Attitudes Toward and Perceptions of the Ambiguity of House and Stock Prices

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This study estimates individuals' attitudes toward and perceptions of ambiguity of house prices and stock prices, using experiment data from the Rand American Life Panel (ALP) survey. We estimate two important parameters in multiple prior models and α-MaxMin ambiguity preferences: the degree of ambiguity aversion and the degree of confidence in the reference prior distribution of future prices, this being a measurement of the perceived level of ambiguity. Regarding attitudes, we find that individuals are slightly ambiguity seeking with regard to house prices while they are slightly ambiguity averse with regard to stock prices. Their degree of confidence in the reference distribution for stocks is lower than for house prices. We also find that increased state-level house price volatility during the past year and growth of house price in the past three years increase perceived ambiguity. Moreover, ambiguity matters in that ambiguity-averse renters are less likely to buy a house. Correspondingly, ambiguity-averse stock investors tend to have less stock holdings. (JEL: D8, R11, G11)

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This paper develops a method to estimate individual's perceptions of and attitudes toward ambiguity with regard to future house and stock prices. We identify individuals' socio-economic characteristics and price trends that correlate with house and stock price ambiguity and then test how ambiguity influences renters' home purchase behavior and the stock holdings of investors. Innovations include our method that simultaneously identifies ambiguity attitudes and perceptions from two experiments and the application to the housing market.

The housing market in the 2000-2015 period differed from prior and subsequent periods in multiple ways. The most notable difference was the large increase in house prices followed by a substantial downturn. At the national level, the annual house price increase averaged 0.084 from the beginning of 2000 through 2006, but fell by -0.058 annually from 2007 through 2011.[1] Apart from the price level, the volatility of house prices also peaked during this period. The standard deviation was 0.018 in the 1980s and 0.026 in the 1990s. It rose to 0.085 in the first decade of the new millennium and then fell back to 0.047 from 2010 to 2017. We argue that this history of house price changes increased individuals' perceptions of risk and the level of ambiguity of house prices. The empirical question addressed is whether this potential increase in ambiguity affected housing market behaviors such as the home purchase decision. Throughout the analysis, we compare our results regarding the ambiguity of the housing market to the same individuals' perceptions of ambiguity in the stock market.

Individuals' attitudes toward and perceptions of ambiguity have been defined and measured in the finance and psychology literatures (e.g. in finance see Ellsberg 1961; Curly and Yates 1985; Machina and Siniscalchi 2013; Dimmock et al. 2015,

[1] The data used are the Freddie Mac House Price Index, which includes all conforming transactions (purchases and refinancing appraisals) from Freddie Mac and Fannie Mae. The method used to compute the price index is based on the repeat sales method. Data at the MSA, state, and national level are available from 1975. http://www.freddiemac.com/finance/fmhpi/archive.html

2016; in psychology see Budescu et al. 1988; Budescu and Wallsten 1995; Du and Budescu 2005). The difference between risk and ambiguity depends on the amount of knowledge about the probability distribution(s) of outcomes of an uncertain event. Risk corresponds to situations where the possible outcomes of a future event are subject to chance and the odds of each outcome are uniquely determined. Ambiguity describes the situations where the odds of each outcome are not uniquely specified. If an individual has a single prior distribution of outcomes with uniquely specified probabilities, the level of ambiguity is zero. If an individual cannot uniquely specify the odds of each outcome of the event, then ambiguity is nonzero.

The source of perceived ambiguity in house prices could derive from two sources. An individual may perceive multiple distributions of outcomes when the set of house price outcomes is contingent on other outcomes. Given that house prices are the outcome of the interaction of supply and demand and both supply and demand are affected by many uncertain economic factors (income, household formation, building regulations, materials costs), an individual's anticipated house price change may require many distributions to describe. Another factor that could result in the perception of house price ambiguity is the presence of a diversity of opinions about future house prices by housing market experts or journalistic sources resulting in individuals receiving mixed information about the likely future path of house prices. For example, in the 2017 Zillow Home Price Expectations Survey (composed of about 100 experts) the respondents' cumulative expected price change after five years ranged from -23 to 37 percent.[2] Such diversity of opinions could influence an individual and result in the person having multiple distributions of expected future house price outcomes.

[2] The resulting standard deviation is 9 percent. The Zillow Home Price Expected Survey is available at http://zillow.mediaroom.com/zillow-home-price-expectations-survey.

Individuals have preferences toward ambiguity, just as they have preferences toward risk. They may be ambiguity averse, neutral, or seeking. Ambiguity-averse individuals prefer a future event where the outcomes can be described by one or a few probability distributions of outcomes. Ambiguity-seeking individuals prefer an event for which there are relatively many distributions of outcomes. Our simple assumption is that an individual has a particular preference for ambiguity, applicable to all uncertain events, this being typical of the assumption made regarding risk preference.

Preferences (attitudes) toward risk can be measured through an individual participating in an experiment. Similarly, an experiment can be used to measure preferences toward ambiguity. Using the data of RAND American Life Panel (ALP) (https://www.rand.org/labor/alp.html), Dimmock et al. (2015) conducted an Ellsberg-like experiment to elicit ambiguity preferences. They asked respondents to choose between an ambiguous environment and an unambiguous, yet risky, environment. We follow their method to elicit respondents' general ambiguity preference by measuring the matching probability of ambiguity aversion (MP_{AA}), defined as the probability at which the respondent is indifferent between an ambiguous environment and the zero ambiguity but risky case.

It is reasonable to assume that individuals are heterogeneous in terms of their attitudes toward risk and ambiguity. We correlate individuals' socio-economic characteristics with their preferences toward ambiguity and find that females, seniors, college graduates and Hispanics tend to be relatively risk averse, while males, youth, college graduates, and individuals with relatively more knowledge about finance tend to be more ambiguity averse. We also study the similarity of individual level preferences toward risk and ambiguity. The correlation is relatively low, 0.144, but is statistically significant at the 1 percent level. Next, we difference the measures of aversion toward ambiguity and risk and regress this difference on a set of socio-economic characteristics of individuals. We find that younger individuals, males, Hispanics and financially knowledgeable individuals are relatively more averse to ambiguity than risk.

The measurement of an individual's perception of the level of ambiguity of house or stock prices is more complex. Anderson, Ghysels and Juergens (2009) employ the dispersion of professional predictions of the stock prices from the Survey of Professional Forecasters to measure the ambiguity of stock prices in time series data. However, this method is unable to measure the perceived ambiguity at an individual level. Dimmock et al. (2015) overcome this drawback by using data from an experiment to estimate individuals' degree of confidence in the reference probability assignments of two possible outcomes of a gamble, this then is used to measure the perception of ambiguity. However, their estimation of perceived ambiguity of a gamble is not applicable to a specific uncertain event such as future house or stock prices.

This paper is novel in that we estimate ambiguity perceptions and preferences toward house and stock prices at the individual level. We extend Dimmock et al.'s (2015) method, combining the multiple prior models and the assumption of $\alpha - MaxMin$ ambiguity preferences, to estimate individuals' degree of confidence in one's subjective reference prior distribution for future house prices as the measurement of perception of ambiguity and the degree of ambiguity aversion, α. After measuring perceived ambiguity, we search for correlates that arguably are causal, finding that past house price trends at the state level affect individuals' perceived ambiguity of house prices. Moreover, we find that ambiguity-averse renters are less likely to buy a house and ambiguity-averse stock investors tend to hold less stocks. This is the first study to augment the explanation of home purchase behavior by including the ambiguity and ambiguity aversion of house prices in the model.

The rest of this paper is organized as follows. Section I describes the data and explains the methodology used to estimate an individual's attitude toward and perceptions of ambiguity with regard to house and stock prices. Section II reports the results of the estimation that yield the measures of ambiguity, first for a representative individual and then allowing for heterogeneity. We then relate ambiguity and risk preferences and perceptions with individuals' characteristics. We measure intertemporal variations in the perception of house price ambiguity and relate these changes to variations in state level house prices. In section III, we estimate the effect of attitudes toward and perceptions of ambiguity on renters' purchase behavior and investors' stock holdings between January 2009 and January 2016 using panel data and a fixed effects model. Section IV concludes the whole paper.

I. Methodology

A. Data Source

The dataset we employ in the study include various modules of RAND American Life Panel (ALP). The ALP is a nationally representative internet survey of more than 6,000 respondents aged 18 or above. In order to be nationally representative, ALP provides sample weights, these used in our descriptive statistics.[3]

The data measuring attitudes toward ambiguity are from the Netspar Uncertainty (NU) module, which is a cross-section conducted from March 20, 2012 to April 16, 2012. In this module, an ambiguity experiment was conducted, consisting of 2,367 respondents.[4] The data we use for measuring the reference prior distribution is from the Effects of Financial Crisis (EFC) module. This module consists of 61 waves from November 2008 to January 2016. We use six waves of the module when an experiment, called "bins-and-balls", was conducted between April 2011 and April

[3] Detailed information about ALP weighting is available at https://alpdata.rand.org/index.php?page=weights.

[4] Respondents are included if they took at least two minutes to complete the experiment and provided information about their characteristics.

2013. We jointly employ the bins-and-balls and the ambiguity attitudes experiment in NU module to measure the level of perceived ambiguity.

B. Measuring General Attitudes Toward Ambiguity

We follow Dimmock et al. (2016) and construct a continuous measurement of an individual's attitude toward ambiguity. In the NU module, all respondents are asked to choose between an unambiguous Box K with known distribution of purple balls and orange balls, and an ambiguous Box U with unknown distribution of the balls for each color. There are a total of 100 balls in each box. After the respondent selects the box, one ball is randomly drawn from the box chosen by the respondent who wins $15 if a purple ball is drawn. Up to four rounds of the experiment is conducted. In the first round, the probability of winning $15 in Box K is exactly 50% (see Figure 1), while the probability of winning in Box U is not given.

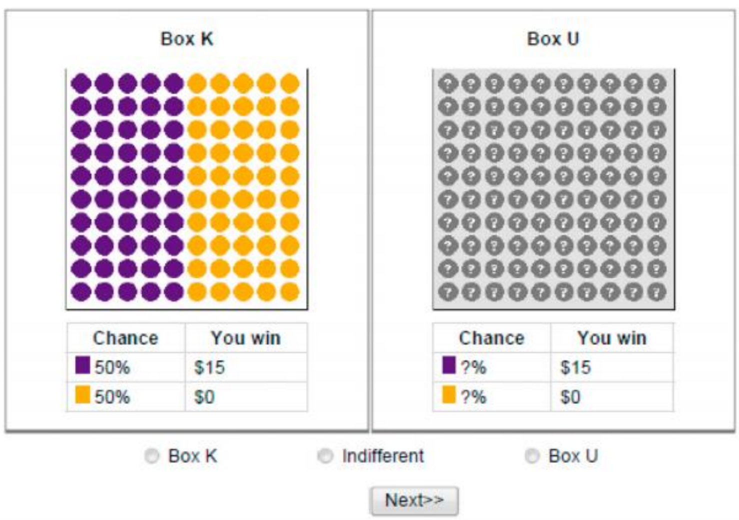

FIGURE 1: FIRST ROUND QUESTION ABOUT ATTITUDES TOWARD AMBIGUITY

Note: The figure is borrowed from Dimmock et. al (2015)

The experiment continues as follows. If the respondent selects Box K in the first round, its probability of winning falls to 25%, while if the respondent selects Box U in the first round, the probability winning in Box K increases to 75%. In round three, the known probabilities are 12.5% and 87.5%. The experiment concludes when the respondent is indifferent between Box K and U, or the final fourth round. The value when indifference is achieved is designated as the matching probability for ambiguity aversion (MP_{AA}) (Wakker 2010; Dimmock et al. 2016).[5] We use MP_{AA} as the continuous measure of attitude toward ambiguity. The respondents with $MP_{AA} > 50\%$ are ambiguity-seeking, those with $MP_{AA} = 50\%$ are ambiguity-neutral and those with $MP_{AA} < 50\%$ are ambiguity-averse.[6] In Dimmock et al.'s (2015) weighted sample, 52.4% of respondents were ambiguity averse, 9.9% neutral, and 37.7% ambiguity seeking.

In order to separate attitudes toward ambiguity from attitudes toward risk, a similar four-round experiment was conducted in the NU module, focusing on risk. In this experiment, respondents were asked to choose between Box A which has a 100% chance of winning the incentive and Box B with a risky, but well-defined probability of winning. The expected returns in the two boxes were equivalent. Based on this experiment, we construct a continuous measure of the attitude toward risk: the matching probability for risk aversion (MP_{RA}).[7] The respondents with $MP_{RA} > 50\%$ are defined as risk-seeking, those with $MP_{RA} = 50\%$ are risk-neutral, and those with $MP_{RA} < 50\%$ are risk-averse. Figure 2 shows the distributions of MP_{AA} and MP_{RA} in our sample. We find that ambiguity aversion is approximately normally distributed in the sample, while highly risk averse and risk

[5] If the respondent selects box K in the first round and then reports indifference in the second, third, or fourth rounds, the assigned MP_{AA}values are 0.25, 0.12, and 0.06, respectively. If the respondent selects box K in the final round, the value assigned is 0.03. Each sequence of choices of boxes generates a corresponding MP_{AA}value between 0 and 1. The precise values are displayed in Table A.1, in an on-line appendix to Dimmock et al. (2016), which is available at http://jfe.rochester.edu/Dimmock_Kouwenberg_Mitchell_Peijnenburg_app.pdf.

[6] Details about and validation of the ALP experiment is contained in Dimmock et al. (2015). They also describe additional experiments that address the issue of an individual's attitude toward ambiguity appearing to differ depending on whether the event is likely or not, and on whether the payoff is a gain or loss.

[7] We define the matching probability for risk aversion as the probability at which the respondent is indifferent between a risk-free box and risky box.

seeking individuals are overrepresented compared to a normal distribution of risk preferences.[8]

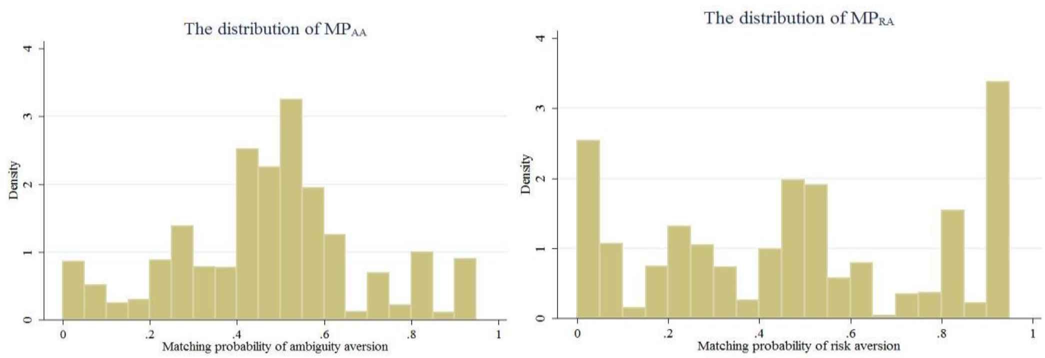

FIGURE 2: DISTRIBUTIONS OF MATCHING PROBABILITY FOR AMBIGUITY AVERSION AND RISK AVERSION

C. Measuring the Reference Prior Distribution

We use ALP's "Bins and Balls" question to measure an individual's reference prior distribution about future house prices. Then we use an extension of Dimmock et al.'s (2015) theoretical model to measure perceptions about the ambiguity of house prices. The bins and balls question was designed to capture a respondent's expectations about future housing prices. Each respondent was assigned 20 balls and 6 bins were presented. Each bin represents a range of percentage price change in the future and the respondents were asked to allocate the 20 balls into the 6 bins. The number of balls allocated to each bin represents the likelihood s/he believes that the price change will be in the range corresponding to the bin. These questions were asked regarding the expectations of housing prices one and five years after the survey date.

8 The extreme values resulted from an individual either selecting the safe bet in all four rounds of the experiment no matter how high the expected value was of the gamble, or always selecting the gamble no matter how poor the expected payout. Experiment conducted by Tanaka, Camerer and Nguyen (2010) also shows that extreme risk-averse and extreme risk-seeking values are overrepresented (see Figure 1, Tanaka, Camerer and Nguyen (2010)).

Figure 3 shows an example of the "bins and balls" question. Here, the respondent allocated balls into three bins, with the 0 to 10 percent price increase bin receiving half of the balls, the 10 percent to 20 percent price increase bin receiving six balls and the 0 to 10 percent price decrease bin receiving four balls. We use the number of balls in the bins to represent the reference probability assignment for each individual.

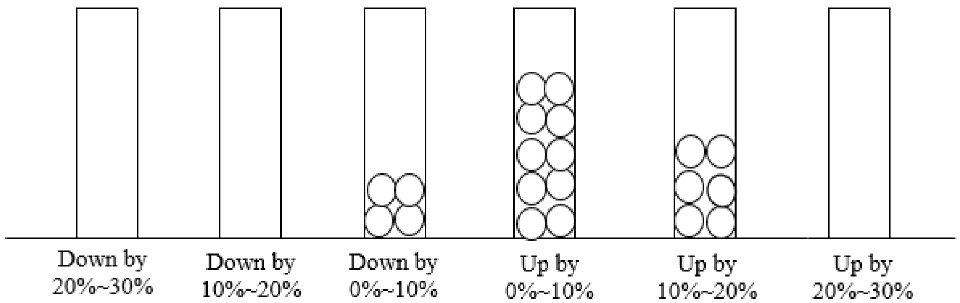

FIGURE 3: EXAMPLE OF ALP "BINS-AND-BALLS" SURVEY QUESTION

D. Theoretical Model

We extend Dimmock et al.'s (2015) theoretical model in order to measure both an individual's attitude toward ambiguity and perceived level of ambiguity. They specify a tractable version of the α-MaxMin utility optimization model, which is a weighted average of the MaxMin and MaxMax models. As described below, this model has two key parameters, one being α, which represents the attitude toward ambiguity and the other being δ, which represents the perceived level of ambiguity of an event.

Suppose we have a state space S consisting of a finite number of possible states of house price growth rates next year: $S = (s_1, s_2, \ldots, s_n)$, where s_i represents one state of the growth rate of house prices. In the "bins-and-balls" questions, $n = 6$ because the number of bins presented to the respondents is six. A probability measure P is an assignment function: $P: s_i \rightarrow R, for\ all\ i$ that assigns a probability value to each possible state. The probability assignment has the following properties: $P(s_i) \in [0,1]\ for\ all\ i, P(\emptyset) = 0, P(S) = 1, P(s_i \cup s_{i' \neq i}) = P(s_i) + P(s_{i' \neq i}), P(s_i \cap s_{i' \neq i}) = 0$. The last two properties reflect the assumption that all possible states of the future house price are mutually exclusive. These properties are consistent with the requirements of the "bins-and-balls" questions. Ambiguity in projecting house prices occurs when an individual cannot form a unique assignment for $P(s_i)$ for all future states.

Derived from the MaxMin model, Gilboa and Schmeidler (1989) propose the multiple prior model, which assumes the agent has a convex set C for all possible probability assignments $P \in C$. Suppose $u(\cdot)$ is a von Neumann-Morgenstern utility function. An ambiguity-averse agent's action-contingent value is characterized as $V(\varphi) = \min_{P \in C} \left(\int_{s_i \in S} u(\varphi(s_i))\, dP(s_i) \right)$, where φ represents an agent's decision as a real-valued function defined on the state space S. Ambiguity-averse agents select the decision φ that maximizes the value $V(\cdot) = \max_{\varphi} \min_{P \in C} \left(\int_{s_i \in S} u(\varphi(s_i))\, dP(s_i) \right)$. Intuitively, this means that ambiguity-averse agents select the act whose most unfavorable prior is the best. An agent is ambiguity-seeking if we replace the min operator with max, where this agent selects the act based on the prior distribution giving the highest expected utility, which is called the MaxMax model. A more general model, called α-MaxMin model, weights the MaxMin and MaxMax models, $\alpha \in [0,1]$, yielding an action-contingent value function of:

(1) $$V(\varphi) = \alpha * \min_{P \in C} \left(\int_{s_i \in S} u\big(\varphi(s_i)\big)\, dP(s_i) \right) + (1 - \alpha) * \max_{P \in C} \left(\int_{s_i \in S} u(\varphi(s_i))\, dP(s_i) \right)$$

As noted by Dimmock et al. (2015), the "*maximum ambiguity aversion occurs at the value* $\alpha = 1$ *(MaxMin), and maximum ambiguity seeking at* $\alpha = 0$ *(MaxMax).*"

In order to estimate perceived ambiguity, we must identify the set of probability assignments *C*. Epstein and Wang (1994) assume that an individual has a single subjective reference probability assignment $\pi(s_i)$ for each possible state, this assumption being part of their "ε-contamination" model.[9] Chateauneuf et al. (2007) assume the decision-maker has a degree of confidence $(1-\delta) \in [0,1]$ in their reference prior distribution. Using this framework, Dimmock et al. (2015) derive the set of possible subjective probability assignments:

(2) $$C_\delta = \{P: 0 \leq (1-\delta)\pi \leq P \leq (1-\delta)\pi + \delta \leq 1\}$$

The probability assignment P among the various sets varies in an interval of length δ around the reference probability π. Importantly, the degree of confidence in the reference probability distribution, $1-\delta$, is used to measure the level of perceived ambiguity.(see Dimmock for the proof)

Dimmock et al. (2015) used data from the ALP Ellsberg urn experiment to estimate α and δ in a gamble (just 2 states). However, their experiment provides a pre-determined objective reference winning probability to the respondents for the gamble and thus their estimates are not specific to any real-world situation where each individual has a subjective reference prior probability but does not know the true probability.

We extend the Dimmock model to measure perceived ambiguity using the ALP bins and balls question, applied to future house price changes. We generalize the set of possible subjective probability assignments to a state-specific set of possible probability assignment on each state s_i, which is characterized as: (we have 6 states)

[9] ε measures the degree that the reference probability is contaminated by other probability beliefs.

(3) $C_\delta = \{P_i: 0 \le (1-\delta)\pi(s_i) \le P_i \le (1-\delta)\pi(s_i) + \delta \le 1, \forall s_i \in S\}$

This means that the domain of the set of probability assignment for each possible state represented by each bin is dependent on the reference probability assignment and the degree of confidence in the reference probability assignment. Without loss of generality we can normalize the utility obtained from state 1 to 0, $u(s_1) = 0$, and assume $u(s_i) > 0$ for $i = \{2,3,\dots n\}$. Given these assumptions, the most unfavorable prior distribution is $P_{i,min} = (1-\delta)\pi(s_i)$ for $i = \{2,3,\dots n\}$, and $P_{1,min} = 1 - \sum_{i=2}^{n} P_{i,min} = 1 - (1-\delta)\sum_{i=2}^{n}\pi(s_i)$.[10] One can show that $P_{i,min}$ is in the feasible domain (3) for all i.[11]

However, we are not able to analytically derive the most favorable prior distribution by simply assuming $P_{i,max}^* = (1-\delta)\pi(s_i) + \delta$ for $i = \{2,3,\dots n\}$ and $P_{1,max}^* = 1 - \sum_{i=2}^{n} P_{i,max}^*$, which assigns greater values to $P_{i\neq 1}$ but lower values to P_1, given that $u(s_1) = 0$ and $u(s_{i\neq 1}) > 0$. That is because $P_{1,max}^*$ in this case is out of domain in (3) if $n \ge 2$.[12] Therefore, for any event that has two or two above possible states, the probability assignments $P_{i,max}^*$ for $i = \{1,2,3,\dots n\}$ are out of the domain in (3). Even though $P_{i,max}^*$ cannot be reached, it is the upper limit of the *max* situation and the true most favorable prior distribution $P_{i,max}$ will satisfy $\sum_{i=1}^{n} P_{i,max}u(s_i) < \sum_{i=1}^{n} P_{i,max}^* u(s_i)$. Thus, the most favorable distribution (which can be solved numerically but not analytically) has a greater value than the analytical solution we use below. We account for this with an inequality.

The α-MaxMin model evaluates an action-contingent value function as:

[10] Conditional on $u(s_1) = 0$ and $u(s_i) > 0$ for $i = \{2,3,\dots n\}$, the most unfavorable prior distribution that gives the lowest expected utility, $\sum_{i=1}^{n} P_i u(s_i)$, is to assign greater P_1 but lower $P_{i\neq 1}$.

[11] $P_{i,min} = (1-\delta)\pi(s_i)$ for $i = \{2,3,\dots n\}$ reaches the lower bound of P_i in (3). And $(1-\delta)\pi(s_1) \le P_{1,min} = 1 - (1-\delta)\sum_{i=2}^{n}\pi(s_i) \le (1-\delta)\pi(s_1) + \delta$ holds for all $\delta \in [0,1]$.

[12] $P_{1,max}^* = 1 - \sum_{i=2}^{n} P_{i,max}^* = 1 - (1-\delta)\sum_{i=2}^{n}\pi(s_i) - (n-1)\delta = 1 - (1-\delta)\sum_{i=2}^{n}\pi(s_i) - (n-1)\delta + (1-\delta)\pi(s_1) - (1-\delta)\pi(s_1) = 1 - (1-\delta) - (n-1)\delta = (2-n)\delta$, which is smaller than 0 if $n \ge 2$.

(4) $\alpha \min_{P_i \in C_\delta} \sum_i^n P_i u(s_i) + (1-\alpha) \max_{P_i \in C_\delta} \sum_i^n P_i u(s_i)$

$$= \alpha \sum_i^n P_{i,min} u(s_i) \quad + \quad (1-\alpha) \sum_i^n P_{i,max} u(s_i)$$

$$< \alpha \sum_i^n P_{i,min} u(s_i) \quad + \quad (1-\alpha) \sum_i^n P^*_{i,max} u(s_i)$$

$$= \alpha \sum_{i=2}^n (1-\delta)\pi(s_i) u(s_i) + \alpha \left[1 - \sum_{i=2}^n (1-\delta)\pi(s_i)\right] u(s_1)$$

$$+ (1-\alpha) \sum_{i=2}^n [(1-\delta)\pi(s_i) + \delta] u(s_i)$$

$$+ (1-\alpha) \left[1 - \sum_{i=2}^n (1-\delta)\pi(s_i) - (n-1)\delta\right] u(s_1)$$

$= \sum_{i=2}^n [(1-\delta)\pi(s_i) + (1-\alpha)\delta]\, u(s_i).$ *(because $u(s_1) = 0$)*

$$= \sum_{i=1}^n [(1-\delta)\pi(s_i) + (1-\alpha)\delta]\, u(s_i).$$

Let m be a positive value such that $m \sum_i^n u(s_i) = \sum_i^n [(1-\delta)\pi(s_i) + (1-\alpha)\delta]\, u(s_i)$. Thus, we can derive:

(5) $$m = \frac{\sum_i^n [(1-\delta)\pi(s_i) + (1-\alpha)\delta] u(s_i)}{\sum_i^n u(s_i)} = \frac{\sum_i^n [(1-\delta)\pi(s_i)] u(s_i)}{\sum_i^n u(s_i)} + (1-\alpha)\delta$$

Let $w_i = \frac{u(s_i)}{\sum_i^n u(s_i)}$ denote the weight of the utility obtained from the state s_i relative to the sum of the utility obtained from every state, thus $\sum_i^n w_i = 1$. Moreover, in the reference prior distribution, we have $\sum_i^n \pi(s_i) = 1$. Substitute w_i into (5) and replace $\pi(s_1)$ by $1 - \sum_{i=2}^n \pi(s_i)$, which yields the m as a function of the reference probability assignment for state s_i, given the parameter set $(w_i \; for \; \forall i, \delta, \alpha)$:

(6) $m = \sum_i^n [(1-\delta) w_i \pi(s_i)] + (1-\alpha)\delta$

$$= (1-\delta) w_1 \left[1 - \sum_{i=2}^{n} \pi(s_i)\right] + \sum_{i=2}^{n} [(1-\delta) w_i \pi(s_i)] + (1-\alpha)\delta$$

$$= \sum_{i=2}^{n} [(1-\delta)(w_i - w_1)\pi(s_i)] + (1-\delta) w_1 + (1-\alpha)\delta.$$

Suppose $\hat{m} \sum_i^n u(s_i) = \alpha \min_{P_i \in C_\delta} \sum_i^n P_i u(s_i) + (1-\alpha) \max_{P_i \in C_\delta} \sum_i^n P_i u(s_i)$, which means that $\hat{m}$ is the matching probability such that an individual is indifferent between an unambiguous event (left-hand side of the equation) and an ambiguous event (right-hand side).[13] Therefore, $\hat{m}$ can be used to measure an individual's degree of ambiguity aversion for house prices if it is observable. Unfortunately, $\hat{m}$ is not observable and we need identify α to measure the degree of ambiguity aversion for house prices. The identification procedure will rely on the analytical relationship between m and $\pi(s_i)$ derived in equation (6), while the analytical relationship between $\hat{m}$ and $\pi(s_i)$ does not exist as we discussed above. We should note that $\hat{m} < m$ based on the inequality in (4).

E. Econometric Model and Identification

In the bins and balls ALP question, s_1 represents the state that "house price next year will decrease by 20% or greater, s_2 represents a decrease by 10%-20%, s_3 a

[13] The definition of $\hat{m}$ is analogous to the definition of matching probability for ambiguity aversion. However, the true matching probability should satisfy the condition that $\sum_i^n \hat{m}(s_i) u(s_i) = \alpha \min_{P_i \in C_\delta} \sum_i^n P_i u(s_i) + (1-\alpha) \max_{P_i \in C_\delta} \sum_i^n P_i u(s_i)$, which means that there exists a matching probability for each possible state s_i and $\hat{m}(s_i)$ is the certain numerical probability in state s_i such that the individual is indifferent between the unambiguous event and the ambiguous event. Nevertheless, we are not able to observe $\hat{m}(s_i)$ for all states, but use a singular value $\hat{m}$ such that $\hat{m} \sum_i^n u(s_i) = \alpha \min_{P_i \in C_\delta} \sum_i^n P_i u(s_i) + (1-\alpha) \max_{P_i \in C_\delta} \sum_i^n P_i u(s_i)$ to represent the matching probability.

decrease by 0%-10%, s_4 an increase by 0%-10%, s_5 an increase by 10%-20%, and s_6 represents an increase by 20% or more. Therefore, each respondent provides a unique subjective probability assignment for each state s_i. We assume that the subjective probability assignment represents their reference probability for each state and thus we can observe $\pi_j(s_i), \forall s_i \in S$, for every individual *j* in the data.

Given m_j for every individual *j*, then we can estimate the following regression:

(7) $$m_j = \sum_{i=2}^{n} \beta_i \pi_j(s_i) + \beta_0 + \epsilon_j$$

From this model, we can obtain the estimates of $\beta_i, i = \{2,3, \dots, n\}$ and β_0, noting that β_1 is omitted because each respondent is required to allocate exactly 20 balls. Comparing (6) with (7), we find:

(8) $$\beta_0 = (1 - \delta)w_1 + (1 - \alpha)\delta$$

and

(9) $$\beta_i = (1 - \delta)(w_i - w_1)$$

Because $u(s_1) = 0$, we know $w_1 = 0$. Applying this to (8) and (9) yields:

(8’) $$\beta_0 = (1 - \alpha)\delta$$

and

(9’) $$\beta_i = (1 - \delta)w_i$$

Next, the slope coefficients over i are summed, and note that the sum of the weights equals one.

(9'') $$\sum_{i=2}^{n} \beta_i = (1 - \delta)$$

From (9''), the degree of confidence in the reference distribution (perceived ambiguity) is found, and from (8'), the attitude toward ambiguity is determined. Thus, the parameters of the α-MaxMin model are identified from the regression as $\delta = 1 - \sum_{i=2}^{n} \beta_i$ and $\alpha = 1 - \beta_0/\delta$. Once m_j is observed δ and α can be identified.

Even though we cannot observe m_j in the dataset for house price, we can observe $\widetilde{m}_j$, the matching probability in a gamble for each respondent j based on the ambiguity attitude experiment in the Netspar Uncertainty (NU) module. It is arguable whether the matching probability in a gamble ($\widetilde{m}_j$) is equivalent to the matching probability in the case of house prices ($\widehat{m}_j$), which means whether an individual's degree of ambiguity aversion is constant across different events. If one believes so, which means that she believes $\widetilde{m}_j = \widehat{m}_j$ for all individual j, we can simply use $\widetilde{m}_j$ to measure the degree of ambiguity aversion of the respondent for all events. However, some literature argue that one's degree of ambiguity aversion is varying across events (Heath and Tversky, 1991). If so, using ambiguity aversion in a gamble to measure the respondent's ambiguity aversion in house prices will generate measurement error problem. Therefore, we need identify α for house prices. As we mentioned above, the identification procedure will rely on the analytical relationship between m_j and $\pi_j(s_i)$ derived in (6).

Suppose $m_j - \widetilde{m}_j = \mu_j$ for individual j, and we assume $E(\mu_j) = k$. Therefore, the relationship between $\widetilde{m}_j$ and $\pi_j(s_i)$ is characterized as:

(10) $$\widetilde{m}_j = m_j - \mu_j$$

$$= \sum_{i=2}^{n} \beta_i \pi_j(s_i) + \beta_0 + \epsilon_j - \mu_j$$

$$= \sum_{i=2}^{n} \beta_i \pi_j(s_i) + \beta_0 - k + \varepsilon_j$$

where $E(\varepsilon_j)$=0. We then estimate the following regression:

(11) $$\tilde{m}_j = \sum_{i=2}^{n} \tilde{\beta}_i \pi_j(s_i) + \tilde{\beta}_0 + \tilde{\epsilon}_j$$

Note that μ_j is unobservable in the regression. Comparing equations (10) and (11), we find $\tilde{\beta}_i = \beta_i$ and $\tilde{\beta}_0 = \beta_0 - k$. Thus, given that μ_j is uncorrelated with $\pi_j(s_i)$, $\tilde{\beta}_i$ is an unbiased estimator of β_i and $\tilde{\beta}_0$ is an unbiased estimator of β_0 if $k = 0$, but the estimate of $\tilde{\beta}_0$ is a biased estimator of β_0 if $k \neq 0$.[14] Because the identification of δ only depends on β_i, we can get the unbiased estimation of δ based on:

(12) $$\tilde{\delta} = 1 - \sum_{i=2}^{n} \tilde{\beta}_i$$

We also find an estimate of:

(13) $$\tilde{\alpha} = 1 - \frac{\tilde{\beta}_0}{\tilde{\delta}} = 1 - \frac{\tilde{\beta}_0}{\delta}$$

Notice that $\tilde{\alpha} - \alpha = \left(1 - \frac{\tilde{\beta}_0}{\delta}\right) - \left(1 - \frac{\beta_0}{\delta}\right) = \frac{k}{\delta}$. This means that $\tilde{\alpha}$ will overestimate the true α by $\frac{k}{\delta}$ if $k > 0$ and underestimate the true α if $k < 0$.[15]

[14] If $k = 0$, then $E(\tilde{m}_j) = E(m_j) > E(\hat{m}_j)$. Because greater values in matching probability represents lower degree of ambiguity aversion, the intuition of $k = 0$ is that population's ambiguity aversion toward the gamble is smaller than the population's ambiguity aversion toward house prices on average. It is possible because the gain or loss in housing market is much greater than the gamble in the experiment, which may make people more ambiguity-averse with regard to house prices.

[15] If one believes that ambiguity aversion in the gamble is equivalent to the ambiguity aversion in house prices ($\tilde{m}_j = \hat{m}_j$), the $\tilde{\alpha}$ estimated by using $\tilde{m}_j$ will overestimate the true α. Because we know $\tilde{m}_j = \hat{m}_j < m_j$, we have $\mu_j = m_j - \tilde{m}_j > 0$ for all j and, thus, $k = E(\mu_j) > 0$. However, if one believes $\tilde{m}_j = \hat{m}_j$, she doesn't need estimate α, but can simply use $\tilde{m}_j$ to measure respondent j's ambiguity aversion for all events.

The theoretical framework is summarized in Table 1. This framework generates an unbiased estimation of δ and an unbiased estimation α if μ_j is unrelated with $\pi_j(s_i)$ and $E(\mu_j) = 0$. However, the estimate of α will be biased if $E(\mu_j) \neq 0$ and the estimate of δ will be biased if μ_j is correlated with $\pi_j(s_i)$.

TABLE 1—THE IDENTIFICATION STRATEGY FOR δ AND α

Matching probability	m_j (Unobserved)	$\widetilde{m}_j$ (Observed)
The relationship with $\pi_j(s_i)$	$m_j = \sum_{i=2}^{n} \beta_i \pi_j(s_i) + \beta_0 + \epsilon_j$	$\widetilde{m}_j = \sum_{i=2}^{n} \tilde{\beta}_i \pi_j(s_i) + \tilde{\beta}_0 + \tilde{\epsilon}_j$
Identification of δ	$\delta = 1 - \sum_{i=2}^{n} \beta_i$	$\tilde{\delta} = 1 - \sum_{i=2}^{n} \tilde{\beta}_i$
Identification of α	$\alpha = 1 - \beta_0/\delta$	$\tilde{\alpha} = (1 - \tilde{\beta}_0/\tilde{\delta})$
Conclusion 1	The true δ and true α can be identified if m_j is observable.	
The relationship between m_j and $\widetilde{m}_j$	$m_j - \widetilde{m}_j = \mu_j$	
Assumption	μ_j is unrelated with $\pi_j(s_i)$	
Conclusion 2	$\delta = \tilde{\delta}$	$\tilde{\delta}$ is the unbiased estimator of true δ
	$\alpha = \tilde{\alpha} - \frac{E(\mu_j)}{\delta}$	$\tilde{\alpha}$ is the unbiased estimator of true α if $E(\mu_j) = 0$;
		$\tilde{\alpha}$ overestimates the true α if $E(\mu_j) > 0$;
		$\tilde{\alpha}$ underestimates the true α if $E(\mu_j) < 0$;

F. Estimating Heterogeneous Attitudes toward and Perceptions of Ambiguity

We next estimate individuals' perceived ambiguity, δ_j, and attitude toward ambiguity, α_j, with regard to house prices by allowing the two parameters to vary across individual characteristics. Because the NU ambiguity attitude experiment is a cross-sectional experiment conducted in April 2012, we can only sample the 697 respondents who completed both the NU ambiguity attitude experiment and the bins-and-balls experiment at the same time period in this section. Suppose that the relationship between m_j and $\pi_j(s_i)$ can be expressed as:

$$(14) \qquad m_j = \sum_{i=2}^{n} \pi_j(s_i)(\sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i) + \beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} + \epsilon_j$$

X_{xj} denotes an individual j's characteristics x, and Q is the total number of individual characteristics. The independent variables are the interaction terms between the reference probability in each state s_i and the individual characteristics. The number of estimated β_{ix} thus will be $n \times Q$. Then, based on equation (6), we find that:

$$(15) \qquad \sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i = (1 - \delta_j)(w_{ij} - w_{1j})$$

and

$$(16) \qquad \beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} = (1 - \delta_j) w_{1j} + (1 - \alpha_j)\delta_j$$

From equation (15) and (16), we can derive:

$$(17) \qquad \delta_j = 1 - \frac{\sum_{i=2}^{n}(\sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i)}{1 - n w_{1j}}$$

and

$$(18) \qquad \alpha_j = 1 - \frac{\beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} - (1 - \delta_j) w_{1j}}{\delta_j}$$

Equations (17) and (18) indicate that perceived ambiguity and attitudes toward ambiguity about house prices are affected by the individual characteristics. Similar to the model for representative agent, we normalize $w_{1j} = 0$ for every respondent j. The intuition of the normalization is that every respondent treats the state 1, s_1, as the worst state.[16] Then,

(17') $$\delta_j = 1 - \sum_{i=2}^{n}(\sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i)$$

and

(18') $$\alpha_j = 1 - \frac{\beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj}}{\delta_j}$$

In the ambiguity attitude experiment, we cannot observe m_j, but can observe $\widetilde{m}_j$. Based on $\widetilde{m}_j = m_j - \mu_j$, we can derive

(19) $$\widetilde{m}_j = \sum_{i=2}^{n} \pi_j(s_i)(\sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i) + \beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} + \epsilon_j - \mu_j$$

$$= \sum_{i=2}^{n} \pi_j(s_i)(\sum_{x=1}^{Q} \beta_{ix} X_{xj} + c_i) + \beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} - k + \varepsilon_j$$

Therefore, we can estimate the following regression:

(20) $$\widetilde{m}_j = \sum_{i=2}^{n} \pi_j(s_i)(\sum_{x=1}^{Q} \tilde{\beta}_{ix} X_{xj} + \tilde{c}_i) + \tilde{\beta}_0 + \sum_{x=1}^{Q} \tilde{\rho}_x X_{xj} + \tilde{\epsilon}_j$$

And we can get:

(21) $$\tilde{\beta}_{ix} = \beta_{ix} \text{ and } \tilde{c}_i = c_i$$

[16] One may argue that renters may not treat the state 1 as the worst state because they can afford a house in the future if the house price next year can decrease by 20% or above. However, the housing bust may adversely affect the renters' welfare by affecting their income. Therefore, assuming $u_j(s_1) = 0$ may not be a bad assumption.

and

$$\tilde{\beta}_0 + \sum_{x=1}^{Q} \tilde{\rho}_x X_{xj} = \beta_0 + \sum_{x=1}^{Q} \rho_x X_{xj} - k \tag{22}$$

Equations (21) and (22) show that $\tilde{\delta}_j$ and $\tilde{\alpha}_j$ that are estimated based on $\widetilde{m}_j$ are unbiased estimators of true δ_j and α_j if, first, μ_j is uncorrelated with reference probability assignments, $\pi_j(s_i)$, and individual characteristics, X_{xj}; and second, $E(\mu_j) = 0$.

G. Measuring Perceived Risk

Because we can observe the entire reference prior distribution of each respondent in "bins-and-balls", we follow Delavande and Rohwedder (2008) to calculate the expectation and variance of the prior by assuming that the probability assignment within each bin is uniformly distributed. Then, we use the expectation of the prior to measure an individual's expected growth rate of house price, and use the variance of the prior to measure an individual's perceived risk.

Suppose $[D_i, D_{i+1}]$ represents the interval of the growth rates of house price in bin $i = \{1,2, \dots, n\}$; $s \in S$ represents the possible growth rate. Then, the expectation of the growth rate derived from "bins-and-balls" questions is characterized as:

$$E(S) = \sum_{i}^{n} \int_{D_i}^{D_{i+1}} s f(s)\, ds \tag{23}$$

Assuming that the probability assignment within each bin is uniformly distributed, then we find the probability density function within each bin $f(s) =$

$\frac{\pi_i}{D_{i+1}-D_i}, for\ s \in [D_i, D_{i+1}]$. π_i represents the probability assignment within *i's* bin, which equals to the number of balls in *i*'s bin times 5%. Therefore, we have:

(24) $E(S) = \sum_i^n \int_{D_i}^{D_{i+1}} \frac{s\pi_i}{D_{i+1}-D_i} ds = \frac{1}{2}\sum_i^n [\frac{s^2\pi_i}{D_{i+1}-D_i}]_{D_i}^{D_{i+1}} = \frac{1}{2}\sum_i^n \frac{\pi_i(D_{i+1}^2-D_i^2)}{D_{i+1}-D_i} = \frac{1}{2}\sum_i^n \pi_i(D_{i+1}+D_i)$

Then, the variance of the distribution can be calculated as (see Appendix 1 for more details):

(25) $Var(S) = \sum_i^n \frac{\pi_i}{D_{i+1}-D_i} [\frac{D_{i+1}^3-D_i^3}{3} - (D_{i+1}^2 - D_i^2)E(S) + E(S)^2(D_{i+1} - D_i)]$

$E(S)$, $Var(S)$ and δ are used to evaluate individuals' price expectations, the level of perceived risk, and the level of perceived ambiguity of in the housing market.

II. Results

A. α-MaxMin Model Estimation Results for Representative

We apply our theoretical model to estimate the level of perceived ambiguity for one-year house prices and one-year stock prices. We first estimate a representative agent model without controlling any individual characteristics. Table 2 shows the results of the regression using ALP data from 2011 to 2013:[17]

[17] For each respondent *j*, the matching probability is computed from the Ellsberg urn experiment and the $\pi_j(s_i)$ are determined by the number of balls this respondent places in each bin.

TABLE 2—REGRESSION RESULTS FOR REPRESENTATIVE AGENT MODEL

Dep variable: MP_{AA}	1-year house prices (1)	1-year stock prices (2)
β_2	0.065*	0.056*
	(0.038)	(0.032)
β_3	0.068**	0.042
	(0.031)	(0.026)
β_4	0.064**	0.049*
	(0.030)	(0.025)
β_5	0.083***	0.081***
	(0.033)	(0.028)
β_6	0.116***	0.080**
	(0.038)	(0.033)
Constant β_0	0.400***	0.417***
	(0.030)	(0.024)
Wave 26	-0.013	-0.017*
	(0.011)	(0.011)
Wave 29	-0.008	-0.010
	(0.010)	(0.010)
Wave 32	-0.015	-0.016
	(0.011)	(0.011)
Wave 35	-0.005	-0.008
	(0.010)	(0.010)
Wave 38	-0.002	-0.005
	(0.010)	(0.010)
Obs.	4,148	4,131
R^2	0.0039	0.0043

Note: Standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%

Column 1 and 2 show the results for house prices and stock prices, respectively. For one-year house prices, the sum of the slope coefficients equals 0.395, meaning that the representative agent has a degree of confidence in the reference prior distribution is 0.395. δ is 1 less this value, equaling 0.605. The attitude toward ambiguity measure, $\alpha,$ equals 0.411, suggesting that a representative individual in this sample was ambiguity seeking with regard to house prices.

For one-year stock prices, the δ and degree of confidence are 0.692 and 0.308 (including the point estimate for β_3, which is not statistically significant), showing that the individual perceives greater ambiguity about stock prices than house prices. The attitude toward ambiguity with regard to stock prices is 0.480, slightly ambiguity-seeking but closer to ambiguity-neutral than the attitude toward ambiguity with regard to house prices. If we set β_3= 0, then δ=0.734, and α =0.510, indicating that the representative agent is slightly ambiguity-averse about stock prices.

B. α-MaxMin Model Estimation Results for Heterogeneous Agents

Because some estimated δ_j and α_j are out of the domain of [0,1], we use the following method to normalize the estimated δ_j and α_j into the domain of [0,1], and we use the normalized δ_j and α_j for the following analysis:

$$Normalized\ \hat{\delta}_j = \frac{\delta_j - min(\delta_j)}{max(\delta_j) - min(\delta_j)}$$

Table 3 shows the summary statistics of attitude toward ambiguity, level of perceived ambiguity and level of perceived risk with regard to house prices and stock prices, respectively. Similar to the results for representative agent model, we find that people perceive larger ambiguity about stock prices than house prices. Moreover, people are ambiguity-seeking with regard to house prices, but ambiguity-averse with regard to stock prices. The mean of individual α_j and of δ_j

for house prices are 0.432 and 0.541, which are close to the α and δ for representative agent model, 0.411 and 0.605. The mean of individual δ_j for stock prices is 0.705, which is close to the δ in representative agent model, 0.734 (excluding insignificant β_3). Nevertheless, the mean individual α_j for stock prices is 0.610, which is more ambiguity-averse than the α in the representative agent model, 0.510.

We also find that people perceive larger risk about stock prices than house prices, too. The index to measure perceived risk, *VAR(S)*, is 0.0066 for stock prices, but 0.0053 for house prices.

TABLE 3— SUMMARY STATISTICS OF AMBIGUITY ATTITUDES, AMBIGUITY AND RISK

	Obs.[18]	Mean	Std.Dev.	Min	Median	Max
1-year house prices						
Attitude toward ambiguity *(α)*	684	0.432	0.078	0.073	0.425	1
Level of perceived ambiguity *(δ)*	697	0.541	0.131	0.034	0.530	1
Level of perceived risk *(VAR(S))*	697	0.0053	0.0057	0.0008	0.0033	0.0601
1-year stock prices						
Attitude toward ambiguity *(α)*	680	0.610	0.057	0.123	0.610	1
Level of perceived ambiguity *(δ)*	693	0.705	0.134	0.007	0.725	1
Level of perceived risk *(VAR(S))*	693	0.0066	0.0062	0.0008	0.0043	0.0633

C. Socio-economic Correlates with Attitudes toward Ambiguity, Ambiguity and Risk

In this section, we show the relationship of attitude toward ambiguity, perceived ambiguity and perceived risk with individual characteristics for house prices and stock prices. Table 4 shows the results of house prices and Table 5 shows the results of stock prices.

[18] The bottom 1% and top 1% estimated α_j are excluded because the scale of the outliers is too large.

We estimate a OLS model to identify which individual characteristics are significantly correlated with attitudes toward ambiguity. Appendix 2 reports variables' definitions, means, and standard deviations. We find the following attributes are significant and increase the tendency for an individual to be ambiguity-averse toward house prices: smaller age and worse health. We also estimate a Tobit model truncated a 0 and 1 for the estimated but non-normalized α_j as a robustness check (see appendix 3 for more details). The following attributes are statistically significant and increase the tendency for an individual to be ambiguity-averse toward house prices in the Tobit model: smaller age, married, Hispanic, employed, financial literacy and worse health. No effect is found for gender, income, education, White, Black, having retirement account or not, the number of household members and wealth.[19]

We also find that following individual characteristics are positively correlated with the level of perceived ambiguity about house prices: greater age, male, income, advanced educational attainment, Black, having retirement account, greater household size, greater wealth and better health. The individual characteristics that are negatively correlated with the level of perceived ambiguity are married, White, Hispanic, employed and greater financial literacy.[20]

Moreover, we find that males and individuals with higher educational attainment perceive less risk about house prices.

TABLE 4— THE RELATIONSHIP OF INDIVIDUAL CHARACTERISTICS WITH AMBIGUITY ATTITUDES, PERCEIVED AMBIGUITY AND PERCEIVED RISK (HOUSE PRICES)

Dependent variable	Ambiguity attitude (α)	Ambiguity (δ)	Risk *Var(S)*
	(1)	(2)	(3)

[19] Our results differ from Dimmock et al. (2015) in that he found a more limited number of significant variables. They included age and Hispanic, with their signs agreeing with ours. For these cases the coefficients are similar in size.

[20] Dimmock et al. (2015) and our results agree on household size and educational attainment, but disagree on White and financial literacy.

Age	-0.0006**	0.0031***	-2.79×10^{-6}
	(0.0003)	(0.0001)	(0.0000)
Male	-0.0079	0.0071***	-0.0012***
	(0.0061)	(0.0019)	(0.0004)
Married	0.0073	-0.0249***	-0.0003
	(0.0071)	(0.0022)	(0.0005)
Log (income)	0.0036	0.0073***	0.0001
	(0.0050)	(0.0015)	(0.0004)
High school	0.0008	0.0803***	-0.0066***
	(0.0184)	(0.0057)	(0.0014)
College	1.95×10^{-5}	0.1078***	-0.0065***
	(0.0188)	(0.0058)	(0.0014)
Graduate+	-0.0014	0.1401***	-0.0062***
	(0.0197)	(0.0060)	(0.0014)
White	0.0069	-0.1025***	0.0009
	(0.0154)	(0.0047)	(0.0011)
Black	-0.0056	0.1151***	0.0014
	(0.0189)	(0.0058)	(0.0014)
Hispanic	0.0136	-0.3142***	0.0004
	(0.0144)	(0.0044)	(0.0010)
Retirement account	-0.0010	0.0507***	0.0005
	(0.0075)	(0.0023)	(0.0005)
Household members	-0.0025	0.0138***	2.86×10^{-5}
	(0.0024)	(0.0007)	(0.0002)
Employed	0.0087	-0.1619***	-0.0001
	(0.0069)	(0.0021)	(0.0005)
Financial knowledge	0.0040	-0.0470***	-0.0003
	(0.0040)	(0.0012)	(0.0003)
Wealth (1 million)	-0.0090	0.0200***	-0.0001
	(0.0081)	(0.0022)	(0.0001)
Good health	-0.0908***	0.1755***	0.0006
	(0.0192)	(0.0058)	(0.0014)
Fair health	-0.0731***	0.1246***	0.0008
	(0.0190)	(0.0057)	(0.0013)
Constant	0.4896***	0.3106***	0.0103***
	(0.0545)	(0.0166)	(0.0040)
Obs.	684	697	697
R^2	0.0565	0.9687	0.0565

Note: Standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%.

We use similar method to estimate relationship for stock prices, which is showed in Table 5. We find that greater age and greater household size are significant and increase the tendency for an individual to be ambiguity-averse toward stock prices according to the result of OLS model. Based on the Tobit model, we find that greater age, male, higher income are significant and increase the tendency to be ambiguity-averse with regard to stock prices, and higher wealth and better health are significant and decrease the tendency to be ambiguity-averse with regard to stock prices.

We also find that following individual characteristics are positively correlated with the level of perceived ambiguity about stock prices: married, advanced educational attainment, White, Black, employed, greater wealth and better health. The individual characteristics that are negatively correlated with the level of perceived ambiguity are age, male, income, Hispanic, having retirement account, greater household size and greater financial literacy.

Moreover, we find that individuals with higher educational attainment perceive less risk about stock prices.

TABLE 5— THE RELATIONSHIP OF INDIVIDUAL CHARACTERISTICS WITH AMBIGUITY ATTITUDES, PERCEIVED AMBIGUITY AND PERCEIVED RISK (STOCK PRICES)

Dependent variable	Ambiguity attitude (α)	Ambiguity (δ)	Risk *Var(S)*
	(1)	(2)	(3)
Age	0.0007***	-0.0025***	5.74×10^{-6}
	(0.0002)	(0.0001)	(0.0000)
Male	0.0049	-0.0352***	-0.0007
	(0.0044)	(0.0014)	(0.0005)
Married	0.0010	0.0083***	-1.99×10^{-5}

	(0.0053)	(0.0017)	(0.0007)
Log (income)	0.0011	-0.0463***	-0.0001
	(0.0037)	(0.0012)	(0.0004)
High school	0.0001	0.1110***	-0.0044***
	(0.0136)	(0.0044)	(0.0015)
College	-0.0163	0.1369***	-0.0043***
	(0.0141)	(0.0045)	(0.0015)
Graduate+	0.0041	0.1342***	-0.0037**
	(0.0146)	(0.0047)	(0.0016)
White	0.0004	0.1725***	-0.0004
	(0.0101)	(0.0036)	(0.0012)
Black	-0.0087	0.1679***	-0.0017
	(0.0138)	(0.0045)	(0.0015)
Hispanic	-0.0009	-0.5115***	-0.0016
	(0.0108)	(0.0034)	(0.0012)
Retirement account	0.0042	-0.0090***	0.0003
	(0.0054)	(0.0017)	(0.0006)
Household members	0.0033*	-0.0064***	0.0003
	(0.0017)	(0.0006)	(0.0002)
Employed	-0.0020	0.0403***	0.0007
	(0.0050)	(0.0016)	(0.0005)
Financial knowledge	0.0020	-0.0072***	0.0003
	(0.0030)	(0.0010)	(0.0003)
Wealth (1 million)	-0.0090	0.0578***	-0.0002
	(0.0057)	(0.0018)	(0.0006)
Good health	-0.0217	0.0508***	0.0003
	(0.0139)	(0.0044)	(0.0015)
Fair health	-0.0137	-0.0052	0.0002
	(0.0137)	(0.0044)	(0.0015)
Constant	0.5740***	1.0545***	0.0100**
	(0.0405)	(0.0130)	(0.0044)
Obs.	680	693	693
R^2	0.0624	0.9824	0.0247

Note: Standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%

When comparing the results between Table 4 and 5, we find a more important finding that the relationship of the variables of ambiguity and risk with individual characteristics are heterogeneous across housing market and stock market. For example, we find that age has significant opposite relationship to the attitude toward ambiguity about stock prices and house prices. The effect of age, gender, marriage status, income, White, retirement account, household members and employment status on the level of perceived ambiguity is varying across markets, too. Gender has significant effect on the perceived risk about house prices but no significant effect on the perceived risk about stock prices.

People perceive heterogeneous ambiguity toward different markets may be because of their various preferences on different markets so that people with similar characteristics are more likely to collect the information about a particular market. According to Dimmock et al. (2016), White, non-Hispanic, married, people living with less number of children, healthier people and wealthier people are more likely to participate in stock market, which implies that they may be more used to collect information about stock market. However, at the era of information explosion, receiving too much information about one market may trigger larger ambiguity perception about the market because of the diverse professional forecasts on future's development of the market (Viscusi and Chesson, 1999). Therefore, people with such characteristics perceive large ambiguity about stock market according to Table 5 in our results.[21]

Moreover, we also find that people's attitude toward ambiguity is heterogeneous across markets. One possible explanation to the phenomenon is competence hypothesis proposed by Heath and Tversky (1991), which claims that people are more ambiguity-seeking toward the event they consider themselves knowledgeable.

[21] Dimmock et al. (2016) also find that high-income and financial knowledgeable people are more likely to participate stock market, but high-income and financial knowledgeable people perceive less ambiguity about stock prices in our results.

For example, elder people perceive larger ambiguity about house prices than younger people, but less ambiguity about stock prices than younger people, which may be because they collect more information and consider themselves knowledgeable about housing market. Therefore, elder people may be more familiar with housing market, while young people may be more familiar with stock market. Based on the competence hypothesis, elder people are hypothesized to be more ambiguity-seeking toward housing market, but more ambiguity-averse toward stock market, which is validated by our results. Competence hypothesis can explain why certain people perceiving larger (smaller) ambiguity about a market are more ambiguity-seeking (ambiguity-averse) toward the market showed in our results. Moreover, comparative ignorance hypothesis proposed by Fox and Tversky (1995) can explain the phenomenon partially as well.[22] If elder people considers themselves more knowledgeable than younger people about housing prices, they should be more ambiguity-seeking than younger people about housing market.

D. Intertemporal Variation of Perceived Ambiguity

The "bins and balls" questions were conducted six times between April 2011 and April 2013 and thus we are able to observe the intertemporal variation in perceptions about the house prices. In Table 6 we show the intertemporal variation of average expected house price growth rates, perceptions of house price risk and ambiguity toward next year's house prices. In Panel A, we show the results derived from "bins and balls". In Panel B, we show the results from Wall Street Journal Economic Forecasting Survey and in Panel C, the results are from the Zillow/Pulsenomics survey of housing experts. The average predicted growth rates of the three sources are relatively close. Panel D contains one-year growth rates

[22] Comparative ignorance hypothesis: ambiguity aversion is triggered when the decision makers compare the prospect with more familiar events or when they feel ignorant to the event compared with other knowledgeable individuals.

from the Case-Shiller repeat sales index. We observe that individuals and professional forecasters overestimated price growth rates during the bust, but underestimated it when house prices increased.

We then follow Anderson, Ghysels and Juergens (2009) to calculate the standard deviation of predicted growth rates from professional forecasters as a time-series measure of ambiguity, and compare it with the mean of estimated δ_j obtained from "Bins-and-Balls". We find that both individuals and professional forecasters perceived relatively small ambiguity in April 2011, but increased ambiguity in July 2011 and Oct 2011. The level of perceived ambiguity decreased from July 2011 to April 2013, according to both ALP respondents and professionals.

TABLE 6— INTERTEMPORAL VARIATION OF THE EXPECTED GROWTH AND PERCEPTIONS OF HOUSE PRICE RISK AND AMBIGUITY

	April 2011	July 2011	Oct 2011	Jan 2012	April 2012	April 2013	Test values
Panel A: Bins-and-Balls							
Average expected growth rate (%,$E(S)$)	0.97	1.18	0.97	1.15	2.26	4.11	8.37***
Value of δ (original values)	0.397	0.480	0.541	0.483	0.418	0.165	3.21***
Value of δ (normalized values)	0.556	0.559	0.562	0.560	0.557	0.546	3.55***
Sample size	1,338	1,393	1,346	1,523	1,588	2,144	
Panel B: WJS Economic Forecasting Survey							
Average expected growth rate (%)	1.93	1.75	0.47	N/A	N/A	5.01	8.18***
Std.dev. of predicted growth rates (%)[23]	1.80	2.01	2.15	N/A	N/A	1.61	3.14*
Sample size	50	46	45	N/A	N/A	36	
Panel C: Zillow Home Price Expectations Survey							
Average expected growth rate (%)	1.26	0.46	-0.13	-0.18	1.39	4.19	13.28***
Std.dev. of predicted growth rates (%)	2.20	2.50	2.52	2.45	2.04	1.85	9.14***
Sample size	111	108	109	109	104	118	
Panel D: Case-Shiller House Price Index							
One-year growth rate (Nominal, %)	-0.47	1.39	4.05	7.59	9.04	7.97	

23 Anderson et al. (2009) use Beta-weighted variance of predictions of forecasters to measure the ambiguity in stock market. Here, we simply assume that the weight is even for all forecasters in the WSJ Economic Forecasting and Zillow/Pulsenomics surveys.

One-year growth rate (Real, %)	-2.71	-0.02	1.85	5.89	7.89	5.91

Note: The test-values are for the null hypothesis that there is no difference on values between the date with highest value and the date with lowest value. The test for "Std. dev. of predicted growth rates" it is a chi-square test, and the others are t-tests. N/A means that data is not available.

Similar to house prices, we calculate the naïve variance of predicted annualized growth rates for S&P 500 in the next 10 years in Survey of Professional Forecaster (SPF) data from the year of 2009 to 2016 and compare the variance of professional forecasts with the mean of individual δ_j estimated in our paper.[24] The blue line in Figure 4, which correspondences to the left y-axis, represents the mean of individual δ_j for one-year-ahead stock price over time estimated in our paper. The orange line, which correspondences to the right y-axis, represents the variance of professional forecasts on SPF. Both lines show that there is a downward trend on perceived ambiguity from 2009 to 2016, except that professional forecasts have a large ambiguity in the year of 2014.

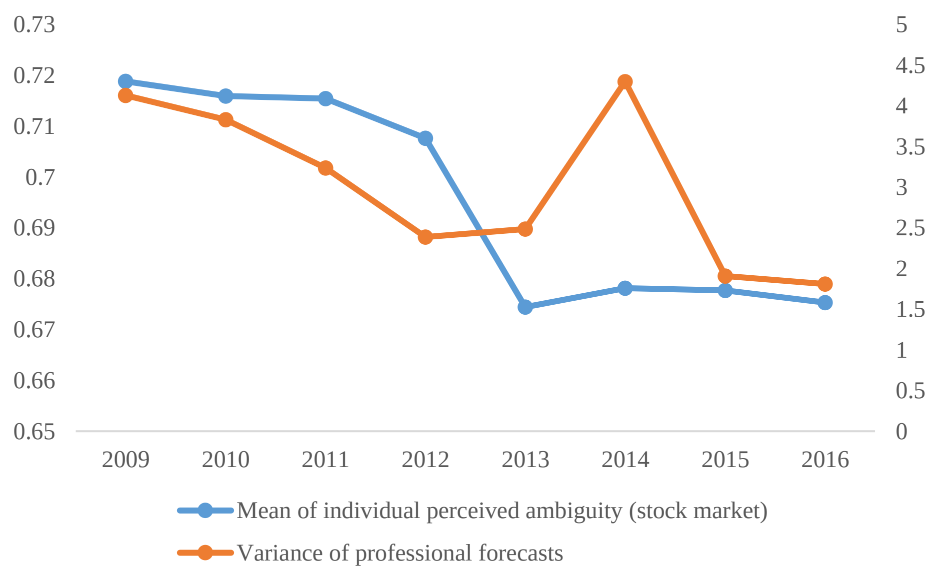

FIGURE 4: TIME-SERIES MEASURE FOR LEVEL OF PERCEIVED AMBIGUITY (STOCK PRICES)

24 Data available at: https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/data-files/stock10

Note: The predicted annualized growth rates about stock prices in SPF is for S&P 500 in next 10 years. Professional forecasts data is available at first-quarter surveys only, at which the professional forecasters are required to submit the predictions by middle February. The individual perceived ambiguity data estimated in our paper is for US stock prices next year, corresponding to the same time point of SPF.
Data source: American Life Panel (ALP), Rand Corporation; Survey of Professional Forecasters (SPF), Federal Reserve Bank of Philadelphia.

E. Price Change and Perceptions of Ambiguity

In this section, we test the effect of price information on individual's level of perceived ambiguity for house prices. We construct three sets of price information for house prices: price level and its lags, absolute growth rates and the variance of prices (volatility) within a time period. For the information of price level, we use the contemporary prices, one-year-lag prices, three-year-lag prices, five-year-prices and ten-year-lag prices. For absolute growth rates and the variance of prices, we use the price information for the past one year, three years, five years and ten years.

In ALP data, we are able to observe the residing state of each respondent. Therefore, we use the Case-Shiller house price index at state level to construct our house price information. We regress the individual level of perceived risk and level of perceived ambiguity on the house price information with the control of individual characteristics. Table 7 and 8 present the regression results with standardized coefficients of one-year house price information and three-year house price information. The house price information at 5-year and 10-year level are not significant, we thus don't report the results.

We find that people's perceptions of risk about house prices are positively affected by the absolute growth rates in recent one year, and perceptions of ambiguity about house prices are positively affected by the price volatility in recent one year and absolute price growth rates in recent three years. One standard deviation increase in the absolute house price growth rate in recent one year leads to 0.073 units increase in the level of perceived risk; one standard deviation increase in the house price volatility in recent one year leads to 0.020 units increase in the level of perceived ambiguity. Moreover, the lower the contemporary house price is and the higher past house prices is, the larger ambiguity people perceive.

TABLE 7—THE RELATIONSHIP OF PERCEIVED RISK AND AMBIGUITY WITH ONE-YEAR HOUSE PRICE INFORMATION

Dependent variable	Perceived risk			Perceived ambiguity		
	(1)	(2)	(3)	(4)	(5)	(6)
Contemporary house price (HP)	0.140			-0.102**		
	(0.280)			(0.048)		
One-year-lag HP	-0.219			0.106**		
	(0.274)			(0.048)		
Abs (one-year HP growth)		0.073*			0.006	
		(0.037)			(0.007)	
One-year HP volatility			0.026			0.020***
			(0.037)			(0.007)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	697	697	697	697	697	697
R^2	0.0633	0.0617	0.0571	0.9688	0.9686	0.9689

Note: Standardized coefficients are presented. Standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%

TABLE 8—THE RELATIONSHIP OF PERCEIVED RISK AND AMBIGUITY WITH THREE-YEAR HOUSE PRICE INFORMATION

Dependent variable	Perceived risk			Perceived ambiguity		
	(1)	(2)	(3)	(4)	(5)	(6)
Contemporary house price (HP)	-0.053			-0.042*		
	(0.120)			(0.022)		
Three-year-lag HP	-0.025			0.047**		
	(0.133)			(0.023)		
Abs (three-year HP growth)		-0.001			0.015**	
		(0.065)			(0.007)	
Three-year HP volatility			-0.002			0.010
			(0.031)			(0.007)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	697	697	697	697	697	697

R^2	0.0625	0.0565	0.0568	0.9687	0.9688	0.9686

Note: Standardized coefficients are presented. Standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%

However, we find that the effect of house price information on perceived risk and ambiguity is relatively smaller than the individual characteristics. The standardized coefficients of male indicator in the regression of perceived risk is 0.099, and the standardized coefficients of three education category variables are above 0.50. Similarly, in the regression of perceived ambiguity, the standardized coefficients of house price information are the smallest compared with other individual characteristics. These results show that people's perceptions of risk and ambiguity are mostly affected by individual characteristics, instead of past house price information.

III. The Effect of Ambiguity and Risk on Activities related to Housing and the Stock Market

In this section, we apply our estimated perceptions of ambiguity and risk to test the effect of the perceptions and attitudes on renter's purchase behavior, investors' stock market participation and their stock holdings if having a stock account. We use MP_{RA} elicited from Netspar Uncertainty attitude experiment to measure the attitude toward risk. Larger MP_{RA} represents more risk-seeking. We use *VAR(S)* obtained from EFC bins-and-balls experiment to measure the level of perceived risk about house prices and stock prices. Moreover, we use the normalized α_j and δ_j to measure the attitude toward ambiguity and perception of ambiguity. Greater α_j represents more ambiguity-averse and greater δ_j means that the individual perceives larger ambiguity. The α_j and δ_j are estimated for the house prices and the stock prices, separately. We also take interaction term between perceived ambiguity (risk) and attitude toward ambiguity (risk) to test if the effect of ambiguity (risk) is sensitive to people's attitude toward ambiguity (risk).

Because we have the panel data observing respondents' activities about housing and the stock market, we conduct fixed-effect analyses to test the effects. In the panel-data analysis, it is straightforward to estimate a δ_{jt} and an α_{jt} for every respondent at every period *t* based on equation (19') and (20') as long as their individual characteristics at time *t* are observable. Then, we estimate the risk perceptions variable (*VAR(S)*) and risk attitudes variable (MP_{RA}) over time based on the change of individual characteristics.

Because we only have observed risk variables at April 2012 (wave 38), we first estimate the variables of interest based on the change in the individual characteristics over time.

We first regress the two risk variables of interest on individual characteristics, respectively.

(26) $$RiskVar_{j,wave=38} = \beta_0 + X'_{j,wave=38}\beta_1 + \varepsilon_i$$

Here, $RiskVar$ represents two risk variables *VAR(S)* and MP_{RA}.

Then, we use the following method to estimate the risk variables by using the change in the individual characteristics over time:

(27) $$\widehat{RiskVar}_{j,t} = RiskVar_{j,wave=38} + (X'_{j,t} - X'_{j,wave=38})\hat{\beta}_1$$

We confess that the ambiguity and risk variables over time are "estimated", instead of being "observed". Therefore, further panel data with observed ambiguity and risk variables is highly demanded in the future.

Given the time-variant ambiguity and risk variables, our two-way fixed effects model is characterized as:

(28) $Y_{j,t} = \beta_0 + \beta_1 \delta_{j,t} + \beta_2 \alpha_{j,t} + \beta_3 Var(S)_{j,t} + \beta_4 MP_{RA_{j,t}} + X'_{j,t} + \gamma_{j,t} + T + \varepsilon_{j,t}$

Here, the dependent variable $Y_{j,t}$ includes the indicator of buying a house, indicator of having stock account and the amount of stock holdings for individual *j* in the period *t*. $\delta_{j,t}$ and $\alpha_{j,t}$ represent the perceptions of and attitudes toward ambiguity with regard to house (stock) prices, respectively. $Var(S)_{j,t}$ represents the perceptions of risk with regard to house (stock) prices and $MP_{RA_{j,t}}$ is the general attitudes toward risk. $X'_{j,t}$ is a vector of individual characteristics, $\gamma_{j,t}$ is the individual fixed effect and *T* represents the time fixed effect. $\varepsilon_{j,t}$ is the error term. The advantage of the two-way fixed effect is to cancel out the potential measurement error that may potentially exist in the estimated $\alpha_{j,t}$ we discuss in section E, if we assume that the measurement error is time-invariant. The intuition of the assumption is that individual measurement error between her matching probability in the gamble and that in house prices is time-invariant.

A. Purchase Behavior of Renters

We sample all renters below 35 years old who enter the survey with no house. We only sample their renting periods, which means that the renter enters the data when he doesn’t own any house, and are excluded from the data after s/he buys a house. There are 2,547 observations for 83 individuals, and 43 observations finished a purchase transaction during the sample periods between January 2009 and January 2016. Therefore, we use the 2,547 observations for the analysis on purchase behavior. The dependent variable equals to 1 if the renter purchases a house at current period.

Table 9 shows the two-way fixed-effect model on purchase behavior for renters who didn't have any house before entering the survey. It shows that only ambiguity-averse renters are less likely to buy a house, but perceptions of ambiguity, perceptions of risk and attitudes toward risk have no significant effect on the purchase behavior. Besides the ambiguity and risk variables, married, high-income, having retirement account and high-wealth are the variables significant and positively related to purchasing a house.

TABLE 9: THE EFFECT OF AMBIGUITY AND RISK ON PURCHASE BEHAVIOR

Dependent variable	Indicator of purchasing a house
Perceived ambiguity (δ)	-0.070
	(0.363)
Attitude toward ambiguity (α)	-0.096*
	(0.057)
Perceived risk (*Var(S)*)	-41.432
	(56.361)
Attitude toward risk (MP_{RA})	0.008
	(0.164)
Individual Fixed-effect	Yes
Wave Fixed-effect	Yes
Obs.	2,547
Within-group R^2	0.2230
Between-group R^2	0.0033
Overall R^2	0.0132

Note: Robust standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%.

B. Stock Market Participation and Stock Holdings of Investors

The panel data analysis estimates two-way fixed-effect models for stock market participation and the amount of stock holdings for stock owners. We sample 27,695 observations of the 697 individuals who took both EFC "bins-and-balls" questions and NU ambiguity attitude experiment. Among the 27,695 observations, 5,726 have a stock account with positive stock holdings. Table 10 shows the summary statistics of the stock market participation and stock holdings.

TABLE 10: SUMMARY STATISTICS OF STOCK MARKET PARTICIPATION AND STOCK HOLDINGS

Variable name	Obs.	Mean	Std.Dev.	Min	Median	Max
Stock market participation	27,695	0.289	0.453	0	0	1
Stock holdings	5,726	134,486.40	258,261.90	1	32,750	2,300,000

Based on the results in table 11, we find that ambiguity variables and risk variables have no effect on stock market participation. However, the table 12 shows that ambiguity-averse investors and investors who perceive larger risks tend to hold less stock, even though level of perceived ambiguity has no significant effect on stock holdings.

TABLE 11: THE EFFECT OF AMBIGUITY AND RISK ON STOCK MARKET PARTICIPATION

Dependent variable	Stock market participation
Perceived ambiguity (δ)	-0.2134
	(0.237)
Attitude toward ambiguity (α)	0.0103
	(0.034)
Perceived risk (*Var(S)*)	8.9849
	(14.039)
Attitude toward risk (MP_{RA})	-0.0066
	(0.133)
Individual Fixed-effect	Yes
Wave Fixed-effect	Yes
Obs.	27,695

Within-group R^2	0.0299
Between-group R^2	0.0932
Overall R^2	0.0721

Note: Robust standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%.

TABLE 12: THE EFFECT OF AMBIGUITY AND RISK ON STOCK HOLDINGS

Dependent variable	Amount of stock holdings (in thousand dollars)
Perceived ambiguity (δ)	253.52
	(160.45)
Attitude toward ambiguity (α)	-62.93**
	(26.00)
Perceived risk (*Var(S)*)	-7.38×10^4***
	(1.97×10^4)
Attitude toward risk (MP_{RA})	113.93
	(123.84)
Individual Fixed-effect	Yes
Wave Fixed-effect	Yes
Obs.	5,726
Within-group R^2	0.2358
Between-group R^2	0.0597
Overall R^2	0.0595

Note: Robust standard errors are in the parentheses.

***: significance at 1%;

**: significance at 5%;

*: significance at 10%.

IV. Conclusions and Discussion

This paper attempts to estimate the individual level of perceived ambiguity and attitude toward ambiguity with regard to future house and stock prices based on the internet survey of the RAND American Life Panel (ALP). We follow the theoretical framework of multiple prior models and the $\alpha-$MaxMin ambiguity preference, and link the results of two experiments from the ALP to estimate two important parameters in the framework: $1-\delta$, which measures the degree of confidence in an individual's reference prior distribution of future prices; and α, which measures the degree of ambiguity aversion. This methodology can be applied to estimate the perceptions of and attitudes toward ambiguity related to other economic factors of interest with two simple experiments.

We estimate a representative agent model without controlling for individual characteristics and a heterogeneous agents model by allowing δ and α to vary across individual characteristics. The results of the representative agent model show that the degree of confidence in the reference prior distribution for the U.S. house prices one year forward is 39.5 percent and the attitude toward ambiguity, α, is 0.411, slightly ambiguity-seeking. This result is close to the result of the heterogeneous agents model, in which the average degree of confidence of the respondents, $1 - \delta$, is 45.9 percent, and the average degree of ambiguity aversion, α, is 0.432.

In addition, we test the relationship of individual characteristics with attitudes toward and perceptions of ambiguity, and perceptions of risk about future house prices. The results show that: 1) ambiguity aversion toward house prices is associated with lower age and worse health; 2) the following individual characteristics are positively correlated with the level of perceived ambiguity about house prices: greater age, male, income, advanced educational attainment, Black, having retirement account, greater household size, greater wealth, and better health. The individual characteristics that are negatively correlated with the level of perceived ambiguity are married, White, Hispanic, employed, and greater financial literacy.

Moreover, we find that the state-level house price volatilities in the past one year and the absolute growth rates in the past three years have a positive effect on the perceptions of ambiguity with regard to future house prices.

We then apply our estimation of individuals' perceptions of and attitudes toward ambiguity and risk to test their effects on renters' purchase behaviors. The results of the fixed effects model indicate that ambiguity-averse renters are less likely to buy a house.

These results offer an additional explanation for the dramatic decrease in housing purchases by young adults after the financial crisis from the demand perspective. Existing literature based on the perspective of credit supply attributes the phenomenon to the inadequacy of credit available to young people wishing to buy a house. Our results provide an alternative explanation to the above phenomenon from the perspective of housing demand: young renters are ambiguity-averse toward house prices, which dampens their incentives to buy a house after the financial crisis.

We also apply our method to estimate the level of perceptions of and attitudes toward ambiguity with regard to stock prices one year forward. The results show that US citizens perceive greater ambiguity about stock prices than house prices, and display ambiguity-averse toward stock prices. Moreover, ambiguity has no effect on stock market participation, but ambiguity-averse stock investors tend to hold less stocks.

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