Information Ambiguity, Market Institutions and Asset Prices: Experimental Evidence*

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Abstract

This paper explores how information ambiguity and traders' attitudes toward ambiguity influence investment decisions and asset prices in three different types of experimental asset markets. Our experiment focuses on the prediction of Epstein & Schneider (2008) that information ambiguity will lead market prices to overreact to bad news and to underreact to good news. We find that such an asymmetric reaction to bad/good news is strongest in individual prediction markets. It occurs to a lesser extent in single price call markets, and is weakest of all in continuous double auction markets. While we find asymmetric reactions at the individual trader level in the double auction market, the lack of an overall asymmetric reaction to bad/good news is due to the fact that the asymmetric reaction on the buyers' side cancels the (opposite) asymmetric reaction on the sellers' side.

Keywords: Ambiguity Aversion, Information Ambiguity, Asset Bubbles, Experimental Finance, Signal Extraction

JEL Classification: C91, C92, D82, G12, G40

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1 Introduction

Participants in financial markets confront many signals about market fundamentals every day. How should they process these signals? According to Epstein & Schneider (2008), agents take the quality of the signals into account when processing the information. They assign more weight to signals from a reliable source and less weight to signals from obscure sources. The variance of a signal serves as a measure of its quality. The quality of a signal is high (low) when the variance of that signal is small (large). While the variance of a signal can be considered as known when it comes from a source with a track record (e.g., earnings reports), there are also ***ambiguous*** signals from previously unknown sources for which the variance may be unknown, (e.g., social media, blogposts). Epstein & Schneider (2008) suggest that when faced with such ***information ambiguity***, investors who are ambiguity averse behave as if they maximize expected utility under a worst-case belief as in Gilboa & Schmeidler (1989) about the quality of the ambiguous signal. Thus, if there are ambiguity averse investors, there will be an asymmetric reaction to ambiguous signals: bad signals that convey information that the realized dividend is lower than the prior will be treated as if they are more accurate (have smaller variance) than good signals conveying that the realized dividend is higher than the prior and ambiguity-averse agents will allocate higher weight to the bad signals when making decisions.[1] Since signals matter for asset price determination, the volatility of asset prices should be greater under ambiguous signals.

The theory that Epstein & Schneider (2008) develop makes use of a representative agent asset pricing model. In this paper, we report on the results of an experiment that tests the implications of Epstein and Schneider's theory under three different market institutions: an individual prediction market, a single price call market, and a continuous double auction market. We consider three different market institutions for asset price determination, since the particulars of the market structure are not considered in Epstein & Schneider (2008)'s representative agent framework. Nevertheless, as we show, the market institution matters for whether we observe an asymmetric reaction to bad or good news.

In our view, the theoretical predictions of Epstein & Schneider (2008) are three-fold. (1) Ambiguity averse participants' ***perceived variance*** of an ambiguous signal is smaller when it conveys ***bad news*** than when it conveys good news. Therefore, (2) ambiguity averse participants allocate a larger weight to signals that convey bad news than to signals that convey the good news. It follows that (3) the ***volatility*** of prices is greater when signals are ambiguous than when they are unambiguous.

[1]Note that in Epstein & Schneider (2008), agents are modeled as net buyers of the asset. Therefore, a higher (lower) dividend is good (bad) news for them. However, a higher (lower) dividend is bad (good) news for a net *seller*, e.g., in a double auction market. We will discuss this difference in further detail in the section on the double auction treatment.

To test these predictions, we design a two-stage experiment. In the first stage, participants' attitudes toward ambiguity are measured, along with measures for their risk aversion. Then, in the second stage, they participate in one of the three different types of experimental asset markets as discussed above where they receive noisy (un)ambiguous signals about the fundamental value of an asset, enabling us to see how they weight such information and how traded prices vary with the ambiguity of the information received.

In the first stage, we measure the participants' ambiguity attitudes using a classic two-color urn choice task following Ellsberg (1961), that is widely used in the literature, e.g., Trautmann et al. (2008), Kocher & Trautmann (2013), Trautmann & Van De Kuilen (2015). Specifically, participants are asked to make a number of choices between pairs of boxes (urns). The "K" or "known" box in each pair has known numbers (or fractions) of purple and orange balls. The "U" or "unknown" box in each pair has unknown numbers (or fractions) of purple and orange balls. Subjects are instructed that if a purple ball is drawn from the box they chose, they will win a positive money amount, and they earn 0 otherwise. Using this task, we find that more than 66% of our participants can be labeled as "ambiguity averse", around 23% are "ambiguity neutral", and the remaining approximately 10% are "ambiguity seeking". Thus, the degree of ambiguity aversion is heterogeneous across participants in our experiment.

In the second stage, depending on the treatment, participants need to predict the fundamental value of an asset based on two signals, a public signal and a private signal and then possibly trade the asset with other participants under a given market institution. The public signal is the known-to-all information that the fundamental value of the asset (more precisely, the dividend realization) is a random variable drawn from a particular normal distribution. The private signal, s, is equal to the actual (but unknown) realization of the fundamental value of the asset, plus some mean zero, normally distributed noise. Thus, the private signal is normally distributed with a mean equal to the realization of the fundamental value in each period and a variance that is known to change every 5 periods. The private signal is *un*ambiguous in the first 15 periods. The variance of the private signal is 1 in periods $1-5$, then $0:25$ in periods $6-10$, and 4 in periods $11-15$. In the last 5 periods, the signal becomes *ambiguous*. In those final five periods, $16-20$, the variance of the signal lies somewhere between $0:25$ and 4, but the actual value of the variance and its distribution is unknown to market participants. We have the subjects start out facing unambiguous private signals in the first 15 rounds because forming expectations with unambiguous signals is easier, and this also provides subjects with the opportunity to learn about the different variances that are possible in the final 5 periods of the ambiguous setting as well as practice with how to form expectations using the two signals (the public and the private signals). Differently from Bleaney & Humphrey (2006), Halevy (2007), Bossaerts et al. (2010), etc., our experiment uses the ***variance*** of the private signal to characterize the ambiguity of the signal information rather than different probabilities in the returns to the asset. We understand that in the literature on risk and uncertainty, situations with unknown variances are sometimes viewed as a compound lottery or a lottery with higher-order risk, e.g., Machina (1989), Miao & Zhong (2012), Noussair et al. (2014), Huang et al. (2020) etc. We stick with the terminology "ambiguous signals" and "information ambiguity" in our paper, following the same language used by Epstein & Schneider (2008). To the best of our knowledge, this is also the first work on financial ambiguity in terms of the variance of signals instead of the probabilities of outcomes. After the subjects submit their predictions and trading decisions, the fundamental value of the asset is revealed. Subjects' payoffs are calculated based on their predictions or trading decisions and the true fundamental value of the asset.

Our experimental results confirm most of the theoretical predictions of Epstein & Schneider (2008). We find that ambiguity averse subjects predict a higher variance for the ambiguous signal. Additionally, ambiguity averse individuals overestimate the variance of good news relative to bad news when the signal is ambiguous. This asymmetric reaction is strongest in the individual prediction market design (Treatment I), less present in the call market design (Treatment C) and weakest in the double auction markets (Treatment DA). Indeed, the asymmetric reaction at the individual trader level also prevails in the double auction markets. The absence of an asymmetric response to bad or good news in the double auction market is due to the fact that the asymmetric reaction on the buyers' side cancels the (opposite) asymmetric reaction on the sellers' side. Finally, we also find a larger mispricing of the asset and greater price volatility when the signal is ambiguous than when it is unambiguous in Treatment I and Treatment C.

Our results provide strong support for the notion that information ambiguity and ambiguity attitudes play an important role in financial market decision-making. The comparison between the three market institutions in our experiment also provides useful insights as to how information ambiguity will influence the market quality and informational efficiency of different market settings and provides useful implications for market regulators and designers of market institutions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the experimental design. Section 4 discusses the experimental results. Section 5 concludes.

2 Literature Review

This study complements and extends previous research on the role of ambiguity and information ambiguity in financial markets in a number of ways.

There have been several seminal studies since the 1990s, e.g., Sarin & Weber (1993), Chen & Epstein (2002), that have addressed the role of ambiguity for assessments of the fundamental value of an asset that have used both decision-theoretic and market-based approaches. A general conclusion from this literature is that ambiguity robustly leads to a ***lower*** price of the asset (the "ambiguity premium") in individual decision-making experiments. In market experiments, the evidence is mixed. While ambiguity unambiguously leads to lower prices under a single price call market mechanism, some studies find that ambiguity also leads to lower prices under a continuous double auction trading mechanism while other studies do not.

Investigations of the role of ***information ambiguity*** for asset pricing, the subject of this paper, are more recent, and most of these studies employ an individual decision-making rather than a market-based framework. A general conclusion from these studies is that, as Epstein & Schneider (2008) predict, subjects overreact to bad news and underreact to good news. To our knowledge, Corgnet et al. (2012) is the only other study that investigates information ambiguity in double auction markets. They find information ambiguity does not seem to lead to lower asset prices.

Table 1 summarizes the studies in the literature that are most closely related to this paper. Our findings complement these prior studies in several ways: (1) in terms of the role of information ambiguity in individual decision-making asset pricing experiments, we find that the theoretical prediction of Epstein & Schneider (2008) also holds in our prediction market institution (using a learning to forecast experimental (LtFE) design) where individuals make only a point prediction for the asset price. (2) The Epstein & Schneider (2008) prediction is weaker under the single price call market institution and is weakest of all in the continuous double auction market, which is consistent with the absence of an effect of information ambiguity in such markets as reported by Corgnet et al. (2012)

Our double auction treatment differs from Corgnet et al. (2012) in several important ways. First, the data generating process in our paper is the same as that of Epstein & Schneider (2008) while theirs departs from Epstein and Schneider in several ways. Second, they study the role of public signals while we focus on ambiguous private signals. Third, they focus on double auction markets while we study the role of information ambiguity in double auction markets, call markets and individual prediction markets. Our results show that information ambiguity leads to a bias in belief updating in individual decision-making problems and to a lesser extent in the call market, while the role of ambiguous information is very limited in double auction markets. Together with the findings from the literature on ambiguity, it seems that the impact of both ambiguity and information ambiguity tend to be more pronounced in individual decision problems, and less so in large, decentralized markets like double auction markets.

In addition, our paper is also related to several strands of the theoretical and empirical literature on the role of ambiguity in asset markets. Theoretical research has investigated how ambiguity aversion leads to asymmetric market reactions to different kinds of information. Zhang (2006) finds that greater information uncertainty leads to higher expected returns following good news and lower expected returns following bad news. Caskey (2008) shows that ambiguity averse investors can result in persistent mispricing of assets. Ambiguity averse investors work to reduce ambiguity at the expense of information loss, which can explain underreaction and overreaction to accounting accruals. Li & Janssen (2018) find that the disposition effect, the reluctance to realize losses and the eagerness to realize gains, can lead investors to underreact to private signal realizations about an ambiguous asset. There is a lot of empirical and theoretical research on ambiguity and asset pricing, e.g., Chen & Epstein (2002), Cao et al. (2005), Gollier (2011), Illeditsch (2011), Jeong et al. (2015), Gallant et al. (2015), Bianchi & Tallon (2018), Brenner & Izhakian (2018). Much of this literature argues that ambiguity aversion leads to a higher equity premium in asset markets. In addition, some studies have shown that ambiguity has an impact on asset prices and volatility.

Finally, our paper contributes to the literature on belief updating about public signals and private signals, e.g., Heinemann et al. (2004), Boswijk et al. (2007), Eil & Rao (2011), De Filippis et al. (2017), Duffy et al. (2018), Enke & Zimmermann (2019), Diks et al. (2019), Hommes et al. (2020), and to the literature on belief updating under compound uncertainty and ambiguity, e.g., Klibanoff et al. (2009), Corgnet et al. (2012), Ert & Trautmann (2014), Moreno & Rosokha (2016), Hanany & Klibanoff (2019), Huang et al. (2020). Our work is distinguished from these papers by allowing belief updating of the ***variance*** of signals rather than the mean of signals.

Table 1
This table summarizes the most related studies in the literature to this paper.

Authors	Setup	Market Design	Type of Ambiguity	Ambiguous Signal	DGP	Result
Sarin & Weber (1993)	Individual Decision	Sealed Bid Auction	Ambiguity		Binary	ambiguity leads to lower prices
	Market Experiment	Double Auction	Ambiguity		Binary	ambiguity leads to lower prices
Chen & Epstein (2002)	Individual Decision	Sealed Bid Auction	Ambiguity		Binary	ambiguity leads to lower prices
Ahn et al. (2014)	Individual Decision	Portfolio Choice	Ambiguity		Binary	most subjects seem to be expected utility maximisers while few exhibit high level of ambiguity seeking/aversion in an individual portfolio choice experiment
Bossaerts et al. (2010)	Market Experiment	Double Auction	Ambiguity		Binary	ambiguity does influence portfolio holding by individual investors and the market price
Füllbrunn et al. (2014)	Market Experiment	Call Market	Ambiguity		Binary	ambiguity leads to lower asset prices
	Market Experiment	Double Auction	Ambiguity		Binary	ambiguity leads to lower asset prices
Epstein & Halevy (2019)	Individual Decision	Sealed Bid Auction	Information Ambiguity	Private Signal	Binary	compared to risky signals, subjects have more di□culty updating their beliefs based on ambiguous signals
Liang (2019)	Individual Decision	BDM Mechanism	Information Ambiguity	Private Signal	Binary	information ambiguity leads to overreaction/underreaction to bad/good news
Corgnet et al. (2012)	Market Experiment	Double Auction	Information Ambiguity	Public Signal	Binary	information ambiguity does not lead to over- or underreaction to signals
This paper	Individual Decision	Prediction Market	Information Ambiguity	Private Signal	Gaussian	information ambiguity leads to strong overreaction/underreaction to bad/good news
	Market Experiment	Call Market	Information Ambiguity	Private Signal	Gaussian	information ambiguity leads to mild overreaction/underreaction to bad/good news
	Market Experiment	Double Auction	Information Ambiguity	Private Signal	Gaussian	information ambiguity does not lead to over- or underreaction to signals

3 Experimental Design

Our experiment consists of three types of experimental markets, namely, the individual prediction market (Treatment I), the single price call market (Treatment C), and the continuous double auction market (Treatment DA). We adopt a two-stage design for each treatment. In the first stage (Part 1), participants' attitudes towards ambiguity are measured along with measures for their risk aversion. Then, in the second stage (Part 2), they participate in an experimental prediction or asset market. The design of Part 1 is the same for all treatments, while the design of Part 2 is different for each treatment.

We recruited 191 undergraduates from Nanyang Technological University as participants in this experiment. Subjects were from various areas of study, but were primarily economics majors. They were awarded a guaranteed show-up fee, 3 Singapore dollars (SGD), and additional earnings based on their performance in the experiment. Table 2 summarizes the number of subjects per treatment, the size of each market in terms of participants, the total number of markets, the average duration of a session of each treatment, and the average payment that each subject received. Note that in the two market treatments, each market involves six participants (both treatment C and Treatment DA).

Table 2
This table summarizes for each treatment, the number of subjects, markets, the average duration of a session of each treatment and the average payments that subjects received

	Treatment I	Treatment C	Treatment DA
Market size	1	6	6
Number of markets	41	15	10
Number of subjects	41	90	60
Average session hours	1.5 hours	1.5 hours	2 hours
Average payoff	23 SGD	19 SGD	22 SGD

3.1 Part 1

We categorize participants using the same method used by Trautmann et al. (2011), Trautmann & Van De Kuilen (2015), Sutter et al. (2013), into "ambiguity averse" types and "non-ambiguity averse" types; the latter can be further divided up between "ambiguity neutral" and "ambiguity seeking" types as well. To ascertain ambiguity attitudes, subjects are asked to make a set of 10 choices between two boxes, Box K and Box U. Each of the two boxes contains 100 balls. The color of the balls is either purple or orange. The numbers (and hence the fraction) of purple and orange balls are ***known*** in Box K, as the subjects can see the numbers of purple and orange balls (and hence the fraction of purple and orange balls) on their computer screen. The numbers (and hence the fraction) of purple and orange balls are ***unknown*** in Box U. After the subject chooses a box (K or U), one ball is drawn randomly from the selected box. Subjects are instructed that they will earn 3 SGD if a purple ball is drawn. Thus, the information about the probability of winning 3 SGD is certain for Box K, while it is ambiguous for Box U. Each of the ten choices between Box K and Box U appears in a single row on the subject's decision screen. From the top row to the last row, the fraction of purple balls in Box K decreases from 100% to 0% with a step decrease of 10%. The participant must choose between Box K or Box U in each of the ten rows. If the participant switches her/his choice from Box K to Box U when the fraction of purple balls in box K is more than 50%, then s/he is ambiguity seeking. If the participant switches her/his choice from Box K to Box U when the fraction of purple balls in Box K is exactly 50%, then s/he is ambiguity neutral. Finally, if the participant switches her/his choice from Box K to Box U when the fraction of purple balls in Box K is less than 50%, then s/he is ambiguity averse.

In addition to eliciting ambiguity aversion, we also use a simplified version of the Holt & Laury (2002) paired lottery choice task to elicit subjects' risk attitudes in a post-experiment survey. Subjects were asked to choose between option A (1 SGD for sure) and option B (3 SGD with probability X and 0 with probability $1 - X$) in each row and for ten sequential rows. From the top row to the last row, the probability of winning 3 SGD increases from 0 to 90% with a step of 10%. The participant can choose between Option A or Option B in each row. If a subject switches from option A to option B when the probability of receiving 3 SGD is larger than 40%, then s/he is risk averse. If the subject switches from option A to option B when the probability of receiving 3 SGD is 40%, then s/he is risk neutral. If the subject switches from option A to option B when the probability of receiving 3 SGD is smaller than 40%, then s/he is risk seeking.

One row is randomly drawn from the ambiguity aversion elicitation task in Part 1 and from the risk aversion elicitation task in the post-experiment survey. The subject's choices for those two rows determine their payoffs. That is, both the ambiguity and risk aversion elicitation tasks are incentivized.

3.2 Part 2

The second part of our experiment is based on the the theoretical framework of Epstein & Schneider (2008), which we briefly review here. Ex-ante, there is no ambiguity in the information that each agent receives. In each period t, each agent is told that the dividend, δ_t, on an asset is a random variable that is drawn from a normal distribution with mean m and variance, σ^2, that is, $\delta_t \sim i.i.d.N(m, \sigma^2)$.

Then, in the ambiguous information setting of Epstein & Schneider (2008), prior to trade in the asset, each agent gets a noisy private signal, s_t, about the likely value of θ_t in this period. Specifically, each agent gets a signal

$$s_t = \theta_t + \epsilon_{i;t};$$

where $\epsilon_{i;t} \sim i.i.d.N(0; \sigma_s^2)$, $\sigma_s^2 \in [\underline{\sigma}_s^2; \overline{\sigma}_s^2]$.

Rational agents would then update their beliefs about θ using Bayes' Rule to obtain a family of posteriors:

$$\theta_t \sim N(m + \frac{\sigma^2}{\sigma^2 + \sigma_s^2}(s - m); \frac{\sigma^2 \sigma_s^2}{\sigma^2 + \sigma_s^2});$$

where $\sigma_s^2 \in [\underline{\sigma}_s^2; \overline{\sigma}_s^2]$.

Following Epstein and Schneider's approach, in each period, agents form their expectations of the dividend of the asset by solving an expected utility maximization problem that uses the worst-case belief about θ chosen from the posteriors. After a signal has arrived, agents respond asymmetrically. For example, when evaluating an asset whose fundamental value is an increasing function of θ, the agent will use a posterior that has a lower mean. Therefore, if the news about θ is "good", specifically if $s > m$, then the agent will evaluate the signal as imprecise ($\sigma_s^2 = \overline{\sigma}_s^2$), while if the signal about θ is bad (i.e., if $s < m$), then the agent will view the signal as reliable ($\sigma_s^2 = \underline{\sigma}_s^2$). As a result, the agent discounts the impact of good news and overestimates the impact of bad news.

In Part 2 of our experiment, there are two types of signals about the asset, a "public" signal and a "private" signal. The public signal is the information about the mean, m and variance, σ^2 of the random dividend variable, θ. For simplicity, we assume that $\theta_t \sim i.i.d.N(m; 1)$, so that $\sigma^2 = 1$, and this information is what is publicly known.

There is also a private signal $s_{i;t}$, which is known to be equal to the realized value of θ_t in each period t plus a normally distributed, mean zero error term, $\epsilon_{i;t}$. The private signal, $s_{i;t}$, is thus normally distributed with a mean realized value of θ_t and a variance of $\sigma_{s;t}^2$. The signal, $s_{i;t}$, is randomly generated in each period and is different for different subjects. Based on the value of the parameter, $\sigma_{s;t}^2$, there are four scenarios in Part 2. The first three scenarios are associated with a constant and known value for $\sigma_{s;t}^2$, and thus correspond to the case of *un*ambiguous information. In the last scenario, the *ambiguous* information scenario, subjects only know that $\sigma_{s;t}^2 \in [\underline{\sigma}_s^2; \overline{\sigma}_s^2]$, but *not* the realized value of $\sigma_{s;t}^2$. Each scenario consists of 5 periods.

In the first three scenarios or $t = 1, 2, \ldots, 15$ periods, the value of $\sigma^2_{s,t}$ is known to subjects and takes on the following values:

$$\sigma^2_{s,t} = \begin{cases} 1, & t \in [1, 5]. \\ 0.25, & t \in [6, 10]. \\ 4, & t \in [11, 15]. \end{cases}$$

If subjects use the signal extraction model, their expectation of θ in each period should be

$$E(\theta_t) = \frac{\sigma^2_{s,t}}{\sigma^2 + \sigma^2_{s,t}} m + \frac{\sigma^2}{\sigma^2 + \sigma^2_{s,t}} s_t \tag{1}$$

Given the public information that $\sigma^2 = 1$, it follows from Equation (1) that the weight assigned to the private signal should be 1/2 in Scenario 1, 4/5 in Scenario 2, and 1/5 in Scenario 3 when subjects are making their decisions based on the two signals (public and private).

In Scenario 4, the final 5 periods, $t = 16, \ldots, 20$, $\sigma^2_{s,t}$ is uniformly distributed between 0.25 and 4 and redrawn in each period. Namely,

$$\sigma^2_{s,t} \sim i.i.d.\ U(0.25, 4)$$

The subjects do not know that the variance is uniformly distributed; they only know the upper and lower bounds of $\sigma^2_{s,t}$. They also do not know the realized value of the variance at the beginning of each period.

Based on the theoretical predictions of Epstein & Schneider (2008), we formulate the following testable hypotheses for our experiment.

Hypothesis 1 : People are more likely to overestimate the variance of the private signal, $\sigma^2_{s,t}$ when the signal is ambiguous, and more ambiguity averse subjects are more likely to do so.

Hypothesis 2 : When the signal is ambiguous, people overweight the variance of the private signal s when $s > m$, and underweight the variance of the private signal s when $s < m$, and ambiguity averse subjects are more likely to do so.

Hypothesis 3 : There is greater mispricing of the asset under ambiguous signals than under unambiguous signals.

Part 2 consists of two tasks, task 1 is about making predictions about the fundamental value of the asset based on the two signals (and in the two market treatments, trading on that information) while task 2 consists of making a prediction of the variance of the private signal in Scenario 4.

The asset lives for one period in all three treatments. Thus the realization of the dividend on the asset represents the asset's fundamental value. Task 1 is an individual prediction task that is paid based on subjects' prediction accuracy and is the same across all three treatments, while task 2 (trading the asset) is determined by the market institution in place in each treatment and is detailed as follows.

Treatment I: We employ a learning to forecast experimental (LtFE, Marimon et al. 1993, Hommes et al. 2005, 2008) design where participants submit their prediction about the fundamental value of the asset. Upon receiving the public and private signals, the participants make their predictions about the fundamental value of the asset, and their payoff is determined by their prediction accuracy. That is, a subject earns more the closer is her/his prediction to the fundamental value of the asset. This treatment is a purely individual decision-making treatment, where each participant's payoff is determined by their own performance alone.

Treatment C: We use a very simple call market mechanism (Akiyama et al., 2017) to determine the single market price of the asset in each period. The participants choose the weight allocation between the public signal and the private signal to make their prediction about the fundamental value of the asset.[2] After subjects submit the weight assigned to the private signal, w, the weight assigned to the public signal is calculated as $1 \quad w$, and the implied prediction of the fundamental value, which is a linear combination of the private and public signals, is determined for each of the 6 subjects in treatment C. The market is automatically cleared at a price equal to the *median* of all 6 subjects' implied predictions for the fundamental value of the asset. If the prediction of subject A is below the market clearing (median forecast) price, then one unit of the asset will be sold by her/him to the other subjects whose prediction is greater than the market clearing price. In this case, subject A is a seller earning a profit of $market\,price \quad realized\,dividend$. Otherwise, if the prediction of subject A is above the market clearing (median forecast) price, then s/he will be a buyer earning a profit of $realized\,dividend \quad market\,price$.

Treatment DA: We use the continuous double auction market mechanism (Smith et

[2]We tried to stay as close to the model setup of Epstein and Schneider (2008) as possible in Treatment C. When we ran Treatment I and DA, we find choosing weights may appear to be "unnatural" in prediction markets and especially in the double auction market. Besides, having a weight allocation phase may be very interrupting and make an experimental session in Treatment DA extremely lengthy. Therefore, we adopt the more "natural" setting of submitting point predictions and price quotes in Treatment I and DA, respectively.

al., 1988) for subjects to trade with other market participants in each period. Upon receiving both the public and private signals about the fundamental value of the asset, the participants had 2.5 minutes (150s) to submit bid offers to buy the asset and/or ask offers to sell the asset. They could also buy/sell assets by accepting another trader's bid/ask offer and withdraw their submission as well. The participants could buy or sell one unit of the asset at a time, and they could trade with others as long as they had enough money or units of assets in their account. Borrowing or short-selling was not allowed. Subjects could observe the outstanding bids and asks of other market participants, the executed market prices, and the price of the asset they sold and/or purchased in the market. Their payoff was determined by their trading performance and the true value of the asset at the end of each period. The instructions and more information about the double market design are presented in Appendix A.

Our consideration of three different institutions for valuation of the uncertain asset was intended to test whether the market institution matters for the theoretical predictions of Epstein & Schneider (2008):

Hypothesis 4 : Hypotheses 1-3 hold, regardless of whether individual prediction markets are used or the asset is traded in a single price call market or using a continuous double auction market.

4 Experimental Results

4.1 Results of Part 1

In this section, we describe the results from the first part of our experiment eliciting ambiguity and risk preferences, which we did at the start of all three treatments.

Following Wakker (2010), we define the "matching probability" as the known probability of winning (that is, the known fraction of purple balls in Box K) when the participant is found to be indifferent between Box K and Box U (the switchover point). For instance, suppose a subject switches from Box K when the winning probability is 20% to Box U, namely, for any winning probability below 20%, the subject prefers Box U. In that case, the subject's matching probability is 20%, which we take as the measure of the subject's ambiguity aversion. As noted earlier, the ambiguity neutral matching probability is 50%. A participant is regarded as ambiguity averse if her/his matching probability is below 50%, ambiguity neutral if her/his matching probability is equal to 50%, and ambiguity seeking if her/his matching probability is above 50%. We follow the same approach as (Dimmock et al. 2015, 2016) to measure the ambiguity preferences of our participants:

$$AM_i = 0{:}5 \quad p_i^M$$

where AM_i is the measure of ambiguity for individual i and p_i^M is the matching probability. The value of this measure will be positive if the individual is ambiguity averse, 0 if the individual is ambiguity neutral, and negative if the individual is ambiguity seeking [3].

The results from our ambiguity preference measure suggest that most of our participants are ambiguity averse, and a very small proportion of them are ambiguity neutral or ambiguity seeking. In treatment I, 65.85% (27 out of 41) of the participants are ambiguity averse, 26.83% (11 out 41) are ambiguity neutral, and 7.31% (3 out of 41) are ambiguity seeking. In treatment C, $66{:}67\%$ (60 out of 90) of participants are ambiguity averse, $22{:}22\%$ (20 out of 90) are ambiguity neutral, and $11{:}11\%$ (10 out of 90) are ambiguity seeking. Finally, in treatment DA, 70% (42 out of 60) of the participants are ambiguity averse, 20% (12 out of 60) are ambiguity neutral, and 10% (6 out of 60) are ambiguity seeking.

We also use the switching point method to measure individuals' attitudes towards risk aversion. We use the ordinality of the row where an individual switches from option A to option B to measure that individual's risk preferences. Participants are considered more risk averse if they switch at the row whose number is larger. A risk neutral participant would switch at row 5, where the probability of receiving 3 SGD is 40%. The results of our risk elicitation suggest that almost all of our participants are risk averse across all treatments. In treatment I, 63.41% (26 out of 41) of the participants are risk averse , 26.83% (11 out 41) are risk neutral, and 9.76% (4 out of 41) are risk seeking. In treatment C, 77.78% (70 out of 90) of them are risk averse, 21.11% (19 out of 90) are risk neutral, and 1.11% (1 out of 90) are risk seeking. Finally in Treatment DA, 71.67% (43 out of 60) of the participants are risk averse, 21.67% (13 out of 60) are risk neutral, and 6.67% (4 out of 60) are risk seeking.

Figure 1 shows cumulative distribution functions for the switching row of the risk attitude elicitation (top panel) and the ambiguity measure, AM (bottom panel) for each of our three treatments. Appendix B presents more details about the results of Part 1.

Interestingly, we do not find evidence of any correlation between ambiguity aversion and risk aversion.[4]

[3]Refer to Dimmock et al. (2016) for further details.

[4]We compare the measure of ambiguity preferences, and the risk elicitation among the three treatments

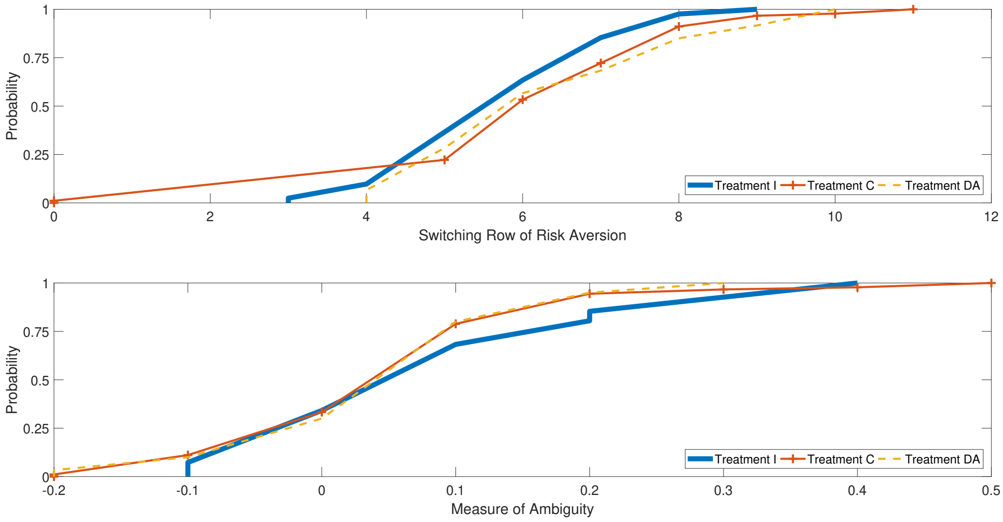

Figure 1: This figure depicts the cumulative distribution function of the switching row of risk attitude elicitation (top panel) and the measure of ambiguity (bottom panel) in each treatment. The x-axis is the value of the switching row (top panel) and measure of ambiguity (bottom panel), and the y-axis is the probability. The blue solid line is for Treatment I, the red line with the plus marker is for Treatment C, and the yellow dashed line is for Treatment DA. The participants are asked to make their choices for ten sequential rows. Some of them do not switch their choices (always chose the box with known probability) for the whole ten rows, so in that case we set the switch row as 11 for those participants.

by employing the Kruskal-Wallis H Test, and we do not find any significant difference in pairwise tests for difference across the three treatments ($^{2} = 0{:}918;\ p = 0{:}6319$ for AM, and $^{2} = 3{:}745;\ p = 0{:}1537$ for the results of risk elicitation).

4.2 Results of Part 2

In this section, we present the results of Part 2 of our experiment in the order of Treatment I, Treatment C, and Treatment DA.

Treatment I

Overestimation of the Variance of Ambiguous Signals

Following Epstein & Schneider (2008), we use subject's guesses (or expectations) about the variance of the private signal in Scenario 4 as a measure for their perceived noisiness of that signal. This method is applied to Scenario 4 in all three treatments. The mean variance expectation of the ambiguous signals is 1.7807 for ambiguity averse individuals, 1.5551 for ambiguity neutral individuals, and 1.7067 for ambiguity seeking individuals. Figure 2 illustrates the cumulative density functions of the variance predictions for ambiguous signals by the ambiguity averse/neutral/seeking subjects. Table C1 of Appendix C reports the descriptive statistics of the variance expectations under ambiguous signals conditional on a subjects' ambiguity classification type-averse, neutral or seeking. The variance expectation of ambiguity averse individuals is *significantly larger* than that of the ambiguity neutral individuals ($z = 1.848;\ p = 0.0646$)[5]. While we do not observe that ambiguity averse individuals have a larger variance expectation than ambiguity seeking individuals ($z = 0.673;\ p = 0.5009$), the ambiguity-seeking comprise the smallest grouping by ambiguity preference. Overall, ambiguity averse individuals have a higher variance expectation in Scenario 4 than non-ambiguity averse individuals ($z = 1.845;\ p = 0.0651$). [6]

Result I.1 *We do not reject Hypothesis 1. We find that ambiguity averse subjects tend to have a higher variance expectation for the ambiguous signal as compared with non-ambiguity averse subjects.*

Asymmetric Response to Ambiguous Signals

According to Epstein & Schneider (2008), after receiving an ambiguous signal, subjects

[5]We employ a nonparametric rank sum test to check whether the distributions of observations obtained between two separate groups on a dependent variable are systematically different from one another.

[6]A Kolmogorov–Smirnov test confirms that the variance prediction for ambiguity averse subjects is larger than for non-ambiguity averse subjects. The largest difference between the distribution functions in this direction is 0.1757 in Treatment I, -0.1067 in Treatment C, and -0.1254 in Treatment DA. The approximate asymptotic p-value for this difference is 0.058 (significant) in Treatment I, and 0.103 (marginally insignificant) in both Treatments C and DA.

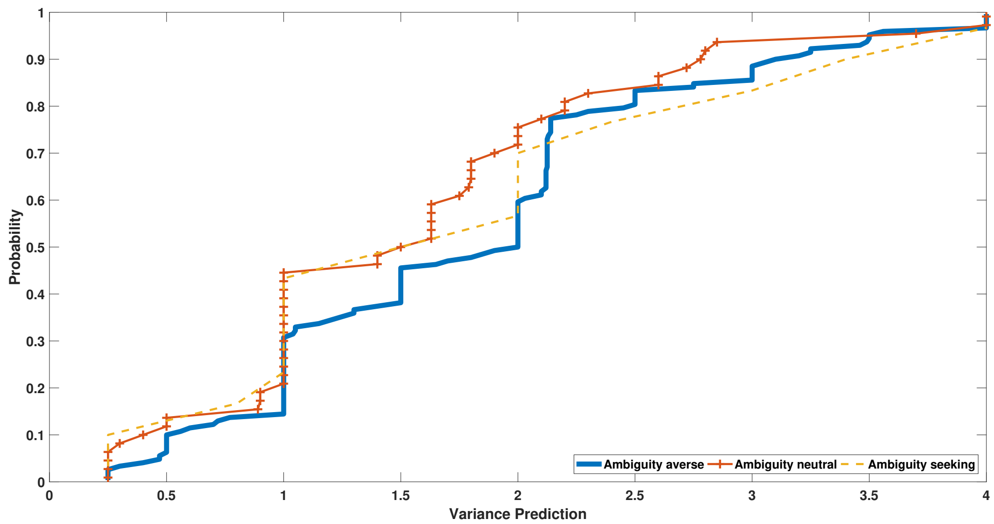

Figure 2: This figure plots the cumulative density function of the variance prediction for ambiguous signals by ambiguity averse subjects (blue solid line), ambiguity neutral subjects (red line with plus marker) and ambiguity seeking subjects (yellow dashed line) in Treatment I. The x-axis is the variance prediction for the ambiguous signals while the y-axis is the cumulative probability.

who are more ambiguity averse are more likely to overestimate the variance of the private signal s when that signal conveys good news (in our experimental setting, when $s > m$), and underestimate the variance of s when the signal conveys bad news (in our experimental setting, when $s < m$).

In other words, they will regard the good news as imprecise, expecting the variance of the ambiguous signal to be higher, and make their prediction far from the good news. On the contrary, they will regard the bad news as more precise, expect a lower variance for the ambiguous signal, and make their prediction closer to the bad news. Subjects are asked to make their predictions between the public signal and the private signal, which means that their prediction must be within the range of the public signal and the private signal. Their prediction of   is a linear combination of the public signal and private signal. Therefore, we could get the implied weight assigned to the private signals $\hat{w}^{implied}$ in the following way:

$$\hat{w}^{implied}_{i;t} = \frac{{}^{e}_{i;t} \quad m}{s_{i;t} \quad m} \tag{2}$$

where ${}^{e}_{i;t}$ is the individual's prediction of the divided , m is the public signal, which is 8 in Treatment I, and s is the private signal that the participant receives in each period.

Subjects will update their priors about the fundamental value of the asset using Bayes rule to obtain their posterior beliefs. Therefore, the theoretical prediction for the weight they assign to the private signal, $\hat{w}^{ss}$, can be written as:

$$\hat{w}^{ss}_{i;t} = \frac{\sigma^2}{\sigma^2 + \sigma^2_{s;t}} \tag{3}$$

Recall that in Part 2, σ^2, the variance of the public signal is perfectly known by subjects and equal to 1. The variance of the private signal, s, $\sigma^2_{s;t}$, in the first three unambiguous scenarios is also perfectly known to be 1, 0.25, and 4, respectively. Recall the theoretical prediction is that subjects should assign a weight of 0.5 to the private signal in Scenario 1, 0.8 in Scenario 2, and 0.2 in Scenario 3. In the experimental data, the mean (median) of the implied weight assigned to the private signal are 0.5043, (0.5) in Scenario 1, 0.7700, (0.7911) in Scenario 2, and 0.2175, (0.2161) in Scenario 3. Overall, we do not observe a significant difference between the implied weight assigned to the private signal and the theoretical prediction in Scenario 1 ($z = 0.573;\ p = 0.5664$). The implied weight assigned to the private signal in Scenario 2 is marginally significantly smaller than the theoretical prediction ($z = -1.833;\ p = 0.0669$). The implied weight assigned to the private signal in Scenario 3 is significantly smaller than the theoretical prediction ($z = -2.012;\ p = 0.0443$). We also check whether the implied weight assignment differs across subjects having different ambiguity attitudes for unambiguous signals. We do not observe a significant difference between the implied weight assignment and the theoretical prediction for ambiguity averse subjects when the signal is unambiguous (More details are reported in Table C2 of Appendix C).

To examine the asymmetric response to the ambiguous signals, we use the variance expectation as an independent variable to check how people evaluate ambiguous signals. If subjects respond to the ambiguous signals asymmetrically, they will give a lower variance expectation to bad news, and a higher variance expectation to good news. The top panel in Figure 3 reports the mean of subjects' variance expectations under ambiguous signals, differentiated according to whether the private signal is good news or bad news. The variance expectation for bad news tends to be lower than that for good news overall and across ambiguity types. The expected variance of bad news (1.5136) is significantly lower than the expected variance of good news (2.0599) among the ambiguity averse individuals ($z = -3.278;\ p = 0.0010$). This result *does not* hold for ambiguity neutral individuals according to the same test ($z = 0.542;\ p = 0.5875$), and also does not hold for ambiguity seeking individuals ($z = 0.099;\ p = 0.9208$). Overall, We observe a lower variance expectation for bad news signals and a higher variance expectation for good news signals ($z = -2.433;\ p = 0.0150$).

Second, we check the implied weight assigned to the private signal. If subjects respond to the ambiguous signals asymmetrically, they will give higher implied weight to bad news and lower implied weight to good news. We report the descriptive statistics of the implied weight assigned to the private signal in the bottom panel of Figure 3. On average, the implied weight assigned to the private signal is 0.4355 for bad news and 0.4085 for good news. We find that the implied weight assigned to bad news is significantly higher than that assigned to good news among ambiguity averse individuals ($z = 2.826; p = 0.0047$). We *fail* to find that ambiguity neutral individuals assign a higher implied weight to bad news than to good news ($z = \ 1.160; p = 0.2459$). Further, we find that ambiguity seeking individuals assign a significantly higher implied weight to *good* news rather than to bad news ($z = \ 1.887; p = 0.0591$). Overall, considering all types, we do not find a significantly higher implied weight assigned to bad news than to good news ($z = 0.875; p = 0.3817$). The detailed statistics are reported in Table C3. That is, the implied weight assigned to bad news is not significantly higher than the implied weight assigned to good news. We only observe that ambiguity averse subjects tend to allocate a higher implied weight to the bad news than to good news for the ambiguous signal. According to the signal extraction model, the variance expectation of the ambiguous signal and the implied weight assigned to the ambiguous signals should be equivalent to measure the asymmetric response to the ambiguous signals. In other words, if individuals expect the variance to be lower, they will assign a higher implied weight to the ambiguous signal, and vice versa. Thus, our experimental results suggest that ambiguity averse individuals tend to use the signal extraction model to update their beliefs for the ambiguous signal.

Result I.2 *We obtain supportive evidence for Hypothesis 2. We find that ambiguity averse participants learn the signal extraction model very well in Treatment I. The implied weight they assign to the unambiguous signal is consistent with theoretical predictions. When the signal is ambiguous, they underestimate the variance of bad news and overestimate the variance of good news. Also, their prediction is closer to the bad ambiguous signal than to the good ambiguous signal, which implies that the weight they assign to bad news is larger than the weight they assign to good news under ambiguous signals. Ambiguity averse individuals behave consistently for both the variance prediction and the prediction of the fundamental value under ambiguous signals.*

Result I.3 *We do not observe that ambiguity neutral and ambiguity seeking participants behave in the same manner as ambiguity averse participants. The former tend to overestimate the variance of bad news relative to good news, and assign a higher implied weight to good news, though we do not obtain significant evidence to support this finding.*

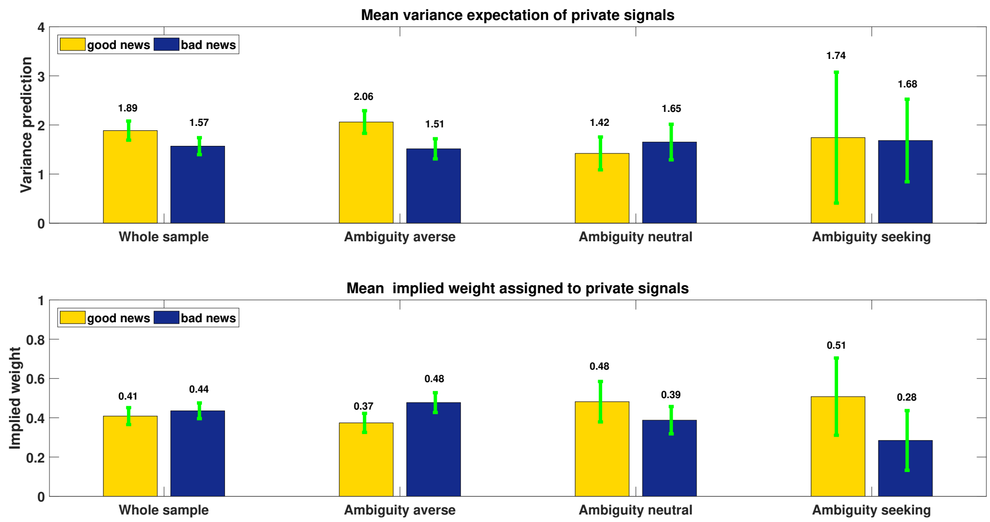

Figure 3: This bar chart depicts the mean variance prediction of the ambiguous signals in the top panel and the mean implied weight assigned to the ambiguous signals in the bottom panel. The yellow (light) bar is good news, and the navy (dark) bar is bad news. The x-axis reports on the whole sample as well as the subsamples of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The y-axis is the variance expectation of the ambiguous signals in the top panel, and the implied weight allocated to the ambiguous signals in the bottom panel. The green error bars show 95% confidence intervals.

Mispricing

We use a similar approach as Stöckl et al. (2010) to measure the mispricing of the asset in treatment I. Specifically, we use the relative deviation forecast (RDF) or the relative absolute deviation forecast (RADF) as mispricing measures. These two indicators measure the relative and relative absolute deviation of forecasts of the asset price from its fundamental value. The relative deviation forecast (RDF) and relative absolute deviation forecast (RADF) of the asset price for market k in period t are defined by:

$$RDF_{k;t} = \frac{p^{e}_{k;t} - p^{FV}_{t}}{p^{FV}_{t}}$$

$$RADF_{k;t} = \frac{|p^{e}_{k;t} - p^{FV}_{t}|}{p^{FV}_{t}}$$

Here, $p^{e}_{k;t}$ is the market price expectation for market k in period t, while p^{FV}_{t} is the fundamental value of the asset in period t.

We do not find that individuals are more likely to overestimate the fundamental value when the signal is ambiguous, but we find that the price expectation significantly deviates from the fundamental value of the asset under ambiguous signals as compared with

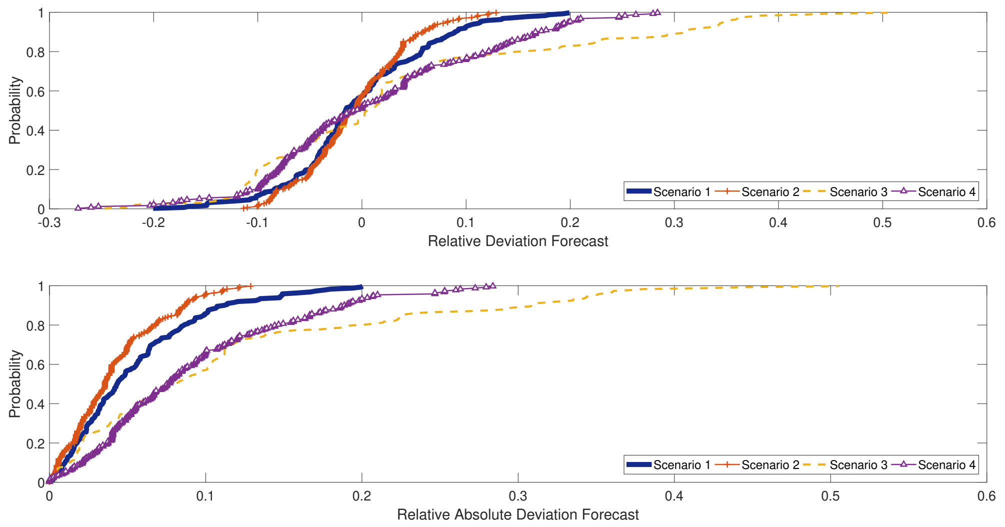

Figure 4: Figure 4 depicts the cumulative distribution function of the RDF (top panel) and RADF (bottom panel) in each scenario. The x-axis is the value of the RDF (top panel) and the RADF (bottom panel), and the y-axis is the probability. The purple dashed line with triangle marker is the RDF/RADF for Scenario 4 (ambiguous signals), the blue solid line is the RDF/RADF for Scenario 1, the red line with plus marker is the RDF/RADF for Scenario 2, and the yellow dashed line is the RDF/RADF for Scenario 3.

unambiguous signals. The mean RDF in the scenarios involving non-ambiguous signals is $0:0078$, while it is $0:0100$ in Scenario 4 with ambiguous signals. Also, the mispricing is larger when the signal is ambiguous. The men RADF is $0:0691$ in the scenario of non-ambiguous signals and $0:0904$ for the scenario of ambiguous signals (refer to Table C4 in Appendix C for more information). The RDF under ambiguous signals is not significantly larger than that found under unambiguous signals ($z = 0:252;\ p = 0:8012$), and the different result in terms of RADF is significant ($z = 5:832;\ p = 0:0000$). Figure 4 depicts the cumulative distribution function of the RDF (top panel) and RADF (bottom panel) in each scenario. It shows that the median RDF is around 0 regardless of the types of signal.

Result I.4 *Hypothesis 3 gains support in Treatment I. Individuals' price expectation deviates significantly from the fundamental value of the asset under ambiguous signals relative to unambiguous signals.*

Our results in Treatment I show that when subjects form forecasts only, their variance prediction and the (implied) weight allocation become more consistent, and they exhibit an asymmetric reaction to good and bad news as predicted by Epstein and Schneider (2008) in both forecasting tasks. The mispricing is larger under ambiguous signals than under unambiguous signals.

Treatment C

Overestimation of the Variance of Ambiguous Signals

In treatment C, the mean variance expectation in Scenario 4 is 1:6073 for ambiguity averse individuals, 1:422 for ambiguity neutral individuals, and 1:4205 for ambiguity seeking individuals as reported in Table C5. Ambiguity averse subjects tend to *significantly overestimate* the variance of ambiguous signals as compared with non-ambiguity averse individuals (z = 1:849; p = 0:0645). The variance expectation of the ambiguity averse individuals is significantly higher than that of the ambiguity neutral individuals (z = 1:784; p = 0:0744). However, the expected variance of the ambiguity averse individuals is not significantly higher than that of the ambiguity seeking individuals (z = 0:934; p = 0:3503).

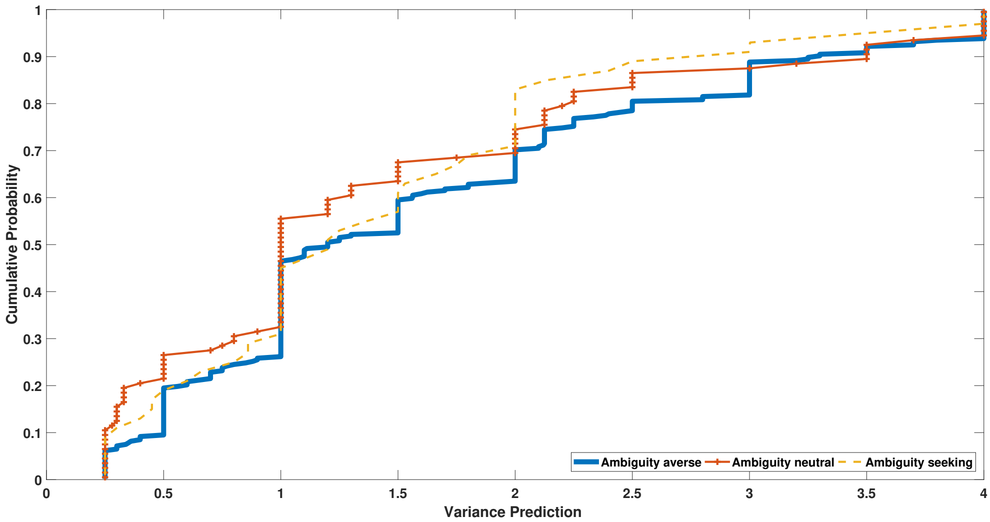

Figure 5: This figure plots the cumulative density function of the variance prediction for ambiguous signal by ambiguity averse subjects (blue solid line), ambiguity neutral subjects (red line with plus marker) and ambiguity seeking subjects (yellow dashed line) in Treatment C. The x-axis is the variance prediction for the ambiguous signals, and the y-axis is the probability.

Result C.1 : *Hypothesis 1 finds some support in Treatment C. There is a significant and positive relationship between ambiguity aversion and subjects' expectations for the variance in the case of ambiguous signals. We find that more ambiguity averse individuals are more likely to overestimate the variance of ambiguous signals.*

Asymmetric Response to Ambiguous Signals

To investigate Hypothesis 2 in treatment C, we follow the same procedure as in Treatment I, which is to first describe individuals' reaction to unambiguous signals and compare that with their reaction to ambiguous signals. The mean and median of the weight assigned to the private signal are 0.5230, 0.5023 in Scenario 1, 0.7897, 0.8289 in Scenario 2, and 0.2246, 0.1810 in Scenario 3. Table C6 reports on descriptive statistics for the weights assigned to the private signals in these first three scenarios. We can infer that people follow the signal extraction model when dealing with unambiguous signals. The actual weight assigned to the private signal in Scenario 1 is marginally significantly larger than the theoretical prediction ($z = 1.652; p = 0.0986$). We do not observe a significant difference between the actual weight assigned to the private signal and the theoretical prediction in Scenario 2 ($z = \ 0.826; p = 0.4089$) and in Scenario 3 ($z = \ 1.101; p = 0.2709$). One possible explanation for this difference is that it takes some time for the participants to learn about the signal extraction model.

As in Treatment I, we also use the variance expectation in Scenario 4 to evaluate participants' reaction to ambiguous signals. The top panel of Figure 6 reveals that the variance expectation is 1.7807 for good news, and 1.1924 for bad news for the whole sample. The variance expectation for bad news tends to be lower than that for good news, overall and across ambiguity types. The expected variance for bad news (1.2173) is significantly lower than the expected variance for good news (1.8674) of the ambiguity averse individuals ($z = \ 5.011; p = 0.0000$). The result holds for ambiguity neutral individuals ($z = \ 2.834; p = 0.0046$), but does not hold for ambiguity seeking individuals ($z = 0.099; p = 0.9208$). Overall, the expected variance of bad news is significantly lower than the expected variance of good news ($z = \ 5.369; p = 0.0000$). We observe a lower variance expectation for bad news signals and a higher variance expectation for good news signals.

We also check the weight that subjects assigned to the ambiguous private signal. We find that the weight assigned to the private signal for bad news tends to be higher than that for good news regardless of the ambiguity attitude as depicted in Figure 6. On average, the weight assigned to the private signal is 0.5010 for bad news and 0.4783 for good news. We do not find a significant difference between the weights assigned to bad news and good news for ambiguity averse individuals ($z = 0.742; p = 0.4578$), ambiguity neutral individuals ($z = 0.7; p = 0.4838$), or ambiguity seeking individuals ($z = 0.139; p = 0.8897$). Overall, we do not find a significant difference between the weight assigned to bad news and the weight assigned to good news ($z = 0.957; p = 0.3387$). That is, the weight assigned to bad news is not significantly higher than the weight assigned to good news. According to the signal extraction model, the variance expectation of the ambiguous signal and the weight assigned to the ambiguous signals should be equivalent to measure the asymmetric response to the ambiguous signals. In other words, if individuals expect the variance to be lower, they will put a higher weight on the ambiguous signal, and vice

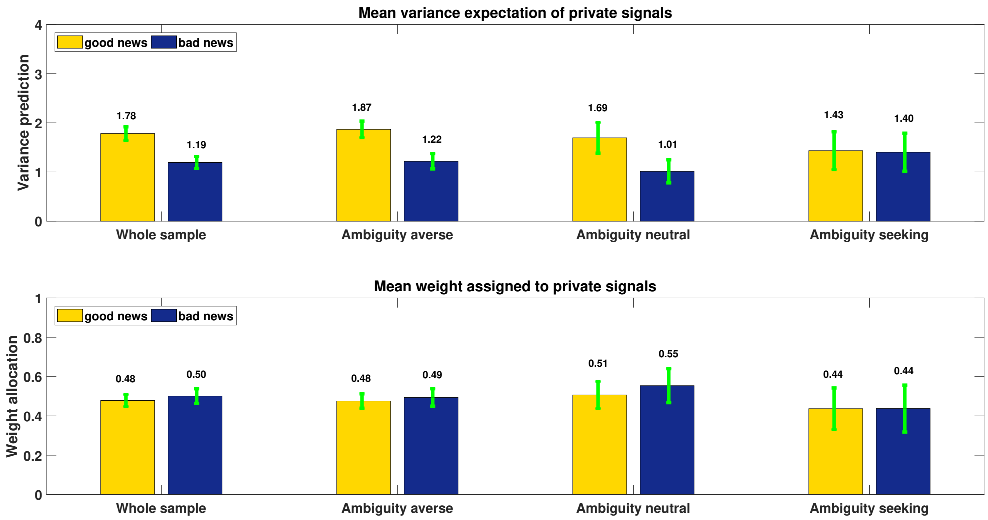

Figure 6: This bar chart depicts the mean variance prediction under ambiguous signals in the top panel and the mean implied weight assigned to ambiguous private signals in the bottom panel. The yellow (light) bar is good news, and the navy (dark) bar is bad news. The x-axis shows results for the whole sample, and for the subsamples of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The y-axis is the variance expectation of the ambiguous signals in the top panel, and the weight assigned to the ambiguous signals in the bottom panel. The green error bars show 95% confidence intervals.

versa. [7]

Result C.2 : *Participants gradually learn to use the signal extraction model for unambiguous signals in Treatment C.*

Result C.3 : *We find mixed support for Hypothesis 2 in Treatment C. On the one hand, ambiguity averse individuals do regard bad news as more precise than good news, as evidenced by their expectation for the variance of bad news ambiguous signals. On the other hand, we do not find that ambiguity averse individuals assign a significantly higher weight to such bad news signals.*

Overall, we find that there is mixed evidence for Hypothesis 2. On the one hand, we observe a consistent response to ambiguous signals. Ambiguity averse individuals provide a lower variance expectation in response to bad news, which indicates that these types regard bad news as being more precise. In theory, they should therefore assign a higher weight to bad news as compared with good news. While we find that ambiguity averse individuals *do* tend to assign a higher weight to bad news than to good news when they face ambiguous signals (Scenario 4) the differences are not statistically significant. When

[7] The top panel of Table C7 reports descriptive statistics on subjects' variance expectations for ambiguous signals, differentiated according to whether the private signal is good news or bad news. The bottom panel of Table C7 reports the descriptive statistics of the weight assigned to the private signal.

the variance of the signal is a certain known value as in Scenarios 1 to 3, individuals do apply the signal extraction model when choosing the weight to assign to the private signal. Hence, they have learned that the variance tells them the accuracy of the signal.

Mispricing

We again make use of the Stöckl et al. (2010), measures of mispricing in experimental asset markets. For treatment C we use the relative deviation (RD) and relative absolute deviation (RAD) measures. These two measures reveal the relative and relative absolute deviation of asset prices from the fundamental value. The relative deviation (RD) and relative absolute deviation (RAD) of the asset price for market k in period t are defined by:

$$RD_{k;t} = \frac{p_{k;t} - p_t^{FV}}{p_t^{FV}}$$

$$RAD_{k;t} = \frac{|p_{k;t} - p_t^{FV}|}{p_t^{FV}}$$

Here, $p_{k;t}$ is the market price for market k in period t, while p_t^{FV} is the fundamental value of the asset in period t.

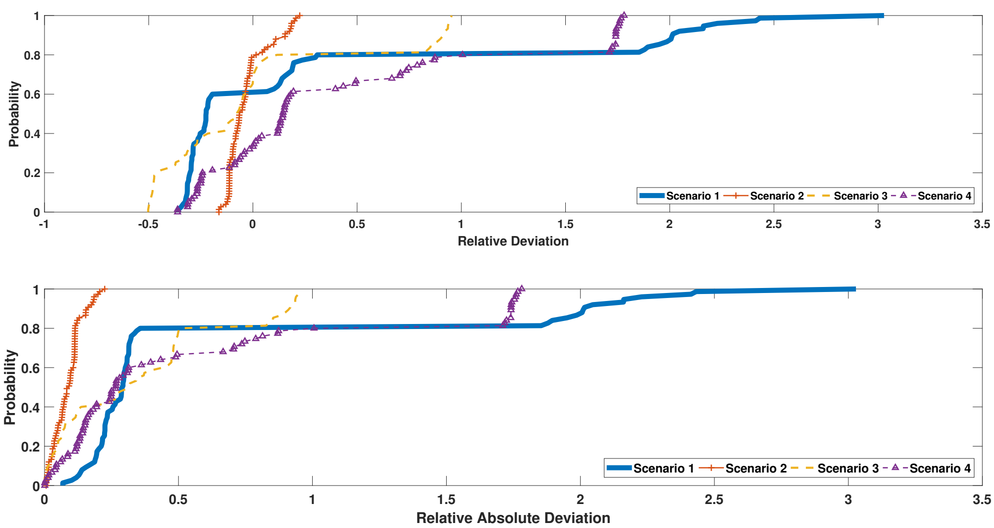

Figure 7: Figure 7 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. The x-axis is the value of RD (top panel) and RAD (bottom panel), and the y-axis is the probability. The purple dashed line with triangle marker is the RD/RAD for Scenario 4 (ambiguous signals), the blue solid line is the RD/RAD for Scenario 1, the red line with plus marker is the RD/RAD for Scenario 2, and the yellow dashed line is the RD/RAD for Scenario 3.

We find that individuals are more likely to overestimate the fundamental value and have larger mispricing when the signal is ambiguous. The mean RD in the scenarios involving non-ambiguous signals is 0.0890, while it is 0.4482 in the scenario of ambiguous signals. Also, mispricing is larger when the signal is ambiguous. The mean RAD is 0.3765 for the scenario of non-ambiguous signals and 0.5783 for the scenario of ambiguous signals (refer to Table C8 in Appendix C for more information). The RD of the ambiguous signals is significantly larger than that of the unambiguous signals ($z = 11.376; p = 0.0000$), and the different results in terms of RAD are also significant ($z = 6.830; p = 0.0000$). Figure 7 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. It shows that the median RD is between 0.5 and 1 for ambiguous signals, and between 0.5 and 0 for all unambiguous signals. The RAD under ambiguous signals is larger than found under unambiguous signals, Scenarios 2 and 3.

Result C.4 : *We cannot reject Hypothesis 3 in Treatment C. We find that mispricing is significantly larger under ambiguous signals than under unambiguous signals.*

Our results in Treatment C suggest that subjects tend to underestimate the variance of bad news as suggested by Epstein & Schneider (2008), but do not assign more weight to bad news. This obvious inconsistency between variance expectation and weight allocation leads us to wonder whether it is due to the subjects' intrinsic behavioral bias, or an artefact due to the call market institution, in contrast to Hypothesis 4.

Treatment DA

Overestimation of Variance of Ambiguous Signals

The mean variance expectation of ambiguous signals in Scenario 4 is 2.0843 for ambiguity averse participants, 2.0011 for ambiguity neutral participants, and 1.7003 for ambiguity seeking participants. The variance expectation of ambiguity averse participants is larger (insignificantly) than that of the ambiguity neutral participants ($z = 0.441; p = 0.6591$). Also, ambiguity averse participants have a significantly larger variance expectation than ambiguity seeking participants ($z = 2.005; p = 0.0449$). Overall, ambiguity averse participants have a higher (but not significant) variance expectation than non-ambiguity averse participants($z = 1.378; p = 0.1682$) as shown in Figure 8. Table C9 in Appendix B reports the descriptive statistics of the variance expectations under ambiguous signals conditional on subjects' ambiguity type classification.

Result DA.1 *We do not find strong evidence for Hypothesis 1 in Treatment DA. We find that ambiguity averse subjects tend to have a higher (but not significantly higher)*

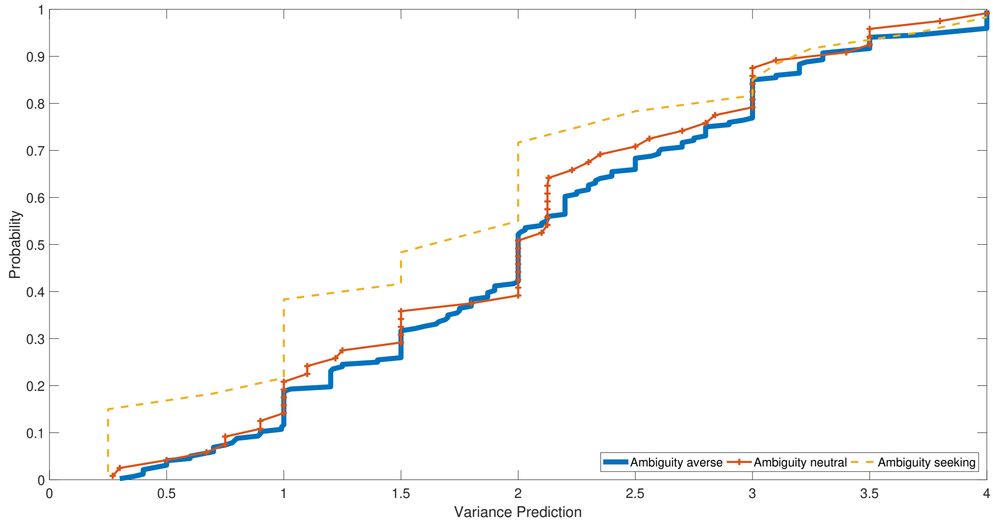

Figure 8: This figure plots the cumulative density function of the variance prediction for the ambiguous signal by ambiguity averse subjects (blue solid line), ambiguity neutral subjects (red line with plus marker) and ambiguity seeking subjects (yellow dashed line) in Treatment DA. The x-axis is the variance prediction for the ambiguous signals, and the y-axis is the probability.

> *variance expectation for the ambiguous signal as compared to non-ambiguity averse subjects. Ambiguity averse subjects are more likely to overestimate the variance of ambiguous signals than ambiguity seeking subjects.*

Asymmetric Response to Ambiguous Signals

We again investigate Hypothesis 2, using the same approach used in Treatments I and C. That is, we ask whether subjects tend to regard good news as imprecise. Therefore they expect the variance of the ambiguous signal to be higher, and they submit bid/ask prices that are further away from good news signals. On the contrary, they regard bad news as more precise, expect a lower variance of the ambiguous signal, and they submit bid/ask prices that are closer to the bad news signal. In the DA treatment, individuals trade in a double auction market, where the bid and ask price is restricted to lie between the public signal and the private signal. The bid/ask price can be no less than the minimum of the public and the private signal and no more than the maximum of the public and the private signal. Thus, the bid or ask price is a linear combination of the public signal and private signal. We impose this restriction because the same restriction was imposed in the other two treatments ($w \in [0; 1]$ implies that the implied price prediction or price quote has to be a linear combination of the two signals). Therefore, we can get the implied weight assigned to private signals, $\hat{w}^{implied}$ in a similar way as in Equation (2):

$$\hat{w}^{implied}_{i,t} = \frac{bid_{i,t}/ask_{i,t} - m}{s_{i,t} - m} \tag{4}$$

where bid/ask is the individual's bid/ask price. Note that both the outstanding bid/ask offers and the executed bid/ask offers submitted by the participants are taken into account to calculate the implied weight $\hat{w}^{implied}$ in this subsection. Here, m is the public signal, which is 8 in Treatment DA and $s_{i,t}$ is the private signal the participant i receives in period t.

Theoretically, ES assumes that individuals apply the Bayes rule to update their priors about the fundamental value of the asset and get their posterior beliefs. The theoretical prediction for the weight they should assign to the private signal, $\hat{w}^{ss}$ is the same as given in Equation (3).

The setting of σ^2 and $\sigma^2_{s,t}$ is the same for all treatments. In the DA treatment, σ^2 is also perfectly known by subjects and equal to 1, while $\sigma^2_{s,t}$ is the variance of the private signal, $s_{i,t}$. The mean and (median) implied weight assigned to the private signal is 0.3730, (0.2348) in Scenario 1, 0.4097, (0.32) in Scenario 2, and 0.2861, (0.1290) in Scenario 3. The statistical results reveal that individuals do not follow the signal extraction model when the signal is unambiguous. They tend to assign a significantly lower weight to the private signal in Scenario 1 ($z = -9.928, p = 0.0000$) and Scenario 2 ($z = -17.257, p = 0.0000$) but a higher weight in Scenario 3. ($z = -5.845, p = 0.0000$). This result is similar to that found in Bao & Duffy (2021) that subjects appear to underweight high probabilities and overweight low probabilities in a similar task. We think this tendency may be stronger in Treatment DA than in the other two treatments of this experiment because the decision task in the DA treatment is more complicated than in the other two treatments and subjects are more likely to become cognitively overloaded. The median implied weight assigned to the private signal in Scenario 4 is also significantly lower than the median theoretical prediction ($z = -2.005, p = 0.0449$).[8] We report the detailed information in Table C10 and Table C14 of Appendix C.

The mean and (median) implied weight assigned to the private signal in bid prices is 0.3743, (0.2329) in Scenario 1, 0.3075, (0.2) in Scenario 2, and 0.2980, (0.1333) in Scenario 3. The mean and (median) implied weight assigned to the private signal in ask prices is 0.3720, (0.2362) in Scenario 1, 0.5173, (0.5263) in Scenario 2, and 0.2786, (0.1232) in Scenario 3. This result also supports the earlier finding that individuals do not seem to follow the signal extraction model when they trade under the double auction market in-

[8]The median theoretical prediction of the ambiguous signals is obtained by substituting the median realized variance of the ambiguous signal into Eq.(3). The median theoretical prediction of weight is 0.3436 in our experiment.

stitution and they tend to assign a lower weight to unambiguous private signals regardless of whether they are submitting a bid or an ask offer. This bias is documented by Allen et al. (2006) who show that people tend to overweight the public signal if they know that all market participants face the same public signal and the public signal is a better predictor of market opinions. Under this bias, traders would put more weight on the public signal and less weight on their own private signal in forming their expectations.

We also observe that individuals tend to overweight good news when the signal is unambiguous, especially in Scenarios 2 and Scenario 3. The mean implied weight assigned to good/bad news is 0.3672, 0.3820 in Scenario 1, 0.4476, 0.3309 in Scenario 2, and 0.3464, 0.2353 in Scenario 3 as shown in Table C11. The mean implied weight assigned to good/bad news is 0.2184/0.6414 in Scenario 1, 0.2353/0.5945 in Scenario 2, and 0.0966/0.5151 in Scenario 3 when participants submit their bid offers. The mean implied weight assigned to good/bad news is 0.4946/0.1976 in Scenario 1, 0.7753/0.2082 in Scenario 2, and 0.5414/0.0892 in Scenario 3 when participants submit their ask offers. We find that individuals assign a significantly higher weight to bad news when they submit a bid offer to buy an asset, while they assign a significantly higher weight to good news when they submit an ask offer to sell the asset. More details are reported in Table C12 and Table C13 of Appendix C.

We use both the variance expectation and implied weight allocation to examine the asymmetric response to the ambiguous signals. ES predicts that individuals tend to overestimate the variance of good news, and underestimate the variance of bad news for ambiguous signals. The top panel of Figure 9 reports the mean of subjects' variance expectations for ambiguous signals, differentiated according to whether their private signal was good news or bad news. The variance expectation for bad news tends to be higher than that for good news, overall and across ambiguity types. The mean variance expectation for bad news (2.260) is significantly higher than that for good news (1.9118) for the ambiguity averse individuals ($z = 2.338; p = 0.0194$).[9] This same result also holds for ambiguity neutral individuals according to the same test ($z = 3.256; p = 0.0011$), but it does not hold for ambiguity seeking individuals ($z = 0.899; p = 0.3689$). Overall, we observe a higher variance expectation for bad news and a lower variance expectation for good news ($z = 3.446; p = 0.0006$) in the DA treatment.

Further, we confirm that people indeed tend to overestimate the variance of bad news regardless of whether they submit bid or ask offers. However, ambiguity averse and ambiguity seeking people seem to react asymmetrically to ambiguous signals concerning variance predictions. As illustrated in the top panel of Figure 10, the mean variance prediction is 1.8442 for good news, and 2.2341 for bad news when subjects submit more

[9]The default is good news in the statistical test.

bid offers than ask offers. We do not find that the variance prediction for bad news is significantly larger than that for good news ($z = 1:107;\ p = 0:2681$) when the participants submit more bid offers than ask offers. When subjects submit more ask offers than bid offers, the mean variance prediction is 2.0407 for good news, and 2.2542 for bad news. The mean variance prediction is slightly significantly larger for bad news than for good news when participants submit more ask offers than bid offers ($z = 1:838;\ p = 0:066$). Also, we find that ambiguity averse and ambiguity seeking subjects seem to have a lower variance expectation for bad news when they are submitting more bid offers than ask offers, and have a higher variance expectation for bad news when they are submitting more ask offers than bid offers. But the evidence is very weak. Ambiguity neutral subjects always have a larger variance prediction for good news (more details are reported in Table C15 of Appendix C).

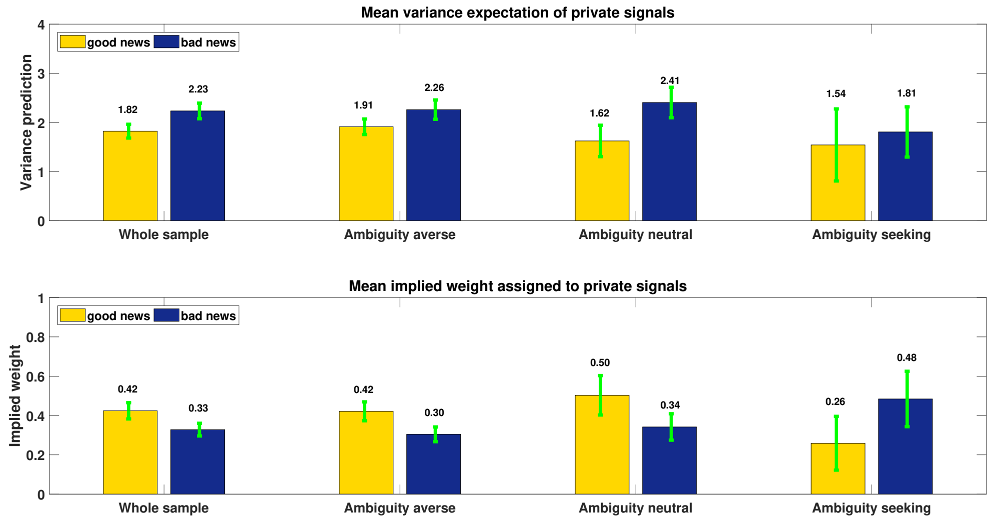

Figure 9: The top panel of this figure shows the mean variance prediction for ambiguous signals of the whole sample, the subsample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects. The bottom panel shows the mean implied weight assigned to the ambiguous signal of the whole sample, and the subsamples of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The yellow bar is good news, and the navy bar is bad news. The x-axis shows results of the whole sample, the subsample of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The y-axis is the variance expectation of the ambiguous signals in the top panel, and the implied weight allocated to the ambiguous signals in the bottom panel. The yellow (light) bar is good news, and the navy (dark) bar is bad news. The green error bars show 95% confidence intervals.

Second, we check whether the implied weight assigned to the bad ambiguous signals is overweighted. If subjects follow Epstein & Schneider (2008)'s prediction when seeing ambiguous signals, bad news will be overweighted, and good news will be underweighted. The bottom panel of Figure 9 depicts the mean implied weight assigned to the private signal. In general, the mean implied weight assigned to good news is 0.4241 and significantly larger than the weight assigned to bad news, which is 0.3282 ($z = \ \ 3.297; \ p = 0.0010$). Table C16 reports the descriptive statistics on subjects' implied weight assigned to the ambiguous signals, differentiated according to whether the private signal is good news or bad news.

Additionally, we examine this hypothesis further by investigating individuals' behavior conditional on the types of their offers, bid offers or ask offers. On average, the implied weight of the private signal is 0.6212 for bad news and 0.15 for good news when participants submit bid offers to buy the asset, which is depicted in the bottom panel of Figure 10. The implied weight of the private signal is 0.1689 for bad news and 0.6794 for good news when participants submit ask offers to sell the asset. The statistical test results confirm that individuals assign a significantly higher weight to bad news when making bid offers ($z = 11.271; \ p = 0.0000$), and a significantly higher weight to good news when making ask offers ($z = \ \ 13.709; \ p = 0.0000$). The results remain consistent for participants regardless of their ambiguity attitudes (refer to Table C16 of Appendix C for more details). Thus, participants tend to rely more on bad news when they want to buy the asset and they rely more on good news when they want to sell the asset. We observe that participants behave in the same way under both unambiguous and ambiguous signals. Their bid price is closer to the bad news when they are buying assets, while their ask price is closer to the good news when they are selling assets.

In conclusion, we find that individuals do not follow Epstein and Schneider's model when they trade in a continuous double auction model in contrast to our Hypothesis 4. They do have a higher variance expectation for bad news than for good news under ambiguous signals. The implied weight assigned to good news is larger than that assigned to bad news. However, this overweighting of good news is also found for unambiguous signals. Additionally, they allocate a higher implied weight to bad news when they submit bid offers to buy the asset, and a higher weight to good news when they submit ask offers to sell an asset for both unambiguous and ambiguous signals. We argue that these findings arise because people are pessimistic and are more likely to become net sellers of the asset, which leads to an overweighting of good news. We compare the number of bids and the number of asks in each scenario; a significantly larger number of asks would support this argument.[10]

Result DA.2 *Individuals tend to underweight private signals regardless of whether the signal is ambiguous or unambiguous.*

Result DA.3 *We do not find support for Hypothesis 2 in Treatment DA. We fail to find*

[10] The sum of bids/asks is 196/270 in Scenario 1, 251/270 in Scenario 2, 197/389 in Scenario 3, and 221/333 in Scenario 4. The sum of asks is significantly larger in Scenario 3 and Scenario 4.

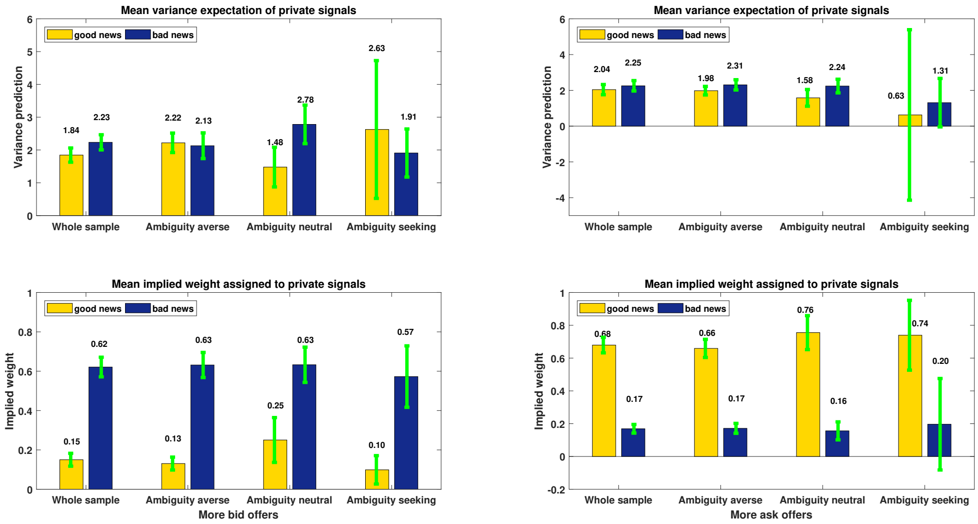

Figure 10: This top panel of the figure demonstrates the mean variance prediction for ambiguous signals of the whole sample, the subsample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects. The bottom panel illustrates the mean implied weight assigned to the ambiguous signal of the whole sample, the subsample of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The left panel demonstrates the scenario where subjects submit more bid offers, and the right panel demonstrates the scenario where subjects submit more ask offers. The yellow (light) bar is good news, and the navy (dark) bar is bad news. The green error bars show 95% confidence intervals.

evidence to support Epstein and Schneider's theoretical prediction that individuals would view bad news as more accurate than good news under ambiguous signals. Instead, we find the opposite for two reasons. First, the asymmetric reaction to good and bad news in the bid and ask o ers cancel out in the market's aggregation; second, when faced with a common public signal, subjects systematically over-weight the public signal and under-weight the private signal due to iterated expectations as suggested by Allen et al. (2006).

Result DA.4 *Individuals behave consistently in the face of both ambiguous and unambiguous private signals: they are more likely to assign a higher weight to bad news when they are making bid o ers to buy the asset but allocate a lower weight to bad news when they are making ask o ers to sell the asset.*

Mispricing

We again follow Stöckl et al. (2010)'s methods for measure mispricing using the same measures as in Treatment C. The only difference relative to treatment C, is that the market price in Treatment DA is the average value. The RD and RAD of the asset price for market k in period t are defined by:

$$RD_{k,t} = \frac{\overline{p_{k,t}} - p_t^{FV}}{p_t^{FV}}$$

$$RAD_{k,t} = \frac{|\overline{p_{k,t}} - p_t^{FV}|}{p_t^{FV}}$$

Here, $\overline{p_{k,t}}$ is the mean market price for market k in period t, while p_t^{FV} is the fundamental value of the asset in period t. Note that the fundamental value of the asset is constant in each period in our experiment.

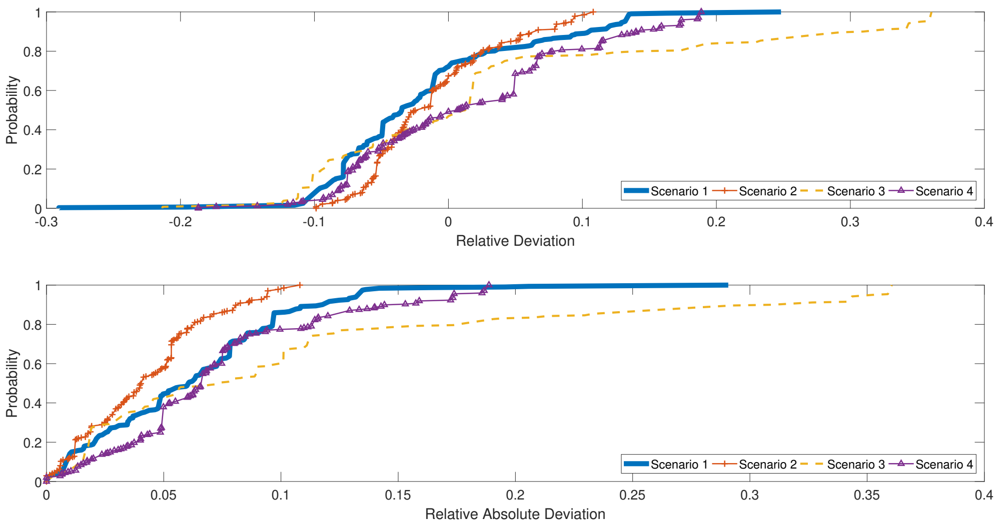

Figure 11: Figure 11 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. The x-axis is the value of RD (top panel) and RAD (bottom panel), and the y-axis is the probability. The purple dashed line with triangle marker is the RD/RAD for Scenario 4 (ambiguous signals), the blue solid line is the RD/RAD for Scenario 1, the red line with plus marker is the RD/RAD for Scenario 2, and the yellow dashed line is the RD/RAD for Scenario 3.

We do not find strongly supportive evidence that individuals tend to overestimate the fundamental value when the signal is ambiguous. The mean RD is negative for non-ambiguous signals and positive for ambiguous signals. Generally, the mean RD in the scenarios involving non-ambiguous signals is -0.0060, while it is 0.0030 in the scenario of ambiguous signals. The mean RAD is 0.0690 in the 3 scenarios involving unambiguous signals and 0.0706 for the scenario involving ambiguous signals (refer to Table C17 in Appendix A). It seems that mispricing is slightly larger when the signal is ambiguous. However, this difference is not significant in the DA treatment. The RD under ambiguous signals is not significantly larger than what is found under unambiguous signals ($z = 0.753$; $p = 0.4515$). We observe the same result for the RAD ($z = 1.555$; $p = 0.12$). Figure 11 depicts the cumulative distribution function of the RD (top panel) and the RAD (bottom panel) in each scenario. It shows that the median RD is between 0 and

0.1 for ambiguous signals and between 0.1 and 0 for all unambiguous signals, but both are near 0. The RAD under ambiguous signals is not significantly larger than that of Scenarios 1 and 3, and significantly larger than that of Scenario 2.

Result DA.5 *Hypothesis 3 is rejected in Treatment DA. We fail to find greater mispricing of the asset when private signals are ambiguous as compared with the case where they are not.*

The results from Treatment DA show that, in contrast to the prediction of ES, traders operating under the DA institution do not overestimate the variance of bad signals or assign a smaller weight to them than good signals. We think there are two reasons for these results. First, in a double auction with both buyers and sellers, what is good news to buyers is indeed bad news to sellers, and vise versa. So, the asymmetric reaction to good and bad news from the buyers side and sellers side cancel each other out in the aggregate. Second, in the double auction market, everyone knows that everyone else has access to the common public signal. This fact will trigger iterated expectations and amplification of the public signal as suggested by Allen et al. (2006) resulting in systematic under-weighting of the private signals. The underweighting of private signals also makes the effect of the asymmetric reaction to good and bad news less salient. In general, our findings suggest that attitudes towards information ambiguity do not matter very much for traders' decisions in the double auction market.

5 Conclusion

In this paper we report on findings from an experiment exploring theoretical insights from a model of information ambiguity in financial markets due to Epstein & Schneider (2008). We consider three different types of experimental markets, a prediction market treatment I, a single price call market treatment C and a double auction market treatment DA. We find that subjects who are more ambiguity averse tend to overestimate the variance of good news, and underestimate the variance of bad news for ambiguous signals, so that bad news is overweighted relative to good news in the aggregate in Treatment I. By contrast, in treatment C, the over/underestimation of the variance of good/bad ambiguous signal still holds at the individual level but the over/underweighting of bad/good ambiguous signals no longer holds in the aggregate. Finally in treatment DA, the asymmetric reaction to good/bad signals is reversed at the individual level and also does not hold in the aggregate. Asset mispricing is significantly greater under ambiguous signals than under unambiguous signals in Treatments I and C, while there is no significant difference in Treatment DA.

Our results show that information ambiguity leads to a bias in belief updating in individual decision problems, and to a lesser extent in the call market, while the role played by biased belief updating under information ambiguity is very limited in double auction markets.

Our paper contributes to the literature on information processing in financial markets. Given our finding that ambiguous signals could be a source of asset mispricing, reducing the ambiguity of information in asset markets may be viewed as a stabilizing policy.

Due to the correlation between investors' attitudes towards ambiguity and information ambiguity, it may also be useful for regulators to elicit attitudes towards ambiguity and use that information when monitoring developments in market composition and price stability. In prediction markets and in single price call markets, a higher average level of ambiguity aversion may be an indicator of larger potential asymmetric market reactions and asset mispricing. In continuous double auction markets, the regulator may need to differentiate between the average ambiguity attitude of net buyers and net sellers.

In future research, it would be useful to consider alternative measures of ambiguity attitudes. Indeed, Trautmann et al. (2011), and Kocher et al. (2018) find that different measures of ambiguity attitudes result in further individual heterogeneity in ambiguity attitudes. While our paper mainly applies the measurement of ambiguity attitudes (risk choices and ambiguous choices) following the Trautmann et al. (2011) procedure, further checks on whether heterogeneity in ambiguity attitudes matter for financial market decisions would be useful. Finally, we note that our design only considers signals with interval ambiguity; it would be of interest to explore other cases where the signals are associated with other types of ambiguities, e.g., disjoint ambiguity or two-point ambiguity as in Chew et al. (2017) to see if subjects process signals with different types of ambiguity in different ways. It may also be interesting to conduct the same experiment on financial professionals like in e.g., Holzmeister et al. (2020), Weitzel et al. (2020) to see if the results are robust in different samples. We leave these extensions to future research.

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Internet Appendix

Appendix A: Experimental Instructions

Welcome to this experiment on economic decision-making. Please read these instructions carefully as understanding it well is crucial for your payoff from the experiment. The experiment consists of two tasks and one survey. Your payoff will depend on your decision in all parts of the experiment.

Instructions for Task 1

In Task 1, you can choose either **Box K** or **Box U** in each row. Each of the two boxes contains 100 balls. The color of the balls is either **purple** or **orange**. Your payoff depends on your choice of the box. You will receive 3 SGD if **a purple ball is drawn**.

The number (and hence the fraction) of purple balls and orange balls is **known** in Box K. The numbers of purple balls and orange balls (and hence the fraction of purple and orange balls) are going to be shown on the computer screen. Thus, the probability for a purple ball to be drawn, namely, for you to win the payment of 3 SGD is **known** for Box K if you choose Box K. If you choose Box K, please click "Box K".

The number (and hence the fraction) of purple balls and orange balls is **unknown** in Box U. Thus, the probability for you to win the payment of 3 SGD is **unknown** if you choose Box U: it can be any probability between 0% and 100%. If you choose Box U, please click "Box U".

When making your choices, you may only switch once between the two boxes, i.e., from Box K to Box U or from Box U to Box K. You cannot switch back and forth. For example, if you choose Box K in Rows 1-2, and Box U in row 3, you will not be allowed to choose Box K again in the remaining Rows 4 and below. (*This example is for illustration purposes only, and is not a suggestion for what you should do in the experiment*).

After you have made all choices, your payoff for Task 1 will be determined as follows. First, we will randomly choose one Row (choice) from all choices that you made. Then, one ball will be drawn randomly from the box K or U that you indicated for that Row (choice). If a purple ball is drawn, you receive 3 SGD; if an orange ball is drawn you receive 0.

The Payment in the Experiment

The payment of this experiment will be the sum of four parts:

The show-up fee, which is S$3.

The payoff (in SGD) in Task 1.

The payoff (in SGD) in Task 2.

The payoff (in SGD) in a survey.

Appendix B: Additional Results from Part 1

Treatment I

In Treatment I, we nd on average, that ambiguity averse individuals switch to Box U when the winning probability is around 31.85%. Ambiguity neutral individuals switch to Box U when the winning probability is 50%. Ambiguity seeking individuals switch to Box U when the winning probability is around 60% on average. Table B1 provides some descriptive statistics regarding ambiguity attitudes. The top panel reports the matching probability while the bottom panel reports the measure of ambiguity, AM_i

Table B1
This table reports descriptive statistics about ambiguity attitudes among our subjects. The top panel reports on the matching probability and the bottom panel reports on the measure of ambiguity attitudes, AM_i.

Matching Probability					
	N	Mean	Median	Min	Max
Ambiguity averse	27	31.85%	40%	10%	40%
Ambiguity neutral	11	50%	50%	50%	50%
Ambiguity seeking	3	60%	60%	60%	60%
Measure of Ambiguity Attitudes, AM_i					
	N	Mean	Median	Min	Max
Ambiguity averse	27	0.1815	0.1	0.4	0.1
Ambiguity neutral	11	0	0	0	0
Ambiguity seeking	3	-0.1	-0.1	-0.1	-0.1

The results of the risk elicitation show that the mean of the switching row is 5.85 for ambiguity averse individuals, 6.48 for ambiguity neutral individuals, and 7.33 for ambiguity seeking individuals. We nd that ambiguity seeking individuals are more risk averse.

Table B2
This table reports descriptive statistics from the risk elicitation using the MPL method.

Result of risk elicitation by MPL method					
	N	Mean	Median	Min	Max
Ambiguity averse	27	5.85	6	3	9
Ambiguity neutral	11	6.18	6	5	8
Ambiguity seeking	3	7.33	8	6	8

Treatment C

In Treatment C, we find on average, that ambiguity that ambiguity averse individuals will switch to Box U when the winning probability is around 35.08%. Ambiguity neutral individuals switch to Box U when the winning probability is 50%. Ambiguity seeking individuals switch to Box U when the winning probability is around 61%. Table B3 summarizes descriptive statistics regarding ambiguity attitudes. The top panel reports on the matching probability and the bottom panel reports on the measure of ambiguity, AM_i.

Table B3
This table reports descriptive statistics about ambiguity attitudes among our subjects. The top panel reports on the matching probability and the bottom panel reports on the measure of ambiguity attitudes, AM_i.

Matching Probability					
	N	Mean	Median	Min	Max
Ambiguity averse	60	35.08%	40%	0%	40%
Ambiguity neutral	20	50%	50%	50%	50%
Ambiguity seeking	10	61%	60%	60%	70%
Measure of Ambiguity Attitudes, AM_i					
	N	Mean	Median	Min	Max
Ambiguity averse	60	0.1491	0.1	0.1	0.5
Ambiguity neutral	20	0	0	0	0
Ambiguity seeking	10	-0.11	-0.1	-0.2	-0.1

We find that all participants in Treatment C are risk averse. The results of the risk elicitation show that the mean of the switching row is 6.57 for ambiguity averse individuals, 6.6 for ambiguity neutral individuals, and 6.9 for ambiguity seeking individuals.

Table B4
This table reports descriptive statistics from the risk elicitation using the MPL method.

Result of risk elicitation by MPL method					
	N	Mean	Median	Min	Max
Ambiguity averse	60	6.5667	6	0	11
Ambiguity neutral	20	6.6	6	5	9
Ambiguity seeking	10	6.9	7	5	9

Treatment DA

In the DA treatment, we find on average that ambiguity averse individuals switch from Box K to Box U when the winning probability is around 36.43%. Ambiguity neutral individuals switch from Box K to Box U when the winning probability is 50%. Ambiguity seeking individuals switch from Box K to Box U when the winning probability is around 63.33%. Table B5 summarizes the descriptive statistics on measures of individual ambiguity attitudes. The top panel reports statistics for the matching probability, and the bottom panel reports the statistics on the measure of ambiguity, AM_i.

Table B5
This table reports on descriptive statistics about ambiguity attitudes among the subjects. The top panel reports on the matching probability and the bottom panel reports on the measure of ambiguity attitudes, AM_i.

Matching Probability					
	N	Mean	Median	Min	Max
Ambiguity averse	42	36.43%	40%	20%	40%
Ambiguity neutral	12	50%	50%	50%	50%
Ambiguity seeking	6	63.33%	60%	60%	70%
Measure of Ambiguity Attitudes, AM_i					
	N	Mean	Median	Min	Max
Ambiguity averse	42	0.1357	0.1	0.1	0.3
Ambiguity neutral	12	0	0	0	0
Ambiguity seeking	6	-0.1333	-0.1	-0.2	-0.1

The results of risk elicitation indicate that the mean switching row is 6.69 for ambiguity averse individuals, 6.25 for ambiguity neural individuals, and 7 for ambiguity seeking individuals. In general, we nd that people are risk averse in this treatment, and less ambiguity averse individuals are more risk averse.

Table B6
This table reports descriptive statistics about the result of risk elicitation by MPL method.

Result of risk elicitation by MPL method					
	N	Mean	Median	Min	Max
Ambiguity averse	42	6.69	6	4	10
Ambiguity neutral	12	6.25	6	5	10
Ambiguity seeking	6	7	7	5	10

Appendix C: Additional Results from Part 2

Treatment I

Table C1
This table for the given number of subjects classified as ambiguity averse, ambiguity neutral and ambiguity seeking, their mean expectation for the variance, as well as the median, standard deviation, minimum, and maximum expectation of the variance in Treatment I.

	N	Mean	Median	Min	Max
Ambiguity averse	27	1.7807	2	0.25	4
Ambiguity neutral	11	1.5551	1.5	0.25	4
Ambiguity seeking	3	1.7067	1.5	0.25	4

Signal Extraction to Unambiguous Signals

We do not observe a significant difference between the implied weight assigned to the private signal and the theoretical prediction for ambiguity averse subjects in Scenario 1 ($z = 1{:}056;\ p = 0{:}2908$), Scenario 2 ($z = \ 1{:}462;\ p = 0{:}1436$) and Scenario 3 ($z = 0{:}676;\ p = 4990$). It seems that ambiguity averse participants learn the signal extraction model very well. Table C2 reports on descriptive statistics for implied weights assigned to the private signals in these first three scenarios. We can infer that it seems that people follow the signal extraction model when dealing with unambiguous signals.

We obtain similar results for ambiguity neutral subjects. We do not observe a significant difference between the implied weight assigned to the private signal and the theoretical prediction for ambiguity neutral subjects in Scenario 1 ($z = \ 0{:}376;\ p = 0{:}7067$), and Scenario 2 ($z = 0{:}177;\ p = 0{:}8594$). But the implied weight assigned to the private signal is significantly larger than the theoretical prediction in Scenario 3 ($z = 2{:}285;\ p = 0{:}0223$). There is no significant difference between the implied weight assigned to the unambiguous private signal and the theoretical prediction for ambiguity seeking participants in Scenario 1 ($z = \ 0{:}332;\ p = 0{:}7395$) and Scenario 3 ($z = 1{:}000;\ p = 0{:}3173$). However, ambiguity seeking participants tend to assign a significantly lower weight to the private signal than the theoretical prediction in Scenario 2 ($z = \ 2{:}702;\ p = 0{:}0069$).

Overall, we do not observe a significant difference between the implied weight assigned to the private signal and the theoretical prediction in Scenario 1 ($z = 0{:}573;\ p = 0{:}5664$). The implied weight assigned to the private signal in Scenario 2 is marginally significantly smaller than the theoretical prediction using a rank-sum test ($z = \ 1{:}833;\ p = 0{:}0669$). The implied weight assigned to the private signal in Scenario 3 is significantly smaller than the theoretical prediction ($z = 2{:}012;\ p = 0{:}0443$). One possible explanation for this difference is that it is obvious to get the mean of public signal and private signal in Scenario 1, but a bit unclear to get the theoretical weight assigned to private signal in Scenario 2 and Scenario 3. The participants are adjusting their predictions gradually in Scenario 2 and Scenario 3. Also, this could be the result of the performance by the ambiguity neutral subjects and ambiguity seeking subjects. In Scenario 2, ambiguity seeking participants make a significantly lower implied weight to the private signal than the theoretical prediction. In Scenario 3, ambiguity neutral participants assign a significantly higher implied weight to the private signal than the theoretical weight. That leads to biased results for the whole sample level.

Table C2
This table reports the descriptive statistics of the implied weight assigned to the unambiguous private signals for Scenario 1, 2 and 3 in Treatment I.

		Mean	Median	Std	Min	Max
Whole sample	Scenario 1	0.5043	0.5	0.1465	0	1
	Scenario 2	0.7700	0.7911	0.1639	0	1
	Scenario 3	0.2175	0.2161	0.1491	0	0.8824
Ambiguity averse	Scenario 1	0.5195	0.5	0.1261	0.0725	1
	Scenario 2	0.7781	0.7857	0.1604	0	1
	Scenario 3	0.2168	0.2086	0.1481	0	0.8824
Ambiguity neutral	Scenario 1	0.4695	0.5	0.1937	0	1
	Scenario 2	0.7564	0.8	0.1847	0	1
	Scenario 3	0.2179	0.2198	0.1360	0	0.6317
Ambiguity seeking	Scenario 1	0.4956	0.5	0.0935	0.2955	0.6609
	Scenario 2	0.7457	0.7538	0.1016	0.5714	1
	Scenario 3	0.2216	0.2394	0.2061	0	0.65

Table C3
This table reports on descriptive statistics of the variance expectation of the ambiguous signals (good news versus bad news) in the top panel, and on descriptive statistics of the implied weights assigned to the ambiguous signal (good news versus bad news) in the bottom panel in Treatment I.

Variance Expectation of the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Whole sample	Good news	1.8850	2	0.9130	0.25	4
	Bad news	1.5677	1.5	0.9528	0.25	4
Ambiguity averse	Good news	2.0599	2.1	0.8529	0.25	4
	Bad news	1.5136	1.5	0.9366	0.25	4
Ambiguity neutral	Good news	1.4204	1.4	1.0043	0.25	2.85
	Bad news	1.6519	1.63	0.7732	0.25	4
Ambiguity seeking	Good news	1.7417	1.5	1.0937	0.25	3.4
	Bad news	1.6833	1.5	1.2698	0.25	4
Implied Weight Assigned to the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.4085	0.4211	0.2114	0	0.9302
	Bad news	0.4355	0.4146	0.2111	0	1
Ambiguity averse	Good news	0.3740	0.3992	0.1968	0	0.9302
	Bad news	0.4773	0.4861	0.2098	0.0198	1
Ambiguity neutral	Good news	0.4819	0.4608	0.2379	0.1370	0.8696
	Bad news	0.3877	0.3517	0.1927	0	0.7937
Ambiguity seeking	Good news	0.5076	0.4913	0.1873	0.25	0.7632
	Bad news	0.2844	0.3191	0.1978	0	0.5574

Mispricing

The mean RDF is -0.0036 in Scenario 1, -0.0065 in Scenario 2, 0.0335 in Scenario 3, and 0.0100 in Scenario 4. RDF is not significantly larger in Scenario 4 than that in Scenario 1 ($z = 0.386; p = 0.6996$), in Scenario 2 ($z = 0.588; p = 0.5568$), and in Scenario 3 ($z = \ 0.357; p = 0.7210$). The mean RADF is 0.0546 in Scenario 1, 0.0409 in Scenario 2, 0.1119 in Scenario 3, and 0.0904 in Scenario 4. RADF in Scenario 4 is significantly larger than that in Scenario 1 ($z = 5.986; p = 0.0000$), and in Scenario 2 ($z = 8.660; p = 0.0000$), but not in Scenario 3 ($z = \ 0.371; p = 0.7110$).

Table C4
This table reports the descriptive statistics of the Relative Deviation Forecast (RDF) for each scenario in the top panel and Relative Absolute Deviation Forecast (RADF) for each scenario in the bottom panel in Treatment I.

Relative Deviation Forecast					
	Mean	Median	Std	Min	Max
Ambiguous signal	0.0100	-0.0080	0.1113	-0.2725	0.2838
Unambiguous signal	0.0078	-0.0051	0.1026	-0.2472	0.5051
	Mean	Median	Std	Min	Max
Scearnio 1	-0.0036	-0.0156	0.0697	-0.2005	0.1993
Scearnio 2	-0.0065	-0.0082	0.0504	-0.1136	0.1288
Scearnio 3	0.0335	0.0051	0.1527	-0.2472	0.5051
Scearnio 4	0.0100	-0.0080	0.1113	-0.2725	0.2838
Relative Absolute Deviation Forecast					
	Mean	Median	Std	Min	Max
Ambiguous signal	0.0904	0.0751	0.0653	0	0.2838
Unambiguous signal	0.0691	0.0450	0.0762	0	0.5051
	Mean	Median	Std	Min	Max
Scearnio 1	0.0546	0.0433	0.0434	0	0.2005
Scearnio 2	0.0409	0.0355	0.0299	0	0.1288
Scearnio 3	0.1119	0.0801	0.1089	0.0011	0.5051
Scearnio 4	0.0904	0.0751	0.0653	0	0.2838

Treatment C

Table C5
This table reports for the given number of subjects classified as ambiguity averse, ambiguity neutral and ambiguity seeking, their mean expectation for the variance, as well as the median, standard deviation, minimum, and maximum expectation of the variance in Treatment C.

	N	Mean	Median	Std	Min	Max
Ambiguity averse	60	1.6073	1.2	1.0843	0.25	4
Ambiguity neutral	20	1.422	1	1.0932	0.25	4
Ambiguity seeking	10	1.4205	1.2	0.9449	0.25	4

Signal Extraction to Unambiguous Signals

We also observe the learning process for ambiguity averse individuals, ambiguity neutral, and ambiguity seeking individuals for unambiguous signals in Treatment C. The actual weight assigned to the private signal is significantly larger than the theoretical prediction in Scenario 1 for ambiguity averse individuals but not significantly larger in Scenarios 2 and 3. The result of rank-sum test for ambiguity averse individuals is $z = 1.683$, $p = 0.0923$ for Scenario 1, $z = 0.673$, $p = 0.5007$ for Scenario 2 and $z = 0.337$, $p = 0.7364$ for Scenario 3. The actual weight assigned to the private signal is significantly lower than the theoretical prediction in Scenario 3 for ambiguity neutral individuals but not significantly different for these types in Scenario 1 and 2. The result of rank-sum test for ambiguity neutral individuals is $z = 3.437$, $p = 0.0006$ for Scenario 1, $z = 0.578$, $p = 0.5631$ for Scenario 2 and $z = 1.735$, $p = 0.0828$ for Scenario 3. There is no significant difference between the actual weight assigned to the unambiguous private signal and the theoretical prediction for ambiguity seeking participants. The result of the rank-sum test for ambiguity seeking individuals is $z = 0$, $p = 1.0000$ for Scenario 1, $z = 0.808$, $p = 0.4139$ for Scenario 2 and $z = 0$, $p = 1.0000$ for Scenario 3. The results above show that individuals do learn to make predictions as if they follow the signal extraction model when the signal is unambiguous.

Mispricing

The mean RD is 0.2979 in Scenario 1, -0.0298 in Scenario 2, 0.0078 in Scenario 3, and 0.4482 in Scenario 4. RD is significantly larger in Scenario 4 than that in Scenario 1 ($z = 6.957; p = 0.0000$), in Scenario 2 ($z = 9.856; p = 0.0000$), and in Scenario 3 ($z = 11.065; p = 0.0000$). The mean RAD is 0.6272 in Scenario 1, 0.0877 in Scenario 2, 0.3625 in Scenario 3, and 0.5783 in Scenario 4. RAD in Scenario 4 is also significantly larger than that in Scenario 2 ($z = 17.787; p = 0.0000$), and in Scenario 3 ($z = 7.022; p = 0.0000$). RAD in Scenario 4 is significantly lower than that in Scenario 1 ($z = 3.845; p = 0.0001$).

Table C6
This table reports the descriptive statistics of the weight assigned to the unambiguous private signals for Scenario 1, 2 and 3.The theoretical prediction of weight is 0.5 in Scenario 1, 0.8 in Scenario 2, and 0.2 in Scenario 3 in Treatment C.

		Mean	Median	Std	Min	Max
Whole sample	Scenario 1	0.5230	0.5023	0.2521	0	1
	Scenario 2	0.7897	0.8289	0.2111	0	1
	Scenario 3	0.2246	0.1810	0.2273	0	1
Ambiguity averse	Scenario 1	0.5354	0.5037	0.2420	0	1
	Scenario 2	0.7929	0.8403	0.2059	0	1
	Scenario 3	0.2396	0.1985	0.2316	0	1
Ambiguity neutral	Scenario 1	0.4777	0.4994	0.2779	0	1
	Scenario 2	0.7839	0.8203	0.2300	0	1
	Scenario 3	0.1965	0.1352	0.2421	0	0.9927
Ambiguity seeking	Scenario 1	0.5386	0.5622	0.2517	0	1
	Scenario 2	0.7827	0.7937	0.2062	0	1
	Scenario 3	0.1910	0.1835	0.1542	0	0.5618

Table C7
This table reports on descriptive statistics of the variance expectation of the ambiguous signals (good news versus bad news) in the top panel, and on descriptive statistics of the weights assigned to the ambiguous signal (good news versus bad news) in the bottom panel in Treatment C.

Variance Expectation of the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Whole sample	Good news	1.7807	1.5	1.1493	0.25	4
	Bad news	1.1924	1	0.8335	0.25	4
Ambiguity averse	Good news	1.8674	1.6625	1.1409	0.25	4
	Bad news	1.2173	1	0.8607	0.25	4
Ambiguity neutral	Good news	1.6948	1.3	1.2084	0.25	4
	Bad news	1.0128	1	0.7337	0.25	3.5
Ambiguity seeking	Good news	1.4329	1.1	1.0298	0.25	4
	Bad news	1.4020	1.225	0.8267	0.25	3.5
Weight Assigned to the Ambiguous Signal						
		Mean	Median	Std.Dev	Min	Max
Whole sample	Good news	0.4783	0.4956	0.2561	0	1
	Bad news	0.5010	0.4983	0.2527	0	1
Ambiguity averse	Good news	0.4758	0.4962	0.2484	0	1
	Bad news	0.4940	0.4991	0.2451	0	1
Ambiguity neutral	Good news	0.5066	0.4977	0.2665	0.0823	1
	Bad news	0.5539	0.4984	0.2703	0.1602	1
Ambiguity seeking	Good news	0.4368	0.3932	0.2823	0	1
	Bad news	0.4374	0.4021	0.2550	0.0930	0.8836

Table C8
This table reports the descriptive statistics of the Relative Deviation (RD) for each scenario in the top panel and Relative Absolute Deviation (RAD) for each scenario in the bottom panel in Treatment C.

Relative Deviation					
	Mean	Median	Std	Min	Max
Ambiguous signal	0.4482	0.1450	0.7256	-0.3614	1.7811
Unambiguous signal	0.0890	-0.0947	0.6491	-0.5440	3.0475
	Mean	Median	Std	Min	Max
Scenario 1	0.2979	-0.2242	0.9474	-0.3571	3.0284
Scenario 2	-0.0298	-0.0638	0.0979	-0.1629	0.2246
Scenario 3	0.0078	-0.0750	0.4835	-0.5025	0.9536
Scenario 4	0.4482	0.1450	0.7256	-0.3614	1.7811
Relative Absolute Deviation					
	Mean	Median	Std	Min	Max
Ambiguous signal	0.5783	0.2663	0.6266	0.0010	1.7811
Unambiguous signal	0.3765	0.2143	0.5361	0.0001	3.0475
	Mean	Median	Std	Min	Max
Scenario 1	0.6272	0.2928	0.7696	0.0682	3.0284
Scenario 2	0.0877	0.0914	0.0525	0.0062	0.2246
Scenario 3	0.3625	0.3154	0.3197	0.0003	0.9536
Scenario 4	0.5783	0.2663	0.6266	0.0010	1.7811

Treatment DA

Table C9
This table is for the given number of subjects classified as ambiguity averse, ambiguity neutral and ambiguity seeking, their mean expectation for the variance, as well as the median, standard deviation, minimum, and maximum expectation of the variance in Treatment DA.

	Variance Expectation				
	N	Mean	Median	Min	Max
Ambiguity averse	42	2.0843	2	0.3	4
Ambiguity neutral	12	2.0011	2	0.27	3.8
Ambiguity seeking	6	1.7003	1.625	0.25	3.7

<u>Signal Extraction to Unambiguous Signals</u>

We check the implied weight allocation across different ambiguity attitudes for unambiguous signals. Ambiguity averse participants assign a significantly lower implied weight to the private signal than the theoretical prediction when they are making bid offers, in Scenario 1 ($z = \ 6{:}678;\ p = 0{:}0000$), Scenario 2 ($z = \ 15{:}876;\ p = 0{:}0000$), and Scenario 3 ($z = \ 4{:}052;\ p = 0{:}0000$). This result holds when they make ask offers. Ambiguity averse participants assign a significantly lower implied weight to the private signal than the theoretical prediction when they are making ask offers, in Scenario 1 ($z = \ 6{:}947;\ p = 0{:}0000$), Scenario 2 ($z = \ 5{:}77;\ p = 0{:}0000$), and Scenario 3 ($z = \ 5{:}142;\ p = 0{:}0000$).

We also observe that the implied weight assigned to the private signal is significantly lower than the theoretical prediction for ambiguity neutral subjects in Scenario 1 ($z = \ 3{:}909;\ p = 0{:}0000$), and Scenario 2 ($z = \ 8{:}085;\ p = 0{:}0000$) when they are submitting the bid offers. Nevertheless, the implied weight assigned to the private signal is larger than the theoretical prediction in Scenario 3 ($z = 0{:}155;\ p = 0{:}8768$). While for ask offers, ambiguity neutral subjects tend to assign a higher weight to the private signal than the theoretical prediction in Scenario 1 ($z = 0{:}501;\ p = 0{:}6163$), but a (marginally) significantly lower weight to the private signal than the theoretical prediction in Scenario 2 ($z = \ 1{:}745;\ p = 0{:}0809$) and Scenario 3 ($z = \ 2{:}169;\ p = 0{:}0301$). Ambiguity seeking participants assign a higher weight to private signals than the theoretical prediction in Scenario 1 ($z = 1{:}01;\ p = 0{:}3123$), but a (marginally) significantly lower weight to the private signal than the theoretical prediction in Scenario 2 ($z = \ 3{:}402;\ p = 0{:}0{:}0007$) and Scenario 3 ($z = \ 1{:}649;\ p = 0{:}0999$) for bid offers. And they assign a significantly lower weight to private signals than the theoretical prediction in Scenario 1 ($z = \ 5{:}016;\ p = 0{:}0000$) and Scenario 2 ($z = \ 1{:}785;\ p = 0{:}0{:}0743$), and a higher weight to private signals than the theoretical prediction in Scenario 3 ($z = 1{:}064;\ p = 0{:}2872$) for ask offers.

Table C10 reports on descriptive statistics for implied weights assigned to the private signals in these first three scenarios in the top panel. The middle/bottom panel includes the statistics for bid/ask offers. We find that the implied weight assigned to the private signal is significantly smaller than the theoretical prediction in Scenario 1 ($z = \ 6{:}735;\ p = 0{:}0000$), in Scenario 2

($z = 17:962; p = 0:0000$), and in Scenario 3 ($z = 3:736; p = 0:0000$) when subjects submit the bid offers. The implied weight assigned to the private signal is significantly smaller than the theoretical prediction in Scenario 1 ($z = 7:29; p = 0:0000$), in Scenario 2 ($z = 6:212; p = 0:0000$), and in Scenario 3 ($z = 4:844; p = 0:0000$) when subjects submit the ask offers. Those statistical results imply that the participants do not follow the signal extraction model when they trade in the asset market with unambiguous signals. We can infer that people do not follow the signal extraction model when submitting their bid offers and ask offers in the auction market with unambiguous signals regardless of their ambiguity attitude. They tend to put less weight on unambiguous private signals to make their bid or ask prices.

Besides, we examine how individuals respond to good and bad news for unambiguous signals. People tend to overweight good news in Scenario 2 ($z = 4:068; p = 0:0000$) and Scenario 3 ($z = 5:585; p = 0:0000$), but not in Scenario 1 ($z = 0:141; p = 0:8875$) as reported in Table C11. We do not observe the difference between the implied weight and the theoretical weight for ambiguity averse subjects ($z = 0:618; p = 0:5363$), ambiguity neutral subjects ($z = 0:723; p = 0:4697$) and ambiguity seeking subjects ($z = 0:088; p = 0:9302$) in Scenario 1. Ambiguity averse subjects are more likely to overestimate good news ($z = 4:386; p = 0:0000$) in Scenario 2, but ambiguity neutral ($z = 0:989; p = 0:3227$) and ambiguity seeking subjects ($z = 1:256; p = 0:2091$) are not. Ambiguity averse ($z = 2:791; p = 0:0053$), ambiguity neutral ($z = 3:732; p = 0:0002$) and ambiguity seeking ($z = 4:527; p = 0:0000$) subjects tend to overestimate the good news in Scenario 3.

We find that individuals assign a higher weight to bad news when they submit their bid offers to buy the asset. Table C12 reports the descriptive statistics of the implied weights assigned to the unambiguous signal for bid offers. The mean implied weight assigned to good/bad news is 0.2184/0.6414 in Scenario 1, 0.2353/0.5945 in Scenario 2, and 0.0966/0.5151 in Scenario 3. The difference between the weight assigned to the bad news is significantly larger than that to the good news for Scenario 1 ($z = 8:470; p = 0:0000$), Scenario 2 ($z = 6:247; p = 0:0000$), and Scenario 3 ($z = 9:244; p = 0:0000$). The results remain consistent for ambiguity averse and ambiguity neutral subjects, but inconsistent for ambiguity seeking subjects. The ambiguity seeking subjects seem not to put a significantly higher weight on bad news in Scenario 1 ($z = 1:024; p = 0:3059$) and Scenario 3 ($z = 0:509; p = 0:6110$). We find that individuals tend to assign a higher weight to good news when they submit their ask offers to sell the asset. Table C13 reports the descriptive statistics of the implied weights assigned to the unambiguous signal for ask offers. The mean implied weight assigned to good/bad news is 0.4946/0.1976 in Scenario 1, 0.7753/0.2082 in Scenario 2, and 0.5414/0.0892 in Scenario 3. The difference between the weight assigned to the bad news is significantly larger than that to the good news for Scenario 1 ($z = 7:428; p = 0:0000$), Scenario 2 ($z = 12:686; p = 0:0000$) and Scenario 3 ($z = 14:939; p = 0:0000$). Participants behave consistently except that the ambiguity seeking individuals do not put a significantly higher weight on the good news in Scenario 2 ($z = 0:599; p = 0:5495$).

Signal Extraction to Ambiguous Signals

Table C10

This table reports on the descriptive statistics of the implied weight assigned to the unambiguous private signals for Scenario 1, 2 and 3. The theoretical prediction is 0.5 for Scenario 1, 0.8 for Scenario 2, and 0.2 for Scenario 3 in Treatment DA.

Implied Weights Assigned to the Unambiguous Signals						
	Scenario	Mean	Median	Std	Min	Max
Whole sample	1	0.3730	0.2348	0.3731	0	1
	2	0.4097	0.32	0.3726	0	1
	3	0.2861	0.1290	0.3354	0	1
Ambiguity averse	1	0.3524	0.2074	0.3620	0	1
	2	0.3910	0.2703	0.3661	0	1
	3	0.2702	0.1220	0.3314	0	1
Ambiguity neutral	1	0.4349	0.3568	0.3835	0	1
	2	0.4290	0.4132	0.3811	0	1
	3	0.3013	0.1348	0.3365	0	1
Ambiguity seeking	1	0.3883	0.25	0.4071	0	1
	2	0.4967	0.4762	0.3891	0	1
	3	0.3413	0.1924	0.3498	0	1
Implied Weights Assigned to the Unambiguous Signals for Bid Offers						
	Scenario	Mean	Median	Std	Min	Max
Whole sample	1	0.3743	0.2329	0.3787	0	1
	2	0.3075	0.2000	0.3217	0	1
	3	0.2980	0.1333	0.3480	0	1
Ambiguity averse	1	0.3395	0.1908	0.3696	0	1
	2	0.2614	0.1786	0.2888	0	1
	3	0.2982	0.1230	0.3612	0	1
Ambiguity neutral	1	0.3473	0.2041	0.3635	0	1
	2	0.3837	0.3638	0.3459	0	1
	3	0.3175	0.2105	0.3267	0	0.9979
Ambiguity seeking	1	0.5555	0.6861	0.3937	0	1
	2	0.4302	0.3261	0.4040	0	1
	3	0.2627	0.0874	0.3275	0	1
Implied Weights Assigned to the Unambiguous Signals for Ask Offers						
	Scenario	Mean	Median	Std	Min	Max
Whole sample	1	0.3720	0.2362	0.3691	0	1
	2	0.5173	0.5263	0.3921	0	1
	3	0.2786	0.1232	0.3273	0	1
Ambiguity averse	1	0.3615	0.2308	0.3571	0	1
	2	0.5162	0.5263	0.3893	0	1
	3	0.2534	0.1064	0.3118	0	1
Ambiguity neutral	1	0.5196	0.6757	0.3861	0	1
	2	0.4954	0.4692	0.4218	0	1
	3	0.2903	0.1117	0.3441	0	1
Ambiguity seeking	1	0.1985	0.0000	0.3361	0	1
	2	0.5613	0.5644	0.3684	0	1
	3	0.3995	0.2813	0.3573	0	1

In this part, we provide more details about the implied weight allocation to ambiguous signals across periods. The mean and median implied weight assigned to the ambiguous private signal

Table C11
This table reports on the descriptive statistics of the implied weights assigned to the unambiguous signal (good news versus bad news) in Treatment DA.

		Scenario 1				
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.3672	0.2157	0.3676	0	1
	Bad news	0.3820	0.2649	0.3819	0	1
Ambiguity averse	Good news	0.3405	0.2041	0.3519	0	1
	Bad news	0.3718	0.2440	0.3783	0	1
Ambiguity neutral	Good news	0.4472	0.3896	0.3886	0	1
	Bad news	0.4072	0.3511	0.3755	0	1
Ambiguity seeking	Good news	0.3755	0.1672	0.4145	0	1
	Bad news	0.3975	0.2765	0.4061	0	1
		Scenario 2				
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.4476	0.3548	0.3744	0	1
	Bad news	0.3309	0.2020	0.3568	0	1
Ambiguity averse	Good news	0.4346	0.3030	0.3675	0	1
	Bad news	0.2835	0.1429	0.3411	0	1
Ambiguity neutral	Good news	0.4480	0.4186	0.3744	0	1
	Bad news	0.4028	0.3918	0.3919	0	1
Ambiguity seeking	Good news	0.5471	0.6404	0.4199	0	1
	Bad news	0.4122	0.4082	0.3213	0	1
		Scenario 3				
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.3464	0.2427	0.3350	0	1
	Bad news	0.2353	0.0675	0.3275	0	1
Ambiguity averse	Good news	0.2995	0.1620	0.3229	0	1
	Bad news	0.2461	0.0781	0.3369	0	1
Ambiguity neutral	Good news	0.3793	0.3175	0.3348	0	1
	Bad news	0.2215	0.0499	0.3209	0	0.9979
Ambiguity seeking	Good news	0.5431	0.5227	0.3325	0	1
	Bad news	0.2044	0.0747	0.2921	0	1

is 0.3541, 0.2736 in Period 16, 0.4116, 0.3704 in Period 17, 0.3791, 0.2002 in Period 18, 0.4416, 0.3333 in Period 19, and 0.2866, 0.1923 in Period 20. The result of rank-sum test reveals that the implied weight is lower (not significantly) than the theoretical weight in Period 16 ($z = 1.195; p = 0.2322$) and Period 17 ($z = 1.474; p = 0.1404$), the implied weight is not significantly different from the theoretical weight in Period 18 ($z = 0.0000; p = 1.0000$), and the implied weight is significantly larger than the theoretical weight in Period 19 ($z = 5.447; p = 1.0000$) and Period 20 ($z = 5.604; p = 1.0000$).

Asymmetric Reaction to Ambiguous Signals

This subsection provides more details about the asymmetric response to the ambiguous signals conditional on the type of offers. We do not observe a consistent and significant pattern of variance prediction for good/bad news for more submission of bid/ask offers across different

Table C12
This table reports on the descriptive statistics of the implied weights assigned to the unambiguous signal (good news versus bad news) for bid offers in Treatment DA.

Implied Weight Assigned to the Unambiguous Signal for Bid Offers						
Scenario 1						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.2184	0.0885	0.3001	0	1
	Bad news	0.6414	0.7453	0.3499	0	1
Ambiguity averse	Good news	0.1802	0.0678	0.2583	0	1
	Bad news	0.6395	0.7544	0.3625	0	1
Ambiguity neutral	Good news	0.2073	0.0843	0.2956	0	1
	Bad news	0.6932	0.7561	0.2769	0	1
Ambiguity seeking	Good news	0.2184	0.0885	0.4202	0	1
	Bad news	0.6414	0.7453	0.3726	0	1
Scenario 2						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.2353	0.1675	0.2555	0	1
	Bad news	0.5945	0.6567	0.3922	0	1
Ambiguity averse	Good news	0.2106	0.1613	0.2238	0	1
	Bad news	0.5538	0.7018	0.4232	0	1
Ambiguity neutral	Good news	0.2867	0.2264	0.2722	0	1
	Bad news	0.5926	0.6567	0.3978	0	1
Ambiguity seeking	Good news	0.3107	0.1125	0.3968	0	1
	Bad news	0.7489	0.6452	0.2078	0.4082	1
Scenario 3						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.0966	0.0444	0.1264	0	0.5833
	Bad news	0.5151	0.5263	0.3792	0	1
Ambiguity averse	Good news	0.0670	0.0310	0.0895	0	0.4464
	Bad news	0.5676	0.5780	0.3721	0	1
Ambiguity neutral	Good news	0.1432	0.0763	0.1614	0	0.5833
	Bad news	0.5699	0.6325	0.3422	0	0.9979
Ambiguity seeking	Good news	0.1773	0.1467	0.1702	0	0.4403
	Bad news	0.2992	0.0691	0.3722	0	1

types of ambiguity attitudes. Ambiguity averse and ambiguity seeking people seem to have a lower variance expectation for bad news when they submit more bid offers, and a lower variance expectation for good news when they submit more ask offers. However, this finding is not insignificant. Ambiguity neutral people tend to have a significantly higher variance expectation for bad news regardless of the type of offers. Table C15 reports on the descriptive statistics of the variance prediction of the ambiguous signals. When subjects submit more bid offers than ask offers, the mean variance prediction is 2.2184 for good news, and 2.1295 for bad news for ambiguity averse participants. Ambiguity averse participants tend to have a lower expectation (but not significant) of variance for bad news than good news ($z = 0.199; p = 0.8424$). The mean variance prediction is 1.4781 for good news, and 2.781 for bad news for ambiguity neutral participants. Ambiguity neutral participants tend to have a significantly higher expectation of variance for bad news than good news ($z = 2.769; p = 0.0056$). The mean variance prediction

Table C13
This table reports on the descriptive statistics of the implied weights assigned to the unambiguous signal (good news versus bad news) for ask offers in Treatment DA.

Implied Weight Assigned to the Unambiguous Signal for Ask Offers						
Scenario 1						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.4946	0.4904	0.3728	0	1
	Bad news	0.1976	0.0507	0.2847	0	1
Ambiguity averse	Good news	0.4645	0.4336	0.3650	0	1
	Bad news	0.2111	0.0667	0.2863	0	1
Ambiguity neutral	Good news	0.6929	0.7692	0.3125	0	1
	Bad news	0.1641	0.0424	0.2594	0	0.9420
Ambiguity seeking	Good news	0.2456	0	0.3811	0	1
	Bad news	0.1664	0	0.3068	0	0.9167
Scenario 2						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.7753	0.8989	0.2808	0	1
	Bad news	0.2082	0.0817	0.2611	0	0.96
Ambiguity averse	Good news	0.7547	0.8889	0.2868	0	1
	Bad news	0.1925	0.0543	0.2521	0	0.9524
Ambiguity neutral	Good news	0.8243	0.9197	0.3051	0	1
	Bad news	0.2487	0.0944	0.3162	0	0.96
Ambiguity seeking	Good news	0.8622	0.9105	0.1676	0.4699	1
	Bad news	0.2228	0.2041	0.1893	0	0.5263
Scenario 3						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.5414	0.5310	0.3172	0	1
	Bad news	0.0892	0.0299	0.1619	0	1
Ambiguity averse	Good news	0.4867	0.4249	0.3214	0	1
	Bad news	0.0992	0.0295	0.1834	0	1
Ambiguity neutral	Good news	0.5902	0.6349	0.3079	0	1
	Bad news	0.0473	0.0194	0.0725	0	0.3289
Ambiguity seeking	Good news	0.7119	0.7189	0.2389	0.2685	1
	Bad news	0.1095	0.0837	0.1290	0	0.6278

is 2.625 for good news, and 1.9075 for bad news for ambiguity seeking participants. Ambiguity seeking participants tend to have an insignificantly lower expectation of variance for bad news than good news ($z = \ 1.193$; $p = 0.2328$).

The mean variance prediction is 1.9817 for good news, and 2.3076 for bad news for ambiguity averse participants when they submit more ask offers than bid offers. The higher variance prediction for bad news is not significant ($z = 1.392$; $p = 0.164$). The mean variance prediction is 1.5806 for good news, and 2.2404 for bad news for ambiguity neutral participants when they submit more ask offers than bid offers. They tend to have a higher variance prediction for bad news than good news ($z = 2.21$; $p = 0.0271$). The mean variance prediction is 0.625 for good news, and 1.3135 for bad news for ambiguity seeking participants when they submit more ask offers than bid offers. They tend to have a higher variance prediction for bad news than good

Table C14
This table reports the descriptive statistics of the implied weight assigned to the ambiguous private signals for Scenario 4. The theoretical prediction is 0.2299 in Period 16, 0.3058 in Period 17, 0.2004 in Period 18, 0.6494 in Period 19 and 0.3436 in Period 20 in Treatment DA.

	Period 16				
	Mean	Median	Std	Min	Max
Whole sample	0.3541	0.2736	0.3315	0	1
Ambiguity averse	0.3255	0.2078	0.3334	0	1
Ambiguity neutral	0.3887	0.4713	0.2884	0	1
Ambiguity seeking	0.4888	0.5464	0.3962	0	1
	Period 17				
	Mean	Median	Std	Min	Max
Whole sample	0.4116	0.3704	0.3723	0	1
Ambiguity averse	0.3936	0.3704	0.3593	0	1
Ambiguity neutral	0.4453	0.4255	0.3756	0	1
Ambiguity seeking	0.4392	0.1176	0.4526	0	1
	Period 18				
	Mean	Median	Std	Min	Max
Whole sample	0.3791	0.2002	0.3978	0	1
Ambiguity averse	0.3794	0.1799	0.4020	0	1
Ambiguity neutral	0.4665	0.4782	0.3974	0	1
Ambiguity seeking	0.1846	0.0452	0.3189	0	0.9626
	Period 19				
	Mean	Median	Std	Min	Max
Whole sample	0.4416	0.3333	0.3612	0	1
Ambiguity averse	0.4516	0.3229	0.3591	0	1
Ambiguity neutral	0.4940	0.3929	0.3932	0	1
Ambiguity seeking	0.2591	0.1408	0.2724	0	0.7547
	Period 20				
	Mean	Median	Std	Min	Max
Whole sample	0.2866	0.1923	0.2908	0	1
Ambiguity averse	0.2660	0.1923	0.2626	0	0.9863
Ambiguity neutral	0.2901	0.1411	0.3321	0	1
Ambiguity seeking	0.6457	0.7317	0.3363	0	1

news ($z = 0.968$; $p = 0.3329$).

All types of participants tend to assign a significantly higher implied weight to the bad news when they submit bid offers to buy the asset, and assign a significantly higher implied weight to the good news when they submit ask offers to sell the asset. Table C16 reports on descriptive statistics of the implied weights assigned to the ambiguous signal. The mean and median implied weight assigned to the good/bad news by ambiguity averse subjects is 0.1307/0.6317 and 0.0610/0.7047 when making bid offers. They tend to assign a higher weight to bad news than good news for bid offers ($z = 9.736$; $p = 0.0000$). The mean and median implied weight assigned to the good/bad news by ambiguity averse subjects is 0.6590/0.1715, 0.7208/0.0988 when they are making ask offers. They allocate a higher weight to good news than bad news for ask offers

Table C15
This table reports on descriptive statistics of the variance prediction of the ambiguous signals (good news versus bad news) in the top panel, and on descriptive statistics of the variance expectation of the ambiguous signals when the number of submitted bid offers is more than that of ask offers in the middle panel, and on descriptive statistics of the variance expectation of the ambiguous signals when the number of submitted ask offers is more than that of bid offers in the bottom panel in Treatment DA.

Variance Expectation of the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Whole sample	Good news	1.8219	2	0.8659	0.25	4
	Bad news	2.2338	2.125	0.9874	0.25	4
Ambiguity averse	Good news	1.9118	2.0625	0.8197	0.36	4
	Bad news	2.260	2	1.0122	0.33	4
Ambiguity neutral	Good news	1.6231	1.5	0.8710	0.27	3.4
	Bad news	2.4053	2.23	0.8138	0.9	4
Ambiguity seeking	Good news	1.5417	1	1.1538	0.25	3.7
	Bad news	1.8061	2	1.0277	0.25	4
Variance prediction When the Number of Bid Offers>Ask Offers						
		Mean	Median	Std	Min	Max
Whole sample	Good news	1.8442	2	0.7279	0.27	4
	Bad news	2.2341	2.28	0.9443	0.25	4
Ambiguity averse	Good news	2.2184	2.065	0.7647	1	4
	Bad news	2.1295	2.15	0.8368	0.36	3.5
Ambiguity neutral	Good news	1.4781	1.1	0.9999	0.27	3
	Bad news	2.781	2.85	0.8216	1.22	4
Ambiguity seeking	Good news	2.625	3.05	1.3200	0.7	3.7
	Bad news	1.9075	2	0.8762	0.25	3.25
Variance prediction When the Number of Ask Offers>Bid Offers						
		Mean	Median	Std	Min	Max
Whole sample	Good news	2.0407	2	0.9460	0.27	4
	Bad news	2.2542	2.28	0.8823	0.25	4
Ambiguity averse	Good news	1.9817	2.2	0.6936	0.5	3.23
	Bad news	2.3076	2.2	0.9934	0.6	4
Ambiguity neutral	Good news	1.5806	2	0.6064	0.5	2.125
	Bad news	2.2404	2.125	0.6590	0.9	3.8
Ambiguity seeking	Good news	0.6250	0.625	0.5303	0.25	1
	Bad news	1.3125	1.5	0.8509	0.25	2

($z = \quad 11:687; \ p = 0:0000$). The mean and median implied weight assigned to the good/bad news by ambiguity neutral subjects is 0.2504/0.6327, 0.1724/0.5913 when making bid offers. They tend to assign a higher weight to bad news than good news for bid offers ($z = 4:482; \ p = 0:0000$). The mean and median implied weight assigned to the good/bad news by ambiguity neutral subjects is 0.7553/0.1562, 0.8621/0.0627 when making ask offers. They allocate a higher weight to good news than bad news for ask offers ($z = \quad 6:569; \ p = 0:0000$). The mean and median implied weight assigned to the good/bad news by ambiguity seeking subjects is 0.0987/0.5727 and 0.0452/0.7230 when making bid offers. They tend to assign a higher weight to bad news than good news for bid offers ($z = 3:24; \ p = 0:0012$). The mean and median implied weight assigned to the good/bad news by ambiguity seeking subjects is 0.7394/0.1966, 0.6918/0.0882 when they are making ask offers. They allocate a higher weight to good news than bad news for ask offers ($z = \ \ 2{:}396;\ p = 0{:}0166$).

Table C16
This table reports on descriptive statistics of the implied weights assigned to the ambiguous signal (good news versus bad news) in the top panel, and on descriptive statistics of the implied weights assigned to the ambiguous signal (good news versus bad news) for bid offers in the middle panel, and for ask offers in the bottom panel in Treatment DA.

Implied Weight Assigned to the Ambiguous Signal						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.4241	0.3448	0.3710	0	1
	Bad news	0.3282	0.2259	0.3301	0	1
Ambiguity averse	Good news	0.4214	0.3333	0.3685	0	1
	Bad news	0.3044	0.1986	0.3160	0	1
Ambiguity neutral	Good news	0.5029	0.4464	0.3811	0	1
	Bad news	0.3418	0.2717	0.3294	0	1
Ambiguity seeking	Good news	0.2589	0.1157	0.3237	0	1
	Bad news	0.4842	0.5738	0.4036	0	1
Implied Weight Assigned to the Ambiguous Signal for Bid Offers						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.1500	0.0669	0.2023	0	1
	Bad news	0.6212	0.6993	0.3010	0	1
Ambiguity averse	Good news	0.1307	0.0610	0.1673	0	1
	Bad news	0.6317	0.7047	0.2861	0	1
Ambiguity neutral	Good news	0.2504	0.1724	0.2995	0	0.9091
	Bad news	0.6327	0.5913	0.2684	0	1
Ambiguity seeking	Good news	0.0987	0.0452	0.1450	0	0.5634
	Bad news	0.5727	0.7230	0.3864	0	1
Implied Weight Assigned to the Ambiguous Signal for Ask Offers						
		Mean	Median	Std	Min	Max
Whole sample	Good news	0.6794	0.7435	0.3042	0	1
	Bad news	0.1689	0.0926	0.2168	0	1
Ambiguity averse	Good news	0.6590	0.7208	0.3135	0	1
	Bad news	0.1715	0.0988	0.2148	0	1
Ambiguity neutral	Good news	0.7553	0.8621	0.2721	0	1
	Bad news	0.1562	0.0627	0.2084	0	0.775
Ambiguity seeking	Good news	0.7394	0.6918	0.2029	0.5348	1
	Bad news	0.1966	0.0882	0.3336	0	1

Mispricing

The mean RD is -0.0237 in Scenario 1, -0.0185 in Scenario 2, 0.0248 in Scenario 3, and 0.0030 in Scenario 4. RD is not significantly larger in Scenario 4 than that in Scenario 1 ($z = 1{:}085;\ p = 0{:}2779$), in Scenario 2 ($z = 0{:}738;\ p = 0{:}4602$), and in Scenario 3 ($z = 0{:}011;\ p = 0{:}9915$). The mean RAD is 0.0611 in Scenario 1, 0.0430 in Scenario 2, 0.1036 in Scenario 3, and 0.0706 in Scenario 4. RAD in Scenario 4 is also not significantly larger than that in Scenario 1 ($z = 1{:}477;\ p = 0{:}1397$), and in Scenario 3 ($z = \ \ 0{:}842;\ p = 0{:}3997$). But RAD in Scenario 4 is significantly larger than that in Scenario 2 ($z = 3{:}139;\ p = 0{:}0017$).

Overall, we fail to find a significant result that people are more likely to overestimate the fundamental value of the asset and make larger mispricing when the signal is ambiguous.

Table C17
This table reports the descriptive statistics of the Relative Deviation (RD) for each scenario in the top panel and Relative Absolute Deviation (RAD) for each scenario in the bottom panel in Treatment DA.

	Relative Deviation				
	Mean	Median	Std	Min	Max
Ambiguous signals	0.0030	-0.0193	0.0854	-0.1733	0.1887
Unambiguous signals	-0.0060	-0.0260	0.0984	-0.2908	0.3605
Scenario	Mean	Median	Std	Min	Max
1	-0.0237	-0.0363	0.0776	-0.2908	0.1348
2	-0.0185	-0.0288	0.0476	-0.0988	0.1012
3	0.0248	0.0064	0.1411	-0.2135	0.3605
4	0.0030	-0.0193	0.0854	-0.1733	0.1887
	Relative Absolute Deviation				
	Mean	Median	Std	Min	Max
Ambiguous signals	0.0706	0.0630	0.0470	0.0058	0.1887
Unambiguous signals	0.0690	0.0488	0.0701	0.0012	0.3605
Scenario	Mean	Median	Std	Min	Max
1	0.0611	0.0488	0.0528	0.0012	0.2908
2	0.0430	0.0397	0.0269	0.0045	0.1012
3	0.1036	0.0828	0.0980	0.0064	0.3605
4	0.0706	0.0630	0.0470	0.0058	0.1887