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

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forthcoming in *Management Science*

Abstract

We explore how information ambiguity and traders' attitudes toward such ambiguity affect expectations and asset prices under three different market institutions. Specifically, we test 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 exists and is strongest in individual prediction markets. It occurs to a lesser extent in single price call markets. It is weakest of all in double auction markets, where buyers' asymmetric reaction to good/bad news is cancelled out by the opposite asymmetric reaction of sellers.

*We thank the editor, Camelia Kuhnen, an associate editor, and two anonymous referees, along with Soo Hong Chew, Ernan Haruvy, Daniel Houser, Shaowei Ke, Juanjuan Meng, Rosemarie Nagel, Ronald Peeters and Songfa Zhong for constructive comments and suggestions that substantially improved the paper. We have also benefited from stimulating discussions of our paper at the 2019 SHUFE Behavioral and Experimental Economics Workshop in Shanghai, the 2019 D-TEA China Conference in Chengdu, the 2019 Society for Experimental Finance Asia-Pacific Annual Regional Conference in Singapore, the 2020 ESA Global Conference, the 2020 Virtual Experimental Finance Workshop and a seminar at Peking University. Financial support from a Tier 1 Grant from MOE of Singapore (RG 69/19), NTU-WeBank JRC (NWJ-2020-003), the National Natural Science Foundation of China (NSFC: 72303170, 72141304), National Key Research and Development Program of China (2022YFC3303304) is gratefully acknowledged. The experimental protocol used in this study was approved by the IRB of NTU Singapore under approval number IRB-2018-01-035.

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

JEL Classification: C91, C92, D81, D83, G12, G40

1 Introduction

Participants in financial markets confront many signals about market fundamentals on a daily basis. How should they process these signals? According to Epstein & Schneider (2008), agents take the *quality* of these signals into account. They assign more weight to signals from a reliable, high quality source and less weight to signals from obscure, low quality sources. The variance of a signal serves as a measure of signal quality. The quality of a signal is viewed as 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 signals that they receive. Thus, if there are ambiguity averse investors, there will be an asymmetric reaction to bad and good ambiguous signals. For instance, bad signals suggesting that the dividend on an asset is lower than the prior will be treated as if they are more accurate (have smaller variance) as compared with good signals suggesting that the realized dividend is higher than the prior. That is, ambiguity averse agents will assign a relatively higher weight to bad signals than to good signals when making decisions. Since signals matter for asset price determination, if there are ambiguity averse investors then the mispricing of assets should be negative, that is, there should be down-pricing of assets under ambiguous signals.

In this paper, we report results from 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 note that Epstein & Schneider (2008) employ a representative agent asset pricing model where the agent is (implicitly) modeled as a net buyer of the asset. Thus, in our first treatment, we employ a representative agent framework similar to Epstein & Schneider (2008). While this representative agent framework and the net buyer assumption is nice for theory development, most real stock exchanges organize trading in a decentralized way, and allow traders to submit both buy and sell orders. Therefore, as a stress test of whether the predictions of Epstein & Schneider (2008) continue to hold in decentralized markets with many agents who can both buy and sell assets, we consider such many-agent markets, where prices are determined by either a call market or a double auction market institution. In these market settings, we show that while asymmetric reactions to good and bad news may still exist at the *individual* subject level, they are largely mitigated at the *aggregate* level, since the asymmetric reactions of buyers and sellers cancel one another out.

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 good news. It follows that (3) the mispricing of assets will be negative –the asset will be undervalued or down-priced– when signals are ambiguous relative to the case where signals are unambiguous.

We test these predictions in a two-stage experiment. In the first stage, we elicit participants' attitudes toward ambiguity.[1] In the second stage, participants are placed in one of three different types of experimental asset markets (as discussed above) where they receive both noisy unambiguous signals about the fundamental value of an asset, and noisy ambiguous signals about the fundamental value 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 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 fraction) of purple and orange balls. The "U" or "unknown" box in each pair has an unknown number (or fraction) of purple and orange balls. Participants are instructed that if a purple ball is drawn from the box they chose, they will win a positive money amount; otherwise,

[1] We also elicit subjects' risk preferences using a standard multiple paired lottery task at the *end* of each experimental session.

they will earn 0. Using this task we find that around 67% 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, the prior m and the signal s and then possibly trade the asset with other participants under a given market institution. The prior, m, 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 having mean of m. The 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 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 signal is *un*ambiguous in the first 15 periods. The variance of the 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. Thus, subjects in our experiment start out facing *un*ambiguous signals in the first 15 rounds because forming expectations with unambiguous signals is easier. It also provides subjects with the opportunity to learn about the different possible variances in the final 5 periods, when signals become ambiguous. Further, the first 15 rounds allow practice with how to form predictions using the prior m and the signal s. After subjects submit their predictions and make their trading decisions, the fundamental value of the asset is revealed. Subjects' payoffs are calculated based on their predictions or their trading decisions and the true fundamental value of the asset.

Differently from Bleaney & Humphrey (2006), Halevy (2007), Bossaerts et al. (2010), etc., 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. 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 nevertheless stick with the terminology "ambiguous signals" and "information ambiguity" in our paper, following the use of that same language 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.

Our experimental results confirm many of the theoretical predictions of Epstein & Schneider (2008). We find that ambiguity averse individuals overestimate the variance of good news relative to bad news when signals are ambiguous. This asymmetric reaction is strongest in the individual prediction market (Treatment I), less present under the call market (Treatment C) and weakest of all under the double auction market (Treatment DA). While we do observe asymmetric reactions to good and bad news at the individual trader level in the double auction market, the absence of an *aggregate* asymmetric response to good or bad news results from the fact that the buyers' asymmetric reactions are counterbalanced by the opposite asymmetric reaction on the sellers' side. Finally, we observe that in Treatment I, the asset tends to be negatively mispriced when the signal is ambiguous compared with when signals are unambiguous. However, this *down-pricing* phenomenon under ambiguous signals is not evident in Treatments C and DA.

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 market quality and the 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 describes the models and hypotheses. Section 4 presents the experimental design. Section 5 discusses the experimental results. Section 6 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 *lower* asset prices, (the "ambiguity premium") in individual decision-making experiments. In market experiments, the evidence is mixed and our findings reinforce this conclusion. While ambiguity generally results in lower asset prices under a single price call market mechanism, some studies find that ambiguity also leads to lower asset 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 a market setting. They use the double auction market institution and find that information ambiguity does not lead to lower asset prices.

Table 1 summarizes the literature most closely related to this paper. Our findings complement these prior studies in two main ways. First, 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 (which uses an individual forecast design) where individuals make only a point prediction for the asset price. Second, 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 priors while we focus on ambiguous 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 larger, decentralized markets like double auction market.

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. J. 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 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), Easley et al. (2014), 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.

Asymmetric reactions to good and bad news may also follow from *confirmation bias*, which is the tendency to seek information that supports a person's prior beliefs (Plous 1993). In the setting we study, if there is confirmation bias, it should result in the overweighting of good news and/or the underweighting of bad news, especially when confirmation bias goes hand in hand with the self-serving bias (Babcock et al. 1996; Babcock & Loewenstein 1997). But notice that this asymmetric reaction is precisely opposite to the theory of Epstein & Schneider (2008), where bad news is over weighted relative to good news. In our reading of the confirmation bias literature, the main factor that determines whether agents overweight good news is whether such news concerns the agent's self-image, or whether it concerns their monetary payoff. Eil & Rao (2011) find that people will update their beliefs following Bayes' rule for good news, and underreact to bad news when they predict their ranking in IQ and beauty as compared to other people. M. Li et al. (2023) also show that managers overweight favorable information about their performance and underweight unfavorable information, resulting in optimistic earnings predictions and inefficient overinvestment. In both cases, people derive positive utility and higher self-esteem from good news. By contrast, in the environment of Epstein & Schneider (2008), information about the profitability of the firm has only *instrumental value* for investors. Thus, there are no grounds for investors to have motivated optimism for good (or bad) news. Instead, to manage their investments in a more prudential way, ambiguity averse decision makers will be motivated to overweight bad news relative to good news to better cope with the worst-case scenario.

Finally, our paper contributes to the literature on belief updating about the prior m and the signal s, e.g., Heinemann et al. (2004), Boswijk et al. (2007), Eil & Rao (2011), De Filippis et al. (2017), Duffy et al. (2019), 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), Asparouhova et al. (2015), 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. Biais et al. (2005) and Biais & Weber (2009) also study the tendency for agents to overestimate the precision of their private information and to underestimate market volatility. Our work is distinguished from these two studies by our focus on asymmetric reactions to good and bad news under ambiguous signals and our analysis of asset pricing under different market institutions.

Table 1
A summary of the literature related 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
Kocher & Trautmann (2013)	Individual Decision	Sealed Bid Auction	Ambiguity		Binary	ambiguity leads to entry to ambiguous market, but no impact on transaction price
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 maximizers 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	no evidence for ambiguity leading to lower asset prices
Epstein & Halevy (2019)	Individual Decision	Sealed Bid Auction	Information Ambiguity	Private Signal	Binary	compared to risky signals, subjects have more difficulty 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 Model and Hypotheses

The main focus of our experiment concerns how subjects update their priors about the dividend, θ_t, earned per unit of an asset in response to new information. The model we used is based on the theoretical framework of Epstein & Schneider (2008), which we briefly review here.

Ex-ante there is no ambiguity; all agents hold the common prior that θ_t is a random variable drawn from a normal distribution with mean m and variance σ_θ^2, that is, $\theta_t \sim i.i.d.N(m, \sigma_\theta^2)$.

However, prior to trade, investors receive a noisy signal about the random variable θ_t that can be interpreted as "news". Specifically, agent i gets a noisy signal, $s_{i,t}$, about the likely value of θ_t in period t:

$$s_{i,t} = \theta_t + \epsilon_{i,t},$$

where $\epsilon_{i,t} \sim i.i.d.N(0, \sigma_s^2)$.

In the case of **unambiguous** signals, σ_s^2 is perfectly known. In that case, subjects should apply Bayes' rule in order to generate their posterior belief about θ_t:

$$E(\theta_t) = \frac{\sigma_s^2}{\sigma_\theta^2 + \sigma_s^2} m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2} s_{i,t} \quad (1)$$

Epstein & Schneider (2008), however, consider the case where the signal noise is **ambiguous** (or low quality). Specifically, they assume that σ_s^2 is *not* precisely known. Instead, agents only know that $\sigma_s^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$. In this ambiguous signal setting, the investor cannot apply Bayes' rule to update her prior in the usual manner. Instead, she uses Bayes' rule to update her prior for θ_t over all possible likelihoods resulting in a non-degenerate *family* of posteriors:

$$\theta_t \sim N(m + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_s^2}(s - m), \frac{\sigma_\theta^2 \sigma_s^2}{\sigma_\theta^2 + \sigma_s^2}),$$

where $\sigma_s^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$.

Following Epstein and Schneider's approach, *ambiguity averse* agents form expectations about the dividend of the asset by solving an expected utility maximization problem that uses the worst-case belief about θ chosen from the family of posteriors. After a signal has arrived, these ambiguity averse agents respond asymmetrically. For example, when evaluating an asset whose fundamental value is an increasing function of θ (as in our setting), the ambiguity averse agent will use a posterior that leads to a lower mean. Therefore, if the news about θ is "good", specifically if $s_{i,t} > m$ (the mean for θ), agent i will evaluate the signal as imprecise ($\sigma_s^2 = \overline{\sigma_s^2}$), while if the signal about θ is "bad" (i.e., if $s_{i,t} < m$), then the agent will view the signal as reliable ($\sigma_s^2 = \underline{\sigma_s^2}$). As a result, an ambiguity averse agent discounts the impact of good news and overestimates the impact of bad news.

Assuming that some subjects are ambiguity averse, we formulate the following testable hypotheses based on the theory of Epstein & Schneider (2008):

Hypothesis 1 *When signals are ambiguous, subjects who are ambiguity averse underestimate the variance of s and overweight it if $s < m$ and overestimate the variance of s and underweight it if $s > m$.*

Hypothesis 2 *There should be greater mispricing of the asset (specifically negative price deviations) under ambiguous signals than under unambiguous signals.*

4 Experimental Design

Our experiment consists of two parts. Part 1 elicits each participant's ambiguity and risk attitudes, and Part 2 is a 20-period individual-decision making or market-trading game that enables us to detect how subjects update their priors in the face of unambiguous and ambiguous signals and under different market mechanisms for determining the price of the asset. The details regarding Part 1 are presented in Section 4.1, with the details about Part 2 are described in Section 4.2.

4.1 Part 1

We focus here on ambiguity attitudes; a discussion of our elicitation of risk attitudes and their correlation with measures of ambiguity attitudes may be found in Online Appendix B. Regarding ambiguity attitudes, we categorize participants using the same method used by Trautmann et al. (2011), Trautmann & Van De Kuilen (2015), into "ambiguity averse" types and "non-ambiguity averse" types; the latter can be further divided up between "ambiguity neutral" and "ambiguity seeking" types. To ascertain ambiguity attitudes, subjects are asked to make 10 choices between pairs of 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 number 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 first row to the final 10th 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 the known Box K to the unknown 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.[2]

One row is randomly drawn from the ambiguity aversion elicitation task in Part 1. The subject's choices for the selected row determine their payoff for Part 1. That is, the ambiguity aversion elicitation task is incentivized.

[2]We are aware that other papers eliciting ambiguity attitudes do not fix the winning color, but according to Dimmock et al. (2016), it does not matter if the winning color is fixed or not.

4.2 Part 2

In Part 2 of our experiment, we instruct subjects that they will receive two types of signals about the dividend earned per share of an asset, the prior m and the signal s. The prior m consists of information about the mean, m, and the variance, σ_θ^2 of the random dividend variable, θ. For simplicity, we assume that $\theta_t \sim i.i.d.N(m, 1)$, so that $\sigma_\theta^2 = 1$. Since this information is provided to all subjects, we regard it as public information and refer to it as a "public signal" in the experiment to make it easier for subjects to understand and differentiate from the other piece of information, a "private signal."

Prior to trade, each subject also receives a noisy "signal", $s_{i,t}$, or "news" about the dividend of the asset which is known to be equal to the true (but unknown) realized value for θ_t in each period t, plus a normally distributed, mean zero error term, $\epsilon_{i,t}$. The 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 and independently generated for each subject in each period. 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 $\sigma_{s,t}^2 \in [\underline{\sigma_s^2}, \overline{\sigma_s^2}]$. That is, they do *not* know the actual value of $\sigma_{s,t}^2$, just as in Epstein & Schneider (2008). Each of the four scenarios consists of 5 periods (20 periods total).

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

$$\sigma_{s,t}^2 = \begin{cases} 1, & t \in [1,5] \quad \text{Scenario 1.} \\ 0.25, & t \in [6,10] \quad \text{Scenario 2.} \\ 4, & t \in [11,15] \quad \text{Scenario 3.} \end{cases} \qquad (2)$$

While all subjects know $\sigma_{s,t}^2$ in these first 15 periods, their own signal, s_t, remains private and unique to them. If subjects apply the Bayesian signal extraction model in these first 15 periods, their posterior expectation for θ should be given by Equation (1). Given the public information that $\sigma_\theta^2 = 1$, it follows from (1) and (2) that the weight assigned to the signal should be $\frac{1}{2}$ in Scenario 1, $\frac{4}{5}$ in Scenario 2, and $\frac{1}{5}$ in Scenario 3 with the remaining weight in each scenario going to the prior.

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

$$\sigma^2_{s,t} \sim i.i.d.\ U(0.25, 4) \quad t \in [16, 20] \text{ Scenario 4.}$$

Subjects *do not know* that the variance is uniformly distributed; they only know the upper and lower bounds for $\sigma^2_{s,t}$, i.e., they are told that $\sigma^2 \in [0.25, 4]$. They also do not know the realized value of the variance at the beginning of each period.

In these last 5 periods, which comprise the ambiguous signal scenario, subjects first receive the signal, s_t, and then they are asked to predict the fundamental value of the asset for period t, corresponding to the dividend value, θ_t. Further, they are asked to predict the unknown variance of the signal draw, $\sigma^2_{s,t}$. Their prediction of $\sigma^2_{s,t}$ is incentivized. Specifically, their payoff is maximal if they correctly guess the variance and their prediction payoff declines with their forecast error - See Appendix A for details. Depending on the treatment, subjects may then also engage in trade in the asset.

Thus, Part 2 consists of 1 to 3 tasks depending on the treatment. In all treatments, subjects make predictions each period about the fundamental value of the asset for that period based on the two signals they receive (the prior m and the signal s for that period). In the ambiguous scenario only (the last 5 periods), they also make an incentivized prediction about the unknown variance of the distribution for the signal in each of the 5 periods of that scenario. Finally, in the two market treatments, they further engage in trade in the asset in each period.

The asset lives for one period in all three treatments. Thus, the realization of the dividend on the asset represents the fundamental value of the asset.

We now describe how the price of the asset is determined under each of the three market institutions that we consider.

Treatment I: We use the design of a simple individual forecast experiment. Upon receiving the prior m and the signal s, participants make predictions about the fundamental value of the asset and their payoff is determined by their prediction accuracy. A subject's earnings are maximized if his/her prediction exactly equals the fundamental value of the asset and declines otherwise in proportion to the forecast error. Thus, this treatment is a purely *individual* decision-making design, where each participant's payoff is determined by their own prediction 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 first receive the prior, m, and their signal, s and then make a prediction about the fundamental value of the asset. After subjects submit their prediction (which also serves as a bid), the market is automatically cleared at a price equal to the *median* of all 6 subjects' 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 equal to: $market\ price -\ realized\ dividend\ \theta$. 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 equal to $realized\ dividend\ \theta -\ market\ price$.[3]

Treatment DA: We use the continuous double auction market mechanism (Smith et al., 1988) for subjects to trade with other market participants in each period. Upon receiving both the prior m and the signal s 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

[3]The call market structure is generally used for organizing small markets or determining the opening price of stock markets. This structure is also used by many governments to sell their instruments such as bonds, notes and bills. Many stock exchanges also use this structure for calculating the opening prices for less active stocks. Real world examples of call markets include the Deutsche Bourse and Euronext Paris Bourse.

We understand that traders in "standard" call markets can submit both bids and asks. Like in Akiyama et al. (2017), a trader submits one buy and one sell offer in each round. Our call market design is in a way more like the English-Dutch call auction market in Deck et al. (2020). The English-Dutch auction begins with a low price at which everyone is willing to buy. As the clock price increases, traders can reduce the number of units they report being willing to buy. At some point, a trader will decide she is not willing to buy any and can indicate she will not be a buyer in the auction. Then for this trader, the clock price represents a price at which the trader can indicate a willingness to sell. The auction ends once the net demand in the market is zero. If each trader is allowed to trade only one unit, the market clearing price in this call auction will be the median of price reports. Indeed, Deck et al. (2020) argue the English-Dutch auction is a very effective institution to reduce asset bubbles. In our experiment, we used our single unit call auction because it generated only one implied weight for signals (like Treatment I), but the traders are incentivized by trading profits rather than forecasting errors (like in Treatment DA). Duffy et al. (2023) use the same, single bid call market mechanism that we use and call it a "bid only call market."

asset. They could also buy/sell assets by directly accepting another trader's bid/ask offer and they could withdraw their offers 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, along with more information about the double auction market design are found in Online Appendix A.

We recruited 353 undergraduates from Nanyang Technological University as participants in this experiment. Subjects were from various areas of study, but were primarily economics majors. Based on pre-experiment survey responses, all of our subjects report having completed a basic course in statistics.

Subjects were awarded a show-up fee of 3 Singapore dollars (SGD) for participating and could earn additional earnings based on their performance in the experiment.

Table 2 summarizes important characteristics of our experimental design including the size of each market in terms of the number of traders, the number of markets conducted per treatment, the total number of subjects per treatment, the average duration of a session of each treatment, and the average payment that each subject received per treatment. Note that in the two market treatments, C and DA, each market involves six participants.

Table 2
Characteristics of the experimental design.

	Treatment I	Treatment C	Treatment DA
Market size	1	6	6
Number of markets	41	27	25
Number of subjects	41	162	150
Average session hours	1.5 hours	1.5 hours	2 hours
Average payoff	23 SGD	22 SGD	26 SGD

Upon arrival, participants are randomly seated in the lab. The experimenter then makes a brief presentation about experimental procedures. After that, subjects are given 30 minutes to read the instructions, during which they are free to ask questions. Participants are required to successfully answer a number of control questions designed to check their comprehension of the instructions before they can begin the experiment.

5 Main Experimental Results

5.1 Results of Part 1

In this section, we report results from the first part of our experiment where we elicited subjects' attitudes toward ambiguity.[4] Recall that in this task, subjects choose between 10 pairs of boxes labeled K for Known and U for Unknown, referring to the distribution of balls colored orange or purple. The fraction of winning "purple" balls in the K box decreases from 100% to 0% in 10% increments.

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 choosing the known Box K and the unknown Box U (i.e., the switch over point). For instance, suppose a subject switches from choosing Box K to choosing Box U when the winning probability (known percentage of purple balls) in Box K is 20%. Thus for any winning probability below 20%, the subject reveals a preference for Box U. In that case, the subject's matching probability is declared to be 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 use the same approach as (Dimmock et al. 2015, 2016) to measure the ambiguity preferences of our participants. Specifically we calculate:

$$AM_i = 0.5 - p_i^M,$$

where AM_i is the measure of ambiguity aversion for individual i and p_i^M is i's matching probability. If $AM_i > 0$, then individual i is labeled as ambiguity averse, if $AM_i = 0$,

[4] Results from our elicitation of risk attitudes are reported in Online Appendix B. As shown there, we do not find any correlation between ambiguity aversion and risk aversion.

then i is labeled ambiguity neutral, and if $AM_i < 0$, then i is labeled ambiguity seeking.[5]

The results from our ambiguity preference measure suggest that a large majority of participants in our study – around two-thirds– can be classified as ambiguity averse, with the remainder being classified as either ambiguity neutral or ambiguity seeking. Specifically, in treatment I, 65.85% (27 out of 41) of 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, 67.28% (109 out of 162) of participants are ambiguity averse, 22.22% (36 out of 162) are ambiguity neutral, and 10.49% (17 out of 162) are ambiguity seeking. Finally, in treatment DA, 66.67% (100 out of 150) of participants are ambiguity averse, 22.67% (34 out of 150) are ambiguity neutral, and 10.67% (16 out of 150) are ambiguity seeking. Figure 1 shows cumulative distribution functions for the measure of ambiguity aversion, AM, for each of our three treatments[6]

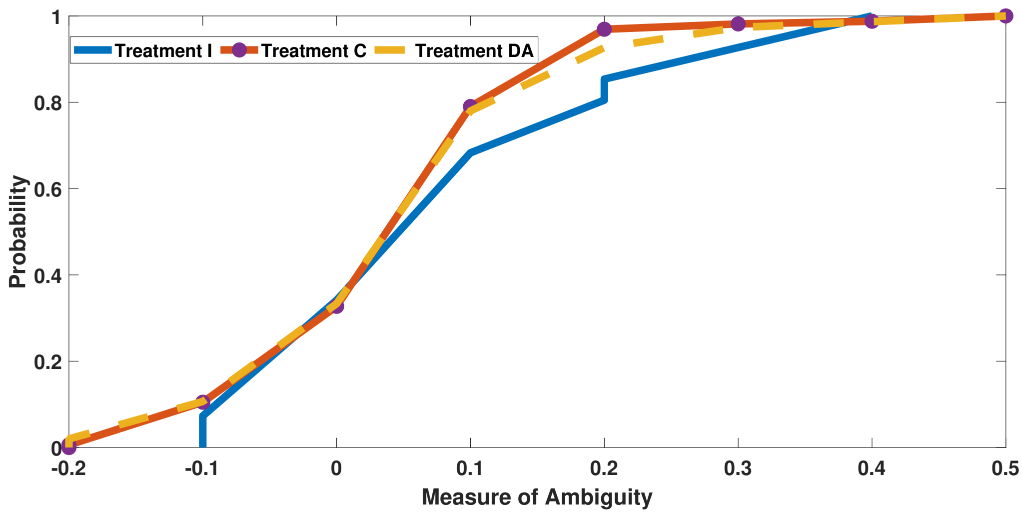

Figure 1: Cumulative distribution functions of the ambiguity measure for each treatment. The x-axis is the value of the ambiguity measure AM and the y-axis is the cumulative probability of observing AM values less than the x-axis value. The blue solid line is for Treatment I, the red line with the plus marker is for Treatment C, and the yellow dashed line is for Treatment DA.

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

[6]The results of Kolmogorov-Smirnov tests show that these cumulative distribution functions for the measure of ambiguity aversion are not different from one another in all pairwise comparisons. The exact p-value is 0.721 for the comparison between Treatment I and Treatment C, 0.886 for Treatment I and Treatment DA and 0.997 for Treatment C and Treatment DA.

5.2 Asymmetric Reaction to Ambiguous Signals

In this section, we connect evidence from part 1 of our experiment with evidence from part 2. Specifically, we provide experimental evidence for Hypothesis 1 in Section 3, which concerns the asymmetric reaction to good and bad ambiguous signals by subjects classified as ambiguity averse. According to Epstein & Schneider (2008), after receiving an ambiguous signal, subjects who are ambiguity averse are more likely to overestimate the variance of the signal s when that signal conveys "good news" (in our experimental setting, when $s > m$), and to underestimate the variance of s when their signal conveys "bad news" (in our experimental setting, when $s < m$). In other words, they will regard good news as imprecise, expecting the variance of the ambiguous signal to be higher and they will assign a smaller weight to it when the signal is above the mean than when it is below the mean, the bad news case.

We address Hypotheses 1 using two measures. The first is subjects' elicited and incentivized estimate for the variance of the ambiguous signal draws $\sigma^2_{s,t}$, that they received in each of the five periods (t = 16,17,...,20) of Scenario 4, i.e., the final 5 rounds of part 2. The second measure is the implied weight that subjects assigned to the signal s_t they received in making their prediction for each period's realization of the fundamental dividend value θ_t, in these same five rounds of Scenario 4. If subjects respond to the ambiguous signals *asymmetrically*, then they should assign higher implied weight to bad news and lower implied weight to good news.

Recall that subjects were asked to make their predictions for the dividend realization each period between the known mean value for θ, m and the ambiguous signal s in Treatment I and in Treatment C. Their prediction for θ was the linear combination of the prior m and the signal s. Therefore, we can calculate the implied weight that subjects assigned to signals $\hat{w}^{implied}$ in the following way:

$$\hat{w}^{implied}_{i,t} = \frac{\theta^e_{i,t} - m}{s_{i,t} - m} \tag{3}$$

where $\theta^e_{i,t}$ is the individual's prediction for the dividend in Treatment I and Treatment C, θ, m is the prior, which is 8 in our experiment, and $s_{i,t}$ is the signal that the participant receives in each period.

In Treatment DA, individuals trade in a double auction market, where the bid and ask prices are restricted to lie between the prior m and the signal s. The bid/ask price can be no less than the min(m, s) and no more than max(m, s). Thus, the bid or ask price is a linear combination of the prior m and the signal s. We impose this restriction because the same restriction was imposed in the other two treatments. The implied weight assigned to signals, $\hat{w}^{implied}$ is found in a similar way as in Equation (3):

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

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.

If subjects update their belief about the fundamental value of the asset following Bayes' rule to obtain their posterior beliefs, then the theoretical prediction for the weight they assign to the signal, $\hat{w}^*$, can be written as:

$$\hat{w}_{i,t}^{*} = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_{s,t}^2} \tag{5}$$

Figure 2 reports on the mean of subjects' variance expectations and implied weight allocations under ambiguous signals for each of the three treatments. The mean variance expectations and implied weights are further differentiated according to whether the signal is good news (above the mean of 8) or bad news (below the mean of 8) and is also constructed for different ambiguity types.

In treatment I, the overall (whole sample) variance expectation for bad news tends to be lower than for good news ($z = -2.433,\ p = 0.0150$); however we do not find a significantly higher implied weight assigned to bad news than to good news for the whole sample ($z = 0.875,\ p = 0.3817$). Among *ambiguity averse* subjects, however, the expected variance for bad news (1.5136) is significantly lower than the expected variance for good news (2.0599) ($z = -3.278,\ p = 0.0010$). Consistent with the theory, the weight these ambiguity averse subjects assigned to bad news (0.4773) is significantly higher than the weight they assigned to good news (0.3740), ($z = 2.826$, $p = 0.0047$).

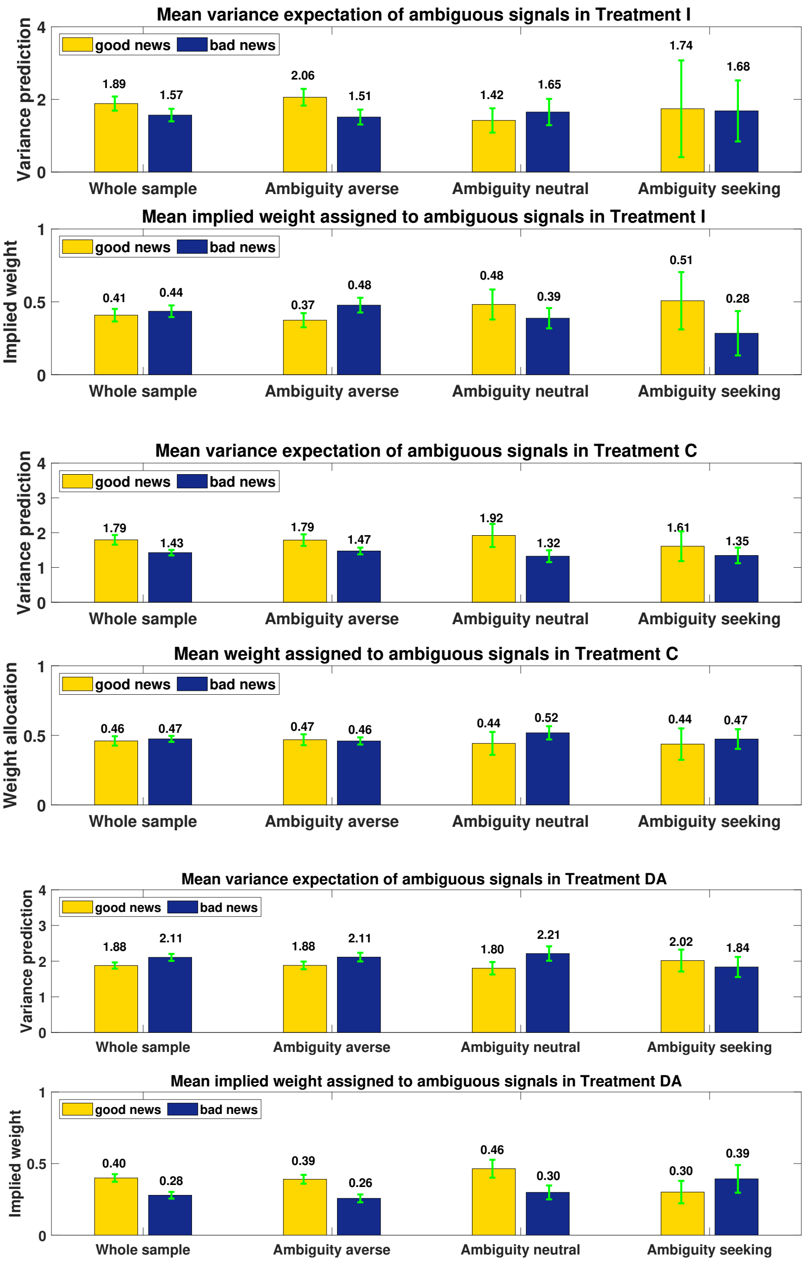

Figure 2: Mean predictions for the expected variance of ambiguous signals and mean implied weights assigned to the ambiguous signal in Treatments I, C and DA both according to whether the signal was good or bad news. The yellow (light) bar is good news, and the navy (dark) bar is bad news. The x-axis reports on the whole sample as well as subsamples of ambiguity averse, ambiguity neutral, and ambiguity seeking subjects. The y-axis is the variance expectation in the top panel and the implied weight allocated to the ambiguous signals in the bottom panel for each treatment group. The green error bars show 95% confidence intervals.

In treatment C, the expected variance associated with bad news is significantly lower than the expected variance associated with good news for the whole sample ($z = -4.161$, $p =$

0.0000), but we do not find that the overall weight assigned to bad news is larger than the weight assigned to good news ($z = 0.781,\ p = 0.4347$). Among ambiguity averse individuals, we find a lower variance expectation for bad news (1.4736) than for good news (1.7857) ($z = -2.781,\ p = 0.0054$), but these ambiguity averse subjects also do not assign a higher weight to bad news (0.4597) than to good news (0.4686), ($z = -0.269,\ p = 0.7882$). Indeed, we cannot reject the null of no difference in weights between good and bad news.

Finally, in treatment DA we observe that the overall variance expectation for bad news is actually greater than for good news ($z = 3.041,\ p = 0.0024$). Further, the weights assigned to good news are significantly greater than the weights assigned to bad news ($z = -10.883,\ p = 0.0000$). This same finding extends to the sub-sample of ambiguity averse individuals as well. The mean variance expectation of the ambiguity averse who receive bad news (2.1136) is significantly higher than their variance expectation for good news (1.8809), ($z = 2.485,\ p = 0.0130$), while the weight they allocate to good news (0.3904) is higher than the weight they allocate to bad news (0.2571). Both of these results run counter to Epstein and Schneider's theory.

Note that in DA markets, participants submit both bid and ask offers. Good news for buyers amounts to bad news for sellers, and vice versa. So, the overall result that we find regarding good/bad news and variance expectations/weighting may be driven by asymmetric reactions to good and bad news by buyers and sellers that cancel out or offset one another. To investigate this possibility, in Figure 3 we dig deeper into reports of subjects' variance expectations and their implied weights for ambiguous signals in the DA treatment. These variance expectations and implied weights are again differentiated according to whether the signal was good or bad news. Here, however, we further consider whether subjects submitted more bid than ask offers in the DA (the top panels) or they submitted more ask than bid offers in the DA (the bottom panels)

When we separate the data variance predictions for participants who primarily submit bid or ask offers, we do not find that the variance prediction for bad news is significantly larger than for good news ($z = 0.351,\ p = 0.7258$) when participants submit more bid offers than ask offers, while the mean variance prediction is slightly significantly larger for bad news than for good news when participants submit more ask offers than bid offers

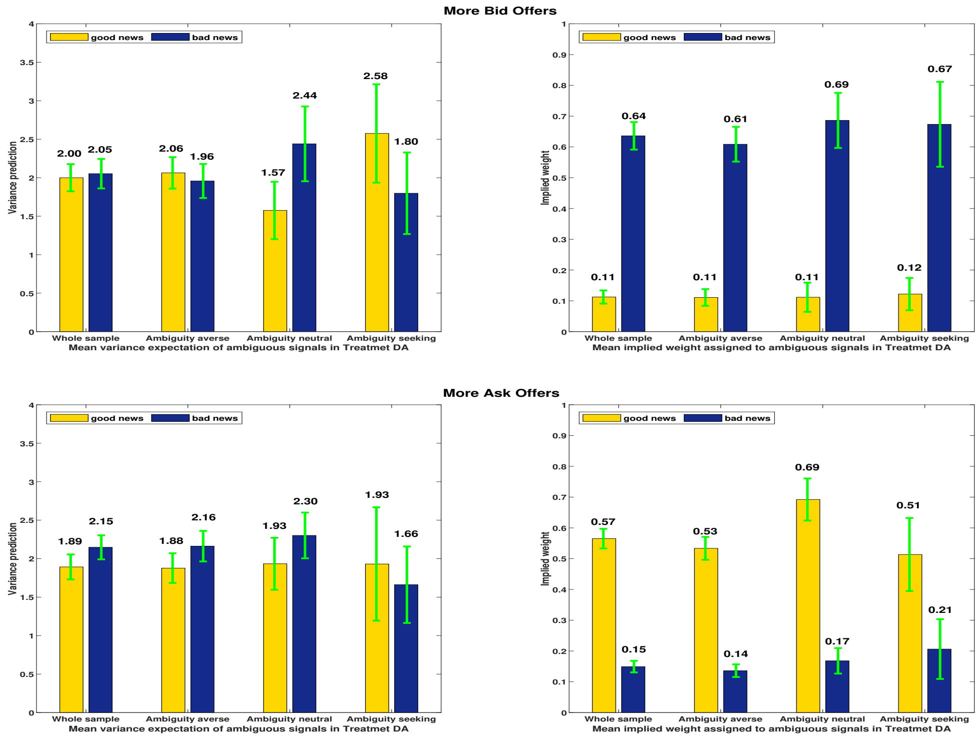

Figure 3: Treatment DA mean variance prediction for ambiguous signals of the whole sample, the subsample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects in the left panel, the mean implied weight assigned to the ambiguous signal in the right panel. The top panel demonstrates the scenario where subjects submit more bid offers, and the bottom 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.

($z = 1.954,\ p = 0.0507$). When subjects submit more bid offers than ask offers, ambiguity averse participants do not have a lower expectation of the variance for bad news (1.9573) than for good news (2.0629), ($z = -0.657,\ p = 0.5115$). When they submit more ask offers than bid offers, the variance prediction for bad news (2.1626) is not significantly larger than that for good news (1.8772), ($z = 1.831,\ p = 0.0671$).

To delve deeper into the determinants of subjects' behavior and to control for possible confounding factors such as gender and risk aversion, we use subjects' variance expectations as the dependent variable in a regression analysis. The main independent variables in this regression analysis are: *Good news* stands for good ambiguous signals and the default is *Bad news*, *AM* is the measure of subject's ambiguity aversion. The higher the *AM*, the more ambiguity averse the subject is. *Risk* stands for subjects' risk aversion, the higher is *Risk*, the more risk averse the subject is. *Male* is a dummy variable equal to 1 if the participant was male, and 0 for female. *Treatment C* equals 1 for Treatment

Table 3
This table reports regression results of variance expectation under ambiguous signals. The dependent variable is the subjects' variance expectation in Scenario 4. The independent variables are: *Good news* stands for good ambiguous signals and the default is *Bad news*, *AM* is the measurement of subject's ambiguity aversion. The higher *AM*, the more ambiguity averse the subject is. *Risk* stands for subjects' risk aversion, with higher values corresponding to greater risk aversion. *Male* is a dummy variable equal to 1 if the participant was male, and 0 for female. *Treatment C* equals 1 for Treatment C, and 0 otherwise, *Treatment DA* equals 1 for Treatment DA, and 0 otherwise, the default is *Treatment I*.

	Treatment I	Treatment C	Treatment DA	Pooled
	(1)	(2)	(3)	(4)
Good news	0.092	0.388**	-0.252**	0.06 8
	(0.11)	(0.20)	(0.10)	(0.11)
AM	-0.628*	0.805	0.323	0.384
	(0.33)	(0.70)	(0.35)	(0.35)
Good news for AM	2.039*	-0.184	0.255	0.261
	(1.05)	(0.62)	(0.75)	(0.48)
Risk	0.085***	0.034	-0.017	0.01
	(0.01)	(0.03)	(0.03)	(0.02)
Male	0.011	0.063	0.038	0.049
	(0.22)	(0.12)	(0.09)	(0.07)
Treatment C				-0.148**
				(0.07)
Treatment DA				0.272***
				(0.05)
Constant	1.117***	1.112***	2.170***	1.542***
	(0.22)	(0.28)	(0.25)	(0.17)
Period FE	Yes	Yes	Yes	Yes
Clustering Level	Session	Session	Session	Session
R2	0.058	0.038	0.02	0.051
No. of observation	205	810	750	1765

C, and 0 otherwise, *Treatment DA* equals 1 for Treatment DA, and 0 otherwise, the default is *Treatment I*. If ambiguity averse subjects respond to the ambiguous signals *asymmetrically* according to whether the signal is good or bad news, then the interaction term of the Good News dummy variable and the participants' degree of ambiguity aversion – in the regression, the variable labeled *Good news for AM* – should be positive and significant.

The regression results reported in Table 3 show that on average, when the *AM* score increases by 0.1, subjects underestimate the variance of bad news by 0.0628, and they overestimate the variance of good news by 0.2039 in Treatment I, which is consistent with the theoretical prediction of Epstein & Schneider (2008).

However, we do not find a significant result regarding the relationship between ambiguity aversion, good/bad news and the overestimation/underestimation of the variance of good/bad news in Treatment C and Treatment DA.

We employ a similar regression analysis (using the same independent variables) to examine determinants of the implied weights that subjects assigned to the signal. Again our aim is to investigate whether there were asymmetric reactions to ambiguous signals, depending on whether the news was good or bad while controlling for other factors.

Table 4
This table reports the regression results of weight allocation in ambiguous signals. The dependent variable is the subjects' implied weight allocation in Scenario 4. The main independent variables are: *Good news* stands for good ambiguous signals and the default is *Bad news*, *AM* is the measurement of subject's ambiguity aversion. The higher the *AM*, the more ambiguity averse the subject is. *Risk* stands for subjects' risk aversion, with higher values corresponding to greater risk aversion. *Male* is a dummy variable equal to 1 if the participant was male, and 0 for female. *Treatment C* equals 1 for Treatment C, and 0 otherwise, *Treatment DA* equals 1 for Treatment DA, and 0 otherwise, the default is *Treatment I*.

	Treatment I	Treatment C	Treatment DA	Pooled
	(1)	(2)	(3)	(4)
Good news	0.027	-0.033	0.120***	0.02
	(0.04)	(0.03)	(0.03)	(0.03)
AM	0.370**	-0.105	0.05	0.013
	(0.15)	(0.15)	(0.17)	(0.10)
Good news for AM	-0.490***	0.21	0.067	0.022
	(0.11)	(0.20)	(0.25)	(0.16)
Risk	-0.02	0.001	-0.011	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)
Male	-0.073***	0.024	0.011	0.006
	(0.02)	(0.02)	(0.03)	(0.02)
Treatment C				0.051***
				(0.02)
Treatment DA				-0.067***
				(0.01)
Constant	0.551***	0.463***	0.353***	0.423***
	(0.05)	(0.05)	(0.06)	(0.03)
Period FE	Yes	Yes	Yes	Yes
Clustering Level	Session	Session	Session	Session
R2	0.071	0.005	0.055	0.036
No. of observation	205	810	358	1373

Table 4 reports regression results using subject's implied weight allocations in ambiguous signals across treatments. The dependent variable is subjects' implied weight allocation, $\hat{w}_{i,t}^{implied}$, in Scenario 4. The independent variables are the same as in Table 3. The result of Treatment I suggests that when the AM score increases by 0.1, the weight assigned to bad news will on average increase with a magnitude of 0.037, while the weight assigned to good news will decrease by 0.049. However, again we do not observe a significant result for Treatments C or DA.

Overall, 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 & Schneider (2008) in both measures.

Our results in Treatment C suggest that subjects underestimate the variance of bad news as suggested by Epstein & Schneider (2008), but do not assign more weight to bad news. This inconsistency between subjects' variance expectation and their weight allocation could be due to the subjects' intrinsic behavioral biases, or might be an artefact of the call market institution.

The results from Treatment DA show that, in contrast to the prediction of Epstein & Schneider (2008), traders operating under the DA market institution do not underestimate the variance of bad signals or assign a greater weight to them relative to 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 for buyers is indeed bad news for sellers, and vice 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 prior as suggested by Allen et al. (2006) resulting in systematic under-weighting of the signals. The underweighting of 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 continuous double auction market.

Result 1 *We find supportive evidence for Hypothesis 1 in Treatment I. When the signal is ambiguous, ambiguity averse subjects underestimate the variance of bad news and overestimate the variance of good news in Treatment I that is in line with Epstein & Schneider (2008). We failed to find supportive evidence for Hypothesis 1 in Treatment C and Treatment DA. We do not observe a clear relationship between the degree of ambiguity aversion and subjects' reaction to ambiguous signals.*

5.3 Mispricing

In this section, we provide experimental evidence for Hypothesis 2 in Section 3, which concerns the extent of mispricing under ambiguous signals as compared with the case of unambiguous signals. We use a similar approach as Stöckl et al. (2010) to measure the mispricing of the asset in our experiment. Specifically, we use the relative deviation forecast (RDF) as our mispricing measures in Treatment I. This indicator measures the relative deviation of forecasts of the asset price from its fundamental value. The relative deviation forecast (RDF) of the asset price for market k in period t is defined by:

$$RDF_{k,t} = \frac{p^{e}_{k,t} - p^{FV}_{i,t}}{p^{FV}_{i,t}} \tag{6}$$

Here, $p^{e}_{k,t}$ is the market price expectation for market k in period t, while $p^{FV}_{i,t}$ is the fundamental value of the asset which is defined below:

$$p^{FV}_{k,t} = \hat{w}^{*}_{i,t} \times s_{i,t} + (1 - \hat{w}^{*}_{i,t}) \times m_t \tag{7}$$

where $\hat{w}^{*}$ is the theoretical weight given in (5). For Treatments C and DA we don't have price forecasts and so we use the relative deviation (RD) measure to measure mispricing. This measure reveals the relative deviation of asset prices from the fundamental value. The relative deviation (RD) of the asset price for market k in period t is defined by:

$$RD_{k,t} = \overline{\sum_{i \in k}^{6} \frac{(p_{i,t} - p^{FV}_{i,t})}{p^{FV}_{i,t}}} \tag{8}$$

Here, $p_{i,t}$ is the price specified in a transacted bid/ask by subject i in period t, while p^{FV}_{t} is the fundamental value of the asset in period t. $RD_{k,t}$ is the mean of the deviation of price expectation from the fundamental value in market k in period t.

In treatment I, the mean RDF in the first three scenarios involving non-ambiguous signals is 0.0021, while it is -0.0147 in the final Scenario 4 with ambiguous signals (refer to Table C2 in Online Appendix C for more information). Indeed, the RDF under ambiguous signals is found to be significantly lower than that found under unambiguous signals ($z = -5.567$, $p = 0.0000$) in Treatment I. Further, the negative sign of RDF indicates underestimation of fundamentals under ambiguous signals.

By contrast, in treatments C and DA we do not find that individuals underestimate the fundamental values only in the ambiguous signals case. The mean RD in the scenarios involving non-ambiguous signals is 0.0047 in Treatment C, and -0.0002 in Treatment DA, while it is 0.0298 in Treatment C, -0.0048 in Treatment DA in the scenario of ambiguous signals. The RD of the ambiguous signals is not lower than that of the unambiguous signals in Treatment C ($z = 0.393$, $p = 0.6946$) or Treatment DA ($z = -0.324$, $p = 0.7458$). Further confirmatory evidence for these findings can be found in the cumulative distribution functions shown in Figure 4, which show the distribution of RDF or RD values by scenarios 1-4 for each treatment I, C, and DA.

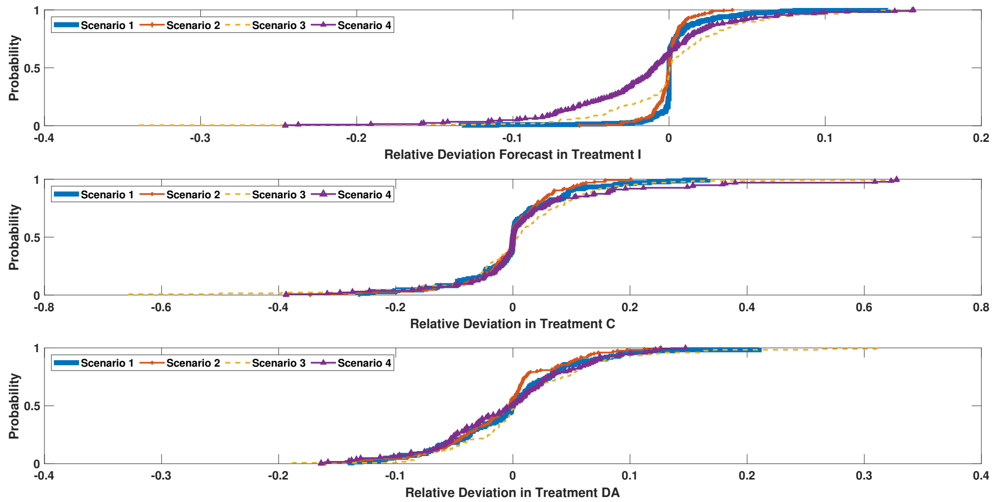

Figure 4: Figure 4 depicts the cumulative distribution function of the RD(F) in each scenario in Treatment I (top panel), Treatment C (middle panel), and Treatment DA (bottom panel). The purple dashed line with triangle marker is the RD(F) for Scenario 4 (ambiguous signals), the blue solid line is the RD(F) for Scenario 1, the red line with plus marker is the RD(F) for Scenario 2, and the yellow dashed line is the RD(F) for Scenario 3.

Table 5 reports on regression results regarding asset mispricing, and largely confirms these same findings, while controlling for other factors such as risk and gender. The dependent variable in these regressions is the RDF in Treatment I and the RD in Treatments C and DA. The main independent variables are: *Ambiguous signals* a dummy variable equal to 1 for ambiguous signals and 0 otherwise, AM is the mean value of the individual ambiguity measure, AM_i in each market k. A higher AM indicates more ambiguity averse subjects. $Risk$ stands for the mean risk aversion value in market k. The higher is $Risk$, the more risk averse subjects are on average. $Male$ is the fraction of male subjects in market k. $Treatment\ C$ is a dummy variable equal to 1 for Treatment C, and 0 otherwise, $Treatment\ DA$ is a dummy variable equal to 1 for Treatment DA, and 0 otherwise, the default is $Treatment\ I$.

The regression results indicate that for treatment I, a higher mean value for the AM measure leads to a significant overestimation of the price relative to fundamentals. However note that this finding is for *all* signals. When we consider the interaction of AM with ambiguous signals only –the variable "Ambiguous signals for AM" – the estimated coefficient suggests that when signals are ambiguous, a greater mean level of ambiguity averse subjects results in significant *under*estimation or down-pricing of the asset, which is consistent with Hypothesis 2. This result also holds for the entire (pooled) sample, but we do not find the same interaction term impacts for the other two treatments, C and DA. We summarize these findings as follows.

Table 5
This table reports the regression results of asset mispricing. The dependent variable is *RDF* in Treatment I, *RD* in Treatment C, and Treatment DA. The main independent variables are: *Ambiguous signals* is 1 for ambiguous signals and 0 otherwise, *AM* is the mean AM_i at each market k. Higher *AM* indicates more ambiguity averse. *Risk* stands for mean risk aversion at market k. The higher the *Risk*, the more risk averse the subject is. *Male* is the fraction of male subjects at market k. *Treatment C* equals 1 for Treatment C, and 0 otherwise, *Treatment DA* is 1 for Treatment DA, and 0 otherwise, the default is *Treatment I*.

	Treatment I (1)	Treatment C (2)	Treatment DA (3)	Pooled (4)
Ambiguous signals	-0.003	0.035	0.005	0.013
	(0.01)	(0.02)	(0.02)	(0.01)
AM	0.029***	-0.021	0.095*	0.035***
	(0.01)	(0.07)	(0.05)	(0.01)
Ambiguous signals for AM	-0.125***	-0.115	-0.11	-0.143***
	(0.02)	(0.23)	(0.17)	(0.03)
Risk	0.001*	0.003	-0.010***	-0.001
	(0.00)	(0.01)	(0.00)	(0.00)
Male	-0.002	0.012	-0.014	-0.002
	(0.00)	(0.02)	(0.01)	(0.00)
Treatment C				0.013***
				(0.01)
Treatment DA				0.001
				(0.00)
Constant	-0.006	-0.021	0.061***	0
	(0.00)	(0.07)	(0.02)	(0.01)
Period FE	Yes	Yes	Yes	Yes
Clustering Level	Session	Session	Session	Session
R2	0.068	0.009	0.024	0.012
No. of observation	820	540	497	1857

Result 2 *Ambiguity averse subjects tend to down-price the asset price when signals are ambiguous as compared to the case of unambiguous signals in Treatment I and in the pooled sample, but not in Treatments C and DA.*

5.4 Robustness Check: Allowing Short-selling in the DA

A potential issue with our DA treatment is that we did not allow for the short-selling of assets. The lack of a short-selling opportunity has two possible implications: First, the down-pricing prediction under ambiguous signals might not be so fully realizable in a DA market setting that does not allow short-selling. By contrast, in treatment C agents were not initially endowed with any assets and were thus free to short-sell. In treatment I, there is no trade in the asset, but one could interpret players who submit very low price expectations as engaging in a kind of short selling. Second, since sellers have the opposite asymmetric reaction to “good" and “bad" news as compared with buyers, i.e., $s > m$ is good new for sellers while $s > m$ is bad news for buyers. Providing a short-selling opportunity to sellers may cause good news ($s > m$) to become more overweighted and bad news ($s < m$) to be underweighted at the aggregate level (which is opposite to the predictions of Epstein and Schneider). Thus, the addition of short-selling could strengthen (more down-pricing) or weaken (greater weighting of bad news) the predictions of Epstein and Schneider.

To address the issue of whether the restriction against short-selling matters for our findings in the DA treatment, we conducted a variant of our double auction treatment where short-selling is allowed. This new treatment, labeled DAS, follows the same experimental design as Treatment DA, except that short-selling is allowed in Treatment DAS. Specifically, subjects are allowed to sell up to 5 assets they do not own so long as they buy those assets back before the market trading period ends. If they are unable to do so, then they must pay the end of market price for those assets. Details can be found in the instructions for treatment DAS in Appendix A. For this new treatment, we recruited 36 subjects from NTU, Singapore and have 6 independent markets for Treatment DAS. Each session of treatment DAS lasts for 2 hours. The average payoff is 28.4 SGD.

As a first check that subjects reacted to the new opportunity to short-sell the asset in treatment DAS, we looked at trading decisions made by each subject in each market. We found that 3.17% of all asks are short sales. Given that some short-selling activity took place we revisit our findings for the DA market with respect to Hypotheses 1 and 2 but using the data from treatment DAS.

5.4.1 Asymmetric Response to Ambiguous Signals

We first consider Hypothesis 1 for Treatment DAS using the same approach used in Treatment DA. The top left panel of Figure 5 reports the mean of subjects' variance expectations for ambiguous signals, differentiated according to whether their signal s

was good news or bad news. Overall, in treatment DAS, individuals do not have a lower variance expectation for bad news and a higher variance expectation for good news ($z = 1.179,\ p = 0.2385$). Among the ambiguity averse, the mean variance expectation for bad news (2.0633) is not significantly lower than for good news (1.7538) ($z = 1.793,\ p = 0.0729$). This is a different result from what we reported earlier for treatment DA (without short-selling) where we found that among the ambiguity averse, the variance expectation for good news was significantly greater than for bad news.

In the final two rows of Figure 5 we also look at variance expectations and implied weights for good versus bad ambiguous signals in the DAS treatment but also based on whether subjects submitted more bids or more ask offers (as we did for the DA treatment in Figure 3). Here, the results for the DAS treatment are similar to what we found in Treatment DA (compare the bottom panels of Figure 5 with Figure 3. Ambiguity averse individuals overestimate the variance of bad news regardless of whether they submit more bid or more ask offers, but the difference is not significant. Specifically, we do not find that the variance prediction for bad news is significantly larger than for good news when the participants submit more bid offers than ask offers ($z = 0.805,\ p = 0.4206$), or when participants submit more ask offers than bid offers ($z = 0.322,\ p = 0.7475$) (more details are reported in Table C9 of Online Appendix C).

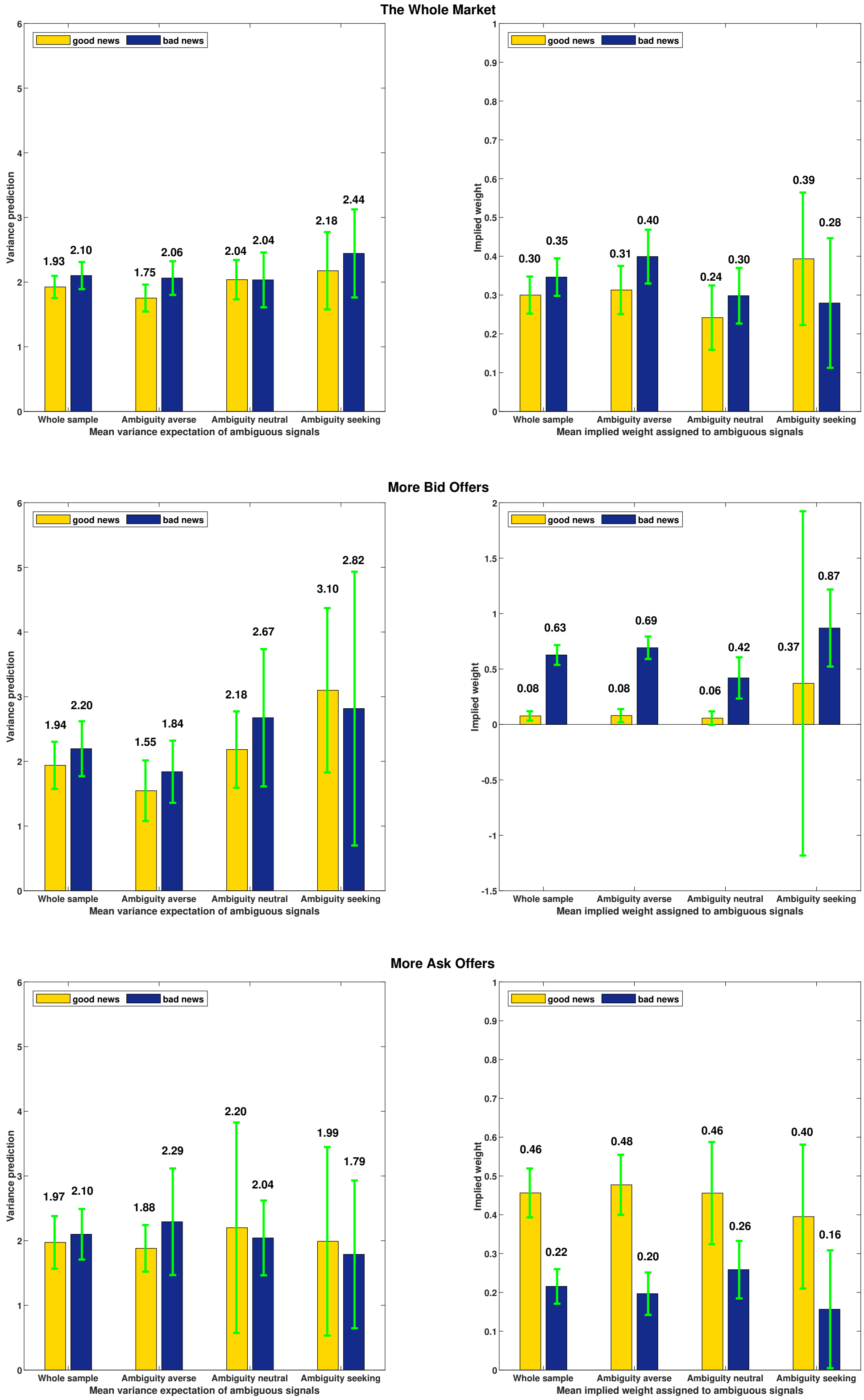

Figure 5: Treatment DAS mean variance prediction for ambiguous signals of the whole sample, the subsample of ambiguity averse, ambiguity neutral and ambiguity seeking subjects in the left panel, the mean implied weight assigned to the ambiguous signal in the right panel. The top panel demonstrates the aggregation of whole market, the middle panel demonstrates the scenario where subjects submit more bid offers, and the bottom 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.

Regarding the implied weights assigned to the signal, the top row of Figure 5 reveals that for the whole sample the mean implied weight assigned to good news is 0.3000 and is not different from the weight assigned to bad news, which is 0.3463 ($z = 0.347,\ p = 0.7284$) (more details are reported in Table C10 of Online Appendix C).

The final two rows of Figure 5 reveal that the implied weight on the signal is 0.6267 for bad news and 0.0768 for good news when participants submit more bid offers to buy the asset. The implied weight on the signal is 0.2154 for bad news and 0.4564 for good news when participants submit more ask offers to sell the asset. A ranksum test confirms that individuals assign a significantly higher weight to bad news when making more bid offers ($z = 16.216,\ p = 0.0000$), and a significantly higher weight to good news when making more ask offers ($z = -15.816,\ p = 0.0000$). The results remain the same for ambiguity-averse participants (refer again to Table C10 of Online Appendix C for more details). This finding is also consistent with what we find in Treatment DA.

In conclusion, we find that individuals do not follow Epstein and Schneider's model when they trade in a continuous double auction model regardless of the constraint of short selling. The findings of Treatment DA are still solid when short selling is allowed in the market.

5.4.2 Mispricing

The measurement of mispricing is exactly the same as in Treatment DA. Still, we find that individuals underestimate the fundamental value regardless of whether signals are unambiguous or ambiguous. The mean RD is −0.0099 in the scenario of unambiguous signals, and −0.0088 for the case of ambiguous signals (refer to Table C11 in Online Appendix C).

We do not observe a smaller RD ($z = 0.327,\ p = 0.7435$) under ambiguous signals than under unambiguous signals. Figure 6 depicts the cumulative distribution function of the RD for each scenario. It shows that the median RD is zero or slightly negative for ambiguous signals and unambiguous signals alike.[7]

[7]The regression results are reported in Table C12 in Online Appendix C.

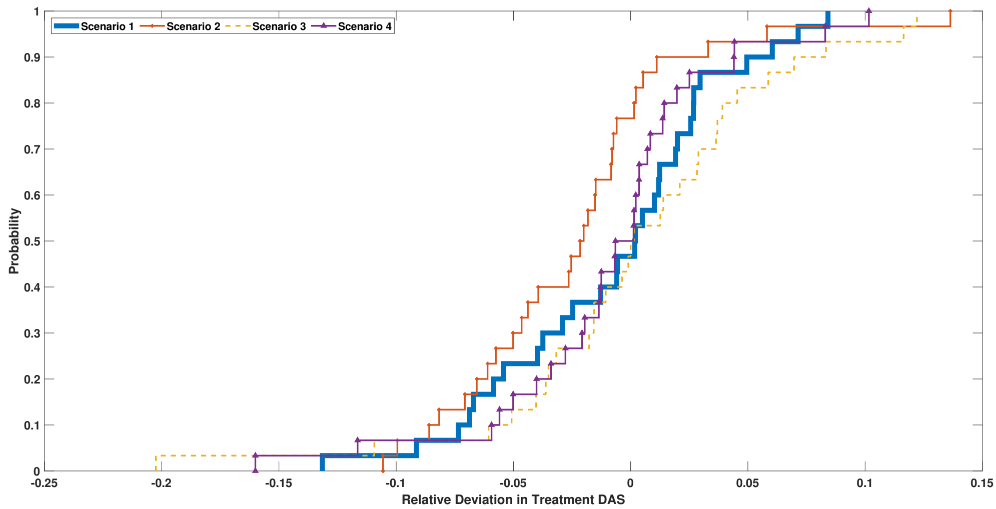

Figure 6: Figure 6 depicts the cumulative distribution function of the RD in each scenario. The x-axis is the value of RD, and the y-axis is the probability. The purple dashed line with triangle marker is the RD for Scenario 4 (ambiguous signals), the blue solid line is the RD for Scenario 1, the red line with plus marker is the RD for Scenario 2, and the yellow dashed line is the RD for Scenario 3.

Overall, almost all findings of the double auction market remain the same regardless of whether short-selling is allowed or not.

6 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). While Epstein & Schneider (2008) only considers the representative agent case, we consider three different types of experimental markets. The first of these, treatment I is effectively an individual agent prediction market. But the other two treatments, a single price call market treatment C and a double auction market treatment DA involve trading decisions of many agents.

In treatment I, consistent with Epstein & Schneider (2008), we find that ambiguity averse subjects tend to overestimate the variance of good news, and underestimate the variance of bad news in the case of ambiguous signals. Therefore, bad news is over-weighted relative to good news in the aggregate. By contrast, in Treatment C, although there is some suggestive evidence that the variance prediction is greater for bad news according to a simple non-parametric test, regression results do not show any significant results on whether people think bad news is noisier or less noisy, or assign to them higher or lower weight in their decisions. Finally, in Treatment DA, while there is evidence that individuals make asymmetric reaction to good and bad news following the Epstein and Schneider model, the asymmetric reaction by buyers and sellers cancel each other, so there is no overall over- or under-weighting of good and bad signals at the aggregate market level.

We further find that the asset is significantly down-priced under ambiguous signals than under unambiguous signals in Treatment I, while there is no evidence of down-pricing in Treatment C and Treatment DA. We also introduce short-selling into Treatment DA. The experimental results remain largely unchanged in that there is no asymmetric reaction to good and bad news at the market level, regardless of whether short-selling is allowed or not in the continuous trading market.

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 matters 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 e.g., Holzmeister et al. (2020), Weitzel et al. (2020) to see if our results are robust to different subject populations. We leave these extensions to future research.

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