On Booms That Never Bust: Ambiguity in Experimental Asset Markets with Bubbles

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Keywords:

Experimental asset markets, bubbles, ambiguity

JEL codes:

C92, D84, G14, G41

Working Paper

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1. Introduction

1.1. Ambiguity in financial markets

Together with artworks and antiques markets, financial markets are one of those places where market participants are unlikely to agree, even when holding the exact same pieces of information, on what the actual value of the traded item is (see Keynes, 1936; Shiller, 1984; 2000).

Given that ambiguity is likely to play a prominent role in understanding asset prices, it is not surprising that models introducing ambiguity-averse agents have rapidly emerged. This theoretical literature has been able to account for major financial anomalies including the equity premium puzzle, or the existence of financial bubbles. The equity premium puzzle according to which stock returns are excessively high compared to bonds (Campbell and Cochrane, 1999) has been accounted for by the existence of an ambiguity premium on stocks which tends to depress prices and increase returns (see e.g., Chen and Epstein, 2002; Maenhout, 2004; Cao et al., 2005; Leippold et al., 2008; Ui, 2010; Ju and Miao, 2012). Using related arguments, several works have also relied on ambiguity aversion to account for the equity home bias by which traders under-invest in foreign assets (see e.g., Epstein and Miao, 2003; André 2014).

Ambiguity attitudes have also been evoked to explain herding in financial markets (see e.g., Avery and Zemsky, 1998). These models have provided a first attempt at formalizing the observation of prominent scholars such as Keynes (1936) and Shiller (2000) regarding the fact that ambiguous asset market values may favor the emergence of bubbles. For example, Ford et al., (2013) use a herding model à la Avery and Zemsky (1998) to show that, taking into account traders' ambiguity can lead them to downplay their private information and mimic other traders' decisions. Their general finding is that, in the presence of ambiguity, herding in financial markets can occur under a broader set of information conditions than envisioned by Avery and Zemsky (1998). Dong et al., (2010) has also shown that herding may be more likely in the presence of traders who have heterogenous attitudes towards ambiguity.

Even though previous research has given a central role to ambiguity in order to account for financial anomalies, empirical evidence has been scarce. The empirical study of the distinctive effect of ambiguity in financial markets is not an easy task. The first difficulty is to assess whether the fundamental value of an asset is risky or ambiguous. Unsurprisingly, we are not aware of any empirical study showing, for example, how the equity premium relates to the ambiguity of the fundamental value of the traded assets. Notwithstanding, a recent study by Dimmock et al., (2016) established a link between ambiguity aversion and US households' trading of stocks. In particular, the authors show that during the financial crisis, ambiguity-averse respondents were more likely to sell stocks.

1.2. Ambiguity in experimental asset markets

Given the difficulty to study the effect of ambiguity on asset markets using archival data, we propose to make use of experimental markets. A growing number of studies have demonstrated the unique benefits of the experimental method when the researcher needs to have control over the stochastic process determining the fundamental value of the asset (e.g., Bossaerts, 2009; Noussair and Tucker, 2014; Frydman et al., 2014). The experimental method thus makes it possible to isolate the effect of ambiguity from risk in the fundamental value of the asset.

However, only few studies have assessed the effect of ambiguity in experimental asset markets with most having a null effect. Camerer and Kunreuther (1989) report no consequential effect when comparing the case of risky and ambiguous asset values in an experimental double auction market for insurance coverage. Füllbrunn et al., (2014) also report a null effect when comparing the asset prices, volumes, shareholding and volatility of risky and ambiguous assets. Importantly, the authors report differences between ambiguity and risk when considering risk and ambiguity attitudes. This leads them to interpret their results as a case in which markets wash out ambiguity effects. A null result regarding ambiguity effects was also stressed by Corgnet et al., (2013) in an environment in which public information was revealed sequentially. Null results regarding the effect of ambiguity in three different market environments contrast with the burst of theoretical research introducing ambiguity in standard financial models. There are, however, reasons to believe that the difference between ambiguity and risk is real. For example, Sarin and Weber (1993), in an environment similar to Füllbrunn et al. (2014), report some evidence of an ambiguity premium in experimental asset markets. However, these positive results are obtained only when ambiguous and unambiguous assets are traded simultaneously. More recently, Bossaerts et al., (2010) also report significant effects of ambiguity in experimental asset markets with portfolio choices. Their results are in line with Dow and Werlang (1992) and Mukerji and Tallon (2001) stressing that when some state probabilities are not known, agents who are sufficiently ambiguity averse may refuse to hold an ambiguous portfolio for a certain range of prices.

The mixed evidence regarding the relevance of ambiguity effects in experimental markets could be potentially due to both the market setup as well as the *procedure* used to generate ambiguity in asset values. We propose to extend previous research by introducing a new technique to generate ambiguity in markets and more generally in any social setting. In addition, we consider a market setup which has not been studied in the presence of ambiguity and for which mispricing has been commonly observed. In particular, we study experimental markets à la Smith, Suchanek and Williams (1988) (SSW, henceforth) in which bubbles typically form. Asset market bubbles have been found to be robust to treatments variations such as short selling, capacity to buy on margin, brokerage fees, limit price change rules and transaction fees (King et al., 1993; Porter and Smith, 1994; Kujal and Powell, 2017). However, the introduction of futures markets may reduce the magnitude of bubbles (Porter and Smith, 1995; Noussair and Tucker 2006) as well as repeating the experiment with the same cohort (e.g., SSW; Dufwenberg et al., 2005; Hussam et al., 2008) of subjects or using a non-declining fundamental value (Noussair et al., 2001; Kirchler et al., 2012; Stöckl et al., 2015).

To ensure the emergence of bubbles in our experimental markets, we thus used the main features of the classical SSW design such as a declining fundamental value while recruiting subjects who did not have any experience in related experiments.

We think that the SSW environment is an adequate framework where traders may downplay their ambiguous information to follow the market trend. In the words of Shiller (2000, page 137): "*in ambiguous situations people's decisions are affected by whatever anchor is at hand*". That is, in an early bubble, the presence of a positive trend in market prices, by providing a possibly positive although weak signal, may well sway people's beliefs. This echoes Keynes' (1936, page 154) view regarding the effect of ambiguity on potentially triggering "animal spirits": "*A conventional valuation which is established as the outcome of the mass psychology of a large number of ignorant individuals is liable to change violently as the result of a sudden fluctuation of opinion due to factors which do not really make much difference to the prospective yield; since there will be no strong roots of conviction to hold it steady.*"

Using the SSW framework, we will be able to study the causal effect of ambiguity on the formation of bubbles and on the occurrence of crashes. In the original SSW environment, the asset to be traded delivers stochastic dividends in each of fifteen trading periods, but is worthless at the end of the experiment. We extend the SSW design to the case in which the fundamental value of the asset is ambiguous so that the probability of occurrence of each possible outcome is not perfectly known to traders.

1.3. The ambiguity protocol

At the methodological level, we introduce ambiguity in the fundamental value of the asset using a protocol which differs from the standard Ellsberg's (1961) procedure. Our aim was to generate a situation in which the fundamental value is ambiguous in the sense that it is *"open to more than one interpretation"* (Oxford Dictionary). In the Ellsberg's (1961) implementation of ambiguity, subjects are *not given any information* regarding the respective probabilities of occurrence of the colored balls in the urn. In the absence of any prior information, the principle of insufficient reason[2] would apply (Machina and Siniscalchi, 2014) so that subjective beliefs are not based on any relevant information (see e.g., Binmore et al., 2012; Ahn et al., 2014; Charness et al., 2013).

The Ellsberg's protocol thus limits the possibility for subjects to learn from each other's views regarding the composition of the run. In sum, the Ellsberg protocol is well-suited in an individual decision-making context in which subjects do not interact and do not learn from each other's subjective beliefs. However, in a social context, as is the case of markets, we want to allow people to learn from others' subjective views in the presence of ambiguity.

In our protocol, ambiguity is generated by relying on people's natural tendency to perceive colors differently (see e.g., Eysenck and Keane, 2015).[3] Our procedure presents subjects with a color mix of blue and green. We tell subjects that the percentage of blue and green colors in the mix determines the exact proportions of blue and green chips in an opaque bag used to select the final payout of the asset at the end of the experiment. In the risk treatment, subjects were told that the color mix was 50% green and 50% blue and were additionally shown the same color mix strip shown in the ambiguity treatment. However, no indication was given regarding the relative proportion of blue and green in the ambiguity treatment. This procedure can be related to the procedure using transparent versus opaque bags filled with balls of two different colors to create risky and ambiguous bets, respectively (see e.g., Chow and Sarin, 2002). Our case can be seen as one in which the bag would be filled with a very large or uncountable number of balls of different colors so that the visual observation of the bag is still ambiguous as different subjects could evaluate the color mix differently. In this way, one can generate bags of increasing levels of

[2] Keynes (1921, pages 52-53) referred to this as the principle of indifference, formulating it as "if there is no known reason for predicating of our subject one rather than another of several alternatives, then relatively to such knowledge the assertions of each of these alternatives have an equal probability".
[3] As an extreme, some people may have difficulty distinguishing colors (especially red and green).

ambiguity by simply increasing the number of balls in the bag. This is the case because the greater the number of balls in the bag, the less measurable uncertainty is.

Alternatively, one could generate ambiguity by asking subjects to bet on actual financial or sports events (see Heath and Tversky, 1991; Fox and Tversky, 1995; see Trautmann and van de Kuilen, 2015 for a review). We did not use this procedure because we wanted to abstract away from the issue of perceived competence in a given domain as stressed by Heath and Tversky (1991) or Fox and Tversky (1995). We opted for color ambiguity instead so as to generate a variety of beliefs across subjects and ensure that all of them could have a say on what they thought the true value of the asset was. Our color mix thus attempts to mimic a situation in which all traders receive the same piece of public information (for example, financial statements) which can be subject to different individual interpretations. Another advantage of our *color ambiguity* protocol is that it can induce risk as well as Ellsberg's ambiguity as special cases.[4]

In our ambiguity treatment, market prices may convey valuable information regarding other traders' perception of the color mix. This is the case because in our *color ambiguity* protocol, unlike the Ellsberg's protocol, people may update theory beliefs regarding the color composition of the color mix and thus their valuation of the asset by taking into account other traders' views. It follows that in our protocol beliefs are *malleable*.

An upward trend in prices which is typical of a bubbling market could then lead traders to update their beliefs along the lines that the color mix is dominated by the color which is associated with the highest payout value. This mechanism may resemble fads as described in the bubbles literature where investors seem to collectively overvalue the prospects of certain assets such as was for example the case for technology stocks in the early 2000s (e.g., Shiller 1984; Camerer, 1989). As Shiller (1984, page 464) states: "*Stock prices are likely to be among the prices that are relatively vulnerable to purely social movements because there is no accepted theory by which to understand the worth of stocks and no clearly predictable consequences to changing one's investments*".

1.4. Findings

In line with our conjecture, we report that the positive trend in prices observed in our ambiguity treatment lasted longer than in the baseline. This is illustrated by the fact that crashes occurred

[4] To generate Ellsberg's ambiguity using our protocol, we could print the color mix in gray scale or hide the color mix entirely.

later and less frequently in this treatment than in the risk treatment. At the individual level, we account for this finding by identifying those traders who are inclined to revise their beliefs upwards regarding the true value of the asset after having observed a positive trend in the ambiguity treatment. Recent research in neuroscience (see De Martino et al., 2013) has identified these types of people as those who possess high theory of mind skills (Baron-Cohen et al., 1997) and who are thus inclined to uncover others' beliefs and intentions (see e.g., Frith and Frith, 1999; see Bossaerts et al., 2018 for a review in the Economics literature). In particular, De Martino et al., (2013) have shown that, in the presence of rising prices, brain regions associated to value computation (i.e., *vmPFC*: ventromedial prefrontal cortex) tend to activate the most for those subjects who possess high theory of mind skills. In our setup, we show that traders possessing high theory of mind skills and who are thus more likely to make active use of market prices as valuable signals of other traders' private perception of colors significantly update their beliefs upwards in the ambiguity treatment whereas this was not the case of low theory of mind traders.

Finally, we also show that prices are generally depressed in the ambiguity treatment thus confirming the crucial role of the ambiguity premium in explaining financial anomalies in recent theoretical works (see e.g., Chen and Epstein, 2002; Maenhout, 2004; Cao et al., 2005; Leippold et al., 2008; Ui, 2010; Ju and Miao, 2012).

2. Design

2.1. The market

We use the seminal asset market design of SSW in which nine subjects trade a unique asset for fifteen periods of three minutes using a computerized double auction platform (see Appendix A for detailed instructions). The trading mechanism was open-book with up to the best four bids and asks visible on traders' screens. Each trader was endowed with a certain amount of cash and shares. Following SSW, we considered three possible endowments with each set of three traders endowed with 2 shares and 1,305¢ in cash, 3 shares and 945¢ in cash and 4 shares and 585¢ in cash, respectively.[5] We did not allow for short selling or buying on margin (see King et al., 1993; Porter and Smith, 1994; Haruvy and Noussair, 2006; Kujal and Powell, 2017).

[5] Because the expected value of the asset was 360¢, regardless of the treatment, the expected value of each trader's portfolio was identical. The values for cash and shares were chosen to ensure a cash to share ratio which is sufficiently high to generate bubbles (Caginalp et al., 1998, 2001; Razen et al., 2017). Following SSW, traders were not informed about the three possible types of endowments.

We deviate from SSW by having a sure dividend of 12¢ at the end of each period. This feature has been found to have no effect on the formation or crash of price bubbles (Porter and Smith, 1995; Corgnet et al., 2015). We did so to ensure that the fundamental value of the asset was declining (starting at 360¢) thus mimicking the original SSW design and ensuring the emergence of bubbles (see Noussair et al., 2001; Kirchler et al., 2012; Stöckl et al., 2015). In addition, the asset delivered a final payout (at the end of period 15) which was equal to either 80¢ or 280¢ with equal chances.

We conducted two treatments which only differed in the mechanism determining the underlying value of the asset. In the risk treatment, the stochastic process determining the final payout of the asset was known to traders whereas in the ambiguity treatment the exact probabilities of occurrence of each value were not known to traders and were depicted by a color mix as explained below.

2.2. The final payout

In both treatments, subjects saw an opaque bag filled with 100 chips in front of the room. Subjects were informed that the bag was filled with blue and green chips.[6] They knew that the proportion of blue and green chips in the bag had been determined based on a colored piece of paper which was given to all subjects at the start of the experiment.[7] More precisely, the proportion of blue and green chips in the bag was exactly the same as the proportion of blue and green that had been mixed to produce the color printed out on their sheet of paper. Along with the color mix, subjects were also shown the original blue and green colors which were used to produce the mix (see Figure 1).

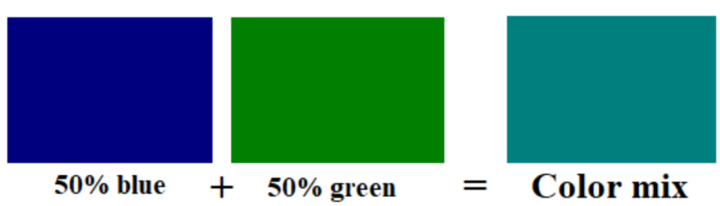

Figure 1. Color mix along with the blue and green colors used for the mix

[6] For fairness concerns, we tried to minimize issues related to colorblindness by using blue and green colors. Evidently, this does not eliminate differences in color perceptions across subjects. These differences are essential to our procedure which aims at generating a diversity of prior beliefs about the proportion of each colors in the mix.

[7] We printed this piece of paper out using the same machine to ensure the uniformity of colors across subjects. We did not want to rely solely on the color as shown on subjects' individual monitor screens because of possible differences in monitor settings.

The risk treatment only differed from the ambiguity treatment in that the subjects were told the exact proportion (50% of each color) of blue and green which were used to produce the color mix. They were also shown the same color mix which was shown in the ambiguity treatment. Therefore, subjects in the risk treatment knew that the final payout would be either 80¢ or 280¢ with equal chances.

After subjects read the instructions and before the market experiment started, we asked a subject at random to flip a coin to determine which of the blue or green color would entail a final payout of 80¢ or 280¢.

2.3. Procedures

All of the subjects who participated in our experiments were recruited on the basis of their prior participation in a one-hour survey which was part of the laboratory policy to collect individual information about subjects who registered in the pool.[8] The survey took place about 6 months before the current study. It was computerized and subjects earned a $15 flat fee. The survey elicited relevant measures of trader performance (see Corgnet et al., 2018) such as theory of mind (see Baron-Cohen et al., 1997) and cognitive reflection (Frederick, 2005).

Before starting the experiment, all subjects had to pass a 6-question quiz ensuring subjects' understanding of the market environment (see Appendix A.2). Following this, we elicited subjects' beliefs regarding the valuation of the final payout in both the ambiguity and the risk treatment using a Becker–DeGroot–Marschak mechanism (see Appendix A.3). We then conducted a 3-minute practice period before the actual experiment.

A total of 108 subjects divided in 6 different sessions for each treatment were recruited.[9] Earnings were on average equal to $27.25 including a $7 show-up fee, for one hour and a half experiment.

3. Conjectures

Given the prevalence of ambiguity aversion in the general population (Ellsberg, 1961; Yates and Zukowski, 1976; Curley and Yates, 1985; Cohen et al., 2011; Dimmock et al., 2016), we expect asset prices in the ambiguity treatment to be on average lower than in the risk treatment.

[8] Due to the recruiter software glitches, we found out that three out of the 108 recruited subjects did not actually complete the survey.

[9] This is a standard number of experimental market sessions for this type of research, see e.g., Eckel and Füllbrunn (2015).

That is, we expect an ambiguity premium to arise, as is the case in standard ambiguity models accounting for the equity premium puzzle (see e.g., Chen and Epstein, 2002; Maenhout, 2004; Cao et al., 2005; Leippold et al., 2008; Ui, 2010; Ju and Miao, 2012), or the home equity bias (see e.g., Epstein and Miao, 2003; André 2014). This leads to our first conjecture.

Conjecture 1. *Asset prices will be lower in the ambiguity treatment than in the risk treatment until a crash occurs in the risk treatment*.

In addition, we have to take into consideration the specific features of the SSW market environment which is prone to the formation of bubbles and crashes (see Palan, 2013; Powell and Shestakova, 2016; Kujal and Powell, 2017). We thus know from previous research that our risk treatment should lead to the emergence of a bubble around period 3 to 4 which achieves a peak around period 8 to 9 before crashing.

We predict that the anatomy of bubbles and crashes will differ between the risk and the ambiguity treatment. One notable difference between our two treatments is that, unlike the risk treatment, subjects in the ambiguity treatment may learn about the actual color mix that determines the asset true value by inferring others' subjective perceptions of the mix from market orders. In the risk treatment, the expected value of the asset follows from the stated probabilities thus preventing any learning across traders. Thus, in the risk treatment there is no reason that a trend in prices will change traders' beliefs about the fact that the asset final payout is either equal to 80¢ or 280¢ with equal chances. As is common place in SSW markets (see Palan, 2013 for a review), prices are expected to crash in the final periods reaching a value close to the expected value of the final payout plus the final dividend of 12¢ (i.e.,192¢).

In the ambiguity treatment, the usual upward trend leading to the formation of bubbles in SSW markets may convey information to subjects regarding others' beliefs about the asset true value. Traders are thus likely to update their beliefs when interpreting the upward trend in asset prices as a signal that other traders tend to perceive the color mix as being largely made up of the high final payout color.

Because traders may change their beliefs upwards as prices rise, we expect asset prices not to exhibit the same type of dramatic crashes in the ambiguity, as in the risk, treatment. This prediction also relates to the models assessing the impact of ambiguity on herding in financial markets (e.g., Dong et al., 2010; Ford et al., 2013). These works stress that the conditions for the formation of bubbles in a herding model à la Avery and Zemsky (1998) are less stringent in the case in which ambiguity in the fundamentals is introduced.

The fact that bubbles can actually change people's beliefs, thus either delaying or preventing the occurrence of crashes, has been eloquently described in Shiller's (1984; 2000) numerous works describing the formation of bubbles in the new technology sector. This sector was indeed characterized by a high level of ambiguity regarding fundamentals so that any early increase in prices was likely to shift investors' beliefs upwards.

In Conjecture 2, we summarize our prediction regarding the anatomy of bubbles and crashes in the two treatments.

Conjecture 2. *Asset prices will be less likely to crash in the ambiguity treatment than in the risk treatment*.

In establishing Conjecture 2, we have stressed the fact that traders will update their beliefs upwards when asset prices surge. It is important to note that not all traders will actively infer other traders' beliefs from market prices and update their beliefs accordingly. It turns out neuroscience research (see De Martino et al., 2013) has precisely identified, using behavioral and fMRI techniques, that those traders who are most likely to update their beliefs upwards when facing rising prices in bubbles episodes possess high theory of mind skills. In addition, we also conjecture that high theory of mind traders will update their beliefs differently across treatments.

In the risk treatment, high theory of mind traders may revise their own attitudes towards risk by observing others' decisions. In particular, as prices go up traders who possess high theory of mind might tone down their risk aversion as the behavior of other traders might indicate that buying the asset is not such a risky choice. In the ambiguity treatment, not only can rising prices tone down a trader's aversion towards ambiguity but it can also provide information regarding other traders' perception of colors thus providing a signal of their estimation of the likelihood of the high final payout. The argument that, in the presence of ambiguity, new information will lead people to learn both about ambiguity attitudes as well as other people's beliefs was already evoked by Keynes (1921) (see also Dominiak et al., 2012 and Baillon et al., 2018). Because high theory of mind traders can learn more from rising prices in the ambiguity treatment than in the risk treatment, we expect that they will be more likely to update their beliefs upwards under ambiguity than under risk.

Below, we summarize our conjecture regarding the evolution of the beliefs of traders who possess high theory of mind skills.

Conjecture 3. *In the ambiguity treatment, traders who possess high theory of mind skills will be more likely to revise their beliefs upwards than those who possess low theory of mind skills. We expect this difference in the revision of beliefs between high and low theory of mind traders to be less pronounced in the risk treatment.*

4. Results

4.1. Aggregate results

To visually assess Conjectures 1 and 2, we represent the average asset prices per period across all sessions for each of the two treatments in Figure 2 (see Appendix C for the individual charts for each of the twelve sessions). On the graph, we represent the fundamental value (FV) for a risk (or ambiguity) neutral trader in the risk (ambiguity) treatment which is computed as follows for any period $t \in \{1, \ldots, 15\}$: $fundamentals_t = (50\% \times 80 + 50\% \times 280) + (16 - t) \times 12$.

In the risk treatment, we note that in line with previous research using the SSW paradigm (see e.g., Palan, 2013) prices exhibit a positive trend which is followed by a crash which occurs in the last five periods.

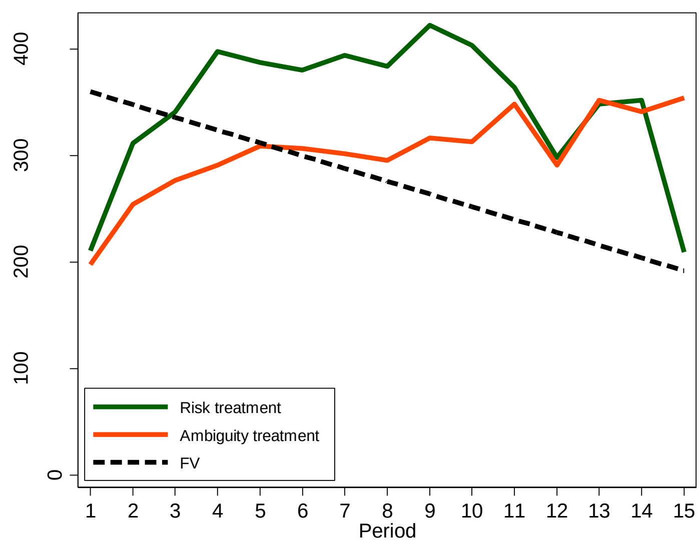

Figure 2. Average asset prices per period across treatments

To test Conjectures 1 and 2, we first conduct a panel regression for average prices to assess whether prices are indeed lower in the ambiguity than in the risk treatment until a crash occurs. In line with Figure 2, we show in Table 1, that average prices are lower in the ambiguity treatment than in the risk treatment in the first ten periods (regression [1]) while no statistical differences are found across treatments between periods 11 and 14 (see regression [2]). Last period prices are significantly lower in the ambiguity than in the risk treatment (see regression [3]).

Table 1.- Linear panel and OLS regressions for average asset prices per period across treatments.

	Periods 1-10 Panel [1]	Periods 11-14 Panel [2]	Period 15 OLS [3]
Constant	693.566*** (121.623)	257.299 (293.190)	209.500*** (31.990)
Ambiguity Treatment Dummy	**-76.557**** **(37.898)**	**-51.226** **(96.120)**	**144.800*** **(78.256)**
Fundamental Asset Value	-1.081*** (0.326)	0.541 (1.137)	-
N	118	41	10
R^2	0.271	0.001	0.278
χ^2	10.41***	0.62	3.48*

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level. Robust standard errors are bootstrapped (see Cameron and Miller, 2011) which is recommended given that we have only 12 session clusters. We use 1000 iterations in the bootstrapping procedure. However, the qualitative nature of the results remained unchanged when using standard errors clustered at the session level. Results are also qualitatively unchanged if we control for trading volumes.

Conjecture 2 hinges upon the fact that the ambiguity treatment is much less likely to exhibit a crash compared to the risk treatment. To assess differences between treatments in crashing patterns, we proceed by identifying the occurrence of a crash in each treatment using structural break tests. To do so, we estimate the following regressions:

$$\begin{aligned} Average\ price_t &= a_0 + a_1 \text{Period Number} + a_2 Dummy(last\ \boldsymbol{x}\ periods) \\ &\quad + a_3 \text{Period Number} \times Dummy(last\ \boldsymbol{x}\ periods) \end{aligned}$$

where the $Dummy(last\ \boldsymbol{x}\ periods)$ takes value 1 for any of the last $\boldsymbol{x}$ periods and value 0 otherwise, and $\boldsymbol{x} \in \{9,10,11,12,13\}$. The values of $\boldsymbol{x}$ are chosen as possible dates for which a break in the upward trend may occur. We do not consider $\boldsymbol{x} = 14$ because there is insufficient data to estimate the break in the trend in that case. Casual inspection of Figure 2 suggests a break in the trend, which is our operationalized definition of a crash, occurs in the risk treatment between periods 9 and 13 (see Table 2) whereas no breaks in trends are observed in the ambiguity treatment, regardless of the break point being considered (see Table D.1).

In Table 2, we find evidence for a downward break in the positive trend in asset prices for the risk treatment. In particular, regression [6] suggests the best estimate of the break is in period 12. Our findings are in line with Conjecture 2 because we identify the occurrence of crashes in the risk treatment whereas we do not in the ambiguity treatment (see Table D.1).

Note that despite notable differences between treatments regarding the anatomy of crashes, they do not differ regarding classical measures of mispricing in bubbles experiments (see Table D.2). This follows from the fact that mispricing is higher at the beginning (before period 5) and at the end of the experiment (period 15) in the ambiguity treatment (see Figure 2) whereas mispricing is more pronounced in the risk treatment in the middle of the experiment (periods 5 to 10).

Table 2.- Linear panel regressions of average asset prices to identify a trend break in the risk treatment.

	Structural Break in Trend in period $\boldsymbol{x}$:					
	$\boldsymbol{x}$ **=9** [1]	$\boldsymbol{x} = \mathbf{10}$ [2]	$\boldsymbol{x} = \mathbf{11}$ [3]	$\boldsymbol{x} = \mathbf{12}$ [4]	$\boldsymbol{x} = \mathbf{13}$ [5]	Any[10] [6]
Constant	258.083*** (23.077)	262.809*** (23.792)	273.822*** (23.129)	283.339*** (19.452)	299.942*** (17.445)	262.886*** (21.412)
Period Number[11]	20.638** (8.251)	19.220** (8.427)	16.182** (7.885)	13.767** (6.668)	9.837* (5.690)	19.790** (7.758)
Dummy last $\boldsymbol{x}$ periods	389.301*** (116.528)	404.172*** (120.421)	420.670** (174.969)	437.956** (213.247)	805.992 (576.914)	-
Period Number × Dummy last 9 periods	**-45.152*** (13.126)**	-	-	-	-	-2.820 (4.587)
Period Number × Dummy last 10 periods	-	**-45.066*** (13.420)**	-	-	-	-2.893 (3.681)
Period Number × Dummy last 11 periods	-	-	**-44.034*** (15.328)**	-	-	-3.142 (5.131)
Period Number × Dummy last 12 periods	-	-	-	**-43.527** (17.880)**	-	**-5.735** (2.691)**

[10] Individual dummy variables are not included because of collinearity issues.
[11] Given the linear relationship between Period Number and the fundamental value of the asset, we do not include the latter variable in the regression in contrast to Table 1.

Period Number × Dummy last 13 periods	-	-	-	-	**-66.558 (41.418)**	-1.660 4.839
N	83	83	83	83	83	83
R^2	0.148	0.146	0.138	0.122	0.097	0.129
χ^2	12.06***	12.98***	12.19***	12.82***	8.24**	31.08***

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level. Robust standard errors are bootstrapped (see Cameron and Miller, 2011) which is recommended given that we have only 12 session clusters. We use 1000 iterations in the bootstrapping procedure. However, the qualitative nature of the results remained unchanged when using standard errors clustered at the session level. The number of observations is 83 instead of 90 because there were two (three) periods without trading in two (one) sessions.

We now turn to Conjecture 3 to assess the relationship between traders' theory of mind scores and their beliefs regarding the value of the asset.

4.2. Beliefs and theory of mind

To test Conjecture 3, we first assess theory of mind skills using subjects' scores on the eye gaze test (Baron-Cohen et al., 1997). We categorize traders as possessing (low) high theory of mind if they scored (lower) higher than the median of all participants in the study.[12] We measure traders' beliefs regarding the valuation of the asset both and after the market experiment using a Becker–DeGroot–Marschak mechanism (see Appendix A.2). We then assess the changes in traders' beliefs regarding the value of the asset by calculating the difference between the willingness to pay before and after the market for a lottery which pays 100 cents if the high payout color is selected from the opaque bag (filled with blue and green chips) and 0 otherwise. Below, we plot the histograms for the difference in beliefs for the ambiguity and risk treatments.

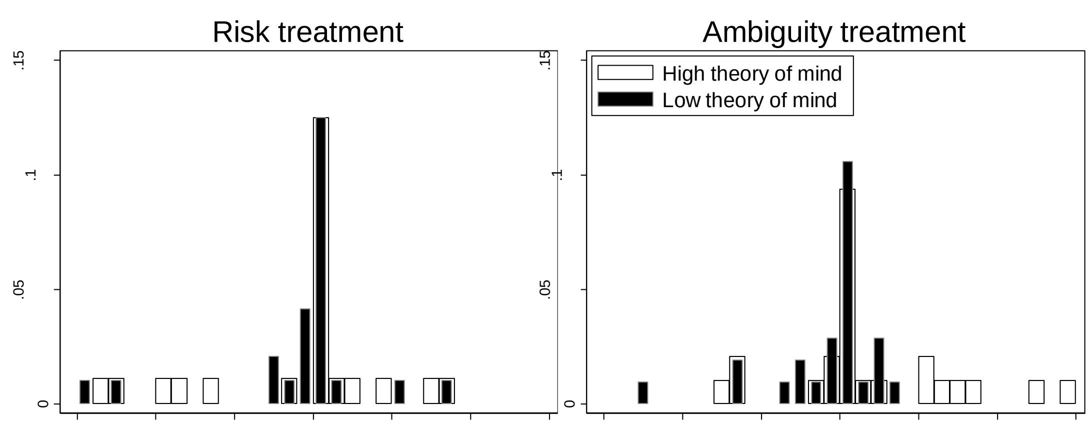

Figure 3. Beliefs regarding the valuation of the asset *after* the market ends minus beliefs regarding the valuation of the asset *before* the markets starts.

[12] In our sample, the median score is 27 which is in line with previous studies (see Corgnet et al., 2018).

In line with Conjecture 3, we observe in Figure 3 that high theory of mind traders tend to update their beliefs upwards (the difference in beliefs is positive) in the ambiguity treatment whereas no such differences are observed in the risk treatment. We confirm this graphical impression by conducting linear regressions of the difference in beliefs with respect to theory of mind skills (measured by a dummy variable (High Theory of Mind Dummy) that takes value 1 if the trader is classified as possessing high theory of mind, and 0 otherwise) for both treatments. We also control for cognitive reflection using the cognitive reflection test (CRT henceforth, Frederick, 2005) which was found to predict traders' performance in similar experimental asset markets (see Corgnet et al., 2015; Noussair et al., 2016). We define the High CRT Dummy as taking value one when a trader scores above the median of CRT scores in the pool of participants.[13] Finally, we control for sex by means of a male dummy which takes value 1 for males and value 0 otherwise.

Table 3.- OLS regression for traders' difference in beliefs regarding the valuation of the asset after and before the market.

	Ambiguity treatment [1]	Risk treatment [2]
Constant	-0.461 (5.180)	1.554 (7.253)
High Theory of Mind Dummy	**13.192*** **(7.751)**	**-9.260** **(8.106)**
High CRT Dummy	-12.767* (7.440)	-2.0.44 (8.314)
Male Dummy	-0.146 (7.790)	-2.041 (7.498)
N	52	48
R^2	0.114	0.034
χ^2	6.48*	1.33

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level. Robust standard errors are bootstrapped (see Cameron and Miller, 2011) which is recommended given that we have only 12 session clusters. We use 1000 iterations in the bootstrapping procedure. However, the qualitative nature of the results remained unchanged when using standard errors clustered at the session level.

Regression [1] in Table 3 shows that those traders who possess high theory of mind skills tend to update their beliefs regarding the value of the asset upwards in the ambiguity treatment compared to those who possess low theory of mind skills. Interestingly, those who possess high

[13] The median CRT score is equal to 3 which is in line with previous studies (see Corgnet et al., 2018).

cognitive reflection tend to respond the opposite way by decreasing their valuation of the asset between the beginning and the end of a market session. That is, reflective traders do not respond to an upward trend in asset prices by updating their beliefs upwards. These traders might understand that the positive trend in prices observed in these markets is unrelated to fundamentals and is thus not informative. In the risk treatment (see regression [2]), neither theory of mind skills nor cognitive reflection lead to a significant update in traders' beliefs.

5. Discussion

Even though financial markets provide an ideal environment to highlight differences between risk and ambiguity, the current experimental literature provide mixed results. To inquire on the potential differences between risk and ambiguity in markets, we contributed to this literature in two ways. First, we developed a new method to induce ambiguity which relies upon people's inherent subjective perception of colors. Unlike the Ellesberg's urn procedure, our protocol allows people to learn potentially valuable information from others' subjective beliefs. Second, ours is the first experiment to compare risk and ambiguity in markets which are prone to bubbles and crashes. This is exactly the type of setup for which Shiller (1984; 2000) and Keynes (1936) have intuited that ambiguity should foster 'animal spirits' and impact prices.

We find that, even though overall mispricing is no different across treatments, the anatomy of bubbles and crashes sharply differs. In particular, prices are generally depressed in the ambiguity treatment compared to the risk treatment although crashes are less likely to occur in the presence of ambiguity. Thus, ambiguity seems to engender 'Booms That Never Bust'. Doing so, our experiment might explain why bubbles may last (e.g., Aliber and Kindleberger, 2015) and why they might inevitably come back (Bishop, 1987).

To understand the underlying behavioral mechanisms explaining our findings, we turn to recent findings in neuroscience suggesting that individuals possessing high theory of mind skills are most likely to increase their valuation of an asset after observing a rising trend in prices (see De Martino et al., 2013). We show that theory of mind skills can indeed lead traders to update their beliefs upwards in the ambiguity treatment. This is not the case in the risk treatment in which the probability of occurrence of a high payout is known thus preventing traders to get any insights about the valuation of the asset from observing market orders. Because ambiguity is likely to be rampant in financial markets, our results suggest that theory of mind should be a key ingredient of any cognitive theory of financial bubbles.

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Appendix A. Instructions

A.1 Main instructions

A.1.1 Ambiguity treatment

INSTRUCTIONS (1/15)

This is an experiment in market decision making. You will be paid in cash for your participation at the end of the experiment. Different participants may earn different amounts. What you earn depends on your decisions and the decisions of others.

The experiment will take place through computer terminals at which you are seated. If you have any questions during the instruction round, raise your hand and a monitor will come by to answer your question. If any difficulties arise after the experiment has begun, raise your hand, and someone will assist you.

INSTRUCTIONS (2/15)

In this experiment you will be able to buy and sell a commodity, called **Shares**, from one another.

At the start of the experiment, every participant will be given either two shares and 1,305 cents in cash, three shares and 945 cents in cash. or four shares and 585 cents in cash.

The shares last for EXACTLY **15** periods of trading. After each trading period the share will earn a dividend of **12** cents. Thus, if you had a share at the end of period 1, you would get a return of **12** cents for that period.

If you held a share from period 1 until the end of period 15, then that share would return to you a total of **$1.80** (15 × 12 cents) in dividends over the 15 periods. Similarly, if you bought a share in period 2 and held it from period 2 until the 15th period, the accumulated dividends would be **$1.68** (14 × 12 cents).

INSTRUCTIONS (3/15)

In addition to each period dividend of **12** cents, each share will earn a final payout of either **80** or **280** cents paid at the end of period 15.

The value of the final payout (**80** or **280**) will depend on drawing a chip from an opaque bag at the end of the experiment.

The opaque bag which is located on the round table in the front part of the room is filled with 100 chips which can be either blue or green. The proportion of blue chips and green chips in the bag is exactly the same as the proportion of the **blue** color and the **green** color that have been mixed to produce the **color** printed out on the sheet of paper on your desk (the mix has been done in Microsoft Word).

INSTRUCTIONS (4/15)

At the end of the experiment, a subject in the room will draw a chip from the opaque bag which will determine the final payout of shares.

Whether drawing a blue chip or a green chip will lead each share to deliver the **280** cents payout or the **80** cents payout will be determined before starting the experiment by having one subject in the room toss a coin.

- If the coin toss is *heads*, drawing a blue chip from the opaque bag at the end of the experiment will lead each share to deliver a **280** cents payout, and drawing a green chip will lead to a **80** cents payout.
- If the coin toss is *tails*, drawing a green chip from the opaque bag at the end of the experiment will lead each share to deliver a **280** cents payout, and drawing a blue chip will lead to a **80** cents payout.

INSTRUCTIONS (5/15)

During every period, traders can buy or sell shares from one another by making offers to buy or to sell.

Every time a trade is made, it will be shown as a dark **GREEN** dot in the graph located on the left of the lower part of your screen. Transactions are also listed on the **Market Book** located on the right of the graph. If you buy a share (or somebody sold it to you), the cell in the Market Book will be shown in light **BLUE**. The cell will be shown in **RED** if you sell a share (or somebody buys it from you). The cells that are shown without colors correspond to transactions in which you are not involved either as a buyer or as a seller.

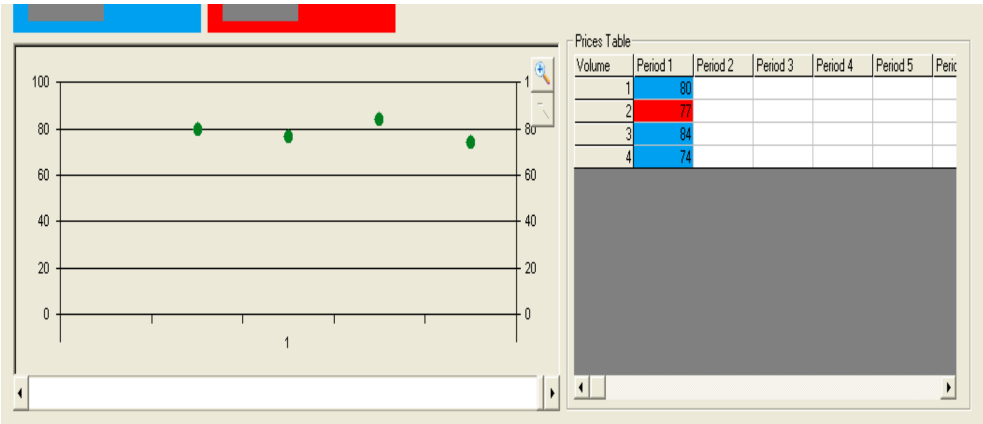


Figure A1: Lower part of your trading screen (graph and market book)

INSTRUCTIONS (6/15)

To enter a new order to buy or to sell a share, type in the price at which you would like to buy, or sell, in the appropriate **Add order to Buy** box or **Add order to Sell** box. Click the **Add order to Buy** or **Add order to Sell** button to submit your order.

Figure A2: Upper part of your screen (Buy and Sell)

INSTRUCTIONS (7/15)

Every time someone posts an order to buy a share, it will be added to the list of best orders to buy (in the **BLUE** quadrant). This list shows only the best **FOUR** orders. Every time someone makes an offer to sell a share, it will be added to the list of the best orders to sell (in the **RED** quadrant). This list shows only the best **FOUR** orders.

The orders to buy will be listed from the highest price to the lowest price, while the orders to sell will be listed from the lowest price to the highest price.

Your own orders in this list will be highlighted in **ORANGE**. For example, you have just posted an order to sell at a price equal to 202 and this corresponds to the third best order in the market (that is, the third lowest order to sell). This order will appear in the third place in the list of orders to sell.

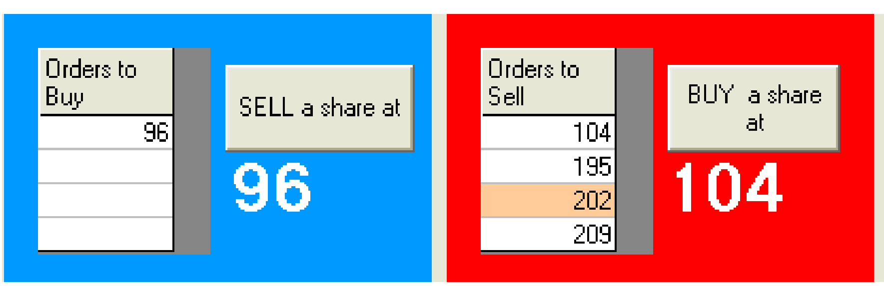


Figure A3: Upper part of your screen (Orders to buy and to sell)

INSTRUCTIONS (8/15)

To accept an existing order from another participant, click the **Buy a share at** or **Sell at share at** buttons located on the right of the list of orders to sell and orders to buy, respectively. The list of orders to buy shows you the four highest orders to buy that are currently available on the market, while the list of orders to sell shows you the four lowest orders to sell. By clicking on the **Buy a share at** button, you buy at the listed price of 104 in the current example; by clicking on the **Sell at share at** button, you sell at the listed price of 96 in the current example. Your own existing orders to buy or sell are highlighted in **ORANGE**.

In the situation illustrated in the following screen shot, the best order to sell corresponds to a price of 104 (the lowest value in the list of orders to sell). This is the price at which you can currently buy the share. The best order to buy corresponds to a price of 96 (the highest value in the list of orders to buy since this is the only order to buy currently available). This is the price at which you can currently sell the share.

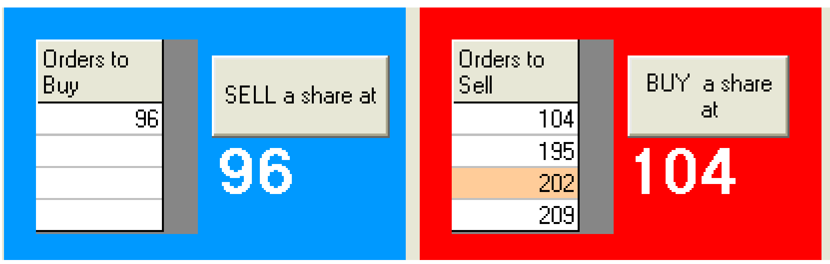


Figure A4: Upper part of your screen (Orders to buy and to sell)

INSTRUCTIONS (9/15)

Whenever you enter new orders to buy, or sell, you will have those orders listed in a table below the list of orders to buy and sell. By double clicking on any cell in the table, you can cancel your own orders.

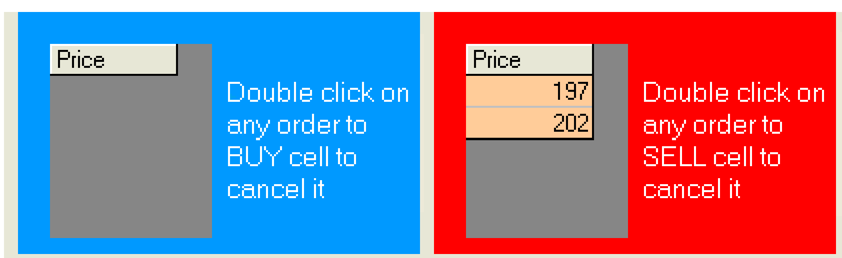


Figure A5: Upper part of your screen (Orders to buy and to sell)

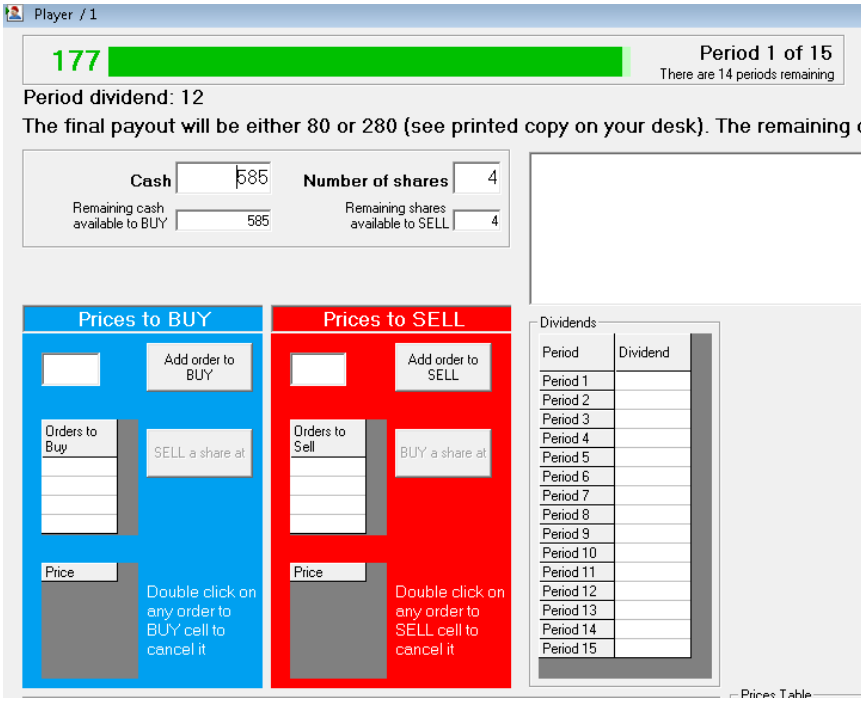
INSTRUCTIONS (10/15)

At the end of every period, each share will pay a dividend of 12 cents. The dividend for each period will appear in the Dividends Table.

The earned dividends (for shares) of each period will be added to the cash account of the holder.

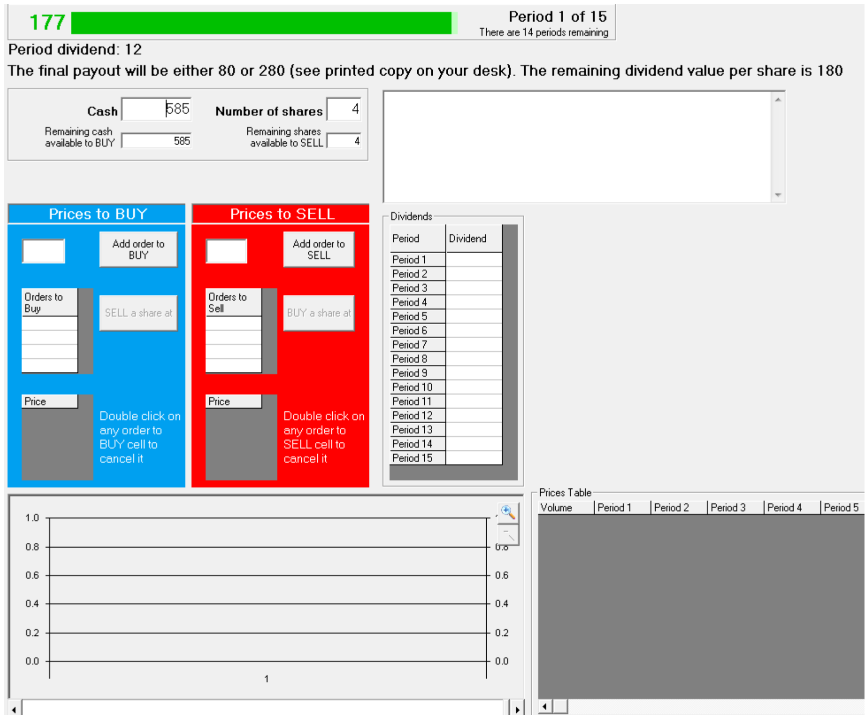
The number of your shares will change, only when you buy, or sell, shares.

Notice that you cannot place orders to buy for an amount that is greater than your current **Cash**. The information regarding the remaining cash available to buy is displayed in the box below your current **Cash**. Also, you cannot place more orders to sell shares than the **Number of shares** you currently hold. The information regarding the remaining shares available to sell is displayed below your current **Number of shares**.



INSTRUCTIONS (11/15)

During a period and each time you place an order or complete a transaction a message will appear in the box above the dividends table. This message box provides indications on whether your order or transaction has been completed successfully. For example, if you attempt to buy a share at a price that is higher than your current cash holdings, a message will appear in the box stating that you do not have sufficient cash to buy this share.



INSTRUCTIONS (12/15)

An example:

Suppose you have 6 shares and 150 in Cash at the start of a period, and you make one transaction during the period purchasing a share for 62 cents within the period, and the dividend for the period is 12 cents, then:

Your Cash holdings will increase by 22 cents (dividends of 12 times 7 shares minus a purchase at 60). Your new cash holding will thus be 150+22=172 cents.

Your share holdings will increase from 6 to 7 units.

INSTRUCTIONS (13/15)

Another example:

At the end of the previous period, you had 4 shares and 242 in Cash.

Suppose in the next period you make two transactions. You sell one share for 130 and another share for 110, and the dividend for the period is 12, then:

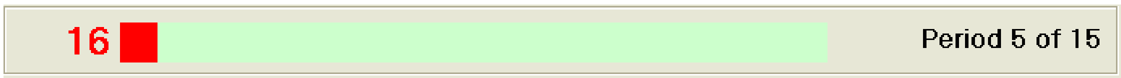
Your Cash holdings will increase by 264 cents (Dividends of 12 times 2 shares plus sales of 130 plus 110). Your new cash holding will thus be 242+264=506 cents.

Your share holdings will, however, decrease from 4 to 2 units.

INSTRUCTIONS (14/15)

This experiment will last for **15 periods**. Each period will last for several minutes. The remaining time (in seconds) will appear on the top of your screen.

When the time is about to expire, the color will change to RED.



We will have a short practice period to allow you to become familiar with entering orders and making trades.

INSTRUCTIONS SUMMARY (15/15)

1. You will be given an initial amount of Cash and Shares.

2. Every share generates a dividend of 12 cents at the end of each of 15 trading periods.

3. In addition, each share will generate a final payout of either 80 or 280 cents, depending on the chip drawn from an opaque bag.

4. You can submit orders to BUY shares and orders to SELL shares.

5. You make trades by buying at the current lowest order to sell or selling at the current highest order to buy.

6. The market lasts for 15 periods. At the end of period 15, there will be one last period dividend draw and a final payout for each share. After that the share expires and is worth nothing to you.

A.1.2. Risk treatment

The main change between risk and ambiguity treatments is on page 3 which is modified as follows:

INSTRUCTIONS (3/15)

In addition to each period dividend of **12** cents, each share will earn a final payout of either **80** or **280** cents paid at the end of period 15.

The value of the final payout (**80** or **280**) will depend on drawing a chip from an opaque bag at the end of the experiment.

The opaque bag which is located on the round table in the front part of the room is filled with 100 chips which can be either blue or green. The proportion of blue chips and green chips in the bag is exactly the same as the proportion of the **blue** color and the **green** color that have been mixed to produce the **color** printed out on the sheet of paper on your desk (the mix has been done in Microsoft Word).

In this experiment, the computer has mixed exactly **50%** of blue and **50%** of green to produce the mixed color. Thus, the opaque bag located on the round table contains exactly 50 green chips and 50 blue chips.

A.2. Quiz

Please answer the following questions carefully:

1. How many trading rounds does this experiment last? (Solution=4)

   - 8
   - 10
   - 12
   - 15

2. At the end of each round, each share earns a dividend of (Solution=1)

   - 12 cents
   - 80 cents
   - nothing
   - 24 cents

3. If you had a share in round 3, and you held it until round 15, what would be the amount of dividends it earned? (Solution=3)

   - nothing
   - 12 cents * 14 = 168 cents
   - 12 cents * 13 = 156 cents
   - 12 cents * 12 = 144 cents

4. You can put a new offer to buy in the market by: (Solution=1)

   - Submiting a new order to buy
   - Submiting a new order to sell
   - Clicking the 'Buy a share at' button
   - Clicking the 'Sell a share at' button

5. You can accept an existing lowest offer to sell in the market by: (Solution=3)

   - Submiting a new order to buy
   - Submiting a new order to sell
   - Clicking the 'Buy a share at' button
   - Clicking the 'Sell a share at' button

6. At the end of round 15, each share you hold will give you a final payout of ___ cents to you, in addition to the dividend. (Solution=4)

   - 12 cents
   - 80 cents
   - 280 cents
   - either 80 or 280 cents

A.3. Beliefs elicitation

A.3.1. Ambiguity

Now that we have just tossed the coin we know which color (either blue or green) will generate the high dividend of **280** cents.

Your task is to decide how much you would be ready to pay for a lottery that gives you **100** cents if the color corresponding to the high dividend is drawn from the opaque bag at the end of the experiment. This lottery gives you **0** if the other color is drawn. The opaque bag is filled with 100 chips which are either blue or green.

To make this decision, we give you 100 cents. You can select any price between 0 and 100 cents up to which you would be willing to buy the lottery. At the end of the experiment, the computer will randomly select an integer number between 0 and 100.

If your stated price is greater than or equal to the number selected by the computer, then you will be given the lottery for a price equal to the randomly selected number.

If your stated price is strictly lower than the number selected by the computer, then you will keep all your 100-cent endowment.

Your earnings on the task will be:

Your endowment of 100 cents – (price you paid for the lottery) + lottery gains

Example 1

You entered a price of 48 and the computer randomly selected number 32. In that case, your stated price is above the selected number so that you will be given the lottery for 48 cents. This lottery will give you 100 cents if the chip drawn from the opaque bag at the end of the experiment corresponds to the high-dividend (280 cents) color, and 0 otherwise. If you got 100 cents from the lottery your earnings will be equal to (100-32) + 100 = 168. If you got 0 from the lottery your earnings will be equal to (100-32) + 0 = 68.

Example 2

You entered a price of 51 and the computer randomly selected number 63. In that case, your stated price is below the selected number so that you will not buy the lottery and keep your 100 cents endowment. In that case, your earnings are equal to your 100 cents endowment.

A.3.2. Risk

Now that we have just tossed the coin we know which color (either blue or green) will generate the high dividend of **280** cents.

Your task is to decide how much you would be ready to pay for a lottery that gives you **100** cents if the color corresponding to the high dividend is drawn from the opaque bag at the end of the experiment. This lottery gives you **0** if the other color is drawn. The opaque bag is filled with 50 blue chips and 50 green chips.

To make this decision, we give you 100 cents. You can select any price between 0 and 100 cents up to which you would be willing to buy the lottery. At the end of the experiment, the computer will randomly select an integer number between 0 and 100.

If your stated price is greater than or equal to the number selected by the computer, then you will be given the lottery for a price equal to the randomly selected number.

If your stated price is strictly lower than the number selected by the computer, then you will keep all your 100-cent endowment.

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Example 2

You entered a price of 51 and the computer randomly selected number 63. In that case, your stated price is below the selected number so that you will not buy the lottery and keep your 100 cents endowment. In that case, your earnings are equal to your 100 cents endowment.

Appendix B. Survey variables

Cognitive reflection test

The original CRT consists of three questions which all have an appealing and intuitive, yet incorrect, answer. Upon reflection, one can disregard the intuitive answer and ascertain the correct one. Although basic cognitive abilities are required to answer the CRT questions correctly, an intelligent person may often rely on automatic or instinctive answers, failing to block intuitive processes by not engaging in reflection. It follows that CRT scores have been found to moderately and positively correlate with general measures of intelligence such as the SAT ($r = 0.44$; Frederick 2005), Wonderlic composite test ($r = 0.43$; Frederick 2005), Wechsler composite index ($r = 0.32$; Toplak, West and Stanovich, 2011), working memory ($r = 0.32$; Toplak, West and Stanovich, 2011) and Raven tests ($r = 0.43$; Corgnet, Espin and Hernan-Gonzalez, 2015). At the end of each experiment, subjects had 5 minutes to complete the CRT. We administered the extended (seven-question) version of the CRT in which the original three questions (Frederick, 2005) are augmented with four additional questions recently developed and validated by Toplak, West and Stanovich (2014). Our measure of cognitive reflection is given by the total number of correct answers (from 0 to 7). The Cronbach alpha reliability score for the extended CRT (0.69) is in line with that of Toplak, West and Stanovich (2014) who reported a reliability of 0.72. The seven questions were as follows.

Taken from Frederick (2005):

(1) A bat and a ball cost $1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? ____ cents

[Correct answer: 5 cents; intuitive answer: 10 cents]

(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes

[Correct answer: 5 minutes; intuitive answer: 100 minutes]

(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____ days

[Correct answer: 47 days; intuitive answer: 24 days]

Taken from Toplack et al., (2014):

(4) If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? _____ days

[correct answer: 4 days; intuitive answer: 9]

(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? ______ students

[correct answer: 29 students; intuitive answer: 30]

(6) A man buys a pig for $60, sells it for $70, buys it back for $80, and sells it finally for $90. How much has he made? _____ dollars

[correct answer: $20; intuitive answer: $10]

(7) Simon decided to invest $8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money

[correct answer: c; intuitive response: b]

Table B.1. Distribution of CRT scores

CRT score	% of subjects
0	15.2
1	10.5
2	19.0
3	17.1
4	16.2
5	6.7
6	12.4
7	2.9
Mean	2.9
Median	3.0
Standard Deviation	2.0

Theory of mind test

Following Bruguier, Quartz, and Bossaerts (2010) and De Martino et al., (2013), we also administered the eye gaze test (Baron-Cohen et al., 1997) to assess subjects' theory of mind skills (i.e, the capacity to infer other's intentions, see, for example, Frith and Frith, 1999). In this task, participants looked at images of people's eyes and had to choose one of four feelings that best described the mental state of the person whose eyes were shown. Our theory of mind score is defined as the number of correct answers to the 36 question, 10-minute test.

This is an example of one of the 36 questions in the test of Baron-Cohen (1997):

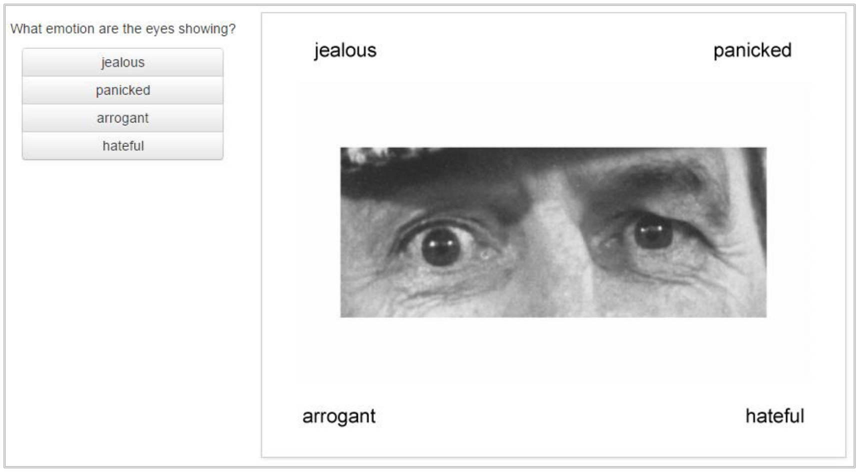

Figure B.1: Example of an eye gaze test question

Table B.2. Distribution of eye gaze test scores

Eye gaze score	% of subjects
0-20	9.0
21-24	12.0
25-28	42.0
29-32	34.0
33-36	3.0
Mean	26.8
Median	27.0
Standard Deviation	4.7

Appendix C. Graphs for the individual sessions

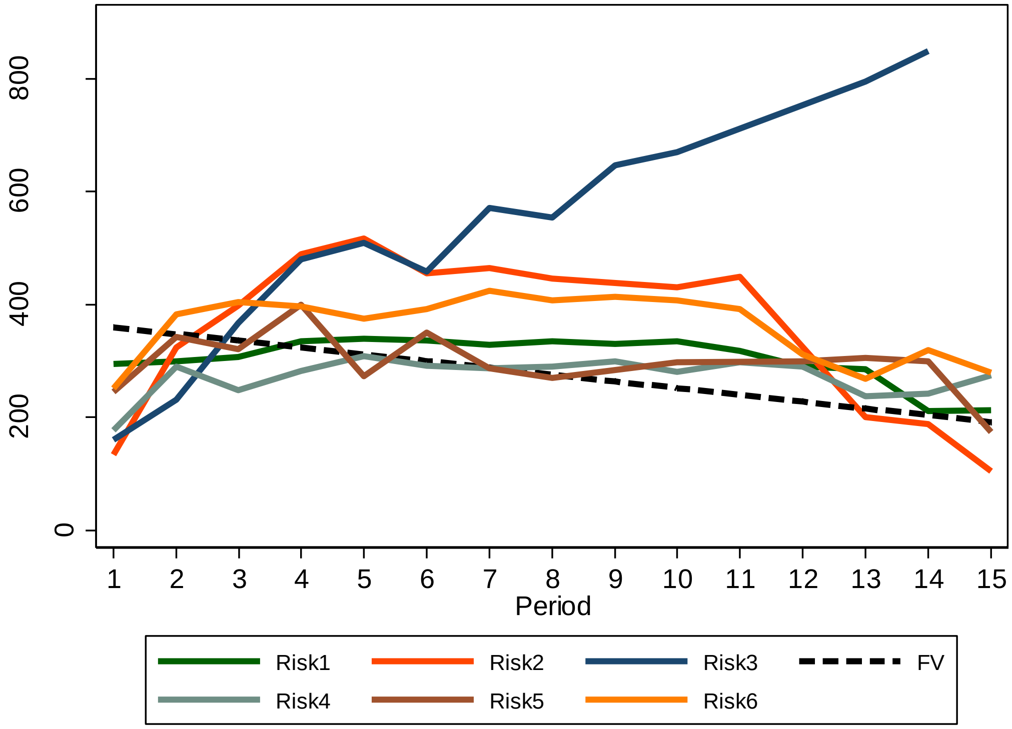

Figure C.1: Average price per period for each of the six sessions in the risk treatment. The fundamental value is represented by a declining (dashed) line.

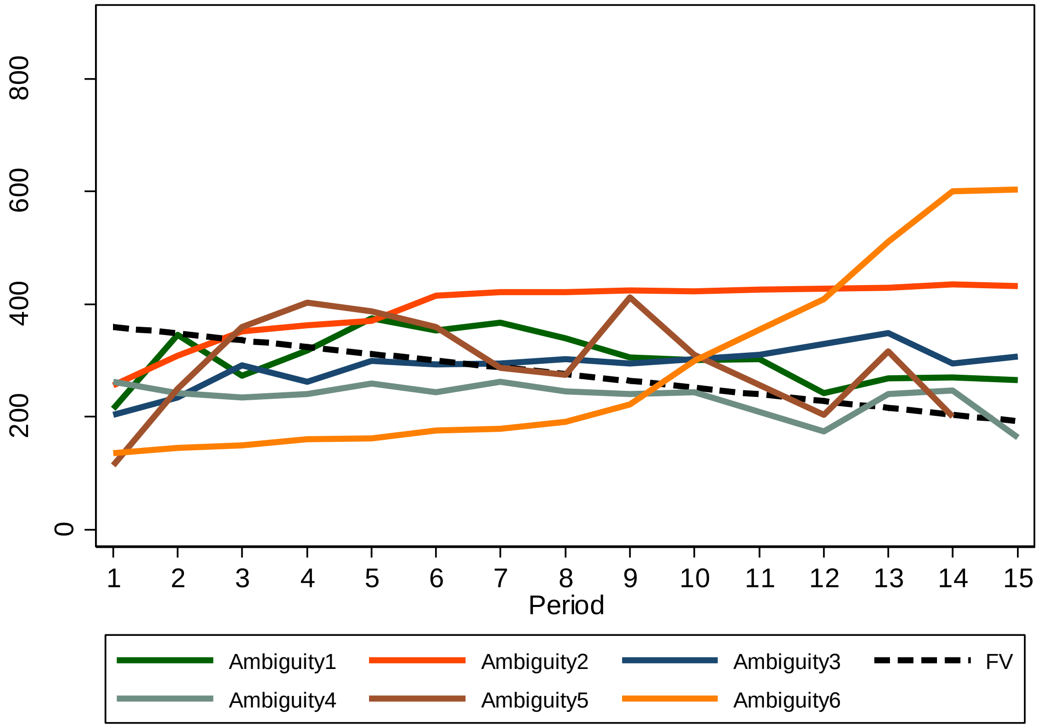

Figure C.2: Average price per period for each of the six sessions in the ambiguity treatment. The fundamental value is represented by a declining (dashed) line.

Appendix D. Additional analyses

Table D.1- Linear panel regressions of average asset prices to identify a trend break in the ambiguity treatment.

	Structural Break in Trend in period $\boldsymbol{x}$:					
	$\boldsymbol{x}$ =**9** [1]	$\boldsymbol{x}=\mathbf{10}$ [2]	$\boldsymbol{x}=\mathbf{11}$ [3]	$\boldsymbol{x}=\mathbf{12}$ [4]	$\boldsymbol{x}=\mathbf{13}$ [5]	Any[14] [6]
Constant	223.833*** (18.612)	227.775*** (20.351)	232.918*** (24.999)	233.566*** (28.307)	242.851*** (32.340)	224.472*** (19.225)
Period Number[15]	12.301*** (2.912)	11.118*** (2.757)	9.716*** (2.410)	9.554*** (2.4846)	7.393** (3.575)	12.188*** (2.806)
Dummy last $\boldsymbol{x}$ periods	25.034 (111.859)	-2.186 (102.280)	-25.632 (109.046)	-142.375 (130.233)	95.942 (177.918)	-
Period Number × Dummy last 9 periods	**-5.610 (13.600)**					-1.929 (1.810)
Period Number × Dummy last 10 periods		**-2.685 (12.133)**				-1.382 (2.271)
Period Number × Dummy last 11 periods			**0.054 (11.472)**			1.174 (1.531)
Period Number × Dummy last 12 periods				**8.536 (11.616)**		-4.698 (2.826)
Period Number × Dummy last 13 periods					**-6.661 (14.486)**	3.558** (1.553)
N	86	86	86	86	86	86
R^2	0.127	0.126	0.123	0.130	0.120	0.140
χ^2	20.41***	17.26***	17.53***	24.47***	11.31**	125.13***

*** Significant at the 0.01 level; ** at the 0.05 level; * at the 0.1 level. Robust standard errors are bootstrapped (see Cameron and Miller, 2011) which is recommended given that we have only 12 session clusters. We use 1000 iterations in the bootstrapping procedure. However, the qualitative nature of the results remained unchanged when using standard errors clustered at the session level. The number of observations is 86 instead of 90 because there was one (two) period(s) without trading in two (one) sessions.

[14] Individual dummy variables are not included because of collinearity issues.
[15] Given the linear relationship between Period Number and Fundamental Asset Value, we do not include the latter variable in the regression in contrast to Table 1.

We use different measures of mispricing considered in the literature in order to check for differences between treatments. We consider the following measures of bubbles:[16]

1. *Amplitude:* Measures the trough-to-peak change in asset value relative to its fundamental value. This is measured as, A = Max{ ($\frac{Pt - ft}{E}$: t = 1…15} - Min{$\frac{Pt - ft}{E}$: t = 1…15}. Where, P_t is the average market price in period t, f_t is the fundamental value of the asset in period t, and E is the expected dividend value over the life of the asset.
2. *Duration:* Measures the length, in periods, in which there is an observed increase in market prices relative to the fundamental value of the asset. Formally, *duration* is defined as:

   $$D = \text{Max}\{m: P_t - f_t < P_{t+1} - f_{t+1} < \ldots < P_{t-m} - f_{t-m}\}.$$
3. *Haessel-R^2* (Haessel, 1978): measures goodness-of-fit between observed (mean prices) and fundamental values. It is appropriate, since the fundamental values are exogenously given. *Haessel-R^2* tends to 1 as trading prices tend to fundamental values.
4. *Normalized Average Price Deviation (NAV):* Sums up the absolute deviation between the average price and the fundamental value for each of the fifteen periods. It is defined as follows:

   $$NAV = \sum_{t=1}^{15} \frac{|Pt - ft|}{15}$$
5. *Normalized Absolute Price Deviation (NAP):* As defined in Haruvy and Noussair (2006), NAP measures the per-share aggregate overvaluation (or undervaluation), relative to the fundamental value of the asset in a given period and is defined as:

   $$NAP = \sum_{k=1}^{K} \frac{|Pk - fk|}{100 \times TS}$$

   where, P_k is the price of the k^{th} transaction in the experiment, *TS* the total number of shares, 100 is a normalization scalar, and f_k is the fundamental value of the asset when the k^{th} transaction takes place. Large values of *NAP* reflect volumetric deviations from fundamentals. This measure is similar to the *Normalized Average Price Deviation*. However, *NAV* does not depend on the number of trades and can then be used to compare the extent of mispricing in sessions with different levels of *trading volumes*.
6. *Number of trades:* number of transactions in a given period.

[16] See Dufwenberg et al., (2005), Corgnet et al., (2010) and Palan (2013).

Table D.2. Classical bubbles measures across treatments

Session	Amplitude	Duration	Haessel-R2	NAV	NAP	Number of Trades
Risk 1	0.410	9	0.315	47.0	1.617	90
Risk 2	1.210	4	0.128	112.9	4.375	69
Risk 3	2.350	4	0.937	230.0	8.534	114
Risk 4	0.738	3	0.024	48.2	3.614	117
Risk 5	0.584	2	0.167	41.8	2.935	74
Risk 6	0.732	3	0.095	100.4	3.137	78
Ambiguity 1	0.624	3	0.074	55.7	5.047	145
Ambiguity 2	0.955	14	0.715	136.9	6.796	147
Ambiguity 3	0.803	8	0.554	61.3	1.791	56
Ambiguity 4	0.415	3	0.318	49.1	1.766	57
Ambiguity 5	1.097	3	0.004	61.4	2.707	56
Ambiguity 6	1.763	14	0.838	182.3	6.371	95
All risk sessions	1.004	4.167	0.278	96.716	4.036	90.333
All ambiguity sessions	0.943	7.500	0.417	91.099	4.080	92.667
Wilcoxon Rank Sum Test Treatment comparison (p-value)	0.749	0.405	0.631	0.522	>0.999	0.748