Asset Pricing with Ambiguous Signals: An Experimental Study*

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Abstract

This paper explores how ambiguous signals and ambiguity aversion influence individuals' expectations and the pricing of assets in experimental financial markets. Epstein and Schneider (2008) suggest that when faced with such ambiguous information, ambiguity-averse investors maximize expected utility under a worst-case belief as in Gilboa and Schmeidler (1989) about the quality of the ambiguous signal. In line with the theory, we find that subjects' degree of ambiguity aversion is positively correlated with their expectations about the variance of ambiguous signals. These signals matter for the determination of asset prices. We find that price volatility is significantly larger under ambiguous signals. Our findings provide evidence in support of the idea that ambiguous information and ambiguity aversion may be a source of mispricing and excess volatility in financial markets.

Keywords: Ambiguity Aversion, Asset Bubbles, Experimental Finance, Signal Extraction, Excess Volatility

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 and Schneider (2008), agents take the ***quality*** of the signals they receive into account when processing such 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 good (bad) 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", there are also ***ambiguous*** signals from previously unknown sources for which the variance may be unknown. Epstein and Schneider (2008) suggest that when faced with such ambiguous information, ambiguity-averse investors maximize expected utility under a worst-case belief as in Gilboa and 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 will be treated as if they are more accurate (have smaller variance) than good signals, and agents will allocate higher weight to bad signals when making decisions. Since signals matter for asset price determination, if there are ambiguity-averse investors pricing assets they will require higher excess returns when signals are ambiguous, and the volatility of prices will also be greater under ambiguous signals.

In this paper, we report the results of an experimental study that tests these implications of Epstein and Schneider's theory (2008). In our view, the theoretical predictions of Epstein and Schneider (2008) are four-fold: (1) Ambiguity averse participants' perceived variance of an ambiguous signal is smaller when it conveys bad news than when it conveys good news; (2) Ambiguity averse participants allocate a larger weight to such signals when they convey bad news than when they convey good news; (3) The response of ambiguity-averse investors to ambiguous information implies that there will be negative skewness in measured excess returns; (4) The volatility of prices is greater when the signal is ambiguous than when it is unambiguous.

To test these hypotheses, we design a two-stage experiment. In the first stage, participants' attitude towards ambiguity is measured, along with measures for their risk aversion. Then, in the second stage they participate in a simplified version of an experimental asset market.

In the first stage, we measure the ambiguity attitudes of participants according to a method used in Trautmann et al. (2008), Kocher and Trautmann (2013), Trautmann and Van de Kuilen (2015). Specifically, participants are asked to make a number of choices between pairs of boxes. The K (known) box in each pair has a known number (or fraction) of purple balls and orange balls. The U (unknown) box in each pair has an unknown number (or fraction) of purple balls 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 0 otherwise. Using this task we find that 66.67% of our participants are ambiguity averse, 22.22% are ambiguity neutral, and 11.11% are ambiguity seeking. Thus the degree of ambiguity aversion is heterogeneous across participants.

In the second stage, participants need to predict the fundamental value of an asset based on two signals: a public signal and a private signal. The public signal is the known-to-all information that the fundamental value of the asset is a random variable drawn from a normal distribution having a mean of 3 and a variance of 1. The private signal, s, is equal to the actual 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 known, fixed variance that is also known to change every 5 periods in the first 15 periods. The variance of the private signal is known to be 1 in periods $1-5$, 0.25 in periods $6-10$, and 4 in periods $11-15$. Thus, the private signal is *un*ambiguous in the first 15 periods. The signal becomes ambiguous only in the last 5 periods. In those final periods, $16-20$, the variance of the signal lies somewhere between 0.25 and 4, inclusive, but the actual value is unknown to participants. We face the subjects with unambiguous private signals first because forming expectations with unambiguous signals is easier, and this also provides subjects with an opportunity to learn how to form expectations with the two signals under different variances, before confronting them with the ambiguous signals case.

In this second stage of the experiment, participants are first shown their private signal and are asked to make an implicit prediction of the fundamental value of the asset by choosing the weight, $w \in [0,1]$, they wish to assign to their private signal. The remaining weight is given to the publicly known mean realization for the public signal, which is fixed across all rounds at 3. In addition, prior the last five periods, subjects are asked to forecast what they think will be the variance of the signal in those last 5 periods. Differently from Bleaney and Humphrey (2006), Halevy (2007), and Bossaerts et al. (2010), our experiment uses the variance of the signal to characterize the ambiguity of the signal information rather than different probabilities in the returns to the asset. To the best of our knowledge, this is the first work on financial ambiguity in terms of the *variance* of signals instead of the probabilities of outcomes. After the subjects choose the weight between the two signals, their implied prediction for the fundamental value of the asset is calculated. Using these forecasts, the asset is then traded using a call market mechanism. Subjects' payoffs are determined by the profitability of their asset market trade outcome, which in turn depends on their use of the public and private signals, or their forecast of the fundamental value of the asset.

Our experimental results confirm some of the theoretical predictions of Epstein and 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. However, they do not assign significantly more weight to bad news than to good news. The distribution of the excess returns of the asset under ambiguous signals is negatively skewed. We also find a significantly larger price deviation and price volatility when the signal is ambiguous than when it is unambiguous.

Asparouhova et al. (2015) present a theory of asset trading with symmetric information but asymmetric reasoning. Asymmetric reasoning is captured by having two kinds of agents. Price-sensitive agents are confident in their reasoning to calculate the possible outcomes and regard asset payoffs as risky (rather than ambiguous). By contrast, price-insensitive agents who observe prices that cannot be reconciled with their reasoning, perceive the prices as ambiguous. Both theory and experimental results confirm that without aggregate risk, mispricing decreases as the fraction of price-sensitive agents increases.

With aggregate risk, price-insensitive agents trade to achieve more balanced portfolios. Recently, Epstein and Halevy (2019) investigate the implications of hard-to-interpret signals on individuals' belief updating behavior. In their paper, they also differentiate between risky signals, for which the accuracy is known, and ambiguous signals, for which the accuracy is uncertain, i.e., subject to two-point ambiguity. They find that compared to the case of risky signals, individuals have more difficulty updating their beliefs following Bayes rule under ambiguous signals, which is called information ambiguity aversion in their paper. While both of these studies are based on Epstein and Schneider (2007, 2008) model, as is our paper, there is an important difference in the source of uncertainty in the accuracy of the signals. In Asparouhova et al. (2015), this uncertainty is generated by the probability of realizations for the state of the world (red asset or black asset) and by the number of red and black balls to be added to the payoff urn to form the signal urn in Epstein and Halevy (2019). Hence, the uncertainty regarding the accuracy of the signal in these studies is related to the first moment of the signal, while in our study it comes from the second moment. A main contribution of our paper is to show that information ambiguity aversion also exists when the uncertainty with the accuracy of the signal is measured by the variance, and it is positively correlated with the degree of ambiguity aversion measured using the matched probability method.[1]

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 in a number of ways.

First, this paper is related to experimental studies on how ambiguity attitudes impact individual decisions and price dynamics in experimental asset markets. The previous literature on this topic usually frames ambiguous portfolios as "lotteries", e.g., Becker and Brownson (1964), Sarin and Martin (1993), Bleaney and Humphrey (2006), Halevy (2007), Bossaerts et al. (2010), Baillon and Bleichrodt (2015), etc. In their design, the "lottery choice" is used to represent "ambiguity" in the financial market. Differently from those studies, and following the theoretical work by Epstein and Schneider (2008), we study the impact of ambiguous signals having unknown variances instead of unknown means. By comparing subjects' attitudes toward ambiguity and their expectations regarding the variance of ambiguous signals, we confirm that ambiguity averse individuals are more likely to apply the worst-case scenario when forming expectations about the variance of ambiguous signals.

[1] Liang (2019) also studied agents' reaction to simple (risky) information, compound information and ambiguous information by eliciting the certainty equivalents of different bets. He finds that subjects under-react to ambiguous and compound information compared to simple information, and the under-reaction is greater for good news than bad news. In addition, he finds there is a lack of correlation between attitudes towards ambiguous priors versus ambiguous signals. Similar to Epstein and Halevy (2019), the accuracy of the signal is related to the first moment of the signal, but not the second moment as in our paper.

Second, our paper is related to the theoretical and empirical literature on how markets react to ambiguous information. Theoretical research has investigated how ambiguity aversion leads to asymmetric responses to information. Zhang (2006) finds that greater information uncertainty would lead to higher expected returns following good news and lower expected returns following bad news. Caskey (2008) shows that markets ambiguity-averse investors can result in persistent mispricing of the assets. Ambiguity-averse investors work to reduce ambiguity at the expense of information loss, which can explain underreaction and overreaction to accounting accruals. Li and Janssen (2018) find that the disposition effect, the reluctance to realized losses, and an eagerness to realize gains leads investors to underreact to private signal realizations. Our paper aims to examine signal extraction under ambiguous signals according to the theoretical work by Epstein and Schneider (2008). We find that ambiguity averse individuals will respond to ambiguous signals asymmetrically. They believe that bad news is more accurate than the good news. To our knowledge, this paper is the first work to investigate this issue experimentally. Additionally, our paper contributes to the literature on belief updating in the face of both public and private signals, e.g., Heinemann et al. (2004), Eil and Mao (2011), De Filippis et al. (2017), Duffy et al. (2018), as well as on belief updating under compound uncertainty and ambiguity, e.g., Klibanoff et al. (2009), Corgnet et al. (2012), Ert and Trautmann (2014), Moreno and Rosokha(2016), Hanany and Klibanoff (2019). Our work is distinguished from these papers by allowing belief updating of the variance of signals rather than the mean of signals.

Third, our paper is related to the literature on ambiguity and the empirical distributional properties of financial market data. There is a lot of empirical and theoretical research on ambiguity and asset pricing, e.g., Chen and Epstein (2002), Cao et al. (2005), Gollier (2011), Illeditsch (2011), Jeong et al. (2015), Gallant et al. (2015), Bianchi et al. (2018), Brenner and 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 its volatility. Epstein and Wang (1994) find that uncertainty can lead to considerable fluctuations in equilibrium prices. They show that some of the equilibrium prices are determined by the degree of ambiguity aversion of agents. Leippold et al. (2008) investigate asset pricing under both learning and ambiguity aversion and find that their model can successfully generate high equity premiums, low interest rates and excess volatility in returns. Our paper is also related to Gilboa and Schmeidler (1989), Hansen, Sargent, and Tallarini (1999) and Anderson, Hansen, and Sargent (2003), etc. However, there are very few experimental studies on the relationship between ambiguity and mispricing, price volatility and the return premium in asset markets. The main exception is Bossaerts et al. (2010), who study the effects of ambiguity and ambiguity aversion on equilibrium asset prices and portfolio choices in laboratory asset markets. They find that ambiguity-averse agents do not directly affect the price of ambiguous securities; rather the presence of such agents directly affects portfolio choices and therefore the distribution of wealth. In this paper, we use the experimental method to address two related questions: first, will ambiguity and ambiguity aversion lead to higher excess returns and/or negative skewness in these excess returns? Second, will ambiguity and ambiguity aversion lead to larger mispricing and price volatility in our experimental asset markets? We find supportive evidence that ambiguity and ambiguity aversion do lead to negative skewness, higher price volatility and asset mispricing.

Fourth, our paper is related to the literature on the measurement of ambiguity attitudes and risk attitudes. Since Knight (1921) and Ellsberg (1961) distinguished between uncertainty (unknown probability) and risk (known probability), there have been many studies on the measurement of risk and ambiguity aversion and the correlation between these two. Most of them find that there is a positive relation between ambiguity aversion and risk aversion. For example, Di Mauro and Maffioletti (2004) find that a "reflection effect" exists in both risky and ambiguous assignments. Du and Budescu (2005) find that in the gain domain, ambiguity aversion is more prevalent, while in the loss domain, ambiguity neutrality dominates. Chakravarty and Roy (2009) find risk and ambiguity aversion has a positive relationship when it comes to the gain domain, but not in the loss domain. Bossaerts et al. (2010), Abdellaoui et al. (2011), Kocher and Trautmann (2013), Butler et al. (2014), and Dimmock et al. (2015; 2016) report a positive relationship between the risk and ambiguity attitudes. While our study finds correlation between ambiguity attitude and information ambiguity attitude, our result suggests that there is no significant correlation between risk aversion and ambiguity aversion.

3 Experimental Design

3.1 Signal Extraction, Ambiguity and Testable Hypotheses

Consider the theoretical framework of Epstein and Schneider (2008) Ex-ante, there is no ambiguity. Each agent has the same, unique normal prior regarding the random dividend , , payment on an asset. That is, $\sim N(m; {}^2)$. Then, prior to trade in that asset, each agent gets a noisy private signal, s, about the likely value of that dividend, . Specifically,

$$s = \; + \; ;$$

where $\sim N(0; {}^2_s)$, ${}^2_s \in [\underline{{}^2_s}; \overline{{}^2_s}]$.

The agents update their beliefs about using Baye's Rule to obtain a family of posteriors:

$$\sim N(m + \frac{{}^2}{{}^2 + {}^2_s}(s - m); \frac{{}^2 \, {}^2_s}{{}^2 + {}^2_s});$$

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

Following Epstein and Schneider's approach, in each period, agents consider buying/selling the asset by solving an expected utility maximization problem that uses the worst-case belief about 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 , s/he will use a posterior that has a lower mean. Therefore, if the news about is "good", specifically if $s > m$, then s/he will evaluate the signal as imprecise (${}^2_s = \overline{{}^2_s}$), while if the about is bad ($s < m$), s/he will view the signal as reliable (${}^2_s = \underline{{}^2_s}$). As a result, the agent discounts good news and overestimates the impact of bad news.

They also find that if individuals overvalue the variance of a signal of uncertain quality, then expected excess returns are higher when the quality of information is more uncertain.

The signals of uncertain quality (ambiguous information) generate negative skewness in excess returns, while the signals of known quality (unambiguous information) generate positive skewness in excess returns.

Based on the theoretical predictions, we formulate the following testable hypotheses for the experiment.

Hypothesis 1 : Ambiguity-averse subjects are more likely to overestimate $^{2}_{s}$ when the signal is ambiguous.

Hypothesis 2 : When the signal is ambiguous, ambiguity-averse subjects overweight the variance of s when $s > m$, and underweight the variance of s when $s < m$.

Hypothesis 3 : The distribution of observed excess returns has negative skewness when the signal is ambiguous, and positive skewness when the signal is unambiguous.

Hypothesis 4 : Ambiguous signals will lead to larger mispricing and greater price volatility.

If Hypothesis 1 is rejected, and the variance expectation of ambiguity averse individuals is not larger when the signal is ambiguous, then there is no supporting evidence that ambiguity aversion will lead to overestimation of the variance under the ambiguous signal. If Hypothesis 2 is rejected, and ambiguity averse individuals do not assign higher weight to bad news and lower weight to good news, then there is no supporting evidence that ambiguity aversion individuals will react asymmetrically to the news. If Hypothesis 3 is rejected, and excess returns have positive skewness when the signal is ambiguous, then individuals require smaller excess returns under the ambiguous signal. If Hypothesis 4 is rejected, mispricing is not significantly different between the ambiguous signal and unambiguous signal. Hence, there is no supporting evidence that ambiguity will lead to price deviation and volatility.

3.2 Experimental Setup

Our experiment consists of two tasks and one survey. The first task is to measure subjects' attitude towards ambiguity, the second task is an asset market game, and the final, survey task involves elicitation of individual risk attitudes. We recruited 90 undergraduates from Nanyang Technological University as participants in this experiment. A typical session lasts 1 hour 40 minutes. The timeline of the experiment is summarized in Figure 1.

We categorize participants using the same method as Trautmann et al., (2011; 2015), Sutter et al. (2013), into the ambiguity-averse types and non-ambiguity averse types; the latter contain 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 balls and orange balls are known in Box K, as the subjects can see the numbers of purple balls and orange balls (and hence the fraction of purple and orange balls) on the computer screen. The

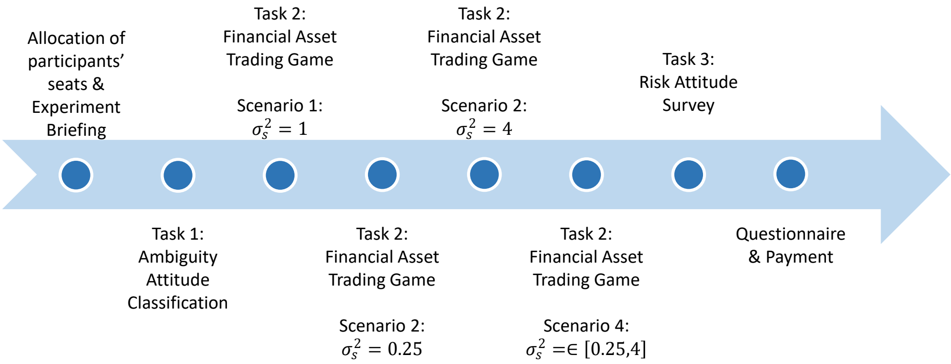

Figure 1: Timeline of Financial Trading Experiment

numbers (and hence the fraction) of purple balls and orange balls are unknown in Box U. One ball will be drawn randomly from the box that the participant chooses, s/he will win 3 SGD if a purple ball is drawn. The information about the probability of winning is certain in Box K, while it is ambiguous in Box U. Each of the 10 choices between Box K and Box U appears in a single row on subject's decisions screens. 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 can choose between Box K or Box U in each row. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are less than 50% for Box K, s/he is ambiguity averse. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are 50% for Box K, s/he is ambiguity neutral. If the participant switches her/his choice from Box K to Box U when the fractions of purple balls and orange balls are more than 50% for Box K, s/he is ambiguity seeking.

In our experiment, there are two types of signals, a public signal and a private signal. The public signal is the information about the mean and variance of the dividend, . For simplicity, we assume that $\sim N(3; 1)$, which means

$$m = 3; \quad {}^{2} = 1$$

There is a private signal s, which is the realized value of plus a normally distributed mean zero error term, . The private signal, s, is thus normally distributed with a mean realized value of and a variance of ${}^{2}_{s}$. Six subjects are randomly selected to form one market. The participants' task is to select the weight, w, assigned to the private signal s; the remaining weight, $1 - w$ is assigned to the public signal, the mean value for , which is known to be 3. Each subject's implied prediction for the dividend, $E_i({}_t)$, would be displayed once they have chosen w. We employ this design because the calculation of the posterior can be tricky for subjects, and by providing them the posterior based on their weight choice, we can help them to focus on the weight choice task. The dividend is the fundamental value of the asset (the one-period-lived asset is traded in a spot market). As for the value of the parameter, ${}^2_s$, there will be four scenarios. The first three are associated with a constant and known ${}^2_s$, the unambiguous case. In the last scenario, the subjects only know that ${}^2 \in [\underline{{}^2_s}; \overline{{}^2_s}]$. Each scenario consists of 5 periods.

Each subject's implied prediction of is

$$Implied\ prediction\ of\ \ = (1 - w) \cdot 3 + w \cdot s$$

where w is the weight that the participants assign to the private signal.

In the first three scenarios or 15 periods, the value of ${}^2_s$ is known to subjects and takes on the following values:

$${}^2_s = \begin{cases} 1; & t \in [1; 5]: \\ 0{:}25; & t \in [6; 10]: \\ 4; & t \in [11; 15]: \end{cases}$$

If subjects use the signal extraction model, their prediction of should be

$$E(\ ) = \frac{{}^2_s}{{}^2 + {}^2_s} m + \frac{{}^2}{{}^2 + {}^2_s} s \tag{1}$$

According to Equation (1), 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. The realized value of s is randomly generated and different in each period.

In Scenario 4, the final 5 periods, ${}^2_s$ is uniformly distributed between 0.25 and 4 and redrawn in each period. Namely,

$${}^2_{s;t} = V_t; \quad V_t \sim i{:}i{:}d{:}U(0{:}25; 4)$$

The subjects know the range of ${}^2_s$ but not the realized value of it in each period. In all scenarios with fixed ${}^2_s$, the subjects will make their implied prediction for only by selecting the weight assigned to the private signal. In the final, fourth scenario with ambiguous ${}^2_s$, in each period subjects will first submit their guess about the value of the variance for that period, ${}^2_s$, and then they will submit a weight to attach to their private signal.

The second stage of the experiment is an asset market experiment. At the beginning of each period, subjects are given an endowment of 7 SGD, which is slightly more than double the mean value of the asset (which is 3). We use a very simple call market mechanism (Akiyama et al., 2017) to determine the single market price of the asset in each period. Subjects know the price determination mechanism of the market, but do not know the decisions made by others. After they submit their weight choice, w, and their implied prediction for , the market will be automatically cleared at a price equal to the median of all 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 him/her to the other subjects whose prediction is higher than the market clearing price. A subject will be a buyer if his/her prediction is higher than the market price, the profit of the buyer is *realized dividend* − *market price*. A subject will be a seller if his/her prediction is lower than the market price, the profit of a seller is *market price* − *realized dividend* .

Subjects submit their implied prediction for in the 5 periods of each of the four scenarios. The signals and realizations of are randomly generated before the experiment, and are different in each period. After each period, the subjects receive feedback about their performance in the last period. They can see the realized market price, p_t, their own weight choice and implied market price prediction, and the actual, ex-post realization of $_t$. Subjects also submit their prediction of the variance of the ambiguous signal in the 5 periods in the final, scenario 4. The payoff for Task 2 is going to be determined in the following way: for the implied prediction of , the subjects are paid according to their trading profit from one randomly-chosen period among the 20 periods of the four scenarios. For the variance prediction task in scenario 4, subjects are paid according to the accuracy of their prediction of the variance in one randomly selected period among those last 5 periods.

Payoff for the implied prediction of :

$$^{Buyer}_{i;t} = 7 - p_t + {}_t$$
$$^{Seller}_{j;t} = 7 + p_t - {}_t$$

Payoff for the prediction of variance:

$$^{Variance}_{i;t} = 8 - \frac{10}{10 - |\ {}^2_{s;t} - E_{i;t}(\ {}^2_s)\ |}$$

The payoff for the whole experiment is the sum of the show-up fee, which is 3 SGD, the earnings from tasks 1, 2 and the survey. The experiment takes 1.5 hours on average, the average total payment is around 19 SGD.[2]

4 Experimental Results

4.1 Ambiguity Attitudes

According to Wakker (2010), the known probability of winning (that is, the known fraction of purple balls in the first stage of our experiment) of Box K is the matching probability when the participant is indifferent between Box K and Box U. In our experiment, the definition of matching probability follows Wakker (2010). If the subject switches from Box K when the winning probability is 20% to Box U, namely, for any winning probability

[2] Refer to Appendix A for more information.

below 20%, the subject prefers Box U. In that case, the subject's matching probability is 20%. As described in the experimental design, the winning probability is the fraction of purple balls in Box K. Therefore, the fraction of purple balls at the switching point is called the matching probability. The ambiguity neutral matching probability is 50%, such that a participant is ambiguity averse if his/her matching probability is below 50%, ambiguity neutral if his/her matching probability is equal to 50%, and ambiguity seeking if his/her matching probability is above 50%. We follow the same approach as Dimmock et al. (2015, 2016) to measure the ambiguity preferences of our participants:

$$AM_i = 0.5 - p_i^M$$

where AM_i is the measure of ambiguity for individual i and p_i^M is the matched 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]

There are 90 participants in our experiment. Using our ambiguity preference measure, we find that 66.67% (60 out of 90) of them are ambiguity averse, 22.22% (20 out of 90) are ambiguity neutral, and 11.11% (10 out of 90) are ambiguity seeking. On average, ambiguity averse individuals will switch to Box U when the winning probability is around 35.08%. Ambiguity seeking individuals will switch to the Box U when the winning probability is around 61%. Ambiguity neutral individuals will switch to the Box U when the winning probability is 50%. Table 1 summarizes the descriptive statistics of the ambiguity attitude. Panel A reports the matching probability and panel B is about the measure of ambiguity.

Table 1
This table reports descriptive statistics about ambiguity attitudes among our subjects. Panel A reports on the matching probability and panel B on the measure of ambiguity attitudes, AM_i.

Panel A: Matching Probability						
	Obs	Mean	Median	Std	Min	Max
Ambiguity averse	60	35.08%	40%	0.0917	0%	40%
Ambiguity neutral	20	50%	50%	0	50%	50%
Ambiguity seeking	10	61%	60%	0.0316	60%	70%
Panel B: Measure of Ambiguity Attitudes, AM_i						
	Obs	Mean	Median	Std	Min	Max
Ambiguity averse	60	0.1491	0.1	0.0917	0.1	0.5
Ambiguity neutral	20	0	0	0	0	0
Ambiguity seeking	10	-0.11	-0.1	0.0316	-0.2	-0.1

We use a simplified version of Holt and Laury (2002) to elicit participant's risk attitudes in the final survey part of the experiment. Subjects were asked to decide between option A (2 SGD for sure) and option B (6 SGD with probability X and 0 with probability Y) in each row and for 10 sequential rows. Similar to the ambiguity measure, if a subject switches from option A to option B when the probability to receive 6 SGD is larger than 40%, then s/he is risk averse. If the subject switches from option A to option B when

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

the probability to receive 6 SGD is 40%, then s/he is risk neutral. If the subject switches from option A to option B when the probability to receive 6 SGD is smaller 40%, then s/he is risk seeking. We do not find any evidence of a correlation between the ambiguity aversion and risk aversion. [4]

In the following subsections, we will use either subjects' individual ambiguity measure, AM_i, or dummy variables categorizing subjects as ambiguity averse, or neutral or loving, test the hypothesis we proposed in the previous section concerning the behavior of ambiguity averse subjects in our experiment.

4.2 Expected Variance of Ambiguous Signals

Following Epstein and Schneider (2008), we use subjects' guess (or expectation) about the variance of the private signal in Scenario 4 as a measure for their perceived nosiness of that signal. As Panel A of Table 2, reveals, the mean variance expectation is 1.6073 for ambiguity averse individuals, 1.422 for the ambiguity neutral individuals, and 1.4205 for the ambiguity seeking individuals. Panel A also reports other descriptive statistics of variance expectations under ambiguous signals conditional on the type of subjects' ambiguity attitudes. There is a significant difference in expected variance between the ambiguity averse and non-ambiguity averse individuals according to the rank sum test ($z = 1.849$ and $p = 0.0645$). The expected variance by the ambiguity averse individuals is significantly higher than that by the ambiguity neutral individuals ($z = 1.784$ and $p = 0.0744$), however, the expected variance by the ambiguity averse individuals is not significantly higher than that by the ambiguity seeking individuals ($z = 0.934$ and $p = 0.3503$) .

To further investigate whether ambiguity aversion will cause overestimation of the variance of ambiguous signals, we calculate the difference ($\sigma^2_{diff,i}$) between the expectation of the variance and the realized value of the variance of the ambiguous signal, that is the $\sigma^2_{diff,i} = E_{i,t}(\sigma^2_s) - \sigma^2_{s_{i,t}}$. Panel B of Table 2 reports the descriptive statistics of this indicator. This difference for ambiguity averse individuals is significantly higher than for non ambiguity averse individuals ($z = 1.849$ and $p = 0.0645$).

To address our first hypothesis regarding whether ambiguity aversion leads to overestimation of the variance of ambiguous signals, we report on various specifications of the following linear, panel data regression model with random effects using all data from our experiment:

$$\sigma^2_{diff,i,t} = c + a_1 AM_i + a_2 RK_i + \epsilon_{i,t} \tag{2}$$

Here, $\sigma^2_{diff,i,t} = E_{i,t}(\sigma^2_s) - \sigma^2_{s_{i,t}}$ is the difference between the expectation of the variance and the realized value of the variance of the ambiguous signal of individual i at period t. AM_i is the measure of individual i's ambiguity attitude RK_i denotes individual i's risk attitude.

The result of the estimation of Equation (2) is reported in Table 3. For Models 1 and 4, AM_i is the continuous measure of ambiguity attitudes. For Models 2, 3, 5, and 6, we use

[4] Refer to Table B1 in Appendix B for more information.

Table 2
Panel A 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. Panels B report these same statistics for the difference between the variance expectation and the realized value of variance of ambiguous signals.

Panel A						
	Obs	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
Panel B						
	Obs	Mean	Median	Std.	Min	Max
Ambiguity averse	60	0.4673	0.2332	1.0432	-1.4414	3.2567
Ambiguity neutral	20	0.282	0.0005	1.0084	-1.4414	2.9943
Ambiguity seeking	10	0.2805	0.0332	0.9433	-1.4414	2.3086

dummy measure of ambiguity attitudes, with $AM_i = 0$ being the default ambiguity averse type, 1 is ambiguity neutral, and 2 is ambiguity seeking. In Models 3 and 6, $AM_i = 0$ is ambiguity averse, 1 is non-ambiguity averse. The dummy variable $RK_i = 0$ means risk averse, while 1 means non-risk averse. The default specification is always ambiguity aversion and risk aversion. Models 1, 2 and 3 exclude the risk attitudes, Models 4, 5 and 6 test all variables in Equation (2) (AM_i is the continuous variable in Model 4), and Model 7 excludes the ambiguity attitudes.

Table 3 reveals that the correlation between the prediction of variance and the measure of ambiguity is positive and the coefficient is significant at the 5% level (Models 1 and 4). The coefficient indicates that when the level of the ambiguity aversion of an individual increases by 0.1, the expectation of variance of the ambiguous signal is 0.0997 higher than the realization of variance. The mean measure of ambiguity is 0.1491 for ambiguity averse individuals, 0 for the ambiguity neutral individuals, and -0.11 for ambiguity seeking individuals. Hence, on average, ambiguity averse individuals have a larger expectation of variance for ambiguous signals by 0.015 as compared with ambiguity neutral individuals, and by 0.0258 as compared with ambiguity seeking individuals. Risk attitudes do not significantly decrease the variance expectation (Model 7). When compared with ambiguity neutral individuals, the ambiguity averse individuals tend to increase their expectation of the variance of the ambiguous signal significantly by 0.185 (Model 2).

To summarize, we do not reject Hypothesis 1 since we find that there is a significant and positive relationship between ambiguity aversion and subjects' expectations for the variance in the case of ambiguous signals. The more ambiguity averse subjects tend to predict a greater variance of the ambiguous signals.

Result 1 : We do not reject Hypothesis 1. We find that more ambiguity averse individuals are more likely to overestimate the variance of ambiguous signals.

Table 3

This table reports the result of the estimation of Equation (2). The dependent variable is ${}^2_{diff;i;t} = E_{i;t}({}^2_s) - s^2_{i;t}$ is the difference between the expectation of the variance and the realized value of the variance of the ambiguous signal of individual i at period t. As for the independent variables, Model 1, Model 2 and Model 3 excludes the risk attitude, Model 4, 5 and 6 test all the variables in the Equation (2) (AM_i is the continuous variable in Model 4), and Model 7 excludes the ambiguity attitude.

Dep var: ${}^2_{diff,t}$	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Measure of ambiguity	0.997***			0.990***			
	(3.83)			(3.83)			
Default: Ambiguity averse							
Ambiguity neutral		-0.185**			-0.184**		
		(-2.00)			(-1.98)		
Ambiguity seeking		-0.187			-0.192		
		(-1.15)			(-1.16)		
Non-ambiguity averse			-0.186**			-0.187**	
			(-2.20)			(-2.21)	
Default: Risk averse							
Non-risk averse				0.0438	0.0615	0.0612	0.0572
				(0.5)	(0.68)	(0.7)	(0.65)
Cons	0.321**	0.467**	0.467**	0.312*	0.454**	0.454**	0.393**
	(2.13)	(2.55)	(2.55)	(1.95)	(2.39)	(2.40)	(2.28)
N	450	450	450	450	450	450	450

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

4.3 Asymmetric Response to the Ambiguous Signals

According to Epstein and Schneider (2008), after receiving an ambiguous signal, more ambiguity-averse subjects are more likely to overestimate the variance of the private signal s when the signal is good news (in our experimental setting, when $s > 3$), and underestimate the variance of s when the signal is bad news (in our experimental setting, when $s < 3$).

In other words, they will regard the good news as imprecise, expect the variance of the ambiguous signal to be higher and assign a lower weight to the good news. On the contrary, they will regard the bad news as more precise, expect a lower variance of the ambiguous signal and assign a higher weight to the bad news. Subjects will update their priors about the fundamental value of the asset based on Bayes rule and obtain their posterior beliefs. Therefore, the theoretical prediction for the weight they assign to the private signal, $\hat{w}^{ss}$, can be written as:

$$\hat{w}^{ss} = \frac{{}^2}{{}^2 + {}^2_s}$$

Recall that in our experiment, ^{2} is perfectly known by subjects to equal 1, while ${}^2_s$ is the variance of the private signal, s. The variance for the private signal, s, in the first three scenarios, when the private signal is unambiguous, is 1, 0.25 and 4, respectively. Theoretically, the subject should select 0.5 as the weight assigned to the private signal in Scenario 1, 0.8 in Scenario 2, and 0.2 in Scenario 3. 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 4 reports on descriptive statistics for 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 using a rank sum test ($z = 1.652$ and $p = 0.0986$). We do not observe a significant difference between the actual weight assigned to the private signal and the theoretical prediction in Scenario 2 ($z = -0.826$ and $p = 0.4089$) and in Scenario 3 ($z = -1.101$, and $p = 0.2709$) according to the rank sum test. One possible explanation for this difference is that there is a learning process for the participants to learn about the signal extraction model. We observe the same result for ambiguity averse individuals, ambiguity neutral and seeking individuals. 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.

Table 4
This table reports the descriptive statistics of the weight assigned to the unambiguous private signals for Scenario 1, 2 and 3.

		Mean	Median	Std	Min	Max	Weight (Default)
All subjects	Scenario 1	0.5230	0.5023	0.2521	0	1	0.5
	Scenario 2	0.7897	0.8289	0.2111	0	1	0.8
	Scenario 3	0.2246	0.1810	0.2273	0	1	0.2
ambiguity averse	Scenario 1	0.5354	0.5037	0.2420	0	1	0.5
	Scenario 2	0.7929	0.8403	0.2059	0	1	0.8
	Scenario 3	0.2396	0.1985	0.2316	0	1	0.2
ambiguity neutral	Scenario 1	0.4777	0.4994	0.2779	0	1	0.5
	Scenario 2	0.7839	0.8203	0.2300	0	1	0.8
	Scenario 3	0.1965	0.1352	0.2421	0	0.9927	0.2
ambiguity seeking	Scenario 1	0.5386	0.5622	0.2517	0	1	0.5
	Scenario 2	0.7827	0.7937	0.2062	0	1	0.8
	Scenario 3	0.1910	0.1835	0.1542	0	0.5618	0.2

To further investigate how the individuals react to ambiguous signals in financial markets, we will focus on Scenario 4, where the variance of the private signal s, is ambiguous and varies between 0.25 and 4. Recall that there are 5 periods in Scenario 4: the news is good in 3 periods (the private signal $s > 3$), and bad in the other two periods (the private signal $s < 3$). In this scenario, the participants are asked to make their implied prediction of the fundamental value by selecting the weight assigned to the private signal and make their variance expectation of the ambiguous signal as well. Therefore, we use the variance expectation and the weight assigned to the private signal as separate dependent variables to find out whether ambiguity averse individuals overestimate bad news and underestimate good news in the setting with ambiguous signals.

First, we use the variance expectation as an independent variable to check how people evaluate the ambiguous signals. If the 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. Panel A in Table 5 reports descriptive statistics on subjects' variance expectations for 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 is significantly lower than the expected variance of the good news of the ambiguity averse individuals according to the rank sum test ($z = -5.011$ and $p = 0.0000$). The result holds for ambiguity neutral individuals according to the same test ($z = -2.834$ and $p = 0.0046$), but does not hold for the ambiguity seeking individuals ($z = 0.099$ and $p = 0.9208$). Overall, The expected variance of bad news is significantly lower than the expected variance of good news based on the rank sum test ($z = -5.369$ and $p = 0.0000$). We observe a lower variance expectation for bad news signals and a higher variance expectation for good news signals.

Second, we check the weight assigned to the private signal. If subjects respond to the ambiguous signals asymmetrically, they will give higher weight to bad news, and lower weight to good news. We report the descriptive statistics of the weight assigned to the private signal in Panel B of Table 5. We find that the weight of the private signal for the bad news tends to be lower than that for good news regardless of the ambiguity attitude. On average, the weight of the private signal is 0.5010 for bad news and 0.4783 for good news. According to the rank sum test, we find that there is no significant difference between the weights assigned to bad news and good news for ambiguity averse individuals ($z = 0.742$ and $p = 0.4578$), ambiguity neutral individuals ($z = 0.7$ and $p = 0.4838$) or ambiguity seeking individuals ($z = 0.139$ and $p = 0.8897$). Overall, we do not find significant difference between the weight of bad news and the weight of good news based on the rank sum test ($z = 0.957$ and $p = 0.3387$). That is, the weight of bad news is not significantly higher than the weight of 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 high weight to the ambiguous signal, vice versa.

Table 5
This table reports on descriptive statistics of the variance expectation of the ambiguous signals (good news versus bad news) in Panel A, and on descriptive statistics of the weights assigned to the ambiguous signal (good news versus bad news) in Panel B.

Panel A: Variance Expectation of the Ambiguous Signal						
		Mean	Median	Std	Min	Max
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
Total	Good news	1.7807	1.5	1.1493	0.25	4
	Bad news	1.1924	1	0.8335	0.25	4
Panel B: Weight Assigned to the Ambiguous Signal						
		Mean	Median	Std.Dev	Min	Max
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
Total	Good news	0.4783	0.4956	0.2561	0	1
	Bad news	0.5010	0.4983	0.2527	0	1

As stated above, we find that the variance expectation of the bad news is significantly lower than that of the good news, and the weight assigned to bad news is not significantly higher than that assigned to the good news. To further check the findings from our descriptive analysis, we again make use of a linear panel data regression with random effects to test the determinants of both the variance expectation of the ambiguous signal as well as the weight that is assigned to private, ambiguous signals:

$$
\begin{aligned}
E_{i;t}(\ {}^{2}_{s}) &= a_0 + a_1 BadNews_{i;t} + \ _{i;t} \\
w_{i;t} &= a_0 + a_1 BadNews_{i;t} + \ _{i;t}
\end{aligned} \tag{3}
$$

Here, $E_{i;t}(\ {}^{2}_{s})$ is the variance expectation of individual i in period t, and $w_{i;t}$ is the weight that individual i assigned to his/her private signal in period t. $BadNews_t$ is a dummy variable for bad news ($BadNews_t = 1$ if $s < 3$, $BadNews_t = 0$ if $s > 3$). The dependent variable in Panel A of Table 6 is the variance expectation. In Panel B of that table, the dependent variable is the weight. Model 1 uses the entire subject pool, Model 2 uses the data on subjects classified as ambiguity averse, Model 3 uses the data on subjects who are ambiguity neutral, and Model 4 uses the data on subjects who are ambiguity seeking.

The results reported in Panel A in Table 6 show that compared with good news signals (the baseline) when individuals receive bad news signals, they tend to significantly lower their expectations for the variance of those signals. The overall decrease for the entire sample is 0.588, which is significantly different from 0 at the 1% significant level. Ambiguity averse individuals lower their variance expectation of bad news even more, by 0.650 (Model 2). This suggests that individuals regard bad news as more precise than good news when the signal is ambiguous. In other words, ambiguity averse individuals react more to bad news than to good news. Importantly, we also find that ambiguity seeking individuals do not lower their variance expectation of bad news (Model 4). Panel B in Table 7 reports on regression results where the dependent variable is the weight that subjects assigned to the private signal, s. The regression results reveal that there is no significant difference between the weight assigned to good news and bad news under ambiguous signals for the whole sample, or for any of the subsamples based on ambiguity attitudes.

Table 6
This table reports the results of panel data estimation of Equation (3). The dependent variable is the variance expectation in Panel A, and the weight assigned to the private signal in Panel B. The first column reports results using the whole sample, the second through fourth columns report the results on each sub-sample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects.

Dependent variable: $E_{i;t}(\ {}^{2}_{s})$	Panel A			
	Whole sample	Ambiguity -averse	Ambiguity -neutral	Ambiguity -seeking
Bad news	-0.588***	-0.650***	-0.632***	-0.0309
	(-6.72)	(-6.02)	(-3.93)	(-0.12)
Cons	1.781***	1.867***	1.695***	1.433***
	(25.10)	(22.04)	(10.06)	(8.66)
Dependent variable: $w_{i;t}$	Panel B			
	Whole sample	Ambiguity -averse	Ambiguity -neutral	Ambiguity -seeking
Bad news	0.0226	0.0182	0.0473	0.000594
	(0.9)	(0.65)	(0.73)	(0.01)
Cons	0.484***	0.483***	0.507***	0.437***
	(27.59)	(24.44)	(12.77)	(6.13)
N	450	300	100	50

t statistics in parentheses *p<0.1 ** p<0.05 *** p<0.01

Overall, we find that there is mixed support for Hypothesis 2. On the one hand, we observe a consistent response to ambiguous signals. Ambiguity averse individuals give a lower variance expectation to the bad news, which indicates that ambiguity averse individuals regard the bad news as being more precise and should put a higher weight to bad news compared with good news. Moreover, if we investigate the weight that individuals assigned to the ambiguous signals, we find that ambiguity averse individuals tend to put a higher weight on the bad news than on good news for ambiguous signals, but the differences are not statistically significant. At the beginning of Section 4.2, we find that when the variance of the signal is a certain number from Scenario 1 to 3, individuals apply the signal extraction model when choosing the weight that is assigned to the private signal. Hence, they have learned that the variance tells them the accuracy of the signal. While in Scenario 4, subjects are asked to make their variance expectation of the ambiguous signals and choose the weight assigned to the ambiguous signals. Subjects focus on the variance expectation more than the weight. They believe that the variance of the ambiguous signal will be lower for the bad news and higher for good news.

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

4.4 Distribution of Excess Returns

The excess return on the asset, R_t, is defined as $R_t = p_t - {}_t$ in our experiment, where p_t is the market price in period t and ${}_t$ is the realized value of in period t. This is a simplification of Epstein and Schneider (2008). First, we check the normality of excess returns in each of our four scenarios. We observe that excess returns under ambiguous signals are significantly different from a normal distribution ($p = 0{:}000$). The same is true of excess returns in Scenarios 1 and 3 as well ($p = 0{:}00$). However, excess returns in Scenario 2 are not significantly different from a normal distribution ($p = 0{:}1970$).

Figure 2 shows the distributions of excess returns in each of our four scenarios. We observe that excess returns are more intensely found to lie above 0 under ambiguous signals, while more intensely distributed below 0 in Scenarios 1, 2 and 3 (unambiguous signals).

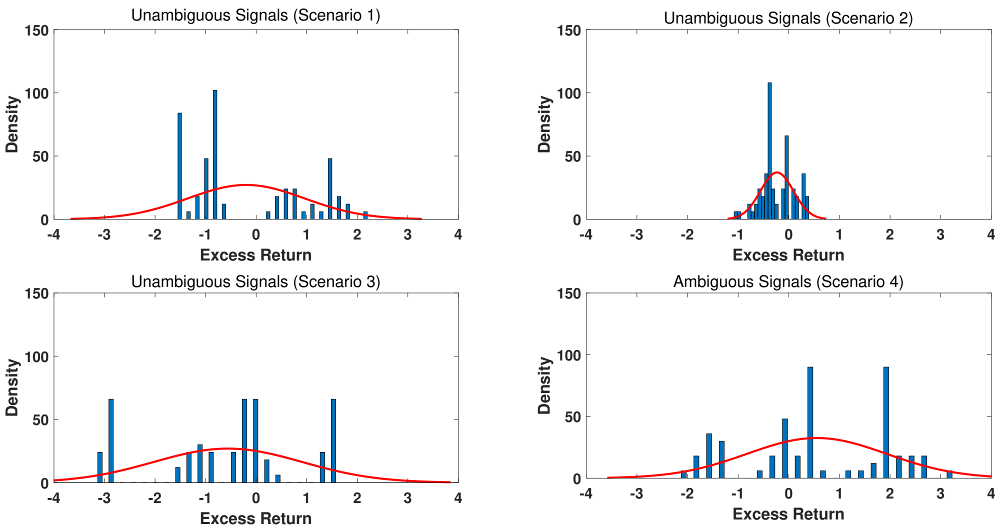

Figure 2: This figure depicts the distribution of the excess return under ambiguous signals and unambiguous signals. Scenario 1 (left top), Scenario 2 (right top) and Scenario 3 (left bottom) includes the unambiguous signals, Scenario 4 (right bottom) consists of the ambiguous signals. The x-axis is the value of the excess returns, and the y-axis is the number of observations.

We calculate the skewness of excess returns for the ambiguous averse individuals under ambiguous signals and unambiguous signals. The skewness is found to be negative under ambiguous signals (-0.1485), and positive (0.5028) in Scenario 1, (0.0095) in Scenario 2. To summarize, there is a negative skewness of excess return under ambiguous signals and positive skewness under unambiguous signals (except Scenario 3) for all individuals. See Table: 7 for further details.

Table 7
This table reports the skewness, mean, median, standard deviation, minimum and maximum of excess returns under each of our 4 scenarios. The variance of the private signal in Scenario 1 is 1, in Scenario 2 is 0.25 and in Scenario 3 is 4, between 0.25 and 4, unknown in Scenario 4.

	Skewness	Mean	Median	std	Min	Max
Scenario 1	0.5028	-0.1978	-0.7932	1.1579	-1.5655	2.2446
Scenario 2	0.0095	-0.2339	-0.3579	0.3251	-1.0716	0.3801
Scenario 3	-0.2901	-0.5595	-0.2202	1.4678	-3.0323	1.5735
Scenario 4	-0.1485	0.5531	0.4390	1.3794	-2.0188	3.2056
Overall	0.0199	-0.1095	-0.1526	1.2409	-3.0323	3.2056

To better understand the skewness of excess returns under ambiguous signals, we look for differences in excess returns when signals are ambiguous (Scenario 4, Period 16 to 20 in our experiment) and when signals are unambiguous (Scenarios 1 to 3, Periods 1 to 15). We find that subjects require a higher return when signals are ambiguous. We observe that excess returns under ambiguous signals are significantly larger than under unambiguous signals according to a rank sum test ($z = 12.711$ and $p = 0.0000$). To confirm that individuals require an excess return premium when the signal is ambiguous, we report estimates from the following panel regression model with random effects of the excess returns in period t, R_t, in Table 8:

$$
\begin{aligned}
R_t &= a_0 + a_1 Unambiguous_t + \epsilon_t \\
R_t &= b_0 + \sum_{K=1}^{3} b_K ScenarioK_t + \epsilon_t
\end{aligned}
\tag{4}
$$

All of the independent variables in this regression analysis are dummy variables. The dummy variable $Unambiguous_t = 0$ when the signal is ambiguous, and 1 otherwise. The dummy variable $ScenarioK_t$ is 1 for each Scenario k=1,2,3, and 0 for the baseline ambiguous signal Scenario 4. The model with the independent variable is $Unambiguous_t$ is reported on in Model 1, and the model with the 3 scenario dummies is reported on in Model 2.

The regression results show that for the whole sample, individuals request significantly higher excess returns, by 0.884, under ambiguous signals than under unambiguous signals. Compared with the three scenarios where the signal is unambiguous with different variances, excess returns in the scenario of ambiguous signals are significantly higher. For example, excess returns tend to be higher by 0.751 in ambiguous scenario a compared with the unambiguous scenario with a variance of 1 at 1% significant level according to Model 2. To summarize, we do not reject Hypothesis 3. We observe negative skewness in excess returns under the ambiguous signal and positive skewness in excess returns under

Table 8

This table reports results from estimation of Equation (4). The dependent variable is excess returns in period t, R_t. The independent variable is a dummy for unambiguous signals in Model 1, and dummies for Scenarios 1-3 in Model 2.

	Model 1	Model 2
Default: Ambiguous signals		
Non-Ambiguous signals	-0.884***	
	(-13.75)	
Default: Scenario 4 (ambiguous signals)		
Scenario 1 (unambiguous signals, $^{2}_{s} = 1$)		-0.751***
		(-9.60)
Scenario 2 (unambiguous signals, $^{2}_{s} = 0{:}25$)		-0.787***
		(-10.06)
Scenario 3 (unambiguous signals, $^{2}_{s} = 4$)		-1.113***
		(-14.23)
Cons	0.553***	0.553***
	(9.94)	(10.00)
N	1800	1800

t statistics in parentheses *p<0.1 ** p<0.05 *** p<0.01

unambiguous signals of all subjects. Indeed, we find that individuals require a higher excess return under ambiguous signals relative to any of our three scenarios involving unambiguous signals.

Result 3 : We do not reject Hypothesis 3. We find that there is negative skewness in the distribution of excess returns under ambiguous signals and positive skewness in the distribution of excess returns under unambiguous signals. Further, individuals require a higher excess return when the signal is ambiguous, relative to cases where the signal is unambiguous.

4.5 Mispricing and Price Volatility

According to Stöckl et al. (2010), mispricing in experimental asset markets can be measured by the relative deviation (RD) or by the relative absolute deviation (RAD). These two indicators measure 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 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.

We find that individuals are more likely to overestimate the fundamental value when the signal is ambiguous. The median RD is negative for non-ambiguous signals, and positive for ambiguous signals. Generally, the median RD in the scenarios involving non-ambiguous signals is 0.0890, while it is 0.4482 in the scenario of ambiguous signals. Also, the price deviation is larger when the signal is ambiguous. The median RAD is 0.3765 for the scenario of non-ambiguous signals and 0.5783 for the scenario of ambiguous signals (Refer to Table B2 in Appendix B). The RD of the ambiguous signals is significantly larger than that of the unambiguous signals ($z = 11.384$ and $p = 0.0000$), and the different results in terms of RAD are also significant ($z = 7.022$ and $p = 0.0000$). Figure 3 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 that of Scenarios 2 and 3. To confirm the findings from the descriptive statistics and the CDFs, we again check Hypothesis 4 using a panel data with random effect regression analysis. The equation tested is given by:

$$
\begin{aligned}
RD_t &= a_0 + a_1 Unambiguous_t + \epsilon_t \\
RD_t &= b_0 + \sum_{K=1}^{3} b_K ScenarioK_t + \epsilon_t \\
RAD_t &= a_0 + a_1 Unambiguous_t + \epsilon_t \\
RAD_t &= b_0 + \sum_{K=1}^{3} b_K ScenarioK_t + \epsilon_t
\end{aligned} \tag{5}
$$

Where all of the independent variables are dummy variables of the same type defined previously in the discussion of Table 8. The dependent variable is RD in Panels A, and RAD in Panels B. The independent dummy variable(s) in Model 1 are $Unambiguous_t$, while in Model 2 they are the dummy variables $ScenarioK_t$ for the three unambiguous signal scenarios.

The results are reported in Table 9. The results of Model 1 indicate that RD under ambiguous signals tends to be significantly higher than RD under unambiguous signals by 0.356 (Panel A). Similarly, RAD tends to be higher by 0.219 (Panel B). The result of Model 1 shows that compared with the three scenarios with unambiguous signals, RD (Panel A) and RAD (Panel B) is significantly larger in the scenario with ambiguous signals. For example, RD and RAD given ambiguous signals are larger by 0.478 and 0.491 as compared with the unambiguous signal scenario 2 with a variance of 0.25.

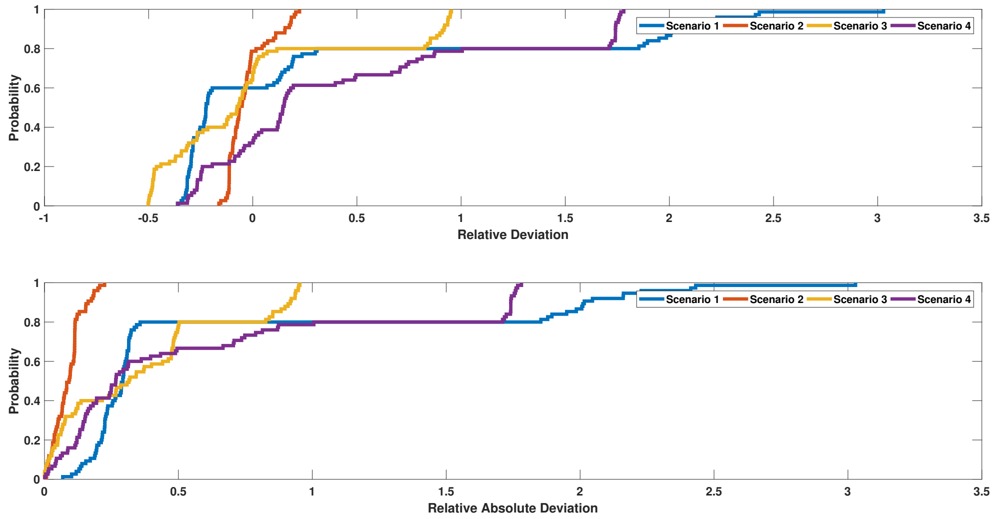

Figure 3: Figure 3 depicts the cumulative distribution function of the RD (top panel) and RAD (bottom panel) in each scenario. The x-axis is the value of RD (top panel) and RAD (bottom panel), and the y-axis is the probability. The purple line is the RD/RAD for Scenario 4 (ambiguous signals), the blue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

Table 9
This table reports results from estimation of Equation (5). The dependent variable is RD in Panels A, and RAD in Panels B. The independent dummy variable(s) in Model 1 are $Unambiguous_t$, while in Model 2 they are the dummy variables $ScenarioK_t$ for the three unambiguous signal scenarios.

	Panel A: RD		Panel B: RAD	
	Model 1	Model 2	Model 1	Model 2
Default: Ambigusou signals				
Non-Ambiguous signals	-0.356***		-0.219***	
	(-9.95)		(-7.25)	
Default: Scenario 4 (ambiguous signals)				
Scenario 1 (unambiguous signals, $^2_s = 1$)		-0.150***		0.0488
		(-3.49)		(1.40)
Scenario 2 (unambiguous signals, $^2_s = 0{:}25$)		-0.478***		-0.491***
		(-11.11)		(-14.10)
Scenario 3 (unambiguous signals, $^2_s = 4$)		-0.440***		-0.216***
		(-10.23)		(-6.20)
Cons	0.448***	0.448***	0.578***	0.578***
	(14.46)	(14.73)	(22.08)	(23.50)
N	1800	1800	1800	1800

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

In line with Epstein and Schneider (2008), our measure of price volatility is the variance of the price, $var(p)$. We find that on average, the price volatility under ambiguous signals is larger than under unambiguous signals. The median price volatility is 0.8125 given unambiguous signals and 1.5087 given ambiguous signals (Refer to Table B3 in Appendix B for more information). Price volatility under ambiguous signals is significantly larger than under unambiguous signals ($z = 3.053$ and $p = 0.0023$) according to a rank sum test. More precisely, the rank sum test reveals that price volatility is significantly larger in Scenario 4 (ambiguous signals) than in Scenario 1 ($z = 7.78$, $p = 0.0000$), and Scenario 3 ($z = 11.284$, $p = 0.0000$). These findings are confirmed using the following linear panel data regression model specifications with random effects:

$$\begin{aligned} var(p_t) &= a_0 + a_1 Unambiguous_t + \epsilon_t \\ var(p_t) &= b_0 + \sum_{K=1}^{3} b_K ScenarioK_t + \epsilon_t \end{aligned} \tag{6}$$

where all of the independent variables are dummy variables, as previously defined and the dependent variable, $var(p_t)$ is the price volatility in period t. The independent variable(s) in Model 1 is the dummy variable, $Unambiguous_t$, while in Model 2 it is the scenario-specific, $ScenarioK_t$ dummy variables for the unambiguous signal cases. The results are reported in Table 10. The price volatility of the ambiguous signal is not significantly larger compared with the unambiguous signals according to Model 1. The results from Model 2, however, shows that relative to the baseline ambiguous signal case, price volatility tends to be lower under unambiguous signals, by 0.565 in Scenario 1 and by 1.209 in Scenario 3.

Table 10
This table reports results from estimation of Equation (6). The dependent variable is price volatility. The independent variable(s) in Model 1 is $Unambiguous_t$, while in Model 2 it is the scenario-specific, $ScenarioK_t$ dummy variables for the three unambiguous signal cases.

Dep var: $var(p_t)$	Model 1	Model 2
Default: Ambiguous signals		
Non-ambiguous signals	0.0351	
	(0.55)	
Default: Scenario 4 (ambiguous signals)		
Scenario 1 (unambiguous signals, $\sigma_s^2 = 1$)		-0.565***
		(-7.48)
Scenario 2 (unambiguous signals, $\sigma_s^2 = 0.25$)		1.879***
		(29.24)
Scenario 3 (unambiguous signals, $\sigma_s^2 = 4$)		-1.209***
		(-19.10)
Cons	1.440***	1.440***
	(25.83)	(25.76)
N	360	360

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Hence, based on the findings above, we do not reject the Hypothesis 4. The larger price deviation is observed given the ambiguous signals. Also, the price volatility is higher in the ambiguous signals. Ambiguous signals will lead to higher price deviation and volatility in the experimental financial market.

Result 4 : We do not reject Hypothesis 4. We find that the price deviation and price volatility under ambiguous signals is significantly larger than under unambiguous signals.

5 Conclusion

This paper tests insights from a theoretical model by Epstein and Schneider (2008) using a laboratory experiment. In general, our results are in line with Epstein and Schneider (2008) theoretical assumptions and predictions. We find that more ambiguity averse individuals are indeed more likely to overestimate the variance of ambiguous signals, they tend to believe that bad news signals are more accurate than good news signals, when there is ambiguity about signal precision. Further, ambiguous signals lead to larger mispricing and price volatility in asset markets. The only discrepancy we find with the theory is that while individuals tend to consider ambiguous signals on bad (good) news as more (less) accurate, they do not assign a significantly different weight to those signals in forming their price expectations.

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

In future research, it would be useful to consider alternative measures of ambiguity attitudes. Indeed, Trautmann et al. (2011) and Kocher, Lahno and Trautmann (2018) find that different measures of ambiguity attitudes result in further individual heterogeneity in ambiguity attitudes. Baillon et al. (2018) elicit ambiguity aversion for natural events with unknown subjective probabilities, which provides a more precise and general measurement of ambiguity aversion. 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. Further, our current work 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. We leave these extensions to future research.

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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**. You 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 the Box The number (and hence the fraction) of purple balls and orange balls is unknown in the 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.

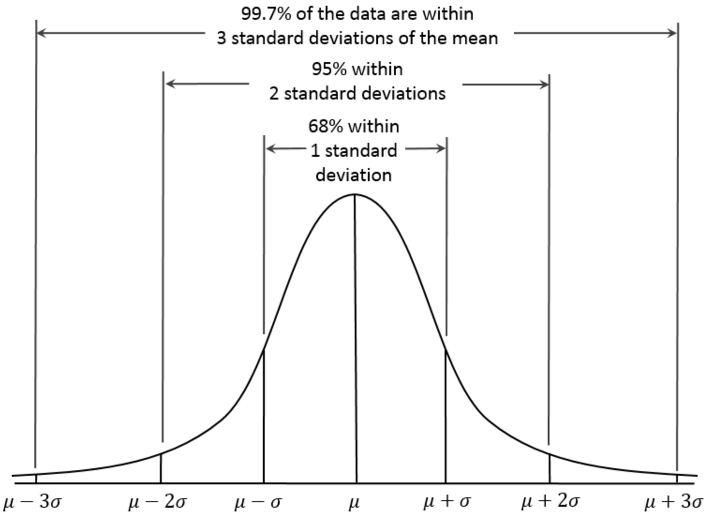
The payoff (in SGD) in Task 1.

The payoff (in SGD) in Task 2.

The payoff (in SGD) in a survey.

Instructions for Task 2

Background knowledge about Normal Distribution



In this experiment, you are going to predict the realized value of **,** a randomly distributed variable following the normal distribution.

If you are not familiar with the normal distribution, here is some basic information about it. The shape of the normal distribution is a bell curve. <u>For a normal distribution (, ^{2}), where is the mean and ^{2} is the variance of the distribution, the probability that the realization of the random variable is close to the mean is larger than the probability that it is far away from the mean.</u> The square root of the variance, , is called the standard deviation of the distribution. For a normal distribution, values of the random variable that are less than one standard deviation away from the mean of the distribution account for 68% of all realizations (or mathematically, $\Pr(\mu - \sigma \leq X \leq \mu + \sigma) \approx 68\%$); while values that are two standard deviations away from the mean account for 95% of all realizations (or mathematically, Pr(− 2 ≤ ≤ + 2) ≈ 95%); finally, values that are three standard deviations away from the mean account for 99.7% or all realizations (or mathematically, $\Pr(\mu - 3\sigma \leq X \leq \mu + 3\sigma) \approx 99.7\%$).

Task 2

In Task 2, you are endowed with 7 SGD in each period. Your task in each period is to predict the intrinsic value (or the true value) of the asset for that period. Here, intrinsic value means the amount of money that you can receive if you hold the asset until the end of the period. The intrinsic value of the asset is denoted by . The realization of the intrinsic value, **,** is drawn at the beginning of each period, but you don't see the realized value immediately. Instead, you predict the value of in each period by choosing the **weights** that you assign to a public and a private signal about the intrinsic value, .

a) **The Public signal**, which you and everyone else is informed about, concerns the **distribution** from which the intrinsic value of the asset, **,** is drawn and its **unconditional mean and variance.**

- The **public signal** is: is randomly generated each period and follows a normal distribution: (3,1). **<u>The mean of is 3 and its variance is 1. This public signal will be constant for all periods</u>. The public signal** tells you that the probability that the realization of lies between [3 − 1,3 + 1], or [2, 4] is 68%; the probably the realization of lies between [3 − 2 × 1,3 + 2 × 1], or [1, 5] is 95%; and the probably the realization of lies between [3 − 3 × 1,3 + 3 × 1], or [0, 6] is 99.7%.

b) **The Private signal,** is a random variable known only to you, and tells you information about the **realization of in this particular period.**

- The **private signal** about the **true value** of the intrinsic value , in period t, equals plus a noise term , which follows the same distribution in all periods in the same block, but takes different realizations in each period.

$$= \quad + \quad \text{, where} \quad \sim \quad (0, \quad ^{2})$$

Where is the unknown intrinsic value of the asset you are trying to forecast. The noise term has zero mean, variance ^{2}.

- So the **private signal** is the true value of plus a small normally distributed error term having a mean of zero and a variance of ^{2}. The realization of the error term is a random drawn from the same distribution, (0, ^{2}) for all participants, but your draw is independent of the draw of others **The realization of both and in each period does not depend on the previous period realizations. Thus, the realization of is a different random draw in each period *t* and therefore the private signal, is a different random draw in every period t.**

<u>contains information about true value of . is a measure of the noisiness of the signal. The signal is more accurate, or less noisy if is smaller.</u>

Assume, for example, that the signal is 4.3, in other words, the information about the realized value of is: The probability that the realization of lies between 4.3 − and 4.3 + is 68%, the probability that the realization of lies between 4.3 − 2 and 4.3 + 2 is 95%, and the probability that the realization of lies between 4.3 − 3 and 4.3 + 3 is 99.7%. For example, the variance of the error term, ^{2}, is known to be 0.25 for that period. You should understand that this means that the standard deviation of the error term, = 0.5, and following the same logic as described earlier, the probably that the realization of lies between [4.3 − 0.5 , 4.3 + 0.5], or [3.8, 4.8] is 68%; the probably the realization of lies between [4.3 − 2 × 0.5, 4.3 + 2 × 0.5], or [3.3, 5.3] is 95%; and the probably the realization of lies between [4.3 − 3 × 0.5, 4.3 + 3 × 0.5], or [2.8, 5.8] is 99.7%.

Instructions:

Your task for 5 consequent periods and for each of the four scenarios (different values of) is to **select the weight, , that you want to assign to the private signal, where ≤ ≤ . Your choice of the weight for the private signal also determines the weight, 1-w, that you attach the public signal, which is simply that the mean value for a is 3. Thus your implied prediction for a in period t, is given by**

$$= \times \qquad + (1 - \ ) \times 3$$

Your **implied prediction** will be closer to the private signal if you assign a higher weight to it, and closer to the public signal, that is, the mean of 3, if you assign a lower weight to the private signal. For example, if the private signal is 2.8 and the weight you choose to assign to it is 0.6, then your implied prediction for is $0.6 \times 2.8 + (1 - 0.6) \times 3 = 2.88$.

Six of you will be randomly assigned to one market. This assignment remains unchanged through the all periods/scenarios of Task 2. After all participants have submitted their weight choices, the implied predictions of , will be computed.

The market price of the asset will be the **median** of all implied predictions of . The median is the number such that half of all predictions lie below it and half lie above it. You can also think of the median of all individuals' expectation as the market value of the asset. The **transaction mechanism** is: If your implied prediction of is **above** the **market price**, which implies that your expected valuation of the asset is higher than the median of all expected values of the asset in the market, then you are a **buyer** and will buy the unit of the asset at the market price. If your implied prediction of is **below** the **market price,** which implies that your expected valuation of the asset is lower than the median of all expected values of the asset in the market, then you are a **seller** and will sell the unit of the asset at the market price.

There are **four scenarios** about the variance ^{2} of the noise term of the **private signal** . They are as below:

(1) = , which means the noise term has zero mean, variance 1 and the standard deviation of 1**;**

(2) = . **,** which means the noise term has zero mean, variance 0.25 and the standard deviation of 0.5;

(3) = , which means the noise term has zero mean, variance 4 and the standard deviation of 2;

(4) . ≤ ≤ **.** In this scenario, We do not know the exact value of the variance ^{2}. We only know that the variance ^{2} is between 0.25 and 4. That is, the lowest possible value of the variance is 0.25, the highest possible value of the variance is 4. The realization of variance of the private signal is randomly drawn at the beginning of each period.

In the first three scenarios, **you need to make your best selection for the weight to assign to the private signal and the implied prediction of .**

In the last scenario, **you need to make two decisions:**

(1) Enter your expectation for the value of the variance (a number between . and 4):

(2) Make your selection of the weight to give to the private signal and the implied prediction of

The Payoff in Task 2

Your total payoff in Task 2 is going to be determined in the following way: for the weight selection task, you are going to be paid according to your performance in a randomly selected period from the 20 periods of four scenarios. For the variance prediction task, you are going to be paid according to your performance in a randomly selected period in the last scenario of 5 periods. The unit of payment is again Singapore dollars.

Recall that at the start of each period you are endowed with 7 SGD. Your **payoff for the weight selection task (profit) in SGD is going to be determined in the following way:**

$$= 7 - \quad + $$

$$= 7 + \quad - $$

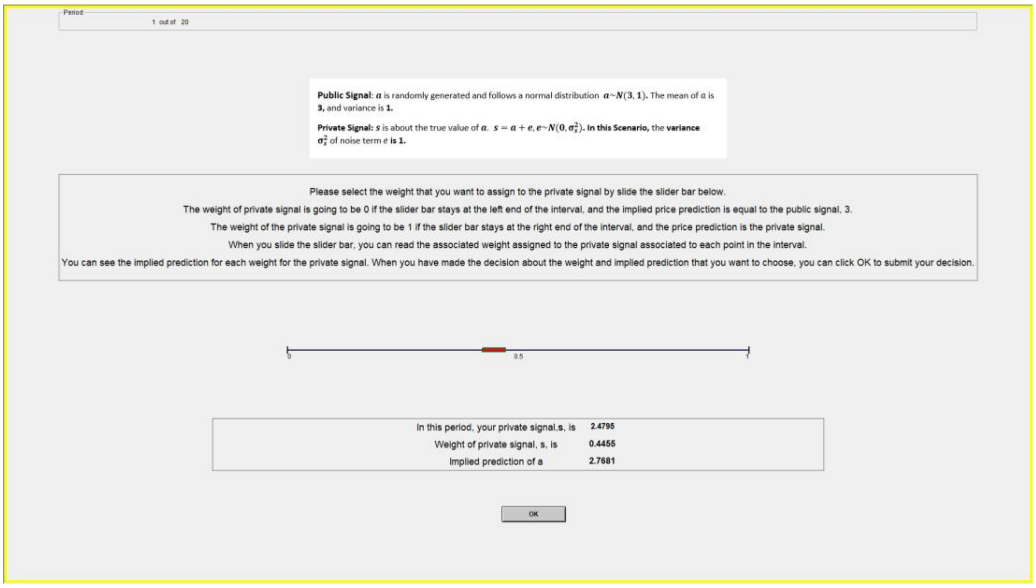
So, if you are a buyer, you buy the asset from your endowment of 7 SGD and get the actual realized value of a in return. If you are a seller, you sell the asset at the market price and in doing so you give up the realized value of the asset, a. As you can see, the profit for a buyer/seller is going to be higher if the realized value of the intrinsic value is higher/smaller than the market price.

The payoff for the prediction of variance task is going to be determined in the following way:

$$= 8 - \frac{10}{10 - | \quad - \quad |}$$

The payoff for the prediction of variance is going to be higher/lower if the prediction error is larger/smaller.

The picture below is the screenshot of Task 2. You have to slide the slider bar to select the weight, , between 0 and 1 that you would like to assign to the private signal. The remaining weight goes to the public signal, the mean of 3. The prediction of will be given according to the weight you selected. You can play with different weights to explore different predictions for . When you are satisfied with your prediction for a, please click the "OK" button to submit.


Period
1 out of 20
Public Signal: a is randomly generated and follows a normal distribution a~N(3, 1). The mean of a is 3, and variance is 1.
Private Signal: s is about the true value of a. s = a + e, e~N(0, σ²s). In this Scenario, the variance σ²s of noise term e is 1.
Please select the weight that you want to assign to the private signal by slide the slider bar below.
The weight of private signal is going to be 0 if the slider bar stays at the left end of the interval, and the implied price prediction is equal to the public signal, 3.
The weight of the private signal is going to be 1 if the slider bar stays at the right end of the interval, and the price prediction is the private signal.
When you slide the slider bar, you can read the associated weight assigned to the private signal associated to each point in the interval.
You can see the implied prediction for each weight for the private signal. When you have made the decision about the weight and implied prediction that you want to choose, you can click OK to submit your decision.
0
0.5
1
In this period, your private signal,s, is 2.4795
Weight of private signal, s, is 0.4455
Implied prediction of a 2.7681
OK

Appendix B

Table B1 reports the numbers of individuals who are ambiguity averse and risk averse/neutral /seeking, ambiguity seeking and risk aversion/neutral/seeking, and ambiguity neutral and risk aversion/neutral/seeking. This table reveals that there is no interaction between ambiguity attitudes and risk attitudes as we have measured them. It can be inferred from the cross tabulation that 52.2% of subjects are both ambiguity averse and risk averse. The test statistics do not report significant interrelation between the frequency of ambiguity attitude and the risk attitude ($Pearson\ {}^2 = 1.6762$ and $p = 0.795$. $p\ of\ Fisher\ statistic = 0.853$). Hence, the two variables (ambiguity attitude and risk attitude) can be viewed as being independent.

Table B1
This table reports the frequency distribution of ambiguity attitudes and risk attitudes. The rows report the numbers of subjects who are ambiguity averse, ambiguity neutral and ambiguity seeking. The columns report the numbers of subjects who are risk averse, risk neutral and risk seeking.

	Risk averse	Risk neutral	Risk seeking	Total
Ambiguity averse	47	11	2	60
Ambiguity neutral	16	4	0	20
Ambiguity seeking	7	3	0	10
Total	70	18	2	90

Table B2
This table reports the descriptive statistics of the Relative Deviation and Relative Absolute Deviation for each scenario in Panel A and Panel B.

Panel A: Relative Deviation					
	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
Unambiguous signal (total)	0.0890	-0.0947	0.6491	-0.5440	3.0475
Scenario 4	0.4482	0.1450	0.7256	-0.3614	1.7811
Overall	0.1810	-0.0489	0.6753	-0.5025	3.0284
Panel B: Relative Absolute Deviation					
	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
Unambiguous signal (total)	0.3765	0.2143	0.5361	0.0001	3.0475
Scenario 4	0.5783	0.2663	0.6266	0.0010	1.7811
Overall	0.4139	0.2133	0.5634	0.0003	3.0284

Table B3
This table reports the descriptive statistics of price volatility for each scenario in Panel A, and with regard to individual's ambiguity attitude in Panel B.

		Mean	Median	Std	Min	Max
Unambiguous signals	Scenario 1	0.8754	0.8125	0.2481	0.5907	1.4354
	Scenario 2	3.3191	3.3969	0.1201	2.4830	4.1549
	Scenario 3	0.2317	0.2131	0.3987	0.0252	0.4080
	Total	1.4754	0.8125	1.3613	0.0252	4.1549
Ambiguous signals	Scenario 4	1.4403	1.5087	0.5283	0.3652	2.4141
Whole sample		1.4666	0.9755	1.2074	0.0252	4.1549