statistics of interest. Using these sampling distributions, we can test whether the estimates obtained using the PSID and SIPP data could have been generated by our model with high probability.

[28] Using a procedure similar to that of Eberly (1994), we filter the data with a regression of the wealth-to-housing ratio on the same set of demographic characteristics that we will include later in the regressions. This procedure absorbs determinants of the wealth-to-housing ratio other than the dynamic variation featured by our model.

To generate a rich model simulated data-set that represents what we observe in reality, we introduce heterogeneity across households in three dimensions. First, we assume five levels of transaction costs ranging from 5% to 25% of the value of their house with a marginal increase of 5%. The current literature does not provide any quantitative assessment of the level of transaction costs that households face in addition to the average real estate agent costs of selling the house. We adopt the following rule to assign a transaction cost level to each household. The higher the number of years that households have lived in the same house, the higher the transaction costs that they face. The intuition behind this rule is that transaction costs are increasing in home tenure due to tax reasons, depreciation of the housing stock and other costs that are difficult to measure. Second, we divide the households into two groups, urban and non-urban, within each state. The only difference between an urban and a non-urban household in U.S. state j is the set of parameters that defines their house price processes and the optimal policies calibrated on the same set of parameters.[29] Overall, 53% of the $2,721$ individual households are classified as urban households. Third, we assume an idiosyncratic house price shock specific to each household. This household-specific parameter allows us to account for further heterogeneity across households without changing the optimal policy rules. Households are homogenous in all other aspects. Additional details on the generation of model-based data are provided in Appendix D.

Moreover, we need to construct an indicator variable that captures the existence of periods of high expected growth in house prices at the U.S. state level. To be consistent with our model, this variable can be inferred from the smoothed probabilities of being in a regime of high growth in house prices. To obtain a binary variable from these estimated probabilities, we assume that the binary variable $\mathbb{1}_{jt}^{\mu_h}$ for U.S. state j (i.e., j=California) at time t is equal to one when the following two conditions hold: (i) the smoothed probability of being in the regime associated with the highest expected real housing return in state j is higher than its historical average plus half of its historical standard deviation for four consecutive quarters; and (ii) the real housing return in state j is higher than the mean real housing return in the high-growth regime for the U.S. aggregate

[29] We average the real house price indexes for the largest MSAs of state j (i.e., Los Angeles and San Francisco for California) creating an urban index for state j and we estimate the three regime Markov switching model using the real housing returns of the same index. Then, we calibrate our model using the same parameters for the five levels of transaction costs considered. We report these house price parameters and the associated optimal policies for a transaction cost level of 10% in the online appendix. We assume that the parameters that define the house price process of a non-urban household living in state j are those reported in Table 1.

house price index in the same four quarters of condition (i). We provide an extensive analysis of the estimation and properties of the indicator variable in Appendix E. This binary variable is based on these two conditions because they embed two specific pieces of information. The first condition captures the likelihood that there has been a regime change in state j based on the probability of a turning point. We define the turning point as the moment when the estimated smoothed probability of being in a regime of high growth in house prices reaches the 90% significance level. The logic underlying the first condition is to detect whether a housing market peak relative to its past historical average in state j has been reached and has lasted for at least four consecutive quarters. Therefore, condition (i) allows us to classify states' house prices according to the degree of cyclicality in their real housing returns.[30] This condition is consistent with previous approaches to determine the turning points of business cycles (see Chauvet and Hamilton (2005)). The second condition verifies whether the real housing return in state j is substantially high when compared to the real mean housing return of 6.37% in high-growth regime that characterizes the overall U.S. housing market over the $2000-2006$ period.[31],[32] Recall that the rise in house prices has been very uneven across the U.S. in the $2000-2006$ period considered here. House price indexes increased by more than 10% per year in several states, including California, Florida, Nevada, Maryland, Rhode Island, New Jersey and Virginia, whereas some states, such as Texas and Ohio, grew at only 2% per year.

Finally, we replicate the indicator in our simulation exercise. Because we simulate the Markov switching process, we clearly identify whether the simulated real house price index of state j is in a high-growth regime. Therefore, we only need to verify whether the housing return of the simulated house price index of state j in a high-growth regime is higher than the real mean housing return

[30]The condition that the smoothed probability of being in the regime associated with the highest expected real housing return reaches the turning point probability is satisfied in some periods by such states as California and Florida in which housing markets experienced a particularly high appreciation in the same periods. Thus, these periods are generally characterized by high and pronounced appreciation in house prices. Alternatively, condition (i) is not satisfied by such states as Alabama and Montana where housing markets experienced prolonged and continuous high-growth phases that are primarily characterized by modest growth in house prices.

[31]An alternative approach would be to infer common Markov-switching regimes in a panel data-set with large cross-section and time-series dimensions. However, this approach raises several challenges regarding how to explicitly model U.S. state house prices similarities and is outside the scope of this paper.

[32]Based on the smoothed probabilities for U.S. aggregate, we identify the period $2000-2006$ as a high-growth period and we calculate a mean annual real growth rate of 6.37%. Accordingly, we use this as our threshold for condition (ii). We check our results for robustness by lowering the threshold to 5%. We find that our empirical results are not significantly affected by the second condition of our indicator (see Tables $9-12$ of the online appendix). Alternatively, we constructed our indicator using the filtered probabilities instead of the smoothed probabilities. Our empirical results are not affected by this modification.

in the high-growth regime of the U.S. aggregate for four consecutive quarters.

In the remainder of this section, we test the model hypotheses using the PSID and SIPP datasets and the model-simulated data. First, we test the effect of transaction costs and house price predictability on housing portfolio choices (Subsection 6.1). Then we test the frequency and size of the housing adjustment (Subsection 6.2). Finally we test the model implications regarding non-housing portfolio choices (Subsection 6.3).

6.1 Housing Portfolio Holdings. Empirical Results

The model predicts that both the upper and lower boundaries of the inaction region are lower in periods of high expected growth in house prices, as stated in Hypothesis 1. We develop a difference-in-differences analysis based on the following reduced form model to test this hypothesis:

$$\begin{aligned} \tilde{z}_{it} =& \gamma_0 + \gamma_1 \cdot m_{BIG_{it}} + \gamma_2 \cdot m_{SMALL_{it}} + \gamma_3 \cdot \mathbb{1}_{kt}^{\mu_h} \\ & + \gamma_4 \cdot m_{BIG_{it}} \times \mathbb{1}_{kt}^{\mu_h} + \gamma_5 \cdot m_{SMALL_{it}} \times \mathbb{1}_{kt}^{\mu_h} + \Gamma \cdot X_{it} + u_{it}, \end{aligned} \tag{20}$$

where $\tilde{z}_{it}$ is the total wealth-to-housing ratio of household i at time t; $m_{BIG_{it}}$ is a dummy variable equal to one if the household is increasing its housing holdings (i.e., moving to a more valuable house); $m_{SMALL_{it}}$ is a dummy variable equal to one if the household is decreasing its housing holdings (i.e., moving to a less valuable house); we interact $\mathbb{1}_{kt}^{\mu_h}$ with $m_{BIG_{it}}$ and $m_{SMALL_{it}}$; and X_{it} contains a set of variables that control for ex-ante changes in the housing stock for reasons not related to the wealth-to-housing ratio such as changes in employment status, family size and marital status.[33] This parameter also includes age, state, and year fixed effects. Households that do not move in periods of medium and low growth in house prices are the benchmark group.

Before analyzing the effects of house price predictability on the boundaries of the inaction region, we explore the existence and geographic heterogeneity of these boundaries in our datasets. Although the existence of these boundaries has been tested in the empirical S-s literature, we confirm that they also exist in the PSID and SIPP data in the context of our model. Columns

[33]The goal is to identify those moves that are triggered by the evolution of wealth and house prices and control for those moves that result from an increase or decrease in family size alone, such as births, deaths, divorces, and emancipations. The identification is not perfect, as having children may be correlated with the wealth level, but the results are robust to the inclusion or exclusion of changes in family size. These robustness checks can be found in Table 7 and 8 of the online appendix.

$(1) - (3)$ of Table 6 present the results from running the pooled regression in equation (20) without the interaction terms. The first two columns indicate that the average value of $\tilde{z}_{it}$ for families that do not move in periods of medium and low growth in house prices, γ_0, is 5.812 for the PSID and 3.569 for the SIPP. Importantly, the total wealth in the total wealth-to-housing ratio includes human capital as calculated in Section 5. The ex-ante average value of $\tilde{z}_{it}$ for households that moved to a more valuable house is 2.662 for the PSID and 1.717 for the SIPP above the non-movers average. This difference is significant at the 99% level for both the PSID and SIPP.[34] We find that γ_1 is significantly positive and different from zero, which means that the total wealth-to-housing ratio of the households that move to a more valuable house is significantly higher than the ratio of those who do not move. Note that γ_2 is not significantly different from zero for the PSID, but is for the SIPP. Thus, the average wealth-to-housing ratio $\tilde{z}_{it}$ for non-movers is not significantly different from the ratio for movers to less valuable houses. It can be inferred that the distribution of the total wealth-to-housing ratio is skewed to the left and, on average, agents are closer to moving down according to our model. We also run a test on the coefficients γ_1 and γ_2 being equal, which is strongly rejected. This result supports the notion that the upper and lower bounds are significantly different.

[TABLE 6 HERE]

Once we have demonstrated the existence of the inaction region, we study the effect of house price predictability on the housing portfolio holdings. Columns (4) and (5) of Table 6 report the results of the differences-in-differences analysis that were specified in equation (20). We choose households that did not move in years of medium-low expected growth in house price, $\mathbb{1}_{kt}^{\mu_h} = 0$, as the control group. The terms in which we interact $m_{BIG_{it}}$ with $\mathbb{1}_{kt}^{\mu_h}$ and $m_{SMALL_{it}}$ with $\mathbb{1}_{kt}^{\mu_h}$ capture the main results in our differences-in-differences analysis. The term $m_{BIG_{it}} \times \mathbb{1}_{kt}^{\mu_h}$ captures the difference between the following two terms: (i) the difference between the average $\tilde{z}_{it}$ for the upper boundary in high and medium-low expected growth years; and (ii) the difference between the average $\tilde{z}_{it}$ for non-movers in high and medium-low expected growth years. The negative sign on the coefficient γ_4 indicates that the decrease in $\tilde{z}_{it}$ at the upper boundary in the transition from medium-low to high growth is lower than the decrease in $\tilde{z}_{it}$ for non-movers in the same transition.

[34] Similar results are obtained when running yearly regressions that are not included in the table for clarity.

However, the coefficient γ_5 associated with $m_{SMALL_{it}} \times \mathbb{1}_{kt}^{\mu_h}$ is not significant for either the PSID or SIPP. These empirical results confirm the model's implications: housing return predictability affects the total wealth-to-housing ratio and the upper bounds. Consequently, the inaction region changes over time.

Column (6) reports the median and the 1^{st} - 99^{th} percentiles of the distribution of the estimated coefficients that we obtain using the simulated data. The most important coefficient for our purposes is γ_4 because it captures the time variation of the upper boundary. The estimates of γ_4 that we obtained using PSID and SIPP data are consistent in sign to the coefficient that we obtain using the simulated data. The sign is negative as expected but the median value is larger than the estimated coefficients, at least for the set of parameters we used in the simulation. Figure 7 displays the distribution of γ_4 from the simulated data. In addition, it indicates that the 99% confidence interval of the coefficient obtained using the SIPP data (which is significantly different than zero) falls within this distribution.[35] The bottom panel displays the equivalent results for the distribution of γ_5. In this case, the simulated model has difficulty in generating a distribution of γ_5, the sign of which should be negative according to the model predictions. The sign of this parameter is positive. In light of this finding, it should not be surprising that our estimates of this parameter using PSID and SIPP data fail to be empirically robust.

[FIGURE 7 HERE]

6.2 Size of Housing Adjustments. Empirical Results

Hypothesis 2 in Section 4 states that, conditional on moving, the size of an upward housing adjustment, in terms of the change in the wealth-to-housing ratio $\tilde{z}_{it}$, is lower in a regime of high growth in house prices than in any lower growth regime. To test this hypothesis using household-level data, we estimate a two-stage selection model, where the first stage captures the homeowner's decision to sell her current house to end up with higher housing holdings as a fraction of total wealth. The second stage estimates the change in her wealth-to-housing ratio conditional on the housing transaction. We use the SIPP data for this test because they include a higher number of housing transactions than the PSID data.

[35] We obtain the same conclusion plotting the 99% confidence interval of the coefficient obtained using the PSID data.

We follow Bertola, Guiso, and Pistaferri (2005) and estimate the selection model introduced by Heckman (1979). Our empirical approach evaluates the effects of housing return predictability on the frequency and size of an increase in the amount of housing holdings. The model predicts that an upward adjustment is more likely to be observed, for a given $\tilde{z}$, when house prices experience high increase. We again use the indicator $\mathbb{1}^{\mu_h}$ to capture the periods of high expected growth in house prices in the state where the households are located. In practice, households can sell a current house located in a state and buy another house in a different state but we do not control for destination prices. The reason for this lack of control is that we only consider households selling the current house to buy a more valuable one in the same U.S. state and the percentage of movers to a different state is substantially low among owners (see Table 5).[36]

In the first stage, we test these predictions using the following specification:

$$\text{Prob(bigger home purchase}_{it} = 1) = \gamma_0 + \gamma_1 \cdot \tilde{z}_{i,t-1} + \gamma_2 \cdot \mathbb{1}^{\mu_h}_{k,t-1} + \Gamma \cdot X_{it} + u_{it}, \qquad (21)$$

where X_{it} contains a set of variables that control for changes in employment status, family size and marital status between t and $t-1$. It also includes age, state, and year fixed effects.

Columns (1) and (2) of Table 7 report marginal effect estimates from the probit regressions for increasing the amount of housing holdings. Column (1) indicates that the probability of increasing housing holdings rises with the value of the total wealth-to-housing ratio, $\tilde{z}$. It also indicates that the indicator $\mathbb{1}^{\mu_h}_{kt}$ positively affects the probability of increased housing holdings as predicted by our model. Both coefficients are statistically significant.

[TABLE 7 HERE]

Column (2) reports the median and the 1^{st} and 99^{th} percentiles of the distribution of estimated coefficients that we obtain using the simulated data. The most important coefficient for our purposes is that of the indicator $\mathbb{1}^{\mu_h}_{kt}$. The sign is positive, as expected, but the median value is larger than the estimated coefficient. However, the coefficient falls in support of the distribution of the

[36] In our setup, we refrain from introducing the option of selling the house at price P in the household's current market and buying a more or less valuable one at the price P' in the region to which the household relocates in the next move. In this setup, the household's indirect utility depends on six state variables, $V(W, P, H, P', j, k)$, where j is the regime (i.e., high, medium or low) characterizing house price P, whereas k is the regime (i.e., high, medium or low) characterizing house price P'. A similar model without house return predictability is developed in Flavin and Nakagawa (2008).

estimated coefficients (see Figure 8). The main reason for this difference between the estimated and the simulated coefficients is the following. In the results obtained using simulated data, moving is primarily triggered by the wealth-to-housing ratio and/or Markov switching regime process in housing returns. However, in the results obtained using SIPP data, moving is less frequent and occurs due to shocks that have not been modeled in our simulation exercise.[37]

[FIGURE 8 HERE]

Our model also predicts that the size of housing adjustments is higher in periods of high expected growth in house prices. We correct for the selection bias by adopting the approach in Heckman (1979). In particular, we use the value of $\tilde{z}_{i,t-1}$ prior to an adjustment as a selection variable because theory predicts that this parameter affects the likelihood of adjusting but not the size of an adjustment if it occurs. We use the log of the adjustment $\ln(\tilde{z}_{i,t-1} - \tilde{z}_{i,t})$ as independent variable to account for an increase in housing holdings, where $\tilde{z}_{i,t-1}$ is interpreted as the upper boundary $\overline{z}$, and $\tilde{z}_{i,t}$ is the optimal return point z^*. Specifically[38]

$$\ln(\tilde{z}_{i,t-1} - \tilde{z}_{i,t}) = \gamma_0 + \gamma_1 \cdot \mathbb{1}^{\mu_h}_{k,t-1} + \Gamma \cdot X_{it} + u_{it}. \tag{22}$$

The results of the second stage of the Heckman selectivity regressions are reported in Column (3) of Table 7.[39] The most important effect is captured by the coefficient of the indicator variable $\mathbb{1}^{\mu_h}_{kt}$. The obtained coefficient implies that the difference in the wealth-to-housing ratio before and after moving is 61.2% lower for households moving during periods of high expected growth in house prices. The effect is statistically significant and economically sizable when households increase their housing holdings. The result implies that the distance between the upper bound $\tilde{z}_{i,t-1}$ and the optimal adjustment point $\tilde{z}_{i,t}$ is lower in periods of high expected growth in house prices or, equivalently, that the increase in housing holdings as a share of total wealth is higher during high

[37] To obtain coefficients for the wealth-to-housing ratio $\tilde{z}_{t-1}$ and the indicator $\mathbb{1}^{\mu_h}_{kt}$ that are significantly similar to those that we obtain using the empirical data, we must include transaction costs on the order of 25% of the value of the house for every household in our simulations. These results are available on request.

[38] In the second stage, we do not include households that sell the current house to buy a more (less) valuable house but those where the wealth-to-housing ratio increases (decreases) between the two purchases. We have two alternative arguments. The first is that total wealth is not following the continuous diffusion process assumed by our model but rather positive or negative jumps may be occurring in the total wealth process. The second is that total wealth might be affected by measurement error.

[39] We implement a standard GLS procedure to calculate appropriate standard errors for the estimated coefficients (see Greene (2008)).

expected growth rate periods.

The bottom panel of Figure 8 displays the distribution of this coefficient from the simulated data (see also Column (4) of Table 7). Two conclusions can be drawn from this figure. First, the median value of the regression coefficient in our model is clearly of the same sign as the empirical result. Second, the magnitude of the coefficient obtained is well within the body of the frequency distribution from the simulations. Therefore, our empirical estimates are within the frequency distribution generated by the simulations.

As a summary, Table 7 provides two relevant empirical findings. First, the probability of an increase in housing holdings is higher during periods of high expected growth in house prices. Second, the size of the increase in housing portfolio holdings is higher during these periods.

6.3 Non-Housing Portfolio Holdings. Empirical Results

The model predicts that the household's risky holdings depend on its wealth-to-housing ratio and the regime of expected growth in house prices. Specifically, it predicts that in periods of high expected growth in house prices, the average share of risky assets is lower than in other housing regimes (Hypothesis 3.1). Moreover, households decrease risky asset holdings to a greater extent during the process of a housing purchase in periods of high expected growth in house prices (Hypothesis 3.2).

One of the most important contributions of our paper is to empirically analyze the effects of housing return predictability on stock holding decisions. Because non-housing and housing portfolio choices are endogenous, they are both affected by unobserved factors (see Cocco (2005) and Davidoff (2010)). Previous empirical work documented the cross-sectional correlation between house values and portfolio choices but it did not identify the causal effect of housing on non-housing portfolios (see Heaton and Lucas (2000), Yamashita (2003), and Cocco (2005)). We follow Chetty and Szeidl (2011) to pursue this empirical analysis. Their empirical strategy exploits the distinction between changes in mortgage debt and changes in home equity wealth to capture the causal effect of housing on portfolio allocations. They provide evidence that an increase in property value mechanically reduces the share of risky stocks in the portfolio as documented in previous studies. However, home equity increases stock holdings through a wealth effect. They exploit two instruments to generate variation in home equity and property value: the real house price index value in the state where the household lives in the current year and the real house price index value in the state in the year that the household bought the house.

We extend their empirical approach to account for predictability in house prices. We use SIPP data because the SIPP is the only survey containing information on the year of the purchase of the house. To test Hypothesis 3.1, we include our indicator $\mathbb{1}_{kt}^{\mu_h}$ and interact $\mathbb{1}_{kt}^{\mu_h}$ with house value and home equity. We instrument for the interaction effects using the interactions of the two FHFA price indices and our indicator $\mathbb{1}_{kt}^{\mu_h}$. We estimate a two-stage Tobit specification to isolate the change in stock shares conditional on participating in the stock market. This model is analogous to the two-stage least-squares estimates, but corrects for the fact that two thirds of the households are non-participants using a Tobit specification in which stock holding is left censored at zero. The dependent variable is stocks in dollar amounts, stocks relative to wealth in liquid assets (LA) and stocks relative to financial wealth (FW):[40]

$$\begin{aligned}\frac{\Theta_{it}}{j_{it}} &= \gamma_0 + \gamma_1 \cdot \text{house value}_{it} + \gamma_2 \cdot \text{home equity}_{it} + \gamma_3 \cdot \mathbb{1}_{kt}^{\mu_h} \\ &\quad + \gamma_4 \cdot \text{house value}_{it} \times \mathbb{1}_{kt}^{\mu_h} + \gamma_5 \cdot \text{home equity}_{it} \times \mathbb{1}_{kt}^{\mu_h} + \Gamma \cdot X_{it} + u_{it}, \end{aligned} \tag{23}$$

where Θ_{it} is the amount invested in risky financial assets by agent i at time t, and $j_{it} = \{1, LA, FW\}$. As we do not have information on the risk characteristics of retirement portfolios in the SIPP, we do not include retirement assets (i.e., IRA and 401k) in the risky stock holdings in this specification. As in Chetty and Szeidl (2011), the set of explanatory variables X_{it} include state, current year, year of housing purchase and age fixed effects, and a 10-piece linear spline for liquid wealth and income.

Table 8 presents the results for the test of Hypothesis 3.1. The coefficient estimates in Column (2) imply that a $\$100,000$ increase in property value reduces the risky share of liquid wealth by approximately 21.7%, whereas a $\$100,000$ increase in home equity increases it by 24.8%. The coefficient on the interaction between home equity and $\mathbb{1}_{kt}^{\mu_h}$ is -11.4% and is statistically significant. Therefore, in a regime of high expected growth, a $100,000 increase in home equity increases

[40] Our specification is similar to that used by Chetty and Szeidl (2011) to examine how the effect of housing on portfolios covaries with the volatility of local housing markets (see Section 4.3 and Table 7 of their paper). To test whether the effects of housing on portfolios differ in high versus low-risk environments, they interact a high-risk indicator with property value and home equity. The high-risk indicator is equal to one when the standard deviation of annual house price growth rates using the FHFA data by state is above the median volatility of 4.5%.

the risky share of liquid wealth by 13.4%(= 24.8% − 11.4%). Thus, housing holdings have a substantial and significant effect on risky stock holdings, as documented by Chetty and Szeidl (2011). Furthermore, house price predictability affects risky stock holdings through the home equity channel. This result is consistent with our model predictions. On average, households hold fewer risky stocks during a period of high house appreciation. Similar conclusions can be drawn when we estimate the same specification using risky stocks in dollar amount (see Column (1)). Column (3) indicates that these results are not significant when we use the portfolio choice measure of risky stocks as a fraction of financial wealth. However, Column (4) shows that these results are significant when we only consider wealthy individuals, that is households with financial wealth greater than $100,000, the behavior of which may be the most relevant for financial market aggregates. The point estimate of the interaction between our indicator and the home equity coefficient is significant and larger in magnitude than those in the full sample. Housing return predictability remains an important determinant of portfolio choice even for wealthier households.

[TABLE 8 HERE]

Because our model mainly provides predictions on the stock share of financial wealth, we perform regressions on this variable using model-simulated data. We estimate OLS regressions instead of two-stage Tobit specifications, because each household in the simulations invests in risky stocks each time. In order to compare the distribution of the OLS coefficients we estimate from the simulated data, Columns (5) and (6) report the marginal effects on the expected value for the left-hand-side variable of Columns (3) and (4).[41] Column (7) reports the median and the 1^{st} and 99^{th} percentiles of the distribution of the OLS coefficients that we obtain using the simulated data. The two most important coefficients for our purposes are House value $\times \mathbb{1}_{kt}^{\mu_h}$ and Equity $\times \mathbb{1}_{kt}^{\mu_h}$. Recall that the first coefficient is not significant in our regressions. Overall, the model produces coefficients that reproduce the empirical results in terms of sign. Figure 9 displays the distribution of both coefficients from the simulated data. The figure illustrates that the 99% confidence interval of the coefficient of the interaction Equity $\times \mathbb{1}_{kt}^{\mu_h}$ obtained using the SIPP data falls within the

[41] The rescaling is obtained by multiplying the γ coefficient of the two-stage Tobit specification by the term $\Phi\left(\frac{X_i\hat{\gamma}}{\hat{\sigma}}\right)$ that is simply the estimated probability of observing an uncensored observation at these values of X. The rescaling is implemented because our model predicts that each household should participate in the stock market, while only one third of the households holds risky stocks in the SIPP survey.

respective distribution. Therefore, the outcomes in the simulations are similar in magnitude to the estimated coefficient.

[FIGURE 9 HERE]

Additionally, Hypothesis 3.2 states that households should decrease stock holdings to a greater extent in periods of high growth in house prices around home purchases. We test this hypothesis using the small subsample of households for which: (i) we observe a home purchase within our data, and (ii) we observe portfolio shares both before and after the home purchase. As in Chetty and Szeidl (2011), we include both individuals who transition from renting to owning and individuals who bought a new and more valuable house within our sample frame. We estimate the following reduced-form model, where the dependent variable is the change in risky stock holdings in dollar terms, risky stock holdings relative to liquid wealth (LA) and the change in risky stock holdings relative to financial wealth (FW) around housing purchases:

$$\Delta\left(\frac{\Theta_{it}}{j_{it}}\right) = \gamma_0 + \gamma_1 \cdot \mathbb{1}^{\mu_h}_{kt} + \gamma_2 \cdot \Delta\text{Property value}_{it} + \gamma_3 \cdot \Delta\text{Wealth}_{it} + \Gamma \cdot \Delta X_{it} + u_{it}, \tag{24}$$

where ΔProperty value$_{it}$ and ΔWealth$_{it}$ denote the changes in value of the house and financial wealth, respectively.[42] As in Chetty and Szeidl (2011), we instrument ΔProperty value$_{it}$ using the state house price index in the year of the home purchase.[43] We extend their empirical strategy by introducing our indicator $\mathbb{1}^{\mu_h}_{kt}$ to account for predictability in housing returns. We also include state, age, and year fixed effects as controls. Similar to the previous specifications, we control for changes in the number of children, marital status, and unemployment status.

Table 9 presents the results of this test. The estimates of the coefficient γ_1 indicate that individuals who buy more valuable houses in periods of high growth in house prices decrease their risky stock holdings in dollar terms to a greater extent (see Column (1) of Table 9). Moreover, the average decrease in risky stock holdings relative to liquid wealth for the same households is approximately 5.2% (see Column (2)). Both coefficients are substantial and significant at the 5% level. When we estimate our specification on risky stock holdings relative to financial wealth, the

[42] To reduce the influence of outliers, we exclude 62 households that report changes in total wealth of more than one million dollars in these specifications.

[43] Because we only observe portfolio shares over one year, there is little difference between house prices at the time of purchase and the point at which we observe portfolio shares. As result, we cannot separately instrument for the effects of changes in wealth (via home equity) on portfolios as in the preceding cross-sectional specifications.

coefficient γ_1 reported in Column (3) is not significant but takes the correct sign. Presumably, changes in financial wealth around home purchases substantially attenuate the estimated effect of the indicator $\mathbb{1}_{kt}^{\mu_h}$ on portfolio shares.

[TABLE 9 HERE]

Column (4) reports the outcomes for the coefficient of the indicator $\mathbb{1}_{kt}^{\mu_h}$ that we obtain using the simulated data. The median value of the distribution is consistent in sign. Figure 10 displays the distribution of this coefficient from the simulated data and illustrates that the coefficient obtained from the SIPP data falls within this distribution.

[FIGURE 10 HERE]

7 Conclusions

The presence of housing price predictability and transaction costs affects the optimal behavior of households. During periods of high growth in housing prices, households that move to a new house end up with larger shares of housing wealth in their portfolios and larger declines in their shares of risky stocks. Moreover, during periods of high growth in housing prices, smaller movements in the wealth-to-housing ratio are required to trigger the purchase of a new home.

To reach these conclusions, this paper extends the seminal work in Grossman and Laroque (1990) by considering predictability in house prices. We estimate and test a three-regime Markov-switching process for the expected growth rate of house prices at the U.S. state level. We document important differences in the magnitude of the expected growth rates and the timing of house price cycles across U.S. states. In our model, households consider two state variables when making their decisions under predictability in house prices and transaction costs: their wealth-to-housing ratio and the time-varying expected growth in house prices. The model provides three novel implications. First, the boundaries of the wealth-to-housing ratio determining the purchase of a new home are time varying and depend on the dynamics of the expected growth rate of house prices. Second, we find lower adjustments in the wealth-to-housing ratio for households that move to a more valuable house during periods of high expected growth in house prices compared to households moving in other periods. Third, we illustrate that the share of wealth invested in risky assets is lower during periods of high expected growth in house prices. In addition, conditional on moving, the change in the households' risky asset holdings relative to their wealth is larger in periods of high expected growth in house prices than in any lower-growth regime.

Empirical tests using PSID and SIPP data confirm the main implications of the model. Our empirical results illustrate that the high growth in house prices in some U.S. states experienced over the 2000-2006 period affected the likelihood of buying a new home and increased the households' investments in housing. We also confirm that housing price predictability has substantial effects on financial portfolios. The empirical evidence suggests that households tended to withdraw funds from stocks over the same period. We also use model-simulated data to replicate the same tests that we run on the PSID and SIPP data. These results indicate that the calibrated model captures most of the empirical results in sign and magnitude.

In sum, our paper demonstrates that the effects of transaction costs and house price predictability are key elements of both housing and non-housing portfolio allocation decisions. We focus on the analysis of these decisions using a partial equilibrium model that takes house price predictability as given. Interesting directions for future research include endogenizing house prices to better understand the general equilibrium implications of house price predictability.

References

Ang, A., and G. Bekaert. 2002. "International Asset Allocation with Regime Shifts." *Review of Financial Studies* 15 (4): 1137–1187.

Attanasio, O. 2000. "Consumer Durables and Inertial Behaviour: Estimation and Aggregation (S,s) Rules for Automobile Purchases." *Review of Economic Studies* 67 (4): 667–696.

Baele, L. 2005. "Volatility Spillover Effects in European Equity Markets." *Journal of Financial and Quantitative Analysis* 40 (2): 373–401.

Barberis, N. 2000. "Investing for the Long Run When Returns are Predictable." *Journal of Finance* 55 (1): 225–264.

Bertola, G., L. Guiso, and L. Pistaferri. 2005. "Uncertainty and Consumer Durables Adjustment." *Review of Economic Studies* 72 (4): 973–1007.

Brennan, M., E. Schwartz, and R. Lagnado. 1997. "Strategic Asset Allocation." *Journal of Economic Dynamics and Control* 21 (8-9): 1377–1403.

Campbell, J. Y., and J. F. Cocco. 2003. "Household Risk Management and Optimal Mortgage Choice." *Quarterly Journal of Economics* 118 (4): 1449–1494.

Campbell, J. Y., and L. M. Viceira. 1999. "Consumption and Portfolio Decisions When Expected Returns are Time Varying." *Quarterly Journal of Economics* 114 (2): 433–495.

Campbell, S. D., M. A. Davis, J. Gallin, and R. F. Martin. 2009. "What Moves Housing Markets: A Variance Decomposition of the Rent-Price Ratio." *Journal of Urban Economics* 66 (2): 90–102.

Chauvet, Marcelle, and James D Hamilton. 2005. "Dating business cycle turning points." Technical Report, National Bureau of Economic Research.

Chetty, R., and A. Szeidl. 2011. "The Effect of Housing on Portfolio Choice." Working paper, University of California, Berkeley.

Cocco, J. F. 2005. "Portfolio Choice in the Presence of Housing." *Review of Financial Studies* 18 (2): 535–567.

Damgaard, A., B. Fuglsbjerg, and C. Munk. 2003. "Optimal Consumption and Investment Strategies with a Perishable and an Indivisible Durable Consumption Good." *Journal of Economic Dynamics and Control* 28 (2): 209–253.

Davidoff, T. 2010. "Home Equity Commitment and Long-Term Care Insurance Demand." *Journal of Public Economics* 94 (1): 44–49.

Davis, Morris A., and Francois Ortalo-Magne. 2011. "Household Expenditures, Wages, Rents." *Review of Economic Dynamics* 14 (2): 248–261.

Davtes, R. B. 1977. "Hypothesis Testing When a Nuisance Parameter is Present only Under the Alternative." *Biometrika* 64 (2): 247–254.

Del Negro, M., and C. Otrok. 2007. "99 Luftballons: Monetary Policy and the House Price Boom across U.S. States." *Journal of Monetary Economics* 54 (7): 1962–1985.

Eberly, J. 1994. "Adjustment of Consumers' Durable Stocks: Evidence from Automobile Purchases." *Journal of Political Economy* 102 (3): 403–436.

Fischer, Marcel, and Michael Z. Stamos. 2013. "Optimal Life Cycle Portfolio Choice with Housing Market Cycles." *forthcoming Review of Financial Studies.*

Flavin, M., and S. Nakagawa. 2008. "A Model of Housing in the Presence of Adjustment Costs: A Structural Interpretation of Habit Persistence." *American Economic Review* 98 (1): 474–495.

Flavin, M., and T. Yamashita. 2002. "Owner-Occupied Housing and the Composition of the Household Portfolio." *American Economic Review* 92 (1): 345–362.

Garcia, R., and P. Perron. 1996. "An Analysis of the Real Interest Rate Under Regime Shifts." *Review of Economics and Statistics* 78 (1): 111–125.

Greene, W. H. 2008. *Econometric Analysis.* 6th. Prentice Hall.

Grossman, S. J., and G. Laroque. 1990. "Asset Pricing and Optimal Portfolio Choice in the Presence of Illiquid Durable Consumption Goods." *Econometrica* 58 (1): 22–51.

Hamilton, J. D. 1990. "Analysis of Time Series Subject to Changes in Regime." *Journal of Econometrics* 45 (1): 39–70.

Heaton, J., and D. Lucas. 2000. "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk." *Journal of Finance* 55 (3): 1163–1198.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica* 47 (1): 153–161.

Jagannathan, R., and Z. Wang. 1996. "The Conditional CAPM and the Cross-Section of Expected Returns." *Journal of Finance* 51 (1): 3–53.

Kim, T. S., and E. Omberg. 1996. "Dynamic Nonmyopic Portfolio Behavior." *Review of Financial Studies* 9 (1): 141–161.

Kocherlakota, N. R. 1996. "The Equity Premium: It's Still a Puzzle." *Journal of Economic Literature* 34 (1): 42–71.

Lynch, A. W., and P. Balduzzi. 2000. "Predictability and Transaction Costs: The Impact on Rebalancing Rules and Behavior." *Journal of Finance* 55 (5): 2285–2309.

Martin, R. F. 2003. "Consumption, Durable Goods, and Transaction Costs." Working paper, Board of Governors of the Federal Reserve System.

Palacios-Huerta, I. 2003. "The Robustness of the Conditional CAPM with Human Capital." *Journal of Financial Econometrics* 1 (2): 272–289.

Shiller, R. J. 2005. *Irrational Exuberance.* 2nd. Princeton University Press.

Stanton, Richard, and Nancy Wallace. 2011. "The Bear's Lair: Index Credit Default Swaps and the Subprime Mortgage Crisis." *Review of Financial Studies* 24 (10): 3250–3280.

Stokey, N. L. 2009a. *The Economics of Inaction, Stochastic Control Models with Fixed Costs.* Princeton University Press.

———. 2009b. "Moving Costs, Nondurable Consumption and Portfolio Choice." *Journal of Economic Theory* 144 (6): 2419–2439.

Van Hemert, O. 2008. "Life-cycle Housing and Portfolio Choice with Bond Markets." Working paper, New York University, Stern Business School.

Yamashita, T. 2003. "Owner-Occupied Housing and Investment in Stocks: An Empirical Test." *Journal of Urban Economics* 53 (2): 220–237.

Yao, R., and H. H. Zhang. 2005. "Optimal Consumption and Portfolio Choices with Risky Housing and Borrowing Constraints." *Review of Financial Studies* 18 (1): 197–239.

Figures and Tables

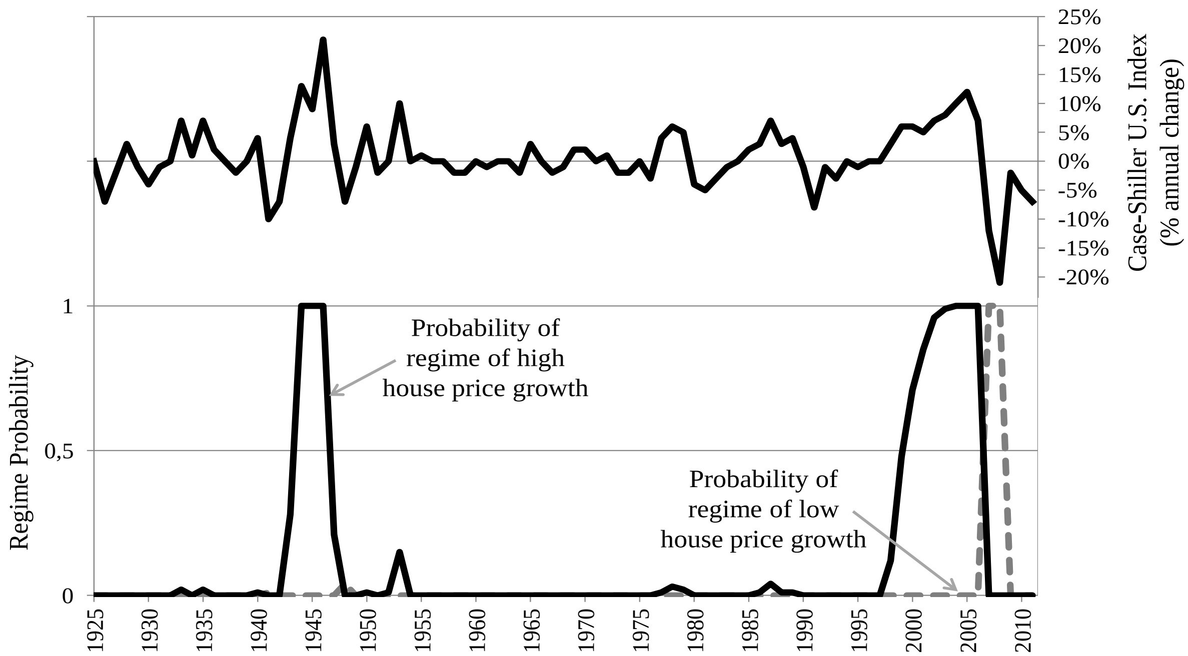
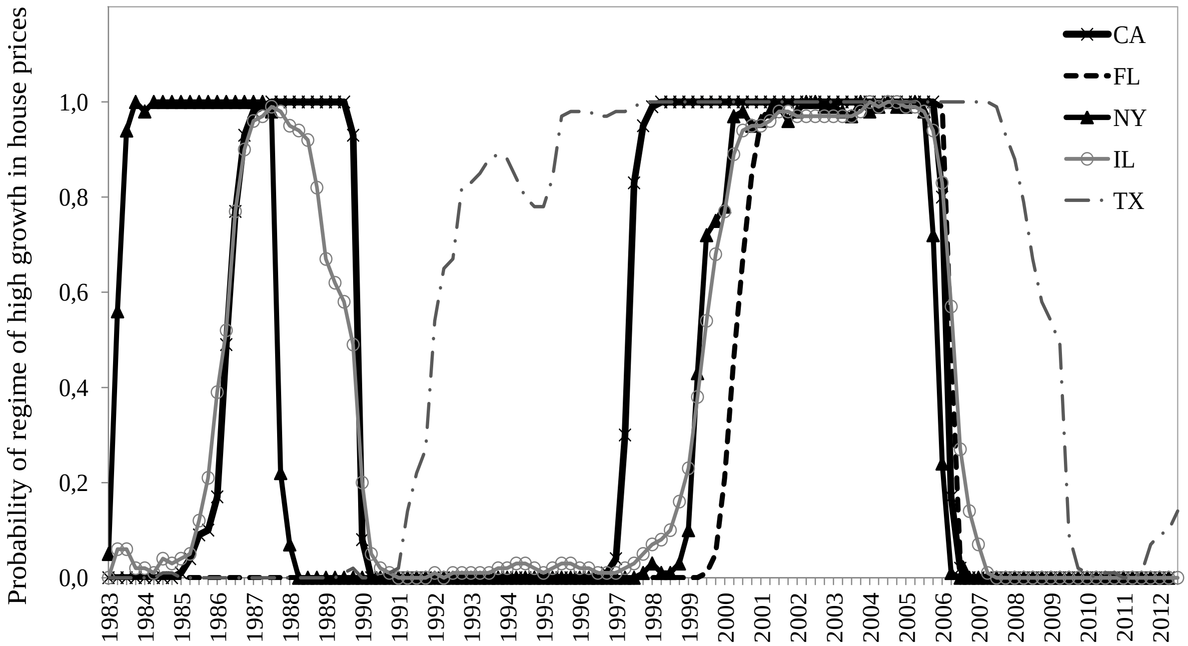


Figure 1: **Probability of being in regimes of high and low growth of housing returns.** The top half of the graph shows the real annual change in the Case-Shiller U.S. Home Price Index and the bottom half shows the smoothed probabilities of being in a regime of high and low growth for the 1925-2011 period. This graph does not plot the probability of being in a regime of medium growth, which is one minus the sum of the probabilities of being in the regimes of high and low growth.



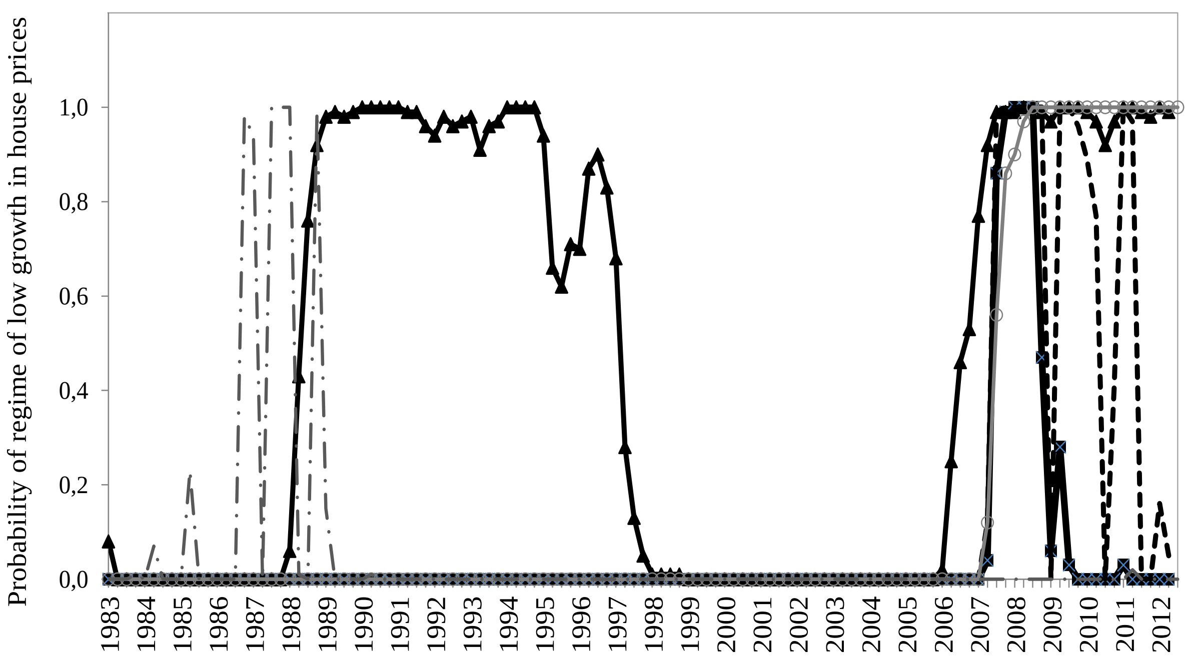


Figure 2: **Geographical heterogeneity of the probability of being in regimes of high and low growth of housing returns.** Smoothed probability of being in a regime of high growth (top panel) and low growth (bottom panel) for the states of California (CA), Florida (FL), New York (NY), Illinois (IL), and Texas (TX) based on estimates of Table 1.

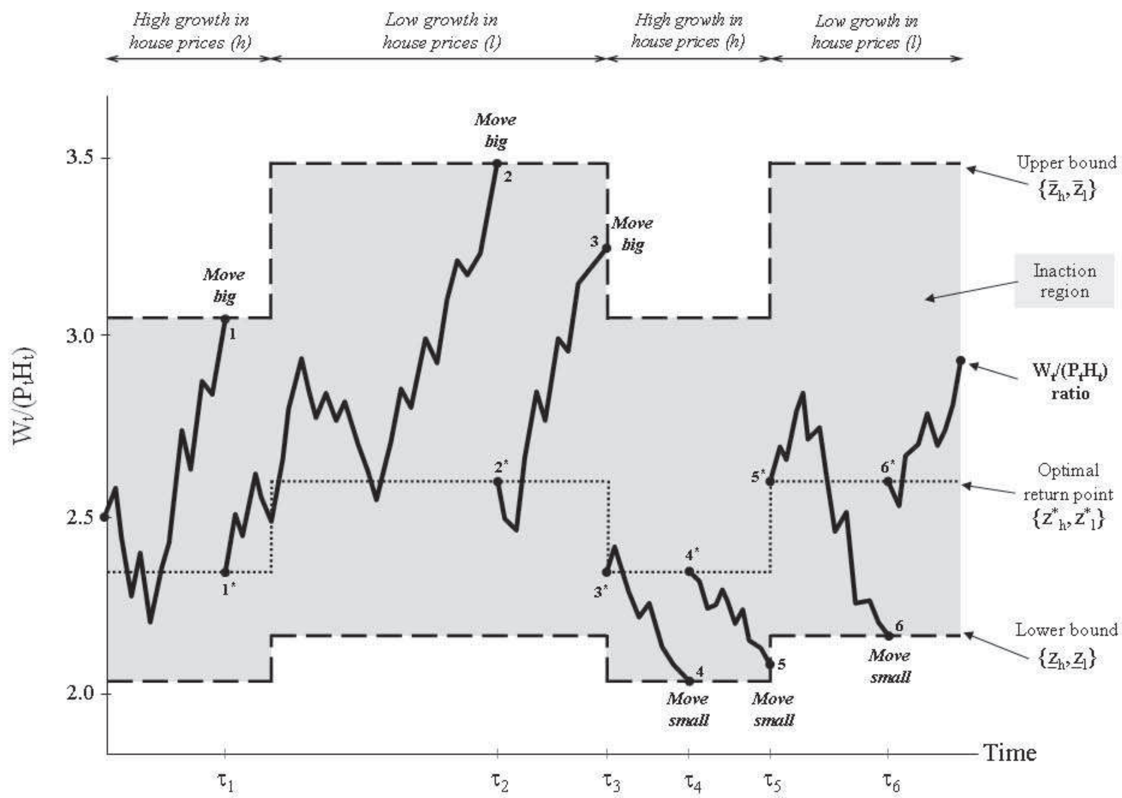


Figure 3: **Illustration.** Hypothetical path of wealth-to-housing ratio and upper and lower bounds for a two regime Markov switching process (i.e., high and low growth of housing returns). Changes in the expected growth of prices cause households to buy or sell the house. When the wealth-to-housing ratio reaches a bound, the benefits of re-sizing the house outweighs the transaction costs.

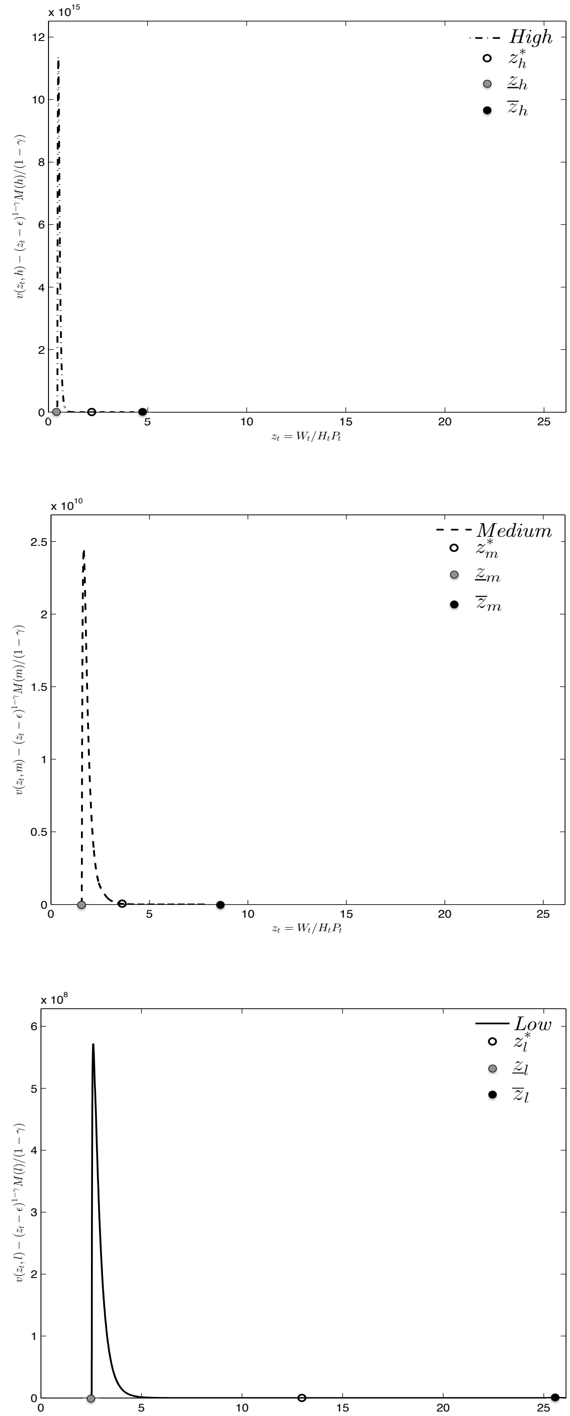


Figure 4: **Value function and value of changing the home. Panel A (high growth), Panel B (medium growth) and Panel C (low growth)** The difference between the value function, $v(z(t), i)$, and the value of changing housing consumption, $(z(t) - \epsilon)^{1-\gamma} M_i/(1-\gamma)$, is plotted against $z(t)$, where $z(t) = W(t)/(H(t)P(t))$, and i. o indicates the optimal return point. These graphs are generated using numerical results that we obtain from the model when we use the parameter values of Table 2 and the parameters of the U.S. aggregate house price process reported in Column (2) of Table 1.

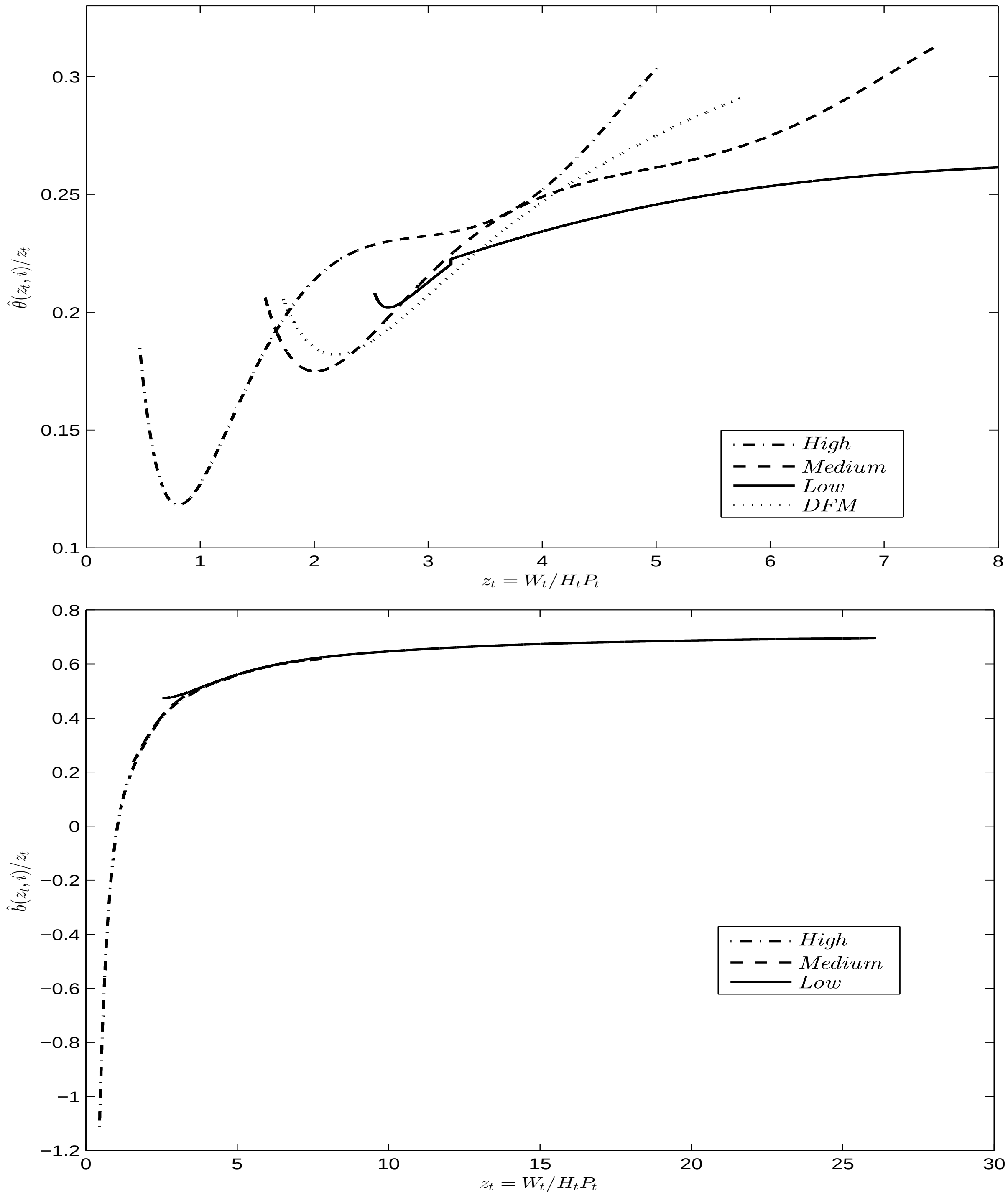


Figure 5: **Portfolio holdings of risky and risk-free assets. Panel A (Share of risky stock) and Panel B (Share of risk-free stock).** Portfolio allocation as a function of $z(t)$ and i: Share of risky assets $\hat{\theta}(z(t), i)/z(t)$ (top) and share of risk-free assets $\hat{b}(z(t), i)/z(t)$ (bottom). These graphs are generated using numerical results that we obtain from the model when we use the parameter values of Table 2 and the parameters of the U.S. aggregate house price process reported in Column (2) of Table 1.

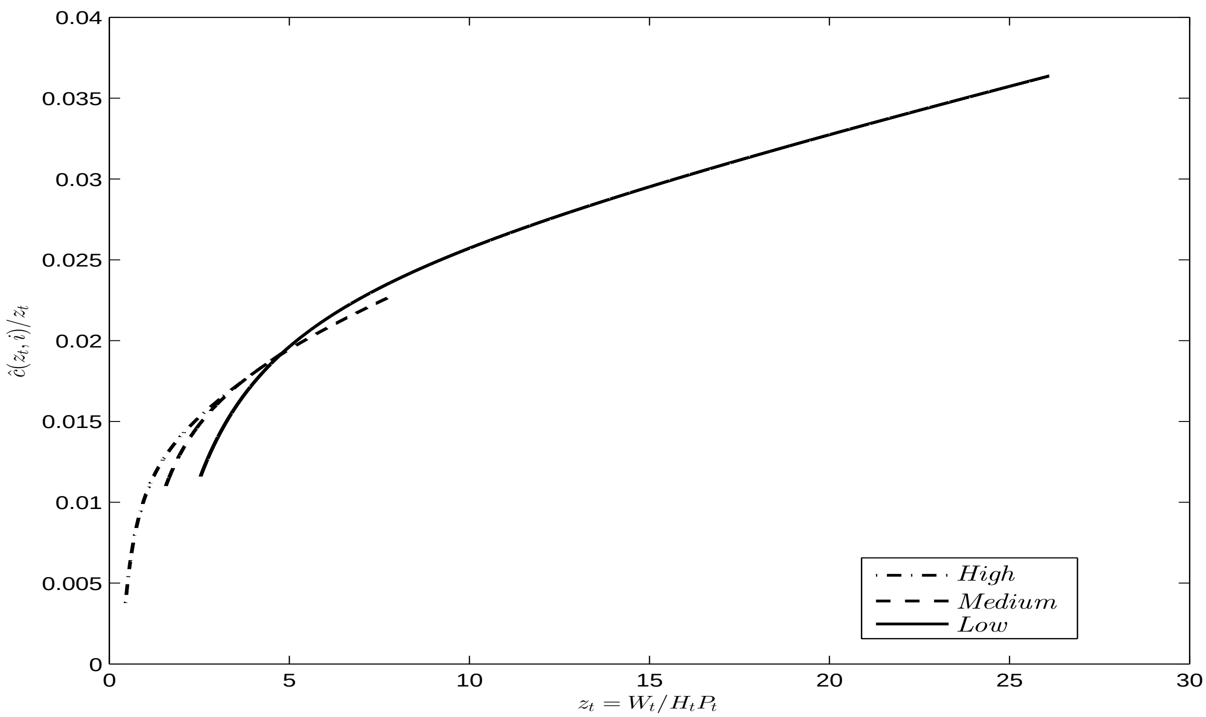


Figure 6: **Numeraire consumption.** Ratio of numeraire consumption to total wealth as function of $z(t)$ and i. These graphs are generated using numerical results that we obtain from the model when we use the parameter values of Table 2 and the parameters of the U.S. aggregate house price process reported in Column (2) of Table 1.

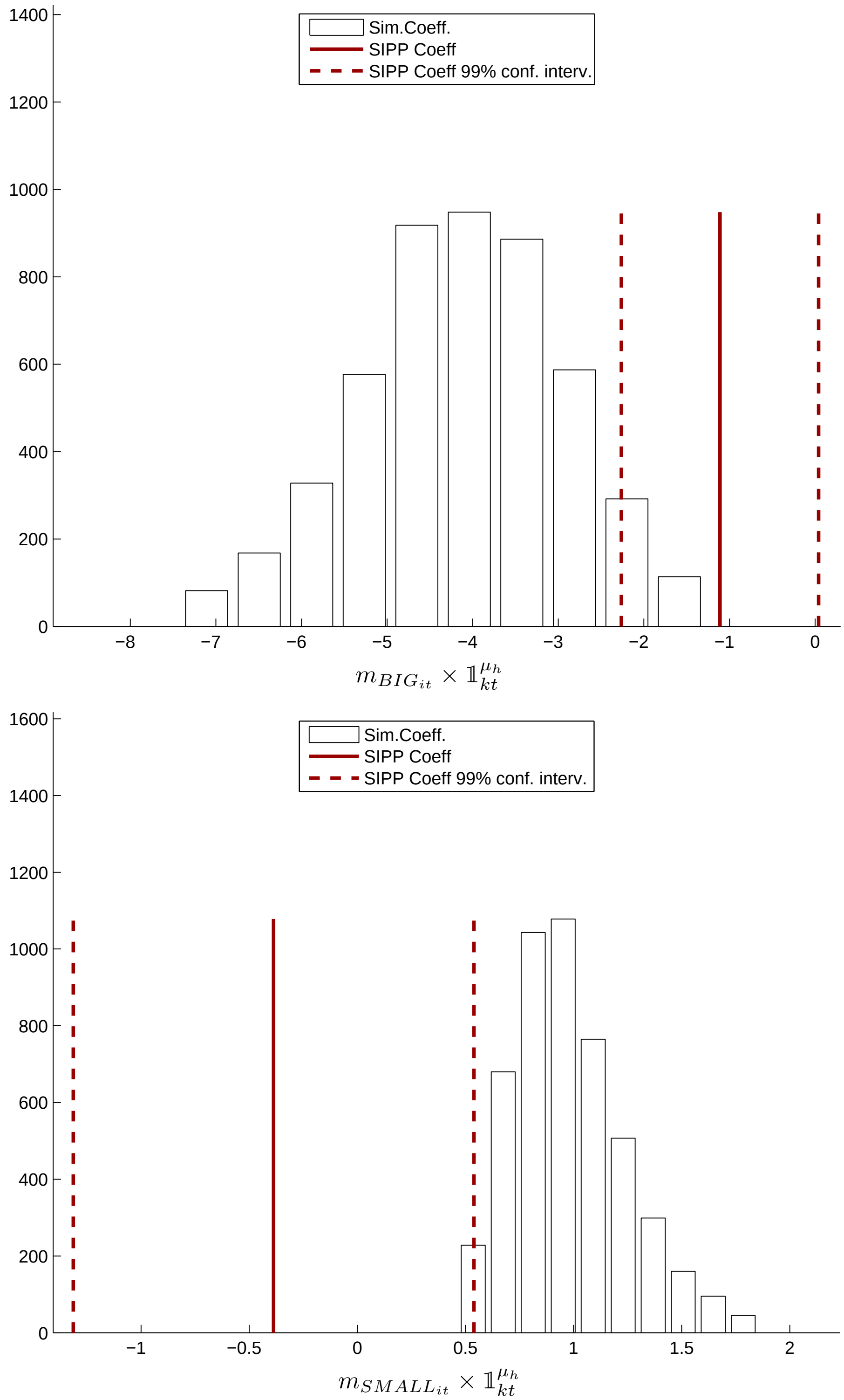


Figure 7: **Hypothesis 1. Distribution of the coefficient $m_{BIG_{it}} \times \mathbb{1}^{\mu_h}_{kt}$ and $m_{SMALL_{it}} \times \mathbb{1}^{\mu_h}_{kt}$ obtained using model simulated data.** The upper (lower) panel is a histogram of the realized coefficient $m_{BIG_{it}} \times \mathbb{1}^{\mu_h}_{kt}$ ($m_{SMALL_{it}} \times \mathbb{1}^{\mu_h}_{kt}$) over $5,000$ simulations. The continuous line marks the equivalent coefficient obtained using SIPP data and the dotted line marks the associated 99% confidence interval.

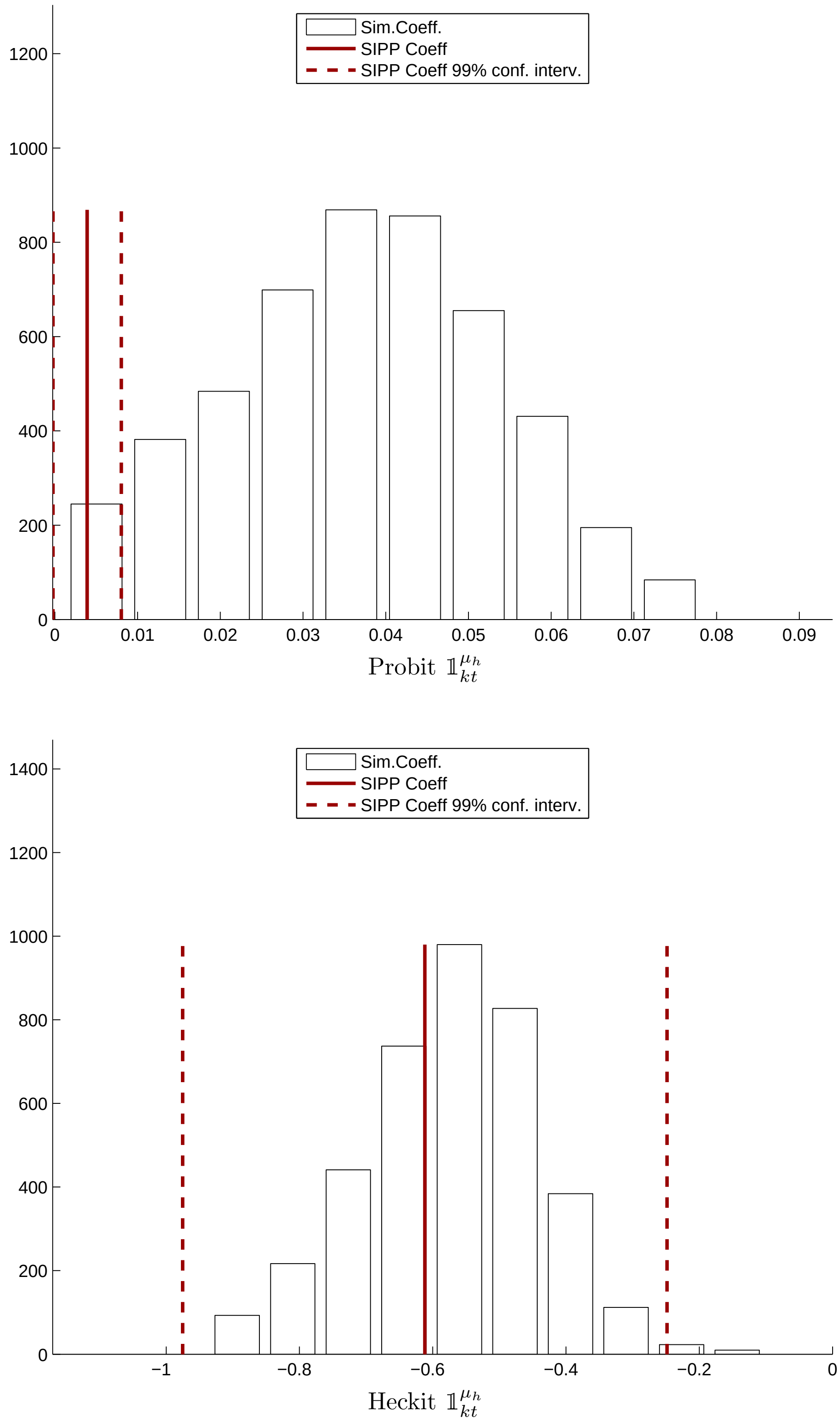


Figure 8: **Hypothesis 2. Distribution of the coefficient $\mathbb{1}_{kt}^{\mu_h}$ for the Probit and Heckit estimation obtained using model simulated data.** The upper (lower) panel is a histogram of the realized coefficient $\mathbb{1}_{kt}^{\mu_h}$ for the Probit (Heckit) estimation over $5,000$ simulations. The continuous line marks the equivalent coefficient obtained using the SIPP data and the dotted line marks the associated 99% confidence interval.

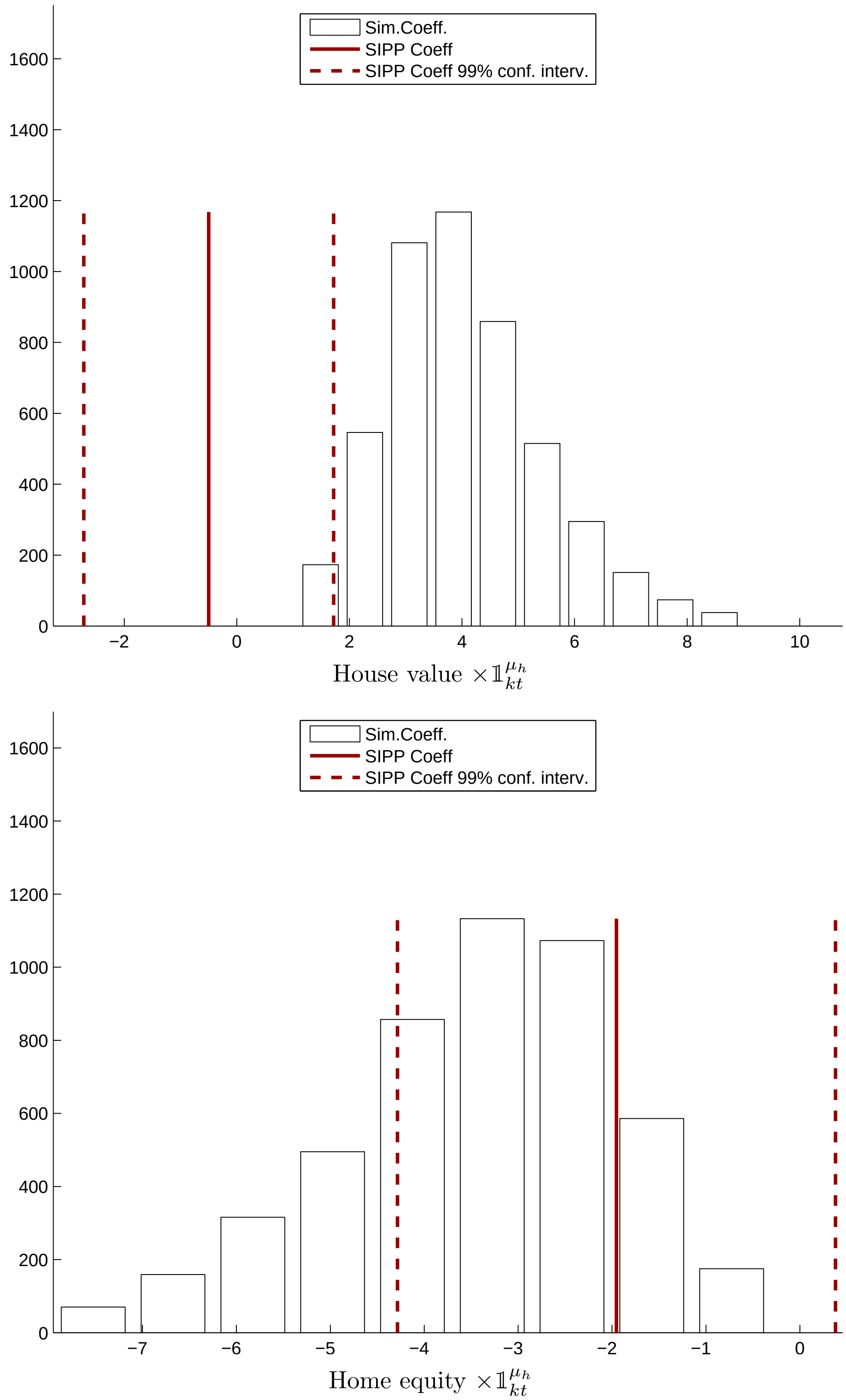


Figure 9: **Hypothesis 3.1. Distribution of the coefficients** $House\ value\ \times \mathbb{1}_{kt}^{\mu_h}$ **and** $Home\ equity\ \times \mathbb{1}_{kt}^{\mu_h}$ **obtained using model simulated data.** The upper (lower) panel is a histogram of the realized coefficient $House\ value\ \times \mathbb{1}_{kt}^{\mu_h}$ ($Home\ equity\ \times \mathbb{1}_{kt}^{\mu_h}$) over $5,000$ simulations. The continuous line marks the equivalent coefficient obtained using theSIPP data and the dotted line marks the associated 99% confidence interval.

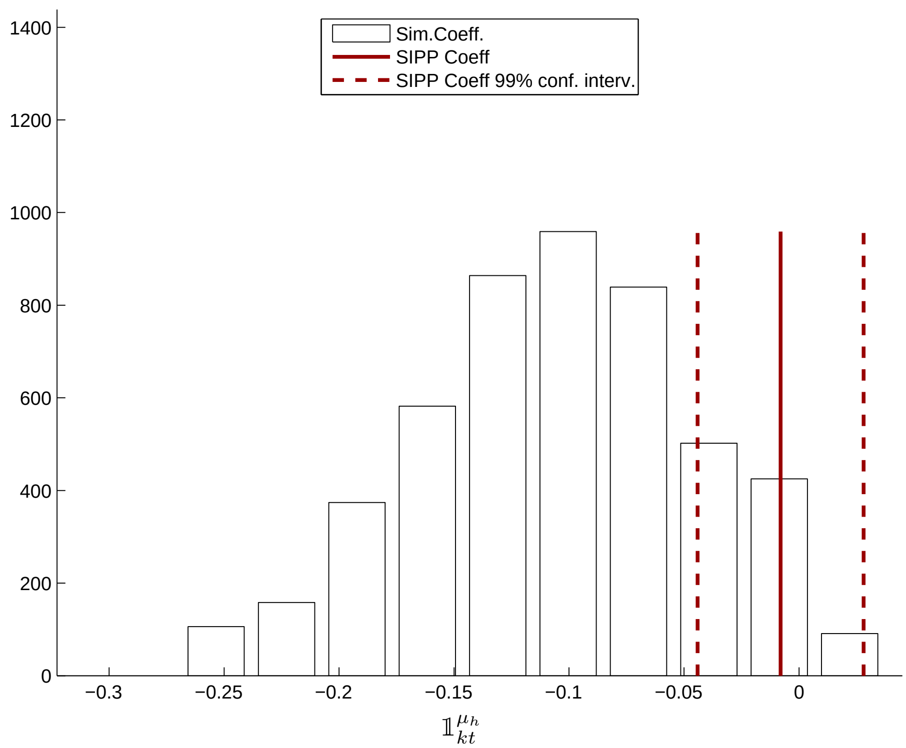


Figure 10: **Hypothesis 3.2. Distribution of the coefficient $\mathbb{1}^{\mu_h}_{kt}$ obtained using model simulated data.** The panel is a histogram of the realized coefficient $\mathbb{1}^{\mu_h}_{kt}$ over $5,000$ simulations. The continuous line marks the equivalent coefficient obtained using SIPP data and the dotted line marks the associated 99% confidence interval.

Table 1: **Parameter values for the house price process.** Estimation of the parameters of the house price process using a 3-regime process. The growth of house prices in each regime i is denoted by μ_i and its standard deviation is denoted by σ_P, where i can be either $i = l$ (low growth regime), $i = m$ (medium growth regime)or $i = h$ (high growth regime). Column 1 shows the parameters for the aggregate U.S. house prices using Case-Shiller data; the parameters are annual; Columns $2-7$ show the parameters for U.S. aggregate and five U.S. states using FHFA data; the parameters are quarterly. The five U.S. states displayed here are, respectively, California, Florida, New York, Illinois and Texas. The likelihood test is used to test the null hypothesis that house prices follow a martingale against the alternative of a regime switching mechanism. Data source: Shiller (2005) and Federal Housing Finance Agency (FHFA).

	Case-Shiller 1925 – 2011	Federal Housing Finance Agency 1983(1Q) – 2012(2Q)					
	U.S.	U.S.	California	Florida	New York	Illinois	Texas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
μ_l	-0.1619	-0.0134	-0.0561	-0.0449	-0.0083	-0.0144	-0.0350
	(0.0286)	(0.0016)	(0.0083)	(0.0039)	(0.0017)	(0.0017)	(0.0036)
μ_m	-0.0015	0.0017	-0.0086	-0.0005	0.0061	0.0031	-0.0052
	(0.0047)	(0.0010)	(0.0019)	(0.0014)	(0.0045)	(0.0012)	(0.0016)
μ_h	0.0942	0.0131	0.0275	0.0305	0.0254	0.0113	0.0045
	(0.0146)	(0.0014)	(0.0021)	(0.0028)	(0.0018)	(0.0014)	(0.0011)
σ_P	0.0383	0.0073	0.0136	0.0121	0.0104	0.0077	0.0074
	(0.003)	(0.0004)	(0.0009)	(0.0008)	(0.0007)	(0.0005)	(0.0005)
λ_{ll}	0.4184	0.7466	0.7550	0.7528	0.9642	1.000	0.4543
	(0.3777)	(0.1296)	(0.4616)	(0.1299)	(0.0652)	(0.03526)	(0.2367)
λ_{lm}	0.5815	0.2533	0.2449	0.2471	0.0357	0.000	0.5456
	(0.3538)	(0.1377)	(0.2467)	(0.1308)	(0.0374)	(0.0063)	(0.2292)
λ_{ml}	-	0.0592	0.0203	0.0394	0.1452	0.0173	0.0734
		(0.0294)	(0.0201)	(0.0223)	(0.0891)	(0.0277)	(0.0501)
λ_{mm}	0.9686	0.9249	0.9470	0.9480	0.7399	0.9411	0.8954
	(0.0246)	(0.0331)	(0.0306)	(0.0254)	(0.1371)	(0.0372)	(0.0578)
λ_{hl}	0.0945	-	-	-	-	-	-
	(0.0929)						
λ_{hm}	0.1209	0.0322	0.0415	0.0441	0.0543	0.0604	0.0196
	(0.1186)	(0.3256)	(0.0295)	(0.04347)	(0.0560)	(0.0543)	(0.0210)
LR-test χ^2:							
$\mu_l = \mu_m = \mu_h$	36.248	82.834	54.607	72.195	101.88	72.61	69.61
P-value	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
Num. Obs.	87	118	118	118	118	118	118

Table 2: **Parameter used for benchmark calibration.**

Variable	Symbol	Value
Curvature of the utility function	γ	10
Time preference	ρ	0.025
House flow services	$1-\beta$	0.4
Risk free rate	r	0.015
Risky asset drift	α_S	0.077
Standard deviation risky asset	σ_S	0.1655
Correlation house price - risky asset	ρ_{PS}	0.25
Transaction cost	ϵ	0.10
House depreciation	δ	0

Table 3: **Numerical results.** Column (1) shows the z ratio that determines the lower bound, the optimal return point (i.e., wealth-to-housing ratio immediately after a housing transaction), and the upper bound, respectively. Column (2) shows the optimal return point for the model with no transaction costs. Columns (3), (4), and (5) show the size of the housing adjustment, the expected time between two consecutive moves, and the drift of the z ratio at the optimal return point, respectively. Column (6) shows the coefficient of relative risk aversion. Columns (7) and (8) show the portfolio holdings of non-housing assets right before a housing transaction for the model with and without transaction costs, respectively. Column (9) shows the average portfolio holdings of non-housing assets. Columns (10) and (11) show the consumption of non-housing goods right before a housing transaction for the model with and without transaction costs, respectively.

	Regime	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	i	$(\underline{z}_i, z_i^*, \overline{z}_i)$	z_i^{*nt}	$E(\tau_i)$	Δz	z drift at z^*	$RRA(z^*, i)$	$\frac{E\left(\frac{\hat{\Theta}^*}{\hat{W}^*}\right)}{E(\tau_i)}$	$\frac{E\left(\frac{\hat{\theta}^{*nt}}{\hat{W}^{*nt}}\right)}{E(\tau_i^{nt})}$	$\Delta \frac{\hat{\Theta}}{\hat{W}}$	$\frac{E\left(\frac{\hat{C}^*}{\hat{W}^*}\right)}{E(\tau_i)}$	$\frac{E\left(\frac{\hat{C}^{*nc}}{\hat{W}^{*nc}}\right)}{E(\tau_i)}$
Panel A												
U.S.	H	$(0.77, 1.40, 5.31)$	1.19	6.92	3.91	−0.010	13.9	0.132	0.153	0.114	0.010	0.021
	M	$(1.42, 2.21, 7.50)$	1.90	9.68	5.29	0.006	12.9	0.197	0.201	0.076	0.016	0.027
	L	$(2.41, 3.67, 13.15)$	3.65	19.09	9.48	0.066	11.2	0.240	0.239	0.043	0.022	0.038
	DFM	$(1.59, 2.03, 6.93)$	1.83	26.66	4.90	0.006	12.2	0.197	0.198	0.075	0.016	0.029
Panel B												
California	H	$(0.49, 1.12, 4.30)$	0.73	5.60	3.18	−0.014	29.8	0.048	0.073	0.204	0.008	0.018
	M	$(1.51, 2.80, 8.12)$	3.44	15.97	5.32	0.035	10.8	0.213	0.236	0.053	0.016	0.023
	L	$(2.11, 8.16, 18.15)$	6.54	1.36	9.98	0.205	10.1	0.264	0.256	0.011	0.032	0.053
Florida	H	$(0.57, 0.99, 4.21)$	0.67	5.20	3.22	−0.006	42.9	0.025	0.055	0.248	0.008	0.018
	M	$(1.51, 3.44, 7.39)$	2.58	12.78	3.95	0.016	10.3	0.233	0.221	0.040	0.018	0.017
	L	$(3.12, 6.68, 17.45)$	5.84	2.22	10.76	0.163	10.0	0.261	0.252	0.016	0.026	0.048
New York	H	$(0.53, 1.73, 4.12)$	0.79	7.25	2.38	−0.034	14.8	0.117	0.089	0.077	0.010	0.017
	M	$(1.42, 2.48, 5.14)$	1.58	14.94	3.65	−0.006	10.8	0.194	0.185	0.059	0.014	0.0160
	L	$(2.01, 2.78, 7.08)$	3.32	16.37	4.27	0.032	10.9	0.217	0.236	0.047	0.015	0.021
Illinois	H	$(1.25, 3.28, 4.22)$	1.38	11.89	2.96	−0.014	10.7	0.224	0.171	0.023	0.017	0.015
	M	$(2.49, 3.61, 6.75)$	2.12	12.82	4.25	0.006	10.5	0.235	0.209	0.033	0.019	0.015
	L	$(3.11, 4.15, 11.65)$	4.00	14.47	8.53	0.053	11.3	0.257	0.242	0.042	0.026	0.026
Texas	H	$(1.51, 2.65, 4.81)$	1.95	22.72	2.16	0.002	10.8	0.216	0.203	0.047	0.015	0.015
	M	$(1.71, 2.91, 6.78)$	2.58	20.49	3.87	0.014	10.7	0.225	0.221	0.044	0.016	0.017
	L	$(2.13, 5.71, 13.50)$	4.39	3.04	7.78	0.122	10.3	0.254	0.250	0.018	0.023	0.053

Table 4: **Descriptive statistics**. Sample averages and standard deviations (in parenthesis) for the main variables used in our analysis from PSID and SIPP data. The variables Move big and Move small correspond to the individuals who moved to a house having a higher and lower value, respectively. Full sample refers to all the individuals in the sample, irrespective of their moving situation. The ratio $z = W/(P \cdot H)$ corresponds to the ratio of financial wealth net of debt over housing value without considering human capital as part of the wealth. The ratio $\widetilde{z} = (W+L)/(P \cdot H)$ corresponds to the ratio of total wealth with human capital L and net of debt over housing value. ΔFamily shows the statistics of changes in family size. ΔMarried is one if the individual gets married, zero otherwise. ΔEmployment is one if the individual changes employment status, zero otherwise. Age corresponds to the age of the household head. Northeast, Midwest, South and West are U.S. macro-region dummies.

	Full sample		Move big		Move small	
	PSID	SIPP	PSID	SIPP	PSID	SIPP
	(1)	(2)	(3)	(4)	(5)	(6)
$z = W/(PH)$	1.388	1.376	1.322	1.36	1.257	1.213
	(1.645)	(1.636)	(1.78)	(1.776)	(1.64)	(1.451)
$\widetilde{z} = (W+L)/(PH)$	8.956	5.944	13.463	9.019	8.928	5.099
	(10.453)	(7.153)	(15.069)	(8.932)	(10.691)	(5.894)
Stock share Θ/W	0.102	0.18	0.124	0.221	0.107	0.143
	(0.225)	(0.372)	(0.248)	(0.392)	(0.2)	(0.327)
Safe asset share B/W	-1.051	-0.779	-1.644	-1.035	-1.682	-0.929
	(2.199)	(2.187)	(2.679)	(2.268)	(2.903)	(2.181)
m_{BIG}	0.063	0.017	-	-	-	-
	(0.243)	(0.129)				
m_{SMALL}	0.023	0.009	-	-	-	-
	(0.149)	(0.092)				
ΔFamily	-0.044	-0.015	0.071	0.077	-0.235	-0.091
	(0.667)	(0.508)	(0.917)	(0.728)	(1.15)	(0.859)
ΔMarried	0.016	0.011	0.067	0.011	0.033	0.048
	(0.126)	(0.106)	(0.25)	(0.105)	(0.179)	(0.215)
ΔEmployment	0.148	0.069	0.101	0.097	0.217	0.127
	(0.356)	(0.253)	(0.301)	(0.297)	(0.413)	(0.334)
Age	49.094	52.987	40.386	43.802	46.07	49.436
	(15.02)	(15.741)	(12.954)	(12.979)	(15.426)	(15.263)
Midwest	26.6%	27.2%	26.9%	27.9%	27%	24.9%
	(0.442)	(0.445)	(0.444)	(0.449)	(0.444)	(0.433)
South	40.9%	36.2%	38.9%	31.7%	42.5%	38.5%
	(0.492)	(0.481)	(0.488)	(0.466)	(0.495)	(0.487)
West	16.9%	18.5%	20.7%	26%	20.6%	22.6%
	(0.374)	(0.389)	(0.405)	(0.439)	(0.405)	(0.419)
Northeast	15.6%	18%	13.5%	14.4%	9.9%	13.9%
	(0.363)	(0.384)	(0.342)	(0.351)	(0.299)	(0.347)
Num. Obs.	20189	105877	1273	1797	456	911

Table 5: **Movers.** Percentage of households that moved over total households in the PSID and SIPP surveys across all years. Columns (1) – (2) show the percentage of households that changed address. Columns (3) – (4) show the percentage of households that moved to a new address in the same U.S. macro region. Columns (5) – (6) show the percentage of households that moved to a new address in the same state. Columns (7) – (8) show the percentage of movers that were not owners in the preceding period.

	Move		Same U.S. region		Same U.S. state		Not Owner at $t-1$	
	PSID	SIPP	PSID	SIPP	PSID	SIPP	PSID	SIPP
Status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Owner	15.43%	13.55%	14.82%	12.74%	14.19%	12.00%	3.79%	5.47%
Renter	28.70%	35.16%	27.03%	33.55%	25.26%	32.17%	25.31%	32.67%
Occupied	4.15%	3.49%	3.87%	3.31%	3.56%	3.09%	3.63%	3.06%

Table 6: **Test of Hypothesis 1.** PSID, SIPP, and model-simulated data. Coefficients are estimated by using a standard OLS model and ex-ante (i.e., before moving) values of $\tilde{z}_{it}$ as endogenous variable. $m_{BIG_{it}}$ ($m_{SMALL_{it}}$) is a dummy variable equal to one if the family is increasing (decreasing) its housing holdings (i.e., moving to a bigger (smaller) house). $\mathbb{1}^{\mu_h}$ is an indicator capturing periods of persistent high appreciation in house prices at U.S. state level. Standard errors, reported in parentheses, are clustered at state level. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level. The regressions include year and state dummies. Column (3) and (6) report the median of the distribution of the estimated coefficients from regressions using simulated panel data and the 5^{th} and 95^{th} of the same distribution in square parentheses. Data source: PSID (1984 – 2005) and SIPP (1997 – 2005).

	PSID (1)	SIPP (2)	Model (3)	PSID (4)	SIPP (5)	Model (6)
constant (γ_0)	5.812***	3.569***	3.002	5.788***	3.559***	4.196
	(0.348)	(0.834)	[1.340, 5.924]	(0.832)	(0.832)	[2.252, 5.917]
m_{BIG} (γ_1)	2.662***	1.717***	5.082	3.218***	1.899***	5.588
	(0.494)	(0.220)	[3.737, 7.174]	(0.534)	(0.263)	[4.021, 7.846]
m_{SMALL} (γ_2)	0.147	−1.328***	−2.062	0.462	−1.282***	−2.654
	(0.375)	(0.216)	[−3.851, −0.894]	(0.442)	(0.238)	[−4.444, −1.505]
$\mathbb{1}^{\mu_h}$ (γ_3)				0.280	−0.041	−2.461
				(0.196)	(0.123)	[−3.552, −0.671]
$m_{BIG} \times \mathbb{1}^{\mu_h}$ (γ_4)				−2.712***	−1.111**	−1.902
				(0.596)	(0.447)	[-4.394,0.068]
$m_{SMALL} \times \mathbb{1}^{\mu_h}$ (γ_5)				−0.944	−0.387	1.974
				(0.780)	(0.359)	[0, 4.251]
ΔFamily	−0.283***	−0.378***		−0.290***	−0.378***	
	(0.104)	(0.069)		(0.103)	(0.069)	
ΔMarried	3.559***	−0.162		3.557***	−0.162	
	(0.722)	(0.229)		(0.720)	(0.228)	
ΔEmployment	0.614**	−0.667***		0.607**	−0.665***	
	(0.282)	(0.098)		(0.283)	(0.099)	
Age	X	X		X	X	
State	X	X	X	X	X	X
Year	X	X		X	X	
R^2	0.429	0.516		0.430		
Num. Obs.	17280	105216		17280		

Table 7: **Test of Hypothesis 2**. Probit for the increase and decrease of housing holdings and the Heckman selectivity model. Column (1) reports the marginal effect estimates from the probit regressions for increasing the amount of housing holdings. Column (3) reports estimates on the log of the housing adjustment $\ln(\overline{z} - z^{*})$ for increasing housing holdings. $\mathbb{1}^{\mu_h}$ is an indicator that captures periods of high expected growth in house prices at the U.S. state level. Standard errors are reported in parenthesesAll the regressions include a constant and a state and year dummies. *** denotes significance at the 1% level, ** at the 5% level, and * at the 10% level. Column (2) and (4) report the median of the distribution of the estimated coefficients from the regressions using the model simulated data. They also report the range defined by the 5^{th} and the 95^{th} percentile of this distribution in square parentheses. Data source: SIPP $(1997 - 2005)$.

	Probability of housing increase		Size of housing increase	
	SIPP	Model	SIPP	Model
	(1)	(2)	(3)	(4)
$\tilde{z}$	0.0004^{***}	0.0003		
	(0.0000)	$[0, 0.0031]$		
$\mathbb{1}^{\mu_h}$	0.0039^{**}	0.0011	-0.6118^{***}	-0.0622
	(0.0016)	$[0, 0.0135]$	(0.1409)	$[-0.4444, 0.1869]$
ΔFamily	0.0037^{***}		-0.3867^{***}	
	(0.0006)		(0.1278)	
ΔMarried	0.0041		-0.1850	
	(0.0042)		(0.2846)	
ΔEmployment	0.0033^{**}		-0.2343^{**}	
	(0.0014)		(0.1153)	
Age	X		X	
State	X	X	X	X
Year	X		X	
R^2			0.368	
Num. Obs.	105759		1361	

Table 8: **Test of Hypothesis 3.1**. Non-Housing Portfolio holdings. Cross Section Two Step Tobit IV Estimates. Standard errors in parenthesis. All the specifications include state, current year, purchase year, and age fixed effects. They also include controls for changes in family size, marriage status, and employment status. Data source: SIPP ($1997-2005$).

	Stocks	Stocks share on Liquid Wealth	Stocks share on Wealth	Stocks share on Wealth (Wealth $> \$100,000$)
	(1)	(2)	(3)	(4)
House value	-24626	-21.716*	-2.974	-2.657
	(16978)	(11.120)	(4.452)	(5.351)
Home equity wealth	39172**	24.821**	-2.766	1.399
	(17945)	(11.761)	(4.956)	(5.799)
House value $\times\ \mathbb{1}_{jt}^{\mu_h}$	-3649	2.998	-1.508	-1.452
	(9259)	(6.060)	(2.373)	(2.491)
Equity $\times\ \mathbb{1}_{jt}^{\mu_h}$	-15153*	-11.352*	-1.532	-5.680**
	(8031)	(5.273)	(2.179)	(2.627)
$\mathbb{1}_{jt}^{\mu_h}$	31222*	10.299	5.218	14.001**
	(17220)	(11.278)	(4.506)	(6.469)
Num. Obs.	35624	35624	35624	22754

Table 9: **Test of Hypothesis 3.2**. Non-Housing Portfolio Changes around Home Purchases. IV Estimates. Standard errors in parenthesis. All the specifications include state, current year, purchase year, and age fixed effects. They also include controls for changes in family size, marriage status, and employment status. Data source: SIPP ($1997-2005$).

	ΔStocks	ΔStocks on Liquid Wealth	ΔStocks on Wealth
	(1)	(2)	(3)
$\mathbb{1}_{jt}^{\mu_h}$	-15373**	-0.052**	-0.008
	(5996)	(0.024)	(0.014)
ΔProperty value	46649*	-0.222	0.003
	(26862)	(0.147)	(0.057)
ΔWealth	14954*	0.093*	0.007
	(8819)	(0.055)	(0.020)
Num. Obs.	5961	5961	5961

Appendix

A Analysis of the Measure of Predictability in House Prices

This appendix provides an analysis on the regime-switching measure of predictability in house prices. Table A-I presents the estimation of the house price regime-switching process using state-level house prices obtained from FHFA. The sample size varies across states. The earlier states to display quarterly house prices series start in 1975 and the latest states start in 1986. The methodology is exactly the same that we used to produce the estimates reported in Table 1.

[TABLE A-I HERE]

In addition to state-level robustness for the Markov-switching estimates, we also follow a different approach to motivate the predictability of housing prices. Following the literature on predictability using valuation ratios, we also run predictability regressions using price-rent ratios. The objective of this appendix is to present evidence on the robustness of the time variation of expected housing returns and, in particular, to show the relation between the Markov switching model used throughout the paper and the predictability generated by price-rent ratio variations. The price-rent ratios have been computed as in Campbell et al. (2009) using annualized quarterly data from 1978 to 2007 on house prices from the FHFA and rents from the Bureau of Labor Statistics (BLS). We use the annualized 1-month Treasury Bill as a risk-free rate to obtain excess returns.

Table A-II presents the results of the in sample predictability regressions. The tables reporting the predictability results at the MSA level using price-rent ratios are available in the online appendix. We regress future housing returns, at different horizons, on current rent-price ratios. We observe that the rent-price ratio has a strong predictive power on future housing returns. At the U.S. aggregate level, a 1% variation in the rent-price ratio implies a 23.02% variation in a three-year horizon return using FHFA data for house prices. For longer horizons, results are even stronger. As we increase the horizon, the coefficient of the rent-price ratios, $(d_t - p_t)$, which forecasts future housing returns, becomes higher and more statistically significant.[44] When forecasting $4-$ and

[44] The explanation for this phenomenon, in the absence of the bubble term, is that the $(d_t - p_t)$ ratios are highly persistent. When estimating an $AR(1)$ to rent-price ratios for the sample, we cannot reject non-stationarity, supporting the idea of bubble-like behavior during the last few years. On the other hand, for the trimmed data set, the autocorrelation coefficient of the rent-price ratios series is 0.93 for annual data. Obviously, this results in a larger R^2 as well.

5−year returns, a 1% increase in rent-price ratios implies an increase of 41% and 47%, respectively, in housing returns at the aggregate level. Similar results appear at the U.S. census macro region level. Panel B shows the results with an alternative dataset. We construct rent-prices data using housing services from NIPA as a proxy for rents, and value of residential investment from the Flow of Funds to compute prices. The results in Panel B are robust to including most of the last decade, as opposed to Panel A, whose results reverse if we include the periods of dramatic increase in house prices.

[TABLE A-II HERE]

Figure A-I plots the rent-price ratio, with a 4−year lead as the regressions suggest, and the probability of home price growth being in the high state. The sample size of the rent-price ratio is substantially shorter but for the period in which the two of them overlap, the peaks in the probability of the high-growth regime correspond to peaks in the rent-price ratio time series. The correlation is positive for most of the sample except for the last few observations. This is in line with the inability of the rent-price ratios to explain expected returns that may be explained only by future expected appreciation. Our partial-equilibrium approach does not allow us to address the origin of a bubble-like outcome. The online appendix provides a robustness analysis on the use of our regime-switching based measure.

[FIGURE A-I HERE]

B Model

B.1 Derivation of the Model

This appendix characterizes the optimal return point of the inaction region. The value function of our problem is

$$V(W(0), P(0), H(0), i) = \sup_{C,\Theta,H(\tau_A),\tau_A} E\left[\int_0^{\tau} e^{-\rho\tau} u(C, H(0)e^{-\delta t})dt + e^{-\rho\tau} V(W(\tau^-) - \epsilon P(\tau)H(\tau^-), P(\tau), H(\tau), i)\right], \quad \text{(B-1)}$$

$i = 1, ..., n$. We can use the homogeneity properties of the value function to reduce the problem with four state variables (W, P, H, i) to one with two state variables $z = W/(PH)$ and i. The value function $V(W, P, H, i)$ is homogenous of degree $1-\gamma$ in (W, H) and of degree $\beta(1-\gamma)$ in (W, P). As as result, for any constant $\phi > 0$ we have

$$V(\phi W, P, \phi H, i) = \phi^{1-\gamma} V(W, P, H, i), \tag{B-2}$$

$$V(\phi W, \phi P, H, i) = \phi^{\beta(1-\gamma)} V(W, P, H, i), \tag{B-3}$$

$i = 1, ..., n$. Because of the homogeneity properties (B-2) and (B-3) of the value function, we have

$$V(W, P, H, i) = H^{1-\gamma} P^{\beta(1-\gamma)} V\left(\frac{W}{PH}, 1, 1, i\right) = H^{1-\gamma} P^{\beta(1-\gamma)} v\left(z, i\right), \tag{B-4}$$

$i = 1, ..., n$ (see Damgaard, Fuglsbjerg, and Munk (2003)). Let us introduce the scaled controls $\hat{c} = C/(PH)$ and $\hat{\theta} = \Theta/(PH)$. Note that $\hat{c}/z = C/W$ and $\hat{\theta}/z = \Theta/W$. Substituting and simplifying, we obtain

$$\begin{aligned} & P(0)^{\beta(1-\gamma)} H(0)^{1-\gamma} v(z(0), i) = \\ & \sup_{\hat{c}, \hat{\theta}, H(\tau_A), \tau_A} E\left[\int_0^{\tau} e^{-\rho\tau} \frac{P(\tau)^{\beta(1-\gamma)} (\hat{c} H(0) e^{-\delta t})^{1-\gamma}}{1-\gamma} dt + e^{-\rho\tau} P(\tau)^{\beta(1-\gamma)} H(\tau)^{1-\gamma} v(z(\tau), i)\right], \end{aligned} \tag{B-5}$$

$i = 1, ..., n$. Following Damgaard, Fuglsbjerg, and Munk (2003), let

$$\begin{aligned} e^{-\rho\tau} P(\tau)^{\beta(1-\gamma)} H(\tau)^{1-\gamma} v(z(\tau), i) &= \\ e^{-\rho\tau} P(\tau)^{\beta(1-\gamma)} H(\tau^-)^{1-\gamma} \left(\frac{H(\tau^-)}{H(\tau)}\right)^{\gamma-1} v\left(\frac{W(\tau^-) - \epsilon P(\tau) H(\tau^-)}{P(\tau) H(\tau)}, i\right) &= \\ e^{-\rho\tau} P(\tau)^{\beta(1-\gamma)} H(\tau^-)^{1-\gamma} \left(\frac{H(\tau^-)}{H(\tau)}\right)^{\gamma-1} v\left(\frac{H(\tau^-)}{H(\tau)} \left(\frac{W(\tau^-)}{P(\tau) H(\tau^-)} - \epsilon\right), i\right) & \end{aligned}$$

and we can derive

$$e^{-\rho\tau} P(\tau)^{\beta(1-\gamma)} (H(0) e^{-\delta\tau})^{1-\gamma} \left(z(\tau^-) - \epsilon\right)^{1-\gamma} \left(\frac{H(\tau^-)}{H(\tau)} \left(z(\tau^-) - \epsilon\right)\right)^{\gamma-1} v\left(\frac{H(\tau^-)}{H(\tau)} \left(z(\tau^-) - \epsilon\right), i\right), \tag{B-6}$$

$i = 1, ..., n$. Let us re-express our Bellman equation

$$P^{\beta(1-\gamma)} v(z(0), i) = \sup_{\bar{c}, \bar{\theta}, \tau_A} E \left[\int_0^{\tau} e^{-\hat{\rho}\tau} \frac{P(\tau)^{\beta(1-\gamma)} \bar{c}^{1-\gamma}}{1-\gamma} dt + e^{-\hat{\rho}\tau} P(\tau)^{\beta(1-\gamma)} M_i \frac{(z(\tau^-) - \epsilon)^{1-\gamma}}{1-\gamma} \right], \tag{B-7}$$

where

$$\begin{aligned} M_i &= \sup_{H(\tau) \leq H e^{-\delta\tau} (z(\tau^-)\epsilon)/\epsilon} (1-\gamma) \left(\frac{H(\tau^-)}{H(\tau)} \left(z(\tau^-) - \epsilon \right) \right)^{\gamma-1} v \left(\frac{H(\tau^-)}{H(\tau)} \left(z_{\tau-} - \epsilon \right), i \right) \\ &= (1-\gamma) \sup_{z \geq \epsilon} z^{\gamma-1} v(z, i), \end{aligned} \tag{B-8}$$

$i = 1, ..., n$ and $\hat{\rho} = \rho + \delta(1-\gamma)$. Also note that

$$z^* = \arg\max_{z \geq \epsilon} z^{\gamma-1} v(z, i) \tag{B-9}$$

is the value of the transformed state variable after the optimal change in the housing holdings at time τ, since

$$z(\tau) = \frac{W(\tau)}{H(\tau)P(\tau)} = \frac{W(\tau^-) - \epsilon H(\tau^-) P(\tau)}{H(\tau)P(\tau)} = \frac{H(\tau^-)}{H(\tau)} (z(\tau^-) - \epsilon) = z^*. \tag{B-10}$$

The new level of housing holdings can be expressed in terms of z^* as $H(\tau) = H(\tau^-)(z(\tau^-) - \epsilon)/z^*$.

B.2 Algorithm for the Numerical Resolution

We adopt a stepwise numerical procedure to find the optimal values $(M_i, \underline{z}_i, \overline{z}_i, z_i^*)$ for $i = 1, ..., n$:

1. Guess $M_i = M_{i,0}$ for $i = 1, ..., n$.

2. Solve the free bound problem as follows:

   (i) Guess $\underline{z}_{i,0}$ for $i = 1, ..., n$;

   (ii) Solve the ODEs equation (10) using as initial conditions the four equations defined by equation (15) until the value-matching conditions are satisfied. We adopt a finite difference scheme to solve the system of ODEs;

(iii) If the smooth pasting conditions specified by equation (16) are satisfied, then the candidate value functions $v_{M_{i,0}}(z,i)$ for $i = 1, ..., n$ are found, otherwise repeat steps (i) and (ii).

3. Compute the implied $M^*_{i,0} = (1-\gamma)\sup_z z^{\gamma-1} v_{M_{i,0}}(z,i) = (1-\gamma) z_i^{*(\gamma-1)} v(z_i^*, i)$ using equation (13). If $M^*_{i,0} = M_{i,0}$ for each $i = 1, ..., n$, the problem is solved, otherwise go to step 1.

As a starting point, we use the solution to the problem of no transaction costs, $\epsilon = 0$, (see the online appendix). That solution consists of the optimal housing-to-wealth ratio $\alpha_{h,i}$, the optimal risky assets ratio $\alpha_{\theta,i}$ and the optimal numeraire consumption ratio $\alpha_{c,i}$, for $i = 1, ..., n$. The first set of iterations uses a fixed portfolio policy. For initial values of M_i and z_i^*, we use $M_i = \alpha_{v,i}$ and $z_i^* = 1/\alpha_{h,i}$, where $i = 1, ..., n$. However, there is little to guide the initial estimations about $\underline{z}_i$ and $\overline{z}_i$, except to require $\underline{z}_i < z_i^*$ and $\overline{z}_i > z_i^*$. After the iterative procedure has converged, the solution is used to construct an approximation to the policy function $\hat{\theta}^*(z,i)$ and $\hat{c}^*(z,i)$. Then, we adopt a value iteration procedure to obtain $(\underline{z}_i, \overline{z}_i, M_i, z_i^*)$ for $i = 1, ..., n$.

C Additional Information About the Data

In this appendix we provide further information on some of the variables we use in the empirical specification, including the computation of the human capital measure. The PSID regularly collects information about home values and mortgage debt; occasionally, the PSID also collects information about behavior on savings and wealth. The SIPP has a detailed inventory of annual real and financial assets and liabilities, containing more frequent measures of assets that are relevant for assistance measures since its main purpose is to evaluate the effectiveness of government transfer programs. The PSID is a nationally representative longitudinal sample of approximately $9,000$ households. At each moment, the SIPP tracks approximately $30,000$ households. During the period considered, information was collected from three consecutive groups of households that were interviewed during the years $1996-2000$ (four times), $2001-2003$ (three times), and $2004-2006$ (two times), respectively. During its active period, each panel is interviewed every year, while panels of households do not overlap across periods. The SIPP over-samples from areas with high poverty concentrations, which should be taken into account when interpreting the results. Its longitudinal features enable the analysis of dynamic characteristics, such as changes in income and in household and family composition, or housing dynamics. Both surveys allow us to study the empirical implications of the model outlined above.

The methodology to impute human capital at the household level is based on Heaton and Lucas (2000) and Eberly (1994). The stream of labor income cash flows is discounted at a real interest rate of five percent per year, $R = 5\%$. We use the current annual total household earned income as the cash flow for the annuity CF_t. We also assume that households earn income until age 65. Therefore, households older than 65 do not accumulate any human capital. Under these assumptions, the human capital of each household i of age n can be computed as:

$$L_{i,t} = \frac{CF_t}{R}\left[1 - \left[\frac{1}{1+R}\right]^{(65-n)}\right]. \tag{C-11}$$

In addition to human capital, we also control for changes in family composition, employment status, and marital status. Δ Family size indicates changes in family size. In some cases, a change in family size, like having a children, does depend on financial wealth. Nonetheless, the goal is to control for exogenous changes in family size and identify those moves that are a result of a financial wealth change. Changes in family size are caused by deaths, emancipation of children, addition of family members to the household, and also by births. Δ Married is a dummy variable which takes a value of one if the individual gets married. Δ Employment is a dummy variable which takes a value of one if the household head changes her employment status.

During the sample period considered, the size of the household (in number of members) decreased by -0.044 in the PSID. The family size increased for movers to a more valuable house, 0.071, whereas it decreased for movers to a less valuable house, -0.235. Marriages also increase, by almost 1.6%. This figure is substantially higher for movers. The average age of the household head is 49.09 years. The age distribution of movers is shifted towards a younger population: 40.38 years is the average age of household heads moving to a more valuable house and 46.07 years for household heads moving to a less valuable house. There are some differences in age composition of the surveys as the youngest group is more represented in the PSID. In terms of moving, the group of movers to a more and less valuable house is lower in the SIPP than in the PSID in percentage terms, although we have more observations for this group in the SIPP.

D Heterogeneous Agents Economy Simulation

This appendix describes the simulation methodology we use to explore the implications of the model. The methodology is based on several steps.

First, we limit our exercise to simulate the choices of households from the five U.S. states for which we present the house price parameters in Section 2. For each U.S. state, we calibrate the model using different sets of parameters to generate heterogeneity across households. First, we divide the households into two groups, urban and non-urban. The only difference between an urban and a non-urban household in U.S. state j is the set of parameters that defines their house price processes and the optimal policies calibrated on the same set of parameters. For a non-urban household the set of parameters is the one reported in Table 1 of Section 2. Instead, for an urban household the set of parameters is reported in Table 5 of the online appendix. We average the real house price indexes of the largest MSAs of the state j (i.e., Los Angeles and San Francisco for California) creating an index of state j and we estimate the three regime Markov switching model using real housing returns of the same index. Second, we assume five levels of transaction costs ranging from 5% to 25% of the value of their house with a marginal increase of 5%. Then, we calibrate the model, computing the lower bound, $\underline{z}_k$, the upper bound, $\overline{z}_k$, the optimal return point, z_k^*, the optimal numeraire consumption, $\hat{c}^*(z,k)$, and the optimal portfolio holdings $\hat{\theta}^*(z,k)$ and $\hat{b}^*(z,k)$ for a fine grid of z for each combination of parameters. Overall, we have 50 optimal policies: 25 (5 U.S. states $\times$ 5 transaction cost levels) for non-urban households and 25 (5 U.S. states $\times$ 5 transaction cost levels) for urban households. Table 6 of the online appendix reports the numerical results based on the parameters of Table 5 of the same document for a transaction cost level of 10%.[45]

Second, to generate model-simulated data, we consider the empirical distribution of the cross-section of wealth-to-housing ratios, z, observable in the SIPP in the first wave of 1996. Overall, we have data for $2,721$ households. We follow Eberly (1994) and Bertola, Guiso, and Pistaferri (2005) to obtain the unconditional distribution of z. We filter the data regressing z on the same set of demographic characteristics we use in the paper which may absorb determinants of the wealth-to-housing ratio other than the dynamic variation of the type featured by our problem. For each

[45] All the optimal policies are available on request.

household, we, then, keep the current wage, the housing value, the household head's age, the year of housing purchase and the MSA residence. The wealth of each household also accounts for the human capital using equation (C-11). Each household i living in the U.S. state j is defined as an urban or a non-urban household based on the MSA residence. 53% of the $2,721$ households are classified as urban households. Then, each household i is matched with a transaction cost level according to the following rule. A 5% transaction cost level is assigned to a household that has lived in the same house for less than five years, a 10% transaction cost level is assigned to a household that has lived in the same house for more than five years but less than ten years and so on. The highest transaction cost level of 25% is assigned to a household that has lived in the same house for more than twenty years.

Third, we generate 50 years of quarterly data for each household. We repeatedly simulate panel data for $5,000$ times. The dynamics of stock, house price index and single house returns are

$$\begin{aligned} dS_t &= S_t\ \alpha_S dt + S_t\ \sigma_S dZ_{1,t}, \\ d\tilde{P}_{j,t} &= \tilde{P}_{j,t}\ \mu_{j,k} dt + \tilde{P}_{j,t}\ \sigma_{1,j,P} dZ_{1,t}, \\ dP_{i,j,t} &= P_{i,j,t}\ \mu_{j,l} dt + P_{i,j,t}\ \sigma_{1,j,P} dZ_{1,t} + \sigma_{2,j,P} dZ_{2,i,j,t}, \end{aligned} \tag{D-12}$$

where i indicates a specific household living in the U.S. state j, whose housing return is in the regime l at time t. We assume that the idiosyncratic house price shock $dZ_{2,i,j,t}$ is specific to each household. For each simulation path, we use the optimal consumption and portfolio rules to trace the evolution of the optimal wealth-to-housing ratio given

$$\begin{aligned} \mathrm{d}z^*_{i,j,t} = &\left((z^*_{i,j,,t}-1)(r+\delta-\mu_{j,k}+\sigma^2_{j,P}) + \hat{\theta}^*_{i,j,k,t}(\alpha_S - r - \rho_{PS}\sigma_{j,P}\sigma_S) - \hat{c}^*_{i,j,k,t}\right)\mathrm{d}t \\ &- \left((z^*_{i,j,t}-1)\sigma_{1,j,P} + \hat{\theta}^*_{i,j,k,t}\sigma_S\right)\mathrm{d}Z_{1,t} - (z^*_{i,j,t}-1)\sigma_{2,j,P} dZ_{2,i,j,t}. \end{aligned} \tag{D-13}$$

We approximate continuous time by evaluating numeraire consumption and portfolio rules at discrete time intervals Δt (i.e., quarterly) given realizations of $z_{i,j,t}$. We, then, simulate the moving shock for each household i living in the U.S. state j. The only approximation in moving from continuous to discrete time is that agents are allowed to adjust their housing consumption only at discrete time. This occurs when (i) $z_{i,j,t}$ reaches the upper bound $\overline{z}_{j,k,\epsilon}$ or lower bound $\underline{z}_{j,k,\epsilon}$ and it readjusts to the optimal return point $z^*_{j,k,\epsilon}$; (ii) a housing regime change occurs and $z_{i,j,t}$ is out of the inaction region; (iii) a moving shock occurs and the household has to relocate. We calculate the house values of each household i living in the U.S. state j, $H_{i,j,t} \times P_{i,j,t}$, and we keep track of agents moving in more or less valuable house calculating the new housing stock, $H_{i,j,t}$. For each household, we calculate the home equity $E_{i,j,t}$ according to

$$E_{i,j,t} = H_{i,j,t} \times P_{i,j,t} - B_{i,j,t} = H_{i,j,t} \times P_{i,j,t}(1 - \tilde{b}_{i,j,k,t}), \tag{D-14}$$

where

$$\tilde{b}_{i,j,k,t} = \min(z_{i,j,t} - 1 - \theta_{i,j,k,t}, 1), \tag{D-15}$$

and $\tilde{b}_{i,j,k,t}$ is the risk-free holdings-to-housing ratio. Then, we keep the observations at end of each quarter, keeping track of agents moving in more or less valuable house in an year interval. Finally, we have a panel data over 45 years for each simulation path, because we discharge the first 5 years of observations.

Fourth, in our empirical Section 6, we use an indicator to capture periods of high expected growth in house price at the U.S. state level. In the simulation, we create an indicator similar to the one we describe in the Appendix E. For each scenario, we know whether the U.S. state j is in a high-growth regime at time t. Therefore, we only need to verify whether the housing return of the simulated index of state j in a high-growth regime is higher than the mean growth rate in the high-growth regime of the U.S. aggregate for four consecutive quarters.

Finally, we estimate the reduced form models used to test Hypothesis 1, 2, 3.1 and 3.2 on the PSID and SIPP data. We repeatedly estimate the models for $5,000$ times to produce a sampling distribution for the statistics of interest. Specifically, we estimate the following specification for Hypothesis 1

$$\begin{aligned} z_{i,j,t} =& \gamma_0 + \gamma_1 \mathbb{1}^{\mu_h}_{j,t} + \gamma_2 m_{BIG_{i,j,t}} + \gamma_3 m_{SMALL_{i,j,t}} \\ &+ \gamma_4 m_{BIG_{i,j,t}} \times \mathbb{1}^{\mu_h}_{j,t} + \gamma_5 m_{SMALL_{i,j,t}} \times \mathbb{1}^{\mu_h}_{j,t} + u_{i,j,t}, \end{aligned} \tag{D-16}$$

Second, we estimate the following specification for Hypothesis 2 in the first stage

$$\text{Prob}(D = \text{move big}_{i,j,t/t+1}) = \gamma_0 + \gamma_1 \mathbb{1}^{\mu_h}_{j,t} + \gamma_2 z_{i,j,t} + u_{i,j,t}. \tag{D-17}$$

In the second stage, we regress the size of adjustment on the high expected growth rate indicator, $\mathbb{1}^{\mu_h}_{j,t}$

$$\ln(\bar{z}_{i,j,t} - z^*_{i,j,t+1}) = \beta_0 + \beta_1 \mathbb{1}^{\mu_h}_{j,t} + \lambda_{i,j,t} + \epsilon_{i,j,t}, \tag{D-18}$$

where $\lambda_{i,j,t}$ is the correction term calculated in the first stage.

Third, we run the following regression for Hypothesis 3.1

$$\begin{aligned}\frac{\Theta_{i,j,t}}{W_{i,j,t}} =& \gamma_0 + \gamma_1 H_{i,j,t} \times P_{i,j,t} + \gamma_2 E_{i,j,t} \\ &+ \gamma_3 \mathbb{1}^{\mu_h}_{j,t} + \gamma_4 H_{i,j,t} \times P_{i,j,t} \times \mathbb{1}^{\mu_h}_{j,t} + \gamma_5 E_{i,j,t} \times \mathbb{1}^{\mu_h}_{j,t} + u_{i,j,t},\end{aligned} \tag{D-19}$$

where $E_{i,j,t}$ is the home equity.

Finally, we run the following regression for Hypothesis 3.2

$$\Delta\left(\frac{\Theta_{i,j,t}}{W_{i,j,t}}\right) = \gamma_0 + \gamma_1 \cdot \mathbb{1}^{\mu_h}_{kt} + \gamma_2 \cdot \Delta H_{i,j,t} \times P_{i,j,t} + u_{i,j,t}. \tag{D-20}$$

E Indicator of High-Growth in Housing Prices

To capture periods of persistent high appreciation in house prices at U.S. state level, we construct a binary variable that is calculated using the estimated smoothed probabilities from the Markov-switching model on real housing returns using the quarterly house price indexes for each state and the U.S. aggregate.

We estimate the Markov switching model on the house price indexes published by the FHFA at U.S. state level. The index is a weighted repeat sales index that measures average price changes in repeat sales or refinancing on the same properties and weights them. The price information is obtained from repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since the first quarter of 1975. While the house price data has been criticized for its construction, to our knowledge it is the best data available to the public at the state level. Subsequently, we work with the growth rates of the housing price data, so issues related to bias in the level estimates are not relevant. The house price indexes data are nominal. We deflate the data using core PCE inflation, which measures inflation in the personal consumption expenditure basket less food and energy.

The house price indexes are available from 1975, but in our estimation we use only data beginning in the first quarter of 1986 for some U.S. states. FHFA data at state level are extremely noisy for a number of states before the mid-eighties as documented by Del Negro and Otrok (2007). From the perspective of the Markov switching model, the noise in the series is not necessarily a problem in terms of estimation, but makes the regime classification uninformative when the time variation is very large, as is the case for the FHFA data. The noise abates considerably for most states after the mid-eighties. Therefore, we estimate the Markov switching model on the subsample $1986(1) - 2010(4)$ for some U.S. states using a volatility threshold criteria. If the house price index volatility of a U.S. state in the subsample $1975(1) - 1985(4)$ is double the house price index volatility of the same U.S. state in the subsample $1986(1) - 2010(4)$, we estimate the Markov switching model on the subsample $1986(1) - 2010(4)$ for that U.S. state. We checked our results for robustness by (i) changing the volatility threshold; and (ii) moving the start date to the first quarter of 1985, and we found that the results are robust.

An important issue in estimating regime switching models is specifying the number of regimes. Because we aim to infer periods where house prices grew markedly at U.S. state level and house price indexes have recently experienced a sharp appreciation immediately followed by a sharp depreciation, we estimate a three regime Markov switching specification. In this case, the growth of house prices in each regime i is denoted by μ_i and i can be either $i = l$ (low-growth regime), $i = m$ (medium-growth regime) or $i = h$ (high-growth regime).

Table A-I reports the parameter estimates for the U.S. states. Overall, our analysis suggests that U.S. states differ markedly in the level of and spread between the high and low-growth regime rates. Using a likelihood ratio test, we test the null hypothesis that housing prices follow a martingale against the alternative of a regime switching mechanism. Then, we provide the Regime Classification Measure (RCM) which captures the quality of a model's regime qualification performance developed by Ang and Bekaert (2002). They argue that a good regime-switching model should be able to classify regimes sharply. This is the case when the smoothed (ex-post) regime probabilities p_i are close to either one or zero. Inferior models, however, will exhibit p_i values closer to $1/k$, where k is the number of regimes. A perfect model will be associated with a RCM close to zero, while a model that cannot distinguish between regimes at all will produce a RCM close to 100. Ang and Bekaert (2002)'s generalization of this formula to the multiple regimes case has many undesirable features.[46] We therefore adopt the measure adapted by Baele (2005):

$$RCM = 100 \times \left(1 - \frac{k}{k-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{k}\left(p_{i,t} - \frac{1}{k}\right)^2\right) \tag{E-21}$$

lies between 0 and 100, where the latter means that the model cannot distinguish between the regimes. Therefore, lower RCM values denote better regime classification. Overall, a three regime Markov switching specification allows a clear regime-classification of the FHFA data.

According to the second condition of the index definition, the real housing return of the state k has to be higher than the mean real housing return in the high-growth regime of U.S. aggregate for four quarters in a row. Based on the smoothed probabilities for U.S. aggregate, we identify the period $2000 - 2006$ as a high-growth period and we calculate a mean annual real growth rate of 6.37%. Accordingly, we use this as our threshold for condition (ii). In the online appendix, we check our results for robustness by lowering the threshold to 5%. We find that are empirical results are not significantly affected by the second condition of our indicator. Alternatively, we constructed our indicator using the filtered probabilities instead of the smoothed probabilities. Our empirical results are not affected by this modification.

[46] More specifically, their measure produces small RCMs as soon as one regime has a very low probability, even if the model cannot distinguish between the other regimes.

Figures and Tables of the Appendix

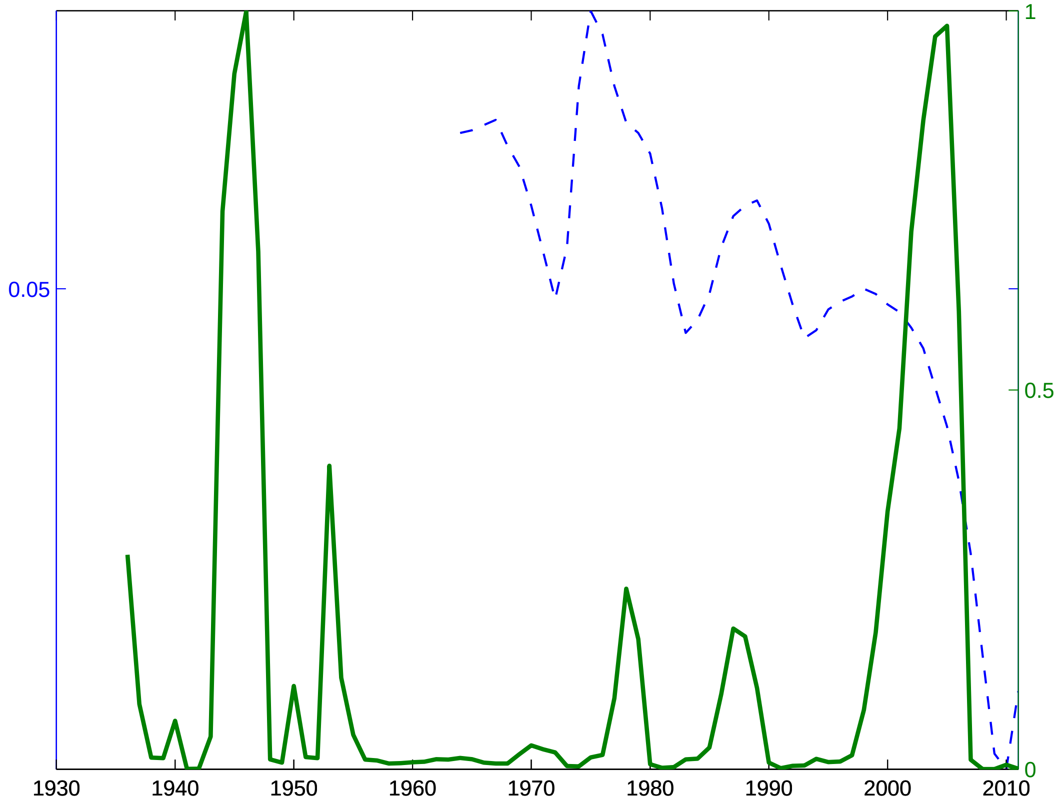


Figure A-I: **Probability of being in a high-growth regime of housing returns vs. rent-price ratio.** The bold line represents the smoothed probability of being in a high regime, on the right axis. The dashed line represents the rent-price ratio, on the left axis.

Table A-I: **Parameter values for the house price process - U.S. states.** Estimation of the parameters of the house price processes using a three regime Markov switching model. The growth of house prices in each regime i is denoted by μ_i and its standard deviation is denoted by σ_P. In a 3-regime process, i can be either $i = l$ (low-growth regime), $i = m$ (medium-growth regime) or $i = h$ (high-growth regime). The conditional probability of moving from regime i to regime j is denoted by λ_{ij}. The likelihood test is used to test the null hypothesis that house prices follow a martingale against the alternative of a regime switching mechanism. RCM refers to the regime classification measure $100 \times \left(1 - \frac{k}{k-1}\frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{k}\left(p_{i,t} - \frac{1}{k}\right)^2\right)$, where $p_{i,t}$ is the smoothed regime probability and k is the number of regimes. Lower RCM values denote better regime classification. All parameters are reported in quarterly basis. Source: FHFA. Period: * 1975 – 2010 - ** 1986 – 2010.

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
Northeast												
New England												
Maine**	−0.0222	0.0052	0.0222	0.0095	0.4254		0.2662	0.7075		0.0625	57.927	17.999
	(0.0030)	(0.0019)	(0.0024)	(0.0008)	(0.1593)		(0.0884)	(0.0925)		(0.0440)	(0.0000)	
New Hampshire**	−0.0376	−0.0049	0.0218	0.0122	0.6007		0.0845	0.8927		0.0521	70.350	12.355
	(0.0060)	(0.0023)	(0.0022)	(0.0010)	(0.1872)		(0.0542)	(0.0589)		(0.0360)	(0.0000)	
Vermont**	−0.0055	0.0100	0.0260	0.0117	0.9710		0.0788	0.8761		0.1177	45.014	20.066
	(0.0019)	(0.0028)	(0.0033)	(0.0009)	(0.0303)		(0.0566)	(0.0734)		(0.0840)	(0.0000)	
Massachusetts*	−0.0152	0.0083	0.0315	0.0137	0.8599		0.1237	0.8342		0.0592	84.829	25.171
	(0.0029)	(0.0043)	(0.0037)	(0.0010)	(0.0774)		(0.0720)	(0.0787)		(0.0447)	(0.0000)	
Rhode Island*	−0.0731	−0.0069	0.0374	0.0213		0.0003	0.0257	0.9425		0.1448	48.579	11.983
	(0.0256)	(0.0032)	(0.0049)	(0.0018)		(1.4120)	(0.0349)	(0.0398)		(0.064)	(0.0000)	
Connecticut*	−0.0126	0.0170	0.04399	0.0174	0.9039	0.0460	0.0324	0.9379	0.3658	0.0021	46.373	17.666
	(0.0093)	(0.0092)	(0.0150)	(0.0054)	(0.1432)	(0.1616)	(0.1448)	(0.1461)	(0.6637)	(1.552)	(0.0000)	
Northeast												
Middle Atlantic												
New York*	−0.0761	−0.0048	0.0260	0.0186			0.0115	0.9750	0.0179	0.0391	54.131	8.220

Table A-I – continued from previous page

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
	(0.0134)	(0.0022)	(0.0029)	(0.0011)			(0.0118)	(0.0175)	(0.0181)	(0.0274)	(0.0000)	
New Jersey*	−0.0434	−0.0029	0.0277	0.0140	0.2882		0.0505	0.9118	0.01637	0.0525	73.713	12.221
	(0.0187)	(0.0036)	(0.0024)	(0.0015)	(0.2862)		(0.0693)	(0.0751)	(0.0246)	(0.0373)	(0.0000)	
Pennsylvania *	−0.0325	0.0002	0.0198	0.0113	0.4539		0.0131	0.9551	0.1600	0.0890	55.592	15.125
	(0.0030)	(0.0019)	(0.0025)	(0.0008)	(0.1294)		(0.0162)	(0.0274)	(0.0642)	(0.049)	(0.0000)	
South												
East South Central												
Kentucky**	−0.0100	0.0044	0.0209	0.0064	0.6374	0.2257	0.0368		0.4557	0.0591	26.776	12.919
	(0.0054)	(0.0009)	(0.0052)	(0.0006)	(0.2864)	0.4004	(0.0300)		(0.3483)	(0.3578)	(0.0016)	
Tennessee**	−0.0119	0.0050	0.0229	0.0073	0.8185	0.1165	0.0344		0.2408	0.2161	34.571	8.766
	(0.0026)	(0.0009)	(0.0048)	(0.0006)	(0.1190)	0.1021	(0.0248)		(0.2351)	(0.2283)	(0.0001)	
Mississippi**	−0.0195	0.0047	0.0088	0.0087	0.4361	0.0022	0.0007	0.9801	0.6258	0.0563	35.594	11.973
	(0.0034)	(0.0013)	(0.0034)	(0.0008)	(0.1933)	(0.3675)	(0.0827)	(0.0250)	(0.3620)	(0.4156)	(0.0001)	
Alabama**	−0.0111	0.0046	0.0165	0.0079	0.7677	0.0572	0.0185		0.4764	0.0006	25.606	7.979
	(0.0022)	(0.0010)	(0.0039)	(0.0006)	(0.1107)	(0.0582)	(0.0227)		(0.1947)	(0.2148)	(0.0025)	
South												
South Atlantic												
Delaware**	−0.0084	0.0100	0.0243	0.0099	0.9676		0.0701	0.8946		0.1078	64.429	15.891
	(0.0017)	(0.0022)	(0.0034)	(0.0008)	(0.0339)		(0.0505)	(0.0615)		(0.0784)	(0.0000)	
Maryland*	−0.0513	−0.0006	0.0268	0.01374	0.4128	0.3000	0.0279	0.9496	0.0216	0.0941	62.801	10.050
	(0.0071)	(0.0016)	(0.0029)	(0.0009)	(0.2104)	(0.2457)	(0.0200)	(0.0252)	(0.0308)	(0.0527)	(0.0000)	
District of Columbia**	−0.0327	0.0005	0.0298	0.0131	0.2827		0.1337	0.8411		0.0506	60.973	13.145
	(0.0072)	(0.0025)	(0.0025)	(0.0011)	(0.2090)		(0.0670)	(0.0715)		(0.0354)	(0.0000)	
Virginia*	−0.0873	−0.0047	0.0168	0.0130			0.0117	0.9731		0.0405	68.579	9.491

Table A-I – continued from previous page

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
	(0.0131)	(0.0016)	(0.0020)	(0.0007)			(0.0117)	(0.0191)		(0.0289)	(0.0000)	
West Virginia**	−0.0216	0.0066	0.0863	0.0097	0.2661		0.1535			0.5000	36.907	9.768
	(0.0034)	(0.0012)	(0.0097)	(0.0008)	(0.1416)		(0.0517)			(0.3536)	(0.0000)	
North Carolina*	−0.0230	0.0040	0.0096	0.0088	0.2579	0.0007	0.0123	0.9876	0.3971	0.0352	50.036	9.933
	(0.0076)	(0.0014)	(0.0036)	(0.0008)	(0.3267)	(0.4336)	(0.0130)	(0.0133)	(0.2161)	(0.0722)	(0.0000)	
South Carolina*	−0.0251	0.0041	0.0205	0.0102	0.3828	0.0243	0.0258		0.5697	0.0984	58.383	3.444
	(0.0030)	(0.0011)	(0.0027)	(0.0006)	(0.1249)	0.0826	(0.0191)		(0.1139)	(0.0809)	(0.0000)	
Georgia*	−0.0201	0.0043	0.0162	0.0098	0.5086	0.0066	0.0304		0.6338	0.1153	45.367	12.136
	(0.0025)	(0.0022)	(0.0034)	(0.0014)	(0.1201)	(0.1164)	(0.0489)		(0.1476)	(0.1248)	(0.0000)	
Florida*	−0.0457	0.0027	0.0541	0.0186	0.7524	0.0641	0.0105	0.9797	0.2194	0.1504	68.823	5.437
	(0.0053)	(0.0018)	(0.0064)	(0.0011)	(0.1152)	(0.0733)	(0.0106)	(0.0143)	(0.1197)	(0.1028)	(0.0000)	
South												
West South Central												
Oklahoma*	−0.0331	0.0013	0.0304	0.0097	0.4078	0.3504	0.0600	0.9110	0.2996	0.2598	52.286	7.907
	(0.0044)	(0.0012)	(0.0029)	(0.0008)	(0.1387)	(0.1459)	(0.0278)	(0.0383)	(0.1821)	(0.2148)	(0.0000)	
Arkansas**	−0.0187	−0.0048	0.0058	0.0078	0.2870	0.4577	0.2958	0.7041	0.0583		24.733	17.341
	(0.0034)	(0.0042)	(0.0010)	(0.0007)	(0.1875)	(0.2577)	(0.3208)	(0.2576)	(0.0363)		(0.0036)	
Texas*	−0.0281	0.0014	0.0261	0.0091	0.4099	0.3379	0.0573	0.9152	0.2640	0.2358	44.045	10.164
	(0.0035)	(0.0010)	(0.0026)	(0.0007)	(0.1416)	(0.1517)	(0.0319)	(0.0348)	0.1255	(0.1337)	(0.0000)	
Louisiana*	−0.0117	0.0068	0.0313	0.0121	0.8502	0.0207	0.0174		0.6076	0.0001	41.259	8.993
	(0.0018)	(0.0016)	(0.0043)	(0.0008)	(0.0548)	(0.0214)	(0.0175)		(0.1555)	(0.0451)	(0.0000)	
Midwest												
West North Central												
North Dakota**	−0.0173	0.0049	0.0239	0.0108	0.6555	0.0643			0.9712		30.721	3.881

Table A-I – continued from previous page

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
	(0.0034)	(0.0012)	(0.0069)	(0.0008)	(0.1542)	(0.0632)			(0.2735)		(0.0000)	
South Dakota**	−0.0166	0.0058	0.0201	0.0079	0.4892	0.0623	0.0358	0.9607	0.5382	0.1266	36.781	8.494
	(0.0020)	(0.0011)	(0.0026)	(0.0006)	(0.1257)	(0.0714)	(0.0397)	(0.0275)	(0.1432)	(0.1007)	(0.0001)	
Minnesota*	−0.0390	−0.0008	0.0159	0.0110	0.3599	0.3017	0.0631	0.9145	0.0428	0.0716	56.794	18.827
	(0.0069)	(0.0019)	(0.0019)	(0.0012)	(0.1586)	(0.1947)	(0.0668)	(0.0734)	(0.0353)	(0.0525)	(0.0000)	
Nebraska**	−0.0104	0.0039	0.0233	0.0064	0.6969	0.2496	0.0605	0.9266	0.5179	0.0049	26.407	14.145
	(0.0024)	(0.0011)	(0.0037)	(0.0006)	(0.1377)	(0.1395)	(0.0407)	(0.0435)	(0.5623)	(0.6278)	(0.0044)	
Iowa**	−0.0275	0.0030	0.0249	0.0076	0.3525		0.0214			0.9400	29.215	1.0568
	(0.0049)	(0.0008)	(0.0073)	(0.0005)	(0.2819)		(0.0150)			(0.4203)	(0.0001)	
Kansas**	−0.0093	0.0047	0.0240	0.0065	0.8873	0.0745	0.0184	0.9695	0.6103	0.0285	43.907	7.704
	(0.0016)	(0.0008)	(0.0044)	(0.0005)	(0.0652)	(0.0550)	(0.0201)	(0.0228)	(0.4215)	(0.3554)	(0.0000)	
Missouri**	−0.0108	0.0056	0.0218	0.0070	0.8596	0.0703	0.0305	0.9694	0.5967		43.563	8.970
	(0.0020)	(0.0009)	(0.0076)	(0.0006)	(0.0860)	(0.0728)	(0.0284)	(0.0276)	(0.5321)		(0.0000)	
Midwest												
East North Central												
Michigan*	−0.0345	0.0062	0.0966	0.0123	0.6646	0.2910	0.0624				77.162	5.645
	(0.0044)	(0.0012)	(0.0123)	(0.0008)	(0.1382)	(0.1320)	(0.0248)				(0.0000)	
Wisconsin**	−0.0146	0.0048	0.0247	0.0073	0.8164	0.0823		0.9445	0.2709	0.4897	32.908	5.426
	(0.0023)	(0.0008)	(0.0034)	(0.0006)	(0.1183)	(0.0954)		(0.0291)	(0.1726)	(0.2036)	(0.0001)	
Illinois*	−0.0356	0.0007	0.0084	0.0099	0.3408	0.6093	0.5479	0.3626		0.0213	86.601	7.966
	(0.0032)	(0.0034)	(0.0009)	(0.0006)	(0.1421)	(0.1934)	(0.1920)	(0.1938)		(0.0163)	(0.0000)	
Indiana**	−0.0215	0.0022	0.0219	0.0063	0.3473	0.4441	0.0303		0.2169	0.2087	38.497	3.104
	(0.0038)	(0.0008)	(0.0033)	(0.0007)	(0.2497)	(0.3199)	(0.0350)		(0.1962)	(0.1929)	(0.0000)	
Ohio*	−0.0292	0.0002	0.0042	0.0089	0.4746	0.3532	0.4509	0.5927	0.0744	0.0540	60.748	15.468

Table A-I – continued from previous page

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
	(0.0035)	(0.0033)	(0.0010)	(0.0005)	(0.1708)	(0.2671)	(0.2501)	(0.3826)	(0.1430)	(0.1284)	(0.0000)	
West												
Pacific												
Hawaii**	−0.0108	0.0128	0.0451	0.0141	0.9744		0.0727	0.8371		0.1369	82.239	13.850
	(0.0021)	(0.0032)	(0.0039)	(0.0011)	(0.0251)		(0.0507)	(0.0804)		(0.0982)	(0.0000)	
Alaska*	−0.1663	0.0023	0.1183	0.0290		0.7589	0.0286	0.9514		0.8011	62.956	2.081
	(0.0167)	(0.0026)	(0.0219)	(0.0019)		(0.2149)	(0.0149)	(0.0201)		(0.2657)	(0.0000)	
Washington*	−0.0390	0.0034	0.0367	0.0106	0.4117	0.3867	0.0598	0.9101		0.2059	86.746	5.275
	(0.0043)	(0.0011)	(0.0023)	(0.0006)	(0.1621)	(0.1647)	(0.0244)	(0.0294)		(0.0839)	(0.0000)	
Oregon**	−0.0206	0.0089	0.0296	0.0094	0.8070		0.0452	0.9213		0.1869	56.884	12.614
	(0.0040)	(0.0015)	(0.0039)	(0.0008)	(0.1328)		(0.0262)	(0.0387)		(0.1213)	(0.0000)	
California*	−0.0750	−0.0075	0.0267	0.0141	0.7292		0.0150	0.9537		0.04310	126.94	5.848
	(0.0086)	(0.0019)	(0.0018)	(0.0008)	(0.2330)		(0.0149)	(0.0261)		(0.0244)	(0.0000)	
West												
Mountain												
Montana**	−0.0176	0.0105	0.0314	0.0113	0.7346		0.0156		0.8575	0.1424	51.204	1.945
	(0.0023)	(0.0013)	(0.0046)	(0.0008)	(0.0907)		(0.0154)		(0.1328)	(0.1340)	(0.0000)	
Idaho**	−0.0285	0.0033	0.0286	0.0102	0.7226	0.1100	0.0623	0.8940		0.3646	41.241	10.887
	(0.0032)	(0.0017)	(0.0032)	(0.0013)	(0.1433)	(0.1077)	(0.0315)	(0.0602)		(0.1719)	(0.0000)	
Wyoming*	−0.0426	0.0075	0.0251	0.0165	0.3447		0.02404		0.5988	0.1670	56.359	9.018
	(0.0040)	(0.0017)	(0.0046)	(0.0010)	(0.1078)		(0.0171)		(0.1269)	(0.1027)	(0.0000)	
Nevada*	−0.0588	−0.0002	0.0530	0.0177	0.5014	0.2499	0.0381	0.9348	0.1295	0.2671	62.215	9.381
	(0.0092)	(0.0021)	(0.0057)	(0.0012)	(0.1773)	(0.1492)	(0.0228)	(0.0270)	(0.1003)	(0.1319)	(0.0000)	
Utah*	−0.0386	0.0006	0.0319	0.0124	0.2755	0.2888	0.0623	0.8798	0.1762	0.2616	38.196	15.332

Table A-I – continued from previous page

	μ_l	μ_m	μ_h	σ_P	λ_{ll}	λ_{ml}	λ_{lm}	λ_{mm}	λ_{lh}	λ_{mh}	LR-test χ^2	RCM
	(0.0048)	(0.0017)	(0.0035)	(0.0009)	(0.1372)	(0.1313)	(0.0279)	(0.0386)	(0.0873)	(0.1099)	(0.0000)	
Colorado*	−0.0282	−0.0013	0.0160	0.0113	0.2315	0.4260	0.1171	0.8569	0.0627	0.0610	30.503	23.408
	(0.0044)	(0.0020)	(0.0018)	(0.0010)	(0.1660)	(0.2051)	(0.0545)	(0.0570)	(0.0491)	(0.0451)	(0.0009)	
Arizona*	−0.0777	0.0012	0.0518	0.0134		0.4971	0.0147		0.6638		77.321	6.3505
	(0.0068)	(0.0011)	(0.0095)	(0.0008)		(0.5957)	(0.0104)		(0.3248)		(0.0000)	
New Mexico**	−0.0161	0.0014	0.0189	0.0083	0.7897	0.1531	0.0667	0.8883	0.0389	0.1505	40.429	20.390
	(0.0034)	(0.0016)	(0.0026)	(0.0007)	(0.1416)	(0.1273)	(0.0415)	(0.0527)	(0.0563)	(0.0995)	(0.0000)	

Table A-II: **Predictability of excess returns and dividend growth with rent-price ratios - U.S.** Predictability of excess returns and dividends growth with rents-to-price ratios, using 4-lags Newey-West corrected standard errors. Data source: Panel A uses annualized price-rent data annualized quarterly data on house prices from the Federal Housing Finance Agency (FHFA) and rents from the Bureau of Labor Statistics (BLS) from 1978 to 2002. Panel B shows the same housing predictability regressions with rent data from NIPA and value data from Flow of Funds from 1960 to 2008. Panel C shows stock return predictability, with stock returns data from CRSP NYSE/Amex/Nasdaq/Arca value-weighted market index from 1926 to 2008.

Panel A - Housing Predictability FHFA

	Excess Returns			Dividend growth		
Horizon	β	t-stat	R^2	β	t-stat	R^2
k=1	-1.43	-0.31	0.01	2.15	0.62	0.05
k=3	23.02	2.04	0.26	8.96	1.83	0.14
k=5	47.71	5.69	0.57	5.60	1.53	0.03

Panel B - Housing Predictability NIPA

	Excess Returns			Dividend growth		
Horizon	β	t-stat	R^2	β	t-stat	R^2
k=1	1.70	3.51	0.30	0.10	0.86	0.01
k=3	8.58	6.69	0.53	-0.07	-0.25	0.00
k=5	22.01	8.00	0.62	-0.84	-1.63	0.08

Panel C - Stock Return Predictability

	Excess Returns			Dividend growth		
Horizon	β	t-stat	R^2	β	t-stat	R^2
k=1	3.63	3.18	0.07	-3.45	-2.19	0.05
k=3	10.95	3.58	0.18	-2.17	-0.97	0.01
k=5	18.85	3.76	0.24	-2.69	-1.16	0.01