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Risk Attitude and Housing Wealth Effect

Wen-Chi Liao · Daxuan Zhao · Tien Foo Sing

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Abstract This paper examines whether the housing wealth effect—the consumption change induced by house price appreciation—is dependent upon households' attitudes toward risk. A simple theoretical model is introduced to highlight a negative relationship between the wealth effect and risk aversion. The paper empirically tests for this negative relationship, using data from the U.S. Consumer Expenditure Survey. The investigation involves two steps. In the first step, we make use of households' demographics and their risky and liquid asset holdings to estimate risk aversion. The Heckman correction model is applied to address the issue of limited stock market participation. For the second step, we construct pseudo panel data through grouping households by their birth years and their predicted values of risk aversion, and then, we estimate the responses of households' consumption changes to house price fluctuations by risk-attitude group. Consistent with the prediction of the theoretical model, the estimation results suggest a significant negative relationship between the housing wealth effect and households' risk attitudes. Households, who are less risk averse, experience greater consumption changes in response to house price appreciation.

Keywords Housing wealth effect · Risk aversion · Pseudo panel data · Heckman correction model

W.-C. Liao (✉) · T. F. Sing
Department of Real Estate and Institute of Real Estate Studies, National University of Singapore,
4 Architecture Drive, Singapore 117566, Singapore
e-mail: wliao@nus.edu.sg

T. F. Sing
e-mail: rststf@nus.edu.sg

D. Zhao
Institute of Real Estate Studies, National University of Singapore,
21 Heng Mui Keng Terrace, #04–02 I-Cube Building, Singapore 119613, Singapore
e-mail: zhaodaxuan@gmail.com

Introduction

Housing is a major source of household wealth. When house prices rise, households' wealth increases, which lead them to consume more. This positive relationship between consumption and house prices is known as housing wealth effect (HWE) in the literature. Researchers have found empirical evidence supporting the HWE; and the results have significant implications for policy makers. However, households with different degrees of risk aversion may react differently, because house prices are volatile and housing is a risky asset. Using data from the U.S. Consumer Expenditure Survey, this paper shows that households who are less risk averse experience a stronger positive relationship between consumption and house price growth. The result brings a new angle to the housing and behavioral research.

The studies of HWE test the relationship between consumption and house prices. Analyzing macro panel data in 14 western countries and the United States, Case et al. (2005) find that the variation in aggregate housing wealth has a significant effect on aggregate consumption, and the effect is much greater than the influence of financial wealth.[1] A 10 % growth in housing wealth increases consumption of households by 1 % and 0.4 % in the western countries and the U.S., respectively. Benjamin et al. (2004) obtain similar results. Noting stickiness of consumer-habit formation and slow response of consumption to shocks, Carroll et al. (2011) distinguish between immediate and eventual wealth effects. The immediate marginal propensity to consume within 3 months when housing wealth increases is about 2 %, whereas the propensity to spend the extra wealth over a time span of several years is around 9 %. Overall, the literature supports a positive HWE.

Despite the positive empirical evidence, the micro-foundation underlying the HWE is not fully understood (Campbell and Cocco 2007; Li and Yao 2007; Gan 2010). The permanent income hypothesis suggests consumption smoothing through borrowing and saving, so households with perfect foresight in a deterministic economy with a risk-free bond market will consume a constant fraction of the permanent income: The perfect consumption smoothing hinders HWE. However, house prices are in fact stochastic, and the shocks may be aggregate shocks. Also, the market may be incomplete, and households may be liquidity constrained. As a result, households' ability to smooth consumption may be limited, and the association between consumption and house-price changes is observable.

HWE varies across heterogeneous households. Sinai and Souleles (2005) point out that higher house prices imply higher implicit rent, and this hinders HWE on homeowners who use their houses as shelters. Their view of HWE has several implications. The wealth effect should be stronger among households who own multiple houses. The effect should be larger among homeowners who have a shorter expected life span and a weaker bequest motive. The effect would also be

[1] Bostic et al. (2009) statistically match the U.S. Consumer Expenditure Survey and the Survey of Consumer Finance. Using the microdata, they also find that the HWE is much stronger than the financial wealth effect.

greater for owners who expect a decrease in family size and plan to downsize their houses. The above situations are more applicable to older homeowners. However, younger homeowners may also experience HWE, because of relaxation of the liquidity constraint (Ortalo-Magne and Rady 2006; Li and Yao 2007). Additionally, HWE may depend upon precautionary saving motive. Consumption growth may be positively correlated with the predictable component of house price growth, because a higher home value reduces the need for precautionary savings (Carroll 1992, 1997; Campbell and Cocco 2007; Gan 2010). Lastly, Buiter (2008) points out that house price appreciation redistributes wealth from households who short housing to those who long housing. Thus, renters and owners could experience different HWEs, and these effects may cancel out at the aggregate level.

Microdata allow empirical investigation into the above theories. Using British Consumer Expenditure Survey, Campbell and Cocco (2007) estimate a larger wealth effect than the comparable results found in the previous studies that use aggregate data, but the estimates vary substantially across household types. When regional house-price growth increases by 1 %, the growth of real non-durable consumption will increase by as much as 1.7 % and 1.0 % for older and younger homeowners, respectively, whereas the increase in the consumption growth is much smaller, if not different from zero, for renters. Their results are in line with the theories. Gan (2010) identifies the importance of three underlying explanations of HWE: the liquidity-constraint hypothesis, the precautionary-saving hypothesis, and the hypothesis that households who own multiple houses increase consumption more when house prices rise. Merging a few sources of data in Hong Kong, she constructs a large panel dataset that tracks housing wealth, mortgage applications and credit card spending. She shows that precautionary saving hypothesis is also an important driver of HWE, in addition to the other two well-received hypotheses.

The HWE literature is emerging. Surprisingly, although house prices are volatile and housing is a risky asset, the literature has said little about how HWE would depend on households' risk aversion, which is widely acknowledged as an important factor in decision making.[2] Intuitively, households' risk aversion should influence consumption decisions. This is because a household with higher risk aversion has a more concave utility function according to the Pratt Theorem. Since a lottery cannot yield the same expected marginal utility for two persons, who only differ in the degree of concavity of their utility functions, an intertemporal state-contingent consumption plan that is optimal to one may not be optimal to the other.

This paper finds a weaker positive relationship between consumption and house price growth for households who are more risk averse. The HWE decreases in household risk aversion. For our analysis, we first lay out a simple theoretical model, where the household owns housing and decides on consumption paths and leverage choices. We use data from the U.S. Panel Study of Income Dynamics, Federal Housing Finance Agency, and the literature to calibrate the model parameters at the empirically plausible values to show the pattern. Then, we use data from the Consumer

[2]For example, Campbell and Cocco (2003) show that households with lower risk aversion are more likely to choose adjustable rate mortgages over fixed rate mortgages.

Expenditure Survey (CEX) to empirically test the relationships between HWE and household risk aversion using a two-step regression approach. The first step makes use of households' demographics and their risky and liquid asset holdings to estimate the relative risk aversion. As a large fraction of households have no risky asset, we address the issue of limited stock market participation using the Heckman correction model. Tobit model is also used as a robustness check. After defining the measure of relative risk aversion, the second step starts with the construction of a pseudo-panel from the CEX dataset. We follow the approach of Campbell and Cocco (2007) to test the impact of house price appreciation on consumption. The main difference from the previous literature is that we explicitly test for the dependence of HWE on households' risk attitude. The positive relationship between consumption and house price growth diminishes when the households are more risk averse.

The rest of the paper is organized as follows. Section "Model" presents the model and the results of calibration. Section "Data" introduces our data for the empirical analysis. Section "Empirical Tests and Results" discusses the estimation methodology and presents the results. The final section concludes.

Model

This section presents a simple theoretical model predicting the relationship between HWE and risk aversion. In the model, a household indexed by i, who receives w_i units of periodic labor income, makes consumption and leverage decisions to maximize utility. Following the framework of Campbell and Cocco (2003), we assume that the household starts off with a house of a given size $\bar{h}_i$ at the beginning of period 1 and remains in the same house during a short T-period of observable time horizon because of high adjustment costs.[3] The household may not own the house free and clear, so we denote $\tilde{l}_{i,0}$ as the initial loan to value ratio at the beginning of period 1.

Let p_{s_1} denote the period-1 house price that is given exogenously. The house price dynamic follows a binomial path, which is driven by a constant growth rate γ and a shock term ε. The two possible states–good and bad–have an equal chance to occur in each period. The house price grows by the rate $\gamma + \varepsilon$ in the good state and by $\gamma - \varepsilon$ otherwise. Let s_t denote the event history up to t and S_t be the set of all possible event histories until t. Thus, the probability for the price p_{s_t} to occur is π_{s_t}, for which $\pi_{s_1} = 1$ and $\sum_{s_t \in S_t} \pi_{s_t} = 1, \forall t \in \{2, 3, ...T\}$.

The household has preferences over consumption, housing and terminal wealth. Assume the utility function is additively separable. This assumption, together with non-adjustable house size, implies that the periodic utility from housing is a constant, which is normalized to 0. Assume the periodic utility from consumption c is given by

$$u\left(c; \eta_i\right) = \frac{c^{1-\eta_i}}{1-\eta_i}$$

[3]The literature has considered the role of adjustment costs in housing choices (e.g., Falavin and Nakagawa 2008). With higher adjustment costs, households will change the house size less frequently.

and the utility from the terminal wealth a is given by

$$v\left(a;\eta_i\right)=\frac{a^{1-\eta_i}}{1-\eta_i}$$

where $\eta_i > 0$ is a parameter that indicates the household's constant relative risk aversion (CRRA). In the special case that $n_i = 1$, the utility function reduces to $u(c) = ln(c)$. With a von Neumann-Morgenstern expected utility representation, the household's utility maximization problem can be written as follows:

$$\begin{aligned}
\max_{\{c_{s_t},l_{s_t}\}_{t=1,s_t\in S_t}^{T}} \quad & \sum_{t=1}^{T}\sum_{s_t\in S_t}\beta^{t-1}\pi_{s_t}u\left(c_{s_t};\eta\right)+\theta\sum_{s_T\in S_T}\beta^{T-1}\pi_{s_T}v\left(a_{s_T};\eta\right) \\
s.t. \quad & c_{s_1} = w+l_{s_1}p_{s_1}\bar{h}-r\tilde{l}_0p_{s_1}\bar{h} \\
& c_{s_t} = w+l_{s_t}p_{s_t}\bar{h}-rl_{s_{t-1}}p_{s_{t-1}}\bar{h} && \forall s_t\in S_t;\ 1<t\le T \\
& a_{s_T} = \left(1-l_{s_T}\right)p_{s_T}\bar{h} && \forall s_T\in S_T \\
& 0\le l_{s_t}\le 1 && \forall s_t\in S_t;\ 1\le t\le T
\end{aligned}$$

For simplicity, the subscript i is suppressed.

The above problem relates to mortgage financing decisions, while the relationship between HWE and CRRA is also justifiable in different model setups.[4] Here, the household chooses a loan-to-value (LTV) ratio l_{s_t} as well as consumption c_{s_t} in each period t and state s. She originates a new loan $l_{s_t}p_{s_t}\bar{h}$ and pays back $rl_{s_{t-1}}p_{s_{t-1}}\bar{h}$, which includes the principal of loan and accrual of interest in period $t-1$ since r equals to 1 plus interest rate. Recall $\tilde{l}_0$ is the exogenous initial LTV ratio. If $\tilde{l}_0 > 0$, the household does not own the house free and clear initially and needs to pay back $r\tilde{l}_0p_{s_1}\bar{h}$ in period 1. The terminal wealth a_{s_T} is the residual home equity at the end of period T. The household values this terminal wealth with a weight θ, whose empirical counterpart may depend upon individual household characteristics, such as the bequest motive, age, family size, etc. The utility from the terminal wealth can be interpreted as the remaining lifetime utility (Campbell and Cocco 2003).

The above utility maximization problem has no closed-form solution, because the marginal utility of consumption is not an additively separable function in its arguments. Thus, we calibrate parameter values and derive numerical solutions using information from various sources. We illustrate the HWE with a two-period case, because given the homogeneity of the life-cycle dimension of the model, the results of the two-period case are not qualitatively different from those cases with more periods. Using the first order conditions, we can solve l_{s_2} as a function of l_{s_1}. Substituting this function for l_{s_2} in the Euler equation, the equation becomes

$$\left(\rho+l_{s_1}^*-r\tilde{l}_0\right)^{-\eta}=\frac{\beta r}{2}\left(\theta^{\frac{1}{\eta}}+1\right)^{\eta}\left(\left(\rho+\gamma+\varepsilon-rl_{s_1}^*\right)^{-\eta}+\left(\rho+\gamma-\varepsilon-rl_{s_1}^*\right)^{-\eta}\right) \tag{1}$$

[4]Previously, we tried an alternative model in which the household owns much housing stock and likes to sell the stock to fund consumption. We derived an analytical solution, for that model which predicts the same relationship between HWE and CRRA.

where ρ is the reciprocal of the initial price to income ratio (i.e., $\rho = \frac{w}{p_{s_1}\bar{h}}$). After calibrating the values of the parameters in Eq. (1), $l^*_{s_1}$ and other elements of the maximizer can be solved numerically. Define the consumption change as $\overline{\Delta c}^* = \sum_{s_2} \pi_{s_2} c^*_{s_2} - c^*_{s_1}$, which is the expected change in consumption when the household enters period 2. We have

$$\overline{\Delta c}^* = \left(\left(\rho + \gamma - r l^*_{s_1}\right) \left(\theta^{\frac{1}{\eta}} + 1\right)^{-1} - \left(\rho + l^*_{s_1} - r\tilde{l}_0\right) \right) p_{s_1} h \tag{2}$$

Numerical solutions of the maximizer and $\overline{\Delta c}^*$ (Eq. (2)) require the inputs of eight parameters ρ, $\tilde{l}_0$, r, γ, ε, β, θ and η, while $p_{s_1}\bar{h}$ is simply a unit of measurement which can be normalized to 1. Table 1 summarizes their benchmark values. For ρ the reciprocal of the initial price to income ratio and $\tilde{l}_0$ the LTV ratio, we set the baseline values using information from the biennial surveys of the Panel Study of Income Dynamics (PSID) for the period between 1997 and 2007. The average price to income ratio was 2.95, which is between the values calculated from using two Census datasets, Census 2000 and American Community Survey 2005–2009 5-year estimates. Thus, ρ is set to 0.35. The PSID also releases information of each family's mortgage loans. Dividing the remaining principal of the first mortgages by home values, the average LTV ratio was 0.41 between 1997 and 2007, while taking the second mortgages into consideration slightly increase the ratio by 0.02. For our purpose, $\tilde{l}_0$ is set to 0.41. For r the interest rate, γ the expected growth rate of house prices, and ε

Table 1 Benchmark values of parameters

Parameter		Benchmark value	Source
ρ	Reciprocal of the price to income ratio	0.35	PSID 1997–2007
$\tilde{l}_0$	Initial loan-to-value ratio	0.41	PSID 1997–2007
γ	Real growth rate of house prices	1.0421	FHFA 1997–2007
ε	Shock term to house price growth	0.022	FHFA 1997–2007
r	Real interest rate of conventional mortgage	1.0415	FHFA 1997–2007
β	Discount factor for periodic utility	0.98	Campbell and Cocco (2003, 2007)
θ	Weighting parameter of terminal wealth	1	Campbell and Cocco (2003, 2007)
η	Constant relative-risk-aversion	(0, 10]	Mankiw and Zeldes (1991), Carroll (1997), Campbell and Cocco (2003, 2007)

the shock term, their baseline values are determined using information from the Federal Housing Finance Agency (FHFA). The House Price Index shows that the annual growth rates of house prices ranged between 2.38 and 10.09 % during the 1997–2007 periods. Taking inflation into account, an average real house-price growth rate is estimated at 4.21 % and a standard deviation is at 2.20 %.[5] Thus, γ and ε are set to 1.0421 and 0.022, respectively. [6] The FHFA also releases mortgage information. The average real interest rate of the conventional single-family mortgages was 4.15 % for the period between 1997 and 2007. Therefore, r is set to 1.0415. For β the discount factor of periodic utility and θ the weighting parameter of terminal wealth, we use the benchmark values of Campbell and Cocco (2003, 2007) and set β to 0.98 and θ to 1. Lastly, we simulate HWE by varying the relative-risk-aversion parameter η. The range that we test is (0, 10], which covers the empirically plausible values.[7] After solving the model with the benchmark parameters,[8] we raise the house price appreciation by 1 extra percent and study the response of consumption change by household's relative risk aversion.

The HWE decreases in η. Panel A of Fig. 1 presents the increment of consumption change as a percentage of initial home value–$p_{s_1}\bar{h}$–given 1 percentage increase in house prices. It depicts a clear downward trend. The HWE is positive and significant when η is small, but it turns negative when η is sufficiently large. When $\eta = 0.1$, each 1 dollar increase in home value increases consumption by 6.5 cents. Panel B shows the HWE in relation to a percentage increase in consumption change. The panel suggests that the 1 extra percent appreciation in house prices can increase consumption change by about 0.8 % for a risk neutral household. However, for risk averse households, the increase is much smaller and in some cases negative.

In addition, we test the sensitivity of HWE with respect to changes in $\tilde{l}_0$ and θ at different η values. Panel A of Fig. 2 shows that households with a lower initial loan to value ratio $\tilde{l}_0$ experience greater HWE. This suggests that households who are less credit constraint are more able to mortgage refinancing to fund extra consumption. Panel B shows that households who put a lower weight on terminal wealth (smaller θ) experience greater HWE. The results are also consistent with some predictions in the previous literature. Older households, whose expected remaining life span is shorter, place a smaller weight on terminal wealth than younger households. As a result, older households are more willing to use home equity to finance consumption.

[5]The average growth rate of real house prices was 5.99 % in PSID, and the standard deviation was 2.67 %. The higher rate and greater volatility was possibly due to the heavier weight of urban families in the sample.

[6]While the illustrative calibration assumes a value of $y > 1$, we are able to show the pattern of diminishing HWE to η with well behaved maximizers using Matlab's basic search algorithm for maximizers as long as we set $y > 0.247$ holding fixed other parameters at their baseline values.

[7]The empirical finance literature often estimates the average relative risk aversion around the range of 1 to 4. Nevertheless, empirical estimates above 6 are not uncommon (Mankiw and Zeldes 1991). For Campbell and Cocco (2003, 2007), they set η to 3. Since our purpose is to simulate HWE for individual households with different degree of risk aversion, we need to test η for a wide range of values.

[8]When $\eta = 3$ and the rest of parameter values equal to the benchmark values, we have $c^*_{s_1} = 0.429$, $c^*_{s_2=g} = 0.444$, $c^*_{s_2=b} = 0.422$, $l^*_{s_1} = 0.506$, $l^*_{s_2=g} = 0.583$ and $l^*_{s_1} = 0.587$. The equilibrium that the model produces is interior and well behaved, over the entire ranges of parameter values that we consider.

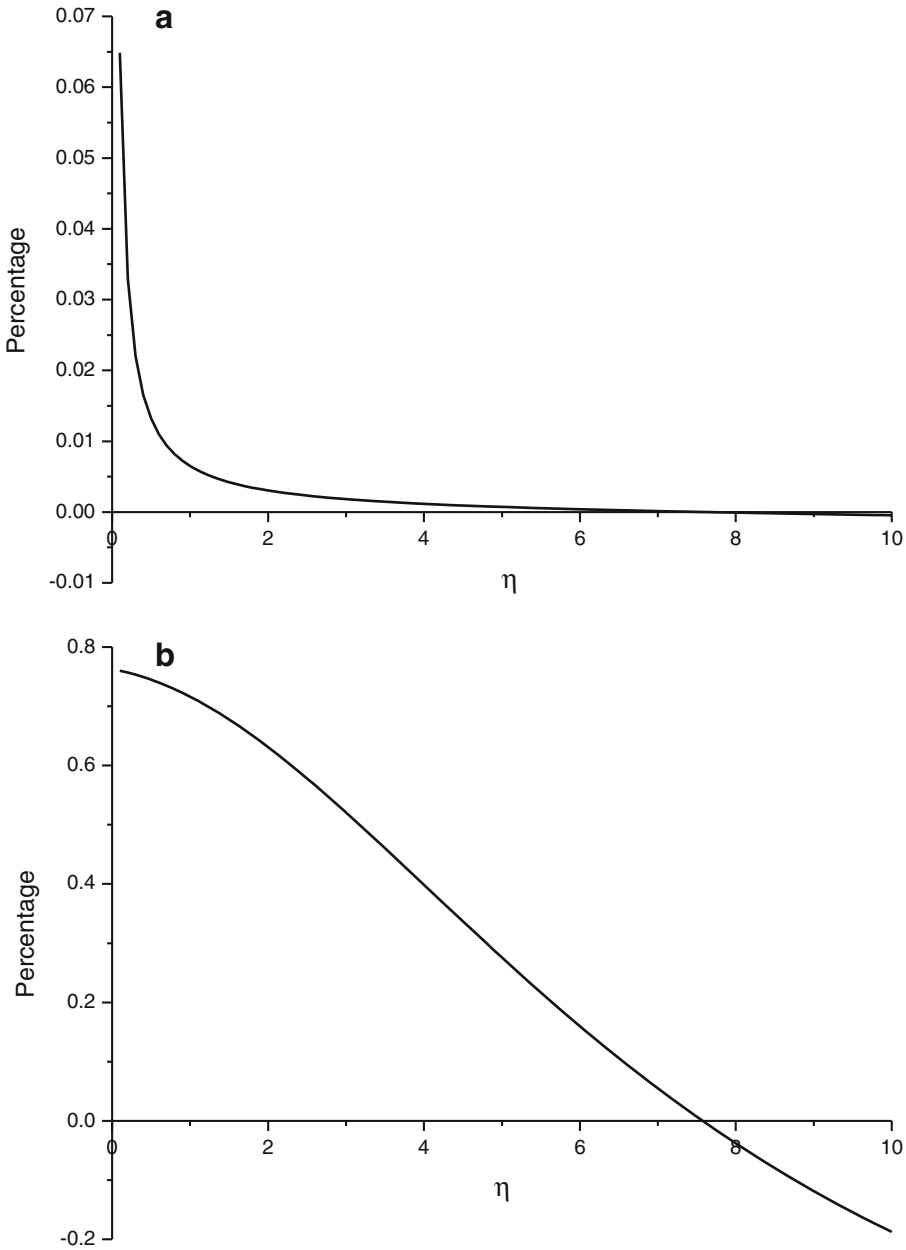

Fig. 1 Housing wealth effect by relative risk aversion. This figure presents two expressions of housing wealth effect due to 1 extra percent increase in house prices. **a** shows the increment of consumption change as a percentage of initial home value by η, the parameter of relative-risk-aversion. **b** shows the percentage increase in consumption change by η

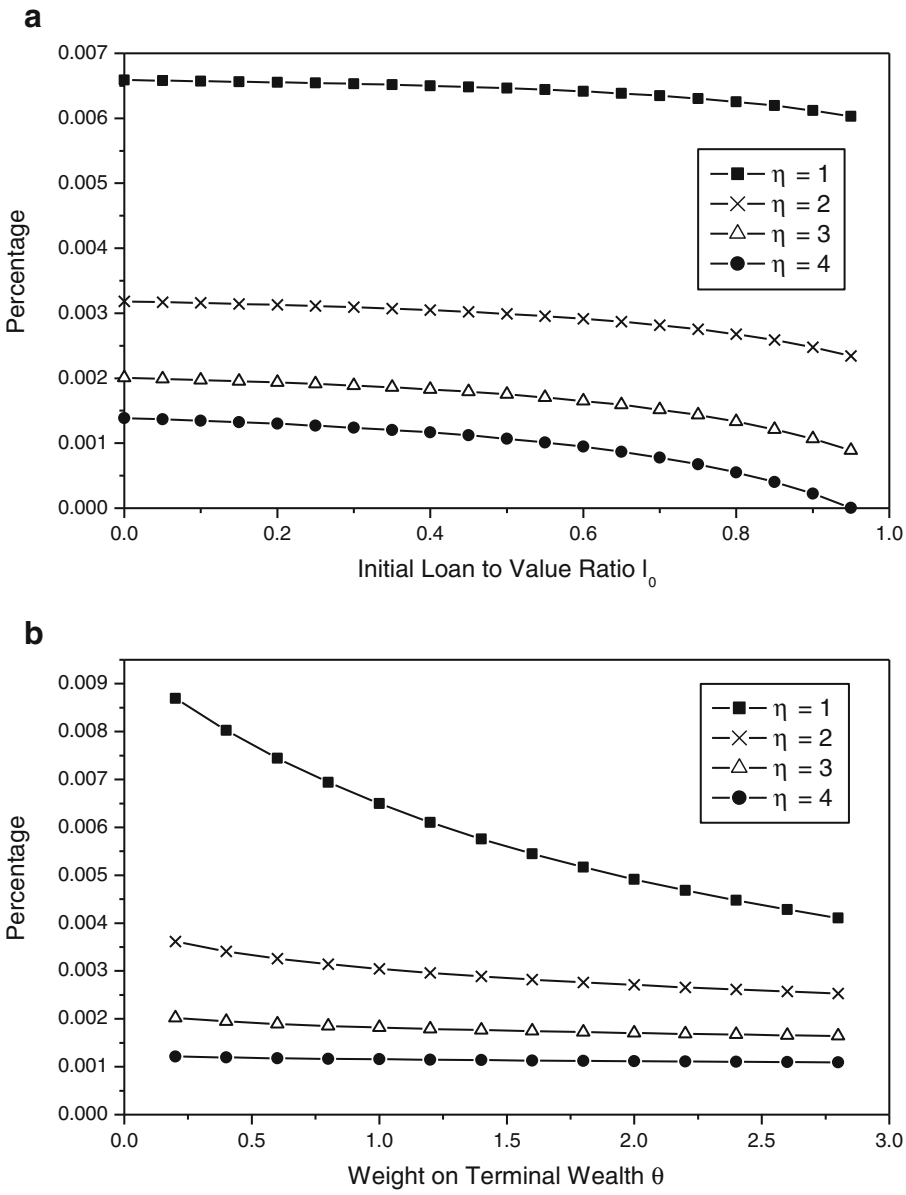

Fig. 2 Housing wealth effect by the initial LTV and weight in terminal wealth. This figure illustrates the sensitivity of housing wealth effect, which is measured in terms of the increment of consumption change as a percentage of initial home value, due to 1 extra percent increase in house prices. **a** presents the effect by $\tilde{l}_0$ the initial loan to value ratio and by η. **b** shows the effect by θ the weight on the terminal wealth and by η

The result also explains why reverse mortgages are more popular among old home owners. Similarly, households who have a stronger bequest motive would experience a smaller HWE, because they place a larger weight on terminal wealth.

Data

This section starts with a brief discussion on the state level house price indices used in the texts. It explains how quarterly data and quarterly consumption change are structured using information from the U.S. Consumer Expenditure Survey (CEX).

The state level house price indices are collected from the Federal Housing Finance Agency (FHFA; formerly the Office of Federal Housing Enterprise Oversight). The FHFA is the federal agency which oversees Fannie Mae, Freddie Mac and the Federal Home Loan Banks. It regularly publishes the House Price Index, which is a weighted, repeat-sales index measuring average price changes of the selected properties. To produce the index, FHFA reviews repeat mortgage transactions on single-family houses whose mortgages have been securitized or purchased by Fannie Mae and Freddie Mac since 1975. The index is a timely, accurate indicator of house price trends that is available at various geographic levels. At the state level, quarterly data are available. This allows us to merge the state house price indices with quarterly consumer expenditure data.

This paper makes use of the Quarterly Family Interview Data of the CEX for the period between 1997 and 2009. The CEX program operated by the U.S. Bureau of Labor Statistics is designed to collect American households' expenditures information to support the bureau's revisions of the Consumer Price Index. Detailed household demographic and financial information is also available.

The CEX is a rotating panel of about four to six thousands of households each quarter. Once selected into the sample, the household is followed five consecutive quarters and interviewed once every 3 months. The first interview is used to check consistency and is not published. When a household retires from the survey, a new one is added in. Generally, one fourth of households are new in each quarter of survey. To reduce labor costs, the administrators do not interview all households in the same month for each quarter of survey. As a result, this dataset is "interlaced," and the data need to be restructured.

To make this point clear, Fig. 3 is presented to illustrate the original data structure of CEX. There are 12 rows; each represents a data line. The first four lines belong to the first tranche, for which interviews are conducted in the first month of each quarter. The next four lines belong to the second tranche, and interviews are in the second month. The interviews for the last four lines are in the third month. The total number of households in these 12 lines was about 4000 in earlier survey years and 6000 in recent years.

In the first data line in the figure, an existing household finished the 5th interview in Oct. 2007. At the same time, a new household was added in and his/her first interview was done. However, this first interview was not published, so that the line is "smoothed"; the data line always contains approximately the same number of households each quarter. In each quarterly survey, every household is asked about his or

	Q3 2007			Q4 2007			Q1 2008			Q2 2008			Q3 200			Q4 2008			Q1 2009			Q1 2009		
	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
1	**4**			*1* **5**			**2**			**3**			**4**			**5** *1*			**2**			**3**		
2	*1* **5**			**2**			**3**			**4**			**5** *1*						**3**			**4**		
3	**2**			**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**		
4	**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**			**2**		
5		**4**			*1* **5**			**2**			**3**			**4**			**5** *1*			**2**			**3**	
6		*1* **5**			**2**			**3**			**4**			**5** *1*			**2**			**3**			**4**	
7		**2**			**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**	
8		**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**			**2**	
9			**4**			*1* **5**			**2**			**3**			**4**			**5** *1*			**2**			**3**
10			*1* **5**			**2**			**3**			**4**			**5** *1*			**2**			**3**			**4**
11			**2**			**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**
12			**3**			**4**			**5** *1*			**2**			**3**			**4**			*1* **5**			**2**

Fig. 3 Structure of Consumer Expenditure Survey (CEX) data. This figure illustrates the original data structure of the CEX. There are 12 rows; each represents a data line. The first four lines belong to the first tranche, for which interviews are conducted in the first month of each quarter. The next four lines belong to the second tranche, and interviews are in the second month. The interviews for the last four lines are in the third month. Upon each interview, the household is asked about expenditures over the past 3 months. As the interviews for the three tranches of households are conducted in different months of each quarter, the expenditure data are interlaced. Nevertheless, restructuring the data is possible, noting that the months with a *light grey* background fall in the last quarter of the survey, and the months with a *dark grey* background fall in the current quarter of the survey

her past-three-months expenditures falling in the last and current quarters, for each item of goods and services. This results in two variables for each item in each quarterly survey. For households in Tranche 1 (lines 1 to 4), they are interviewed in the very beginning of the current quarter, so their past-three-months expenditures all fall in the last quarter, and their expenditures in the current quarters are always zero. For households in Tranche 2, one of the past 3 months is in the current quarter of the interview (the months with dark gray background are in the current quarter). Thus, when the variable, current quarter expenditure, is divided by the other variable, last quarter expenditure, the mean is always around 0.5. For households in Tranche 3, dividing their current quarter expenditure by past quarter expenditure, the mean is always around 2.

Because the original CEX data are interlaced, we shall not simply sum up the two variables—the last and current quarter expenditures—in the "quarterly" surveys and merge with the quarterly house price indices. The data need to be restructured. Note that for households in Tranche 1, the last quarter expenditure in the Q1 2008 survey was the expenditure in Q4 2007, and so on and so forth. For households in Tranches

2 and 3, the sum of the current quarter expenditure in the Q4 2007 survey and the last quarter expenditure in the Q1 2008 survey was the expenditure in Q4 2007, and so on and so forth. Keeping this in mind, we are able to construct a quarterly data structure as illustrated in Fig. 4. Then, the quarterly data are merged with quarterly house price indices. Nevertheless, we lost about 20 % of data, because complete information on those cells marked with slashes in the figure is not available.

Empirical Tests and Results

This section introduces the estimation methods and presents the results. The first step is to estimate households' attitudes toward risk using their liquid asset compositions and demographic characteristics, and the second step is to pin down the relationship between HWE and relative risk aversion.

Estimate Risk Attitude

Risk aversion is characterized by the concavity of the von Neumann-Morgenstern utility function. Pratt (1964) and Arrow (1965) suggest that the elasticity of marginal utility with respect to wealth, $-wu''(w)/u'(w)$, is an appropriate measure of relative

	Q3 2007			Q4 2007			Q1 2008			Q2 2008			Q3 200			Q4 2008			Q1 2009			Q1 2009		
	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
1	4			1 5			2			3			4			5 1			2			3		
2	1 5			2			3			4			5 1			2			3			4		
3	2			3			4			5 1			2			3			4			1 5		
4	3			4			5 1			2			3			4			1 5			2		
5		4			1 5			2			3			4			5 1			2			3	
6		1 5			2			3			4			5 1			2			3			4	
7		2			3			4			5 1			2			3			4			1 5	
8		3			4			5 1			2			3			4			1 5			2	
9			4			1 5			2			3			4			5 1			2			3
10			1 5			2			3			4			5 1			2			3			4
11			2			3			4			5 1			2			3			4			1 5
12			3			4			5 1			2			3			4			1 5			2

Fig. 4 Reconstruction of Consumer Expenditure Survey (CEX) data. This figure illustrates the restructured CEX data. Household expenditure data become quarterly data that can be merged with quarterly house price index. Information regarding the cells covered by slashes is lost

risk aversion.[9] Empirically, households' utility functions are difficult to identify, but their investments in risky assets are observable. Empirical works invariably use the compositions of liquid assets in portfolios to identify risk attitudes of households (e.g., Friend and Blume 1975; Siegel and Hoban 1982; Morin and Suarez 1983), as the relative risk aversion is inversely related to the share of asset allocated to risky asset (Friend and Blume 1975).[10] Morin and Suarez (1983) find that the ratio of risky assets to wealth is significantly dependent upon household age, and a considerable amount of more recent research has examined the relationship between risk aversion and demographic variables. Halek and Eisenhauer (2001) provide a literature review.

We use the demographic and financial information from the CEX data to estimate households' risk attitudes. The CEX provides households' financial information including their assets in saving, checking and bond and security accounts. Their assets in the security accounts are marked to the market. The balances in the four accounts are aggregated to give the value of the total liquid asset, whereas the balances in the security accounts, which consists of investments in stocks and mutual funds, are summed collectively to derive the value of risky assets. For the periods from 1997 to 2010, 43,611 CEX sample observations that have complete information on liquid asset are collected, and of which 31 % of the households own risky asset. The number falls within the range of the figures estimated by Mankiw and Zeldes (1991) and Malmendier and Nagel (2011).[11]

The ratio of risky asset to total liquid asset can be used in measuring households' attitudes toward risk, as in Morin and Suarez (1983) and Malmendier and Nagel (2011), but a caveat needs attention. Households who do not own risky asset weigh a large fraction in the data. The finance literature refers to this as "limited stock market participation", which may be caused by a fixed entry cost into the stock market (Basak and Cuoco 1998; Cocco 2005; Luttmer 1999). The decision to participate is dependent on investor's willingness to pay for the fixed entry cost, which can be predicted by using variables such as demographics like age and education (Guiso and Jappelli 2002), covariance between income and risky-asset returns (Massa and Simonov 2006), and awareness to asset risks (Guiso and Jappelli 2003). To address the selection issue, a two-step Heckman correction model (Heckman 1979) is used to handle households' self-selection in owning risky asset in our model. The first step uses a probit model to predict the likelihood of owning risky asset. Then, the

[9] Arrow showed that this measurement is directly related to one's insistence on favorable odds when putting some fraction of wealth at risk, and Pratt demonstrated that the relative risk aversion is proportional to the insurance premium one is willing to pay to avoid a given risk. While Arrow and Pratt both postulate increasing relative risk aversion with wealth, the empirical literature has shown that the relative risk aversion can be increasing, constant or decreasing, depending on how wealth is defined.

[10] Friend and Blume (1975) show the inverse relationship in several model settings. In the simplest set-up, the relationship is

$$\alpha_i = \frac{E\left(r_m - r_f\right)}{\sigma_m^2}\frac{1}{A_i}$$

where a_i is individual i's share of wealth put in risky assets, and A_i is the individual's relative risk aversion. The subscripts m and f stand for market and risk free, respectively.

[11] Mankiw and Zeldes (1991) use PSID data, and Malmendier and Nagel (2011) use the Survey of Consumer Finance.

predicted propensity for owning the asset is used in the second step GLS regression to obtain unbiased coefficient estimates (corrected for the selection bias) in explaining risky asset composition.

The results of the second step GLS regression of the Heckman correction model are reported in Column 1 of Table 2, while the outcomes of the first step probit regression are put in the table in the Appendix. Among the observable demographic characteristics, wealth is the dominant determinant of risk aversion. The literature often divides wealth into two parts: one is the accumulated wealth and the other is the value of human capital. We measure the former by the holdings of the total liquid asset and the latter by current income. Following Morin and Suraz (1983), we interact the age dummy variables with the two measures of wealth to capture the life-cycle effects of wealth on risky asset holdings.

The total liquid asset has significant positive influence on risky asset composition in household portfolios, and the positive impact exhibits a hump shape over the life cycle. For young households below 30 years old, a 1 % increase in total liquid asset raises the share of risky asset allocation 0.034 percentage point. For middle-age households between 50 and 59 years old, they experience the largest effect, where a 1 % increase in total liquid asset leads to 0.077 percentage point increase in risky asset holdings. Overall, the coefficient estimates on the total liquid asset suggest decreasing relative risk aversion in accumulated wealth, which is consistent with Cohn et al. (1975) and Morin and Suarez (1983), and the middle-age groups are the least risk averse. The coefficient on income is significantly negative. The coefficients of the interaction terms for the younger groups are close to zero and insignificant, but the coefficients are significantly positive for the older groups. The patterns indicate constant relative risk aversion among older households, and higher risk aversion among the young.

In addition to the age and year dummies, we also include the birth year of the household head to control the cohort effect. The results show that households, whose heads were born before 1939 and experienced the "Great Depression", have a smaller fraction of risky asset composition in the portfolios. They tend to be more risk averse.

The model in Column 1 also includes other controlling demographic variables. The education dummy has a value of 1, if household head has a college degree; and 0, otherwise. The racial dummy equals 1, if the head is white; and 0, otherwise. Households whose heads are white are less risk averse. More educated households are more risk averse, but this is only significant at 10 % level. Lastly, households with a bigger family size are more risk averse. Meanwhile, the coefficient of Inverse Mills' Ratio is 0.220 and is significant. Overall, the Wald statistics of this model is significant; and the results are consistent with the literature. The household risk attitude is predicted using the coefficients on the demographic characteristics as shown in Column 1. A higher predicted value implies the household is less risk-averse.[12]

[12]The CEX program only collects financial information in each household's fifth quarterly interview. Thus, the estimation of risk attitude is based on the demographic and financial data from the fifth interviews, but the coefficient estimates of the demographic variables are also used to predict risky asset composition for the other three quarters of the published data.

Table 2 Regression of risky asset composition on household demographics

Variable	(1) Heckman correction		(2) Tobit model	
	Coef.	Std. err.	Coef.	Std. err.
Ln(total asset)	0.034**	0.007	0.252**	0.008
Ln(total asset) interacted with age dummies				
(30–39)	0.035**	0.007	0.045**	0.010
(40–49)	0.034**	0.007	0.035**	0.010
(50–59)	0.043**	0.007	0.042**	0.010
(60–69)	0.035**	0.008	0.032**	0.010
(70–79)	0.023**	0.008	0.014	0.011
(80–89)	0.024**	0.010	−0.014	0.013
Ln(income)	−0.019 ∗ ∗	0.006	−0.009	0.008
Ln(income) interacted with age dummies				
(30–39)	0.000	0.008	0.001	0.010
(40–49)	0.008	0.007	0.001	0.010
(50–59)	0.009	0.007	0.006	0.010
(60–69)	0.016*	0.009	−0.007	0.012
(70–79)	0.022**	0.011	0.019	0.015
(80–89)	0.024*	0.013	0.042**	0.019
Cohort effect (birth year)				
(1920–1929)	0.066**	0.027	0.055	0.040
(1930–1939)	0.109**	0.033	0.165**	0.050
(1940–1949)	0.129**	0.038	0.260**	0.057
(1950–1959)	0.119**	0.042	0.282**	0.064
(1960–1969)	0.114**	0.046	0.309**	0.070
(1970–1979)	0.083	0.051	0.267**	0.078
(After 1980)	0.041	0.060	0.149*	0.088
Ln(family size)	−0.011∗	0.006	−0.026 ∗ ∗	0.009
Education	−0.015∗	0.008	0.092**	0.011
Race	0.028**	0.011	0.087**	0.014
Age dummies	Yes		Yes	
Year dummies	Yes		Yes	
Coef. of IMR	0.220**		0.022	
Observations	43611		43611	
Wald Chi2 (43)	625.1		20391.33	

This table reports regression coefficients and standard errors for household demographics affecting risk attitude from both Heckman Correction Model and Tobit Model. The dependent variable is the ratio of risky asset to total liquid asset—the risky asset composition, which is inversely related to the relative risk aversion. The independent variables include logarithmic total liquid asset and income, and their interactions with age dummies. In order to control the cohort effect, the birth year is included in the regression. The independent variables also include logarithmic family size and several fixed effect variables. The education dummy equals 1 if the head has a bachelor degree; the race dummy is 1 if the head is white. The last line reports Wald test statistic. The labels ** and * indicate 5 % and 10 % levels of significance, respectively.

An alternative method for estimating risk attitudes is the Tobit model (Tobin 1958), which can handle the censoring problem. This model can obtain unbiased estimates for the relationships between dependent and explanatory variables, when observations are concentrated at the bound of the dependent variable. The maximum likelihood estimation in the Tobit model takes the truncated distribution into consideration. The risky asset composition of households is truncated at 0 on the left, because of the limited stock market participation; and it is also bounded at 1 on the right, because of the borrowing constraint. Considering the left and right boundaries of risky asset composition, we run Tobit model as a robustness test of risk attitude prediction. The results of Tobit model are reported in Table 2, Column 2. Generally, the coefficients of the demographic variables have similar predicted significance as in the Heckman correction model. The total liquid asset has a larger influence on risky asset holdings in Tobit model, but the same life-cycle pattern is observed. The coefficients of the income variables in the Tobit model are insignificant, but they generally have the same sign as those in the Heckman's model. The insignificant coefficient estimates suggest constant relative risk aversion in income or human capital.

The CEX data do not have information on the balances of pension accounts (e.g., IRA and 401K). We tried the Survey of Consumer Finance (SCF), where the information on these accounts are available, to cross-check our first-step results. The coefficient estimates are consistent and comparable with the results derived from using the CEX data. The SCF data also include a variable for which the households are asked to self-evaluate their risk aversion, and the variable is in the form of order data. Using this variable can avoid issues of asset allocation due to reasons such as tax purposes. Following Malmendier and Negal's (2011) methodology, we replaced risky asset composition by the measure of the self-reported risk attitude, and we regressed the measure against the demographic variables in an ordered probit model. The coefficients have the same signs and the same life cycle patterns. Nevertheless, SCF has no information on consumption expenditure, it is a system of triennial cross-sectional surveys, and it is perceived as a sample biased dataset. Performing the two stages of our estimation approach with two very different datasets or making an attempt to bridge or statistically match the two datasets for our purpose would cost more than it benefits. Thus, we use CEX data throughout the analysis.

Estimate HWE by Risk Attitude

The second step of the estimation is to identify the HWE on consumption—growth in household consumption in response to growth in house price. The house price change is measured by the change of the state level House Price Index, because CEX does not have house values. The non-durable consumption is defined as the household total expenditure minus housing expenditure, which include rent, tax, down payment, mortgage installment, and maintenance costs, and other durable goods expenditure. However, measuring durable goods expenditure (such as purchases of vehicles and apparels) covering a series of service flows over a long period time to households is difficult. Most of the existing empirical literature excludes durable goods in testing consumption hypotheses; and we are no exception. We convert consumption, house price and income into real terms using the Consumer Price Index. Households in the

top and the bottom 5 % percentiles of the consumption distributions are filtered out from the sample in order to reduce the disturbance, because HWE for households in the tail of distribution would not be linear.

Wealth effect is dynamic under the life cycle hypothesis. Controlling for demographic changes using the CEX data is difficult, because of its' sampling strategy that keeps only a small panel of households in the repeated survey each year.[13] Pseudo panel data are thus constructed in this study to estimate the wealth effect. The pseudo panel data methodology is introduced by Browning et al. (1985) and Deaton (1985). While the ordinary panel data keep track of individuals, the pseudo panel data keep track of cohorts. A cohort is a group of individuals sharing a common characteristic, and individuals in each cross-sectional survey can be grouped into cohorts according to the observable characteristics. If the survey samples are large, successive surveys will generate consecutive random samples of individuals for different cohorts. The summary statistics of the random samples can generate a time series to infer behavioral relationships of the cohort just as if panel data were available. The key idea of this method is to extract pseudo "cohort individuals" from successive surveys based on some common characteristics, while other idiosyncratic characteristics of individuals in the cohorts are averaged out. The sample cohort means of the surveys are error-ridden estimates of the true cohort means, yet they are consistent. Thus, the sample cohort means from the successive surveys can be used as panel data for the estimation, if either number of individuals in each cohort is sufficiently large, or an errors-in-variables technique is used.

We use quarterly survey data over a 13-year period from 1997 to 2009 to construct 7 age-cohorts and examine the life-cycle patterns of consumption and income. Each cohort consists of households, whose heads were born within one five-year period. The youngest cohort comprises households whose heads were born between 1970 and 1974, and the oldest cohort include those whose household heads were born between 1940 and 1944. For each cohort, the weighted average of quarterly income and consumption are calculated. The income and consumption are then regressed against 91 year- and cohort-specific dummies, as well as quarterly dummies, which control seasonal effects. The coefficients on the year-cohort dummies represent the means of quarterly consumption and income for the corresponding years and cohorts. Figure 5 plots the coefficients to illustrate how average household consumption and income change over the life cycle. Each line represents the income and/or consumption of a cohort. The lines collectively constitute the life-cycle patterns. The income pattern shows a clear hump shape, whereas the consumption pattern is relatively smooth. These results are consistent with Campbell and Cocco (2007), Attanasio and Browning (1995), Carroll (1997) and Gourinchas and Parker (2002) who suggest that the constructed pseudo panel is appropriate.

[13] CEX tracks each single households for five continuous quarters, but only reports the last four surveys. Because of the construction method of our database (presented in previous section), each household only has three continuous records maximally.

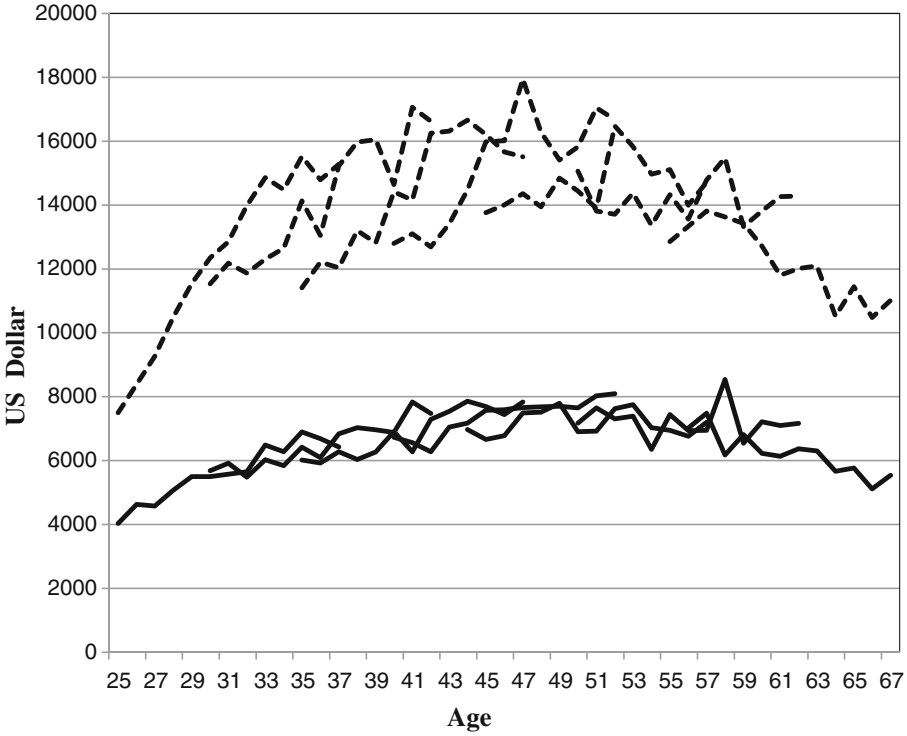

Fig. 5 Consumption and income over life cycle. This figure plots the quarterly consumption (*solid line*) and income (*dashed line*) over life cycle for three different cohorts. The data is from CEX from 1997 to 2009. The vertical axis is the U.S. dollar in 1997 level

In applying pseudo panel data in the tests, a sufficiently large number of observations should be kept in each cohort. Given the large sample size of CEX data, we construct nine cohorts based on two variables. First, there are three age-cohorts based on the year of birth of the household heads: 1950–1959, 1960–1969, and 1970–1979. Households, whose heads were born before 1950, are excluded, because of small sample size of these households. The second household cohorts are defined based on their attitudes toward risk. From the predicted risky asset composition for each household in the first-step Heckman correction model, the top (third) tercile of households are the least risk-averse cohort, the next tercile of households are the medium risk-averse cohort, and the remaining households are in the most risk-averse cohort. By interacting the age-cohort with the risk attitudes, nine pseudo-cohorts are created.[14]

[14]For the reason explained in the last paragraph, the number of observations in each cohort must be large enough. Hence, we shall not build more cohorts. Furthermore, if the number of households in a age cohort is less than 200 in a particular quarterly survey, that data point is dropped.

The nine cohorts are stratified by risk-attitude cohorts and regressions are run for each strata. The model regresses consumption growth on house price growth controlling for household income and other characteristics:

$$\Delta c_{i,t+1} = \beta_0 + \beta_1 \Delta p_{i,t+1} + \beta_1 \Delta y_{i,t+1} + \beta_2 Z_{i,t+1} + \varepsilon_{i,t+1}$$

where the subscript i indicates a cohort individual, $\Delta c_{i,t+1} = \ln(c_{i,t+1}) - \ln(c_{i,t})$ is the real non-durable consumption growth, $\Delta p_{i,t+1} = \ln(p_{i,t+1}) - \ln(p_{i,t})$ is the real house price growth, $\Delta y_{i,t+1} = \ln(y_{i,t+1}) - \ln(y_{i,t})$ is the real income growth, and $Z_{i,t+1}$ is a vector of other control variables. The time periods are defined by quarters. As explained in Deaton (1985), the values of the variables of a cohort should be the weighted averages of the households in that cohort. We also control for changes in family size and homeownership rate, which is the percentage of households who are home owners in the corresponding cohort. The real interest rate is included to control for macro-economic influence on consumption. The housing price level in the last period is included to set a benchmark of housing price. Lastly, changes in age and squared age variables are also included to eliminate errors in building cohorts.[15]

Table 3 reports the regression outcomes sorted by risk attitude. First, we find significant positive HWE, as the coefficient estimates of house price changes are significantly positive in the least risk-averse cohort. On average, a 1 % growth in house price significantly increases consumption growth by 0.184 % for the least risk-averse household cohort. However, the wealth effect is not significant for the most and the medium risk-averse cohorts. The coefficient on house price changes is relatively small at −0.003 for the most risk-averse cohort. The results are consistent with our model's prediction, which suggest that the wealth effect is bigger for households who are less risk averse, and a negative coefficient is possible for highly risk averse households. Comparing the wealth effect in our tests using data from the U.S. consumer expenditure survey with the effect found by Campbell and Cocco (2007) using data in the British consumer expenditure survey, our coefficient estimates are smaller. This seems to in line with Case et al. (2005) who found that the HWE in the U.S. is substantially smaller than the effect in other western countries.

The regression results also indicate significant dependence of consumption growth and some other variables.[16] Income growth and increase in family size both drive consumption growth. The real interest rate is negatively related to consumption growth. This may be led by saving incentive, as this effect is only significant in the most risk-averse group.

[15] In the ideal situation, the change of age should be constant for each age cohort. The variation of age change captures the errors during the process of building cohorts.

[16] One might concern that stock market growth could be correlated with house price growth. We checked the S&P 500 index during the sample period, 1997–2009, but found that the correlation between the stock price and house price growth was only about 0.07. We do not include stock information because the financial data, which we obtained from the CEX, are not as good as SCF. However, the low correlation suggests that the omission of stock return would not cause a significant bias to the coefficient estimates of the HWE.

Table 3 Cohort regression of consumption change by risk attitude

Variable	Δ Consumption		
	(1) Highest risk aversion	(2) Medium risk aversion	(3) Lowest risk aversion
Δ Housing price	−0.003 (0.119)	0.002 (0.141)	0.184** (0.095)
Δ Income	0.279** (0.055)	0.373** (0.072)	0.301** (0.049)
Δ Family size	0.055** (0.027)	0.088** (0.029)	0.037 (0.033)
Δ Homeownership rate	0.146 (0.194)	0.252** (0.113)	0.319** (0.100)
Real interest rate	−0.007* (0.003)	−0.003 (0.004)	−0.003(0.003)
Lagged housing price	−0.021 (0.034)	−0.020 (0.038)	−0.003(0.028)
Δ Age	0.034 (0.040)	−0.011 (0.040)	0.012 (0.001)
Δ Age square	−0.000 (0.001)	−0.000 (0.001)	−0.000 (0.001)
Constant	0.033 (0.029)	−0.015 (0.032)	−0.009 (0.025)
Observations	145	145	145
R^2	31.00	36.42	40.38

This table reports the results of age cohort regression by the three groups of households characterized by different levels of risk aversion, which is predicted by Heckman correction model. The dependent variable is the change of logarithmic consumption. The independent variables include changes of logarithmic house prices, income and family size, changes of homeownership rate, age and age square, as well as the real interest rate and lagged housing price. Standard errors are in parentheses. The labels ** and * indicate 5 % and 10 % levels of significance, respectively.

Table 4 reports the results of a *t*-test examining whether the coefficient of the HWE of one group is significantly different from other groups. Overall, HWE is decreasing with households' relative risk aversion. The coefficient of the least risk-averse group is larger than and statistically different from the other two groups at 1 % significance

Table 4 Comparison of the housing wealth effect across risk attitude groups

	(1) Highest risk aversion	(2) Medium risk aversion	(3) Lowest risk aversion
Wealth effect	−0.003	0.002	0.184
Std. err.	0.119	0.141	0.095
H0:	Wealth effect in col(1)≥col(2)	Wealth effect in col(2) ≥col(3)	
T-test value	0.301	12.867***	

This table reports the outcomes of the hypothesis testing examining whether the housing wealth effect differs across the three groups of households with different risk attitudes. The wealth effect estimates are from the cohort regression. The label *** indicates 1 % level of significance.

level. As for the coefficients of the medium and the most risk-averse groups, the former is larger, but the difference is insignificant. This seems to be in line with a modeling outcome that the marginal change of HWE may be smaller when risk aversion is higher.

Table 5 reports the robustness test results of the cohort regressions stratified by the risk attitude groups predicted by the Tobit model. We find that HWE for the least risk-averse group is still significantly positive. And, the coefficient of HWE is bigger than that in Table 3. The HWEs for the medium risk-averse group and the most risk-averse group are insignificant, although their signs are different from our predictions. It may imply that Tobit model is less effective in separating risk attitude of households, who do not own risky asset. Other variables in this robustness test have similar coefficients as in Table 3.

Conclusion

The housing wealth effect (HWE) literature which predicts a positive relationship between consumption and house prices, has not examined how the effect would depend on households' attitudes toward risk. This paper theoretically and empirically argues that risk aversion matters, because house prices are volatile and housing

Table 5 Robustness test of cohort regression based on risk attitude predicted by Tobit Model

Variable	ΔConsumption		
	(1) Highest risk aversion	(2) Medium risk aversion	(3) Lowest risk aversion
Δ Housing price	0.043 (0.119)	−0.162 (0.139)	0.281** (0.100)
Δ Income	0.210** (0.054)	0.427** (0.068)	0.243** (0.054)
Δ Family size	0.061** (0.029)	0.102** (0.029)	0.047 (0.032)
Δ Homeownership rate	0.321** (0.097)	0.230** (0.101)	0.247** (0.105)
Real interest rate	−0.007∗ (0.004)	−0.003 (0.004)	−0.004 (0.003)
Lagged housing price	−0.022 (0.033)	−0.026 (0.037)	−0.004 (0.028)
Δ Age	0.041 (0.040)	−0.047 (0.041)	0.008 (0.035)
Δ Age square	−0.000 (0.001)	0.001* (0.001)	−0.000 (0.001)
Constant	0.034 (0.029)	−0.017 (0.032)	−0.012 (0.025)
Observations	145	145	145
R^2	31.34	42.01	31.40

This table reports the results of age cohort regression by the three groups of households characterized by different levels of risk aversion, which is predicted by Tobit model. The dependent variable is the change of logarithmic consumption. The independent variables include changes of logarithmic house prices, income and family size, changes of homeownership rate, age and age square, as well as the real interest rate and lagged housing price. Standard errors are in parentheses. The labels ** and * indicate 5 % and 10 % levels of significance, respectively.

is a risky asset. Using a model in which the household makes leverage decisions, we show that at empirically plausible parameter values, HWE is a decreasing function of the households' relative risk aversion. The effect is positive for less risk averse households, but it can be negative among households who are highly risk averse. Additionally, the model has implications on how HWE would be affected by household demographics.

This paper makes use of U.S. Consumer Expenditure Survey and applies a two-stage approach to estimate a negative relationship between HWE and households' risk attitudes. In the first stage, we gauge the risk attitudes using information on household demographics and risky asset holdings, and we apply Heckman correction model to handle the issue of limited stock market participation. The Tobit model is also used as a robustness check. We construct pseudo panel data to perform the second stage estimation. Stratifying households according to their degrees of risk aversion, we estimate the effect of house price growth on consumption growth for each group. The empirical results are consistent with our model prediction. The HWE varies significantly across groups, and it is decreasing in risk aversion. Households in the least risk averse group are expected to experience a significant 0.2 %–0.3 % growth in real non-durable consumption in response to a 1 % growth in house prices. On the other hand, the wealth effect for the most risk averse group is negative, although that coefficient is insignificant.

The tests of HWE are based on pseudo panel data. In our case, the demographic characteristics of individual observations in each cohort are averaged out. This effectively eases the collinearity between household demographics and risk attitude in the second stage estimation, even though the risk attitude is predicted by the demographics. The variables in the pseudo panel data are cohort means from the surveys and are error-ridden; they tend to increase the standard errors of the coefficient estimates. However, the variables are consistent estimates of the true cohort means. Practically, reliable estimates can be obtained if the numbers of individuals in the cohorts are not too small and the length of the time series is not too short. Since our data construction does keep the sizes and lengths of cohorts reasonably large, the clear pattern of decreasing HWE in risk aversion from the estimation adds new insight.

The negative relationship between HWE and households' risk aversion may advance our knowledge of the cross-sectional variation in the HWE. For example, consistent with Malmendier and Nagel (2011), the results of our first stage regression suggest a significant cohort effect on risk attitude. Macroeconomic experiences could affect risk taking, and households who experienced a great loss from a significant economic crisis (e.g., Asia Financial Crisis) could become more risk averse. The findings of this paper indicate that these households may be reluctant to cash out home equity when house prices rise. Future research can study this indication. If the indication is true, then this paper has an important implication to macroeconomics-policy makers who wish to use house prices to stimulate consumption.

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Appendix

Table 6 First step probit model of Heckman Correction

Variable	Coef.	Std. err.
Ln(total asset)	0.431**	0.016
Ln(total asset) interacted with age dummies		
(30–39)	0.093**	0.020
(40–49)	0.088**	0.019
(50–59)	0.110**	0.019
(60–69)	0.087**	0.020
(70–79)	0.031	0.022
(80–89)	−0.042*	0.025
Ln(income)	−0.003	0.014
Ln(income) interacted with age dummies		
(30–39)	0.003	0.018
(40–49)	−0.007	0.017
(50–59)	0.014	0.018
(60–69)	−0.021	0.022
(70–79)	0.034	0.028
(80–89)	0.069**	0.034
Cohort effect (birth year)		
(1920–1929)	0.049	0.074
(1930–1939)	0.227**	0.093
(1940–1949)	0.411**	0.108
(1950–1959)	0.452**	0.121
(1960–1969)	0.517**	0.133
(1970–1979)	0.466**	0.146
(After 1980)	0.322**	0.164
Ln(family size)	−0.035 **	0.016
Education	0.196**	0.020
Race	0.147**	0.026
Age dummies	Yes	
Year dummies	Yes	
Observations	43611	
Wald Chi2	19718.71	

This table reports the first step result of Heckman correction. The dependent variable is household stock market participation. The independent variables include logarithmic total liquid asset and income, and their interactions with age dummies. In order to control the cohort effect, the birth year is included in the regression. The independent variables also include logarithmic family size and several fixed effect variables. The education dummy equals 1 if the head has a bachelor degree; the race dummy is 1 if the head is white. The last line reports Wald test statistic. The labels ** and * indicate 5 % and 10 % levels of significance, respectively.

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