Thar she resurges: The case of assets that lack positive fundamental value*
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Abstract:
This experimental study investigates the trading of assets that mimic the features of most cryptocurrencies. Groups of traders are randomized into asset markets where fundamental values are either positive, zero, or negative. Our findings indicate the presence of much larger bubbles in asset markets with non-positive fundamental values than in asset markets with positive fundamental values, with either risky or risk-free dividends. We show that these findings are consistent with trader expectations but not with loss aversion and complexity. This study provides experimental evidence that supports the need for particular scrutiny of asset markets that lack positive fundamental value.

Key Words: Asset market experiment, cryptocurrency, fundamental values

JEL codes: C92, D14, D81, D84, G01, G11

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**Introduction:**

Cryptocurrencies\(^1\) have rattled financial markets. The market capitalization of these digital currencies amounted to over US$835 Billion\(^2\) at its peak in 2018, which, at that time, was larger than the market valuation of companies like Apple, Google, or Facebook. Due to their recent popularity, they are now considered as a new asset class that typically does not deliver any cash flow unlike most other assets\(^3\), is not accepted as fiat currency. The majority of cryptocurrencies neither provide dividends, does not have face value, and does not satisfy the criteria to be a medium of exchange.\(^4\) Another common characteristic of these assets is their extraordinary volatility. From January 2015 to May 2019, the average variance of the daily return of these currencies has been more than 25 times higher than that of the S&P 500 index. These dramatic price fluctuations take a toll on traders’ mental health (Fortune, December 8, 2017), and have likely led to significant reallocations of resources. These characteristics of cryptocurrencies and the consequent potential social instability have alerted policymakers around the world. For instance, the Chinese government banned the exchanges of cryptocurrencies. In Columbia, investments in cryptocurrencies are strictly prohibited. In the US, two congressmen introduced Bills\(^5\) to prevent cryptocurrency price manipulation and protect their investors (CNN News, July 12, 2018).

However, whether this new asset class induces more speculation than other traditional assets and, thus, should be treated differently remains an open question. In this experimental study, we provide a first glimpse into the extent and nature of mispricing of assets that have zero and negative fundamental value (FV, henceforth). To this end, we conduct a laboratory asset market experiment where groups of individuals trade shares that generate zero or negative cash flows. In the first set of treatments, shares

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\(^1\) According to Hileman & Rauchs (2018), cryptocurrencies are digital assets that use cryptography to secure the creation, transaction, and verification processes. They use decentralized control as opposed to the central banking system; nevertheless, they may function as a medium of exchange.

\(^2\) https://coinmarketcap.com/charts/

\(^3\) There are some asset-backed cryptocurrencies like Stablecoins and there are a few other cryptocurrencies like Bitcoin which are known to serve as a medium of exchange on a small scale, but the majority of them do not have any obvious value.

\(^4\) Many argue that most cryptocurrencies fail the criteria to be an asset and fiat money thus has zero fundamental value (e.g., Cheah & Fry 2015 and Yermack 2015).

\(^5\) Representatives Darren Soto (Democrat) and Ted Budd (Republican) jointly announced that their two bills – “The Virtual Currency Consumer Protection Act of 2018” and the “U.S. Virtual Currency Market and Regulatory
generate risk-free cash flows. The shares with zero FV mirror the feature of most cryptocurrencies as they never generate any cash flows to the holders. To simulate the periodic fees charged by many cryptocurrency brokers (trading websites), we also address assets with negative FV, which always incur costs to the holder.\(^6\)

We find clear evidence of high levels of speculation in the presence of assets that lack positive FV. The data show that zero FV shares are traded at a price that is much higher than zero, and the size of bubbles is larger for negative FV shares. Compared to markets with positive FV shares, we observe that bubbles are approximately 3–4 times larger when shares have zero or negative FV, respectively.

We also test markets where assets earn risky dividends and incur holding costs.\(^7\) In the second set of treatments, we use a stochastic dividend process and implement fixed holding costs but keep FVs comparable to the first set of treatments. As traders can incur losses in each trading period if the dividend does not cover the cost, we expect to observe significant loss aversion and bubble deflation. However, we observe the opposite, and bubbles increase up to three times, holding FVs constant.

A potential explanation for the observed bubble patterns is based on price expectations. More precisely, some traders might believe that other traders are willing to pay a premium above the FV and that this premium is systematically linked to the FV and dividend variance. We test this explanation in a guessing game where we incentivize inexperienced subjects to accurately predict the pricing patterns in some of the proposed treatments. We find that guessers successfully anticipate the existence of bubbles in zero FV markets and correctly guess relative bubble sizes in markets with different FVs. These findings suggest that markets with zero and negative FV assets have a natural tendency toward larger bubbles.

This study contributes to different strands of literature in economics and finance. First, it complements the nascent empirical literature on cryptocurrencies that investigates market efficiency.

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\(^6\) The certain losses in this treatment also shed light on assets that have negative (real) interest rates and losses like 30 years German government bonds, which carry negative returns in certain periods in 2019.

\(^7\) In addition to the literal holding costs like taxes and brokerage, readers may also consider the psychological discomfort (i.e., stress, depression), operational costs (i.e., computer depreciation, electricity), and opportunity costs (i.e., time, forgone interest of money) involved in the trading as holding costs in a broader sense.
(Bartos, 2015; Urquhart 2016), volatility (Dyhrberg 2016; Borri 2019), the possibility to use
cryptocurrencies as a medium of exchange (Glaser et al. 2014; Böhme et al. 2015; Fry & Cheah 2016;
Foley et al. 2019) and other features (Biais et al. 2019; Cong & He 2019). By experimentally studying
asset markets in the laboratory, we isolate the impact of each asset feature and bypass the limitations of
cryptocurrency data, which are often subject to manipulations, black-market activities, market
regulations, and self-selection bias.

Second, this study substantially expands the literature on asset market bubbles. Since Smith et
al. (1988), ample evidence has shown a considerable mispricing in traditional asset markets with
positive FV (Ball & Holt 1998; Bostian, Goeree & Holt 2005; Dufwenberg, Lindqvist, & Moore 2005;
Eckel & Füllbrunn 2015; Haruvy, Lahav, & Noussair 2007; Hussam, Porter, & Smith 2008; Lei,
Noussair, & Plott 2001; Noussair & Powell 2010; Smith, Suchanek, & Williams 1988; Sutter et al. 2012;
Kirchler 2008; Cason & Samek 2015; Cheung, Hedegaard, & Palan 2014; Breaban & Noussair 2015;
Baghestanian, Lugovskyy, & Puzzello 2015; Bao, Hommes, & Makarewicz 2017) and variations of this
set-up are commonly used to motivate and test theories. Charness & Neugebauer (2019) and Cipriani
et al. (2018), for example, study the Modigliani-Miller invariance theorem and the Law of One Price
using a similar market design. However, the literature contributes exclusively to the trading of assets
with positive FV and knowledge about markets with no positive FV assets is lacking. We fill this gap
by investigating markets with non-positive FV assets. We find that applying the insights from existing
studies on assets with positive FV to assets with non-positive FVs may be misleading. For example, the
evidence from positive FV asset markets shows that bubbles are smaller in less complex market
environments (e.g., Huber & Kirchler 2012; Kirchler, Huber, & Stöckl 2012), thus suggesting that
bubbles are small in simple environments (such as markets where FVs are zero). Further evidence shows
the importance of loss aversion (Kahneman & Tversky 1979; Tversky & Kahneman 1991; Burgstahler
& Dichev 1997; Haigh & List 2005; DellaVigna 2009, among the others) thus suggesting that bubbles
are smaller when traders can make losses, in contrast with this study’s observations. In addition,
contrary to Porter & Smith (1995) and Childs & Mestelman (2004), who find that an increase in the
variance of the dividends has limited impact on the size of bubbles, we find that bubbles are larger when
variations in the dividends are observed, and they can be negative. The proposed study of shares with non-positive FV uncovers some of the largest bubbles in experimental asset markets. The study’s findings suggest that the current experimental literature, which is exclusively based on positive FV, may underestimate the severity of bubbles.

1. Experimental Design

Table 1 summarizes how the proposed $3 \times 2$ experimental design expands the experimental asset market literature. Two treatment dimensions are considered: the type of FV and the type of dividend. More precisely, we allow the FV to be positive, zero, or negative and dividends to be fixed or variable.

Table 1: Experimental design in context of existing literature

<table>
<thead>
<tr>
<th></th>
<th>Negative FV</th>
<th>Zero FV</th>
<th>Positive FV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk-free dividends</td>
<td>No literature</td>
<td>No literature&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Literature available&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Risky dividends</td>
<td>No literature</td>
<td>No literature</td>
<td>Literature available&lt;sup&gt;c&lt;/sup&gt;</td>
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Notes: This table summarizes the proposed $2 \times 3$ experimental design and related papers. Two treatment dimensions are considered: the type of FV and the type of dividend. We allow FV to be positive, zero, or negative and dividends to be fixed or variable.

<sup>a</sup>To our best knowledge, there is no SSW-type asset market literature fits in this cell. The “A1” markets in Smith et al. (2000) are related, as there is no dividend payment at the end each period, but the FV in their markets are still positive because the cumulative dividends are paid after the terminal period. There is also a strand of literature in fiat money flowing McCabe (1989), but the currency is always served as a medium of exchange.

<sup>b</sup>e.g., Porter & Smith (1995); Ball & Holt (1998).

<sup>c</sup>e.g., Bostian, Goeree, & Holt (2005); Dufwenberg, Lindqvist, & Moore (2005); Eckel & Füllbrunn (2015); Haruvy, Lahav, & Noussair (2007); Hussam, Porter, & Smith (2008); Lei, Noussair, & Plott (2001); Noussair & Powell (2010); Smith, Suchanek, & Williams (1988); Cason & Samek (2015).

Experimental asset markets with zero and negative FV

A total of 288 subjects (six groups of eight traders in each of the six treatments), inexperienced in asset market experiments, participated in the study. The experiment was programmed in z-Tree (Fischbacher 2007), and the subjects were recruited from SONA. Participants earned, on average, AUD $35, and the experiment lasted for approximately two hours. Before the beginning of the experiment, we asked traders to read an information sheet and sign a consent form. We then read the instructions out loud. Afterward, traders were given sufficient time to read the instructions on their own and ask
questions. We then implemented two practice rounds and asked traders to answer a set of quiz questions. After everyone correctly answered these questions, the asset market experiment started. When all traders completed the asset market experiment, we administered a short demographic questionnaire.

1.1 Market Environment

In the proposed asset market environment eight traders form a trading group to trade shares with each other for 15 trading periods. At the beginning of the first trading period, all traders have an initial endowment of tokens and shares to trade. Traders have 100 seconds of trading time during which they can buy and sell shares in each of the 15 trading periods. At the end of each trading period, each share pays a dividend (and/or incurs a holding cost as a negative dividend, depending on the treatments). Individual inventories of shares and tokens owned by a trader carry over from one period to the next. After period 15, we convert tokens to Australian Dollar at the rate of 50 tokens=$1.

The double auction mechanism is similar to Smith, Suchanek, & Williams (1988), where traders can buy and sell as many times as they wish in each trading period, as long as they have enough tokens or shares. Shares are only traded in whole units, while the prices are quoted to two decimal places. To buy a share in the experiment, a trader can accept the ask offer at the minimum ask price. Alternatively, the trader can make a bid offer to buy cheaper than the minimum ask price; if the bid is accepted, then the trader buys the corresponding shares, and receives nothing otherwise. Analogously, to sell a share in the experiment, a trader can accept the bid offer with the highest bid price. Alternatively, the trader can make an ask offer that is higher than the maximum bid price; if this bid is accepted, then the trader sells the corresponding shares, and sells nothing otherwise. It is important to note that ask and bid prices can take negative values. Outgoing tokens and shares in outstanding offers are frozen during the trading

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8 Each practice round corresponds to a real trading period, except that we hide the realization of the dividend and earnings at the end of the practice round. We also inform the participants that the practice rounds are for them to get familiar with the experimental software, and they are not paid for these rounds.
9 A trading group of eight traders is common in the experimental asset market literature. Many recent studies use trading groups with seven to ten individuals (e.g., Haruvy, Lahav, & Noussair 2007; Haruvy & Noussair 2006; Kirchler, Huber, & Stöckl 2012; Lei, Noussair, & Plott 2001; Stöckl, Huber, & Kirchler 2015; Bao et al. 2020).
10 Providing participants with heterogeneous endowments and different cash/asset ratios is common (Palan 2013). We describe the endowment for each trader in Appendix A2.
period in which the offers are made. All offers are canceled at the end of the trading period, and the corresponding frozen shares and tokens are released. The program is set up such that purchases occur at the minimum ask price and sales at the maximum bid price. Only one type of share exists, and no tax, brokerage, short-selling, or margin buying is considered. We report the experiment instructions and describe the treatments in Appendix A1.

The proposed experiment also involved a repetition (Hussam, Porter, & Smith 2008; King et al. 1993; Van Boening, Williams, & LaMaster 1993): each group of traders took part in a second trading block of this experiment, identical to the first trading block. Importantly, traders were unaware of the second trading block before it took place. However, they were aware that another task was scheduled after the first trading block. They also knew that at the end of the experiment, the outcomes of one of the two tasks (the first or second trading block) were to be randomly paid out. For brevity and because they are qualitatively similar, we mainly focus on the first trading block and report the complete findings from both blocks in Appendix A3.

1.2 Treatments

Table 2 provides further detail of the comprehensive 3 × 2 experimental design. As mentioned above, we allow variations in two dimensions: three risk-free fundamental values (negative, zero, and positive FVs) and the dividend process (fixed vs. variable). The first dimension explores assets with zero and negative FV generating fixed (risk-free) cash flows. The zero and negative FV assets mimic cryptocurrencies in the absence/presence of costs, such as brokerage and operational costs. The second treatment dimension allows us to investigate the trading behavior of normal assets that generate variable (risky) dividends and incur holding costs (which are larger, equal to, or smaller than the expected dividends in the negative, zero, and positive FV treatments). The comparison across the two treatment dimensions, holding the FV constant, allows to test the proposed models, which predict opposite pricing patterns, as elaborated in Section 3.

INSERT TABLE 2 ABOUT HERE
To investigate the behavior of assets with zero and negative fundamental values, share prices are allowed to take negative values in our experiment. To render subject bankruptcy unlikely, each participant receives a starting endowment of 1000 tokens (the equivalent of $20) in addition to a $15 show-up fee. Further, to minimize the likelihood of bankruptcy, participants with insufficient funds are not allowed to sell shares at negative prices or buy shares at positive prices.

We follow the convention to frame negative dividends as holding costs (e.g., Noussair, Robin, & Ruffieux 2001; Noussair & Powell 2010; Stöckl, Huber, & Kirchler 2015) and take additional measures to make losses (and gains) clear and salient. In particular, we include in the instructions a neutral sentence informing traders of the net loss (or profit) of holding one share in each period. Further, we force traders to acknowledge the correct net loss (or benefit) of holding a share per each period through the quiz administered before the first trading period. Last, we inform each trader of the net cash flow per share and the net cash flow from all shares he/she holds at the end of each period.

Treatments with shares that pay fixed dividends

In treatments (-2.5,-2.5), (0,0), and (2.5,2.5), the dividend in trading period $t \in \{1, 2, 3, \ldots, 15\}$ is fixed. The shares in the zero FV treatment (0,0) do not generate any cash flow in any trading period. We denote this treatment as (0,0) because shares pay 0 tokens as a dividend in both high and low states. We investigate the price patterns of shares with negative FVs by addressing treatment (-2.5,-2.5), where shares always charge 2.5 tokens as holding costs. We compare trading in these two markets to the standard assets addressed by the literature, which generate a positive FV. In treatment (2.5,2.5), the

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11 To completely rule out bankruptcy in all the proposed treatments, a $108 show-up fee would be required. However, paying such a large show-up fee is problematic for various reasons, including the potential to distort incentives (Azrieli, Chambers, & Healy 2018), and causes a large house money effect in multi-period financial settings (Ackert et al. 2006). The proposed measures proved successful in reducing the risk of bankruptcy. Only three participants’ payoffs were below $10, the minimum payment of a typical experiment conducted in the laboratory, in the first trading block.

12 The literature typically uses a two-point uniform distribution (e.g., Lei et al. 2001; Lei & Vesely 2009; Childs 2009) to capture randomness in the dividends. Lei et al. (2001) and van Boening et al. (1993) also suggest that using either a two-, four-, or a five-point symmetric dividend does not have a significant impact on the pricing patterns.
shares always pay 2.5 tokens, regardless of whether the state is high or low. Table 3 describes the FVs for each asset in each period under different treatments.

INSERT TABLE 3 ABOUT HERE

Treatments with shares that pay variable dividends

In treatments (-5,10), (-10,10), and (-15,10), we allow variations in the dividend process and implement a holding cost but keep the FV constant to the corresponding treatments with fixed dividends. The positive, zero, and negative FVs mimic the cases where the expected dividends are more than, equal to, and less than the holding costs. The dividends in this set of treatments always follow two-point uniform distributions depending on the dividend state at the end of each trading period. The states are pre-drawn with the help of a fair coin, and they are fixed across all treatments in this set. We describe the realizations of the state in Appendix A2. In the treatment with positive FV, the shares generate 10 tokens when the state is high and charge five tokens when the state is low. We denote this treatment as (-5,10). In the treatment with zero FV, the shares generate 10 tokens when the state is high and charge 10 tokens when the state is low. We denote this treatment as (-10,10). In the treatment with negative FV, the shares generate 10 tokens in the high state and charge 15 tokens in the low state. We denote this treatment as (-15,10). The risk-free FV of each treatment is the same as its counterpart with a fixed dividend. We describe the dividend for each asset in each period in Appendix A2.

2. Hypotheses

While standard theories (e.g., Samuelson 1965; Fama 1970) predict no systematic mispricing in the studied asset markets, a rich body of experimental evidence suggests otherwise. The two primary insights from previous asset market experiments are that (i) bubbles are common (most previous asset market experiments find price bubbles), and (ii) the bubble size increases with the complexity (i.e., number of mathematical manipulations required to calculate the FV) of the cash flow process (Huber & Kirchler 2012; Kirchler, Huber, & Stöckl 2012; Galanis 2018).

In the proposed experimental design, we systematically vary complexity across treatments. First, the zero fundamental value treatment (0,0) arguably presents the least complex environment as there is no cash flow—no mathematical manipulation is required to calculate the FV; analogously, (-
10,10) is less complex than the other treatments with variable dividends as the only mathematical step required is to take the expectation. Second, the cash flow is less complex in the treatments with constant FV (-2.5,-2.5), (0,0), (2.5,2.5) as compared to the treatments with variable FV (-10,5), (-10,10), (-10,15) since the latter involves taking an extra step— taking the expectation. Thus, we derive the following prediction based on the complexity argument:

**Hypothesis (complexity):** (i) Bubbles occur in (0,0); (ii) among the fixed dividend treatments, (0,0) is characterized by the smallest bubbles, and among the variable dividend treatments, (-10,10) is characterized by the smallest bubbles; (iii) for each level of FV, the treatment with fixed dividend is characterized by smaller bubbles than its variable dividend counterpart.

However, substantial evidence indicates that people are loss averse (Kahneman & Tversky 1979). In the context of the proposed experiment, the theory suggests that a cash outflow generates a more significant impact than a cash inflow of the same amount. A novel feature of the proposed experimental design is that we can test the role of loss aversion in asset markets as traders can have gains and losses in each trading period in the treatments with variable dividends. While our research hypothesis based on the previous experimental asset market literature predicts that bubbles are larger when dividends are variable, loss aversion generates the opposite prediction.

**Hypothesis (loss aversion):** (i) Among fixed dividend treatments, (-2.5,-2.5) is characterized by the smallest bubbles; (ii) for each level of non-negative FV, the treatment with fixed dividend is characterized by larger bubbles than its variable dividend counterpart.

### 3. Experimental Findings

In this section, we present the data obtained from the six treatments that took place in the Monash Laboratory of Experimental Economics (MonLEE) between July 2018 and March 2019. We

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13 Loss aversion depends on the assumption of the reference point. We follow Kahneman & Tversky (1979); Benartzi & Thaler (1995); Odean (1998) and assume that zero net cash flow (the status quo) serves as the neutral reference point. To make the gain and losses salient, we inform participants of the net cash flow generated by the dividends and holding costs after each trading period.

14 Breaban and Noussair (2015) find that a greater loss aversion measure of the trader cohort correlates to with a lower volume transacted, but they did not provide a clear interpretation of how loss aversion affects prices.
first report mispricing in the markets with zero and negative FVs (4.1) and then compare the results to mispricing in markets with positive FVs (4.2). Finally, this section compares mispricing in markets with fixed and variable dividends (4.3).

3.1 Bubbles in markets with zero and negative fundamental values

Figure 1a provides a first overview on the trading patterns for the three assets (0,0), (-2.5,-2.5), and (2.5,2.5) by illustrating average prices over trading periods across all groups. We observe that price trends are similar across the three assets. As in the standard asset with positive fundamental value, prices slowly decline over trading periods in (0,0) and (-2.5,-2.5). More importantly, we observe that average prices are positive in all the 15 trading periods for the asset with zero FV and in the first 10 periods for the asset with negative FV. The market with zero FV has an average price of 18.6 (tokens), significantly higher than zero, thus providing evidence of the presence of significant bubbles (p<.001).

The average price in market (2.5,2.5) is 26 (the average FV is 20), which is not statistically higher than in (0,0) (p=.2). The average price in (-2.5,-2.5) is 4.9, smaller than in the other two asset markets (p<.05 in both cases) but still significantly larger than zero (p<.01).

Finding 1: Bubbles occur in asset markets with zero and negative FVs.

3.2 Relative bubble size

Figure 1b corresponds to Figure 1a but illustrates the average bubble size or mispricing (i.e., price – fundamental value). Bubbles are common in asset markets with zero and negative FV. More precisely, we observe that bubbles occur in all trading periods of (0,0) and (-2.5, -2.5). In (2.5,2.5), bubbles occur in 13 out of the 15 trading periods. Importantly, we observe much larger bubbles in (0,0) and (-2.5, -2.5) than in (2.5, 2.5) in the first 10 trading periods. The average bubble size is 18.6 (p=.03)

15 We report trading volumes in Appendix A4. There are no significant differences in trading volumes across the different treatments.

16 Without further specification, all p-values reported in this paper are from two-tail Mann-Whitney tests on variables aggregated at the group level (so that all observations are independent).

17 Haruvy & Noussair (2006) introduced “price dispersion,” which we call “mispricing” in this study. Powell (2016) provides a comprehensive survey on the measurements of price bubbles. However, most of these measures are not well-defined in the zero FV treatments addressed by this study. Mispricing allows us to compare different treatments in the proposed experiment.
in (0,0) and 24.9 (p<.01) in (-2.5, -2.5), significantly larger than in (2.5, 2.5), where the average bubble size is 6.0.

**Finding 1b:** Bubbles in asset markets with zero and negative FVs are larger than in markets with positive FVs.

### 3.3 Bubbles and variances in the dividends

**Insert Figure 1b about here**

Table 4 corroborates the previous result using four Ordinary Least Squares (OLS) models of the following regression specification:

\[ pd_{g,t} = c + \delta_1 I_{g,t}^{\text{zero}} + \delta_2 I_{g,t}^{\text{negative}} + \sum_{\tau=2}^{15} \alpha_\tau I_{g,t}^\tau + \gamma_1 female_{g,t} + \gamma_2 knowledge_{g,t} + \epsilon_{g,t}, \]

where \( pd_{g,t} \) is the mispricing of group \( g \) in trading period \( t \); \( I_{g,t}^{\text{zero}} \) and \( I_{g,t}^{\text{negative}} \) are indicator variables that take value 1 when the corresponding logic statement is true, and 0 otherwise.

For example, \( I_{g,t}^{\text{zero}} \) and \( I_{g,t}^{\text{negative}} \) take value 1 when the FV is zero and negative, respectively; and \( I_{g,t}^\tau \) takes value 1 when \( t = \tau \); \( female_{g,t} \) documents the number of female traders in the group, and \( knowledge_{g,t} \) records the number of traders who have taken courses in asset pricing. \( I_{g,t}^{\text{zero}} \) and \( I_{g,t}^{\text{negative}} \) capture the differences in mispricing caused by changes in FV; \( I_{g,t}^\tau \) controls for the heterogeneity across periods; \( female_{g,t} \) and \( knowledge_{g,t} \) control for some potentially important variations across groups. We cluster the standard errors at the group level and allow variations in the control variables reported in Table 4 to verify the robustness of our second finding.

**Insert Table 4 about here**

In Model 1, we exclude the control variables for period effects (\( \sum_{\tau=2}^{15} I_{g,t}^\tau \)), number of females in the group (\( female_{g,t} \)), and participants’ knowledge on asset pricing (\( knowledge_{g,t} \)) and sequentially add these controls in Models 2–4. The point estimates of the treatment effect (\( \delta_1 \) and \( \delta_2 \)) are economically large and significantly higher than zero in all regression specifications. We observe, for example, that the coefficient for negative (zero) FV in Model 1 is approximately four (two) times as large as the constant for the positive FV.

**Finding 2:** Bubbles in asset markets with zero and negative FVs are larger than in markets with positive FVs.
Figure 2a illustrates the trading patterns in the treatments with variable dividends (-5, 10), (-10, 10), and (-15, 20). We observe that prices are positive in all trading periods of treatments (-10, 10) and (-5,10), and in 14 out of 15 periods in (-15, 10). In line with the asset markets with fixed dividends, prices start very high and then decline over trading periods. The average price in (-10, 10) is 28 (tokens), which is not statistically different from 27.4 in (-15, 10) (p=1). The average price in (-5, 10) is 39.9, larger than in (-10, 10) and (-5,10) but statistically insignificant (p=.34 and p=.15, respectively). The average price in (-10, 10) and (-15, 10) is significantly higher than 0 (p<.01), and the price is insensitive to the drop of the FV from positive to zero and then negative when the dividend is variable. This result provided further evidence of the existence of large bubbles in zero and negative FV asset markets.

INSERT FIGURE 2a ABOUT HERE

Figure 2b corresponds to Figure 2a but plots the average bubble size. Bubbles are prevalent in all the three treatments. We observe that bubbles occur in all trading periods in all treatments except the last period of (-15,10). In addition, (-15,10) is characterized by the largest bubbles in the first 14 periods, while (-5,10) is characterized by the smallest bubbles in the first seven periods and behaves similarly to (-10,10) afterward. The average bubble size of (-15,10) is 47.4, which is larger than 28 (p=.15) in (-10,10) and 19.9 (p=.055) in (-5,10).

INSERT FIGURE 2b ABOUT HERE

Next, we investigate whether bubbles increase (complexity hypothesis) or decrease (loss aversion hypothesis) when we introduce the variance of dividends. Figure 3 provides a first illustration by pooling the three fixed and three variable dividend treatments and illustrates the average bubble size throughout the experiment. A clear pattern emerges. Bubbles are larger when dividends are variable, which is consistent with our complexity hypothesis. The average bubble size is 31.8, with variable dividends compared to only 16.5 when dividends are fixed (p<.05).

INSERT FIGURE 3, 3a-3c ABOUT HERE

Figures 3 a-c correspond to Figure 3 but compares bubbles across the different treatments holding FV constant. We observe that the bubble size is larger in most periods when the dividend is
variable, regardless of the FV (negative, zero, or positive). In addition, (-10,10) has a larger bubble than (0,0) in all 15 periods, (-15,10) has a larger bubble than (-2.5,-2.5) in 13 out of 15 periods, and (-5,10) has a larger bubble than (2.5,2.5) in 14 out of 15 periods. In Table 5, we report the average bubble size for each treatment. The bubble size for (-10,10) is 28, 18.6 for (0,0) (p=.63), 19.9 for (-5,10), and 6.0 for (2.5,2.5) (p=.037). The bubble size is 47.4 for (-15,10) and 24.9 for (-2.5,-2.5) (p=.055).

We also run different OLS regressions to include all dependent observations across trading periods. As a result, we obtain a comprehensive view on the bubble pattern across treatments. We estimate the following model:

\[
p_{d_{g,t}} = c + \beta_1 f_{g,t}^{(-5,10)} + \beta_2 f_{g,t}^{(0,0)} + \beta_3 f_{g,t}^{(-10,10)} + \beta_4 f_{g,t}^{(-2.5,-2.5)} + \beta_5 f_{g,t}^{(-15,10)} \\
+ \sum_{\tau=2}^{15} \alpha_{\tau} T_{g,t}^\tau + \gamma_1 female_{g,t} + \gamma_2 knowledge_{g,t} + \epsilon_{g,t},
\]

where \( I \) is an indicator variable, which takes value 1 if group \( g \) participates in the treatment indicated by the superscript, and 0 otherwise. The set of indicator variables \( I \) compares the bubble size across treatments. Table 6 plots the estimation of the regression model with variations in the control variables.

In Model 1, we exclude the control variables for the period effects (\( \alpha_{t} T_{g,t}^\tau \)), number of females in the group (\( female_{g,t} \)), and participants’ knowledge on asset pricing (\( knowledge_{g,t} \)) and subsequently include these controls in Models 2–4. The relative bubble size (point estimates of \( \beta \)’s) is robust to the inclusion of different control variables. In Model 4, which includes most controls, the previous results hold: (i) holding the nature of the dividend (fixed or variable) constant, the treatment with the lower FV is always characterized by the larger bubble size, (ii) fixing the level of the FV, the price is always higher in the variable dividend treatment. With respect to bubbles sizes, we find the following ordering:

\[(2.5,2.5)<(0,0)<(-2.5,-2.5)<(-5,-10)<(-10,10)<(-15,10).\]
The point estimates from the four models also show that the treatment effects are meaningful and large. For example, in Model 4, the point estimate for the positive variable dividend treatment $(I_{y,t}^{(-5,10)})$ is 21.54, which implies that the bubble size of (-5,10) is more than 84% bigger than that of (2.5,2.5) in the first trading period.

**Finding 3:** Bubbles are larger in asset markets with variable dividends than in the presence of fixed dividends. Bubbles are the largest in asset markets with negative FV and variable dividends and the smallest in asset markets with positive FV and fixed dividends.

Bubbles occur in all treatments, but their size is hard to reconcile with loss aversion predictions based on Prospect Theory. For example, (-2.5,-2.5) markets are characterized by larger bubbles than (2.5,2.5) and (0,0) markets, and in treatments with variable dividends and potential losses, bubbles are larger than in their fixed dividend counterparts, in contrast with the predictions of loss aversion. A model based on complexity correctly predicts that variations in the dividends inflate the bubble, but it neither explains the large bubbles in the markets with zero FV nor predicts the relative bubble size within each set (fixed dividend or variable dividend) of treatments. One explanation of these patterns is that there are systematic difference in term of understanding of the tasks across treatments, but this does not seem to be the case. First, from the post-experiment questionnaire, only 6% of participants find the instructions difficult to understand and there is no significant difference across treatments. Second, there is no significant difference in the speed of finishing quiz questions, nor in the demographic variables we collected across treatments (p>0.1 using F-tests). The next section provides and tests an alternative explanation based on trader expectations.

### 4. An Explanation Based on Price Expectations

Bubbles may be driven by trader expectations about the behavior of other traders in the different treatment scenarios (e.g., Cheung, Hedegaard, & Palan 2014; Holt, Porzio, & Song 2017). In particular, traders may believe that other traders are willing to pay high prices for assets with zero FV and higher prices for assets with variable dividends compared to fixed dividends. In this case, an optimal strategy...
is to pay high prices for these assets to then sell them for even higher prices. To test this alternative explanation, we conduct a second experimental study.

4.1 Study 2: The guessing game

We invited 83 participants, inexperienced in asset market experiments, to analyze how expectations help explain the observed price patterns. The proposed guessing game was programmed in z-Tree (Fischbacher 2007), and the participants were recruited from SONA. Participants earned, on average, AUD $17, and sessions lasted for approximately 45 minutes. Before the experiment, participants read an information sheet and signed a consent form. Participants read the instructions and were then asked to guess prices in different asset markets. The instructions and a short demographic questionnaire are reported in Appendix A5.

The set-up of the guessing game is as follows. Each participant guesses the average price of each of the 15 periods in the first trading block of one asset market and then the average price for 15 periods in another asset market. We randomize the two sets of instructions. We do not provide participants with any information about their performance throughout the experiment. Guessers are monetarily incentivized using the binary scoring rule (Hossain & Okui 2013): each guess within five tokens of the actual price is awarded $2. To examine (i) whether guessers expect large bubbles in zero FV treatments, and (ii) whether they expect different bubble sizes among markets with different FV, the analysis considers the following two treatments.

4.2 Treatments (guessing game)

(0,0) vs. (-10,10)

We ask the first set of participants (n=54) to guess the average price across the studied six markets (to moderate some extreme values) in all the 15 trading periods of asset markets (0,0) and (-10,10). We denote this treatment as “(0,0) vs. (-10,10)”. This approach allows us to investigate trader expectations about the bubbles in zero FV treatments.

(-15,10) vs. (-10,10)
We let the second set of participants (n=29) guess the average prices (across the six markets of all the 15 trading periods) of (-15,10) and (-10,10). We denote this treatment as “(-15,10) vs. (-10,10)”. This treatment explores guessers’ expectation about the relative bubble sizes between (-15,10) and (-10,10).

4.3 Results (guessing game)

Figure 4 plots the median bubble size based on all the prices guessed. Among the 83 guessers, only four guessed at least one zero price, and none of them guessed a single negative price. Participants predicted large bubbles and anticipated the relative bubble size between these three treatments. The average predicted bubble size is 41 (tokens) for (0,0), 51 for (-10,10), and 99 for (-15,10), which are all larger than the actual values (p<.05 for all three cases).

INSERT FIGURE 4 ABOUT HERE

To compare these bubble sizes rigorously, we estimate the following model:

$$\bar{d}_i = c + \beta_1 I_i^{(-15,10)} + \beta_2 I_i^{(-10,10)} + \gamma_1 I_{i,male} + \gamma_2 I_{i,knowledge} + \epsilon_i$$

where $\bar{d}_i$ is the average bubble size guessed by guesser $i$, $I$ is an indicator variable that takes value 1 when the logic condition in its superscript is true. For example, $I_i^{(-15,10)}$ takes value 1 when the treatment guessed by $i$ is (-15,10); $I_{i,male}$ takes value 1 when $i$ is a male; $I_{i,knowledge}$ takes value 1 when $i$ had taken courses related to asset pricing.

Table 7 plots the estimation of the regression results considering variations in the control variables and estimation methods. Model 1 only includes treatment dummies and is estimated by OLS. Model 2 includes the same set of variables as Model 1 but is estimated using the quantile regression (QR) method to moderate the impact of outliers in the sample. Model 3 includes all the control variables and is estimated by OLS to check the robustness of this specification. Model 4 corresponds to Model 3 but uses QR. We cluster the errors at the individual level in all regressions. These models show that the relative bubble sizes observed in Figure 4 are robust to different model specifications. In Model 4, after controlling for individual characteristics and moderating the impact of outliers, we find that guessers predict a large bubble of 58 (tokens) in (0,0), which is significantly higher than zero (p<.01). Guessers
also correctly predict that (-15,10) has the largest bubble, which is 77.56 higher than (0,0) and 56.36 higher than (-10,10) (p<.05 in both cases).

**Finding 4:** Individuals predict (i) the positive price in the treatments with zero FV, (ii) that variations in the dividends increase the bubble size, and (iii) that the bubble size increases when the FV drops from zero to negative values. Expectations motivate the price patterns that complexity theory cannot explain.

### 5. Conclusion

Thousands of cryptocurrencies have been created in the last decade (2009-2019), and their market capitalization rocketed from close to zero to more than half a trillion US dollars at their peak. This price surge may be due to several factors. For example, the exchange of cryptocurrencies may be stimulated by illicit market activities and/or caused by manipulation carried out by large players. Traders in cryptocurrency markets may also be subject to self-selection. In the present analysis, we exclude these complications and provide a first glance into the price patterns in markets with zero and negative FV assets using a controlled experiment.

In the primary study, we fix the risk-free FV (positive, zero, or negative) of shares and allow the nature of the dividends to vary in two sets of treatments. In the first set of treatments, the shares generate risk-free (fixed) cash-flows, which mirror the nature of cryptocurrencies (zero FV) and a realistic scenario where trading cryptocurrencies involves costs in different forms (negative FV). In the second set of treatments, the shares pay risky (variable) cash flows, which mimic the shares from sunset industries with high holding costs. We find several interesting patterns. First, bubbles occur in all treatments, even in the simple zero FV case. Second, the bubbles inflate when the FV drops to zero and negative values, *ceteris paribus*. Third, the bubbles expand when the cash flow is variable, while the level of FV is fixed. These findings suggest that zero and negative FV *per se* foster price bubbles.
Beyond exploring the relative bubble sizes across treatments, we also investigate the relationship between trader expectations and bubbles. We find that expectations match the actual relative bubble size. Our findings suggest that traders have a natural tendency toward trading assets with non-positive FV at positive prices, even without considering other features that may lead to price surges. This result also implies that the existing literature may underestimate the severity of price bubbles for these types of assets. Thus, it seems important to regulate all assets with non-positive FVs.

This study is a first attempt to probe into the new domain of assets with non-positive FVs. Although ample evidence shows that lab experiments capture the essence of the real-world behavior (see e.g., Haigh & List 2005; Benz & Meier 2008; Fehr & Leibbrandt 2011), caution should be exercised when extrapolating our findings to outside the laboratory environment. The negative cash flow in our experiment is a proxy for holding costs, but traders in the real market may view it differently. Our study also excludes aspects of cryptocurrencies like mining and black market transactions. More research is encouraged to increase the understanding of markets with zero FV and the external validity of these results. Apart from studying zero and negative FV per se, we envision several important extensions for future research. It seems worthwhile to switch between positive and negative FV regimes to address the asset market performance in economic booms and deep recessions. Further, the potential mechanisms that cause behavioral differences between positive and non-positive regimes is another promising area of research.
References


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Tables

Table 1: Experimental design in context of existing literature

<table>
<thead>
<tr>
<th></th>
<th>Negative FV</th>
<th>Zero FV</th>
<th>Positive FV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk-free dividends</td>
<td>No literature</td>
<td>No literature⁵</td>
<td>Literature available⁶</td>
</tr>
<tr>
<td>Risky dividends</td>
<td>No literature</td>
<td>No literature</td>
<td>Literature available⁶</td>
</tr>
</tbody>
</table>

Notes: This table summarizes the proposed 2 × 3 experimental design and related papers. Two treatment dimensions are considered: the type of FV and the type of dividend. We allow FV to be positive, zero, or negative and dividends to be fixed or variable.

⁵ To our best knowledge, there is no SSW-type asset market literature fits in this cell. The “A1” markets in Smith et al. (2000) are related, as there is no dividend payment at the end each period, but the FV in their markets are still positive because the cumulative dividends are paid after the terminal period. There is also a strand of literature in fiat money flowing McCabe (1989), but the currency is always served as a medium of exchange.

⁶ e.g., Porter & Smith (1995); Ball & Holt (1998).

⁷ e.g., Bostian, Goeree, & Holt (2005); Dufwenberg, Lindqvist, & Moore (2005); Eckel & Füllbrunn (2015); Haruvy, Lahav, & Noussair (2007); Hussam, Porter, & Smith (2008); Lei, Noussair, & Plott (2001); Noussair & Powell (2010); Smith, Suchanek, & Williams (1988); Cason & Samek (2015).
### Table 2: Experimental design

<table>
<thead>
<tr>
<th></th>
<th>Positive FV</th>
<th>Zero FV</th>
<th>Negative FV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed dividends</td>
<td>(2.5,2.5)</td>
<td>(0,0)</td>
<td>(-2.5,-2.5)</td>
</tr>
<tr>
<td>Variable dividends</td>
<td>(-5,10)</td>
<td>(-10,10)</td>
<td>(-15,10)</td>
</tr>
</tbody>
</table>

Notes: This table provides details on the proposed 3×2 experimental design. The first treatment dimension varies the level of FV, and the second dimension varies the dividend processes. The numbers in the brackets are the net cash flows generated by a share in the high and low states, respectively. Each treatment is assigned six independent groups of eight traders.
Table 3: Risk-free fundamental values for positive, zero, and negative treatments

<table>
<thead>
<tr>
<th>Trading Period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatments</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive</td>
<td>37.5</td>
<td>35</td>
<td>32.5</td>
<td>30</td>
<td>27.5</td>
<td>25</td>
<td>22.5</td>
<td>20</td>
<td>17.5</td>
<td>15</td>
<td>12.5</td>
<td>10</td>
<td>7.5</td>
<td>5</td>
<td>2.5</td>
</tr>
<tr>
<td>Zero</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Negative</td>
<td>-37.5</td>
<td>-35</td>
<td>-32.5</td>
<td>-30</td>
<td>-27.5</td>
<td>-25</td>
<td>-22.5</td>
<td>-20</td>
<td>-17.5</td>
<td>-15</td>
<td>-12.5</td>
<td>-10</td>
<td>-7.5</td>
<td>-5</td>
<td>-2.5</td>
</tr>
</tbody>
</table>

Notes: This table lists the risk-free FV for all treatments in each period. The value in period $t$ ($FV_t$) is calculated as $FV_t = \sum_{t=1}^{15} E(d_t)$, where $d_t$ is the (expected) dividend in period $t$. 
Table 4: Comparison of the bubble sizes in treatments with positive, zero, and negative FVs

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero FV ($\delta_1$)</td>
<td>12.60**</td>
<td>12.67**</td>
<td>14.86**</td>
<td>14.11**</td>
</tr>
<tr>
<td></td>
<td>0.019</td>
<td>0.021</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>Negative FV ($\delta_2$)</td>
<td>20.46***</td>
<td>20.01***</td>
<td>19.66***</td>
<td>20.94***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Constant (c)</td>
<td>5.96*</td>
<td>15.05**</td>
<td>20.50***</td>
<td>21.92***</td>
</tr>
<tr>
<td></td>
<td>0.063</td>
<td>0.017</td>
<td>0.010</td>
<td>0.006</td>
</tr>
<tr>
<td>Period effects ($\Sigma \alpha_t I^t$)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># of females (female)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># have taken asset pricing classes (knowledge)</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: This table shows the estimation results for whether FVs have a significant impact on the bubble size. We use 262 observations for each regression, and all standard errors are clustered at the group level (we exclude eight trading periods where no trade takes place). We report the p-value under each point estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Table 5: Actual bubble size in different treatments

<table>
<thead>
<tr>
<th></th>
<th>Positive FV</th>
<th>Zero FV</th>
<th>Negative FV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed dividends</td>
<td>6.05</td>
<td>18.56</td>
<td>24.92</td>
</tr>
<tr>
<td>Variable dividends</td>
<td>19.91</td>
<td>28.00</td>
<td>47.42</td>
</tr>
<tr>
<td>with loss possible</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p-value</td>
<td>0.037</td>
<td>0.63</td>
<td>0.055</td>
</tr>
</tbody>
</table>

Notes: This table reports the bubble size (mispricing) for each treatment. The p-value in the bottom row compares the bubble size of the fixed dividend treatment with the variable one at the corresponding level of FV.
Table 6: Comparison of the bubble sizes in treatments with fixed and variable dividends

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Variable ($\beta_1$)</td>
<td>20.61*</td>
<td>20.69*</td>
<td>20.56*</td>
<td>21.54</td>
</tr>
<tr>
<td></td>
<td>0.094</td>
<td>0.097</td>
<td>0.093</td>
<td>0.131</td>
</tr>
<tr>
<td>Zero fixed ($\beta_2$)</td>
<td>12.60**</td>
<td>12.68**</td>
<td>13.59**</td>
<td>13.24**</td>
</tr>
<tr>
<td></td>
<td>0.012</td>
<td>0.013</td>
<td>0.020</td>
<td>0.020</td>
</tr>
<tr>
<td>Zero variable ($\beta_3$)</td>
<td>22.05**</td>
<td>22.13**</td>
<td>22.58**</td>
<td>21.87**</td>
</tr>
<tr>
<td></td>
<td>0.022</td>
<td>0.024</td>
<td>0.025</td>
<td>0.040</td>
</tr>
<tr>
<td>Negative fixed ($\beta_4$)</td>
<td>20.46***</td>
<td>19.72***</td>
<td>19.58***</td>
<td>20.13***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Negative variable ($\beta_5$)</td>
<td>41.47***</td>
<td>41.55***</td>
<td>41.42***</td>
<td>41.00***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Constant (c)</td>
<td>5.96*</td>
<td>23.67***</td>
<td>25.91***</td>
<td>26.45***</td>
</tr>
<tr>
<td></td>
<td>0.051</td>
<td>0.000</td>
<td>0.006</td>
<td>0.007</td>
</tr>
<tr>
<td>Period effects ($\Sigma \alpha_t \tau^t$)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># of females (female)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># have taken asset pricing classes (knowledge)</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: This table shows the estimation results for whether the nature of the dividends has a significant impact on the bubble size. We use 532 observations for each regression, and all standard errors are clustered at the group level (we exclude eight trading periods where no trade takes place). The data refer to the first trading block. We report the p-value under each point estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Table 7: Comparison of the guessed bubble sizes in different treatments

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative variable ($\beta_1$)</td>
<td>99.36*</td>
<td>67.33**</td>
<td>98.23*</td>
<td>77.56**</td>
</tr>
<tr>
<td></td>
<td>0.064</td>
<td>0.014</td>
<td>0.082</td>
<td>0.017</td>
</tr>
<tr>
<td>Zero variable ($\beta_2$)</td>
<td>20.13</td>
<td>17.86</td>
<td>19.73</td>
<td>21.2</td>
</tr>
<tr>
<td></td>
<td>0.398</td>
<td>0.247</td>
<td>0.429</td>
<td>0.160</td>
</tr>
<tr>
<td>Gender ($\gamma_1$)</td>
<td>-</td>
<td>-</td>
<td>-70.79*</td>
<td>-11.33</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.091</td>
<td>0.634</td>
</tr>
<tr>
<td>Knowledge ($\gamma_2$)</td>
<td>-</td>
<td>-</td>
<td>-8.14</td>
<td>-24.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.884</td>
<td>0.296</td>
</tr>
<tr>
<td>Constant ($c$)</td>
<td>125.47***</td>
<td>50.00***</td>
<td>158.13***</td>
<td>58.00***</td>
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<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.007</td>
</tr>
<tr>
<td>Estimation method</td>
<td>OLS</td>
<td>QR</td>
<td>OLS</td>
<td>QR</td>
</tr>
</tbody>
</table>

Notes: This table shows the estimation results for whether the nature of the dividends has a significant impact on the bubble size. We use 166 observations for each regression, and all standard errors are clustered at the individual level. Quantile regressions are estimated for the median response (quantile=0.5). We report the p-value under each point estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The reason why OLS regressions have much larger constants is that some guessers indicated large numbers, and OLS estimation is sensitive to outliers.
Figures

Figure 1a: Prices for treatments with fixed dividends (trading block 1)

Notes: This graph shows the average price of six markets for each treatment with fixed dividend over the 15 trading periods in trading block 1.
Figure 1b: Bubble size of treatments with fixed dividends (trading block 1)

Notes: This graph shows the bubble size of six markets for each treatment over the 15 trading periods in trading block 1.
Figure 2a: Prices for treatments with variable dividends (trading block 1)

Notes: This graph shows the average price of six markets for each treatment with variable dividend over the 15 trading periods in trading block 1.
Figure 2b: Bubble size of treatments with variable dividends (trading block 1)

Notes: This graph shows the average bubble size of six markets for each treatment over the 15 trading periods in trading block 1.
Figure 3: The average bubble size of three variable dividend treatments and three fixed dividend treatments

Notes: This graph shows the average bubble size of three treatments where dividends are variable and the average mispricing of three treatments where dividends are fixed over the 15 trading periods in trading block 1.
Figure 3a: The average bubble size of (2.5,2.5) and (-5,10)

Notes: This graph shows the average bubble size of six markets for the (2.5,2.5) and (-5,10) treatments over the 15 trading periods in trading block 1.
Figure 3b: The average bubble size of (0,0) and (-10,10)

Notes: This graph shows the average bubble size of six markets for the (0,0) and (-10,10) treatments over the 15 trading periods in trading block 1.
Figure 3c: The average bubble size of (-2.5,-2.5) and (-15,10)

Notes: This graph shows the average bubble size of six markets for the (-2.5,-2.5) and (-15,10) treatments over the 15 trading periods in trading block 1.
Figure 4: Prices predicted for (-15,10), (-10,10), and (0,0)

Notes: This graph shows the median guessed price of all 15 trading periods in (-15,10), (-10,10), and (0,0).
Appendix

A1. Instructions for the main study treatment (-10,10)

Here, we provide the instructions for the treatments with zero FV and variable dividends. The instructions for the other treatments only differ in the value of the dividends and holding costs and available upon request.

Instructions

Thanks for your participation! There are 2 tasks in this experiment, and you will be paid for only 1 randomly chosen task in private and in cash at the end of the experiment. The instructions below describe task 1. The instructions of task 2 will be announced after task 1.

1. General Instructions (Task 1)

Please read this instruction carefully. The amount you will earn depends on the decisions you make, thus a good understanding of the instructions is crucial to your earnings. After reading the instructions, there will be a 2-period practice round to help you familiarize with the experimental software. The earnings in the practice round do not enter your final payment. After the practice round, there will be some questions to guarantee that everyone understands the task. The main part will start after everyone has answered the questions correctly.

The game money in this task is called Token and the game commodity that can be traded is called Goods. Prices quoted in the task have two decimal places and Goods must be traded in whole units.

If you have any questions during the task please raise your hand and the experimenter will come to you. Please do not ask your questions out loud, or attempt to communicate with other participants, or look at other participants’ computer screens at any time during the task. Please turn your phone to silent mode and place it on the floor.

2. Market Environment

Market setup

In this task, 8 participants (including you) form a market. Each participant can appear as a buyer and a seller at the same time to buy and sell Goods. This market will be open for 15 trading periods. At
the beginning of the first period, participants are endowed with Tokens and Goods for trading. Tokens and Goods you hold at the end of each trading period will carry over to the subsequent period. In each trading period, the market will be open for 100 seconds, during which you may buy and sell Goods.

**Dividends and holding costs**

After each trading period, each Good pays a dividend and incurs a holding cost. The dividend can either be 20 Tokens or 0 Token with equal probability, while the holding cost is always 10 Tokens per Good.

At the end of period 15, each Good pays a dividend and incurs a holding cost (as in previous periods) and then become useless.

**To sum up**

Each Good earns a dividend minus a holding cost after each trading period ends. The dividend in each period can either be 20 or 0 Tokens per Good, but the holding cost is always 10 Tokens per Goods. So the net benefit of holding a Good is either 10 Tokens or -10 Tokens per period with equal probability. Goods become useless after the payment of the dividend and the charge of the holding cost in period 15.

**3. Earnings**

The amount of Tokens you will earn in task 1 is equal to:

Tokens you receive at the beginning of the task

+ Dividends you receive throughout the task

- Holding costs you paid throughout the task

+ Tokens received from sales of Goods

− Tokens spent on purchases of Goods

The Tokens will be converted to Australian Dollars with the exchange rate of 50 Tokens=$1. If task 1 is chosen for the payment, then your will receive the amount converted from the Tokens plus a $15 show-up fee.
4. How to Use the Software

There are two ways to buy Goods. Firstly, you can buy from an existing seller by accepting the ask offer made by the seller. To do this, you need to enter the quantity you want to buy and then click the “Buy” button. The quantity you get is the minimum of the quantity offered by the seller and the quantity you entered, and the amount of Token you pay is the ask price times the quantity. You must buy from the lowest (cheapest) ask price.

Secondly, you can make a bid offer to be accepted by potential seller(s). To do this, you need to enter the price and quantity you want to buy and then click the “Bid to buy” button. The quantity you get is the amount accepted by the potential seller(s). If no one accepts your bid offer, then you buy nothing. You must submit a bid price lower than the lowest ask price, otherwise, you should use the “Buy” button.

Similarly, there are two ways to sell Goods. Firstly, you can sell to an existing buyer by accepting the bid offer made by the buyer. To do this, you need to enter the quantity you want to sell and then click the “Sell” button. The quantity you sell is the minimum of the quantity offered by the buyer and the quantity you entered, and the amount of Tokens you receive is the bid price times the quantity. You must sell to the highest (most lucrative) bid price.

Secondly, you can make an ask offer to be accepted by potential buyer(s). To do this, you need to enter the price and quantity you want to sell and then click the “Ask to sell” button. The quantity you sell is the amount accepted by the potential buyer(s). If no one accepts your ask offer, then you sell nothing. You must submit an ask price higher than the highest bid price, otherwise, you should use the “Sell” button.

Bid or ask offers cannot be withdrawn once made and the corresponding Tokens and Goods are frozen. This means that if you have non-transacted ask/bid offers outstanding, then the amount of Goods/Token you may further use to sell/buy is less than the balance that appears on your screen. Non-transacted offers will be cancelled at the end of each trading period and the frozen Tokens and Goods will defreeze. You cannot buy from or sell to yourself. Please turn to the next page to see the window you will see during the trading time.
A2. Details about endowments and dividends in the main study

In this section, we provide more details about endowments, and realization of the dividends in each trading periods.

A3. Combined analysis for both trading blocks

In this section, we replicate the analysis presented in the main paper but include data from both trading blocks. Results using both trading blocks are qualitatively similar as compared to using only the first block.

Bubbles in markets with zero and negative fundamental values

Relative price levels between (2.5,2.5), (0,0), and (-2.5,-2.5) do not change when including the second trading block. The market with zero fundamental value has an average price of 10.1 (Tokens), which is significantly higher than zero providing evidence for significant mispricing/bubbles (p<.01). The average price in market (2.5,2.5) is 23.1 (the average fundamental value is 20), which is statistically higher than in (0,0) (p=.016). The average price in (-2.5,-2.5) is -2.89 (the average fundamental value is -20), which is smaller than in the other two asset markets (p<0.05 in both cases) but significantly bigger than its FV -20 (p<.01).

Finding A1: There are bubbles in asset markets with zero and negative fundamental values.

Relative bubble size

Bubbles are omnipresent in asset markets with zero and negative fundament value. More precisely, we observe that there are bubbles in all trading periods of (0, 0) and (-2.5, -2.5). In (2.5,2.5), there are bubbles in 14 out of the 15 trading periods. Importantly, we observe larger bubbles in (0,0)
and (-2.5, -2.5) than in (2.5, 2.5) in the first 11 trading periods. The average bubble size is 10.1 in (0,0) and 17.1 in (-2.5, -2.5), which is significantly larger in than in (2.5, 2.5) where it is 3.1 (p=.1 for (0, 0) and p=.078 for (-2.5, -2.5)).

Table A3 correspond to Table 4 and compares bubbles in zero and negative FV markets using OLS models of the following regression specification:

$$pd_{g,t} = c + \delta_1 I_{g,t}^{\text{zero}} + \delta_2 I_{g,t}^{\text{negative}} + \sum_{t=2}^{15} \alpha_t I_{g,t}^\tau + \gamma_1 female_{g,t} + \gamma_2 knowledge_{g,t} + \epsilon_{g,t}.$$  

We cluster the standard errors at the group level in our analyses and vary control variables in Table A3 to check for the robustness of our second finding.

**Finding A2:** Bubbles in asset markets with zero and negative fundamental values are larger than in markets with positive fundamental values.

**Bubbles and variances in the dividends**

As in the asset markets with fixed dividends, prices start very high and then decline over trading periods. The average price in (-10, 10) is 17.36 (Tokens), which is not statistically different from 26.42 in (-5, 10) (p=.2). The average price in (-15, 10) is 15.8 which is very similar to (-10, 10), but statistically smaller than (-5, 10) (p=.025). The average price in (-10, 10) and (-15, 10) is significantly bigger than
0 \text{ (p<.01)} \) and the price is insensitive to the drop of the FV from 0 to -2.5 when the dividend is variable, providing further evidence for bubbles in zero and negative FV asset markets.

When we convert the price level to mispricing, we find bubbles are prevalent in all three treatments. We observe that there are bubbles in all trading periods among all three treatments but in the second period of (-5,10). (-15,10) has the biggest bubbles, followed by (-10,10) and (-5,10) the smallest bubbles. The average bubble size of (-15,10) is 35.8, which is larger than 17.36 in (-10,10) and 6.42 in (-5,10) (p=.1 for (-10,10) and p=.037 for (-5,10)).

Next, we study whether bubbles increase (hypothesis on complexity) or decrease (loss aversion) when we introduce variances in dividends. We pool the three fixed and three variable dividend treatments and find bubbles are larger when dividends are variable, which is consistent with our complexity hypothesis. The average bubble size is 19.86 with variable dividends compared to only 10.10 when dividends are fixed (p=.018). Table A4 show the pattern is qualitatively true regardless of fundamental value (negative, zero, and positive). The price dispersion for (-10,10) is 17.36 while it is 10.12 for (0,0) (p=.34); it is 6.42 for (-5,10) and 3.06 for (2.5,2.5) (p=.1); and it is 35.80 for (-15,10) and 17.11 for (-2.5,-2.5) (p=.01).

INSERT TABLE A4 ABOUT HERE

We also run OLS regressions to include all dependent observations across trading periods to have a panoramic view on the bubble pattern across treatments. In concrete, we estimate the following model:

\[
p_{d|g,t} = c + \beta_1 f^{(-5,10)}_{g,t} + \beta_2 f^{(0,0)}_{g,t} + \beta_3 f^{(-10,10)}_{g,t} + \beta_4 f^{(-2.5,-2.5)}_{g,t} + \beta_5 f^{(-15,10)}_{g,t} \\
+ \Sigma_{t=2}^{15} \alpha_t T^\tau_{g,t} + \gamma_1 female_{g,t} + \gamma_2 knowledge_{g,t} + \epsilon_{g,t}.
\]

Table A5 correspond to table 6 and plots the estimation of the regression model with variations on the control variable.

INSERT TABLE A5 ABOUT HERE
We exclude the control terms for period effects ($\alpha_t T^t_{g,t}$), number of females in the group ($female_{g,t}$) and participants’ knowledge on the asset pricing ($knowledge_{g,t}$) in Model 1 and include these controls from Model 2 to Model 4. The relative bubble size (point estimates of $\beta$s) are robust to the different control variables. In Model 4, with the most comprehensive controls, our previous results hold: (i) holding the nature of dividend (fixed or variable) constant, the treatment with the lower FV always has the larger bubble size, (ii) fixing the level of FV, the price is always higher in the variable dividend treatment. In concrete, for bubbles sizes we find the following ordering:

$$(2.5, 2.5) < (0, 0) < (-2.5, -2.5) < (-5, -10) < (-10, 10) < (-15, 10).$$

The point estimates from the four models also show that the treatment effects are meaningful and large. For example, in Model 4, the point estimate for positive variable dividend treatment ($I^{(-5,10)}_{g,t}$) is 11.82, implying that the bubble size of (-5,10) is more than 46% bigger than that of (2.5,2.5) in the first trading period.

**Finding A3:** *Bubbles are larger in asset markets with variable dividends than in asset markets with fixed dividends. Bubbles are largest in asset markets with negative fundamental value and variable dividends and smallest in asset markets positive fundamental value and fixed dividends.*

**A4. Transaction volume**

**INSERT TABLE A6 ABOUT HERE**

Table A6 shows the average trading volume per period in all 6 treatments in trading block 1. On average, 43.87 shares were bought and sold in each trading period. There is no clear pattern across treatments and Mann-Whitney tests indicate that there is no treatment effect between any of these two treatments ($p > .1$ for all pairwise comparison).

**INSERT TABLE A7 ABOUT HERE**

Table A7 shows the average trading volume per period in all 6 treatments for the two trading blocks pooled. On average, 37.29 shares were bought and sold in each trading period. Same as the data from
only block 1, there is no clear pattern across treatments and Mann-Whitney tests confirm this (p>.1 for all pairwise comparisons).

A5. Instructions of the guessing game

INSERT FIGURE A3 ABOUT HERE
Appendix tables

Table A1: Endowments at the beginning of the first trading period

<table>
<thead>
<tr>
<th>Endowment groups</th>
<th>Assets</th>
<th>Tokens</th>
<th>Number of traders</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5</td>
<td>1000</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>1000</td>
<td>4</td>
</tr>
</tbody>
</table>

Notes: This table lists the exact endowment of all 8 participants at the beginning of each trading block.
Table A2: Realized dividend series for variable FV treatments

<table>
<thead>
<tr>
<th>Trading block</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>L</td>
<td>H</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>L</td>
<td>L</td>
</tr>
<tr>
<td>2</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>L</td>
<td>L</td>
<td>L</td>
<td>H</td>
<td>H</td>
<td>H</td>
<td>H</td>
</tr>
</tbody>
</table>

Notes: This table lists our dividend states when the dividends are variable. All traders in markets with variable dividends treatments observe the same dividend realization. H and L indicate high and low dividend states, respectively.
Table A3: Compare the bubble size between treatments with positive, zero, and negative FVs

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zero FV (δ₁)</td>
<td>6.33</td>
<td>6.07</td>
<td>7.05</td>
<td>5.77</td>
</tr>
<tr>
<td></td>
<td>0.133</td>
<td>0.154</td>
<td>0.154</td>
<td>0.183</td>
</tr>
<tr>
<td>Negative FV (δ₂)</td>
<td>9.71*</td>
<td>9.64*</td>
<td>9.53*</td>
<td>11.59***</td>
</tr>
<tr>
<td></td>
<td>0.059</td>
<td>0.059</td>
<td>0.061</td>
<td>0.005</td>
</tr>
<tr>
<td>Constant (c)</td>
<td>6.15*</td>
<td>16.61***</td>
<td>18.89**</td>
<td>21.79***</td>
</tr>
<tr>
<td></td>
<td>0.069</td>
<td>0.005</td>
<td>0.011</td>
<td>0.003</td>
</tr>
<tr>
<td>Period effects (ΣαₜIₜ)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># of females (female)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># have taken asset pricing classes (knowledge)</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: This table shows the estimation results for whether FVs have any impact on the bubble size. There are 509 observations for each regression and all standard errors are clustered at the group level (we exclude 31 trading periods where no trade took place in either trading block). We report the p-value under each point estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Table A4: Actual bubble size

<table>
<thead>
<tr>
<th></th>
<th>Positive FV</th>
<th>Zero FV</th>
<th>Negative FV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed dividends</td>
<td>3.06</td>
<td>10.12</td>
<td>17.11</td>
</tr>
<tr>
<td>Variable dividends</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>possible with loss</td>
<td>6.42</td>
<td>17.36</td>
<td>35.80</td>
</tr>
<tr>
<td>p-value</td>
<td>0.1</td>
<td>0.34</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Notes: This table reports the bubble size (price dispersion) of each treatment. The p-value in the bottom row compares the bubble size of the fixed dividend treatment with the variable one at the corresponding level of FV.
Table A5: Compare the bubble size between treatments with fixed and variable dividends

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive Variable</td>
<td>9.17</td>
<td>9.08</td>
<td>8.92</td>
<td>11.82</td>
</tr>
<tr>
<td></td>
<td>0.209</td>
<td>0.218</td>
<td>0.218</td>
<td>0.119</td>
</tr>
<tr>
<td>Zero fixed</td>
<td>6.33</td>
<td>5.91</td>
<td>6.92</td>
<td>5.85</td>
</tr>
<tr>
<td></td>
<td>0.119</td>
<td>0.150</td>
<td>0.132</td>
<td>0.163</td>
</tr>
<tr>
<td>Zero variable</td>
<td>14.85**</td>
<td>14.88**</td>
<td>15.06**</td>
<td>13.31**</td>
</tr>
<tr>
<td></td>
<td>0.016</td>
<td>0.017</td>
<td>0.017</td>
<td>0.037</td>
</tr>
<tr>
<td>Negative fixed</td>
<td>9.71**</td>
<td>9.58**</td>
<td>9.47*</td>
<td>11.05***</td>
</tr>
<tr>
<td></td>
<td>0.048</td>
<td>0.049</td>
<td>0.053</td>
<td>0.007</td>
</tr>
<tr>
<td>Negative variable</td>
<td>33.40***</td>
<td>33.32***</td>
<td>33.49***</td>
<td>31.73***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Constant (c)</td>
<td>6.15*</td>
<td>21.41***</td>
<td>23.79***</td>
<td>25.78***</td>
</tr>
<tr>
<td></td>
<td>0.057</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Period effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(Σα_t𝜏_t)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of females (female)</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td># have taken asset pricing classes (knowledge)</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: This table shows the estimation results for whether the nature of the dividends have any impact on the bubble size. There are 1042 observations for each regression and all standard errors are clustered at the group level (we exclude 38 trading periods where no trade took place). We report the p-value under each point estimate. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.
Table A6: Compare the trading volume across treatments (block 1)

<table>
<thead>
<tr>
<th></th>
<th>Positive</th>
<th>Zero</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>38.62</td>
<td>55.02</td>
<td>41.88</td>
</tr>
<tr>
<td>Variable</td>
<td>40.42</td>
<td>42.22</td>
<td>45.08</td>
</tr>
</tbody>
</table>

Notes: This table shows the average period trading volume in each treatment in trading block 1.
Table A7: Compare the trading volume across treatments (block 1 & 2)

<table>
<thead>
<tr>
<th></th>
<th>Positive</th>
<th>Zero</th>
<th>Negative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed</td>
<td>33.2</td>
<td>42.63</td>
<td>37.55</td>
</tr>
<tr>
<td>Variable</td>
<td>35.87</td>
<td>36.39</td>
<td>38.1</td>
</tr>
</tbody>
</table>

Notes: This table shows the average period trading volume in each treatment in trading block 1 and 2.
Appendix Figures

Figure A1: screenshot of the instructions

1. Goods and Tokens you have now.

2. Summary of own purchases and sells in the current period (including corresponding quantities and prices).

3. Bid box: make a bid offer to buy lower than the current lowest ask price. You have to enter the quantity and price you are willing to buy. Trade does not take place until another participant accepts your offer.

4. Ask box: make an ask offer to sell higher than the current highest bid price. You have to enter the quantity and price you are willing to sell. Trade does not take place until another participant accepts your offer.

5. List of all ask offers from all participants. Your own ask offers are written in blue. The ask offers are listed from the lowest price to the highest. The ask offer listed on the top is always the lowest ask (i.e., the cheapest one for the buyers).

6. Accept other participant’s ask offer. You buy the entered quantity given the price with the blue background. If you enter a higher amount than offered in the blue box, you buy the offered quantity at most.

7. Accept other participant’s bid offer. You sell the entered quantity given the price with the blue background. If you enter a higher amount than offered in the blue box, you sell the offered quantity at most.

8. List of all bid offers from all participants. Your own bid offers are written in blue. The bid offers are listed from the highest price to the lowest. The bid listed on the top is always the highest bid (i.e., the most profitable one for the sellers).

9. Price chart of current period. The vertical axis is price while the horizontal axis is time in second.

10. The price quoted in the most recently accepted offer.
After each trading period, you will see a summary table like this to summarize essential trading history for you.

- **Goods you own right before the market closes.**
- **Number of Goods multiplied by net payment per Good.**
- **Tokens you have right before the market closes.**
- **Price-chart, displaying closing prices of all previous periods.**
- **Actual dividend minus the holding cost per Good.**
- **Last price before the market closes.**
In order to earn money in today's experiment you need to closely read the instructions placed on your table. They are printed in black ink. Six groups of eight participants (that is a total of 48 individuals playing in 6 different markets) took part in the market game described in the instructions. In each group, half of the participants were endowed with 1000 Tokens and 10 Goods, and the other half 1000 Tokens and 5 Goods. Your task is to provide your best guess on the average closing price across all 6 different markets. You will have to provide your best guess for each of the 15 trading periods in the boxes below.

Each answer within five Tokens of the actual value earns you AUD $2.

If you have any question regarding to the instruction, please raise your hand. The experimenter will come to you.

<table>
<thead>
<tr>
<th>Trading period</th>
<th>Your guess of the average price</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
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<td>3</td>
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<td>4</td>
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<td>15</td>
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