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

Brice Corgnet[a], Roberto Hernán-González[b], Praveen Kujal[c]

Abstract

We study the effect of ambiguity on the formation of bubbles and crashes in experimental asset markets à la Smith, Suchanek, and Williams (1988) by allowing for ambiguity in the fundamental value of the asset. Although bubbles form in both the ambiguous and the risky environments we find that asset prices tend to be lower when the fundamental value is ambiguous than when it is risky. Bubbles do not crash in the ambiguous case whereas they do so in the risky one. These findings, regarding depressed prices and the absence of crashes in the presence of ambiguity, are in line with recent theoretical work stressing the crucial role of ambiguity to account for surprisingly low equity prices (high returns) as well as herding in asset markets.

Keywords: Experimental asset markets, bubbles, ambiguity.

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[a] emlyon business school, GATE UMR 5824, F-69130 Ecully, France.

[b] Univ. Bourgogne Franche Comté, Burgundy School of Business-CEREN (EA 7477), 29 rue Sambin, 21000 Dijon, France.

[c] Department of Economics, Middlesex University Business School, London, U.K.

1. Introduction

1.1. Ambiguity in financial markets

Together with artworks and antiques markets, financial markets are one of those places where holding the exact same pieces of information individuals are unlikely to agree on the actual value of the traded item (see Keynes, 1936; Shiller, 1984; 2000). Given that ambiguity is likely to play a prominent role in understanding asset prices, models introducing ambiguity-averse agents have rapidly emerged. This literature has been able to account for major financial anomalies including the equity premium puzzle, the equity home bias, herding, or the existence of financial bubbles (Campbell and Cochrane, 1999; Chen and Epstein, 2002; Epstein and Miao, 2003; Maenhout, 2004; Cao et al., 2005; Leippold et al., 2008; Ui, 2010; Ju and Miao, 2012; André 2014; Dong et al., 2010; Ford et al., 2013; De Filippis et al., 2017).

This literature stresses that ambiguity in the fundamental value of the asset will depress asset prices thus generating an ambiguity premium (see e.g., Chen and Epstein, 2002; Maenhout, 2004; Cao et al., 2005; Leippold et al., 2008; Ui, 2010; Ju and Miao, 2012). The existence of an ambiguity premium in asset markets thus motivated our first conjecture.

The herding models incorporating ambiguity (Dong et al., 2010; Ford et al., 2013; De Filippis et al., 2017) motivated our second conjecture regarding the effect of ambiguity on the emergence of bubbles and on the occurrence of crashes.[2] In the presence of ambiguity, we expect that an upward trend in prices will likely raise traders' beliefs regarding the true asset value thus leading investors to downplay their own ambiguous information and instead follow the market trend. It follows that, in the presence of ambiguity, a streak of investors' purchases is likely to be followed by further purchases (Dong et al., 2010; Ford et al., 2013).[3] Ambiguity renders traders' beliefs more malleable and more likely to be affected by other traders' decisions. As stated by Shiller (2000, page 137): "*in ambiguous situations people's decisions are affected by whatever anchor is at hand*". This also echoes Keynes' (1936) view regarding the effect of ambiguity on potentially triggering "animal spirits". Our second conjecture thus claims that in the presence of ambiguity the upward trend in prices which characterizes the emergence of bubbles might shift traders' beliefs upwards, thus either delaying or preventing the occurrence of crashes.

[2] These models can be seen as a first attempt at formalizing the observation that ambiguous asset market values may favor the emergence of bubbles (see e.g., Keynes, 1936 and Shiller, 2000).
[3] In De Filippis et al., (2017), ambiguity concerns the strategy of other investors.

Our third conjecture states that the traders who are most likely to raise their beliefs of the value of the asset after observing a positive trend are those who actively extract information from market orders. Recent research in finance and neuroscience suggests high theory of mind traders are more likely to make active use of market prices as valuable signals of other traders' private information (see De Martino et al., 2013; Corgnet et al., 2018; see also Bossaerts et al., 2018 for a review).

To test our conjectures, we develop an experimental protocol in order to exogenously control the level of ambiguity in the fundamental value of the asset (e.g., Bossaerts, 2009; Noussair and Tucker, 2014; Frydman et al., 2014).[4] Our experimental design is based on the seminal work of Smith, Suchanek and Williams (1988) (henceforth SSW) where bubbles are typically observed[5] and we modify it to study the causal effect of introducing ambiguity on the formation of bubbles and subsequent crashes. We do so by comparing our modified *ambiguity treatment,* with ambiguous fundamental value for the asset, against the standard *risk treatment* where the fundamental value follows a known stochastic process.

We induced ambiguity in the fundamental value relying upon the fact that individuals naturally perceive colors differently (see e.g., Eysenck and Keane, 2015). In our procedure we present subjects with a color mix of blue and green which will determine the final payout of the asset. In particular, 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 whereas no indication was given regarding the relative proportion of each color in the ambiguity treatment.

In line with our first conjecture, we find that asset prices were lower in the ambiguity than in the risk treatment. In line with our second conjecture, we report that asset prices crashed in the risk

[4] This level of control over ambiguity is not achievable with field data because of the impossibility to exogenously manipulate the degree of ambiguity in actual stock markets. However, recent progress has been made to quantify the extent of ambiguity in stock prices by making use of stock market volatility expectations (Williams, 2015) and disagreement between analysts regarding the stock market valuation (Anderson et al., 2009). Recently, Brenner and Izhakian (2018) have deployed a new method to disentangle risk and ambiguity and assess the extent to which the equity premium puzzle can be accounted for by the ambiguity attitudes of investors. However, these recent advances fall short of providing a causal test of the effect of ambiguity on stock market prices.

[5] 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 of subjects (e.g., SSW; Dufwenberg et al., 2005; Hussam et al., 2008) or using a non-declining fundamental value (Noussair et al., 2001; Kirchler et al., 2012; Stöckl et al., 2015).

treatment whereas this was not the case in the ambiguity treatment. At the individual level, we show that, in line with our third conjecture, traders possessing high theory of mind skills significantly updated their beliefs upwards in the ambiguity treatment whereas this was not the case for low theory of mind traders.

1.2. Ambiguity in experimental asset markets

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. A null result regarding ambiguity effects was also obtained by Corgnet et al., (2013) in an environment in which public information was revealed sequentially. Despite the null results regarding the effect of ambiguity in the abovementioned experimental literature there are reasons to believe that the difference between ambiguity and risk is real. For example, in an environment similar to Füllbrunn et al., (2014), Sarin and Weber (1993) 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) who stress 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.

2. Design

2.1. The market

Most features of our experimental design were similar to the seminal asset market design of SSW (1988). Nine subjects traded a unique asset for fifteen periods of three minutes each using a computerized double auction platform (see Appendix A for an instruction summary).[6] 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

[6] The complete set of instructions is available in Appendix O1 online.

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.[7] 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).

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 used a sure dividend instead of a stochastic draw in order to avoid subjects from learning the composition of the ambiguous bag across periods. Even though we decided not to use a stochastic dividend, we still wanted the asset to deliver a dividend each period so as 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).

We thus opted for a single source of risk or ambiguity related to the final payout of the asset (delivered at the end of period 15). This final payout was equal to either 80¢ or 280¢. We conducted two treatments which only differed in the mechanism determining the final payout. 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 blue and green[8] chips in front of the room. 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.[9] 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

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[7] 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.

[8] 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 color in the mix.

[9] 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.

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).

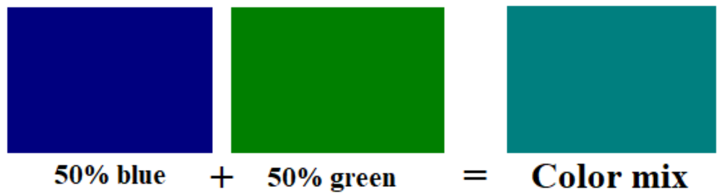

Figure 1. Color mix along with the blue and green colors used for the mix

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.[10] Subjects in the risk treatment 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¢.[11]

Our protocol contrasts with Ellsberg's (1961) implementation of ambiguity where subjects are *not given any information* regarding the respective probabilities of occurrence of the colored balls in the urn.[12] The Ellsberg protocol thus limits the possibility for subjects to learn from each other's views regarding the composition of the run. In our ambiguity treatment, market prices may convey valuable information regarding other traders' perception of the color mix. This implies that for our *(color) ambiguity* protocol, individuals, by observing trading prices, may update their own beliefs

[10] Extensive tests with the color mix prior to conducting the experiment have showed that choosing a large proportion of either blue or green instead of an equal mix made it easy to figure out the dominant color and the respective color proportions. As in Cooper and Rege (2011), we aimed at picking a protocol in which social learning prevails so that a person originally seeing the mix as green could end up seeing it as blue if market prices indicated blue was the winning color. Notwithstanding, we acknowledge that this choice might have led subjects to stick to a focal point which corresponds to a 50% mix of blue and green. In our beliefs elicitation task, 13% of the subjects indeed valued the asset at 50 in the ambiguity treatment. We believe this anchoring would tend to weaken rather than strengthen the reported effect of the ambiguity treatment as it would make traders' beliefs in the risk and ambiguity treatments more similar.

[11] This was done to ensure subjects would not speculate on the experimenters' motivation to choose the color that would minimize subjects' earnings (see Oechssler and Roomets, 2015 for a discussion of what they refer to as "strategic" uncertainty).

[12] In the absence of any prior information, the principle of insufficient reason 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).

regarding the color composition of the color mix and subsequently the valuation of the asset. Beliefs, thus, would be *malleable* in our protocol.[13] Our procedure resembles the implementation of ambiguity used in Cooper and Rege (2011) and Hey, Lolito and Maffioletti (2010). Cooper and Rege (2011) scrambled cells of three different colors in a 20×20 square to produce an ambiguous pattern of colors.[14] Hey, Lolito and Maffioletti (2010), meanwhile, drew balls from a transparent bingo blower filled with balls of three different colors where the balls are in constant motion. The idea behind the implementations is the same. That is, it is difficult for subjects to actually count the number of balls or cells of each color so that the probabilities of occurrence of each color are not perfectly known. Our protocol can be seen as a limit case of the previous methods in which the number of cells or balls is arbitrarily high. This is the case in which ambiguity is the highest because subjects will surely not be able to count balls and cells of different colors.

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.[15] 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 online Appendix O2 and Corgnet et al., 2018 for details) 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.

[13] 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).

[14] The authors also use a blackout protocol in which they hide some of the cells in the square (see also Chow and Sarin, 2002 for a similar approach).

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

A total of 108 subjects divided in 6 different sessions for each treatment were recruited.[16] Earnings were on average \$27.25 including a \$7 show-up fee, for a 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. 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 in the ambiguity treatment will be lower 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 know from previous research that the 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 the 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 learning across traders regarding the value of the final payout. By design, these probabilities are fixed in the risk treatment. Thus, unlike the ambiguity treatment, it seems improbable 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. Thus, as is common place in SSW

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

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¢).

However, traders might still learn about the strategic sophistication of other traders in both the risk and ambiguity treatments. This learning occurs because traders might update their beliefs regarding other traders' risk attitudes and rationality levels. Recent research (Cheung et al., 2016; Akiyama et al., 2017) has indeed put forth the relevance of strategic uncertainty in a SSW setting.[17] The difference between the risk and ambiguity treatments is thus a matter of degree. Learning in the risk treatment is confined to other traders' preferences and rationality levels whereas learning in the ambiguity treatment also applies to beliefs about the true asset value.

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 assets' true value. Traders are thus likely to mistakenly 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. This type of learning errors resembles the phenomenon of *information mirages* according to which traders might falsely believe that the decisions of uninformed traders contain additional information (see Camerer and Weigelt, 1991; Noussair and Xu, 2015).

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 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. As is argued by Miller (1977), these optimistic beliefs are unlikely to be challenged by pessimists when short-selling is absent, as is the case in

[17] We thank two anonymous reviewers for highlighting these possibilities.

our setting. In Conjecture 2, we summarize our prediction regarding the occurrence of 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 in the ambiguity treatment 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. 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 conjecture that high theory of mind traders will update their beliefs differently across treatments.

In the ambiguity treatment, rising prices can provide information regarding other traders' perception of colors thus providing a signal of their estimation of the likelihood of the high final payout. The underlying mechanism is similar to rational herding (see Bikhchandani et al., 1992; Devenow and Welch, 1996) in which rising prices might provide valuable information regarding other traders' valuation of the asset which cannot be fully ignored.

The argument that, in the presence of ambiguity, new information will lead people to learn about other people's beliefs was 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.

It is also worth noting that high theory of mind traders might learn about others' preferences and rationality levels, regardless of the treatment. In our setup, high theory of mind traders may revise, for example, their beliefs regarding others' risk attitudes. In particular, as prices move up, traders who possess high theory of mind might infer that other traders are risk seeking. As a result of the rising trend, traders may also revise their beliefs about the strategic sophistication of others. They may infer that other traders' exhibit social conformity thus following the herd and buying the asset at increasing prices (Goeree and Yariv, 2015; Bernheim, 1994).

Below, we summarize our conjecture regarding the evolution of the beliefs of traders who possess different levels of theory of mind skills.[18]

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

Figure 2 shows the average asset prices per period across all sessions for each of the two treatments (see Appendix B for the individual charts for each of the twelve sessions). 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 $t \in \{1, \ldots, 15\}$: $fundamentals_t = (50\% \times 80 + 50\% \times 280) + (16 - t) \times 12$. We also display the lowest (LB) $(80 + (16 - t) \times 12)$ and highest (UB) $(280 + (16 - t) \times 12)$ possible values of the asset in the ambiguity treatment.

We note that in line with previous research in the risk treatment (see e.g., see Palan, 2013; Powell and Shestakova, 2016; Kujal and Powell, 2017) prices exhibit a positive trend which is followed by a crash which occurs in the last five periods.

[18] Ours is a setting in which mispricing is high and following the trend further sharpens this mispricing. However, we could envision markets (e.g., Plott and Sunder, 1982) in which information aggregates efficiently in the presence of ambiguity. In that setup, price movements would convey private information regarding traders' private valuation so that high theory of mind traders who actively learn by following price signals would end up forming more informed guesses about the true asset value. This reasoning could explain why traders possessing high theory of mind skills perform well in information aggregation markets à la Plott and Sunder (1982) (see Bruguier et al., 2010) while not doing so well in bubbles markets (see De Martino et al., 2013).

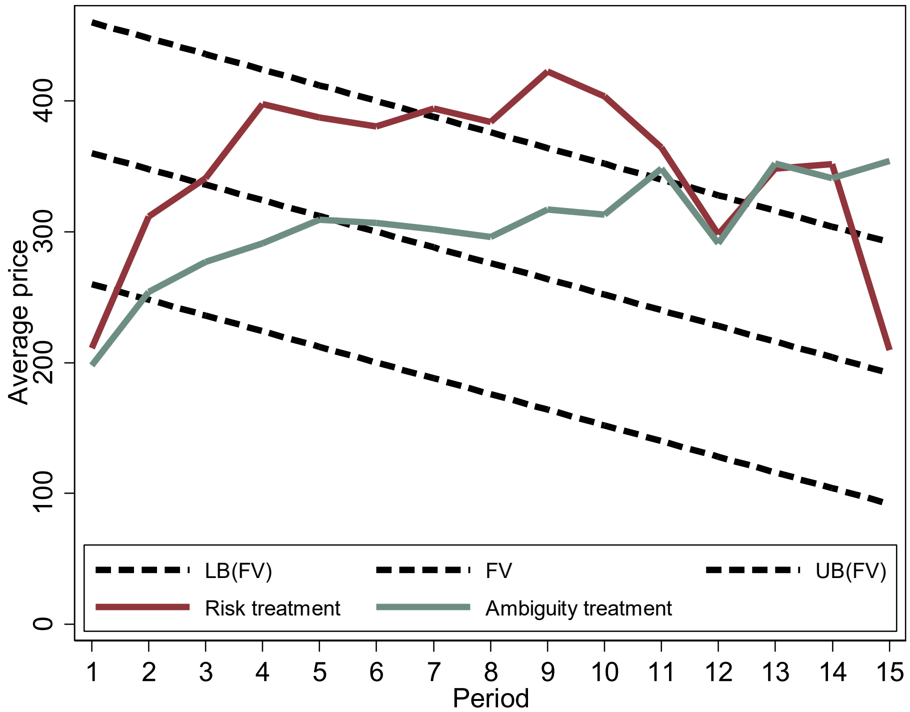

Figure 2. Average asset prices per period across treatments along with fundamental values. LB(FV) and [UB(FV)] refer to the lowest [highest] possible value of the asset in the ambiguity treatment

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 (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 higher in the ambiguity than in the risk treatment although this effect is not significant at standard levels (see regression [3], p-value = 0.061).

Note that our results hold for a wide range of choices of the cutoff periods used to define the time span considered in the three regressions in Table 1 (see Tables O3.1.1 to O3.1.5 in the online Appendix O3).[19]

[19] Our results also hold when controlling for the possibility of autocorrelation (see Table O3.2 in Appendix O3), when controlling for the average theory of mind scores in a given market or when using two-sample tests instead of panel regressions (although p-values are higher in that case, between 0.05 and 0.10) (see Table O3.1.6 in Appendix O3).

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	10.970***	0.620	3.350*

*** Significant at the 0.001 level; ** at the 0.01 level; * at the 0.05 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:

$$Average\ price_t = \alpha_0 + \alpha_1 \text{Period Number} + \alpha_2\ Dummy(last\ \boldsymbol{x}\ periods)$$
$$+\alpha_3\ \text{Period Number} \times Dummy(last\ \boldsymbol{x}\ periods)$$

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 C1 in Appendix C for a statistical analysis).[20]

[20] Figure 2 seems to indicate that a second break in trend might occur around period 11 or 12 in the ambiguity treatment. However, the variables (Period Number × Dummy last 11 periods) or (Period Number × Dummy last 12 periods) are positive but not significant (see Table C1).

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. This, however, is not the case for the ambiguity treatment (see Table C1).

Table 2.- Linear panel regressions of average asset prices to identify a trend break in the risk treatment.[21]

	Structural Break in Trend in period $\boldsymbol{x}$:					
	$\boldsymbol{x = 9}$ [1]	$\boldsymbol{x = 10}$ [2]	$\boldsymbol{x = 11}$ [3]	$\boldsymbol{x = 12}$ [4]	$\boldsymbol{x = 13}$ [5]	Any[22] [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[23]	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)**
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***

[21] Controlling for the average theory of mind scores in a given market does not affect the qualitative findings in Table 2.
[22] Individual dummy variables are not included because of collinearity issues.
[23] 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.

*** Significant at the 0.001 level; ** at the 0.01 level; * at the 0.05 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.

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 Tables C2.1 and C2.2). 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).

In Figure 2, as well as in Figure B2, we observe a substantial proportion of trades above 280 in the last period in the ambiguity treatment (6 out of 11 trades) compared to the risk treatment (1 out of 9 trades). The difference in proportions is actually significant across treatments (Proportion test, p-value = 0.043). As is put forth in Lei et al., (2001) irrational behavior may still persist in SSW environments even in the absence of speculative motives, which corresponds to the last period in our experiment. These irrational trades could partly be due to subjects possessing low cognitive skills (see Corgnet et al., 2015; Noussair et al., 2016). It could be the case that the uncertainty inherent to the ambiguity treatment impairs traders' cognitive skills thus leading to more irrational trades. In the ambiguity treatment traders might continuously evaluate which of the possible colors is most likely to be represented in the color mix thus generating an effect similar to cognitive load. As we know from recent research in neuroscience, the uncertainty generated by ambiguous outcomes is key to induce stress in people (De Berker et al., 2016; Peters et al., 2017), which in turn impairs cognitive skills (see e.g., Arnsten, 2009). Our interpretation of these unreasonable market orders in the ambiguity treatment based on the cognitive load it generates echoes recent findings in Kocher et al., (2018) according to which prices were substantially higher in a SSW setting in which traders' cognitive skills had been depleted by a standard Stroop task compared to a baseline treatment.

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 subjects in the study.[24] We measure traders' beliefs regarding the valuation of the asset both before and after the market experiment using the Becker–DeGroot–Marschak mechanism (see Appendix A.3). Changes in traders' beliefs regarding the valuation of the asset are then assessed 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.

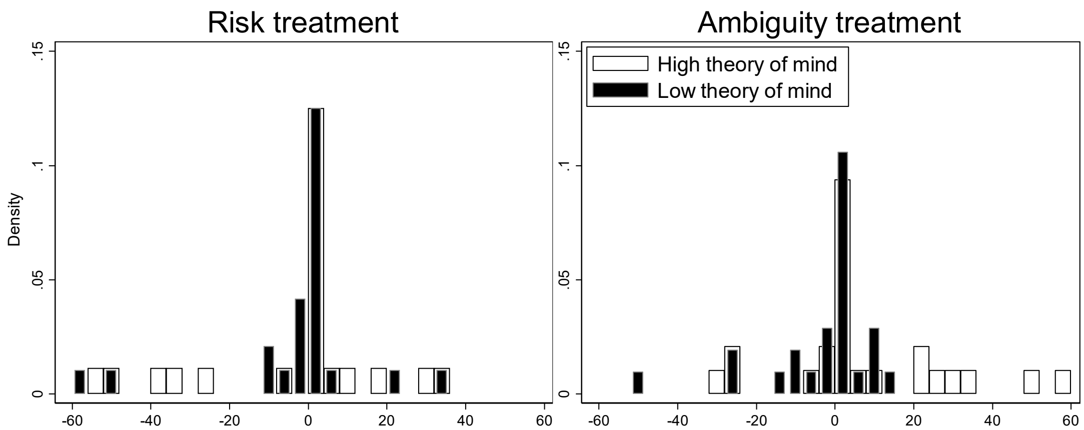

Figure 3. Beliefs regarding the valuation of the asset *after* the market ends minus beliefs regarding the valuation of the asset *before* the markets starts.

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 difference is observed in the risk treatment. We confirm this 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 (see Table 3). 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 subjects.[25] Finally, we control for sex by means of a male dummy which takes value 1 for males and value 0 otherwise.

[24] In our sample, the median score is 27 which is in line with previous studies (see Corgnet et al., 2018).
[25] The median CRT score is equal to 3 which is in line with previous studies (see Corgnet et al., 2018).

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

	All treatments
Constant	3.681 (5.758)
Ambiguity Treatment Dummy	**-6.441** **(6.202)**
High Theory of Mind Dummy	**-9.062** **(7.877)**
Ambiguity Treatment Dummy x High ToM Dummy	**21.099*** **(10.592)**
High CRT Dummy	-7.002 (5.738)
Male Dummy	-1.888 (5.576)
N	100
R^2	0.063
χ^2	7.09*

*** Significant at the 0.001 level; ** at the 0.01 level; * at the 0.05 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.

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 (see the positive coefficient for the interaction effect 'Ambiguity Treatment Dummy x High ToM Dummy', p-value = 0.043). Interestingly, those who possess high cognitive reflection 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, neither theory of mind skills nor cognitive reflection lead to a significant update in traders' beliefs.

For the sake of completeness and to position in our work more firmly in the existing literature in experimental finance, we aimed at replicating the positive relationship between traders' CRT scores and earnings (Corgnet et al., 2015; Noussair et al., 2016). Table C3 confirms such positive relationship although theory of mind scores fail to reach statistical significance in explaining traders' earnings. Similar results were obtained using the Somers' Delta (Somers, 1962) which is an ordinal association measure which is equivalent to the Gini Coefficient.[26] This is consistent with the works of De Martino et al., (2013) and Hefti et al., (2016) according to which the positive effect of theory of mind skills uncovered in Bruguier et al., (2010) and Corgnet et al., (2016) in markets with private information can be offset in bubbles markets because high theory of mind traders tend to chase the trend and engage in momentum trading strategies which are typically less profitable than fundamentalist or rational speculation strategies (see Haruvy and Noussair, 2006). Thus, theory of mind skills can be maladaptive in the context of financial bubbles. In line with this argument, we also found that traders with high theory of mind skills were more likely to follow momentum strategies than those with low theory of mind skills (although the difference of proportions does not reach statistical significance, p = 0.109) (see Table O3.3 in the online Appendix O3). In Appendix O3, we provide an extensive analysis of other possible differences in trading behavior between low- and high- theory of mind traders. We show no significant relationship between theory of mind skills and market variables such as number of trades, buying and selling prices or the bid-ask spread (see Table O3.4).

5. Discussion

Even though financial markets provide an ideal environment to highlight differences between risk and ambiguity, the current experimental literature provides mixed results. We contribute to this literature in two ways.

First, we propose another method to induce ambiguity which relies upon people's inherent subjective perception of colors. As earlier mentioned, our method can be considered as a limit case of the bingo blower (Hey, Lolito and Maffioletti, 2010) or scrambled cells (Cooper and Rege, 2011) procedures where the number of cells or balls is arbitrarily high. We argue that ambiguity is especially high in our case because subjects cannot count balls and cells of different colors. Unlike the Ellsberg'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,

[26] Using Somers' Delta, we did not find a significant effect of theory of mind on trader earnings (S=0.13, p-value = 0.14; S=-0.09, p-value = 0.29; S=0.03, p-value = 0.64 for the risk, the ambiguity and both treatments, respectively).

even though overall mispricing is no different across treatments, the anatomy of bubbles and crashes sharply differ. 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).

Our findings imply that the mixed results regarding the existence of an ambiguity premium in experimental asset markets (e.g., Camerer and Kunreuther, 1989; Corgnet et al., 2013) do not carry over to a market in which mispricing is prevalent. This is good news for the recent financial literature which explained many financial anomalies, including the equity premium puzzle, based on the existence of an ambiguity premium. Future research should also compare different methods to induce ambiguity in order to assess the extent to which our color ambiguity protocol is useful to unveil critical differences between risk and ambiguity.

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 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.

We should stress that our findings are only tentative and should be interpreted with caution. Despite recruiting a total of 108 traders, we conducted only twelve independent market sessions thus making it difficult to pinpoint the individual mechanisms underlying our findings. Future research should thus add to the current data and investigate further the individual drivers of any differences between risky and ambiguous environments.

6. References

Ahn, D., Choi, S., Gale, D. and S. Kariv (2014) "Estimating Ambiguity Aversion in A Portfolio Choice Experiment," *Quantitative Economics* 5(2), 195-223.

Akiyama, E. Hanaki, N. and R. Ishikawa (2017) "It is Not Just Confusion! Strategic Uncertainty in an Experimental Asset Market," *Economic Journal* 127, 563-580

Aliber, R. and C. Kindleberger (2015) "Manias, Panics, and Crashes: A History of Financial Crises," *Palgrave Macmillan UK*, *seventh edition*.

Anderson, E., Ghysels, E. and J. Juergens (2009) "The Impact of Risk and Uncertainty on Expected Returns," *Journal of Financial Economics* 94, 233-263.

André, E. (2014) "Optimal Portfolio with Vector Expected Utility," *Mathematical Social Sciences* 69, 50-62.

Arnsten, A. (2009) "*Stress Signalling Pathways That Impair Prefrontal cortex structure and function*," *Nature Reviews Neuroscience* 10, 410-422.

Avery, C. and P. Zemsky (1998) "Multidimensional Uncertainty and Herd Behavior in Financial Markets," *American Economic Review* 88(4), 724-748.

Baillon, A., Bleichrodt, H., Keskin, U., l'Haridon, O and C. Li (2018) "The Effect of Learning on Ambiguity Attitudes," *Management Science* 64(5), 2181-2198.

Baron-Cohen, S., Jolliffe, T., Mortimore, C. and M. Robertson (1997) "Another Advanced Test of Theory of Mind: Evidence From Very High Functioning Adults With Autism or Asperger Syndrome," *Journal of Child Psychology and Psychiatry* 38, 813-822.

Bernheim, B. (1994) "A Theory of Conformity," *Journal of Political Economy* 102, 841-877.

Bikhchandani, S., Hirshleifer, D. and I. Welch (1992) "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy* 100, 992-1026.

Binmore, K., Stewart, L. and A. Voorhoeve (2012) "How Much Ambiguity Aversion? Finding Indifferences Between Ellsberg's Risky and Ambiguous Bets," *Journal of Risk and Uncertainty* 45(3), 215-238.

Bishop, J. (1987) "Stock Market Experiment Suggests Inevitability of Booms and Busts," *Wall Street Journal*, November 17.

Bossaerts, P. (2009) "What Decision Neuroscience Teaches us About Financial Decision Making," *Annual Review of Financial Economics* 1, 383-404.

Bossaerts, P., Ghirardato, P., Guarnaschelli, S. and W. Zame (2010) "Ambiguity and Asset markets: Theory and experiment," *Review of Financial Studies* 23, 1325-1359.

Bossaerts, P., Suzuki, S. and J. O'Doherty (2018) "Perception of Intentionality in Investor Attitudes Towards Financial Risks," *Journal of Behavioral and Experimental Finance*, In Press.

Breaban, A. and C. Noussair (2015), "Trader Characteristics and Fundamental Value Trajectories in an Asset Market Experiment," *Journal of Behavioural and Experimental Finance* 8, 1-17.

Brenner, M. and Y. Izhakian (2018) "Asset Prices and Ambiguity: Empirical Evidence," *Journal of Financial Economics* 130, 503-531.

Bruguier, A. Quartz, S. and P. Bossaerts (2010) "Exploring the Nature of Trading Intuition," *Journal of Finance*, 65, 1703-23.

Caginalp, G., D. Porter and V. Smith (1998) "Initial Cash/Stock Ratio and Stock Prices: An Experimental Study," *Proceedings of the National Academy of Sciences* 95(2), 756-61.

Caginalp, G., D. Porter and V. Smith (2001) "Financial Bubbles: Excess Cash, Momentum, and Incomplete Information," *Journal of Behavioral Finance* 2(2), 80-99.

Camerer, C. (1989) "Bubbles and Fads in Asset Prices: A Review of Theory and Evidence," *Journal of Economic Surveys* 3, 3-41.

Camerer, C. and H. Kunreuther (1989) "Experimental Markets for Insurance," *Journal of Risk Uncertainty* 2(3), 265-299.

Cameron, A. and D. Miller (2011) "Robust Inference with Clustered Data," *Handbook of Empirical Economics and Finance*, 1-28.

Camerer, C. and K. Weigelt (1991) "Information Mirages in Experimental Asset Markets," *The Journal of Business* 64, 463-493.

Campbell, J. and J. Cochrane (1999) "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy* 107, 205-251.

Cao, H., Wang, T. and H. Zhang (2005) "Model Uncertainty, Limited Market Participation, and Asset Prices," *Review of Financial Studies* 18(4), 1219-1251.

Charness, G., Karni E. and D. Levin (2013) "Ambiguity Attitudes and Social Interactions: An Experimental Investigation," *Journal of Risk and Uncertainty* 46(1), 1-25.

Chen, Z. and L. Epstein (2002): "Ambiguity, Risk, and Asset Returns in Continuous Time," *Econometrica* 70, 1403-1443.

Chow, C. and R. Sarin (2002) "Known, Unknown and Unknowable Uncertainties," *Theory and Decision* 52, 127-138.

Cheung, S. Hedegaard, M. and St. Palan (2014) "To See is to Believe: Common Expectations in Experimental Asset Markets," *European Economic Review* 66, 84-96.

Cohen, M., Tallon, J. and J. Vergnaud. (2011) "An Experimental Investigation of Imprecision Attitude and its Relation With Risk Attitude and Impatience," Theory and Decision, 71-81.

Cooper, D. and M. Rege (2011) "Misery Loves Company: Social Regret and Social Interaction Effects in Choices Under Risk and Uncertainty," *Games and Economic Behavior* 73, 91-110.

Corgnet, B., DeSantis M. and D. Porter (2018) "What Makes a Good Trader? On the Role of Reflection and Intuition on Trader Performance," *Journal of Finance* 73(3), 1113-1137.

Corgnet, B., Hernan-Gonzalez, R, Kujal, P. and D. Porter (2015) "The Effect of Earned Versus House Money on Price Bubble Formation in Experimental Asset Markets," *Review of Finance* 19, 1455-1488.

Corgnet, B., P. Kujal and D. Porter (2010) "The Effect of Reliability, Content and Timing of Public Announcements on Asset Trading Behavior," *Journal of Economic Behavior and Organization* 76(2), 254-266.

Corgnet, B., P. Kujal and D. Porter (2013) "Reaction to Public Information in Markets: How much does Ambiguity Matter?" *Economic Journal*, 6, 699-737.

Curley, S. and F. Yates (1985) "The Center and Range of the Probability Interval as Factors Affecting Ambiguity Preferences," *Organizational Behavior and Human Decision Processes* 36, 272-287.

De Berker, A., Rutledge, R., Mathys, C., Marshall, L., Cross, G., Dolan, R. and S. Bestmann (2016) "Computations of Uncertainty Mediate Acute Stress Responses in Humans," *Nature*

Communications 7, 10996.

De Filippis, R., Guarino A., Jehiel, P. and T. Kitagawa (2017) “Updating Ambiguous Beliefs in a Social Learning Experiment,” CeMMAP working papers CWP13/17, Centre for Microdata Methods and Practice, Institute for Fiscal Studies.

De Martino, B., O’Doherty, J., Debajyoti, R., Bossaerts, P. and C. Camerer (2013) “In the Mind of The Market: Theory of Mind Biases Value Computation During Financial Bubbles,” *Neuron* 79, 1222-1231.

Devenow, A. and I. Welch (1996) “Rational Herding in Financial Economics,” *European Economic Review* 40, 603-615.

Dimmock, S., Kouwenberg, R., Mitchell, O. and K. Peijnenburg (2016) “Ambiguity Aversion and Household Portfolio Choice Puzzles: Empirical Evidence,” *Journal of Financial Economics* 119(3), 559-577.

Dominiak, A., Duersch, P. and J. Lefort (2012) “A Dynamic Ellsberg Urn Experiment,” *Games and Economic Behavior* 75(2), 625-638.

Dong, Z., Gu, A. and X. Han (2010) “Ambiguity Aversion and Rational Herd Behaviour,” *Applied Financial Economics* 4, 331-343.

Dow, J. and S. da Costa Werlang (1992) “Uncertainty Aversion, Risk Aversion, and the Optimal Choice of Portfolio,” *Econometrica* 60, 197-204.

Dufwenberg, M., Lindqvist, T. and E. Moore (2005). ‘Bubbles and Experience: An Experiment’, *American Economic Review* 95, 1731-1737.

Eckel, C. and S. Füllbrunn (2015) “Thar SHE Blows? Gender, Competition, and Bubbles in Experimental Asset Markets,” *American Economic Review* 105(2), 906-20.

Ellsberg, D. (1961). ‘Risk, Ambiguity, and the Savage Axioms’, *Quarterly Journal of Economics*’, 75, 643-669.

Epstein, L. and J. Miao (2003) “A Two-Person Dynamic Equilibrium under Ambiguity,” *Journal of Economic Dynamics and Control* 27, 1253-1288.

Eysenck, M. and M. Keane (2015) “Cognitive Psychology: A Student's Handbook,” *Psychology Press*.

Ford, J., Kelsey, D. and W. Pang (2013) “Information and Ambiguity: Herd and Contrarian Behaviour in Financial Markets,” *Theory and Decision* 75(1), 1-15.

Fox, C. and A. Tversky (1995) “Ambiguity Aversion and Comparative Ignorance,” *Quarterly Journal of Economics* 110, 585-603.

Frederick, S. (2005) “Cognitive Reflection and Decision Making,” *Journal of Economic Perspectives* 19(4), 25-42.

Frith, C. and U. Frith (1999) “Interacting Minds—A Biological Basis,” *Science* 286, 1692-1695.

Frydman, C., Barberis, N., Camerer, C., Bossaerts, P. and A. Rangel (2014) “Using Neural Data to Test a Theory of Investor Behavior: An Application to Realization Utility,” *Journal of Finance* 69 (2), 907-946.

Füllbrunn, S., Rau, H. and U. Weitzel (2014) “Does Ambiguity Aversion Survive in Experimental Asset Markets? *Journal of Economic Behavior and Organization* 107, 810-826.

Gächter, S., Johnson, E. and A. Herrmann (2007) “Individual-level Loss Aversion in Riskless and Risky Choices,” CeDEx Discussion Paper No. 2007-02.

Goeree, J and L. Yariv "Conformity in the Lab," *Journal of Economic Science Association* 1, 15-28.

Haessel, W. (1978) "Measuring Goodness of Fit in Linear and Nonlinear Models," *Southern Economic Journal* 44(3), 648-652.

Haruvy, E., Noussair, C. and O. Powell (2013) "The Impact of Asset Repurchases and Issues in an Experimental Market," *Review of Finance* 18(2), 681-713.

Haruvy, H. and C. Noussair (2006) "The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Asset Markets," *Journal of Finance* 61(3) 1119-1157.

Heath, C. and A. Tversky (1991) "Preference and Belief: Ambiguity and Competence in Choice under Uncertainty," *Journal of Risk and Uncertainty* 4(1), 5-28.

Hefti, A., Heinke, S. and F. Schneider (2016) "Mental Capabilities, Trading Styles, and Asset Market Bubbles: Theory and Experiment," Working paper, Research Gate.

Hey, J., Lotito, G. And A. Maffioletti (2010) "The Descriptive and Predictive Adequacy of Theories of Decision Making Under Uncertainty/Ambiguity," *Journal of Risk and Uncertainty* 41 (2), 81-111

Hussam, R., D. Porter and V. Smith (2008) "Thar She Blows: Can Bubbles Be Rekindled with Experienced Subjects?" *American Economic Review* 98(3), 924-937.

Ju, N. and J. Miao (2012) "Ambiguity, Learning, and Asset Returns," *Econometrica* 80, 559-591.

Keynes, J. (1921). *A treatise on probability*, London: Macmillan.

Keynes, J. (1936) "The General Theory of Employment, Interest and Money," *London: Macmillan*.

King, R., Smith, V., Williams, A. and M. Van Boening (1993) "The Robustness of Bubbles and Crashes in Experimental Stock Markets," In *Nonlinear Dynamics and Evolutionary Economics*, Oxford University Press, 183-200.

Kirchler, M., Huber, J., and T. Stöckl (2012) "Thar She Bursts – Reducing Confusion Reduces Bubbles," *American Economic Review* 102(2), 865-883.

Kocher, M., Lucks, K. and D. Schindler (2018) "Unleashing Animal Spirits – Self-control and Overpricing in Experimental Asset Markets," *Review of Financial Studies*, forthcoming.

Kujal, P. and O. Powell (2017) "Bubbles in Experimental Asset Markets," *Revista de Economía Industrial-Special issue in Experimental Economics, forthcoming.*

Lei, V., Noussair, C. and C. Plott (2001) "Nonspeculative Bubbles in Experimental Asset Markets: Lack of Common Knowledge of Rationality vs. Actual Irrationality," *Econometrica* 69, 831-859.

Leippold, M., Trojani, F. and P. Vanini (2008) "Learning and Asset Prices Under Ambiguous Information," *Review of Financial Studies* 21, 2565-2597.

Machina, M. and M. Siniscalchi (2014) "Ambiguity and Ambiguity Aversion," *Handbook of the Economics of Risk and Uncertainty* 1, 729-807.

Maenhout, P. (2004) "Robust Portfolio Rules and Asset Pricing," *Review of Financial Studies* 17(4), 951-983.

Mukerji, S. and J. Tallon (2001) "Ambiguity Aversion and Incompleteness of Financial Markets," *Review of Economic Studies* 68, 883-904.

Noussair, C., Robin, S. and B. Ruffieux (2001) "Price Bubbles in Laboratory Asset Markets with Constant Fundamental Values," *Experimental Economics* 4(1), 87-105.

Noussair, C. and S. Tucker (2006) "Futures Markets and Bubble Formation in Experimental Asset Markets," *Pacific Economic Review* 11(2), 167-184.

Noussair, C. and S. Tucker (2014) "A Collection of Surveys on Market Experiments," *Journal of Economic Surveys* 27(3), 395-397.

Noussair, C., and Tucker, S. and X. Yilong (2016) "Futures Markets, Cognitive Ability, and Mispricing in Experimental Asset Markets," *Journal of Economic Behavior and Organization* 130, 166-179.

Miller, E (1977) "Risk, Uncertainty, and Divergence of Opinion'" *Journal of Finance* 4, 1151-1168.

Noussair, C. and Y. Xu (2015) "Information Mirages and Financial Contagion in an Asset Market Experiment", *Journal of Economic Studies* 42, 1029-1055.

Oechssler, J. and A. Roomets (2015) "A Test of Mechanical Ambiguity," *Journal of Economic Behavior & Organization* 119, 153-162.

Palan, S. (2013) "A Review of Bubbles and Crashes in Experimental Asset Markets," *Journal of Economic Surveys* 27(3), 570-588.

Peters, A., McEwen, B. and K. Friston (2017) "Uncertainty and Stress: Why it Causes Diseases and How it is Mastered by the Brain," *Progress in Neurobiology* 156,164-188.

Plott, C. and S. Sunder (1982) "Efficiency of Experimental Security Markets with Insider Information: An Application to Rational expectations Models," *Journal of Political Economy* 90, 663-698.

Porter, D. and V. Smith (1994) "Stock Market Bubbles in the Laboratory," *Applied Mathematical Finance* 1(2), 111-128.

Porter, D. and V. Smith (1995) "Futures Contracting and Dividend Uncertainty in Experimental Asset Markets," *The Journal of Business* 68(4), 509-541.

Powell, O. (2016) "Numeraire independence and the measurement of mispricing in experimental asset markets," *Journal of Behavioral and Experimental Finance*, 9, 56-62.

Powell, O. and N. Shestakova (2016) "Experimental Asset Markets: A Survey of Recent Developments," *Journal of Behavioral and Experimental Finance* 12, 14-22.

Razen, M., Huber, J. and M. Kirchler (2017) "Cash Inflow and Trading Horizon in Asset Markets," *European Economic Review* 92, 359-384

Sarin, R. and W. Weber (1993) "Effects of Ambiguity in Market Experiments," *Management Science* 39, 602-615.

Shiller, R. (1984) "Stock Prices and Social Dynamics," *Brookings Papers on Economic Activity* 2, 457-510.

Shiller, R. (2000) "Irrational Exuberance," *Princeton University Press*.

Smith, V., Suchanek, G. and A. Williams (1988) "Bubbles, Crashes and Endogenous Expectations in Experimental Spot Asset Markets," *Econometrica* 56, 1119-1151.

Somers, R. (1962) "A New Asymmetric Measure of Association for Ordinal Variables," *American Sociological Review* 27, 799-811.

Stöckl, T., Huber, J., and Kirchler, M. (2010) "Bubble measures in experimental asset markets," *Experimental Economics*, 13(3), 284-298.

Stöckl, T., Huber, H. and M. Kirchler (2015) "Multi-period Experimental Asset Markets With Distinct Fundamental Value Regimes," *Experimental Economics*, 18(2), 314-334.

Toplak, M. E., West, R. F., and Stanovich, K. E. (2011) "The Cognitive Reflection Test as a predictor of performance on heuristics and biases tasks," *Memory & Cognition*, 39, 1275-1289.

Toplak, M. E., West, R. F., and Stanovich, K. E. (2014) "Assessing miserly processing: An expansion of the Cognitive Reflection Test," *Thinking & Reasoning*, 20, 147-168.

Trautmann S. and G. van de Kuilen (2015) "Ambiguity Attitudes," *Handbook of Judgment and Decision Making*.

Ui, T. (2010). "The Ambiguity Premium vs. the Risk Premium Under Limited Market Participation," *Review of Finance* 14, 1-31.

Yates, F. and L. Zukowski (1976) "Characterization of Ambiguity in Decision Making," *Behavioral Science* 21, 19-25.

Williams, C. (2015) "Asymmetric Responses to Earnings News: A Case for Ambiguity," *The Accounting Review*," 90, 785-817.

Appendix A. Instruction summary

(see online Appendix O1 for the complete set of instructions)

A.1 Main instructions

A.1.1 Ambiguity treatment

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).

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).

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.

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.

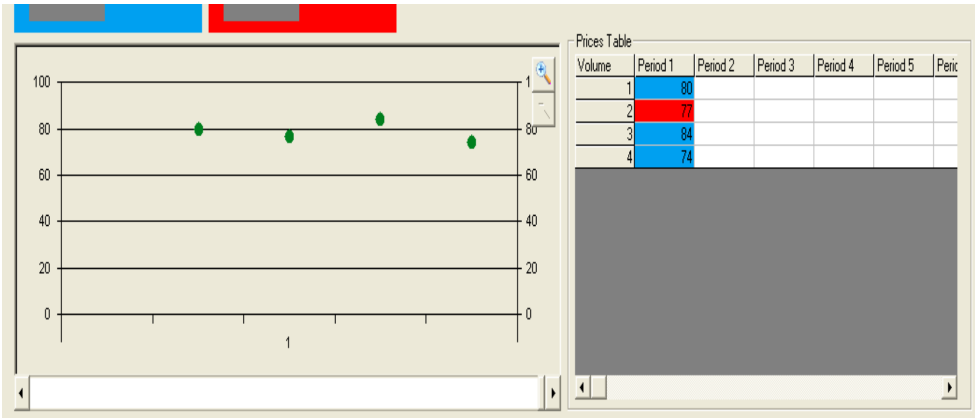

Figure A1: Lower part of your trading screen (graph and market book)

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**.

A.1.2. Risk treatment

The main change between risk and ambiguity treatments are shown below:

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

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.

Your earnings on the task will be:

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

Appendix B. Graphs for the individual sessions

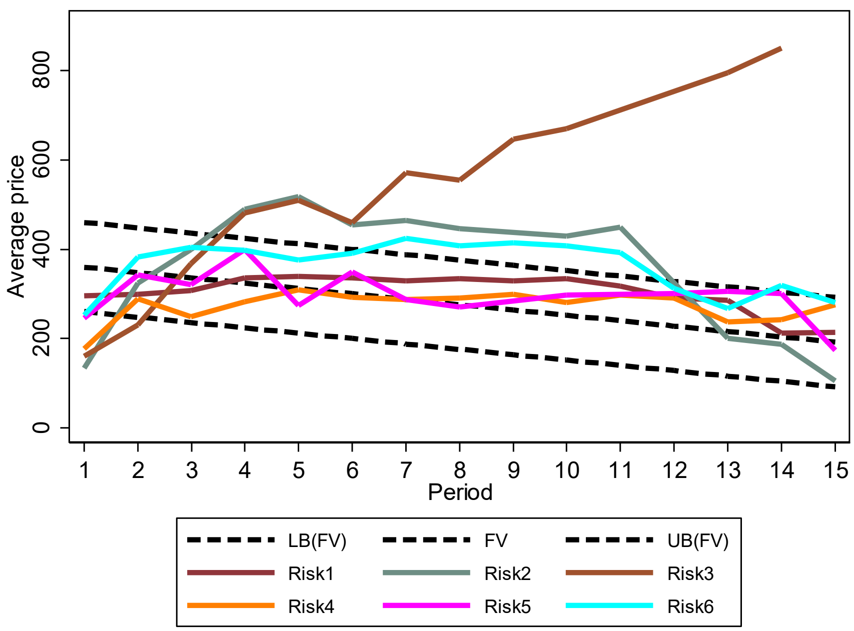

Figure B1: Average price per period for each of the six sessions in the risk treatment. The fundamental value is represented by a declining (dashed) line.

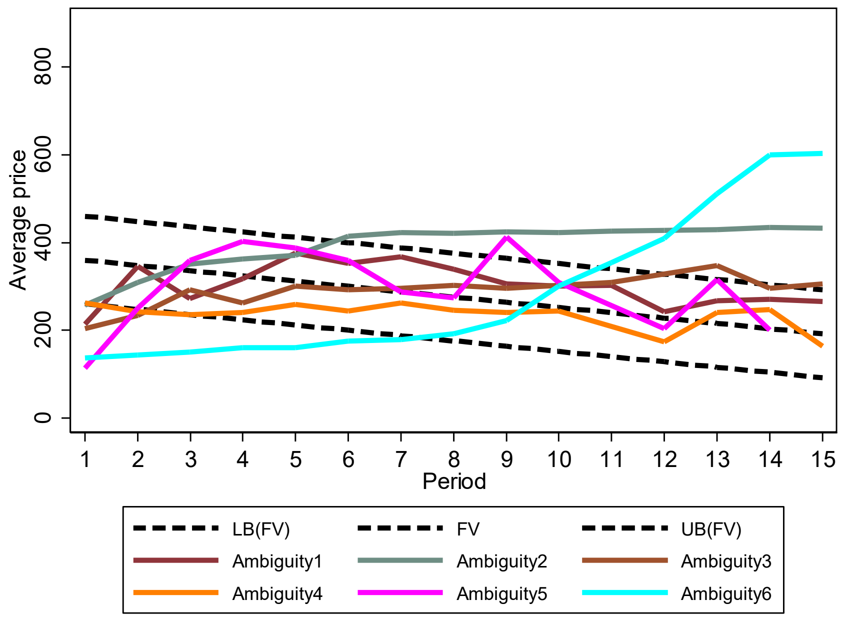

Figure B2: Average price per period for each of the six sessions in the ambiguity treatment. The fundamental value is represented by a declining (dashed) line.

Appendix C. Additional analyses

Table C1- 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[27] [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[28]	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 0.001 level; ** at the 0.01 level; * at the 0.05 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.

[27] Individual dummy variables are not included because of collinearity issues.

[28] 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:[29]

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:
$$D = \text{Max}\{m\colon P_t - f_t < P_{t+1} - f_{t+1} < \ldots < P_{t-m} - f_{t-m}\}.$$
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 session.

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

7. *Relative Deviation (RD) and Relative Absolute Deviation (RAD):* As defined in Stöckl et al., (2010), RD (RAD) measures the average (absolute) deviation between the average price and the fundamental value divided by the average value of the fundamental value for all the fifteen periods. They are defined as follows:

$$RD = \frac{\sum_{t=1}^{15}(Pt - ft)}{\sum_{t=1}^{15} ft} \qquad RAD = \frac{\sum_{t=1}^{15}|Pt - ft|}{\sum_{t=1}^{15} ft}$$

8. *Geometric Deviation (GD) and Geometric Absolute Deviation (GAD):* As defined in Powell (2016), GD (GAD) measures the geometric mean of the (absolute) deviation between the average price and the fundamental value. They are defined as follows:

$$GD = exp\left\{\frac{1}{15}\sum_{t=1}^{15} Ln\left(\frac{Pt}{ft}\right)\right\} - 1 \qquad GAD = exp\left\{\frac{1}{15}\sum_{t=1}^{15}\left|Ln\left(\frac{Pt}{ft}\right)\right|\right\} - 1$$

Table C2.1. Classical bubbles measures across treatments

Session	Amplitude	Duration	Haessel-R2	NAV	NAP	Number of Trades	RD	RAD	GD	GAD
Risk 1	0.410	9	0.315	47.0	1.617	90	0.102	0.170	0.111	0.178
Risk 2	1.210	4	0.128	112.9	4.375	69	0.262	0.464	0.149	0.521
Risk 3	2.350	4	0.937	230.0	8.534	114	0.809	0.991	0.671	1.049
Risk 4	0.738	3	0.024	48.2	3.614	117	-0.010	0.175	-0.000	0.200
Risk 5	0.584	2	0.167	41.8	2.935	74	0.064	0.172	0.067	0.187
Risk 6	0.732	3	0.095	100.4	3.137	78	0.312	0.364	0.318	0.382
Ambiguity 1	0.624	3	0.074	55.7	5.047	145	0.097	0.202	0.104	0.220
Ambiguity 2	0.955	14	0.715	136.9	6.796	147	0.427	0.496	0.439	0.529
Ambiguity 3	0.803	8	0.554	61.3	1.791	56	0.033	0.235	0.044	0.272
Ambiguity 4	0.415	3	0.318	49.1	1.766	57	-0.154	0.189	-0.146	0.221
Ambiguity 5	1.097	3	0.004	61.4	2.707	56	0.045	0.248	0.007	0.294
Ambiguity 6	1.763	14	0.838	182.3	6.371	95	0.039	0.660	-0.085	0.923
All risk sessions	1.004	4.167	0.278	96.716	4.036	90.333	0.256	0.389	0.219	0.420
All ambiguity sessions	0.943	7.500	0.417	91.099	4.080	92.667	0.081	0.338	0.060	0.410
Wilcoxon Rank Sum Test Treatment comparison (p-value)	0.749	0.405	0.631	0.522	>0.999	0.748	0.200	0.522	0.150	0.522

Table C2.2 Classical bubbles measures in the ambiguity treatment using the lower and upper bounds of the fundamental value.

FV	Session	NAV	RD	RAD	GD	GAD
FV = 80 + (16 – t) x 12	Ambiguity 1	132.776	0.72	0.754	0.782	0.828
	Ambiguity 2	218.262	1.238	1.24	1.322	1.326
	Ambiguity 3	111.229	0.608	0.664	0.673	0.747
	Ambiguity 4	54.188	0.32	0.325	0.373	0.379
	Ambiguity 5	117.432	0.61	0.732	0.586	0.802
	Ambiguity 6	172.165	0.629	0.978	0.477	1.042
	All ambiguity sessions	134.342	0.687	0.782	0.702	0.854
	WRSt(p-value) vs. Risk sessions	0.150	0.037	0.078	0.016	0.078
FV = 280 + (16 – t) x 12	Ambiguity 1	73.295	-0.195	0.195	-0.197	0.245
	Ambiguity 2	88.485	0.047	0.235	0.047	0.268
	Ambiguity 3	91.063	-0.24	0.257	-0.238	0.34
	Ambiguity 4	133.41	-0.378	0.378	-0.377	0.605
	Ambiguity 5	81.892	-0.226	0.245	-0.26	0.377
	Ambiguity 6	209.209	-0.238	0.556	-0.334	1.001
	All ambiguity sessions	112.892	-0.205	0.311	-0.226	0.472
	WRSt(p-value) vs. Risk sessions	0.522	0.007	0.631	0.007	0.522

Table C3- Linear regressions of subjects' earnings.

	Risk treatment	Ambiguity treatment	Both treatments
Constant	1531.799*** (362.152)	2,246.079*** (271.627)	1,896.555*** (259.929)
Female	-483.414 (322.313)	-573.168 (308.467)	-486.972* (232.433)
High ToM	580.591 (302.063)	-52.997 (305.092)	218.654 (202.889)
High CRT	1059.786*** (315.533)	240.804 (271.084)	647.518** (233.405)
Ambiguity Treatment Dummy	-	-	-85.598 (222.025)
N	48	52	100
R^2	0.255	0.061	0.169
χ^2	22.100***	6.670	16.930**

*** Significant at the 0.001 level; ** at the 0.01 level; * at the 0.05 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 100 instead of 108 because there were six (two) subjects who did not complete the ToM test.