Discontinuous Evolution of Housing Shares in Households' Portfolios

Yubing Cui *
Brandeis University

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Abstract

Housing assets earn higher long-run returns, expand the borrowing limits and save rental expenditures, so households save more in liquid wealth to lower the housing shares when the lagged values are high and save less in liquid wealth to raise the housing shares when the lagged values are low, to satisfy the intertemporal consumption allocations. However, the probabilities to adjust housing assets jump up when the lagged shares cross the thresholds of an optimal region due to the fixed costs, which leads to discontinuities and kinks in the evolution of housing shares around the thresholds. I empirically estimate the thresholds in the jumps of average probabilities of making transactions and the magnitudes of the kinks around the thresholds, showing households infrequently change housing assets to smooth consumption given variations in average portfolio returns and total wealth.

Keywords: Housing Stock, Saving, Asset Allocation, Housing Demand

JEL Codes: E20, E21, G11, R21

*International Business School, Brandeis University, 415 South Street, Waltham, MA 02453; email: helen-cui@brandeis.edu. I thank my advisors Kathryn Graddy, George Hall, Blake LeBaron, Daniel Tortorice, Zhuan Pei, Jens Hilscher and Robert Reitano together with all other seminar participants at the Brandeis PhD seminar for their valuable comments and suggestions. All errors are of my own.

1 Introduction

Housing has similarities and differences with durable goods. Both provide streams of service flows to consumers and are traded in lump-sum amounts due to fixed costs. However, as an illiquid asset, the price of the housing asset fluctuates over time with average returns higher than the risk-free rates over the long run and housing is often used as collateral to finance its own purchases and other consumption. Although the fixed costs in housing transactions are constant, the losses in the utility of households' consumption vary at different levels of total wealth conditional on making transactions, which affects the relative costs and benefits of the housing choices. In contrast, durable goods rarely have rising values, but rather depreciate once consumers purchase them. The consumption of durable goods therefore has optimal stopping behaviors due to the constant costs from replacements in the infinite horizon. There is a target level of the durables, and households sell the old goods and replace them with new ones if the current stock of the durables falls far below the target.

The housing investments of consumers, on the contrary, involve more complex adjustments than just buying and scrapping assets over the life cycle. Households choose to buy, upsize, downsize or sell housing wealth to change the allocations between housing and liquid assets given unexpected income shocks, expected changes in households' income, movements in the housing collateral due to unexpected housing price shocks, etc., which results in different intertemporal consumption decisions. Lower housing shares in households' portfolios lead to lower future consumption and make them more likely to increase housing assets, while higher housing shares discourage current period's consumption and make them more likely to reduce housing assets.[1] Households make discrete housing transactions according to the changing relative costs and benefits from different choices, since variations in housing assets affect the borrowing limits, average portfolio returns and expenditures on housing services. My work proposes new models for housing investments with multiple thresholds in the function of optimal housing shares, reflecting different housing choices conditional on prior housing allocations.

Therefore, this paper studies the discontinuous changes in the optimal ratios of illiquid housing assets relative to liquid assets over time. As housing assets of constant qualities, albeit of varying sizes, on average earn higher returns in the long run and save rental expenditures, it is optimal for households to hold some housing wealth even without taking into account other homeownership benefits. The optimal amounts of housing assets should yield a range of home values over liquid wealth that satisfy the consumption optimality conditions given the prior housing allocations, total wealth and other state variables. Households do not change the housing assets if their relative housing shares are within this range, because trading is costly.

[1] Even during periods when housing returns drop below the risk-free rates, the declines in home values lower the housing ratios, which in turn raises the average portfolio returns and prompts households to save more and lower consumption.

However, once the lower or upper bound of the optimal range is reached, the households are very likely to choose to upsize or downsize. The desired housing shares within the optimal region are indicative of probabilities of future housing adjustments. Also the boundary values are endogenously determined by households' state variables, market returns on different assets, trading costs and credit limits from the aggregate economy. I empirically estimate the upper and lower bounds by identifying the largest jumps in the average transaction probabilities at different levels of the lagged housing ratios. I then present the policy functions for the discontinuous evolution of the average housing shares and employ semiparametric and regression discontinuity methods to estimate the discontinuities and kinks in the optimal shares conditional on the jumps and kinks in the likelihoods of making transactions. Those functions with thresholds provide a new model for studying adjustments of illiquid assets in households' portfolios and explain the sluggish behaviors in changing housing shares over time.

The paper is organized as follows. Section 2 reviews the literature in the estimations of housing demand and consumers' choices for the optimal portfolios in the presence of illiquid assets. It also summarizes related papers in the application of optimal stopping behaviors and regression discontinuity methods. Section 3 discusses the determinants of boundary values in the optimal ratios of home value over liquid wealth and explains the effects of different factors on shifting the thresholds and changing the likelihoods of home transactions. Section 4 proposes new models for the evolution of housing assets over liquid assets across time and explains the optimal region and thresholds in determining discrete housing choices. Section 5 presents data analysis of households' housing decisions in terms of both transaction frequencies and sizes of changes in housing wealth for different transactions. Section 6 empirically estimates the models using discrete choice regressions and tests if current ratios of home value over liquid wealth affect the likelihoods of future housing transactions. Section 7 employs semiparametric regressions to estimate both the average thresholds and the sizes of kinks for the proposed functions of optimal housing shares. Section 8 offers conclusions for this paper.

2 Literature Review

My study is closely related to the literature in the estimations of housing demand and consumption of housing services. Hanushek and Quigley (1982) estimates a dynamic partial adjustment model in housing stocks and captures the lumpiness in housing assets through different responses to the contemporaneous changes in the desired levels of housing demand and the accumulated levels of disequilibrium. The paper finds the price elasticity of housing demand is larger in the short run than in the long run, while income elasticity is more significant over a longer course with housing adjustments evolving slowly. Charlier, Melenberg, and van Soest (2001), on the other hand, presents evidence of consumer choices in the consumption of housing expenditures through an endogenous switching model. The paper models the demand of housing consumption as streams of service flows and takes into account the endogenous decisions in homeownership. It finds the price elasticity is negative for housing expenditures and there is a U-shaped probability of owning in age from semiparametric regressions. In addition, the elasticity of housing expenditures is negative to total consumption expenditures, and households' transitory income does not affect homeownership decisions. However, both studies simply assume housing service flows are a fraction of the housing assets and do not take into account consumers' choices to invest in different assets to maximize total consumption, which possibly leads to biased estimates of the housing demand.

Related papers in this area also include Venti and Wise (2001) that studies how changes in households' income and family demographics affect their homeownership decisions at older ages. The authors find that conditional on the moving decisions, the changes in housing assets tend to be positive for higher-income and smaller-family households and that people are less likely to move out of homeownership even in the presence of precipitating shocks. Their empirical findings are similar to the data shown in this paper.

Another strand of the literature on housing demand includes papers about portfolio choices for illiquid assets, which is also closely related to my study, because adjustments in households' portfolios indicate the optimal evolution of different assets. Faig and Shum (2002) explains how lumpiness in illiquid assets requires more savings in liquid wealth when there are large penalties with discontinuing or under-investing in illiquid objects. The paper shows households tend to save more and have less risky investments prior to the purchase of illiquid housing wealth or acquiring personal business. Cocco (2005) shows investments in housing wealth reduce poorer and younger households' stock holdings and housing price shocks increase the crowding-out effects among those who have low financial net-worth. Those papers consider housing assets as investment decisions and ignore the facts that households consume housing services by owning housing wealth. My study, on the other hand, adds expenditures of housing services to total consumption while taking into account the housing investment decisions, which might yield better model fits to the data.

In addition, some characteristics of the durable goods resemble those of the housing assets. For example, durable goods are also costly to replace and provide service flows to consumers. Thus, studies on durable consumption are related to this work as well. The literature on durable consumption then uses the optimal stopping model with a single state variable to test if there is a fixed target level of durable goods and households replace the durables if the current stock falls below the target. Bar-Ilan and Blinder (1988) shows consumers choose to maximize consumption over an optimal range of service flows from durable goods and the aggregation of individual durable consumption displays very large short-run elasticity to changes in permanent income. The dynamic implications of durable consumption are distinct from those implied by traditional life-cycle models. Grossman and Laroque (1990) finds similar results by studying the optimal consumption and portfolio selections for households. The paper proves that there is one target level of the ratio of durable consumption to wealth and that if the current ratio falls below the lower bound due to large changes in the stock market, consumers sell the smaller durable and buy a larger one. However, there is no change in consumption when the ratio stays within the lower and upper bounds. Attanasio (2000) and Caballero and Engel (1991) form micro and aggregate tests for the expenditures of durable goods using the optimal (S,s) policies. Both papers allow for idiosyncratic shocks and heterogeneity in the optimal bandwidth and derive the aggregate implications for durable consumption.

My work differs from the literature of optimal stopping behaviors by not directly modeling the single state variable of the housing stock that has distributional assumptions, but rather considers the discontinuous changes in the ratios of home value over liquid wealth in the consumption problem, which generates different implications for the optimal housing allocations over time. The model resolves the issue of fixed bandwidth in housing shares, because the average thresholds in housing transactions are endogenously determined in the market based on households' state variables. My paper identifies the different average thresholds in making discrete housing transactions and provides empirical examinations of the housing behaviors for the average households aggregated across other state variables such as total wealth, age, income state and marriage status in addition to the implicit rental income shocks at different levels of the lagged housing ratios, which shows the implied optimal housing allocations from the model are consistent with the data.

Lastly, this study employs the regression discontinuity methods to estimate the kinked functions, where the methods are studied in many RD papers in the literature, such as Hahn, Todd, and Van der Klaauw (2001), Porter (2003), Card, Lee, Pei, and Weber (2012), etc. Examples of the empirical applications in the Regression Discontinuity Design include Angrist and Lavy (1999), Jacob and Lefgren (2004) and Matsudaira (2008) among many other studies. Card, Mas, and Rothstein (2008) provides methods of identification and estimation for the endogenous thresholds.

3 Determinants of the Thresholds

Consumers allocate assets to maximize consumption given stochastic income. Housing assets of constant qualities yield higher average returns over the long run,[2] but the fixed costs and downpayment requirements make it costly to constantly adjust housing assets to smooth consumption given unexpected income shocks. Thus, savings in liquid wealth are used to buffer those shocks and other expected income falls.[3] The optimal allocation of wealth is determined

[2]The average treasury yield on a 30-year bond of constant maturity is 5.07% between 1999 and 2009, and an equivalent measure of the value-weighted housing returns on the same houses from PSID is estimated at 5.61%. The comparison does not consider the extra risk premium required for the 30-year mortgages including the prepayment and mortgage default risks, because they are not modeled in the study.

[3]Throughout the paper, liquid wealth is defined as the sum of net savings in other assets excluding mortgages.

by the amount of total savings and the value-weighted average returns in households' portfolios due to changes in other households' state variables and market conditions. The three boundaries are defined as H/W^*_{up}, H/W^*_{down} and H/W^*_{sell}, and they are simultaneously set by the households given the same total wealth and other demographic variables, e.g., age or marriage status, as follows:

$$H/W^*(H/W^*_{up}, H/W^*_{down}, H/W^*_{sell}) = f(Y^p, r, r_H, \theta, \delta, P^{rental}) \quad (1)$$

H/W^* is the set of the three thresholds, which is a nonlinear function of households' permanent income Y^p, assets' average expected returns r and r_H, credit constraint θ, transaction cost δ and the price of the rental services P^{rental}. Those variables jointly impact the optimal levels of total savings and the housing allocations in the structural model. The permanent income affects the amounts of housing and liquid assets that households choose to save to maximize and smooth consumption, which in turn changes the housing shares due to the fixed costs and borrowing limits. Income uncertainties and credit constraints influence the allocations between the two assets due to the precautionary saving's motive and therefore total savings. On the other hand, the two assets' average returns and mean prices of rental services have an impact on both levels of consumption and asset allocations due to changes in the relative prices between housing and liquid assets or changes in the relative costs of homeownership. Moreover, the large fixed costs affect the housing allocations for households with similar housing and liquid wealth conditional on being close to the thresholds, as housing transactions are relatively more costly before reaching the thresholds. This leads to discontinuous jumps in the likelihoods of different transactions.

Given unexpected income shocks, households are more likely to adjust liquid wealth first to smooth consumption, because housing transactions incur fixed costs. The changes in liquid wealth not only affect the total amount of savings but also inversely affect the average returns of the portfolio, both of which influence the intertemporal consumption allocations.[4] Given lower total wealth, households with higher housing ratios increase liquid wealth more due to the higher average returns of the portfolio, which leads to higher future consumption and lower average returns. This in turn reduces households' incentives to save more next period. After reaching a lower bound in the housing ratios, the average returns are so low that households have lower levels of consumption due to smaller housing capital gains, which means they are more likely to pay for the fixed costs and downpayments to increase housing wealth for higher average returns and higher future consumption. H/W^*_{up} is the lowest boundary that determines if homeowners are more likely to buy larger houses. However, negative income shocks are likely to reduce liquid wealth even conditional on lower total savings, so those households are more likely to have much higher housing ratios and choose to sell houses to raise and

[4]The discussion here refers to the condition that housing assets earn higher returns than the liquid assets.

smooth consumption. H/W^*_{sell} is the highest boundary that determines if households are more likely to sell homes. On the other hand, given higher total savings and lower housing ratios, homeowners optimally reduce liquid wealth more to raise consumption, which increases the housing ratios and lowers the incentives to save less next period. If the housing shares reach an upper bound due to negative income shocks, homeowners make costly transactions to reduce housing wealth to smooth consumption, which lowers the total savings and the average returns. Thus, H/W^*_{down} is the middle boundary that determines if homeowners are more likely to buy smaller houses.

The probability to buy larger houses jumps up when the housing shares fall below H/W^*_{up}, because liquid savings are so high that it is optimal to increase housing assets and achieve higher housing shares to raise consumption. The probability to downsize rises if the housing shares increase above H/W^*_{down}, indicating homeowners with declining liquid wealth are very likely to buy smaller houses to adjust the housing allocations after the housing ratios reach the downsizing threshold. Those homeowners usually have larger houses, so they optimally choose to reduce housing wealth instead of completely selling homes. When the housing shares exceed H/W^*_{sell}, it means households have very low liquid wealth to smooth consumption and they are more likely to sell houses to increase liquid savings. As households with higher housing assets are likely to first downsize to raise consumption and after they move to smaller houses, those homeowners have much higher probabilities to sell homes once the liquid wealth drops to very low levels, i.e., once their housing ratios reach to very high levels even with smaller houses.

The optimal housing shares between H/W^*_{up} and H/W^*_{down} indicate not only households' desired sizes of housing wealth but also possible distances of the deviations from current housing shares to the thresholds, which implies different expectations of future adjustments. For example, households with lower liquid wealth can choose to buy smaller houses today, which leads to higher probabilities of housing upgrade in the future. The choice to buy smaller houses today is optimal, because waiting to buy larger ones tomorrow is more costly. Additionally, the distances between the thresholds also affect the magnitudes of changes in housing ratios once the thresholds are reached, because the probabilities to trade decrease when the thresholds are further apart. If households with extreme housing ratios are closer to the thresholds, smaller changes in housing assets are sufficient to shift the housing ratios back to the optimal region, even if the optimal region changes over time.

Moreover, the factors determining the boundary values not only directly affect the optimal ratios but also shift the thresholds. Housing price shocks affect the housing shares through changes in current home values or changes in average housing returns. Temporary housing shocks move the home values upward or downward, and if there are no shifts in the thresholds, homeowners who experience bigger shocks have larger increases in the probabilities of making transactions. However, if housing price shocks also affect the average housing returns, the new thresholds are shifted. Higher prices lead to wider differences in asset returns between housing and liquid assets. As a result, renters' threshold in buying homes is shifted to the left, because housing offers higher capital gains and more people with low liquid wealth buy smaller houses and become homeowners earlier. Homeowners' three thresholds are probably all shifted to the right,[5] because higher housing returns lead to more housing allocations. As the region between H/W^*_{up} and H/W^*_{down} is moved to the right, the overall optimal housing shares increase. Given the shifts and a prior distribution of housing shares, a larger fraction of the homeowners are below H/W^*_{up} than previously, so the number of households who are likely to upgrade increases. On the other hand, fewer households are likely to downsize or sell their houses, because the number of the households below H/W^*_{down} and H/W^*_{sell} decreases.

Income shocks and rental price shocks also impact the optimal housing shares, either directly through changes in liquid savings and expenditures on housing consumption or indirectly through changes in permanent income and relative costs of homeownership. If current housing shares are moved outside the optimal region, households are very likely to adjust housing assets to shift the ratios back to the optimal region. Those factors not only affect the likelihoods of future housing adjustments but also the sizes of changes in housing shares.

4 Models of Discontinuous Evolution

4.1 Homeowners' optimal housing shares

Homeowners have some initial housing wealth and liquid wealth. The fixed costs in trading housing assets and the downpayment requirements induce the discontinuities and kinks in the evolution of housing shares, and households make discrete and lumpy changes to the housing shares according to the kinked function. In Figure 1, I propose the optimal policy function of H_t/W_t against the lagged ratio of H_{t-1}/W_{t-1} for homeowners conditional on making different housing transactions. The solid line depicts the evolution of the average housing allocations over different ranges of the lagged values among households with varying other state variables who choose to keep, upsize, downsize or sell housing assets. K_1, K_2 and K_3 are the thresholds for H/W^*_{up}, H/W^*_{down} and H/W^*_{sell}, where the households are more likely to make housing transactions once the thresholds are reached.

H_t/W_t is a kinked function and has different slopes at different values of the lagged ratios, where the kinks indicate the slope differences in the function of average housing shares around the thresholds due to the housing transactions, i.e., home upsizing, downsizing and selling. Conditional on the previous housing ratios H_{t-1}/W_{t-1}, households with different amounts of total wealth and other state variables such as age, marriage status and housing or income shocks along with the rental price shocks choose their own housing allocations, which generates dif-

[5] For a graphical representation, please refer to the discussions in Section 4.1.

ferent values of H_t/W_t in the function of housing shares. However, when integrating those housing shares with respect to the joint distribution of the lagged total wealth, other state variables and unobservables, the average housing shares are the observed values in the function of H_t/W_t at each level of the lagged ratios given the different transactions. The three boundaries in Figure 1 also define the average thresholds of the optimal region for the heterogeneous households, reflecting the points where discontinuities and kinks in the probabilities of making transactions occur. Shifts in the boundary values not only affect the jumps in transaction probabilities but also the magnitudes of average slope differences and jumps around the thresholds.

If a consumer has a housing ratio between K_1 and K_2, she is very unlikely to make housing transactions and the next period's ratio tends to stay within the same region because of incremental changes in liquid wealth given unexpected income shocks. The household saves more to lower the housing ratio when the lagged ratio is higher and current wealth is lower, and she saves less to raise the ratio when the lagged ratio is lower and current wealth is higher. Equivalently, if liquid wealth is relatively lower, saving more reduces the likelihoods of downsizing and makes the household smooth and maximize consumption. If liquid wealth is relatively higher, she saves less to decrease the likelihoods of upsizing and consumes a little more intertemporally. This range of relative housing shares are the optimal housing allocations without making costly transactions given other unexpected shocks, because the household achieves the highest consumption streams from both housing capital gains and savings from rental expenditures while keeping sufficient liquid wealth to buffer income shocks.

When the ratio of home value over liquid wealth is below K_1, for example at k_1', the optimal choice is to sell the current house and buy a larger one. Therefore, the next period's ratio goes back to the optimal region at k_1''. The upward kink ensures the household only makes one big change to housing assets instead of multiple small changes to shift the ratio back to be within K_1 and K_2. As the lagged housing ratio just below K_1 also needs to be increased, a positive discontinuity is necessary for a higher ratio and the upper bound of the optimal region limits the positive jump at K_1.[6] When the initial housing share is further away from the optimal region, i.e., when the household has abundant liquid wealth but relatively small housing wealth, the next period's ratio is unlikely to be very high after home upsizing due to higher liquid savings. Thus, the slope of the linear relationship between time t-1 and time t ratios needs to be larger than one. The points below the threshold are feasible, because households with varying total wealth, income or demographics have different upsizing probabilities even after reaching the average threshold. The average changes in their housing shares are also different based on the lagged housing allocations. Consequently, we can observe the different lagged housing ratios after K_1 from the data. However, there needs to be a minimum ratio of H/W at K_{min}, because residential houses have at least some positive numerical values and the levels of liquid

[6]The jump at K_1 is bounded below the vertical value of K_2, because otherwise the point just below the threshold can not be shifted back to the optimal region.

wealth are bounded from above. The minimum ratio K_{min} reflects the lowest fraction of home value over liquid wealth in the household's portfolio. As a result, the points below K_{min} are infeasible.

Similarly, if H_{t-1}/W_{t-1} is above K_2 and below K_3, the household is expected to reduce housing wealth and lower the ratio to be back to the optimal region, which indicates the slope of the policy function within this region needs to be smaller than one. This is because when the housing share is much higher than K_2, the household has relatively more housing assets and the housing ratio after downsizing is likely to be lower than that when the housing share is close to the optimal region. However, the discontinuity could be either positive or negative depending on the magnitude of negative slope differences, even if the lower bound of the optimal region limits the downward jump at K_2 and the upper bound limits the upward jump.[7] For example, if the initial ratio is at k_2', one downward adjustment can move the ratio to be at k_2'' without the need of further transactions. Contrary to the model's prediction that housing shares decline slightly over time when the housing allocations are higher, the optimal ratios can also cross the threshold of K_2. The same reason of varying households' state variables lead to the different values in lagged ratios from the data, showing different transaction probabilities given the average threshold K_2. Those households' housing choices are not the same even after crossing the boundary values. If consumers cannot smooth consumption without making downward adjustments, they are likely to buy smaller houses at high H_{t-1}/W_{t-1} ratios.

For values above K_3, housing wealth compared to liquid wealth is rather too high, i.e., the household is very likely to be liquidity constrained and has limited savings in both liquid wealth and housing wealth. To smooth consumption, the optimal housing choice is to sell current home completely and transfer all assets into liquid wealth.

Therefore, the probabilities to change housing stocks on either side of any of the thresholds are less likely to be constant. This is because whether to make transactions also depends on other households' variables, such as total savings, households' income, demographics and local housing market conditions. There are uncertainties in housing transactions even when the boundary values are reached. Moreover, households at extreme values of H_{t-1}/W_{t-1} gain more benefits from housing transactions with larger increases in the sum of expected discounted utilities of consumption compared to the alternative choice of not making transactions. Therefore, their probabilities to change housing stocks are higher than the probabilities for those who are closer to the optimal region between K_1 and K_2 given other covariates.

4.2 Renters' optimal housing shares

Renters have no initial housing wealth, and they accumulate liquid wealth to buy the optimal houses in the future. Similar to the homeowners' optimal policy function, a threshold in liquid

[7] The discontinuity at K_2 is bounded between the vertical distances of K_1 and K_2.

wealth W^*_{buy} exists where heterogeneous renters with more savings above the average threshold have jumps in the probabilities of buying homes compared to those with savings below the threshold. After the threshold is reached, renters with relatively lower liquid savings are very likely to buy smaller houses but with higher average ratios due to the liquidity constraints and expect higher probabilities to upsize after becoming homeowners. As liquid wealth increases, renters can afford larger houses and the average housing shares first increase with liquid wealth. However, the average ratios of home value over liquid wealth decrease with liquid wealth after the highest possible optimal housing shares are reached, because buying larger houses with ratios exceeding H/W^*_{down} and H/W^*_{sell} increases the likelihoods of home downsizing and selling in the future and reduces the households' ability to buffer income shocks. This means the amounts of housing assets purchased are bounded by the maximum optimal allocation of housing wealth indicated by the permanent income and aggregate threshold values. The maximum housing ratio is the largest possible mean housing allocation for renters.

Renters' heterogeneities other than the lagged liquid wealth also affect the likelihoods of homeownership and initial housing allocations. If some households are younger, they could buy even smaller houses conditional on lower lagged liquid wealth and expect higher likelihoods of home upsizing in the future. Their housing allocations are then possible to fall outside the optimal region between H/W^*_{up} and H/W^*_{down} defined by the average homeowners.

Figure 2 exhibits the policy function for the average initial housing ratios as a function of lagged liquid wealth among the renters with different other state variables. The average threshold W^*_{buy} is also affected by the households' permanent income and the same market variables as in equation (1). Conditional on buying houses, the average housing shares jump from zero to large positive values to be within H/W^*_{up} and H/W^*_{down}, because those renters optimally choose the amounts of housing assets that satisfy the lifetime asset-allocation decisions. Moreover, the average housing shares are very likely to be in the higher end of the optimal range due to large decreases in liquid wealth and large increases in housing wealth. The housing ratios then decline gradually over time, as savings in liquid wealth are likely to rise after buying homes.

There are also uncertainties in buying homes at the threshold W^*_{buy}. For example, households with higher income volatilities are very likely to save more for precautionary purposes, so even if their liquid wealth crosses the threshold, they are less likely to buy houses compared to those with lower income volatilities. The probabilities of becoming homeowners are also not constant at either side of the threshold but rather increase with liquid wealth, as renters with higher liquid savings are more likely to become homeowners.

5 Data Description

The data used in this study is from the Panel Study of Income Dynamics (PSID), which is longitudinal household-level survey data. I use the sample from 1999 to 2009 with households aged between 25 and 75. I drop the observations without any consumption and age data. Due to the survey frequency, I group all observations by 2-year cohorts. PSID also provides sampling probability weights which represent the individual's sample selection probability in the population, and I use those sample weights in the summary statistics and regressions. The variables include households' demographics, income, wealth, housing and mortgage information.

a Transaction frequencies

PSID collects the information on homeownership in every survey and asks a separate question about if the households sold any real estate property which served as the main dwellings in the past two years. Furthermore, a follow-up question about the transaction value, net of any fees and commissions, is asked if the respondents answered yes to the previous question. Based on the two pieces of information, I could identify each household's ownership transition and the corresponding self-reported house value. For renters, they can keep renting (Renter-Renter), buy homes to be owners (Renter-Buyer), or buy and sell houses between two years (Renter-Seller). For homeowners, they can remain in the same houses (Owner-Owner), move to new houses (Owner-Buyer), or sell their houses to be renters (Owner-Seller). The last category of transition is households who make transactions before the first year they enter the sample (Pre-Sample), which I could not identity the transaction type. Each type of housing transition is counted as one adjustment, even though one adjustment could involve two transactions. For example, households in the Owner-Buyer category need to first sell the old houses and then buy new houses, yet the two transactions are counted as one adjustment, because the homeowners only move to different houses once. It is arguable that paying for two fixed costs involves two transactions, which are two adjustments, i.e., homeowners sell homes to be renters and then buy housing assets again. However, this identification is only possible when homeowners do become renters first and rent for at least one period before they buy houses. Otherwise the sample of homeowners who upsize or downsize cannot be separated from the sample of homeowners who do not move. The classification of housing transitions using Owner-Buyer, Owner-Seller and Owner-Owner categories is therefore more consistent with the data.[8] For missing observations in the unbalanced panel, if the homeownership status changes or the households report that they have sold houses between two non-adjacent survey observations, I simply assume the transactions have occurred during the most recent past two years.[9]

Table 1 shows the average frequencies of housing transactions in the sample period in the first panel. About 35 percent of the households make at least one transaction during the periods when they remain in the sample. Around 25 percent of the population change their housing assets only once. People rarely make more than three transactions in the sample period. Among the households who never trade in any year, 60 percent of them are homeowners who have

[8]The fixed costs can be assumed the same for Renter-Buyers and Owner-Buyers.

[9]No such assumption is made for all the other lagged variables used in the estimations.

bought houses before the sample starts.

The second panel shows the fraction of population by housing transitions over year. The Renter-Buyer transition accounts for about half of all the transactions each year, while the Owner-Buyer transition is the second largest type of transactions. Both probabilities increase until 2005 and decline sharply in 2009. In contrast, the probability for homeowners to become renters (Owner-Seller) is rather low compared to other transitions, but it increases in 2009 when more homeowners sell their homes and go through foreclosures. The sum of probability-weight adjusted homeownership rate (Owner-Buyer + Renter-Buyer + Owner-Owner) is slightly higher than the Census data,[10] probably because the sample only includes households aged between 25 and 75. The last column in Table 1 is the sum of probabilities of different transactions, which shows on average 11 percent of the households trade in the housing market every two years and this fraction of population fluctuates in the same direction with aggregate housing prices.

b Sizes of changes in housing assets

To understand the magnitude of changes in housing assets over two years, I compute (a) pure price changes in home values: housing returns of the same houses if homeowners stay in the same houses or the actual returns from sales of the current houses; (b) price plus quantity changes: housing wealth growth from total changes in housing assets; (c) value-weighted price changes: value-weighted returns of the same houses with previous survey's home values as value weights;[11] and (d) housing returns from an aggregate price index: housing price returns from the S&P Case-Shiller 20-City Home Price Index.[12] Table 2 summarizes those data. Home price returns in the first column show percentage changes in housing prices from last year's reported values to this year's values if there are no transactions or to the actual selling prices if households sell their homes. For example, if a homeowner sells an old house and buys another house between 2001 and 2003, the home price return$_{03}$ = selling price$_{03}$/home value$_{01}$-1. Housing wealth growth in the second column measures the nominal changes in housing wealth including quantity changes. Therefore, the same household from the previous example has housing wealth growth$_{03}$ = home value$_{03}$/home value$_{01}$-1.

The returns differentiated by housing transitions in Table 2 indicate that the measure of housing price return is much smaller than the measure of housing wealth growth. If homeowners choose not to move (Owner-Owner), their average two-year home price return is 14.37 percent across the full sample period. However, if homeowners move to different houses (Owner-Buyer), the mean housing wealth growth, capturing both price and quantity changes, is 52.14 percent. This

[10]The average homeownership rate in the PSID sample is 70.68%, and the overall US homeownership rate in the Census is about 68% on average from 1999 to 2009.

[11]The value-weighted returns use the sample of households living in the same houses between two years, and the returns are weighted by last year's reported home values over total housing stocks in the same sample last year.

[12]The S&P Case-Shiller 20-City non-seasonally adjusted monthly price index is used to compute the annual average of monthly two-year returns. For example, $Ret_{2001} = (\sum_{t=1}^{12}((Indx_t/Indx_{t-24}) - 1))/12$.

shows current homeowners on average purchase larger or expensive houses by more than 50 percent when they move again. On the other hand, because the simple average returns could be driven by extreme values from cheaper houses, I also compute the value-weighted returns using last year's home values over total housing stocks as weights, which yields an average return of 11.52 percent across years, slightly lower than the simple average of returns as larger houses with lower returns are weighted more. Comparing those returns to the market returns from the Case-Shiller 20-City Home Price Index, households report lower home values than the market prices when housing prices are rising and they report higher home values when prices are dropping. Despite this, the reported housing returns move in similar directions with the market returns.

For the Owner-Buyers, the average home price return is -0.63 percent in 2001, i.e., after all fees, homeowners on average sell the old houses with prices close to last year's reported values. Looking across years, the capital gains from selling the old houses are higher at 5.72 percent and 4.06 percent in 2005 and 2007 respectively. When the housing bubble bursts in 2009, there are net losses of 7.52 percent if homeowners try to sell the old houses. As homes are cheaper, housing wealth growth is only 21.87 percent for homeowners who move to different houses in 2009, less than half of the increases in previous years. Moreover, the Owner-Sellers also have higher mean net losses when selling their homes in 2009 at -18.10 percent compared to other years. This is most likely because when sellers have to increase savings and finance consumption by selling their homes in a down market or when they are under water and have to go through foreclosures, the housing prices from distressed sales are much lower than the average market prices.

As shown, the changes in housing assets can contain both price changes and households' decisions to move to different houses and the variations in housing shares depend on the market prices and individual choices. Different housing returns also lead to different thresholds in the optimal housing shares every year and further affect the likelihoods of housing transactions.

6 Discrete Housing Choices

Based on the optimal policy functions, the probabilities of different housing choices are affected by the lagged housing shares and other households' heterogeneities given one set of the thresholds, I present the regression analysis for the consumers' discrete choices of housing transactions here.

6.1 Homeowners' choices

In Table 3, I test the effects of H_{t-1}/W_{t-1} on homeowners' probabilities of making four housing choices: living in the same houses (=1), buying larger houses (=2), buying smaller houses

(=3) and selling to be renters (=4) in a multinomial logit model.[13] The regressions include log households' income at time t-1, dummies for age, marriage status, gender and family composition, along with year fixed effects.[14] The ratio of H_{t-1}/W_{t-1} is defined as the reported home value over net liquid wealth excluding the remaining mortgage balances.

The results from the baseline model are presented in the first three columns using the choice of homeowners living in the same houses as the baseline category. $\ln(H_{t-1}/W_{t-1})$ is significantly correlated with the probabilities of different choices. As the lagged housing share is lower, the probability to buy larger houses increases and the probability to buy smaller houses or to sell houses decreases, which is consistent with the model's predictions in Figure 1. The coefficient on $\ln(H_{t-1}/W_{t-1})$ is also larger in choice (4) than in choice (3), indicating the probability to sell housing assets increases more when the lagged housing share is higher.

Households' lagged income is positively correlated with home upsizing and negatively correlated with home selling. If a homeowner has relatively higher income and conditional on a lower H_{t-1}/W_{t-1} ratio, she is very likely to move to a larger house as income increases. If she has very low income and given a higher ratio of H_{t-1}/W_{t-1}, she is very likely to sell housing assets and move into home rental when income declines. Married households are more likely to buy larger houses and less likely to sell homes to be renters conditional on all other covariates. Yet they are equally likely to downsize as single homeowners.

However, a lower lagged housing ratio does not necessarily indicate higher liquid wealth, because housing assets might also be low, which leads to a lower overall ratio. To control for the level of liquid wealth or equivalently the level of total wealth, I define an indicator for households who have lagged liquid wealth below the 25th percentile in each year and add the interaction term of H_{t-1}/W_{t-1} with the indicator in the regression. The results in the last three columns of Table 3 show the second model has a higher pseudo R^2.

The coefficients on $\ln Y_{t-1}$ and $\ln(H_{t-1}/W_{t-1})$ all have similar signs and significance levels as in model 1 for the alternative choice of upsizing. Households who have higher income and lower housing shares are more likely to upsize. The coefficients on the indicator variable and the interaction term are not statistically significant, and this is possibly because households who choose to buy larger houses are less likely to be liquidity constrained and the fraction of households with low liquid wealth is very small compared to the baseline category. Most of the homeowners who upsize have relatively more liquid wealth.

On the other hand, the coefficients on the indicators and interaction terms for the choices of downsizing and selling are all statistically significant, albeit with opposite signs. After adding

[13]The estimated model does not meet the asymptotic assumptions in the Hausman test. In addition, the Small-Hisao test of the assumption of Independence of Irrelevant Alternatives is also rejected by the model.

[14]The regressions use all the observations of H_{t-1}/W_{t-1} above zero. An alternative test based on the sample of households with at least one transaction gives similar results.

controls for very low liquid wealth, the coefficient on $\ln(H_{t-1}/W_{t-1})$ becomes smaller in choice (4) than in choice (3), because households with higher liquid wealth are more likely to downsize than to move out of homeownership when the indicator is zero. The interaction terms also indicate liquidity constrained households are more likely to downsize and less likely to sell homes if they have higher housing assets compared to those with lower housing assets. In addition, lagged income is no longer significantly correlated with the relative probability of downsizing or selling after controlling for lower liquid wealth, even if the coefficients on other demographic variables exhibit no significant changes compared to the results in model 1.[15]

6.2 Renters' choices

Table 4 gives estimates of renters' probabilities to purchase houses using a logistic model in the full sample.[16] I also test a logit model with random effects to take into account the rental price shocks. I include lagged log income to test the effects of households' income on the probability of buying houses conditional on variations in other households' variables. The covariates include the same dummies used in the homeowners' regressions and year fixed effects.

The first column in Table 4 examines how renters' income and liquid savings affect their choices of home purchases given specific age, marriage status and family size in the pooled regression. The results show lagged liquid wealth is positively correlated with the purchase probability. As renters accumulate more savings, they are very likely to buy houses to be homeowners. The coefficient on the linear term of lagged income is significantly positive, which indicates households with higher income have higher probabilities to make home purchases, though of different sizes conditional on the level of savings and income. As people age, the probabilities to transition into homeownership decrease for renters. In addition, the probabilities for married households to be homeowners are higher than the probabilities for single households. I also test a specification with a quadratic term of liquid wealth, but the coefficient on the quadratic term is not statistically significant.

In model 2, I generate an indicator for households with income lower than the 20th percentile and add the interaction term of the indicator with liquid wealth in the regression. Both coefficients are statistically significant and show households with lower income are less likely to be homeowners, but as savings increase, the likelihoods also increase.

People might also differ in unobserved variables, such as the implicit rental income earned by homeowners. Those variables are affected by the local rental prices and influence renters' housing choices.[17] I model those unobserved variables using random-effect regressions and

[15] Due to the complex computation of the probabilities with intercorrelated random effects, I assume there are no unobserved random shocks in homeowners' housing choices.

[16] The estimates using samples with at least one transaction yield very similar results. Here I include all the renters in the pooled regression to model their housing decisions.

[17] Even though rental expenditures are observed for renters, income is very likely to influence the consumption

assume the shocks to the implicit rental income are normally distributed.

The last two columns in Table 4 fit the random-effect logistic model and estimate the probability of renters moving into homeownership using the same variables as in the pooled regressions. The linear terms of lagged income are still statistically significant and have the same signs as before. The coefficients on year dummies are more significant with higher probabilities from 2003 to 2005 and show smaller declines in purchase probabilities in 2009. The results confirm the empirical observations that probabilities of home purchases increase when market prices are rising and decrease otherwise. Households' demographics are strongly correlated with the probability of buying houses, and households with lower income are less likely to buy houses. As liquid wealth rises, people start to move into homeownership and increase housing wealth.

Those empirical regressions show how the probabilities of different housing transactions are affected by the lagged ratios of home value over liquid wealth for homeowners or by the lagged liquid wealth for renters, and the results confirm changes in lagged housing shares or liquid wealth can predict housing changes in the future conditional on other covariates.

In addition, I test the multinomial logit models and logit models in each year and compare the estimates to the pooled regressions. Similarly, homeowners have higher upsizing probabilities when the lagged housing ratios are lower and income is higher. The declines in the upsizing probabilities given one percent increase in the lagged ratios are lower in the boom periods and higher in the bust periods.[18] The probabilities of downsizing increase with higher lagged housing ratios, even if households with lower liquid wealth and smaller houses are less likely to downsize than to sell homes. The increases in the downsizing probabilities given one percent increase in the lagged ratios are smaller when the housing market is booming. In addition, the selling probabilities also increase with higher lagged ratios, and households with lower liquid wealth and smaller houses are more likely to sell homes. However, the increases in the selling probabilities given one percent increase in the lagged ratios are larger when the housing market collapses in 2007 and 2009. For renters, the purchase probabilities rise with higher liquid wealth and income, and the increases in the probabilities are larger until year 2005 given one percent increase in the lagged liquid wealth but smaller after year 2007. The results are generally consistent with the regressions in this section.

7 Semiparametric Estimations

To estimate the optimal policy functions specified in Section 4, I first identify the locations of the endogenous thresholds from the data and then I use semiparametric regressions to estimate

level of housing services. Thus, the estimates of the impacts of rental prices on homeownership decisions are biased. I solve this issue by assuming the shocks to rental prices are i.i.d. normally distributed and are household-specific random errors, which can be estimated in the random-effect logit model.

[18] The homeowners' regression of Model 2 in year 2005 has a convergence problem due to the definition of the indicator variable of low liquid wealth.

homeowners' kinked functions conditional on the jumps and kinks in the likelihoods of trading housing assets. Furthermore, I utilize the sample selection regressions to estimate renters' conditional housing shares with discontinuities in the purchase probabilities in this section.

7.1 Identifications of the thresholds and discontinuities in the likelihoods

The threshold values in optimal housing shares are endogenously determined by both households' permanent income and market conditions each year. Because the observed frequencies of different housing transactions are relatively low in each year, I simply assume the parameters of the model are constant on average in the sample period. Additionally, as the locations of the thresholds are unknown, regressions testing for the discontinuities while estimating the parameters have specification errors. To address this issue, I follow the methodology from Card, Mas, and Rothstein (2008). I use a random subsample of households to identify the locations of the thresholds and use the rest of the sample to estimate the parameters and derive inferences. One complication in my data is the low frequencies of households making different transactions, and a random draw from the full sample leads to too few observations in the subsamples. Therefore, I first separate the households based on whether they have ever been observed to make a specific transaction such as upsizing, downsizing, selling or buying a house. I then randomly draw 1/2 of the households from this sample and 1/2 of the households from the sample where they are never observed to make this specific transaction to form the first subsample. The other 1/2 of the two samples are subsequently combined as the second subsample. The procedure generates two random groups of observations for testing and estimating the thresholds of H/W^*_{up}, H/W^*_{down}, H/W^*_{sell}, or W^*_{buy} separately.

I describe below the procedures in finding the first threshold of H/W^*_{up}, and the rest of the three thresholds are identified in similar steps. Using one of the two random subsamples from homeowners who make at least one upsizing transaction and one from homeowners who never trade up, I compute the probability of upsizing within each bin of the lagged ratios of H_{t-1}/W_{t-1} with a bin width of 0.1.[19] I restrict the test to be within households with positive ratios of home value over liquid wealth at time t-1 and time t, because the sample size drops significantly when the ratios turn negative. After the computation, based on the nonparametric method of estimating change points in Loader (1996), I fit a one-sided polynomial regression using triangle kernels on either side of a possible change point and compare the fitted values at the threshold from both sides of the point. The point that maximizes the jump in the upsizing probabilities is the local threshold of discontinuity. Due to the fixed bandwidth, some values close to the boundary of the kernel give the largest jumps. Thus, I run another set of regressions using the optimal bandwidth from Imbens and Kalyanaraman (2012) and filter out the points generated

[19] The total number of bins is 80, evenly divided between the value of 0 and 8. The sample is censored from both above and below based on the lagged values of H_t/W_t, which accounts for 60.05% of all the observations greater than zero in this subsample.

by extreme values.[20] Using this procedure, the first threshold of H/W^*_{up} is determined at 2.35. I repeat the same process to estimate the other three thresholds. H/W^*_{down} and H/W^*_{sell} are set at 4.45 and 6.65, and W^*_{buy} of the lagged log liquid wealth is determined at 8.6.

a Discontinuities in owners' transaction likelihoods

Figure 3.1 plots the upsizing and downsizing probabilities along each bin of H_{t-1}/W_{t-1}. The left figure compares the observed upsizing probabilities at both sides of K_1. The dots are the average estimated probabilities within each bin, and the lines fit local linear regressions around K_1.[21] The upsizing probabilities are on average lower after the threshold value is crossed, and the regressions show a significant discontinuity in the upsizing probabilities at 2.35. In the right figure, I observe higher downsizing probabilities when H_{t-1}/W_{t-1} is higher than the second threshold at 4.45.[22] Households are more likely to buy smaller houses when they have lower liquid wealth relative to the housing wealth.

The plots exhibit jumps in the likelihoods of housing transactions around the thresholds and indicate the probabilities of observing transactions are much less than one even after reaching the thresholds. Therefore, the lagged housing ratio is not the only predictor for the discrete changes in housing shares, but other covariates also affect households' choices. If I assume the probabilities are kinked without jumps at the thresholds, the estimated kinks in the local polynomial regressions with bias-corrected robust confidence intervals are -0.204 and -0.619.[23]

b Discontinuities in renters' transaction likelihoods

Renters are less likely to purchase housing assets when liquid wealth is low, so a discontinuous jump in the buying probabilities is expected when the threshold W^*_{buy} is reached. As liquid wealth increases, the probabilities should be higher when renters are richer. When I test for the location of the threshold in the first random subsample, the size of the subsample used for identification is reduced to 2/5 of the all the renters, because later estimations require more observations. I also test the threshold using 1/2 of the sample, and the result shows the reduction in the number of observations for the identification does not affect the location of the threshold. Using the same identification algorithm, the cut-off point is therefore found at 8.6.

I set the bin width again at 0.1 for the lagged liquid wealth and restrict the sample to be within 6.05 and 13.15, as there are no observed home purchases at extreme values. Figure 4.1 plots

[20] The computation of the optimal bandwidth is from Nichols (2011), but I run separate nonparametric regressions using the steps outlined in the text.

[21] The optimal bandwidth is 1.089, and the local Wald estimator is statistically significant at -3.402%.

[22] The optimal bandwidth is 1.335, and the local Wald estimator is not significant at 1.491%. But the 25% multiple of the optimal bandwidth has a significant coefficient of 5.149%.

[23] The robust standard errors of the estimates are 0.222 and 0.368 using the optimal bandwidth selection methods in Calonico, Cattaneo, and Titiunik (2014).

the observed purchase probabilities and local linear fits around the threshold. The local Wald estimator for the discontinuity is weakly significant at 6.32 percent, which means the probabilities of home purchases jump up when the threshold value is reached. One possible concern is that the probabilities are just a nonlinear function of lagged liquid wealth, and the discontinuity is mistakenly estimated. I test this assumption using a logit model and add polynomial terms of $\ln(W_{t-1})$ to the regression, but the coefficients on the polynomial terms are not significant, indicating a discontinuity is more likely to be the case.

7.2 Estimations of the kinked functions

After identifying the thresholds in the likelihoods of housing transactions, I test if the average slope coefficients in the function of optimal housing shares are different on both sides of the thresholds and give empirical estimates of the average differences in the derivative of $\Delta H_t/W_t$ against H_{t-1}/W_{t-1} conditional on the kinks in the likelihoods of making transactions around the thresholds. The differences in the slope coefficients on the lagged housing shares reveal the magnitudes of the kinks, which indicate the effects of housing transactions on the optimal housing ratios when households are close to the boundary values. For renters, given the estimated threshold in the purchase probabilities, the function of the chosen H_t/W_t ratios conditional on home purchases is also estimated.

a Homeowners' estimates

Figure 3.2 presents a graphical examination of the different slope coefficients around the thresholds, following Calonico, Cattaneo, and Titiunik (2014). It plots average $\Delta H_t/W_t$ against H_{t-1}/W_{t-1} in two subsamples with H_{t-1}/W_{t-1} ranging from 0 to K_2 and K_1 to K_3. The data is from the second random subsample generated from the previous section and different from the one used for identifications of the thresholds.

The left figure shows the slope coefficient of $\Delta H_t/W_t$ on H_{t-1}/W_{t-1} is positive when the lagged housing shares are below K_1, indicating more households buy larger houses and increase housing shares when their housing assets are lower relative to the liquid assets. The $\Delta H_t/W_t$ incorporates both discrete changes in housing ratios and the jumps in probabilities of upsizing. On the contrary, the slope coefficient is near zero when the lagged ratios are above K_1, which indicates those who are on the right of the threshold with higher housing shares are less likely to make upsizing transactions. The average changes in housing shares beyond K_1 are not significantly different from zero due to drops in the probabilities of upsizing.

The figure on the right compares the slope coefficients for households at both sides of the second threshold of K_2. Homeowners who have rather high H_{t-1}/W_{t-1} ratios are more likely to downsize and reduce housing wealth, so the slope of $\Delta H_t/W_t$ is more negative beyond K_2 compared to the slope below K_2. This means the average decreases in housing shares are much larger when the lagged ratios are above the downsizing threshold due to both jumps in the downsizing probabilities and large reductions in the housing ratios. Again before reaching K_2, $\Delta H_t/W_t$ is only slightly negative due to increases from liquid wealth. The right side of the left figure should have a similar negative slope coefficient with the left side of the right figure, but since the two plots use two separate subsamples, the fitted slope is slightly different.[24]

After the graphical presentations, I model the different slopes for the function of optimal housing shares using fuzzy regression kink methods as follows:

$$\begin{cases} \Delta \frac{H_t}{W_t} = \alpha + \beta_1 \frac{H_{t-1}}{W_{t-1}} + \beta_2 T_t + \epsilon_t, \text{ if } \frac{H_{t-1}}{W_{t-1}} \in [0, K_2] \\ p(T_t = 1 | \frac{H_{t-1}}{W_{t-1}}) = g_0(\frac{H_{t-1}}{W_{t-1}}) + [g_1(\frac{H_{t-1}}{W_{t-1}}) - g_0(\frac{H_{t-1}}{W_{t-1}})] D_t \end{cases} \tag{2}$$

$$\begin{cases} \Delta \frac{H_t}{W_t} = \theta + \delta_1 \frac{H_{t-1}}{W_{t-1}} + \delta_2 T_t + \eta_t, \text{ if } \frac{H_{t-1}}{W_{t-1}} \in (K_1, K_3] \\ p(T_t = 1 | \frac{H_{t-1}}{W_{t-1}}) = h_0(\frac{H_{t-1}}{W_{t-1}}) + [h_1(\frac{H_{t-1}}{W_{t-1}}) - h_0(\frac{H_{t-1}}{W_{t-1}})] D_t \end{cases} \tag{3}$$

Equation (2) states when H_{t-1}/W_{t-1} are within 0 and K_2 and given an indicator D_t for values below the threshold, the causal effect of home upsizing on the changes in the optimal housing shares is β_2. In addition, there are uncertainties in making housing transactions even after crossing the upsizing threshold. The probability for the households to actually upsize housing assets when $\frac{H_{t-1}}{W_{t-1}}$ reaches K_1 is g_1, otherwise it is g_0. Equation (3) follows a similar structure and estimates the effect of home downsizing on the changes in the optimal housing shares when H_{t-1}/W_{t-1} are within K_1 and K_3. The indicator variable D_t now represents values exceeding the second threshold K_2. The causal effect is estimated as δ_2 if households actually downsize housing assets, and there are also uncertainties in making transactions after crossing the downsizing threshold. The probability to downsize is h_1 if the threshold is crossed, otherwise the probability is h_0. The equations are not functions of other covariates, because conditional on making transactions, other variables do not affect the changes in optimal housing shares.

As the treatment variable T_t is not deterministic in the lagged ratios at the thresholds, the probabilities are functions of the lagged housing ratios and the dummies for the thresholds. Households' demographic variables affect the locations of the average endogenous thresholds, so they are not included in the regressions. Thus, the treatment variable is estimated in a linear probability model as:

$$\begin{cases} T_t &= \pi_0 + \pi_1 \frac{H_{t-1}}{W_{t-1}} + \pi_2 D_t + \pi_3 D_t \frac{H_{t-1}}{W_{t-1}} + \upsilon_t \\ D_t &= 1, \text{ if } \frac{H_{t-1}}{W_{t-1}} < K_1 \text{ or } \frac{H_{t-1}}{W_{t-1}} > K_2 \end{cases} \tag{4}$$

The estimation strategy in my paper follows the RD literature and uses 2SLS to derive a structural estimator for the slope differences conditional on the kinks in probabilities to receive

[24] The average slope of the homeowners' function in the optimal region changes as the thresholds shift with the determinants over time.

treatment, which is however limited in estimating the discontinuities in the proposed functions and requires the jumps in the probabilities at the thresholds to be zero. The kinks in the function of optimal housing shares are identified by exploiting the kinks in the probabilities of making transactions around the endogenous thresholds. The RKD estimator of interest is β_2 or δ_2, which should be positive for upsizing households within [0, K_2] and negative for downsizing households within (K_1, K_3]. Formally,

$$\begin{cases} \Delta \frac{H_t}{W_t} & = \alpha + \beta_{j1} \sum_{j=1}^{p} (\frac{H_{t-1}}{W_{t-1}})^j + \beta_2 \hat{T}_t + \beta_{j3} D_t \sum_{j=2}^{p} (\frac{H_{t-1}}{W_{t-1}})^j + \tau_t \\ T_t & = \pi_0 + \pi_{j1} \sum_{j=1}^{p} (\frac{H_{t-1}}{W_{t-1}})^j + \pi_{j2} D_t \sum_{j=1}^{p} (\frac{H_{t-1}}{W_{t-1}})^j + \xi_t \end{cases} \tag{5}$$

The specification drops the dummy variable D_t and only estimates the slope differences around K_1 and K_2, because parallel shifts in the optimal function around the thresholds lead to similar changes in housing ratios regardless of the distances between the lagged ratios and thresholds. Only discontinuities at the thresholds are unlikely when households near the optimal region tend to make smaller changes to the housing assets to shift the ratios.[25] Therefore, I focus on the slope differences around the thresholds, and the discontinuities at K_1 and K_2 due to the jumps in the transaction probabilities cannot be estimated simultaneously in the fuzzy regression kink models. The kinks are estimated separately in the subsamples of homeowners who make at least one upsizing or downsizing transaction, and Table 5 gives the results.

The local linear estimate in the upsizing sample shows the slope difference on both sides of the threshold due to home upsizing, i.e., the coefficient on the observed upsizing indicator T_t, is very large and statistically insignificant. However, the sign on the coefficient indicates home upsizing increases the slope of the function for $\Delta H_t/W_t$ around the lower bound of the optimal housing ratios. In contrast to the left plot in Figure 3.2 with a difference in the slope coefficients being close to 0.51, the estimator of the average slope difference on $\Delta H_t/W_t$ seems a bit high.[26] This is probably due to the fact that housing upgrade is only one of the reasons to have large increases in H_t/W_t between two years, and there might be other reasons, such as large short-term reductions in liquid wealth or large increases in housing prices without buying larger houses. Thus, by attributing all the variations in $\Delta H_t/W_t$ to housing transactions, I underestimate the probability of having large increases in H_t/W_t and overestimate the average changes in relative housing shares around K_1 conditional on the kink in upsizing probabilities.

When testing the model with households making downward adjustments, the coefficient on the observed downsizing indicator T_t is also statistically insignificant at about -10 in the local linear regression. The implied decline in the slope coefficients seems smaller than the empirical

[25]If assuming only discontinuities are present, the estimated shifts of the function are 90.85 and 61.15 in local linear and local polynomial regressions at K_1, -0.93 and 4.74 at K_2. All the estimates are statistically insignificant and beyond the limits set by the optimal boundaries.

[26]The standard error of the difference of slope coefficients in the global linear regression is 0.140.

observation of -0.61 in the right plot of Figure 3.2, but still shows home downsizing reduces the housing ratios once the lagged housing shares are beyond the threshold K_2.[27] The estimates are also possibly biased, because there are households who do not make downward transactions but have much lower H_t/W_t ratios compared to the previous period. Since downsizing is only one of the sources of changes in households' asset holdings, the 2SLS regression underestimates the probabilities of having lower H_t/W_t ratios by predicting only home downsizing and overestimates the size of the kink at the threshold conditional on the kink in downsizing probabilities. Even if the two local polynomial estimates of T_t in Table 5 yield coefficients with opposite signs, the local linear regressions still have correct estimates for the kinks in the function of optimal housing shares.

Moreover, to verify the estimated thresholds in the full sample, I also test the models in equation (5) separately in each survey year. The upsizing thresholds are then found at 2.2, 2.2, 2.4, 2.5 and 1.8, the corresponding downsizing thresholds are at 5.0, 5.4, 4.8, 3.1 and 3.4, and the selling thresholds are at 6.2, 6.6, 6.0, 3.4 and 3.8, relative to the distribution of the lagged ratios. The results show that using the repeated cross-sectional data identifies the largest jump in the probabilities of making different housing transactions at the average thresholds of 2.35, 4.45 and 6.65.[28] The changes in the thresholds and sizes of the kinks reflect that the upsizing probabilities increase until 2005, remain at higher levels in 2007 and then decline sharply in 2009, while the downsizing probabilities decrease until 2005, rise in 2007 and decline again in 2009. The magnitude of the slope differences in the optimal housing shares conditional on the kinks in the transaction probabilities also varies accordingly across the sample period.[29]

b Renters' estimates

Since renters hold zero housing wealth prior to home purchases and there are no observed variations in relative housing shares, I cannot use the same fuzzy regression kink models as the homeowners'. However, once households become homeowners, I can observe their initial housing assets relative to the liquid assets and estimate the average optimal housing shares at each level of the lagged liquid wealth. As noted before, a Tobit model with discontinuities in the households' purchase probabilities can be used in estimating renters' housing ratios conditional on the homeownership decisions.

Before testing the model, I also present a graphical examination with the second random subsample for renters. All the estimates and tests in this section restrict the sample to have lagged liquid wealth within about the bottom and top one percent of the data. I set the bin width again

[27] The standard error of the difference of slope coefficients in the global linear regression is 0.162.

[28] The estimated upward kinks in the local polynomial regressions are -9.81, 144.89, 44.04, 35.13 and -106.36, and the downward kinks are -83.51, -375.86, 129.20, - and 0.82 in each year, although all the coefficients are statistically insignificant. The regressions use 60% of the data for identifications.

[29] The predicted slope differences around the thresholds are generally overestimated than the empirical observations in both the upsizing and downsizing samples.

at 0.1 for lagged liquid wealth. Figure 4.2 plots the average ratios of home value over liquid wealth conditional on owning houses within each bin and fits a local linear regression on both sides of the threshold. The conditional means of optimal housing shares do not exhibit a discontinuity at the threshold with an insignificant coefficient of -1.14. However, the shape of the average ratios indicates as people save more for home purchases, the relative housing shares first increase with liquid wealth until the maximum optimal shares are reached and then decline with liquid wealth gradually even if those richer renters buy larger houses, which is consistent with the renters' model in Section 4. The range of values in chosen housing shares are not all within the optimal region, because in addition to the market determinants and households' permanent income, other households' variables change the renters' choices for housing assets and future probabilities of home transactions.

As a robustness check, I also compute the likelihoods of buying homes with a logit fit on both sides of the estimated threshold of 8.6 using this subsample. The estimation procedure can be found in the Robustness Appendix A2. The probability has a clear discontinuity at the cut-off point. Before reaching the threshold value, the probability for renters to buy houses is around 10 percent, and after reaching the threshold value, the probability increases significantly and reaches above 20 percent. The graph gives similar results as in Figure 4.1.

The equations used to estimate the renters' optimal housing shares are very similar to the standard sample selection model in Heckman (1977) and shown as follows:

$$\begin{cases} \ln(\frac{H_t}{W_t}) & = \pi_0 + \pi_1 z_t + \psi_t, \text{ if } y_t^* > 0 \\ y_t^* & = \beta_0 + \beta_1 w_{t-1} + \beta_2 D_t(w_{t-1} > K) + \omega_t \end{cases} \tag{6}$$

y_t^* is a latent variable to indicate if renters purchase homes to have positive H_t/W_t ratios. w_{t-1} is the lagged log liquid wealth, and $D_t(w_{t-1} > K)$ is a dummy variable which equals to one if w_{t-1} exceeds the threshold value of 8.6. The interaction term of $D_t(w_{t-1} > K)$ with w_{t-1} is not included, because the regressions yield statistically insignificant coefficients on both the dummy variable and the interaction term. Other explanatory variables that affect the average buying threshold are also excluded, such as the households' lagged income, age, gender, marriage status and year fixed effects. $(\omega_t, \psi_t) \in N(0, \Sigma)$, which is a bivariate normal distribution with a possible correlation ρ. When $y_t^* > 0$, we can observe strictly positive H_t and compute the mean ratios of H_t/W_t. z_t is another set of regressors that satisfy the exclusion restrictions, which explains the variations in relative housing shares. It contains a quadratic function of w_{t-1} to fit the data along with age dummies and year fixed effects. This specification is chosen because the regressions yield higher Wald Chi2 and have better predictability in the optimal housing shares.

The first two columns in Table 6 show the results for the full subsample two-step selection regressions. In the selection equation for Buy_t, the dummy variable for the threshold is statistically significant and has a positive coefficient of 0.239, indicating the purchase probability has a positive discontinuity once w_{t-1} reaches the threshold.[30] The coefficient on lagged liquid wealth is also significantly positive, and households are more likely to transition into homeownership as liquid savings increase. After controlling for the selection bias, the relative housing shares have a hump shape in liquid wealth with a negative sign on the linear term and a positive sign on the quadratic term.[31] The estimates are consistent with the graphical examination in Figure 4.2. Lagged income is not included in the main regression since it is not significantly correlated with the optimal housing ratios, i.e., households have similar housing shares once they choose to be homeowners regardless of their lagged income, conditional on all other covariates. However, senior renters are more likely to buy larger houses and have higher housing ratios due to their low probabilities of buying homes.

After the estimations, I compute the average expected log housing ratios conditional on buying homes, which is 1.88, slightly higher than the average log housing ratios of 1.67 from the data. However, the predicted probability of observing the conditional housing ratios being in the optimal region is around 9.77%, where the empirical probability is 18.76%, indicating a larger fraction of renters choose the housing allocations to the right of the optimal region given home purchases.[32] The probability for the expected ratios to fall between the upsizing and selling thresholds is higher at 17%, compared to the empirical estimate of 28%. Consumers are very likely to have really low liquid wealth after buying homes and are expected to accumulate more savings to gradually reduce housing shares over time. Conditional on having the housing ratios in the optimal region after being selected, the expected value of predicted housing ratios is around 1.22, very close to the sample average of 1.18.

As in the RD regressions, using the entire sample tends to have a larger bias in deriving the estimate for discontinuities. Thus, I test a local selection model with w_{t-1} between the optimal bandwidth of 2.38 on either side of the threshold.[33] The results are shown in the last two columns of Table 6, and the sample size drops from 3,035 to 2,494.

In the selection equation, the dummy variable $D_t(w_{t-1} > K)$ is close to be statistically significant with a coefficient of 0.178, which means a smaller discontinuous increase in purchase probabilities at the threshold compared to the full-sample estimates. Lagged liquid wealth remains positive and significant in predicting purchase probabilities as before. In the main equation, the quadratic terms of lagged liquid wealth are not statistically significant, because the calculated highest housing ratio is too close to the lower band in the local selection model.[34]

[30]The estimated discontinuity in the purchase probabilities are larger than the local Wald estimator with kernel weights as in Figure 4.1.

[31]The maximum of the quadratic function lies between the two boundary values in the distribution of w_{t-1}.

[32]The regressions predict log housing ratios, so the optimal region in log terms is within [0.85, 1.49].

[33]The optimal bandwidth is determined by the Mean Squared Error minimization function as in Imbens and Kalyanaraman (2012).

[34]A different regression including only the linear term in lagged liquid wealth yields a significantly negative

However, the shape of the function still indicates as liquid wealth increases, households have lower housing ratios conditional on buying homes to reduce the likelihoods of selling and downsizing in the future. On the other hand, senior households tend to have higher housing ratios compared to other age groups, and this is probably because those who choose to buy houses at senior years are more likely to choose larger houses relative to the liquid wealth as they tend to lower the probabilities of upsizing again later in life. The results from the local sample selection model are very consistent with the full-sample estimates.

Because renters' relative housing shares are not linear in w_{t-1}, I also test a partial linear model against the data. Robinson (1988) provides semiparametric estimation methods for the partially linear model using double residual nonparametric regressions if a variable enters the model nonlinearly. The details for the estimation are provided in the Robustness Appendix A1. The estimates on the linear part in Table A.1 have very similar coefficients as in the sample selection model with an insignificant coefficient on households' income. Moreover, the nonparametric part of the model in Figure A.1 also shows a hump-shaped nonlinear function in $\ln(H_t/W_t)$, so the relative housing shares first increase and then decline as liquid wealth rises, which confirms the findings in Table 6. Another test based on the sample of households whose initial housing ratios are within the optimal region further shows the nonlinear function of $\ln(H_t/W_t)$ is still hump-shaped and households with higher liquid wealth tend to have lower housing ratios and lower expected probabilities of home downsizing and selling.

Similar to the homeowners' tests, the positive discontinuity in the purchase probabilities is verified separately in each survey year as well. The identification of the thresholds uses 50% of data in each year. W^*_{buy} is then found at 8.5, 8.7, 9.2, 9.5 and 9.7 from 2001 to 2009 respectively. Conditional on the jump in the probabilities of buying homes, the chosen housing shares all have a hump shape in lagged liquid wealth between 2001 and 2005, but the function becomes downward-sloping in 2007 and 2009 due to drops in the purchase probabilities in the two years.[35] Those results confirm that the average threshold of 8.6 from the full-sample estimates reflects the largest jump in the average purchase probabilities across years.

In sum, both the homeowners' fuzzy regression kink model and renters' sample selection model yield estimates consistent with the kinked functions of optimal housing shares in Section 4. Renters experience jumps in the purchase probabilities when savings increase, and they choose home values that yield housing shares to be within the optimal range. Households with lower liquid wealth buy smaller houses first to have the benefits of homeownership once their liquid savings cross the boundary value of home purchases. With lower initial housing assets, those homeowners are more likely to upgrade in the future. On the other hand, wealthier households tend to buy larger homes to have higher housing shares and reduce the probabilities of costly

coefficient on the independent variable, indicating lower housing ratios with higher lagged liquid wealth.

[35]The coefficients on the dummy variable $D_t(w_{t-1} > K)$ in the selection models are 0.02, -0.23, 0.24, -0.09 and 0.37 in each year between 2001 and 2009, although the estimates are not statistically significant.

transactions in the future. As liquid wealth increases, the chosen housing shares decline gradually even if those households buy larger houses. Households also differ in other demographic variables, which leads to possible deviations in housing shares from the optimal region and uncertainties in future housing transactions.

After becoming homeowners, changes in the ratios of home value over liquid wealth exhibit kinks and discontinuities over time. Large discrete changes in housing stocks are more likely to occur when the relative ratios go beyond the optimal boundaries. If the relative housing shares cross the thresholds of downsizing or selling due to negative income shocks, homeowners optimally adjust housing assets to lower the ratios to be back to the optimal region. On the other hand, when the housing ratios are relatively lower due to owning smaller housing assets, positive income shocks are likely to increase the probabilities of upsizing and households accumulate more liquid wealth to buy larger houses. Other demographic variables also help explain variations in the likelihoods of housing transactions given the average thresholds.

8 Conclusion

Estimations for the changes in the optimal ratios of home value over liquid wealth are complicated, because housing assets have distinct characteristics compared to other liquid assets and durable goods. This paper characterizes the possible discontinuous evolution of relative housing shares to show consumers experience jumps in the likelihoods of home transactions when current savings, income, demographics, housing prices and other market conditions vary. Those factors affect both the values of the housing ratios and the thresholds, which creates more nonlinearities in the choices for housing wealth. The study provides new models in measuring discrete changes in consumers' optimal housing shares and empirically tests the implications of illiquid housing allocations in the consumption maximization problem.

For future research, estimations of the price or income elasticity of the housing demand based on the kinked functions of housing shares can be used to quantify and predict changes in housing assets given changes in prices and income. It is also important to distinguish whether or how those variables affect the threshold values and sizes of the kinks. A consumption model for the optimal housing assets can be developed to offer theoretical foundations for the understanding of the movements in illiquid housing wealth.

Robustness Appendix

A1 Estimations of the partial linear model

In this appendix, I provide details for the estimations of renters' optimal housing shares using Robinson (1988)'s partial linear model. I restrict the lagged liquid wealth to be within around the bottom and top one percent of the data, and each household is from the second random subsample not used in identifications. The model is specified as follows:

$$\ln(\frac{H_t}{W_t}) = X_t'\beta_0 + m(\ln(W_{t-1})) + \epsilon_t, \text{ if } \frac{H_t}{W_t} > 0 \quad \text{(A.1)}$$

Variables for the linear part of the model include households' lagged income, three age dummies, households' marriage indicator, dummies for family size and a dummy for head's gender. The estimation method uses the double residual regressions to derive the coefficients for the linear terms. After the first-stage regressions, we can then subtract the predicted linear values from the data and use nonparametric regressions to fit the nonlinear function in $\ln(W_{t-1})$.

The results are displayed in Table A.1. The coefficient on lagged income is insignificant even though the sign is positive. Thus, conditional on the nonlinear function of lagged liquid wealth, the relative housing shares are not significantly related to households' income. Yet the coefficients on households' age dummies and the marriage indicator are all statistically significant. Married households are more likely to have higher ratios than single households, because expected increases in family size might lead to purchases of larger houses. As people age, their housing shares increase over time conditional on all other explanatory variables, possibly because senior households tend to buy larger houses to reduce future upsizing probabilities.

The nonlinear part of the model $m(\ln(W_{t-1}))$ is plotted against the raw data in Figure A.1. The graph shows a hump-shaped nonlinear function in $\ln(H_t/W_t)$. Also we can notice the density of the raw data is more sparse at smaller values of lagged liquid wealth, i.e., there are fewer households who move from renting to owning when savings are low, but the probability increases when liquid wealth rises.

A2 The discontinuities in the purchase probabilities with logit fits

In this robustness appendix, I test if the likelihoods of making home purchases have a discontinuity at the estimated threshold. I also present graphical examinations using renters' second random subsample. Households are divided based on their lagged liquid wealth with a bin width of 0.1. Included households all have lagged liquid wealth within bottom 1 percent and top 99 percent of the data.

Within each bin of the lagged liquid wealth, I calculate the fraction of renters who purchase houses in this subsample. I then fit a logit model by regressing the indicator variable for home purchases on households' lagged liquid wealth $\ln(W_{t-1})$ on either side of the threshold (W^*_{buy}=8.6). After the logit regressions, the predicted probabilities are averaged across each bin and plotted against the observed probabilities. This is an alternative method to compare the average likelihoods at the threshold in addition to the local linear regressions. Figure A.2 presents the plot. The logit fits exhibit a clear jump at the threshold, and the probabilities increase with higher liquid wealth on both sides of the threshold. The estimates are very similar to the discontinuity plot in Figure 4.1 from the first random subsample of renters.

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Table 1: Shares of population with each type of transitions (%)

# of adj	0	1	2	3	4	5		
% of HH	64.29	24.78	8.13	2.41	0.38	0.01		
Year	Pre-Sample	Owner-Buyer	Owner-Seller	Renter-Seller	Renter-Buyer	Renter-Renter	Owner-Owner	Adj-All
2001	0.5	3.8	2.1	0.3	4.8	26.1	62.5	11.0
2003	0.5	4.2	2.9	0.2	5.3	24.5	62.4	12.5
2005	0.3	4.4	3.2	0.2	5.3	24.8	61.8	13.1
2007	0.4	4.3	2.9	0.2	4.8	26.1	61.3	12.2
2009	0.2	2.2	3.2	0.1	3.9	28.1	62.4	9.3

Notes: Transitions are identified from each survey by comparing current homeownership status to that in the previous survey year. The sample starts from 1999. P-S: households make transactions before entering the sample; O-B: homeowners move to different houses; O-S: homeowners move to renting; R-S: renters buy and sell houses within two years; R-B: renters buy houses; R-R: renters keep renting; O-O: homeowners stay in the same houses; Adj-All: the total fraction of population making different housing transactions every two years.

Table 2: Comparisons of home price return and housing wealth growth (%)

Year	Home price return			Housing wealth growth		Value-weighted return	Market return
	O-B	O-S	O-O	O-B	O-O	O-O	R-S
2001	-0.63	-2.63	17.34	63.94	17.34	15.28	21.59
2003	-5.45	12.90	17.05	57.04	17.05	14.86	21.55
2005	5.72	4.89	24.71	66.65	24.71	22.41	33.56
2007	4.06	5.16	16.77	51.18	16.77	13.30	3.75
2009	-7.52	-18.10	-4.00	21.87	-4.00	-8.23	-26.89

Notes: The estimates are average two-year housing returns of the same houses in columns 3, 5 and 6; actual realized capital gains from sales of the old houses in columns 1 and 2; actual growth in housing wealth including quantity changes in column 4; and average two-year returns on monthly Case-Shiller 20-City HPI in column 7. O-B: homeowners move to different houses; O-S: homeowners move to renting; O-O: homeowners stay in the same houses; R-S: repeated sales.

Table 3: Estimations of homeowners' housing choices

	Model 1			Model 2		
	(2)	(3)	(4)	(2)	(3)	(4)
$\ln Y_{t-1}$	0.298^{***}	0.138	-0.118^{**}	0.294^{***}	0.115	-0.069
	(0.066)	(0.085)	(0.050)	(0.067)	(0.084)	(0.052)
$\ln(H_{t-1}/W_{t-1})$	-0.071^{**}	0.132^{***}	0.160^{***}	-0.075^{*}	0.175^{***}	0.106^{*}
	(0.034)	(0.049)	(0.043)	(0.039)	(0.057)	(0.056)
year03	0.209	-0.149	0.271	0.208	-0.156	0.278
	(0.138)	(0.236)	(0.175)	(0.138)	(0.236)	(0.177)
year05	0.215	-0.341	0.090	0.214	-0.355	0.114
	(0.142)	(0.228)	(0.180)	(0.142)	(0.228)	(0.182)
year07	0.093	0.011	0.161	0.092	-0.008	0.189
	(0.142)	(0.212)	(0.168)	(0.142)	(0.213)	(0.170)
year09	-0.945^{***}	-0.355	-0.015	-0.947^{***}	-0.381^{*}	0.025
	(0.188)	(0.222)	(0.174)	(0.188)	(0.223)	(0.177)
45<Age<65	-1.062^{***}	-0.242	-0.849^{***}	-1.064^{***}	-0.256	-0.814^{***}
	(0.106)	(0.156)	(0.129)	(0.107)	(0.156)	(0.130)
Age>=65	-1.178^{***}	-0.126	-1.699^{***}	-1.187^{***}	-0.156	-1.580^{***}
	(0.218)	(0.268)	(0.288)	(0.218)	(0.271)	(0.280)
Married	1.265^{***}	0.325	-0.866^{***}	1.264^{***}	0.256	-0.784^{***}
	(-0.405)	(-0.371)	(-0.232)	(-0.407)	(-0.370)	(-0.235)
Male	-0.827^{**}	-0.161	0.543^{***}	-0.828^{**}	-0.148	0.523^{***}
	(-0.332)	(-0.312)	(-0.188)	(-0.333)	(-0.312)	(-0.190)
$LowW_{t-1}$				-0.353	-4.314^{**}	1.676^{***}
				(-0.575)	(-2.080)	(-0.333)
$LowW_{t-1} *$				0.120	1.159^{*}	-0.389^{***}
$\ln(H_{t-1}/W_{t-1})$				(-0.188)	(-0.627)	(-0.124)
Constant	-6.116^{***}	-5.649^{***}	-1.574^{***}	-6.065^{***}	-5.288^{***}	-2.279^{***}
	(-0.747)	(-1.027)	(-0.595)	(-0.762)	(-1.028)	(-0.622)
Observations	15,230	15,230	15,230	15,230	15,230	15,230
Pseudo R2	6.06%	6.06%	6.06%	6.47%	6.47%	6.47%

Notes: Multinomial logit regressions for homeowners. The baseline choice is to live in the same houses. Choice (2) is to buy larger houses, choice (3) is to buy smaller houses and choice (4) is to sell current houses. Controls include households' variables and year dummies. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Estimations of renters' housing choices

	Model 1	Model 2	Model 3	Model 4
$\ln Y_{t-1}$	0.229^{***}	0.195^{*}	0.462^{***}	0.447^{***}
	(0.080)	(0.100)	(0.069)	(0.092)
year03	0.035	0.033	0.269^{**}	0.264^{**}
	(0.145)	(0.145)	(0.130)	(0.130)
year05	0.208	0.208	0.329^{**}	0.318^{**}
	(0.145)	(0.145)	(0.134)	(0.134)
year07	-0.109	-0.109	0.131	0.121
	(0.148)	(0.149)	(0.139)	(0.139)
year09	-0.421^{***}	-0.417^{***}	-0.241^{*}	-0.246^{*}
	(0.145)	(0.145)	(0.140)	(0.139)
$45 \leq$Age< 65	-0.518^{***}	-0.510^{***}	-0.349^{***}	-0.344^{***}
	(0.106)	(0.105)	(0.101)	(0.100)
Age≥ 65	-1.246^{***}	-1.303^{***}	-0.579	-0.636^{*}
	(0.433)	(0.435)	(0.354)	(0.355)
Married	0.682^{***}	0.665^{***}	0.926^{***}	0.916^{***}
	(0.201)	(0.201)	(0.175)	(0.175)
Male	-0.158	-0.155	-0.163	-0.171
	(0.176)	(0.176)	(0.157)	(0.157)
$\ln(W_{t-1})$	0.257^{***}	0.229^{***}	0.248^{***}	0.218^{***}
	(0.033)	(0.035)	(0.029)	(0.032)
$LowY_{t-1}$		-1.394^{**}		-1.359^{**}
		(0.683)		(0.592)
$LowY_{t-1}*$		0.133^{*}		0.143^{**}
$\ln(W_{t-1})$		(0.074)		(0.067)
Constant	-5.872^{***}	-5.190^{***}	-8.766^{***}	-8.288^{***}
	(0.739)	(0.984)	(0.736)	(0.957)
Observations	5,011	5,011	5,088	5,088
R2/Wald Chi2	0.116	0.118	283.5	284.7
Random Effects	No	No	Yes	Yes

Notes: Logit regressions for renters with the baseline choice as to keep renting. Independent variables include households' variables such as lagged liquid wealth and lagged income. The last two columns report logit regressions with i.i.d. random effects. Clustered standard errors in parentheses for the logit regressions. *** p<0.01, ** p<0.05, * p<0.1

Table 5: 2SLS estimations of the changes in optimal housing shares

	RKD of upsizing on [0,K2]		RKD of downsizing on (K1,K3]	
	Local Linear	Local Polynomial	Local Linear	Local Polynomial
1st Stage Estimation				
$\frac{H_{t-1}}{W_{t-1}}$	-0.006	-0.027	-0.025	-0.345^{*}
	(0.007)	(0.031)	(0.020)	(0.200)
$\frac{H_{t-1}}{W_{t-1}} * D_t$	0.003	-0.031	0.011	0.144
	(0.013)	(0.054)	(0.009)	(0.095)
$(\frac{H_{t-1}}{W_{t-1}})^2$		0.004		0.048^{*}
		(0.008)		(0.029)
$(\frac{H_{t-1}}{W_{t-1}})^2 * D_t$		0.020		-0.031
		(0.026)		(0.021)
Constant	0.116^{***}	0.137^{***}	0.122^{*}	0.637^{*}
	(0.017)	(0.029)	(0.066)	(0.341)
2nd Stage Estimation				
$\hat{T}_t$	137.014	-85.723	-9.786	11.179
	(696.104)	(154.812)	(26.155)	(22.370)
$\frac{H_{t-1}}{W_{t-1}}$	1.010	-2.474	0.068	3.324
	(4.340)	(4.936)	(0.266)	(2.808)
$(\frac{H_{t-1}}{W_{t-1}})^2$		0.546		-0.352
		(1.045)		(0.378)
$(\frac{H_{t-1}}{W_{t-1}})^2 * D_t$		0.654		-0.015
		(1.166)		(0.093)
Constant	-15.064	11.993	2.333	-5.328
	(82.686)	(19.456)	(1.839)	(5.943)
Observations	1,798	1,798	719	719
Wald Chi2	0.08	0.46	0.32	1.90

Notes: 2SLS regressions of changes in optimal housing shares in the samples of lagged ratios of home value over liquid wealth within [0, K2] and (K1, K3]. Observed values T_t are instrumented using the interaction terms of the indicator variables for the thresholds and lagged housing ratios, $D_t * (H_{t-1}/W_{t-1})$. Independent variables are local polynomials in H_{t-1}/W_{t-1}. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Estimations of $\ln(H_t/W_t)$ in the sample selection model

	(1) Full Sample Selection		(2) Local Sample Selection	
Dep:	$\ln(H_t/W_t)$	$Buy_t = 1$	$\ln(H_t/W_t)$	$Buy_t = 1$
$\ln W_{t-1}$	0.620	0.126^{***}	0.240	0.161^{***}
	(0.480)	(0.026)	(0.988)	(0.049)
$(\ln W_{t-1})^2$	-0.050^{**}		-0.046	
	(0.019)		(0.045)	
year03	0.130		-0.003	
	(0.146)		(0.166)	
year05	0.100		0.004	
	(0.152)		(0.177)	
year07	0.135		0.038	
	(0.166)		(0.188)	
year09	0.443^{***}		0.220	
	(0.162)		(0.189)	
$45 \leq$Age< 65	-0.092		-0.013	
	(0.113)		(0.134)	
Age≥ 65	1.195^{**}		1.112^{**}	
	(0.577)		(0.566)	
$D_t(\ln W_{t-1} > K)$		0.239^{***}		0.178
		(0.090)		(0.113)
lambda	-0.545		-2.035	
	(1.101)		(2.034)	
Constant	1.099	-2.254^{***}	6.588	-2.524^{***}
	(4.307)	(0.202)	(8.189)	(0.381)
Observations	530	3,035	401	2,494
Chi2	43.72		12.08	

Notes: Sample selection models use Heckman's two-step estimators. $D_t(\ln(W_{t-1}) > K)$ indicates households with lagged liquid wealth above W^*_{buy}. The full-sample estimation uses households with lagged log liquid wealth between 1% and 99% of the data. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.1: Estimations of $\ln(H_t/W_t)$ in the partial linear model

Partial Linear Model for $\ln(H_t/W_t)$						
$\ln Y_{t-1}$	45$\leq$Age<65	Age$\leq$65	Married	Male	Obs	Chi2
0.037	-0.107	1.065^{***}	0.436^{*}	-0.423^{**}	517	0.042
(0.089)	(0.125)	(0.362)	(0.256)	(0.215)		

Notes: Partial linear model regresses the log ratio of home value over liquid wealth with a nonparametric term in lagged liquid wealth and other linear regressors. The sample uses households with lagged log liquid wealth between 1% and 99% of the data. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Plot of H_t/W_t as a function of H_{t-1}/W_{t-1}

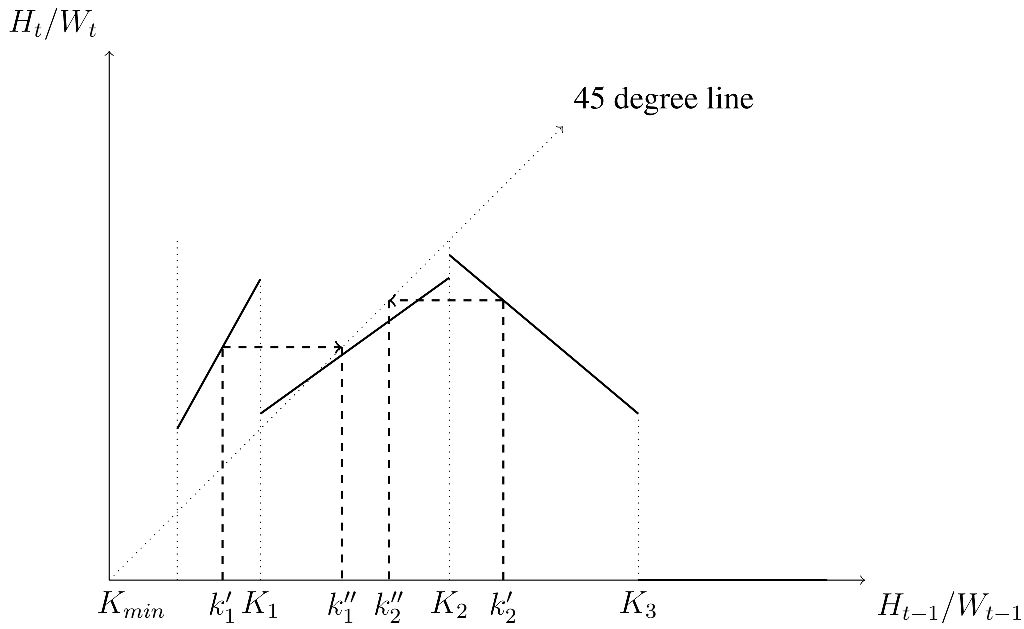


Figure 2: Plot of H_t/W_t as a function of W_{t-1}

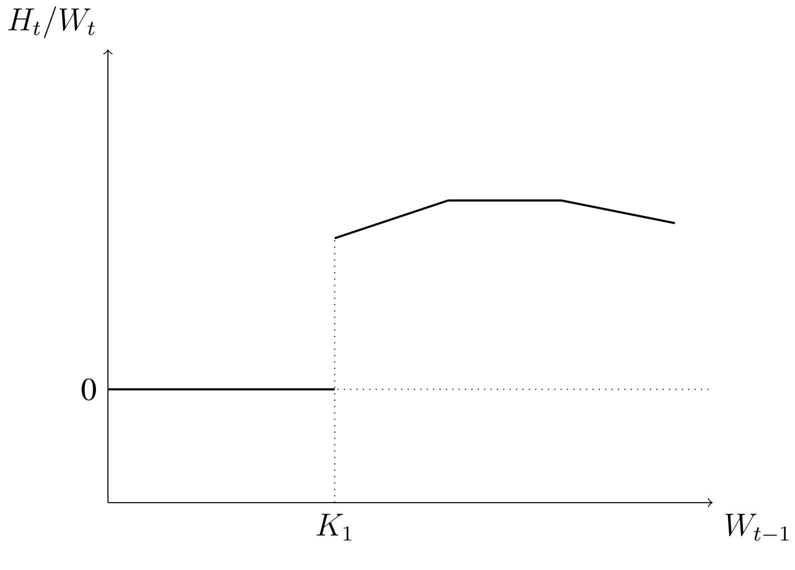
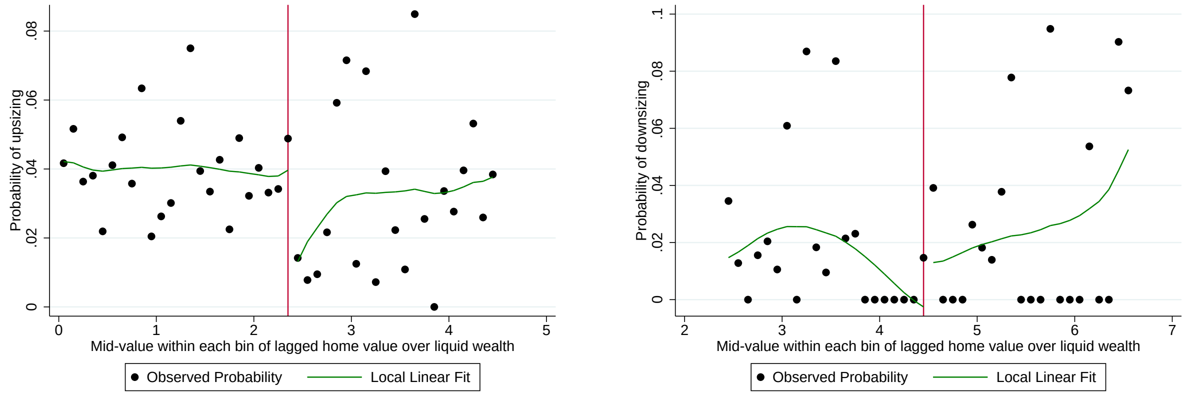
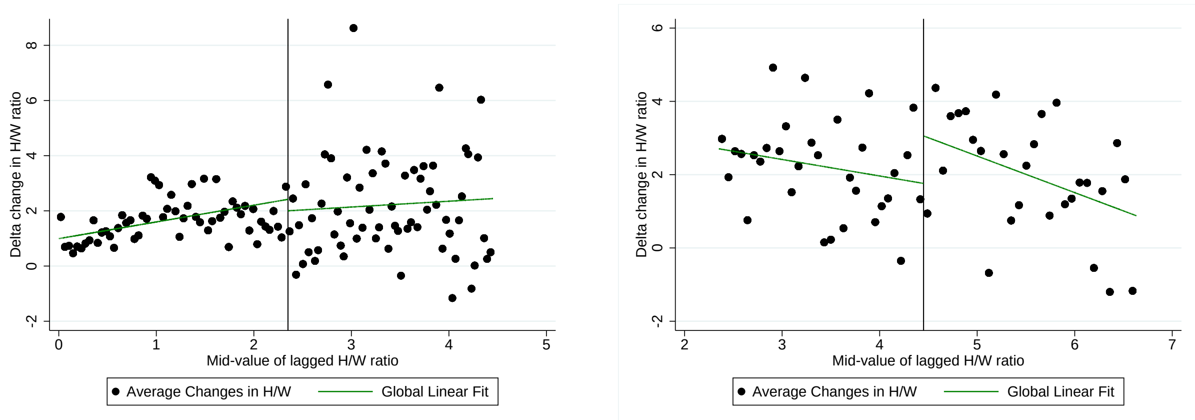


Figure 3.1 Probabilities of upsizing and downsizing within each bin of H_{t-1}/W_{t-1}



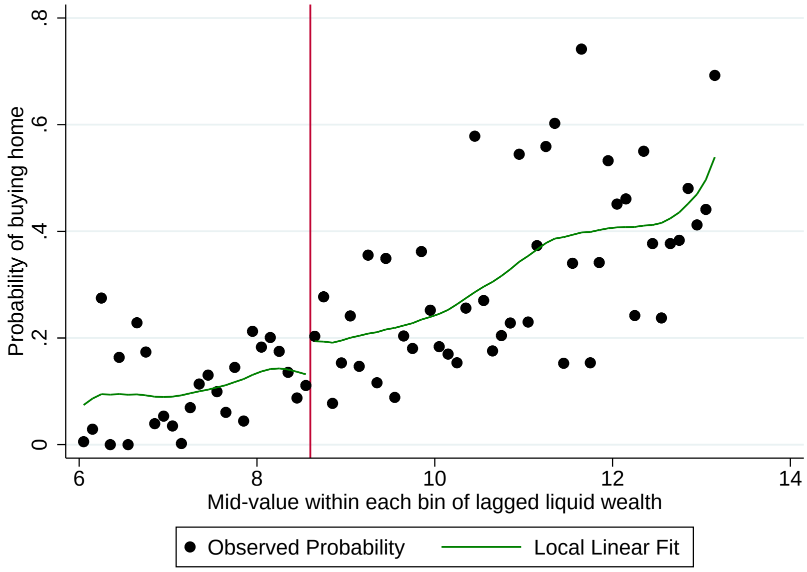
Notes: The left figure plots the observed probabilities of upsizing within each bin of H_{t-1}/W_{t-1} between 0 and K_2 in the upsizing random subsample with local linear fits. The optimal bandwidth is 1.089. The right figure plots the observed probabilities of downsizing within each bin of H_{t-1}/W_{t-1} between K_1 and K_3 in the downsizing random subsample with local linear fits. The optimal bandwidth is 1.335.

Figure 3.2 Regression discontinuity plots of average $\Delta H_t/W_t$ within each bin of H_{t-1}/W_{t-1}



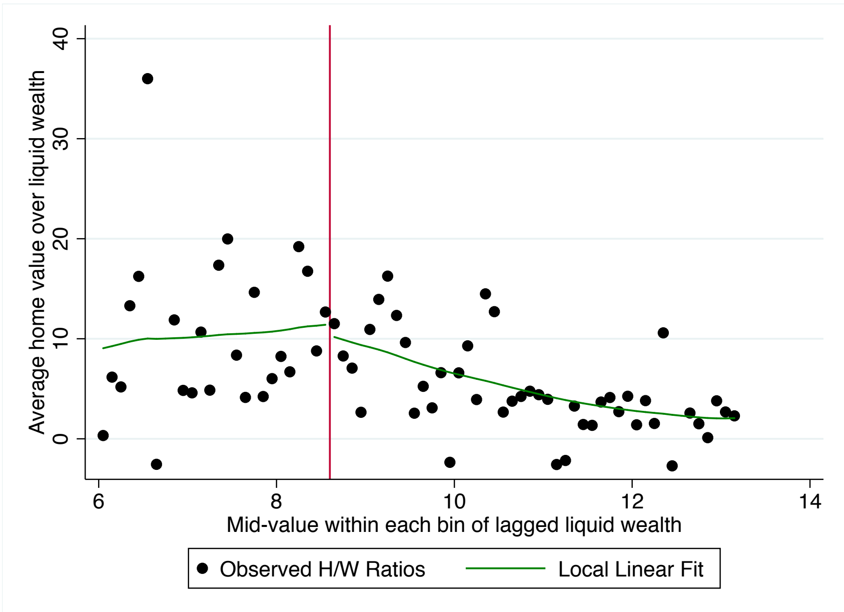
Notes: The left figure uses the second subsample generated using the criteria of observing at least one upsizing transaction, and it plots the mean values of $\Delta H_t/W_t$ within each bin of H_{t-1}/W_{t-1} from 0 to 4.45 and a linear fit on either side of the threshold K_1=2.35; the right figure uses the second subsample generated using the criteria of observing at least one downsizing transaction, and it plots the mean values of $\Delta H_t/W_t$ within each bin of H_{t-1}/W_{t-1} from 2.35 to 6.65 and a linear fit on either side of the threshold K_2=4.45.

Figure 4.1 Renters' purchase probabilities within each bin of $\ln(W_{t-1})$



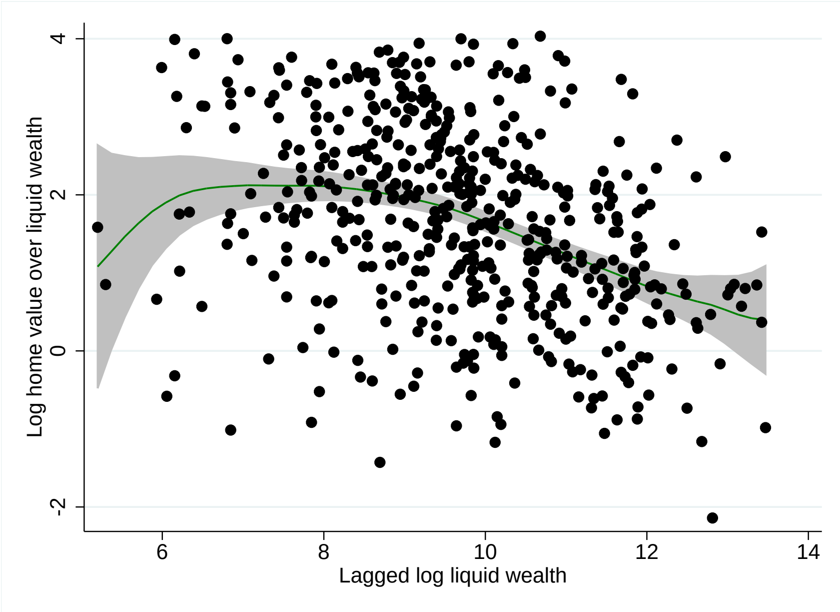
Notes: The figure plots the observed probabilities of buying homes within each bin of $\ln(W_{t-1})$ in the renters' subsample with local linear fits. The optimal bandwidth is 1.189.

Figure 4.2 Renters' conditional average H_t/W_t



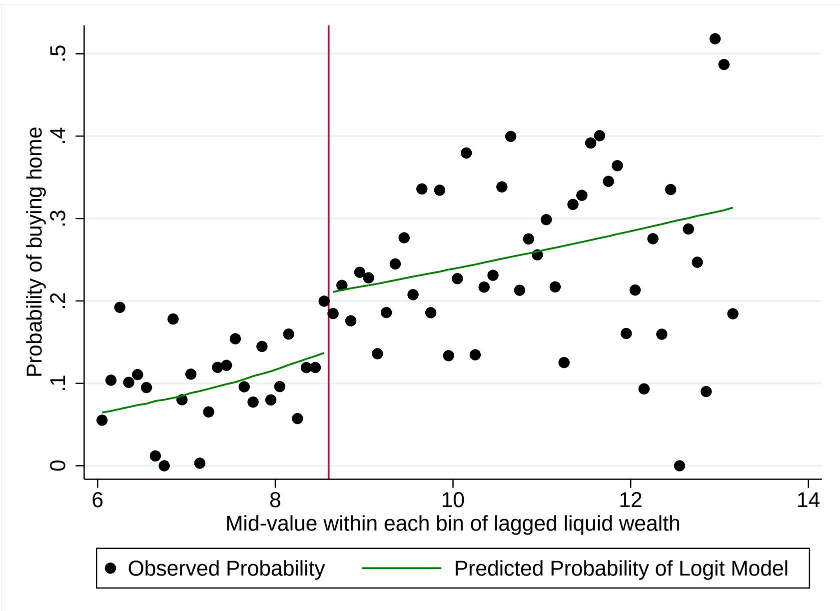
Notes: The figure uses the second random subsample for renters and plots the average ratios of H_t/W_t conditional on buying homes within each bin of $\ln(W_{t-1})$ and a local linear fit on either side of the threshold. The local Wald estimator is statistically insignificant at -1.140 with an optimal bandwidth 3.042. The bin width for lagged liquid wealth is set at 0.1.

Figure A.1: Nonparametric model fit of $\ln(H_t/W_t)$ over $\ln(W_{t-1})$



Notes: Nonparametric model fit from the partial linear model. The regression uses double residual nonparametric estimators with controls on households' lagged income and demographic variables.

Figure A.2: Renters' purchase probabilities with logit fits



Notes: The figure plots the observed probabilities of home purchases within each bin of $\ln(W_{t-1})$ with a logit fit on either side of the threshold. The bin width is set at 0.1.