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The effect of ambiguity on price formation and trading behavior in financial markets*

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Abstract

This paper sets up an experimental asset market in the laboratory to investigate the effects of ambiguity on price formation and trading behavior in financial markets. The obtained trading data is used to analyze the effect of ambiguity on various market outcomes (the price level, volatility, trading activity, market liquidity, and the degree of speculative trading) and to test the quality of popular empirical market-based measures for the degree of ambiguity. We find that ambiguity decreases market prices and trading activity; ambiguity leads to lower market liquidity through wider bid-ask spreads; and ambiguity leads to less speculative trading. We also find that popular market-based measures of ambiguity used in the empirical literature do not seem to correctly capture the true degree of ambiguity.

Keywords: ambiguity, financial market, market price, volatility, trading activity, bid-ask spread, market-based measure of ambiguity, laboratory experiment
JEL code: D81, G10

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1 Introduction

Ambiguity widely exists in financial markets, and its presence can bring about substantial effects on market outcomes. A typical example of extreme ambiguity could be a financial crisis, in which large uncertainty emerges and investors' behaviors are affected. In this sense, it is important to fully understand the effect of ambiguity in financial markets. There is an ongoing debate about the effect of ambiguity on financial markets. Recent financial literature mainly focuses on the effects of ambiguity on market outcomes such as price formation (Brenner and Izhakian 2018), and the effects on investors' behaviors such as market participation (Cao et al. 2005; Kostopoulos et al. 2020) as well as portfolio choice (Bianchi and Tallon 2019; Dimmock et al. 2016). The effects of ambiguity on other market outcomes, such as the volatility of market prices, market liquidity, and speculative trading, are less studied. In addition, as is well documented in empirical works, it is usually difficult to measure ambiguity in a market environment. The existing measures either lack a solid theoretical foundation or are not empirically tested regarding their validity. For instance, the volatility of volatility of market prices (VOV, hereafter) is widely used to quantify the degree of ambiguity in a market, but such measure seems to lack a theoretical foundation. Another measure, the empirical $\mho^2$ (Brenner and Izhakian 2018), builds on a solid theoretical foundation, but its quality in representing ambiguity is not yet tested empirically.

This paper confronts these issues and contributes to the current literature as follows. First, this paper extends the analyses of the effects of ambiguity on the less studied market outcomes mentioned above. Altogether, we focus on five particular market outcomes: market prices, the volatility of market prices, trading activity, bid-ask spreads (market liquidity), and speculative trading. We manage to partial out the confounding factors, such as subjects' beliefs and attitudes in the analyses, and cleanly extract the effect of ambiguity on each market outcome. Second, we test the quality of two empirical measures of ambiguity based on market data, i.e. VOV and the empirical $\mho^2$. The experimental market setting enables a controllable, estimable, and market-independent measure of the degree of ambiguity. By testing the relation between VOV (the empirical $\mho^2$) and the recovered degree of ambiguity, we find that neither VOV nor $\mho^2$ seems to correctly capture the true degree of ambiguity in a market.

Ambiguity arises when the probabilities of the outcomes of an event are unknown or unclear (Becker and Brownson 1964; Ellsberg 1961; Epstein 1999; Knight 1921). To operationalize an experimental financial market with ambiguity, we design an asset with a binary payoff: The asset pays out either a high payoff (i.e. a positive financial reward) or a low payoff (fixed at zero). Neither the likelihood of the high payoff nor the likelihood of the low payoff is known to any investor in this market. Thus, a financial market filled with ambiguous assets is set up. An investor trades the assets with other counterparts in a 15-period market. That is, we adopt a market setting in which investors can interact with each other. This setting enables us to directly investigate the five market outcomes, which does not seem to be possible with other approaches applied in the literature, such as sealed bid auction, and Becker–DeGroot–Marschak (BDM) method (Ahn et al. 2014; Baillon et al. 2018; Chen et al. 2007; Chew et al. 2017; Sarin and Weber 1993). In addition, we design an experimental financial market in which some other investors trade risky assets, i.e. a control group. A risky asset has an identical design as the ambiguous asset, except that the true likelihood of the high/low payoff (unknown in case of an ambiguous asset) is known to the investors. That is, we rigorously pair an ambiguity treatment market with its risk control market. Such clean control is usually not possible in real financial markets. This experimental design allows us to cleanly extract the effects of ambiguity by contrasting the market outcomes in the treatment group with those in the control group. To guide our analyses, we formulate the following five hypotheses, with each hypothesis pertaining to one of the five market outcomes.

Hypothesis 1: *Ambiguity decreases market prices.*

The first hypothesis pertains to the effect of ambiguity on market prices. This topic is widely studied in previous literature. A sizable number of theoretical works axiomatize price discounts ascribed to ambiguity aversion (Chen and Epstein 2002; Izhakian 2020; Izhakian and Benninga 2011; Maccheroni et al. 2013, to name a few). It is also well documented in experimental studies that the presence of ambiguity decreases asset prices. Among them, a stream of literature elicits subjects' certainty equivalents of financial assets, e.g. lotteries with unknown probabilities of payoffs (Baillon et al. 2018; Chen et al. 2007; Chew et al. 2017; Sarin and Weber 1993). The authors find that investors price ambiguous assets lower than their risky counterparts. These papers employ sealed bid auctions or the Becker–DeGroot–Marschak method (BDM method, Becker et al. 1964) for the elicitation. Such a method does not incorporate interactions between subjects. Another stream of experimental studies, though in a small quantity, employ market settings to study subjects' trading behaviors under ambiguity. For instance, Bossaerts et al. (2010) study how subjects trade bonds and à-la-Ellsberg Arrow securities (Ellsberg 1961) in an experimental market. Our paper follows the latter stream of the experimental literature, setting up a market environment in which subjects can interact with each other.

Hypothesis 2: *The volatility of market prices is unaffected by ambiguity.*

The second hypothesis pertains to the relation between ambiguity and the volatility of market prices. In theory, the volatility of asset returns represents the degree of risk embodied in the asset (see Arrow-Pratt approximation: Pratt 1964). Thus, in many empirical studies, the volatility of returns is regarded as a good proxy for the market aggregate degree of risk. Examples include VIX in Huang et al. (2019), Brenner and Izhakian (2018); VSTOXX in Kostopoulos et al. (2020); the variance of return rates based on the data of Standard & Poor's Depositary Receipt (SPDR) in Brenner and Izhakian (2018). Analogously, the volatility of market prices should fall into the category of the measure of risk. Since ambiguity is a different concept from risk, it is intuitive to suggest that the measure of risk should be independent of the degree of ambiguity. This is stated in Hypothesis 2. Failing to reject Hypothesis 2 also implies that subjects react to risk in an ambiguous environment as they react to risk in a purely risky environment. In general, the consistency in reaction to risk is essential for theorizing subjects' attitudes towards risk. Therefore, it is meaningful to test Hypothesis 2.

Hypothesis 3: *Ambiguity reduces trading activity.*

Through the third hypothesis, we investigate the effect of ambiguity on trading activity, i.e. how active investors participate in the trading. We consider two market outcomes that can be used to represent the trading activity in a market: the trading volume, and the number of quotes (bids and asks), in a period. The higher the value is, the more actively subjects participate in trading. Previous literature studying the effect of ambiguity on trading activity seems to be inconclusive. On one hand, it is shown that ambiguity gives rise to limited market participation (Cao et al. 2005; Dow and da Costa Werlang 1992; Easley and O'Hara 2009; Epstein and Schneider 2010). On the other hand, empirical evidence shows that activity represented by transaction frequency or account log-in frequency may instead increase when ambiguity intensifies (Kostopoulos et al. 2020). Hypothesis 3 is motivated by the mixed evidence regarding this topic.

Hypothesis 4: *Ambiguity widens bid-ask spreads.*

We follow the theory in Dow and da Costa Werlang (1992) to formulate Hypothesis 4. The authors conclude that due to ambiguity aversion, there exists a price interval within which an investor neither buys nor sells an ambiguous asset. The investor is willing to buy the asset at prices below the lower bound of this interval, and is willing to sell the asset at prices above the upper bound of this interval. This price interval thus generates a bid-ask spread. In a market populated by subjects with different levels of ambiguity aversion, an aggregate bid-ask spread should be visible. In contrast, in theory a bid-ask spread does not exist on an individual level in case that the asset is purely risky: bid and ask prices collide into the individual's certainty equivalent (CE) of the risky asset. In a market populated by subjects with diverse CEs, an aggregate bid-ask spread may arise. Hypothesis 4 tests whether the aggregate market spreads in the ambiguity treatment group are wider than those in the risk control group.

Much empirical evidence supports the theory that ambiguity results in wider bid-ask spreads (Sarin and Weber 1993; Yates and Zukowski 1976). A more recent study is Ngangoué (2018). The author finds that the bid-ask spread is wider when the return distribution of the asset is ambiguous rather than objectively known, and that such spread does not close down as learning evolves. Opposite evidence, however, is also documented in empirical literature. For instance, Eisenberger and Weber (1995) discover that the average ratio of willingness-to-accept to willingness-to-pay for ambiguous lotteries is almost the same as the average ratio for risky lotteries. Our research adds new insights to this debate. Moreover, the empirical studies mentioned above all adopt non-interaction auctions or choice tasks in the experiments, in which subjects make decisions independently. We analyze this issue based on an interactive market setting. This allows us to provide a new perspective: whether bid-ask spreads survive interactions.

The bid-ask spread is regarded as a de facto measure of market liquidity: wide spreads correspond with low liquidity since in this case buyers and sellers are hard to match. In this sense, through Hypothesis 4 we also test the effect of ambiguity on market liquidity.

Hypothesis 5: *Ambiguity leads to less speculative trading.*

The fifth hypothesis pertains to the effect of ambiguity on speculative trading. Speculative trading refers to the purchase of an asset at a price higher than the asset's fundamental value, with the hope that the asset will become even more valuable in the near future. In this paper, we choose price bubbles to proxy speculative trading. Different literature uses different ways to identify and measure price bubbles. A short summary can be found in Cheung and Palan (2012). In this paper, we define a bubble as the price difference between the actual market price (at which an asset gets traded) and the fundamental value of this asset. The fundamental value is calculated as the reservation value of the asset, which is determined by the beliefs, attitudes towards risk, and attitudes toward ambiguity of all subjects in the market. In this sense, a price bubble tends to be a good proxy for speculative trading, since it directly measure to what extent the actual market price deviates from the fundamental value of the asset.

Many empirical studies which employ experimental market settings discuss the bubble issue (Ackert and Church 2001; Haruvy et al. 2007; Noussair et al. 2001; Smith et al. 1988). Among them, Smith et al. (1988) first document that there exists a price pattern which starts out with negative bubbles before rising up to positive bubbles, and then the bubbles crash at the end. Noussair et al. (2001) discover that the possibility of a bubble sustains in case that the fundamental value remains constant over the course of the trading. Haruvy et al. (2007) relate price deviations from asset fundamental values to belief factors in a risk market setting. Our paper confirms the findings in Smith et al. (1988) and in Noussair et al. (2001). Furthermore, we go beyond the mentioned literature by extending the analysis of bubbles to an ambiguous market environment.

Apart from the effects of ambiguity on market outcomes, this paper also tests the quality of two empirically-applicable measures for the degree of ambiguity based on market data, i.e. VOV and the empirical $\mho^2$ (Brenner and Izhakian 2018). Our experiment design embeds a decreasing trend of the degree of ambiguity along the 15-period trading process. The degree of ambiguity at each point in time is controllable and estimable (by elicited belief data, which is independent of market data). This allows us to test the quality of the market-based VOV ($\mho^2$) in representing ambiguity. For this issue, we formulate two additional hypotheses.

Hypothesis 6: *VOV is a good empirical measure for the degree of ambiguity in a market*

A mainstream of financial literature uses VOV to empirically quantify the degree of ambiguity in financial markets. A larger VOV value implies a higher degree of ambiguity, with zero VOV implying the absence of ambiguity. Hypothesis 6 is constructed in line with this perspective. In practice, VOV is usually computed based on price index data (e.g. S&P 500, DAX, etc.). For instance, Kostopoulos et al. (2020) use the V-VSTOXX to estimate the expected ambiguity degree of the stock market over the following 30 days. Hollstein and Prokopczuk

(2018) and Huang et al. (2019) use VVIX to represent ambiguity. Both V-VSTOXX and VVIX denote the volatility of volatility of asset prices based on some price index. We test the quality of this conventional empirical proxy of ambiguity in Hypothesis 6.

Hypothesis 7*: The empirical $\mho^2$ proposed by Brenner and Izhakian (2018) is a good measure for the degree of ambiguity in a market.*

A more recent study, Brenner and Izhakian (2018), proposes another market-based measure of ambiguity. This measure, defined as the empirical $\mho^2$, computes the volatility of the expected probabilities of the market prices. Empirically, Brenner and Izhakian (2018) compute $\mho^2$ based on the data of Standard & Poor's Depositary Receipt (SPDR). Unlike VOV which is derived from prices, $\mho^2$ is derived from the probability distributions of prices. This makes $\mho^2$ independent of investors' attitudes towards risk and towards ambiguity, thus a measure incorporating fewer confounding factors than VOV. From a theoretical perspective, the theoretical counterpart of $\mho^2$ (Izhakian 2020) is equivalent to the variance of the second-order distribution in the KMM model (Klibanoff et al. 2005). This variance is in theory an appropriate measure of the degree of ambiguity (Izhakian and Benninga 2011; Maccheroni et al. 2013). This gives the empirical $\mho^2$ a rather solid theoretical foundation in representing ambiguity.

Apart from VOV and the empirical $\mho^2$, other empirical measures of ambiguity are also seen in the current literature. Some authors treat variance risk premium (i.e. the difference between implied and realized asset return variances) as a good measure of market uncertainty (Bali and Zhou 2016; Barndorff-Nielsen and Veraart 2012; Bollerslev et al. 2009). In other studies, the volatility of the return rate means (Vol-mean) has been used as a proxy for ambiguity (Cao et al. 2005; Garlappi et al. 2007). Carriero et al. (2018) and Jurado et al. (2015) quantify ambiguity based on macroeconomic variables. Among these measures, we choose to discuss VOV and the empirical $\mho^2$, since the former is one of the most used measures, and the latter has a theoretical counterpart with a solid theoretical foundation.

This paper reaches the following main findings: (a) The presence of ambiguity decreases market prices, supporting Hypothesis 1. (b) Volatility of market prices tends to be unaffected by ambiguity, which supports Hypothesis 2. (c) Trading activity, represented by trading volume and the number of quotes, is significantly lower in the presence of ambiguity, supporting Hypothesis 3. (d) Significantly wider bid-ask spreads are observed in ambiguity markets (treatment group) than in risk markets (control group), which supports Hypothesis 4. (e) In comparison with risk, ambiguity leads to less speculative trading. This supports Hypothesis 5. Moreover, in the ambiguity markets, market prices are mostly below the market-median fundamental value, resulting in negative bubbles. (f) Neither VOV nor the empirical $\mho^2$ tends to be correlated with the degree of ambiguity in the market. This leads to the rejection of Hypothesis 6 and 7.

The rest of the paper is organized as follows: Section 2 introduces the experiment design. Section 3 presents the descriptive summary of the experimental data. Section 4 tests Hypothesis 1-5, analyzing the effects on ambiguity on the five market outcomes, respectively. Section 5 tests Hypothesis 6 and 7, discussing the quality of VOV and the empirical $\mho^2$ in representing the degree of ambiguity. Section 6 concludes.

2 Experiment design

This paper uses experimental experiments to investigate the effect of ambiguity on financial markets. We design a financial market in the laboratory in which subjects can buy and sell assets with each other. This market design develops the experimental setting in Haruvy et al. (2007) (only involving risk) and in Bossaerts et al. (2010) (Ellsberg-featured assets). The experiment in our paper unveils how subjects respond to ambiguity in an interactive market setting. This provides new evidence regarding how the presence of ambiguity affects various aspects of a financial market.

2.1 The assets

Prior to the asset trading experiment, we introduce an urn to the subjects. This urn is used to operationalize the ambiguous environment. Subjects are told that there are in total 100 balls in the urn, and that each ball is either a white ball or a black ball. However, neither the number of white balls nor the number of black balls is known to any subject. No information is conveyed regarding how the urn is assembled. Therefore, a completely ambiguous environment is set up. Based on this urn, we further design an asset. Subjects are told that the payoff of the asset is determined by a random draw from the urn. In case that a white ball is drawn out, the asset pays out a positive financial reward (i.e. a high payoff); in case that a black ball is drawn out, the asset pays out zero (i.e. a low payoff). Since the composition of the urn is unknown to the subjects, this asset is thus an ambiguous asset. Given this setting, a white draw is always regarded as good news, which results in a positive payoff, while a black draw is always regarded as bad news, which results in zero payoff. The true composition of the urn is fixed at 40 white balls and 60 black balls (of course, unknown to the subjects throughout the experiment). This 40:60 setting avoids the prominent 50:50 setting, but still roughly balances the frequency of white draws and the frequency of black draws. One benefit is that subjects' decisions in response to both good news and bad news are relatively evenly observed. In addition, the 40:60 setting allows us to analyze the features of the markets in which assets are conceived to take immediate, non-extreme values.

To compare the decision making under ambiguity with the decision making under risk, we design an urn with known composition, and accordingly a risky asset. That is, in some experiment sessions, subjects are told that there are 40 white balls and 60 black balls in the urn. Accordingly, subjects know that the risky asset pays out a positive payoff (in case of a white draw) with the probability of 0.4, and that the asset pays out zero (in case of a black draw) with the probability of 0.6. In fact, except that subjects know the composition of the urn (and accordingly, the probability scheme of the asset's payoff), all designs of the asset trading in a risk market are the same as in an ambiguity market. This parallel design allows us to compare subjects' trading behaviors under ambiguity directly with behaviors under risk. For simplicity, we call the markets in which subjects trade ambiguous assets *ambiguity markets*, and the markets in which subjects trade risky assets *risk markets*. In total, we collect data from ten ambiguity markets and four risk markets for this paper.

2.2 Asset trading

Prior to trading, the subjects participating in a specific experiment session, are first randomly assigned into separate markets. Each market is populated by seven subjects and subjects remain in their assigned markets throughout the experiment. A subject can only trade with the other subjects in the same market. A market opens 15 times for trading, with each time lasting for 120 seconds. These 15 sequential trading periods are denoted as $t = 1, 2, \cdots 15$. A subject always has two accounts: an asset account, and an ECU account. In each period t, once the market opens, subjects can trade assets, using the ECU as the medium of exchange. At the beginning of period 1, a subject is endowed with five units of asset and 2000 ECU[1].

The asset trading follows the rule of continuous open book double auction: A subject can always simultaneously act as a seller and as a buyer. To indicate her willingness to sell an asset, she can post a sell offer with a certain selling price, known as the ask price. Symmetrically, to indicate her willingness to buy an asset, she can post a buy offer with a certain purchasing price, known as the bid price. Apart from proactively posting offers, a subject can also directly accept outstanding ask offers (bid offers) posted by other subjects in the same market, realizing the trading as a buyer (a seller). A subject is also free to remove her own outstanding ask and bid offers from the market. In principle, a subject can post as many asks/accept as many bids as her current stock balance allows. Similarly, a subject can post as many bids/accept as many asks as her current ECU balance can afford. In other words, subjects are not permitted to sell short or borrow funds. In addition, a subject can only post a new ask whose price is lower than her current cheapest outstanding ask. Analogously, a subject can only post a new bid whose price is higher than her current most expensive outstanding bid. This design helps narrow down the market bid-ask spread and accelerate the matching of buyers and sellers. Once an ask or a bid offer is accepted, the trading is realized and the transaction of the asset and the ECU is immediately executed. The asset accounts and the ECU accounts of the two traders are accordingly updated. Figure 1 displays the computer interface of the market platform.

After the 120-second trading, the market closes. In an ambiguity market, a random draw is implemented to determine the per-unit asset payoff in this period. As explained above, in an ambiguity market, the draw is operated using the ambiguous urn (with unknown composition). Each ambiguity market is equipped with one ambiguous urn (with identical design) and implements the draw independently. That is, over the 15 periods, the ten ambiguity markets would generate ten independent, probably non-identical, draw history paths. This induces more data variation. A subject can only observe the draw history in her own market. The draw history is also the only source for a subject to update her beliefs about the composition of the urn (i.e. the probability of the high payoff).

For the risk markets, a draw history is generated as follows: we pair each risk market with a preceding ambiguity market. The two markets in a pair experience the identical draw history.

[1]The pre-announced exchange rate is 400 ECU=1 Euro)

Although copied from a previous session, the draw history in a risk market can also be seen as randomly generated, only that the 15 random draws are implemented prior to the experiment, and are presented one by one to the subjects along the 15 periods. In total, there are four risk markets in our experiment. They are paired with four different ambiguity markets, respectively (details in Table 2). This pairing setting improves the comparability between markets under ambiguity and markets under risk.

As the market closes and the draw result is announced, a subject's ECU balance is updated: the total asset payoff, if any, is calculated and added to her ECU balance. At last, a personalized summary of this period is displayed on the screen. The summary displays the ECU balance and the asset balance at the beginning of this period, the ECU balance change in transaction, the draw result (i.e. the per-unit payoff of the asset), the total asset payoff, plus the ECU balance and the asset balance at the end of this period. Then period t officially ends, and next period $t+1$ (for $t < 15$) starts immediately, following the same procedure. Figure 1 summarizes the timeline of the asset trading experiment.

To allow more variation of the market design, we include an additional dimension which divides the 14 markets (ten ambiguity markets plus four risk markets) into two types, i.e. Type I and Type II (details in Table 2). In a market of Type I, ECU and assets can be carried over from one period to the next. That is, a subject carries her ECU balance and asset balance at the end of period t (for $t < 15$) to period $t+1$, and continues using them for trading in period $t+1$. This setting implies that an asset lives for 15 periods and can potentially generate 15 payoff floats. In other words, when a subject in a Type I market evaluates the value of an asset in period t, the asset still has the potential to generate $16 - t$ payoff floats. In Type I markets, the high payoff of an asset is fixed at 100 ECU; the low payoff, zero. A subject's final ECU balance at the end of period 15 is paid for real (after exchanged into Euro, 400 ECU=1 Euro). The assets, after the payoff realization in period 15, have no extra value.

In a market of Type II, a subject's ECU and assets cannot be carried down to the next period. As in period 1, a subject's ECU account and asset account is always reset to 2000 ECU and five units of asset, respectively, at the beginning of each period t (for $t > 1$). At the end of a period (after the asset payoff is calculated and added into a subject's ECU balance), a subject's end-of-period ECU balance is noted, and then all her ECU and assets are discarded. When a new period starts, she is endowed again with 2000 ECU and five units of asset. The setting of the Type II market implies that an asset only lives for one period, and that each period is independent. In Type II markets, the high payoff of an asset is fixed at 1500 ECU; the low payoff, zero. A subject's average end-of-period ECU balance across the 15 periods is paid for real (after exchanged into Euro). The setting of the high payoff and the payment calculation method facilitates that subjects participating in either Type I markets or Type II markets see a similar earning potential.

2.3 Other information

This paper shares the experiment design with Li and Wilde (2021a) and Li and Wilde (2021b). In a complete experiment session, a subject also plays some other games apart from the asset trading. These games include the *guess games* and the *choice lists*. Since they are not the main interest of this paper, we suppress the extensive introduction about them. It is worth mentioning that the guess games investigate a subject's personal beliefs regarding the composition of the urn (i.e. probability of the high payoff) along with the draw implementations; the choice lists investigate a subject's attitude towards risk and attitude towards ambiguity. Later in the analysis of the effect of ambiguity, we derive a variable which incorporates a subject's estimated beliefs and attitudes, estimated from her entries in the guess games and in the choice lists. This variable allows us to partial out the heterogeneity represented by subjects' beliefs and attitudes when analyzing the effect of ambiguity on market outcomes. This enhances the explanatory power of our analysis.

All experiment sessions are computerized by z-Tree (Fischbacher 2007). Seven experiment sessions are conducted, with 14 markets of seven subjects (in total, 98 subjects). The subjects are all randomly selected from the subject pool of the Frankfurt Laboratory for Experimental Economic Research (FLEX), Goethe University Frankfurt. Only those who have no former experience in economic experiments are eligible for participation. Most of the selected subjects are students from Goethe University Frankfurt, with various demographic and educational backgrounds. At the beginning of each experiment session, subjects are randomly assigned to PC terminals in the laboratory and receive printed instructions. Verbal explanation from the experimenter, short quiz, and practice rounds are conducted to help subjects fully understand the setting. To better introduce the key concept, the ambiguous urn/asset, we prepare a big box (functioning as an urn) filling with 100 chips, with either "white" or "black" written on a chip. This prop is presented before the subjects (in the ambiguity markets) without letting anyone peeping into it. Some trial draws from a 50:50 risky urn are presented in all markets to assist the introduction of the urn and of the asset payoff.

At the end of the experiment, subjects fill in a questionnaire. Then they are paid by their earnings and leave the laboratory. A complete experiment session lasts about 2 hours and 15 minutes on average. The total earning per subject is on average 31 Euro.

3 Descriptive summary of the data

In this section, we provide some descriptive evidence directly observed from the experimental data. We first present how ambiguity affects the five market outcomes (i.e. market prices, volatility of market price, trading activity, bid-ask spreads, and speculative trading), respectively. Additionally, we present the relation between the market-based measure of ambiguity (VOV, the empirical $\mho^2$) and the belief-based degree of ambiguity.

3.1 Market outcomes: ambiguity markets vs risk markets

For each of these five market outcomes, we report graphically the data distribution of the ten ambiguity markets versus the data distribution of the four risk markets. The differences between the two distributions partially reflect the effects of ambiguity. The results are illustrated in Figure 2.

Market price. One of the main objectives of this paper is to investigate how the presence of ambiguity affects the market price. A price is a market price if and only if an asset is traded between two subjects at this price. For the comparability across markets, we first standardize all price data in the following way: a standardized price is always a price for the per-period value of an asset, which pays out 100 ECU in case that the high payoff is realized, and pays out zero in case that the low payoff is realized. The price standardization is summarized as follows[2]:

$$\text{standardized price}=\begin{cases} \dfrac{\text{observed trading price in period } t}{16-t}; & \text{market of Type I} \quad (1) \\ \dfrac{\text{observed trading price in period } t}{15}; & \text{market of Type II} \quad (2) \end{cases}$$

Furthermore, for each market in each period, we compute the market median value of the market prices. Figure 2a box-plots these market median values across periods in the ambiguity markets (the left box), versus in the risk markets (the right box). As can be seen, the market prices tend to be lower in the ambiguity markets than in the risk markets. This is supported by the fact that the median line of the ambiguity market distribution is lower than that of the risk market distribution, by around 5 ECU. It can also be seen that the interquartile of the ambiguity market distribution sits in a lower domain than the risk market distribution does.

Figure 2b illustrates the CDF (cumulative density function) of the market median values of the market prices combing all periods in the ambiguity markets versus in the risk markets. It shows that the distribution of the risk markets tends to FOD (first-order dominate) the distribution of the ambiguity markets, since the red curve is mainly below the blue curve. Only inside a narrow support range, $[10, 20]$ ECU, the red CDF curve is slightly above the blue curve. But the spread is relatively small, compared with the spread at the support $[30, 50]$ ECU. This indicates that the distribution represented by the blue CDF curve (for ambiguity markets) tends to have a lower mean value than the distribution represented by the red CDF curve (for risk markets). The findings in both Figure 2a and 2b imply that the presence of ambiguity decreases market prices.

Volatility of the market prices. The volatility of market prices of a market in a given period represents the dispersion of the market prices of this market in this period. In this paper, we define the volatility of variable Y as the ratio of the standard deviation of Y to the mean value of Y. Hence, the volatility of the market prices in market m in period t, denoted by $Vol\text{-}price_{m,t}$, can be written as:

$$Vol\text{-}price_{m,t} = \frac{\sqrt{\mathrm{Var}(price_{m,t})}}{\mathbb{E}(price_{m,t})} \quad (3)$$

[2]In Type I markets, an asset can generate 100 ECU in a period in case of a high payoff. But assets can be carried down across periods and thus generate multiple times of payoffs. Hence, an observed trading price in period t is an asset evaluation corresponding with the payoff stream in the remaining periods, not an evaluation for per-period asset value. Therefore, the price standardization divides a trading price in period t by the number of the remaining periods (i.e. the remaining frequency of payout realizations, standing at period t). In Type II markets, an asset can generate 1500 ECU in a period in case of a high payoff, and an asset only survives one period (i.e. payoff realization takes place only once). Hence, the price standardization simply divides a trading price by 15.

where $price_{m,t}$ represents the market prices in market m in period t. The expectation (variance) term is computed over all market prices in a given market in a given period. Figure 2c box-plots the volatility of market prices in all periods in the ambiguity markets versus in the risk markets. As can be seen, the volatility seems to be slightly higher in the ambiguity markets than in the risk markets. However, the difference is relatively negligible, with the difference between the two median values less than 0.02. The two boxes also have a similar shape. Therefore, there is no clear evidence that the presence of ambiguity substantially increases or decreases the volatility of market prices.

Trading activity. The trading activity represents how active subjects participate in the trading. We choose two variables to measure the trading activity of a market in a period, i.e. the trading volume, and the number of quotes (bids and asks). Figure 2d box-plots the trading volume in all periods in the ambiguity markets, versus in the risk markets. It can be seen that the median value of the ambiguity markets is lower than the median value of the risk markets, by around 2 trades. This indicates that on average a subject in the ambiguity market trades approximately two units of assets fewer than a subject in a risk market per period. In addition, the interquartile range (25%-75% percentile) of the ambiguity market distribution covers a lower domain than the risk market distribution. In sum, it is rather clear that the trading volume tends to be lower in case that ambiguity is present.

Similarly to the trading volume, the number of quotes is also lower under ambiguity. This can be seen in Figure 2e. Analogously, we box-plot the number of quotes in all periods in the ambiguity markets, versus in the risk markets. It can be seen that the median value, as well as the interquartile range, is lower in the ambiguity markets than in the risk markets. In summary, the descriptive evidence of both variables regarding trading activity indicates that subjects are less active in trading when ambiguity is present.

Bid-ask spread (market liquidity). The bid-ask spreads represent market liquidity: wider bid-ask spreads indicate lower market liquidity, since in this case buyers and sellers are hard to match and it is harder to obtain a good price for a party willing to trade. Intuitively, a bid-ask spread should be smaller in a risk market than in an ambiguity market. It is because when sellers and buyers are more likely to reach similar evaluations of the asset value, the spreads are small, and market liquidity is high.

For this analysis, we first pin down the best available ask (min. ask among all open asks) and the best available bid (max. bid among all open bids)[3] at each second during a 120-second trading period, for each market and each period. Subsequently, we compute the bid-ask spread at each second. Then we extract the earliest showing-up spread and all spreads at each spread-value changing point along the timeline. At last, for each extracted spread, we compute its relative value: the width of the spread divided by the price level of the mid-point of the spread. These relative spreads form the data points for each market in each period.

Figure 2f box-plots the spreads in the ambiguity markets, versus the spreads in the risk markets. The results tend to be in line with the intuition: The bid-ask spreads tend to be larger in the ambiguity markets than in the risk markets, represented by the higher median line as well as the higher interquartile range of the ambiguity market distribution. This implies that

[3] All ask and bid prices are standardized following Equation (1)-(2)

the presence of ambiguity seems to result in larger bid-ask spreads, i.e. lower market liquidity.

Speculative trading. As mentioned above, speculative trading refers to the situation when a trader purchases an asset at a price higher than the asset's fundamental value, and hopes that the asset will become even more valuable in the near future. We use price bubble as a proxy for speculative trading, since a price bubble is defined as the price difference between the market price of the asset and the fundamental price of the asset. That is, a price bubble directly captures to what extent the market price of the asset deviates from the fundamental value of the asset. Hence, price bubble is a good proxy for speculative trading. The fundamental value of the asset in a market in a period is represented by the median value of subjects' reservation values regarding the asset in this market in this period. Each reservation value represents a subject's evaluation of the asset based on her beliefs regarding the asset payoff, her attitude towards risk, and her attitude towards ambiguity. Subjects' reservation values are estimated following the method in Li and Wilde (2021b). For comparability across markets, we define a (relative) price bubble as the price difference between a market price of the asset and the fundamental value of the asset, relative to the latter term.

Figure 2g box-plots the relative bubbles in all periods in the ambiguity markets, versus in the risk markets. As can be seen, price bubbles tend to be smaller (more negative) in the ambiguity markets than in the risk markets. This is supported by the lower median line of the ambiguity markets. In addition, in the ambiguity markets, negative bubbles seem to prevail: Its interquartile range mostly sits in the negative domain. It is rather evident that the presence of ambiguity downsizes positive bubbles, and/or produces bubbles with more negative measures.

3.2 Measure of ambiguity: VOV and the empirical $\mho^2$

In this part, we illustrate the descriptive evidence of the market-based measure of ambiguity: VOV and the estimated $\mho^2$. Figure 3 depicts these two terms against the belief-based degree of ambiguity, respectively. Empirically, the belief-based degree of ambiguity is represented by the volatility/variance of the second-order distribution, which is in theory an appropriate measure of ambiguity. Thus, the correlation between VOV (the estimated $\mho^2$) and the belief-based degree of ambiguity reflects to what extent VOV (the estimated $\mho^2$) correctly captures the true degree of ambiguity.

VOV. For each market in each period, we first derive the volatility of the market prices (Equation 3). To obtain a meaningful inter-period VOV, we cut the 15 trading periods into three time intervals: periods 1-5, periods 6-10, periods 11-15. Then, for each market, we compute VOV within each time interval, using the data (the volatility of the market prices) within the corresponding five periods. The formal definition of VOV reads:

$$VOV_{m,j} = \frac{\sqrt{Var_{t\in j}(Vol\text{-}price_{m,t})}}{\mathbb{E}_{t\in j}(Vol\text{-}price_{m,j})} \tag{4}$$
$$j = 1, 2, 3; \quad t = 1, 2, \cdots, 15$$

where j denotes the time interval, with $j = 1$ representing periods $t = 1, 2, \cdots, 5$, $j = 2$ representing periods $t = 6, 7, \cdots, 10$, and $j = 3$ representing periods $t = 11, 12, \cdots, 15$. $Vol\text{-}price_{m,t}$

denotes the volatility of market prices in market m in period t (defined in Equation 3). The operator $\mathbb{E}_{t\in j}$ ($Var_{t\in j}$) computes the mean (variance) of $Vol\text{-}price$ of market m within the given time interval j. Hence, each market has three data points for VOV.

For a meaningful comparison, we follow the same spirit to derive the market-measure belief-based degree of ambiguity within each time interval j. We first estimate each subject's belief distribution (conceived second-order probability) in each period, following the method in Li and Wilde (2021a). Then, we derive the volatility of each subject's belief distribution (the volatility of a distribution is equal to the standard deviation of the distribution divided by the mean of the distribution.). At last, for each market m and each time interval j, we derive the median value of the volatility across the subjects within the interval j, denoted as $\text{MedVolBelief}_{m,j}$. This variable, derived from subjects' belief data, represents market m's degree of ambiguity in time interval j. Figure 3a illustrates the frequency distribution of $\text{MedVolBelief}_{m,j}$ for all ambiguity markets. Since beliefs are not elicited for a risk market, we exclude the four risk markets from this analysis.

Following these definitions, VOV and the belief-based degree of ambiguity are comparable. Figure 3b plots VOV against the belief-based degree of ambiguity represented by $\text{MedVolBelief}_{m,j}$. Each ambiguity market contributes three dots in the graph, with 30 dots in total. As can be seen in Figure 3b, there exists no evident relation between VOV and the belief-based degree of ambiguity. The 30 dots seem to sporadically scatter without forming any pattern. This implies that VOV tends to be uncorrelated with the degree of ambiguity.

The empirical $\mho^2$. To empirically compute $\mho^2$, we first cut the asset price range into eleven bins: $[0, 10], (10, 20], \cdots, (90, 100], (100, \infty)$ ECU. For each market in each period, based on the market price data, we then construct a probability distribution of the market price over the eleven-bin support. Subsequently, for market m we compute $\mho^2_{m,j}$ within the time interval j, using the corresponding five distributions in j. This can be written as follows:

$$\mho^2_{m,j} = \sum_{b=1}^{11} \mathbb{E}_{t\in j}[Prob(b|m,t)] \cdot Var_{t\in j}[Prob(b|m,t)] \tag{5}$$

$$b = 1, 2, \cdots, 11; \quad j = 1, 2, 3; \quad t = 1, 2, \cdots, 15$$

where b indexes the eleven bins. $Prob(b|m,t)$ denotes the probability mass of price bin b, in market m in period t. The operator $\mathbb{E}_{t\in j}$ ($Var_{t\in j}$) computes the mean (variance) of the probability mass within the given time interval j. Hence, each market has three data points for $\mho^2$. It is worth mentioning that a $\mho^2_{m,j}$ value derived from Equation (5) is an empirical estimation of the theoretically-defined $\mho^2$ (Izhakian 2020). Such estimation method follows the spirit of Brenner and Izhakian (2018), who estimate the monthly-measure $\mho^2$ based on real market data.

As for the belief-based degree of ambiguity, we inherit the method in Section 3.2 "VOV analysis" to derive its market measure, except that the volatility of the belief distribution is replaced by the variance of the belief distribution. This variable is denoted as $\text{MedVarBelief}_{m,j}$. Replacing the volatility by the variance is to match the theoretical definition of $\mho^2$ (which can be proved equivalent to the variance of the second-order distribution, i.e. the variance of the belief distribution). Figure 3c illustrates the frequency distribution of $\text{MedVarBelief}_{m,j}$ for all ambiguity markets. The four risk markets are excluded from this analysis.

Figure 3d plots the estimated $\mho^2$ against the belief-based degree of ambiguity. Each ambiguity market contributes three dots in the graph, with 30 dots in total. Again, we exclude the four risk markets from this analysis. The result shows that the estimated $\mho^2$ tends to be uncorrelated with the belief-based degree of ambiguity. This observation casts doubt on the empirical method in quantifying ambiguity in Brenner and Izhakian (2018).

4 The effect of ambiguity on market outcomes

In this section, we run linear regressions to investigate how the presence of ambiguity affects the five market outcomes, respectively. This also allows us to test Hypotheses 1-5 listed in the introduction. As mentioned above, the five market outcomes include market prices, volatility of market prices, trading activity, bid-ask spreads, and price bubbles. The general form of the regression equation reads:

$$Depvar_{m,t} = \gamma_0 + \gamma_1 1[ambiguity]_m + \boldsymbol{\gamma}_c \mathbf{X} + u_{m,t} \tag{6}$$

where $Depvar_{m,t}$ denotes the dependent variable of interest, indexed by the market subscript (m) and the period subscript (t). In each analysis, we specify $Depvar_{m,t}$ with one of the market outcome variables. The dummy variable $1[ambiguity]_m$ is equal to one if ambiguous assets are traded in market m (i.e. ambiguity treatment market), and equal to zero if risky assets are traded (i.e. risk control market). This variable distinguishes trading under ambiguity from trading under risk. Therefore, γ_1 represents the effect of ambiguity, and thus it is our main interest in each analysis. We rely on the sign, size, and significance level of each $\hat{\gamma}_1$ to test the corresponding hypothesis. $u_{m,t}$ denotes the error term. $\mathbf{X}$ denotes the vector of control variables, which include:

(a) $1[Type\_I]_m$: market type of market m. It is equal to one in case of Market Type I (i.e. assets can be carried down to the next period); otherwise, zero (Market Type II).

(b) $MedRV_{m,t}$: median value of estimated reservation value of the asset in market m in period t. For each subject in market m in period t, we first estimate her reservation value of the asset following the method in Li and Wilde (2021b). Then, we compute the market median. Since the reservation values are derived based on subjects' estimated beliefs, estimated risk attitudes, and estimated ambiguity attitudes, the variable $MedRV_{m,t}$ controls for subjects' beliefs and attitudes. This partials out the heterogeneity in belief and in attitude in the analysis, and improves the cleanness when measuring the effect of ambiguity.

(c) $BayesRV_{m,t}$: the asset's reservation value in period t of a (conjectured) Bayesian updater with risk-neutral and ambiguity-neutral attitude, who observes the draw history as in market m. This variable is derived based on the method in Li and Wilde (2021b). Bayesian updates are only related to the draw history and thus homogeneous within market. Hence, $BayesRV_{m,t}$ is a market measure which controls the effect of public information (draw history).

(d) $1[period = t]$ for $t = 1, \cdots, 15$: period dummy, equal to one if $period = t$; otherwise, zero. These 15 dummy variables control for the period fixed effect.

(e) $1[pair = s]_m$ for $s = 1, 2, 3, 4$. As introduced in the experiment design, each risk market is paired with an ambiguity market. The two markets in a pair share an identical draw history. We define four pair dummies to control for the pair fixed effect: $1[pair = s]$ (for $s = 1, 2, 3, 4$) is equal to one if market m belongs to pair s; otherwise, zero. When controlling for $1[pair = s]$, the effect of ambiguity is extracted by comparing the ambiguity market with the risk market of the identical realized asset payoff floats. When controlling for the pair dummies, the sample reduces to eight markets.

Apart from the main regression in Equation (6), we run additional regressions for each market outcome by replacing the ambiguity dummy in Equation (6) with the belief-based degree of ambiguity of each market:

$$Depvar_{m,t} = \eta_0 + \eta_1 \text{ MedVolBelief}_{m,t} + \boldsymbol{\eta}_c \mathbf{X} + \epsilon_{m,t} \tag{7}$$

where $\text{MedVolBelief}_{m,t}$ denotes the belief-based degree of ambiguity in market m in period t. To compute this term, we first recover each subject's belief distribution in each period following the estimation method in Li and Wilde (2021a). Then, we derive the volatility of her belief distribution in each period. The volatility of the belief distribution represents a subject's conceived degree of ambiguity. $\text{MedVolBelief}_{m,t}$ denotes the market median value of the volatility data over all subjects in market m in period t. $\text{MedVolBelief}_{m,t}$ is equal to zero in case that market m is a risk market. Therefore, $\text{MedVolBelief}_{m,t}$ is a market-level quantitative estimation for the degree of ambiguity, and η_1 reflects how the variation of the degree of ambiguity affects a market outcome.

Based on Equation (6) and (7), we vary the dependent variable $Depvar_{m,t}$ to investigate the effects of ambiguity on the five market outcome variables, respectively. The results are reported in Table 4 (for regressions based on Equation 6) and in Table 5 (for regressions based on Equation 7). Each column corresponds with one market outcome. We discuss the results below.

4.1 The effect of ambiguity on market prices

In this section, we first focus on the effect of ambiguity on market prices (Hypothesis 1). We choose the median value of all market prices in market m in period t to represent the aggregate market price. $Depvar_{m,t}$ in Equation (6) is thus specified by this median value. Table 4 Column (1) reports the results, with panel A based on the full sample and Panel B restricting to the four pairs of markets (each pair contains one ambiguity market and one risk market, which share the identical draw history). Both regressions lead to the following result:

Result 1*: Ambiguity decreases market prices.*

It is shown that the market prices in the ambiguity markets are overall lower than those in the risk markets. On average, the ambiguous assets are priced 12.3 ECU cheaper than the risky assets in the full sample (Panel A, Column 1). When restricted to the sub-sample of the four pairs of two markets (Panel B, Column 1), the effect of ambiguity on market prices is robust and even stronger, around −16.3 ECU. These findings imply that Hypothesis 1 cannot be rejected.

The regressions based on Equation (7) also lead to the same conclusion. As can be seen in Table 5 Column 1 (both panels), when the belief-based measure of ambiguity increases, market price decreases. This supports the finding that ambiguity decreases market prices.

Result 1 confirms the findings in many previous studies of asset trading under ambiguity. Among the empirical works, Sarin and Weber (1993) find that the individual bids and market prices for lotteries with ambiguous probabilities are consistently lower than the corresponding bids and market prices for equivalent lotteries with well-defined probabilities, both in sealed-bid auctions and in double-oral auctions. Chen et al. (2007) discover that bids are lower in the presence of ambiguity in the first-price as well as in the second-price sealed-bid auction. Our paper adopts the market setting following the open book double auction rule. This allows more interactions between subjects than the sealed-bid auction and the double-oral auction. A sizable number of theoretical literature ascribes such decrease in price to ambiguity aversion (Izhakian (2020); Izhakian and Benninga (2011); Maccheroni et al. (2013), to name a few). Our findings are in line with this theoretical literature: Most subjects in our sample display ambiguity aversion (shown by Li and Wilde 2021b, who analyze the ambiguity attitude of each subject participating in the ambiguity market).

4.2 The effect of ambiguity on the volatility of market prices

In this section, we investigate the effect of ambiguity on the volatility of market prices (Hypothesis 2). The dependent variable is thus specified by the volatility of market prices as defined in Equation (3). The regression results are reported in Table 4 Column 2. The finding can be summarized as follows:

Result 2*: The volatility of market prices tends to be unaffected by ambiguity.*

As can be seen in Column 2, neither of the two panels displays a significant coefficient of the ambiguity dummy. This means that the volatility of market prices tends to be independent of whether the traded assets are ambiguous assets or risky assets. This implies that Hypothesis 2 cannot be rejected. In addition, the price volatility seems to be correlated with the market type: the volatility is higher in Market Type I (assets can be carried over to the next period) than in Market Type II. This is supported by the positively significant coefficients of $1[Type\_I]_m$ in both panels. Such finding tends to suggest that the volatility of market prices is more related to the trading rule, rather than whether the assets are ambiguous or risky.

The regressions based on Equation (7) also reach similar findings. As can be seen in Table 5 Column 2, the volatility of market prices is only slightly significantly correlated with the ambiguity measure in Panel A. In Panel B, the significance disappears. These findings confirm Result 2.

4.3 The effect of ambiguity on trading activity

In this section, we study the effect of ambiguity on trading activity (Hypothesis 3). We choose two dependent variables to represent subjects' activity in market m in period t: the trading volume, and the number of quotes (i.e. the number of bids and asks). A higher value represents higher activity in trading. Table 4 Column 3 reports the results with the trading volume being the dependent variable, and Column 4 reports the results with the number of quotes being the dependent variable. We summarize the findings as follows:

Result 3: *Ambiguity decreases trading activity*

This result is in line with Hypothesis 3. It is shown that, in the ambiguity markets, the trading volume is on average $2.5 - 2.8$ units lower per period than in the risk markets. In other words, subjects are in general less active under ambiguity than under risk. This is supported by the negative coefficients of the ambiguity dummy in both panels. Moreover, subjects trade less actively when assets can be carried over to the next periods (market Type I). This can be seen from the negative coefficients of $1[Type\_I]_m$ in both panels.

The effect of ambiguity on trading activity is also robust if activity is represented by the number of quotes. Both panels of Table 4 Column 4 show that subjects tend to post fewer asks and bids per period in the ambiguity markets than in the risk markets. This confirms the finding that subjects are in general less active under ambiguity. Compared with the trading volume, ambiguity drags down the volume of bids and asks even more evidently. This is supported by the more negative coefficient of the ambiguity dummy in Column 4 than in Column 3 of both panels.

The regressions based on Equation (7) again confirm our findings. As can be seen in Table 5 Column 3-4 (both panels), trading activity decreases when the degree of ambiguity increases.

Our findings challenge the empirical evidence of the positive effect of ambiguity on trading activity. For instance, Kostopoulos et al. (2020) analyze the trading records of German retail investors, and discover that investors' frequency of log-in to the trading platform and the frequency of trading increase as aggregate ambiguity intensifies. In their analysis, however, the measure of ambiguity differs from that in our paper. This may lead to the different results regarding the effect of ambiguity on trading activity in their paper.

On the other hand, our findings are in line with a stream of literature which documents the negative effect of ambiguity on market participation: Cao et al. (2005) demonstrate that limited participation can arise in the presence of ambiguity and heterogeneous ambiguity-averse investors; Dow and da Costa Werlang (1992) show that in the presence of ambiguity there is a price interval within which an investor stays inactive. Both papers use MEU (Gilboa and Schmeidler (1989)) to represent an investor's preference. The empirical evidence in our paper does not rely on any preference specification. This makes our findings more general.

4.4 The effect of ambiguity on bid-ask spreads (market liquidity)

A bid-ask spread describes the price difference between a bid offer and an ask offer. The bid-ask spread in a market is regarded as a de facto measure of the market liquidity: in case that the spread is wide, it is difficult for buyers and sellers to match, and thus it is hard to obtain a good price. In other words, a wide bid-ask spread implies low market liquidity, while a narrow spread implies high market liquidity. In theory, ambiguity tends to widen bid-ask spreads in financial markets and thus results in lower market liquidity, in comparison with the case if only risk is involved (Dow and da Costa Werlang (1992); Yates and Zukowski (1976)). Hypothesis 4 is in line with this theory. To test Hypothesis 4, the dependent variable in Equation (6) is specified by the bid-ask spreads of each market.

Following the definition in Section 3.1 (the bid-ask spread paragraph), this dependent variable is constructed as follows: For each market in each period, we first pin down the best available ask (min. ask among all open asks) and the best available bid (max. bid among all open bids) at each second during the 120-second period. Subsequently, we compute the bid-ask spread at each second. Then we extract the earliest showing-up spread and all spreads at each value-changing point along the timeline. Subsequently, for each *extracted* spread, we compute its relative value: the width of the spread divided by the price level of the mid-point of the spread. At last, we take the median value of these relative bid-ask spreads in this market in this period. This median value constitutes one data point of the dependent variable. We repeat this computation for each market in each period. The formal definition is written as below:

$$spread_{m,t} = \text{median}\left\{\frac{Ask_{m,t,s} - bid_{m,t,s}}{(Ask_{m,t,s} + bid_{m,t,s})/2}; \quad \text{for all } s\right\} \tag{8}$$

where s indexes the extracted spreads

Table 4 Column 5 reports the regression results. We summarize the main findings below.

Result 4*: Ambiguity widens bid-ask spreads, and thus lowers market liquidity.*

As is shown in Table 4 Column 5, the coefficients of the ambiguity dummy are significant at 5% in both panels. This implies that the presence of ambiguity leads to wider market bid-ask spreads and thus lower market liquidity. This result supports Hypothesis 4. The size of the effect of ambiguity indicates that the relative bid-ask spreads in an ambiguity market are higher than those in a risk market by six to seven percentage points. This also justifies the finding in Figure 2f that the two median lines differ in value by 0.06-0.07. In addition, Result 4 is confirmed by the regressions based on Equation (7). As can be seen in Table 5 Column 5 (both panels), the bid-ask spread increases as the degree of ambiguity increases, significant at 5% at least.

Result 4 is in line with the findings in empirical literature such as Ngangoué (2018), Sarin and Weber (1993), but contrasts the findings in Eisenberger and Weber (1995). In addition, we go beyond this literature by investigating this issue in an interactive market environment. Result 4 also implies that direct interactions between investors do not eliminate bid-ask spreads in a market.

4.5 The effect of ambiguity on speculative trading

At last, we analyze the effect of ambiguity on speculative trading (Hypothesis 5). In this paper, we use "price bubble" to proxy speculative trading. A price bubble is defined as the price difference between a market price of the asset and the fundamental value of the asset. In case of a positive bubble, the asset is over-priced. In case of a negative bubble, the asset is under-priced. Formally, the price bubble of market m in period t is defined as follows:

$$Bubble_{m,t} = \frac{Med\text{-}price_{m,t} - MedRV_{m,t}}{MedRV_{m,t}} \tag{9}$$

where $Bubble_{m,t}$ denotes the market bubble of market m in period t. For comparability across markets, $Bubble_{m,t}$ is defined as a relative term. $Med\text{-}price_{m,t}$ denotes the median value of all market prices in market m in period t. $MedRV_{m,t}$ denotes the median value of subjects' conceived reservation values regarding the asset in market m in period t. This term represents the asset's fundamental value of market m in period t. Table 4 Column 6 reports the regression results when the dependent variable is $Bubble_{m,t}$. To alleviate endogeneity, $MedRV_{m,t}$ is not controlled in either panel, since it is a part of the dependent variable. The main finding can be summarized as follows:

Result 5: *There is less speculative trading under ambiguity than under risk.*

This result supports Hypothesis 5. As can be seen, the bubble variable is significantly negatively correlated with the ambiguity dummy. That is, in case of a positive bubble, the bubble is smaller in an ambiguity market than in a risk market; in case of a negative bubble, the bubble is more negative in an ambiguity market than in a risk market. In addition, a bubble tends to be larger in case of a positive bubble (or less negative in case of a negative bubble) in Market Type I than in Market Type II. This means that, when assets survive for multiple periods, more speculative trading is observed.

Negative relations between the bubble size and the degree of ambiguity are also documented in Table 5 Column 6 (both panels). These findings confirm Result 5.

4.6 Robustness check

As robustness check, for each hypothesis, we re-run the main regressions based on Equation (6), varying the control variables. The results are reported in Table 7 in the Appendix. Each panel represents a specific market outcome and is related to one of the hypotheses 1-5. In particular, Panel 3a and 3b report the results related to the trading activity (Hypothesis 3), and the trading activity is represented by the trading volume in Panel 3a and by the number of quotes in Panel 3b. Panels 1-2 and 4-5 correspond to Hypotheses 1-2 and 4-5, respectively. In each panel, both the regressions based on the full sample and the regressions based on the sub-sample of the four pairs of markets are included. The two sample choices correspond with the choices in Table 4 Panel A and B, respectively.

As can be seen in Table 7, the findings summarized in Results 1-5 are very robust. All regressions with different control variables tend to lead to the same results as in Results 1-5. This consolidates our findings related to the effects of ambiguity on the five market outcomes.

5 Empirical measures of ambiguity based on market data

5.1 VOV

One widely-applied measure of ambiguity in the empirical literature is the volatility of volatility of market prices (VOV). Based on the experimental data, we examine the link between VOV (derived from the market trading data) and the true degree of ambiguity in the markets (estimated by the belief data, independent of market trading data). This allows us to test Hypothesis 6, that is, whether VOV is a good measure of ambiguity in an empirical setting.

We follow the definition of VOV discussed in Section 3.2. A market measure of VOV is derived over a time interval spanning five periods. It is formally defined in Equation (4). As for the true degree of ambiguity in a market at a particular point in time, we choose $\text{MedVolBelief}_{m,j}$ as proxy. This variable is also defined in Section 3.2. The regression equation reads:

$$VOV_{m,j} = \zeta_0 + \zeta_1 \cdot \text{MedVolBelief}_{m,j} + \nu_{m,t} \tag{10}$$

where $\nu_{m,t}$ denotes the error term. For risk markets, $\text{MedVolBelief}_{m,j}$ is set to zero. Table 6 Panel A reports the regression results. We summarize the results as follows:

Result 6*: VOV does not seem to be a good empirical measure for the degree of ambiguity.*

As is shown in Column (1)-(3) Panel A, the coefficients are insignificant in the regressions based on different samples. The pair-wise correlations between $VOV_{m,j}$ and $\text{MedVolBelief}_{m,j}$, reported in the last row of Panel A, confirm this finding. Moreover, the constant terms should be equal to zero in case that VOV perfectly reflects the degree of ambiguity. That is, zero degree of ambiguity (i.e. absence of ambiguity) should result in zero VOV. The significantly positive constants in Column (1)-(3) indicate that if extrapolated to the scenario of zero ambiguity, VOV does not reflect ambiguity correctly. As a robustness check, the explanatory variable is replaced by the ambiguity dummy in Column (4)-(5). The results show that there seems to be no substantial difference between the ambiguity markets and the risk markets in terms of VOV. This means that from VOV values, we cannot distinguish cases with ambiguity from cases without ambiguity. In addition, the low (negative) adjusted R^2 values also imply that there is essentially no relation between VOV and the ambiguity representations (i.e. the presence of ambiguity and the degree of ambiguity).

In sum, Result 6 leads to the rejection of Hypothesis 6. This finding challenges the convention in the mainstream of the finance empirical literature, in which VOV is regarded as a good measure for ambiguity (Bali and Zhou 2016; Baltussen et al. 2018; Barndorff-Nielsen and Veraart 2012; Bollerslev et al. 2009; Epstein and Ji 2013; Hollstein and Prokopczuk 2018; Huang et al. 2019; Kostopoulos et al. 2020).

5.2 The empirical $\mho^2$

Another possible measure of ambiguity based on empirical market data is proposed by Brenner and Izhakian (2018). The authors use real market data (Standard & Poor's depository report) to quantify ambiguity empirically. In this section, we test whether such an empirical method is a good method to measure the degree of ambiguity empirically. This pertains to Hypothesis 7.

The empirical $\mho^2$ is formally defined in Equation (5). To test whether the empirical $\mho^2$ correctly reflects the true degree of ambiguity in the market, we choose $\text{MedVarBelief}_{m,j}$ to proxy the true degree of ambiguity. This variable is defined in Section 3.2. The regression equation reads:

$$\mho^2_{m,j} = \zeta'_0 + \zeta'_1 \cdot \text{MedVarBelief}_{m,j} + \nu'_{m,t} \tag{11}$$

where $\nu'_{m,t}$ denotes the error term. For risk markets, $\text{MedVarBelief}_{m,j}$ is set to zero. Table 6 Panel B reports the regression results, which can be summarized as follows:

Result 7*: The empirical $\mho^2$ does not seem to be a good empirical measure for the degree of ambiguity.*

As is shown in Column (1)-(3) Panel B, the coefficients are insignificant in the regressions based on different samples. The pair-wise correlations between $VOV_{m,j}$ and $\text{MedVarBelief}_{m,j}$, reported in the last row of Panel B, also confirm this finding. Moreover, the constant terms should be equal to zero in case that $\mho^2$ perfectly reflects the degree of ambiguity. The significantly positive constants in Column (1)-(3) indicate that the empirical $\mho^2$ does not correctly quantify zero ambiguity. As a robustness check, the explanatory variable capturing the degree of ambiguity is replaced by the ambiguity dummy in Column (4)-(5). The results show that there seems to be no substantial difference between the ambiguity markets and the risk markets in terms of empirical $\mho^2$. The low (negative) adjusted R^2 values also imply weak links, if any, between the empirical $\mho^2$ and the ambiguity representations (i.e. the presence of ambiguity and the degree of ambiguity).

In sum, Result 7 speaks against the empirical $\mho^2$ as a good method to quantify ambiguity empirically. Therefore, Hypothesis 7 can be rejected. This result also indicates that the empirical $\mho^2$ proposed by Brenner and Izhakian (2018) does not seem to be a good estimate for the theoretical $\mho^2$ defined in Izhakian (2020).

6 Conclusion

This paper provides new insights on the effect of ambiguity on trading behavior and market outcomes. It is based on an experimental market environment with good control of the degree of ambiguity. We contrast subjects' trading behavior in markets involving ambiguity with that in markets involving only risk. This allows us to cleanly extract the effects of ambiguity on several market outcomes.

We mainly focus on the effects of ambiguity on five particular market outcomes. These include market prices, volatility of market prices, trading activity, bid-ask spreads, and speculative trading. Our analyses lead to the following conclusions: (1) Ambiguity decreases market prices. (2) The volatility of market prices tends to be unaffected by ambiguity. (3) Ambiguity decreases trading activity. (4) Ambiguity widens bid-ask spreads and thus lowers market liquidity. (5) There is less speculative trading under ambiguity than under risk. We also find that the higher the degree of ambiguity is, the larger the effect of ambiguity on market outcomes is (except for the effect of ambiguity on the volatility of market prices).

This paper also tests the validity of two empirical measures of the degree of ambiguity, i.e. VOV, and the empirical $\mho^2$ proposed by Brenner and Izhakian (2018). The controllable, estimable degree of ambiguity in our experiment setting enables this analysis. The results imply that neither of the two measures is significantly related to the true degree of ambiguity in the market. This indicates that neither VOV nor the empirical $\mho^2$ tends to quantify the degree of ambiguity correctly. This finding challenges the conventional perspective in many empirical works that VOV is a good measure for ambiguity. The result also implies that although the theory of $\mho^2$ in Izhakian (2020) has a solid theoretical foundation in measuring the degree of ambiguity, it seems to be questionable that its empirical counterpart (i.e. the empirical $\mho^2$) is a suitable measure to quantify ambiguity empirically.

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Table 1: Experiment procedure

This table reports the main procedure of a complete experiment session. Some parts may show up only in some sessions, rather than all sessions. The time-line applies to all sessions. t denotes the trading period. In total, 15 periods are included.

t=1 →	**t=2** →	···	**t=15** →	After trading
Choice lists				
↓				
Guess game	Guess game	···	Guess game	Guess game
↓	↓		↓	↓
Asset Trading	**Asset Trading**	···	**Asset Trading**	Choice lists
Initial endowment: 2000 ECU and 5 assets.	In Type I markets: end-of-period ECU/asset balance in $t = 1$.	···	In Type I markets: end-of-period ECU/asset balance in $t = 14$.	Earning announced
	In Type II markets: 2000 ECU and 5 assets.	···	In Type II markets: 2000 ECU and 5 assets.	Questionnaire
↓	↓		↓	↓
Market opens for 120 seconds	Market opens for 120 seconds	···	Market opens for 120 seconds	Final payment
↓	↓		↓	
Market closes and the 1^{st} draw* is made	Market closes and the 2^{nd} draw is made	···	Market closes and the 15^{th} draw is made	
↓	↓		↓	
End-of-period ECU/asset balance is calculated	End-of-period ECU/asset balance is calculated	···	End-of-period ECU/asset balance is calculated	

*Each market implements its own draw. In an ambiguity (risk) market, an urn with unknown (known) composition is used for 15 periods. In each period, one ball is randomly drawn out from the urn with replacement. In case of a white draw, each unit of asset pays out 100 ECU in a Type I market (1500 ECU in a Type II market). In case of a black draw, zero (in any market).

Table 2: Asset trading experiment

This table reports the experiment information regarding subjects, traded assets, and markets. In total seven experiment sessions are conducted. In each session, subjects are divided into two markets, with each market populated by seven subjects. In a market, either ambiguous assets or risk assets are available for trading. For an ambiguous asset, the payoff (either high or low) is determined by a random draw from an ambiguous urn. Subjects know that the urn contains 100 balls, and that a ball is either a white ball or a black ball. Neither the number of white balls nor the number of black balls is known to any subject trading ambiguous assets. The true composition of the ambiguous urn is 40 white balls and 60 black balls (unknown to the subjects trading ambiguous assets). For a risky asset, the payoff is determined by a random draw from a risky urn with 40 white balls and 60 black balls. That is, subjects who trade risky assets know the probability of each payoff. In all markets, in case of a white draw, the high payoff is realized; in case of a black draw, the low payoff (fixed at zero). Based on the high payoff value and the asset life duration, markets can be divided into two types: In a market of Type I, the high payoff is 100 ECU, and an asset survives for 15 periods. An asset in period t can still generate $16 - t$ times of payoff, one in each remaining period. Subjects carry the end-of-period balance (of ECU and of assets) in period t to the next period $t + 1$ and continue trading. In a market of Type II, the high payoff is 1500 ECU, and an asset survives for only one period. The ECU (asset) account is reset to 2000 ECU (5 units) at the beginning of each period. Each ambiguity market (markets 1-10) implements its own draw, generating independent draw history paths 1-10. Each risk market (markets 11-14) is paired with an ambiguity market: the two markets in a pair have an identical draw history.

Session ID	Market ID	No. of subjects	Asset feature	Market Type	Draw history	Pairing
1	1	7	ambiguous	Type I	Path 1	
	2	7	ambiguous	Type I	Path 2	
2	3	7	ambiguous	Type II	Path 3	
	4	7	ambiguous	Type II	Path 4	
3	5	7	ambiguous	Type II	Path 5	Pair 3
	6	7	ambiguous	Type II	Path 6	Pair 4
4	7	7	ambiguous	Type II	Path 7	
	8	7	ambiguous	Type II	Path 8	
5	9	7	ambiguous	Type I	Path 9	Pair 1
	10	7	ambiguous	Type I	Path 10	Pair 2
6	11	7	risky	Type I	Path 9	Pair 1
	12	7	risky	Type I	Path 10	Pair 2
7	13	7	risky	Type II	Path 5	Pair 3
	14	7	risky	Type II	Path 6	Pair 4

Summary: 7 sessions; 14 markets; 98 subjects; 10 ambiguity markets (in which ambiguous assets are traded) plus 4 risk markets (in which risk assets are traded); 6 markets of Type I plus 8 markets of Type II; 10 draw history paths; 4 pairs of two markets sharing the same draw history.

Table 2 Asset trading experiment (Continued)

Summary: No. of subjects by market type/asset feature

	Ambiguous asset (i.e. ambiguity market)	Risky asset (i.e. risk market)	Total
Market Type I	28	14	42
Market Type II	42	14	56
Total	70	28	98

Table 3: Explanatory variables in Table 4-6

Variable	**Type**	**Definition**
$1[ambiguity]_m$	dummy	"=1" for ambiguity markets; "=0" for risk markets.
$1[Type\_I]_m$	dummy	"=1" for Type I markets (in which assets survive for multiple periods); "=0" for Type II markets (in which assets survive only one period).
$MedRV_{m,t}$	continuous	The market median of subjects' estimated reservation values of the asset, in market m in period t. A subject's reservation value incorporates her beliefs regarding the likelihood of each possible scenario, her risk attitude, and her ambiguity attitude.
$BayRV_{m,t}$	continuous	The reservation value in period t of a Bayesian updater with neutral risk and ambiguity attitude, who observes the draw history of market m.
Period FE	dummy	Consisting of 15 period dummies: $1[period = t]$ for $t = 1, 2, \cdots, 15$. The dummy variable $1[period = t] = 1$ in case that period=t; Otherwise, zero.
Pair FE	dummy	Consisting of 4 dummies: $1[pair = s]$ for $s = 1, 2, 3, 4$. Each pair consists of one ambiguity market and one risk market, with the two markets sharing the identical draw history. There are in total 4 pairs of markets, indexed by s. The dummy variable $1[pair = s] = 1$ in case that the market belongs to the pair s; Otherwise, zero.
$\text{MedVolBelief}_{m,t}$ ($\text{MedVarBelief}_{m,t}$)	continuous	The volatility (variance) of the belief distribution, in the form of the market median value across subjects in market m in period t. This variable represents the (estimated) belief-based degree of ambiguity in market m in period t.
$\text{MedVolBelief}_{m,j}$ ($\text{MedVarBelief}_{m,j}$)	continuous	The volatility (variance) of the belief distribution, in the form of the market median value across subjects in market m within time interval j. The 15 trading periods is partitioned into three time intervals: $j = 1, 2, 3$, representing periods 1-5, periods 6-10, and periods 11-15, respectively. This variable represents the (estimated) belief-based degree of ambiguity in market m within the time interval j.

Table 4: The effect of ambiguity on market outcomes

This table reports the regression results regarding the effects of ambiguity on the market outcomes. All regressions are based on Equation (6). Panel A reports the results based on the full sample (ten ambiguity markets plus four risk markets). Panel B restricts to the sub-sample of the four pairs of two markets. Each pair consists of one ambiguity market and one risk market, and the two markets in a pair observe the identical draw history. In both Panel A and B, each column corresponds with a specific dependent variable (a market outcome variable): In Column (1), a market price is a price at which an asset is traded; The volatility of market prices in Column (2) is computed based on Equation (3); In Column (3)-(4), the trading activity is represented by the trading volume (i.e. No. of assets traded) and No. of quotes (i.e. No. of asks and bids), respectively. In Column (5), bid-ask spreads are derived based on Equation (8), representing the market liquidity. In Column (6), bubbles are derived based on Equation (9). The explanatory variables are defined in Table 3. All dependent and explanatory variables are market-level variables.

Panel A: full sample	Dependent variables					
	Market price (1)	Volatility of price (2)	Trading volume (3)	No. of quotes (4)	Bid-ask spread (5)	Bubble (6)
$\mathbf{1}[\boldsymbol{ambiguity}]_{\boldsymbol{m}}$	-12.330***	0.008	-2.466***	-5.255***	0.059**	-0.336***
$1[Type\_I]_m$	6.774**	0.033**	-3.197***	-2.499**	0.120***	0.164**
$MedRV_{m,t}$	0.165	0.000	0.035	0.335***	-0.002	
$BayRV_{m,t}$	26.500	0.020	6.926**	9.245	0.194	-0.063
Period FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	210
No. of markets	14	14	14	14	14	14
Adjusted R^2	0.073	0.142	0.218	0.130	0.171	0.098

Panel B: four pairs of markets	Dependent variables					
	market price (1)	Volatility of price (2)	Trading volume (3)	No. of quotes (4)	Bid-ask spread (5)	Bubble (6)
$\mathbf{1}[\boldsymbol{ambiguity}]_{\boldsymbol{m}}$	-16.340***	0.007	-2.802***	-7.712***	0.069**	-0.341***
$1[Type\_I]_m$	21.650***	0.066**	-3.239***	-2.923	0.168***	0.588***
$MedRV_{m,t}$	-0.827	0.004*	0.255***	0.498***	0.000	
$BayRV_{m,t}$	6.284	-0.611**	-14.040	-32.690	0.013	-1.906
Period FE	✓	✓	✓	✓	✓	✓
Pair FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
N	120	120	120	120	120	120
No. of markets	8	8	8	8	8	8
Adjusted R^2	0.164	0.279	0.266	0.260	0.324	0.148

Table 5: Effect of the degree of ambiguity on market outcomes

This table reports the regression results regarding the effects of ambiguity on the market outcomes. All regressions are based on Equation 7. Panel A reports the results based on the full sample (ten ambiguity markets plus four risk markets). Panel B restricts to the sub-sample of the four pairs of two markets. Each pair consists of one ambiguity market and one risk market, and the two markets in a pair observe the identical draw history. In both Panel A and B, each column corresponds with a specific dependent variable (a market outcome variable): In Column (1), a market price is a price at which an asset is traded; The volatility of market prices in Column (2) is computed based on Equation (3); In Column (3)-(4), the trading activity is represented by the trading volume (i.e. No. of assets traded) and No. of quotes (i.e. No. of asks and bids), respectively. In Column (5), bid-ask spreads are derived based on Equation (8), representing the market liquidity. In Column (6), bubbles are derived based on Equation (9). The explanatory variables are defined in Table 3. All dependent and explanatory variables are market-level variables.

Panel A: full sample	Dependent variables					
	Market price (1)	Volatility of price (2)	Trading volume (3)	No. of quotes (4)	Bid-ask spread (5)	Bubble (6)
$\mathbf{MedVolBelief}_{m,t}$	-20.870**	0.069*	-3.992***	-7.691**	0.186***	-0.476**
$1[Type\_I]_m$	6.877**	0.034**	-3.171***	-2.419**	0.122***	0.168**
$MedRV_{m,t}$	-0.014	0.001	-0.001	0.261***	-0.001	
$BayRV_{m,t}$	25.320	0.007	6.644**	8.436	0.178	-0.351
Period FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	210
No. of markets	14	14	14	14	14	14
Adjusted R^2	0.050	0.155	0.177	0.084	0.190	0.058

Panel B: four pairs of markets	Dependent variables					
	Market price (1)	Volatility of price (2)	Trading volume (3)	No. of quotes (4)	Bid-ask spread (5)	Bubble (6)
$\mathbf{MedVolBelief}_{m,t}$	-37.030***	0.031	-8.483***	-22.540***	0.211**	-0.570*
$1[Type\_I]_m$	21.930***	0.066**	-3.217***	-2.853	0.168***	0.600***
$MedRV_{m,t}$	-1.099	0.004*	0.176**	0.294	0.001	
$BayRV_{m,t}$	-0.496	-0.623**	-13.210	-31.170	-0.010	-2.366
Period FE	✓	✓	✓	✓	✓	✓
Pair FE	✓	✓	✓	✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓
N	120	120	120	120	120	120
No. of markets	8	8	8	8	8	8
Adjusted R^2	0.136	0.281	0.300	0.293	0.333	0.111

Table 6: Empirical measures of ambiguity based on market data

This table reports the regression results regarding the validity of two empirical measures of the degree of ambiguity. The explanatory variables are defined in Table 3. In Panel A, the dependent variable, $VOV_{m,j}$, represents the volatility of the volatility of the market prices in market m within the time interval j (each time interval covers five trading periods). $VOV_{m,j}$ is computed based on Equation (4). The regressions in Panel A are based on Equation (10). In Panel B, the dependent variable, $\mho^2_{m,j}$ is computed based on Equation (5). It is an empirically-based variable which quantifies the degree of ambiguity. The regressions in Panel B are based on Equation (11). In the row of "No. of markets", "14" represents the full sample (ten ambiguity markets plus four risk markets); "8" represents the four pairs of two markets (Each pair consists of one ambiguity market and one risk market, and the two markets in a pair observe the identical draw history.). "10" represents the ten ambiguity markets. "corr(,)" denotes the correlation.

Panel A	Dependent variable: $VOV_{m,j}$				
	(1)	(2)	(3)	(4)	(5)
$\mathbf{MedVolBelief}_{m,j}$	-0.211	0.071	-0.050		
$1[ambiguity]_m$				-0.095	-0.050
Constant	0.690***	0.663***	0.625***	0.701***	0.701***
N	42	24	30	42	24
No. of markets	14	8	10	14	8
Adjusted R^2	-0.006	-0.043	-0.035	-0.004	-0.039
corr(VOV, MedVolBelief)	-0.135	0.045	-0.018		

Panel B	Dependent variable: $\mho^2_{m,j}$				
	(1)	(2)	(3)	(4)	(5)
$\mathbf{MedVarBelief}_{m,j}$	0.185	0.878	-0.151		
$1[ambiguity]_m$				0.018	0.012
Constant	0.0654***	0.0511***	0.0800***	0.0574***	0.0574***
N	42	24	30	42	24
No. of markets	14	8	10	14	8
Adjusted R^2	-0.019	0.066	-0.033	-0.002	-0.029
corr($\mho^2$, MedVarBelief)	0.075	0.326	-0.048		

Figure 1: Interface of asset trading experiment

This figure displays the computer screen a subject sees during the asset trading experiment. Column (1) displays her current ECU balance (Money) and asset balance. She can ask with a certain "Sell Price" in column (2). Column (3) displays all currently outstanding ask offers in her market. The subject can accept ask offers posted by the other subjects in her market by clicking "Buy" (after choosing some specific offer). Column (4) displays her outstanding ask offers, where she can remove some or all of them as she wishes. Symmetrically, she can bid with a certain "Buy Price" price in column (8). Column (7) displays all currently outstanding bid offers in her market. The subject can accept bid offers posted by the other subjects in her market by clicking "Sell" (after choosing some specific offer). Column (6) displays her outstanding bid offers, where she can remove some of all of them as she wishes. Subjects can trade assets for 15 periods (denoted as $t = 1, 2 \cdots 15$), with each period lasting for 120 seconds. Inactivity is allowed.

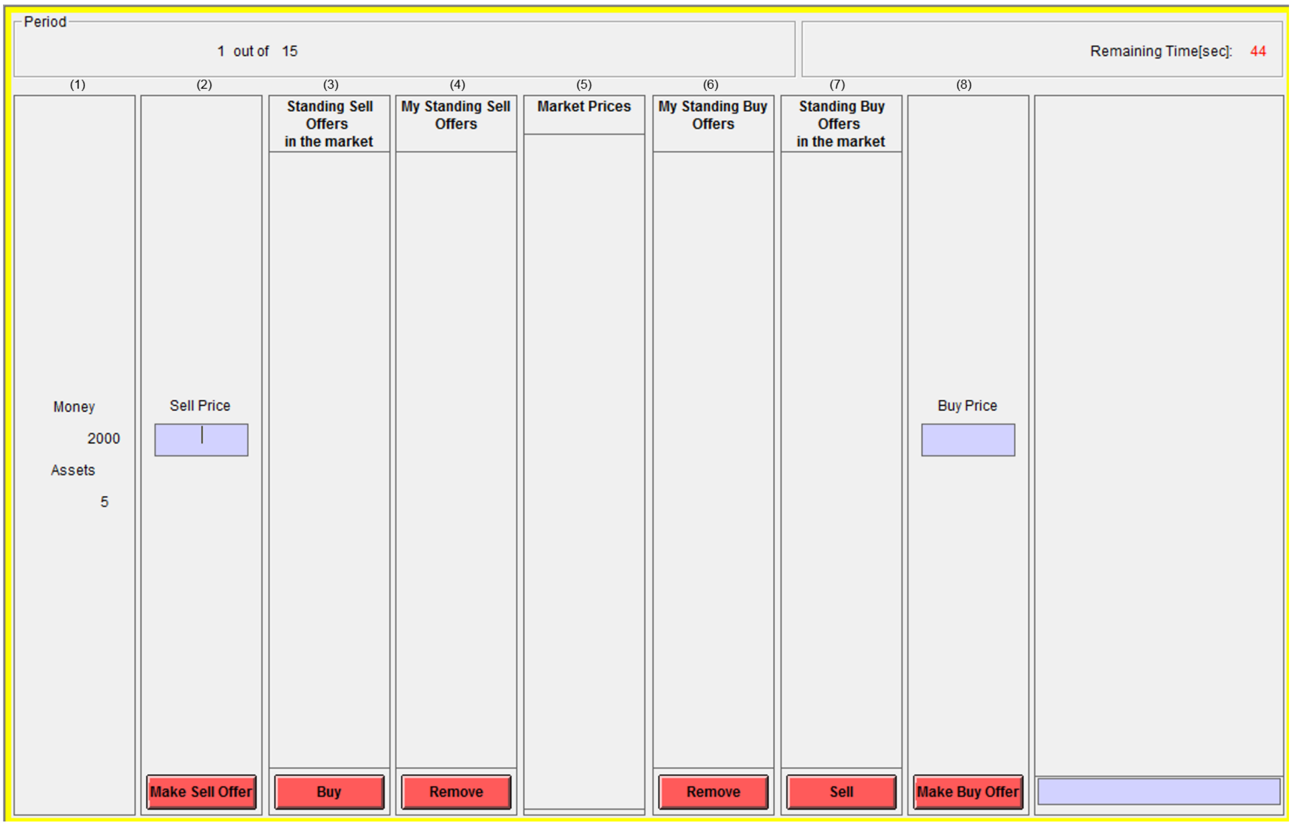
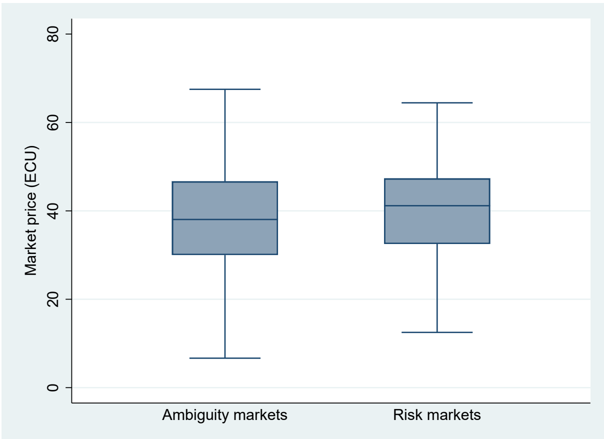


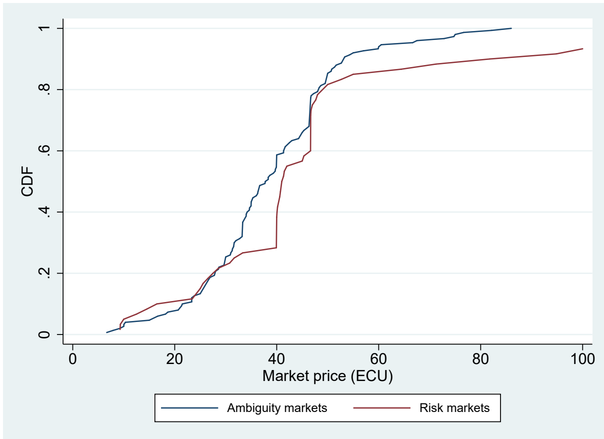
Figure 2: The effect of ambiguity on market outcomes

These diagrams compare market outcomes in the ambiguity markets with the market outcomes in the risk markets. Each figure illustrates a specific market outcome variable. Figure (a) box-plots the market prices. A market price denotes a price at which an asset is traded. For each market in each period, the market-median value of the market prices is derived. The box plots the market-median data in all periods in the corresponding markets. Figure (b) illustrates the corresponding CDF curves. Figure (c) box-plots the volatility of market prices, computed based on Equation (3). Figure (d) box-plots the trading volume (i.e. the number of assets traded), and Figure (e) box-plots the number of quotes (i.e. the number of bids and asks). These two variables proxy the trading activity. Figure (f) box-plots the (relative) bid-ask spreads. At each second when the market is open, a market's bid-ask spread is defined as the difference between the current minimum outstanding ask price and the current maximum outstanding bid price in the market at this second. The relative term is computed by dividing the bid-ask spread by the mid-point of the min. ask price and max. bid price used for the spread computation. For each market in each period, along the 120-second trading timeline, we extract the first show-up relative bid-ask spread, and all relative spreads at the point when its value changes. This forms the data points for a market in a period. Figure (g) box-plots the (relative) bubbles. A relative bubble is defined as the difference between a market price and the market measure (median) of subjects' conceived reservation values, relative to the latter term. A subject's reservation value is derived from her estimated beliefs and attitudes (based on the methods in Li and Wilde 2021b). In all figures, a box plots the corresponding variable, using the data of the corresponding markets from all 15 periods.

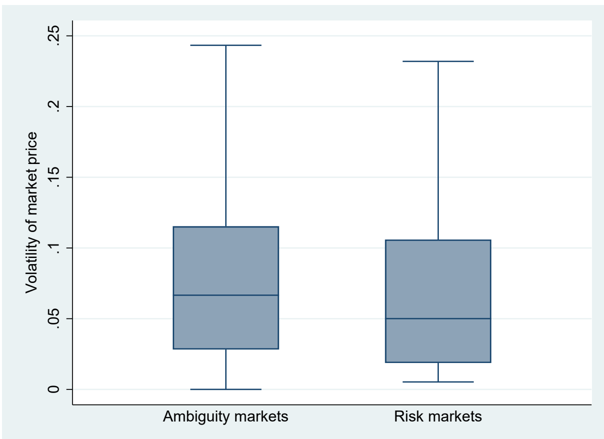
(a) Market price



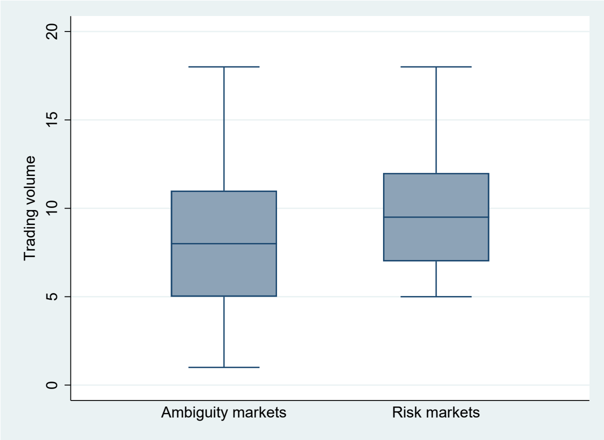
(b) Market price: CDF



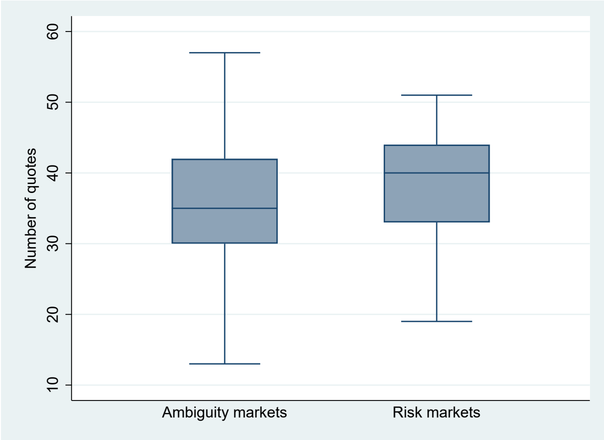
(c) Volatility of market price



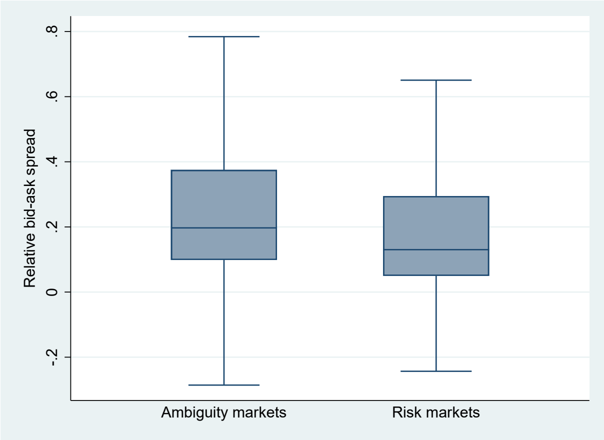
(d) Trading volume



(e) Number of quotes (bids and asks)



(f) Bid-ask spread



(g) Bubble

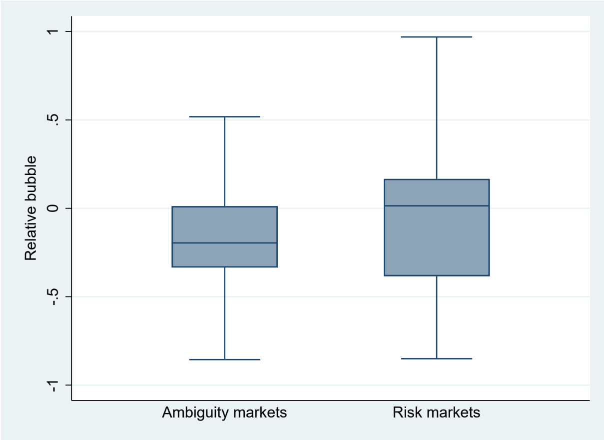
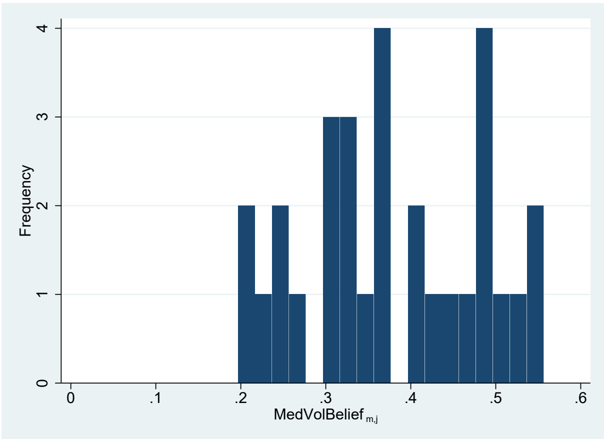


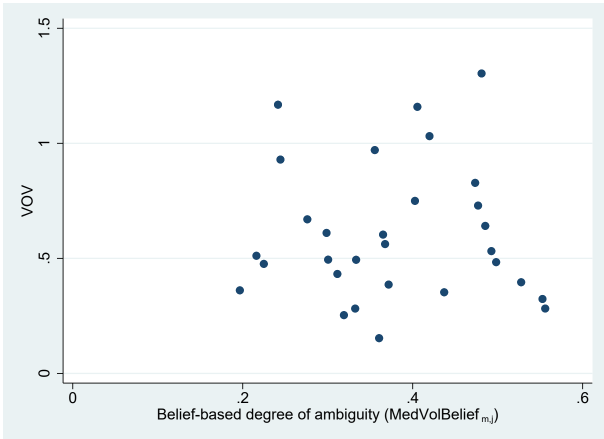
Figure 3: Empirical measures of ambiguity: VOV and $\mho^2$

These diagrams illustrate the empirical measures of ambiguity based on the market data. The 15-period trading timeline is partitioned into three time intervals: periods 1-5, periods 6-10, and periods 11-15. Figure (a) illustrates the frequency distribution of $\text{MedVolBelief}_{m,j}$, i.e. the volatility of the belief distribution, in the form of the market median across subjects in market m within time interval j. This variable represents the belief-based degree of ambiguity. Figure (b) illustrates VOV against $\text{MedVolBelief}_{m,j}$. VOV (i.e. the volatility of the volatility of market prices) is derived based on Equation (4). This is an empirical measure of the degree of ambiguity based on the experimental market data. Figure (c) illustrates the frequency distribution of $\text{MedVarBelief}_{m,j}$, i.e. the variance of the belief distribution, in the form of the market median across subjects in market m within time interval j. This variable is another representation of the belief-based degree of ambiguity. Figure (d) illustrates the empirical $\mho^2$ against $\text{MedVarBelief}_{m,j}$. The empirical $\mho^2$ (Brenner and Izhakian 2018), computed based on Equation (5), is another empirical measure of the degree of ambiguity based on the experimental market data.

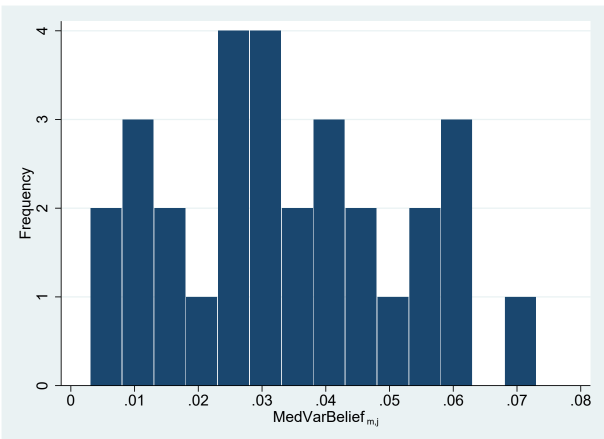
(a) $\text{MedVolBelief}_{m,j}$



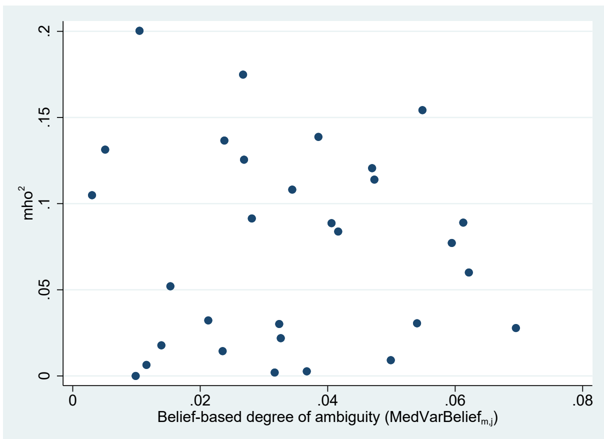
(b) VOV



(c) $\text{MedVarBelief}_{m,j}$



(d) The empirical $\mho^2$



Appendix

Table 7: The effect of ambiguity on market outcomes: robustness check

This table reports the regressions results based on Equation (6). Each panel represents a specific dependent variable (a market outcome variable): In Panel 1, a market price is a price at which an asset is traded; In Panel 2, the volatility of market price is computed based on Equation (3); In Panels 3a (3b), the trading activity is represented by the trading volume (No. of quotes, i.e. No. of asks and bids). In Panel 4, bid-ask spreads are derived based on Equation (8), representing the market liquidity. In Panel 5, bubbles are derived based on Equation (9). The explanatory variables are defined in Table 3. Columns (1)-(5) in Panels 1-4, and Columns (1)-(4) in Panel 5, are results based on the full sample. The first columns in Panels 1-5 are identical to the results reported in Table 4 Panel A Column (1)-(6), respectively. Columns (6)-(8) in Panels 1-4, and Columns (5)-(7) in Panel 5, are results based on the sub-sample of the four pairs of markets (Each pair consists of one ambiguity market and one risk market, and the two markets in a pair observe the identical draw history.). The last columns in Panels 1-5 are identical to the results reported in Table 4 Panel B Column (1)-(6), respectively. As the robustness check, control variables are varied across columns.

Panel 1	Dependent variable: **market price**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[ambiguity]_m$	-12.33***	-10.94***	-10.33***	-11.47***	-11.68***	-15.89***	-16.66***	-16.34***
$1[Type\_I]_m$	6.77**		6.09*	6.23*	6.49*		21.26***	21.65***
$MedRV_{m,t}$	0.17			0.26	0.16		-1.18*	-0.83
$BayRV_{m,t}$	26.50				13.84		21.65	6.28
Period FE	✓							✓
Pair FE						✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	120	120	120
No. of markets	14	14	14	14	14	8	8	8
Adjusted R^2	0.073	0.036	0.047	0.049	0.046	0.154	0.167	0.164
Panel 2	Dependent variable: **volatility of market price**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[ambiguity]_m$	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
$1[Type\_I]_m$	0.03**		0.03**	0.03**	0.03**		0.06**	0.07**
$MedRV_{m,t}$	0.00			0.00	0.00		0.00	0.00*
$BayRV_{m,t}$	0.02				0.11		-0.23	-0.61**
Period FE	✓							✓
Pair FE						✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	120	120	120
No. of markets	14	14	14	14	14	8	8	8
Adjusted R^2	0.142	-0.004	0.010	0.008	0.009	0.106	0.105	0.279

Table 7: the effect of ambiguity on market outcomes: robustness check (Continued)

Panel 3a	Dependent variable: **trading volume**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[ambiguity]_m$	-2.47***	-1.64***	-1.98***	-2.35***	-2.46***	-3.07***	-2.81***	-2.80***
$1[Type\_I]_m$	-3.20***		-3.37***	-3.33***	-3.20***		-3.25***	-3.24***
$MedRV_{m,t}$	0.03			0.08***	0.03		0.24***	0.26***
$BayRV_{m,t}$	6.93**				7.00**		-13.50*	-14.04
Period FE	✓							✓
Pair FE						✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	120	120	120
No. of markets	14	14	14	14	14	8	8	8
Adjusted R^2	0.218	0.032	0.213	0.236	0.251	0.265	0.314	0.266

Panel 3b	Dependent variable: **No. of quotes (bids and asks)**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[ambiguity]_m$	-5.26***	-3.03**	-3.32**	-5.03***	-5.15***	-8.28***	-7.78***	-7.712***
$1[Type\_I]_m$	-2.50**		-2.88**	-2.68**	-2.53**		-3.00	-2.92
$MedRV_{m,t}$	0.34***			0.38***	0.32***		0.45**	0.50***
$BayRV_{m,t}$	9.25				8.26		-29.00*	-32.69
Period FE	✓							✓
Pair FE						✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	120	120	120
No. of markets	14	14	14	14	14	8	8	8
Adjusted R^2	0.130	0.021	0.045	0.158	0.159	0.286	0.315	0.260

Panel 4	Dependent variable: **bid-ask spread**							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$1[ambiguity]_m$	0.06**	0.05	0.06**	0.06**	0.06*	0.07**	0.07**	0.07**
$1[Type\_I]_m$	0.12***		0.12***	0.12***	0.12***		0.17***	0.17***
$MedRV_{m,t}$	0.00			0.00	0.00		0.00	0.00
$BayRV_{m,t}$	0.19				0.32**		0.18	0.01
Period FE	✓							✓
Pair FE						✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	210	120	120	120
No. of markets	14	14	14	14	14	8	8	8
Adjusted R^2	0.171	0.008	0.098	0.094	0.107	0.269	0.258	0.324

Panel 5	Dependent variable: **bubble**						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$1[ambiguity]_m$	-0.336***	-0.355***	-0.339***	-0.322***	-0.360***	-0.342***	-0.341***
$1[Type\_I]_m$	0.164**		0.166**	0.158*		0.587***	0.588***
$BayRV_{m,t}$	-0.0629			-0.350		-1.819	-1.906
Period FE	✓						✓
Pair FE					✓	✓	✓
Constant	✓	✓	✓	✓	✓	✓	✓
N	210	210	210	210	120	120	120
No. of markets	14	14	14	14	8	8	8
Adjusted R^2	0.098	0.068	0.082	0.081	0.128	0.133	0.148

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