

Fundamental value trajectories and trader characteristics in an asset market experiment

Adriana Breaban and Charles N. Noussair ¹

Abstract

We report results from an asset market experiment, in which we investigate how the time path of the fundamental value trajectory affects the level of adherence to fundamentals. In contrast to previous experiments with long-lived assets, there is a phase in which fundamental values are constant before the onset of a trend. The trend is either increasing or decreasing, depending on the treatment. We compare the level of mispricing between the decreasing and increasing fundamental value trajectories. Before the market begins, risk aversion, loss aversion, and cognitive reflection protocols are administered to traders. We find evidence for closer adherence to fundamental values when the trajectory follows a decreasing, than when it has an increasing, trend. Greater average risk aversion on the part of traders in the market predicts lower market prices. The greater the level of loss aversion of the trader cohort, the lower the quantity traded. The greater the average cognitive reflection test score, the smaller the differences between market prices and fundamental values. The variation between groups in risk aversion, loss aversion, and CRT score, explains 45% and 18% of the cohort-level variation in price level and mispricing, respectively.

Keywords: Bubble, Fundamental Value, CRT, Crash

JEL classification: C92, G02

1. Introduction

The tendency for experimental markets for long-lived assets to price at levels that differ from intrinsic values is one of the most robust and puzzling results from research in experimental markets. This result, first established by Smith et al. (1988), has been replicated in numerous studies, though the extent and

¹ Breaban: Dept. of Economics and LEE, University Jaume I, Castellon, Spain, email: breaban@uji.es. Noussair: Dept. of Economics, Tilburg University, Tilburg, The Netherlands, email: C.N.Noussair@tilburguniversity.edu. We thank Yen Nguyen for research assistance and comments. We thank the Center for Economic Research at Tilburg University and the Generalitat Valenciana (GV/2012/045) and Bancaja Foundation (P11A2010-17) for Dept. of Economics, Tilburg University, Tilburg, The Netherlands, email: C.N.Noussair@tilburguniversity.edu. We thank Yen Nguyen for research assistance and comments. We thank the Center for Economic Research at Tilburg University and the Generalitat Valenciana (GV/2012/045) and Bancaja Foundation (P11A2010-17) for financial support.

pattern of mispricing is affected by a number of factors. These include the levels of endowment of shares and cash available for transactions (Caginalp et al., 1998; 2000), the trading institutions employed (Lugovskyy et al., 2012), the training of subjects (Lei and Vesely, 2009), and the induction of emotions (Andrade et al, 2012; Lahav and Meer, 2010). See Palan (2013) for an overview of this research.

One factor that has long been suspected as a source of mispricing in the Smith et al. (1988) experiment is the declining time path of the fundamental value. Because the asset is finitely-lived, and pays a dividend in each period, the intrinsic value, which equals the expected sum of future dividends, declines after each dividend has been paid. Some authors have claimed that this declining fundamental value structure is unfamiliar to experimental subjects, who are typically used to appreciating assets outside the laboratory (Noussair et al., 2001; Kirchler et al., 2012). The claim is that the declining fundamental value serves as a source of confusion for subjects. Indeed, it does appear that subject misunderstanding plays a role in generating mispricing in such an environment (Lei et al., 2001; Lei and Vesely, 2009; Kirchler et al., 2012; Cheung et al., 2013).

There is evidence that the time path of fundamentals can affect the extent to which prices track fundamentals. Noussair et al. (2001) compare markets in which the fundamental value is constant over time to ones in which it is decreasing. They find that the setting with constant fundamentals generates less mispricing. Giusti et al. (2012) compare settings in which fundamentals are increasing versus decreasing. In their setting, the cash held by traders earns interest, and with a sufficiently high interest rate, the fundamental value of the asset increases over time. They observe a strong pattern; fundamental value trajectories with an increasing trend are more conducive to pricing close to fundamentals than those that are decreasing. Huber et al., (2012) implement decreasing fundamental value trajectories with dividend payments, and increasing time paths by imposing taxes (in effect negative dividends), on those who hold units at the end of each period. They observe that a decreasing trend leads to overpricing and an increasing trend to underpricing, though the increasing trajectory departs to a lesser extent from fundamental pricing. Both treatments exhibit a rapid adjustment of prices in the direction of the fundamental near the end of the life of the asset.

The most closely related study to the one reported here is that of Noussair and Powell (2010). They study two treatments, called Peak and Valley. The treatments differ from each other in only one aspect. In Peak, the fundamental value of the asset increases for first eight periods of the 15-period horizon, and then declines for the remaining seven. Under Valley, the value declines for the first eight periods and then increases for seven. There is a strong difference in the speed and extent of price discovery between the two treatments. Prices adhere to fundamentals much more closely in the Peak than in the Valley

treatment. When the early and late periods of the asset's time horizon are considered separately, the decreasing trajectory exhibits better price discovery when it follows a phase of increase than when it precedes it. In contrast, prices under the increasing trajectory track fundamentals more closely when it constitutes the first phase of the time path rather than the second.²

The above discussion suggests that the timing of the onset of a fundamental trend and the time path of intrinsic value preceding the beginning of the trend might be a crucial factor influencing price discovery. A phase of trading before the onset of a trend allows a redistribution of units and cash among traders, as well as the accumulation of experience. Thus, the trend in fundamentals begins under different conditions than it would if were to set in immediately. In this paper, we report the results of a new experiment that is designed to consider the relationship between the time path of fundamental value and the price discovery process under such conditions. The experiment has two treatments. In the *Bullmarket* treatment, the time path is constant for the first half of the life of the asset, after which there is an increasing trend in fundamental value for the remainder of the life of the asset. In the *Bearmarket* treatment, the phase of constant fundamentals is instead followed by a decreasing trend in the second half of the asset's life. We find that the Bearmarket treatment exhibits closer adherence to fundamental value than the Bullmarket treatment. Thus, the addition of the initial phase with constant fundamentals before the onset of the trend induces a reversal of the results of Giusti et al (2012) and Huber et al. (2012), who observe that price discovery is better for increasing trends.

In our experiment, before subjects participate in the asset market, they complete three individual choice tasks. These are described in detail in section 2.2. First, participants' loss aversion is measured with a version of the protocol used in Fehr and Goette (2007). Second, the willingness/ability to reflect about their decisions is elicited with a cognitive reflection test (CRT) as described in Frederick (2005). Third, risk aversion is measured with the procedure of Holt and Laury (2002). The data from these tasks permit us to consider the link between risk aversion, loss aversion, and cognitive ability on one hand, and market behavior and individual trading strategies on the other.

As described in section two, we advance a number of hypotheses about the relationship between loss aversion, risk aversion, cognitive reflection, and market behavior. In particular, we hypothesize that the average risk aversion of participants in a market is correlated with the average price level, with more risk aversion associated with lower prices. We also hypothesize that the average level of loss aversion of market participants is predictive of the quantity traded, with more loss aversion correlating with lower

² It is important to note that in all of the previous experimental studies mentioned in this introduction, subjects know what the fundamental value of the asset would be at each time period in the future. Thus, fundamental value trends are always accurately anticipated in advance. In the study we conduct here, we continue with this practice.

transaction volume. The last hypothesis is that greater average CRT score among the trader cohort predicts lower mispricing relative to fundamental value. As described in section four, all three of these hypotheses are supported, at least to some extent. Furthermore, we observe correlations between the responses on these measurement protocols and trading strategies. Risk-averse agents are less likely to trade based on market momentum, and loss-averse agents are less likely to speculate. Those scoring more highly on the cognitive reflection test are more likely to behave as fundamental value traders. Thus, intuitive relationships exist between measures of individual characteristics and trader behavior in the asset market.

2. The Experiment

2.1. General structure

The experiment consisted of sixteen experimental sessions. Twelve of these sessions were conducted at the CentER laboratory at Tilburg University, the Netherlands. The other four took place at the Laboratorio de Economía Experimental (LEE) facility at the University of Jaume I, Castellon, Spain. The sessions at Tilburg were conducted in English and those in Castellon were in Spanish. The English version of the instructions can be found in the Appendix. All participants were students enrolled at one of the two universities. Between 7 and 9 individuals participated in each session. Each session consisted of four parts and took on average approximately two hours. Average earnings were 22.64 Euro.

2.2. Risk Aversion, Loss Aversion, and Cognitive Reflection Measures

Each session consisted of four parts. The first part was the administration of a protocol to measure loss aversion. We employed a version of the elicitation procedure used by Fehr and Goette (2007), which is a series of six choices, presented in a price list format. Subjects completed the task using a pen and paper. The choices were presented on one sheet of paper. This meant that subjects could revise their earlier decisions in light of their choices in subsequent ones.

Each task required the person to indicate whether she would like to play a gamble which yielded a gain of 4.5 Euro with probability .5 or a loss of an amount x with probability .5. Depending on the decision task, x took on values of $\{.5, 1.5, 2.5, 3.5, 4.5, \text{ and } 5.5 \text{ Euros}\}$. Each value of x appeared in exactly one decision task that each subject completed. Subjects submitted all of their choices simultaneously when they turned in their sheet of paper to the experimenter. Only one of the decisions counted toward their earnings. The decision task this would be was determined after all decisions were turned in. A die was rolled, determining which decision would count for each participant. If a subject had chosen not to play the relevant gamble, she received a payoff of zero for part I of the experiment. If a participant chose to accept the selected gamble, a coin was flipped to determine whether she received 4.5 Euro or the negative payment specified in the gamble. A separate coin was flipped for each participant who chose the gamble. We used the number of gambles one was not willing to accept as a measure of her loss aversion.

Parts two, three, and four of the experiment were computerized. In the second part of the experiment all subjects completed the cognitive reflection test developed by Frederick (2005). Subjects were given three minutes to answer three questions, and they received 1 Euro for each correct answer. The three questions were:

1. A bat and a ball cost a total of 1.10 Euro. The bat costs 1 Euro more than the ball. How much does the ball cost?
2. If it takes five people five minutes to make five widgets, how long does it take 100 people to make 100 widgets?
3. In the lake there is a patch of lily pads, which doubles in size every day. It takes 48 days for the patch to cover the entire lake. How many days does it take the patch to cover half of the lake?

This test has been used extensively in experimental economics to measure the ability (or willingness, depending on the researcher's interpretation of the test) to reflect in answering a question. The questions have the feature that the first answer that typically springs to mind is an incorrect one, but that the correct answer is simple upon some reflection. We took the number of correct answers as a measure of how prepared an individual is to reflect about a decision situation.

In part three, subjects' risk aversion levels were measured using the Holt-Laury (2002) protocol. Under this procedure, subjects make a series of 10 choices between a relatively low-variance, and a relatively high-variance, lottery. The choices follow a price list format, in which the high-variance lottery takes on an ever greater expected value relative to the low-variance lottery. The probability at which the individual becomes willing to accept the riskier lottery implies a level of risk aversion. Specifically, there is a series of ten choices between two lotteries of the form $p \cdot x_1 + (1-p) \cdot x_2$ and $p \cdot y_1 + (1-p) \cdot y_2$, where $y_2 > x_2 > x_1 > y_1$, and p varies monotonically from .1 to 1 in increments of .1 in the ten different choices. In our experiment, we set $y_2 = 3.85$, $x_2 = 2.00$, $x_1 = 1.60$, and $y_1 = 0.10$, denominated in Euro. Thus, a person choosing the relatively low-variance lottery ($p \cdot x_1 + (1-p) \cdot x_2$) for $p \leq .4$, and the high-variance lottery ($p \cdot y_1 + (1-p) \cdot y_2$) for $p > .4$, was consistent with risk neutrality, the maximization of expected value. Fewer (more) than four safe choices are consistent with risk-seeking (risk-averse) preferences. The ten decisions were presented on one screen, so that individuals could revisit and revise their responses to previous questions in light of latter ones. When they were satisfied that they did not want to change any of their responses, they submitted all ten of them simultaneously. One of the 10 questions was randomly selected to count toward earnings.

2.3 The Market and the Two Treatments

The fourth phase of the experiment was the most lengthy and consisted of a sequence of two asset markets, both identical in parametric structure. Each market consisted of 15 periods, during which individuals could trade units of an asset. The asset's lifetime equaled the 15 periods during which the market was in operation. An experimental currency called ECU, converted to Euros at the end of the

experiment, was used for all payments, transactions, taxes and dividend distributions. After the first 15-period market had elapsed, a second market was conducted. The second market was reinitialized to conditions identical to those prevailing at the beginning of the first market. Thus the first and second markets began under identical conditions except for the level of experience of traders.

There were two treatments, called *BearMarket* and *BullMarket*. The *BearMarket* treatment was characterized by a time path of fundamentals that was constant during the early portion of each market and decreasing during the latter portion. The decreasing trend began in period 8 of each market. The *BullMarket* treatment consisted of markets in which the fundamental value was constant in the early periods of the market, and increasing beginning in period 8. The time path of fundamentals in the two treatments is illustrated in Figures 1a and 1b. In the figures, the horizontal axis indicates the period number. The vertical axis indicates the fundamental value, in terms of ECU, the experimental currency. Subjects knew at all times what the fundamental value would be in all future periods, and thus the change in the trend of fundamentals was anticipated.

[Figure 1: About Here]

The fundamental value of the asset arose from three sources: dividends, taxes/subsidies, and a final buyout. This final buyout was a payment for each unit of asset held at the end of the market, that is, at the end of period 15, to the unit's owner. All three components of fundamental value were in effect payments to or by the current owners of the asset on each unit they held. Because the asset is finitely lived, at any point in time the fundamental value was the sum of the expected net future financial flows from all three sources. Specifically, the fundamental value of a unit of the asset during any period was equal to the sum of the expected dividends and final buyout it would generate, minus any taxes and plus any subsidies that remained to be paid on the unit. Thus, the fundamental value of one unit of the asset at any point in time was the expected value of the stream of payments that resulted from holding the unit for the remainder of the current market. The three different sources of value were included in the design merely to induce the appropriate dynamic patterns in fundamental values. All three components were present in both treatments so that both conditions had the same level of complexity. The number and timing of future dividend draws, tax payments, and final buyouts in the current market was always common knowledge.

After every period, each unit of the asset paid a dividend to its current owner. Dividends were drawn independently for each period from a two-point distribution with equal probability of +10 or -10. In the experiment, the dividends were determined with a public coin flip. The result of the coin flip was

then entered into the computer by the experimenter. The expected dividend in any period, and thus the expected future dividend stream, was equal to 0 ECU.

In periods 8 – 15 of each market in the BullMarket treatment, taxes were paid. After each of these periods, all subjects paid a fixed inventory tax of 10 ECU for each unit in their possession. The effect of these taxes was to create an increasing fundamental value trend during the periods that the tax was in effect. Each tax payment reduced the future tax liability on each unit by 10 ECU, and thereby increased the fundamental value by the corresponding amount.

In the BearMarket treatment, in periods 8 – 15 of each market, a subsidy of 10 ECU was paid in each period to the holder of any unit of asset. This had the effect of reducing the fundamental value in each of the last eight periods of the life of the asset. As each subsidy was received, the future flow of subsidy payments decreased by 10 ECU.

The third component of the fundamental value was the final buyout. This was a payment to the holder of each unit of asset at the end of the 15-period life of the asset. This payment was equal to 200 ECU in the BullMarket treatment and to 40 ECU in the BearMarket treatment. The values were chosen to make the fundamental value equal to an identical value of 120 over the first seven periods in both treatments. The final buyout ensured that the fundamental value of the asset was always positive.

Dividends, subsidies and final buyout payments were added to individuals' cash balances at the time they were paid out, and taxes were subtracted from cash balances at the moment they were incurred. This meant that positive dividend payments and subsidies added to the cash could be used for subsequent purchases. Negative dividends and taxes reduced the cash available for later purchases.

At the beginning of period 1 in each market, agents received an initial endowment of 10 units of asset and 3600 ECU of cash that they could use for transactions. Cash balances and asset inventories were required to be positive. In other words, margin buying and short-selling were not allowed. The markets were computerized and used continuous double auction trading rules (Smith, 1962) implemented with the z-Tree computer program (Fischbacher, 2007).

In a continuous double auction, the market is open for a fixed interval of time. At any time, any agent, who has sufficient cash or units to conclude the transaction, may submit an offer to the market. An offer specifies a price at which the agent is willing to either buy or sell a share. Any trader with sufficient funds and units of asset to complete the transaction may accept any outstanding offer at any point in time. All offers are displayed to all agents on their computer screens. Upon acceptance of an offer, a trade is concluded and the asset and cash transferred between the transacting parties. Within our 15-period markets, inventories of assets and cash carried over from one period to the next so that for each individual, the quantities of cash and assets held at the beginning of period $t+1$ were the same as those

held at the end of period t , adjusting for any dividends and subsidies received as well as for any taxes paid. Each of the 15 periods of a market lasted two minutes.

A subject's entire earnings over a market were equal to the amount of cash he held at the end of the final period of that market, after the last dividend, tax/ subsidy, and final buyout were paid. This was equal to his initial endowment of cash, plus any earnings from dividends, plus any subsidies received, minus any taxes paid, plus proceeds from sales of shares, minus expenditures on purchases of shares, plus any final buyout received. ECU were converted to Euros at a rate of 500 ECU = 1 Euro.

3. Hypotheses

The five hypotheses we advance concern market-level activity, and are based on previous studies in experimental and behavioral economics. We readily concede that we anticipated some of the hypotheses to be more likely to be upheld in the data than others. Nevertheless, the hypotheses express what might reasonably be predicted from previous studies. The first is that the two treatments, BullMarket and BearMarket, would exhibit equally effective price discovery. Although Giusti et al. (2012) and Huber et al., (2012) find that increasing fundamental value trajectories exhibit better price discovery than decreasing ones, both of these studies differ from ours in a number of ways. The most basic difference is, of course, that our design features a delayed onset of the fundamental value trend. Thus, we maintain the ex-ante expectation that there would be no difference in adherence to fundamentals between the two treatments.

Hypothesis 1: The Bullmarket and Bearmarket treatments track fundamentals equally closely.

To evaluate hypothesis 1, we compare the *Average Dispersion (AD)* between the two treatments. This is an overall measure of market mispricing relative to fundamentals over the entire lifetime of the asset. It is defined as $AD = \sum_t |p_t - f_t|/15$, where p_t is the average price in period t and f_t is the fundamental value in period t . AD is the absolute difference between price and fundamental, averaged over the 15 period horizon. Hypothesis 1 is that AD is not different between the increasing and the decreasing treatments.

The second hypothesis also originates from previous experimental studies. These have shown that as the same subjects participate in a second market under identical conditions, the prices at which they trade move closer to fundamentals (Smith et al., 1988; Dufwenberg et al., 2005; Haruvy et al., 2007). Nevertheless, it is possible that the convergence to fundamentals would occur at different rates in the two treatments. This is suggested by the results of Noussair and Powell (2010), who find that experience leads to more rapid price discovery in their Peak than in their Valley treatment. This would suggest that

convergence would occur faster in the BearMarket than in the BullMarket treatment. This is because the Bullmarket treatment has an upward fundamental trend in the latter part of the session, like the Valley treatment. In contrast, Bearmarket has a downward trend like the Peak treatment. However, our view is that the analogy is too speculative to advance an ex-ante hypothesis that convergence would occur at different rates in the two treatments.

Hypothesis 2: Greater experience leads to closer adherence to fundamental values. Market 2 tracks fundamentals more closely than Market 1.

The next three hypotheses concern the relationships between each of tasks in phases 1 - 3 and market activity in market 4. They concern whether measurement of traders' characteristics, such as risk aversion, loss aversion, and tendency to reflect, can predict the activity in the market in which they participate. Hypothesis three relates to risk aversion. Because the asset traded in our markets is a risky lottery, it should be valued less by relatively risk-averse agents. Thus, we hypothesize that a greater average level of risk aversion among participants in the session, as measured in part three of the session, would correlate negatively with price level in part four.

Hypothesis 3: Greater risk aversion on the part of the average trader is correlated with lower prices in the asset market.

We quantify price level using a measure called *Average Bias* or *AB* (Haruvy and Noussair, 2006). This equals $AB = \sum_t (p_t - f_t)/15$ and is a measure of price level relative to fundamentals. We correlate it with the average level of safe choices in part three, using each session as the unit of observation. Furthermore, within each session, we expect that relatively risk-averse individuals would be net sellers of units to relatively risk tolerant ones, exploiting the gains from exchange that can ensue from such a transfer of risk. By the end of the market, relatively risk tolerant agents should hold more units of asset than more risk averse ones.

Just as we assert that risk aversion is related to the price level, we hypothesize that loss aversion is related to the quantity transacted. Consider a loss-averse agent who has purchased a unit and now wishes to sell a unit. This agent may be reluctant to sell a unit at a price lower than the last price at which he purchased. Alternatively, this reluctance could occur at another reference price, such as the average price paid in previous purchases, but a similar intuition would emerge. Similarly, consider a loss-averse agent deciding whether or not to purchase a unit. He may be reluctant to purchase the unit at a price greater than a reference price, which might be for example the one at which he concluded his last sale.

This reluctance to trade may create friction which would lower transaction volume. On the basis of this intuition, we hypothesize that the average loss aversion of a cohort measured in part 1 of the session is negatively correlated with the average quantity transacted in the markets, in which the cohort participates in later in the session.

Hypothesis 4: Greater loss aversion is correlated with lower transaction volume in the asset market.

At the individual level, we would expect the relatively loss-averse individuals within a session to conclude fewer trades than their less loss-averse counterparts. The final hypothesis concerns the relationship between market activity and the cognitive reflection test administered in part two of the experiment. The CRT test measures the willingness to think about a decision problem, and it is plausible to conjecture that individuals who are prepared to do so are also more likely to thinking about the fundamental value of the asset when trading in the market. Thinking about the fundamental might encourage an individual to use it as a limit price. Indeed, Corgnet et al., (2012) report that subjects with higher CRT scores tend to make purchases at price below, and sales at prices above, fundamental values. It is likely that the greater the proportion of people who approach their trading decisions in this way, the greater the tendency is for prices to be close to fundamentals. We thus hypothesize that Average Dispersion would be negatively correlated with the average CRT score of the traders in the market

Hypothesis 5: Greater average CRT score is correlated with closer adherence to fundamental values.

4. Results:

4.1 Market Price Patterns and Treatment Differences

Figure 2 below shows the time series of transaction prices for each market in the two treatments. Each individual time series corresponds to the activity of one of the 16 groups. The two panels in the upper portion of the figure correspond to the first and second markets of the BullMarket treatment. The vertical axes indicate the price, the horizontal axes mark the time period, and the fundamental value is given by the bold black line. Each time series represents the average price in each period in one of the sessions. The middle portion of the figure represents the analogous data for the BearMarket treatment for the sessions conducted at Tilburg University. The lower portion contains the data from the BearMarket sessions run at Jaume I.

Figure 2 illustrates several basic patterns. The first is that prices in the BearMarket treatment are closer to fundamental values than those in the BullMarket treatment, especially for market 2 in the sessions conducted at Tilburg. The second is that prices in the second market within each treatment are closer to fundamentals than those in the first market in some sessions but not in others. In the BearMarket treatment sessions conducted at Tilburg, pricing in market 2 is obviously closer to fundamentals than market 1. The sessions conducted at Jaume I tend to exhibit greater deviations from fundamentals than those conducted at Tilburg. In the Bullmarket treatment, in the first eight periods, prices depart substantially from fundamental values, even in market 2.

[Figure 2: About here]

Statistical tests conducted using the 12 Tilburg sessions, enabling control for subject pool effects, confirm the impressions gleaned from the figures. A Mann-Whitney rank sum test fails to reject the hypothesis that the average dispersion is equal between the Bullmarket and Bearmarket treatments in market 1 ($z = 1.441$, $p = .0149$). For market 2, however, the test yields $z = 2.082$ ($p = .0379$), which is significant at conventional levels. We thus support hypothesis 1, but only in market 2, when subjects have previously obtained experience with the market process. In market 2, the Bearmarket treatment leads to more accurate pricing.

The average dispersion is lower in market 2 than in market 1 in only three of the six Bullmarket sessions. However, in all six sessions of Bearmarket conducted in Tilburg, prices exhibit lower average dispersion in market 2 than in market 1 ($z = 2.082$, $p < 0.037$). Thus, there is mixed support for hypothesis 2. It is supported in the Bearmarket treatment, but not in Bullmarket.

Figure 3 shows the relationship between the average risk aversion of session participants and the price level in each market. The risk aversion of each individual is weighted by her *market power* in the experiment, and this new variable constitutes the horizontal axis. The market power is a weighted average of the percentage of the shares outstanding and the percentage of the total stock of cash that an individual holds. It is used as a measure of influence in the market (see Haruvy and Noussair, 2006, or Haruvy et al., 2013). The market power of individual i , denoted as MP_i , equals $.5 * s_{it} / \sum_i s_{it} + .5 * m_{it} / \sum_i m_{it}$. The variable s_{it} equals the number of units of asset that i has at the beginning of period t and m_{it} is the amount of cash that individual i has at the beginning of the period. The weighting of risk aversion by market power is intended to reflect the fact that the risk attitudes of those individuals with greater capacity to buy and sell tend to have more influence on market activity.

In figure 3, The Average Bias for a market is indicated on the vertical axis. Each data point corresponds to one market in one session. The figure shows the relationship suggested in hypothesis three for the BullMarket treatment, though the relationship does not appear for BearMarket. For the pooled data from both treatments however, the correlation between average risk aversion for a trader cohort and the Average Bias in their market is $-.528$, significant at the $p = .035$ level in market 1. The correlation is $-.511$ in market two, significant at $p = .042$. Thus, we find strong support for hypothesis three in BullMarket and mixed support overall.

Figure 4 illustrates the relationship between average trader loss aversion by session and the volume of trade in each treatment. The loss aversion of individuals in the session, weighted by their market power, is plotted against the volume of trade by session. The figure shows that there is a negative relationship ($\rho = -.19$) in market 1 for the BearMarket treatment, which is consistent with hypothesis 4, though the correlation is not significant. The relationship is weaker in market two ($\rho = -.12$), suggesting that the relationship becomes yet weaker with experience. There is no relationship between these two measures in the BullMarket treatment. Overall, we find only very weak support for hypothesis 4.

Figure five relates the average CRT score of session participants, weighted by their market power, to the Average Dispersion in each session. The figure shows that the greater the average CRT of the group, the closer is their conformity to fundamentals. The correlation is $-.433$ and significant in market 1, ($p = .093$) as well as market 2, $-.442$ ($p = .086$). Thus there is strong support for hypothesis 5.

4.1.1 Summary of market level results

This subsection has provided evidence that the BearMarket treatment adheres more closely to fundamentals than the BullMarket treatment. These results contrast with typical results obtained in markets for assets exhibiting an immediate onset of a trend in fundamental value, in which decreasing fundamentals are associated with greater mispricing. Also, under BearMarket, there is a systematic decrease in the level of mispricing in the second market that a cohort participates in compared to the first. The average risk aversion of traders correlates negatively with the price level. The average CRT score correlates negatively with the distance between price and fundamentals. In the next subsection, we explore the individual behavior underlying these patterns.

[Figures 3 – 5: About here]

4.2. Individual Behavior

4.2.1. Risk aversion, loss aversion, CRT score, and individual trading behavior

We have observed, in section 4.1, that greater average risk aversion among market participants is negatively correlated with price level. We now consider whether relatively risk-averse individuals tend to sell to those who are less risk averse. This pattern would be reflected in a relationship between an individual's risk aversion, as measured in part 1 of the sessions, and how many units of the asset she holds at the end of the last period of the market. Figure 6 shows the relationship between an individual subject's risk aversion and her final asset holding at the end of markets 1 and 2. The vertical axis is the measured level of risk aversion in part 3 of the session, with 10 corresponding to the greatest, and 1 to the lowest, possible risk aversion level. Each data point in figure 6 is the average quantity held at the end of a session by individuals of a given risk aversion level. Larger circles indicate a larger number of individuals with the corresponding risk aversion level. The Appendix contains histograms of the risk aversion, loss aversion and cognitive reflection measures for our sample of participants.

The figure illustrates the tendency of individuals who are relatively risk averse to sell to those who are less risk averse. This intuitive relationship exploits potential gains from trade as risk is transferred to those who have a lower cost of bearing it. The correlation between the final inventory of an individual and her risk aversion in the BearMarket treatment is $\rho = -.197$, significant at $p = .073$. However, the correlation is insignificant under BullMarket ($\rho = -.035$, $p = .802$).

At first glance this last result seems inconsistent with the fact that the overall correlation between average risk aversion of a cohort and price level is greater in BullMarket than in BearMarket. However, the latter, a between-session correlation, is perfectly compatible with the stronger within-session relationship in BearMarket between individuals' risk aversion and their holdings. Figure 7 documents the relationship between loss aversion and individual trading behavior. The vertical axis shows the value of the loss aversion measure in part 1 of the experiment. Higher values indicate greater loss aversion. Loss aversion is plotted against the total number of units the individual trade, that is, the sum of her purchases and sales, over a 15-period market. Each data point is the average number of units individuals with a given loss aversion level trade over the course of their 15-period market.

The figure shows, in the BearMarket treatment, a relationship between an individual's loss aversion and how much trade he engages in, with relatively loss-averse individuals involved in fewer trades. The correlation is $-.180$ ($p = .035$) in Market 1 and $-.094$ ($p = .275$) in Market 2. While this relationship does not appear significantly at the market level, in that a more loss averse group trades less than a relatively less loss averse group, it is clear that within a session, it is the less loss averse people who trade more. It seems that the relatively low number of observations at the market level and the

greater presence of within- rather than between-group heterogeneity likely accounts for the lack of a significant relationship at the market level.

Figure 8 plots the CRT score of an individual minus the average for her session on the horizontal axis, and her earnings on the vertical. Each data point represents an individual participant. The figure shows that higher CRT scores are related to higher earnings. The correlations are highly significant for the Bullmarket treatment .291 ($p = .000$) and for Bearmarket treatment .285 ($p = .009$). In markets with a dispersion of CRT scores, those with lower scores earn less, indicating that they make unprofitable trades. In markets in which the average score is high, few traders make poor decisions, and prices stay relatively close to fundamentals.

[Figures 6, 7, and 8, About Here]

4.2.2. Risk aversion, loss aversion, CRT score, and trader strategies

We now consider how the risk aversion, loss aversion, and cognitive reflection measures we have elicited correlate with trading strategies. To classify traders according to the strategies they tend to employ, we use the framework of Haruvy and Noussair (2006) and Haruvy et al. (2013). They classify traders into three types, called *Fundamental Value* Traders, *Momentum* Traders, and *Rational Speculators*. We classify each of the traders participating in our experiment as one of the three types, according to the following criteria.

We define an individual's behavior as consistent with the *Fundamental Value* Trader type in period t if either one of two conditions holds. The first condition is that, if $p_t > f_t$, then $s_{it} < s_{i,t-1}$, where p_t is the average price in period t , f_t is the fundamental value in period t , and s_{it} is the number of units of asset that individual i holds in period t . This means that if prices are above fundamentals, trader i is a net seller of units in period t . The second condition is that if $p_t < f_t$, then $s_{it} > s_{i,t-1}$. If prices are below fundamentals, trader i is a net buyer in period t . The fundamental value trader, then, acts as if she is using the fundamental value as a limit price.

A trader's behavior is consistent with the *Momentum* Trader type if either of two conditions holds. The first is that, if $p_{t-1} < p_{t-2}$, then $s_{it} < s_{i,t-1}$. The second is that, if $p_{t-1} > p_{t-2}$, then $s_{it} > s_{i,t-1}$. The momentum traders is a net purchaser in period t if there has been an increasing price trend in the last two periods, and sells off units if there has been a decreasing trend.

A trader's behavior is consistent with the *Rational Speculator* Trader type if her behavior in period t satisfies one of the following two conditions. The first is that, if $p_{t+1} < p_t$, then $s_{it} < s_{i,t-1}$, and the

second is that, if $p_{t+1} > p_t$, then $s_{it} > s_{i,t-1}$. This type of agent anticipates the price in the next period in an unbiased manner. She makes positive net purchases if the price is about to increase between the current and the next period. She makes net sales if the price is about to decrease.

To classify a subject as one of the trader types, we count the number of periods during which a person is consistent with each type, and then classify him as the type with which he is consistent for the greatest number of periods. If there is a tie between two types, we classify the trader as belonging to each type with proportion .5. If there is a tie between all three types, he is assigned each type with proportion .33.

Table 1 shows the percentage of traders of each type in each treatment and market. It shows several interesting patterns. Despite the fact that the BearMarket treatment tracks fundamentals more closely than the Bullmarket treatment, the percentage of individuals classified as each type is very similar. Furthermore, the proportion of players of each type in market 1 is very similar to the two previous studies in which a similar classification was made for subjects with no prior experience in the same experiment (Haruvy and Noussair 2006, and Haruvy et al., 2013)³. The fraction of players that are Momentum traders decreases between markets 1 and 2 while the proportions that are of the Fundamental Value and Rational Speculator types increase. This change in distribution suggests that positive reinforcement is occurring, since momentum trading is irrational, resulting in relatively low earnings, while the other two types describe trading behaviors that reflect different notions of rationality.

[Tables 1 and 2: About Here]

Table 2 shows the correlations between risk aversion level, loss aversion level, CRT score, and each of the three types. Each individual trader constitutes one observation. The table reveals the following patterns. Cognitive reflection test scores exhibit a significant correlation with being a fundamental value type in market 1. This is consistent with previous results reported by Corngnet et al., (2012). CRT score is negatively correlated with momentum trading. These are intuitive relationships since momentum trading is an irrational strategy, while fundamental value trading requires the trader to interpret the future streams of dividends, final buyout value, taxes and subsidies as a limit price.

³ Both Haruvy and Noussair (2006) and Haruvy et al. (2013) classified 33.1% of their traders as Fundamental Value Traders, 25.4% as Rational Speculators, and 36.5% as Momentum Traders. Haruvy et al. (2013) categorized 40.1% of their participants as Fundamental Value Traders, 23.8% as Rational Speculators, and 36.1% as Momentum Traders.

In market two, other intuitive relationships appear, perhaps because traders have had some time and experience so that they are able to formulate trading strategies that more accurately reflect their preferences. In market 2, there is a significant positive correlation between risk aversion and fundamental value trading. This relationship reflects risk-averse agents selling their units in large quantities when prices are greater than fundamentals. Loss averse agents are also less likely to be rational speculators in market 2, likely reflecting their desire to avoid the potential losses that one risks when speculating. There is no significant relationship between risk aversion, loss aversion, and CRT score, suggesting that they are largely orthogonal characteristics.

[Table 3: About Here]

Table 3 illustrates how much between-session variation in market prices that risk aversion, loss aversion and CRT score can explain. The dependent variables in the estimations reported in the table are the Average Dispersion and Average Bias. Model 1 includes the experience level of the subjects (whether the data come from market 1 or market 2), the treatment in effect, and the location in which the session was conducted. These variables explain 24% of the variance in AD and only 1% of the variance in AB. When the average risk aversion, loss aversion, and CRT score are added to the specification in model 2 (location is dropped because the different subject pools differ in the average level of the three characteristics), the explanatory power of the model increases substantially, to 42% for AD and 46% for AB. Thus, knowing the average risk aversion, loss aversion, and CRT score of a group of traders allows 46 times as much price level variation to be explained than when these measures are unavailable.

5. Conclusion

In this paper, we have studied markets in which a trend in fundamentals sets in after an interval of constant value. Though the effect requires some trader experience before it sets in, prices tend to track fundamentals more closely when the trend is decreasing, in the BearMarket treatment, than when it is increasing, in the BullMarket treatment. The contrast between our results and those from previous studies indicate that the timing of the onset of a trend in fundamentals is an important feature influencing how the trend affects the price discovery process. This suggests that markets for assets which have a declining fundamental value trend from the moment of their creation, such as some bonds and options, or depreciating capital, might exhibit differences in pricing behaviour from those such as stocks and commodities that may experience episodes of declining value at later points in their lifetimes.

We observe correlations between risk aversion, loss aversion, cognitive reflection test scores, and market outcomes. The greater the average CRT score of the trader cohort, the less prices in their market

deviate from fundamentals. Greater average risk aversion among the cohort of traders correlates with lower prices, though the effect is only significant for the BearMarket treatment. Risk aversion, loss aversion, and CRT scores, explain much of the between-session variation in market outcomes. It is already known that market parameters such as the amount of liquidity and the quantity of units of the asset available, as well as institutional features such as the availability of short-selling and of future markets, influence pricing in experimental markets. Our results underscore that trader characteristics are also important determinants of market behaviour. More risk-averse individuals are more likely to sell units and to trade on fundamentals. They are also less likely to trade on momentum. Loss-averse individuals trade less than their less loss-averse counterparts, and are less likely to speculate. Traders with higher CRT scores are more likely to trade on fundamentals and to achieve greater earnings. Traders with low CRT scores are more likely to be momentum traders.

References

- Andrade E., S. Lin, and T. Odean (2012), "Bubbling with Excitement: An Experiment", working paper, University of California at Berkeley.
- Caginalp, G., D. Porter, and V. Smith (1998) "Initial Cash/asset Ratio and Asset Prices: An experimental study", *Proceedings of the National Academy of Sciences*, Vol. 95, pp. 756–761
- Caginalp, G., D. Porter, and V. Smith (2001) "Financial Bubbles: Excess Cash, Momentum, and Incomplete Information", *The Journal of Psychology and Financial Markets*, Vol. 2, No. 2, 80–99
- Cheung, S, Hedegaard, M and Palan, S., (2012) "To See Is To Believe: Common Expectations In Experimental Asset Markets," *European Economic Review* 66, 84 - 96.
- Corgnet B., R. Hernán, P. Kujal, and D. Porter (2013) "The Effect of Earned vs. House Money on Price Bubble Formation in Experimental Asset Markets", Working Paper 13-04, Chapman University, Economic Science Institute.
- DeLong, J. B., A. Shleifer, Summers, L. H. and Waldmann, R. J. (1990) "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance*, 45(2), 379-395.
- Dufwenberg, M., Lindqvist, T. and Moore, E. (2005), Bubbles & Experience: An Experiment, *American Economic Review* 95, 1731-37.
- Fehr, E. and L. Goette L.(2007), "The Robustness and Real Consequences of Nominal Wage Rigidity," Kiel Working Paper 1343, Kiel Institute for the World Economy.
- Fischbacher U. (2007), "Z-Tree: Zurich Toolbox for Ready-made Economic Experiments," *Experimental Economics* 10(2), 171-178.
- Frederick, S. (2005), "Cognitive Reflection and Decision Making." *The Journal of Economic Perspectives*, 19(4): 25-42.

- Giusti, G., J. Jiang, and Y. Xu (2012), “Eliminating Laboratory Asset Bubbles by Paying Interest on Cash”, Working Paper, Bank of Canada.
- Haruvy, E., Y. Lahav, and C. N. Noussair (2007), “Traders’ Expectations in Asset Markets: Experimental Evidence”, *American Economic Review*, 97(5), 1901-1920.
- Haruvy, E. and C. N. Noussair (2006), “The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Asset Markets”, *Journal of Finance* 61, 1119-1157.
- Haruvy E., C. N. Noussair and O. Powell (2013) “The Impact of Asset Repurchases and Issues in an Experimental Market”, *Review of Finance*, forthcoming.
- Holt, C and S. Laury (2002), “Risk Aversion and Incentive Effects” *American Economic Review* 92(5), 1644-1655.
- Huber J., M. Kirchler and T. Stoeckl (2012) “Backward and Forward Looking Information and Its Importance for Market Efficiency. Evidence from the Lab”, working paper, University of Innsbruck.
- Kirchler, M., Huber, J., Stöckl, T. (2012), “Thar She Bursts – Reducing Confusion Reduces Bubbles”, *American Economic Review* 102(2): 865-883
- Lahav, Y. and S. Meer (2010), “The Effect of Induced Mood on Prices in Asset Prices: Experimental Evidence”, working paper, Ben Gurion University of the Negev.
- Lei, V., C. N. Noussair, and C. R. Plott, (2001) Non-Speculative Bubbles in Experimental Asset Markets: Lack of Common Knowledge of Rationality or Actual Irrationality, *Econometrica*, 69, 830-859.
- Lei, V and Vesely, F. (2009) "Market Efficiency: Evidence From A No-Bubble Asset Market Experiment," *Pacific Economic Review*, Wiley Blackwell, vol. 14(2), pages 246-258.
- Lahav, Y. and S. Meer (2010), “The Effect of Induced Mood on Prices in Asset Prices: Experimental Evidence”, working paper, Ben Gurion University of the Negev.
- Lugovskyy, V., D. Puzzello, and S. Tucker (2012) “An Experimental Study of Bubble Formation in Asset Markets Using the Tatonnement Pricing Mechanism”, working paper, Indiana University,
- Noussair C. N., S. Robin and B. Ruffieux (2001), “Price Bubbles in Laboratory Asset Markets with Constant Fundamental Values”, *Experimental Economics* 4(1), 87-105.
- Noussair C. N. and S. Tucker (2006), ““Futures Markets and Bubble Formation in Experimental Asset Markets”, *Pacific Economic Review*, June 2006, Vol. 11, No 2, pages 167-184
- Noussair C. N. and O. Powell (2010) “Peaks and Valleys: Price Discovery in Experimental Asset Markets with Non-Monotonic Fundamentals”, *Journal of Economic Studies*, 152-180
- Palan, S. (2013), “A Review of Bubbles and Crashes in Experimental Asset Markets”, *Journal of Economic Surveys* 27(3), 570 – 588.
- Smith, V. (1962) “An Experimental Study of Competitive Market Behavior”, *Journal of Political Economy* 70, 5, 111-37.

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

Table 1: Proportion of Individuals of Each Trader Type, by Treatment and Market

	Market1		Market2	
	Flat FV	Increasing FV	Flat FV	Increasing FV
Fundamental Value	39.00%	33.33%	32.08%	34.91%
Momentum	28.61%	45.61%	28.30%	30.18%
Rational Speculator	32.39%	21.06%	39.62%	34.91%

	Market1		Market2	
	Flat FV	Decreasing FV	Flat FV	Decreasing FV
Fundamental Value	33.94%	39.97%	45.79%	44.00%
Momentum	30.92%	44.19%	20.47%	35.55%
Rational Speculator	35.14%	15.85%	33.74%	20.46%

Table 2: Correlation between trader type, risk aversion, loss aversion, and CRT score

Market 1	Fundamental Value	Momentum	Rational Speculator	Risk aversion	Loss aversion	CRT
Risk aversion	0.0228	0.0047	-0.0771	1		
Loss aversion	0.0775	-0.0902	-0.0337	0.1124	1	
CRT	0.2373***	-0.1934**	-0.0248	-0.0394	0.0990	1

*** correlation sig. at $p < .01$

** correlation sig. at $p < .05$

Market 2	Fundamental Value	Momentum	Rational Speculator	Risk aversion	Loss aversion	CRT
Risk aversion	0.1647**	-0.1446*	0.0259	1		
Loss aversion	0.1470*	0.0056	-0.1593*	0.1124	1	
CRT	0.1336	-0.2371***	0.0696	-0.0394	0.0990	1

*** correlation sig. at $p < .01$

** correlation sig. at $p < .05$

* correlation sig. at $p < .1$

Table 3: Determinants of Average Dispersion and Bias with and without Risk Aversion, Loss Aversion, and CRT as Explanatory Variables

	Average dispersion Model 1	Average dispersion Model 2	Average Bias Model 1	Average Bias Model 2
Treatment	-24.04**	-29.52***	9.64	30.78**
Experience	-6.39	-6.39	4.73	4.73
Subject pool	31.66***		-10.88	
Risk Aversion		14.75***		-33.09***
CRT Score		-23.28***		21.84**
Loss Aversion		4.79		-2.41
	$R^2 = 0.2464$	$R^2 = 0.4207$	$R^2 = 0.0184$	$R^2 = 0.4604$

Figure 1: Fundamental Value Time Paths, Both Treatments

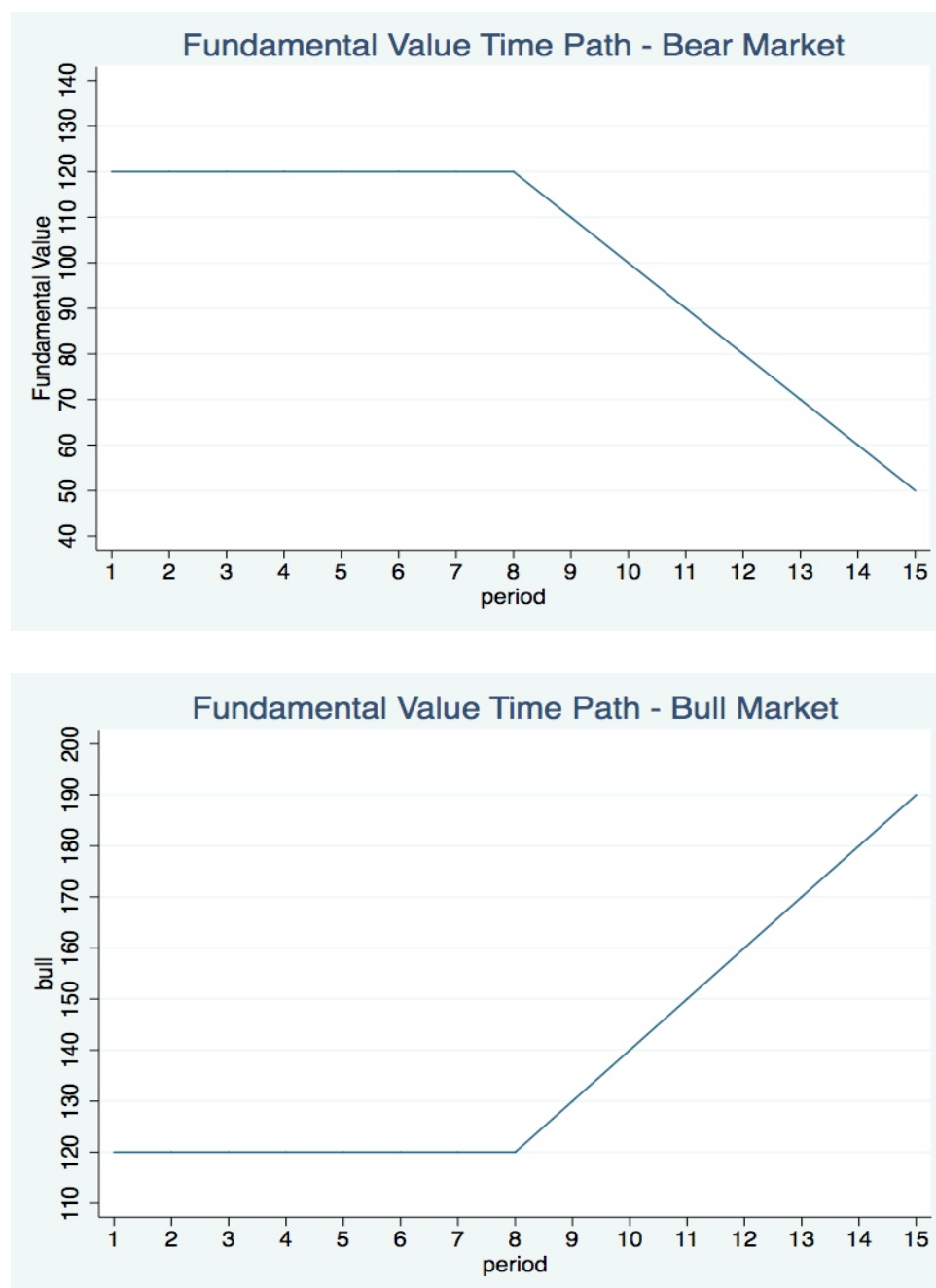
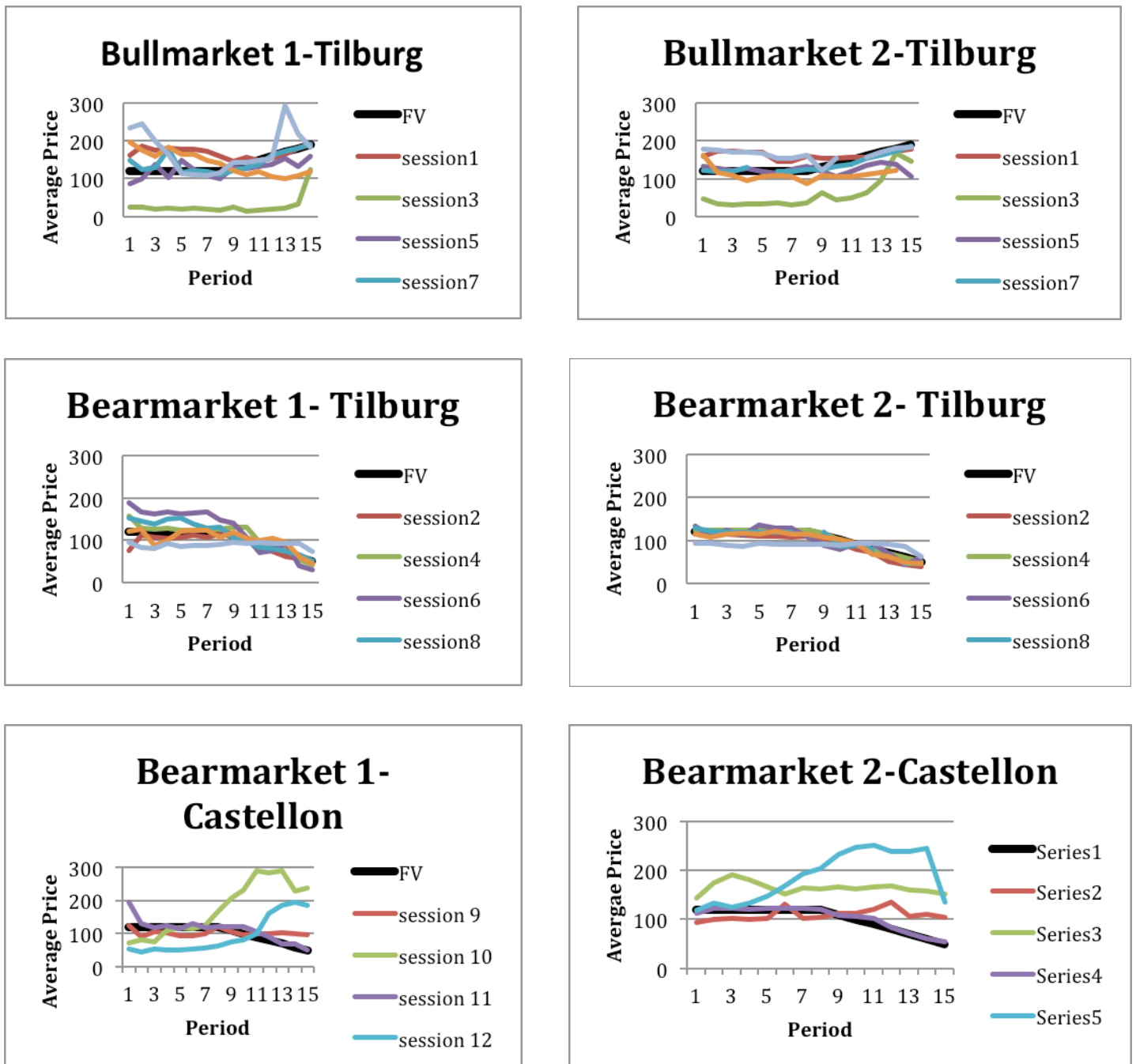
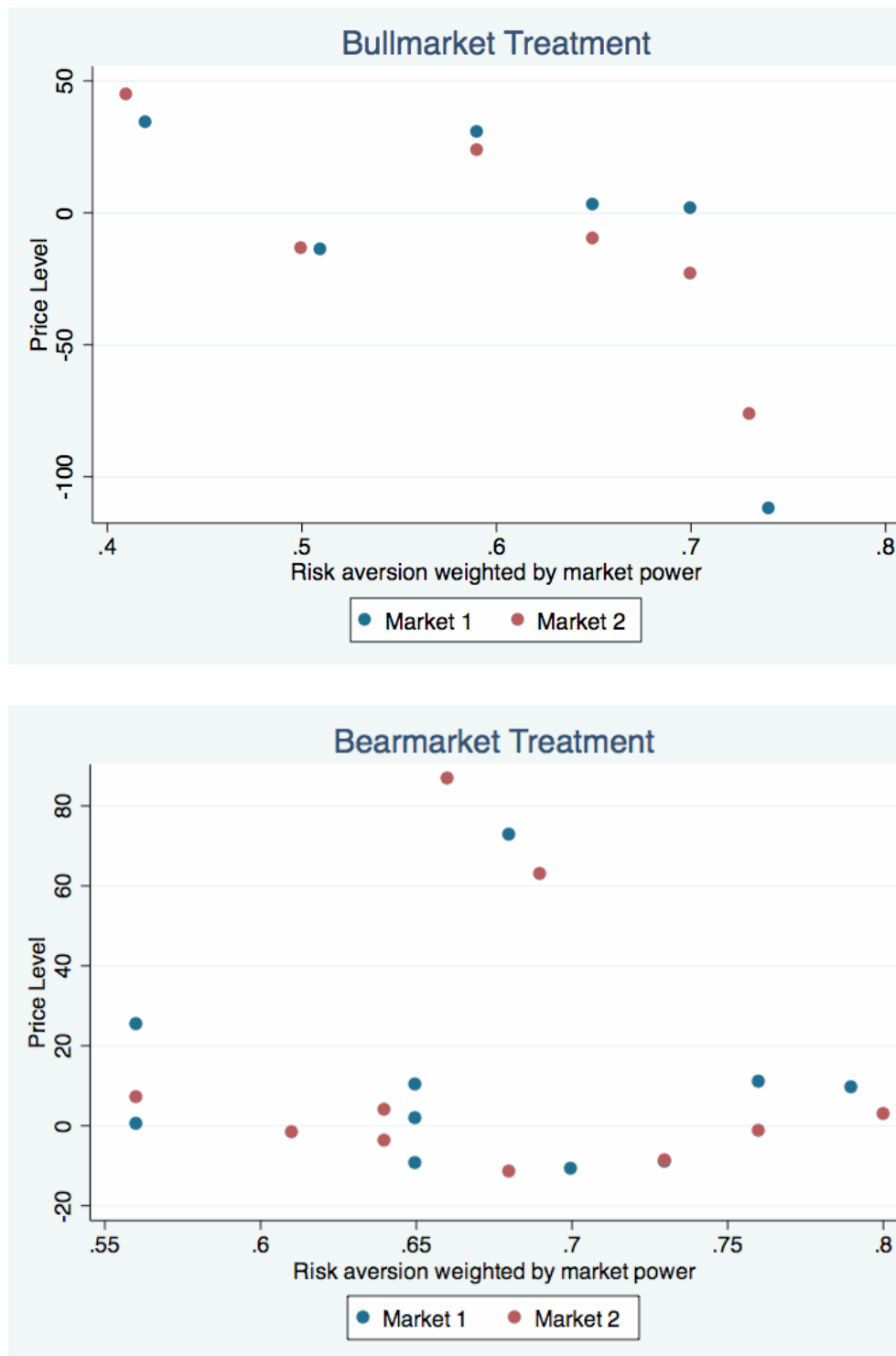


Figure 2: Average Market Prices, All Markets



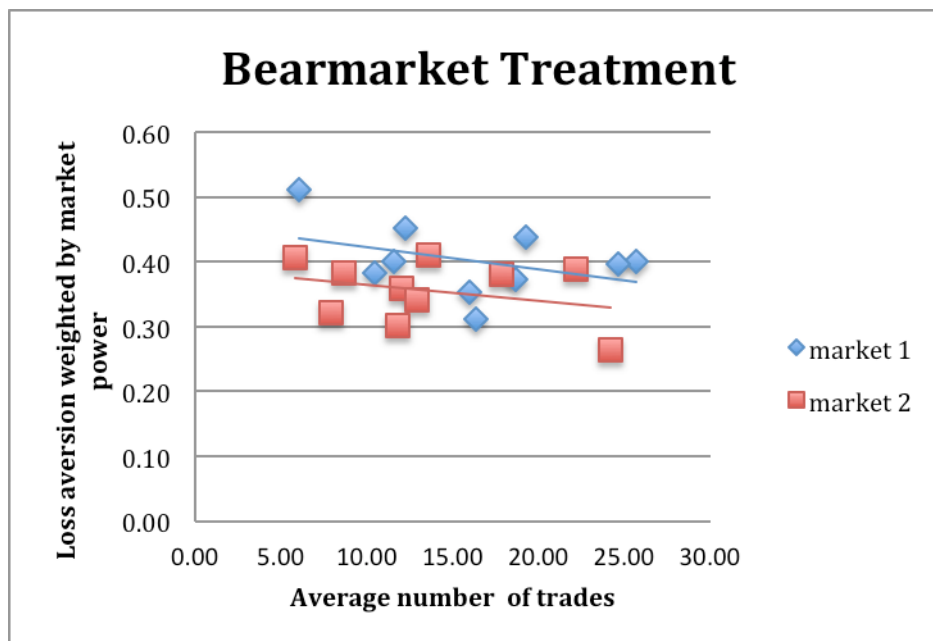
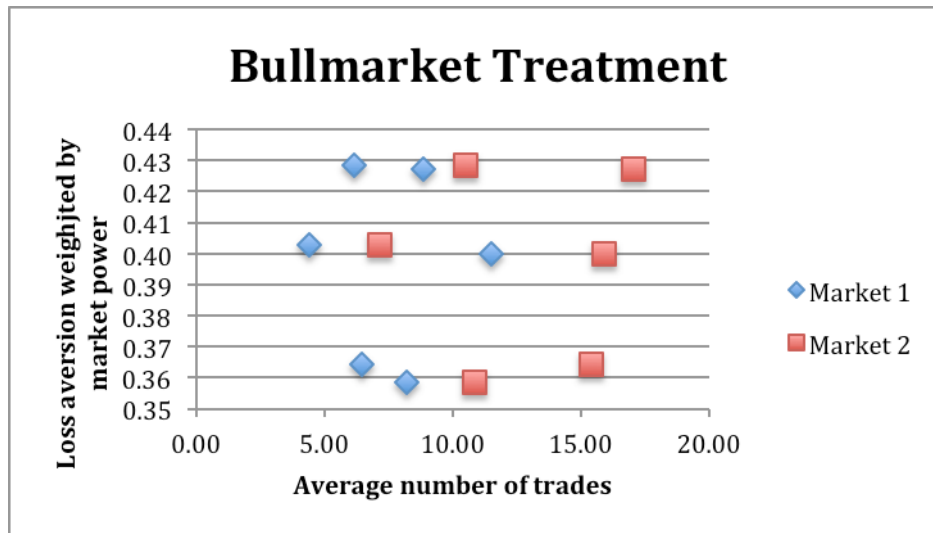
Left Panels: Market 1, Right Panels, Market 2. The data are the average transaction price in a period. Each time series is a separate session

Figure 3: Correlation between risk aversion weighted by market power and average price in each market, both treatments



Risk aversion weighted by market power equals $[(\text{Number of safe choices in part 3 by individual } i) \times (i\text{'s average market power over the 15 period market})]$, averaged over all traders in the market.

Figure 4: Relationship between loss aversion and number of transactions in a market, both treatments



Loss aversion weighted by market power equals $[(\text{Number of safe choices in part 1 by individual } i) \times (i\text{'s average market power over the 15 period market})]$, averaged over all traders in the market.

Figure 5: Cognitive Reflection Test Score and Average Bias, All Markets.

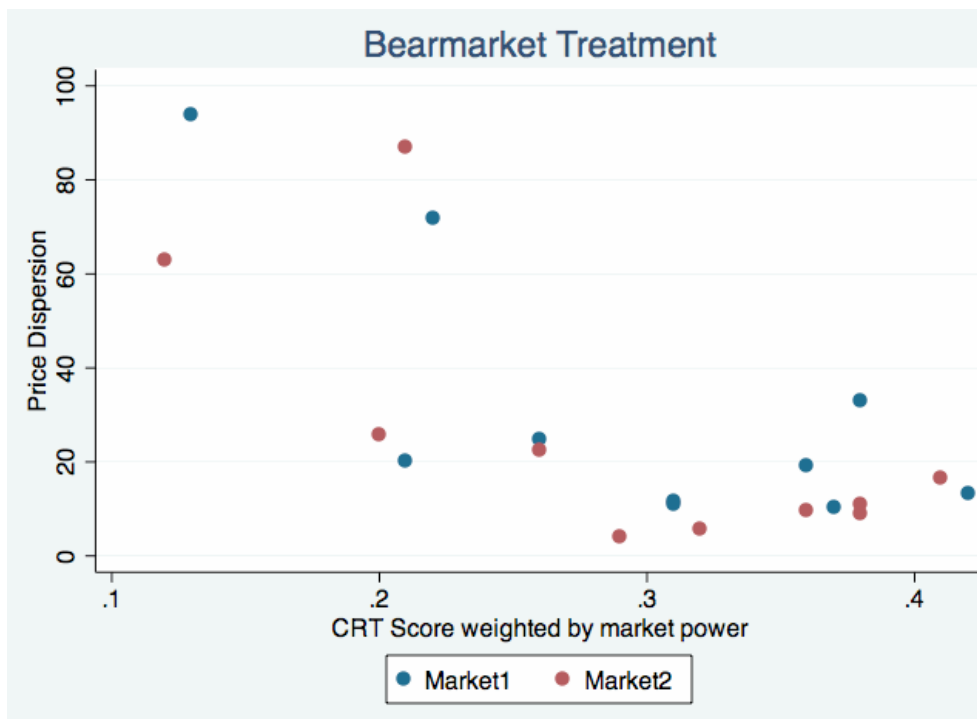
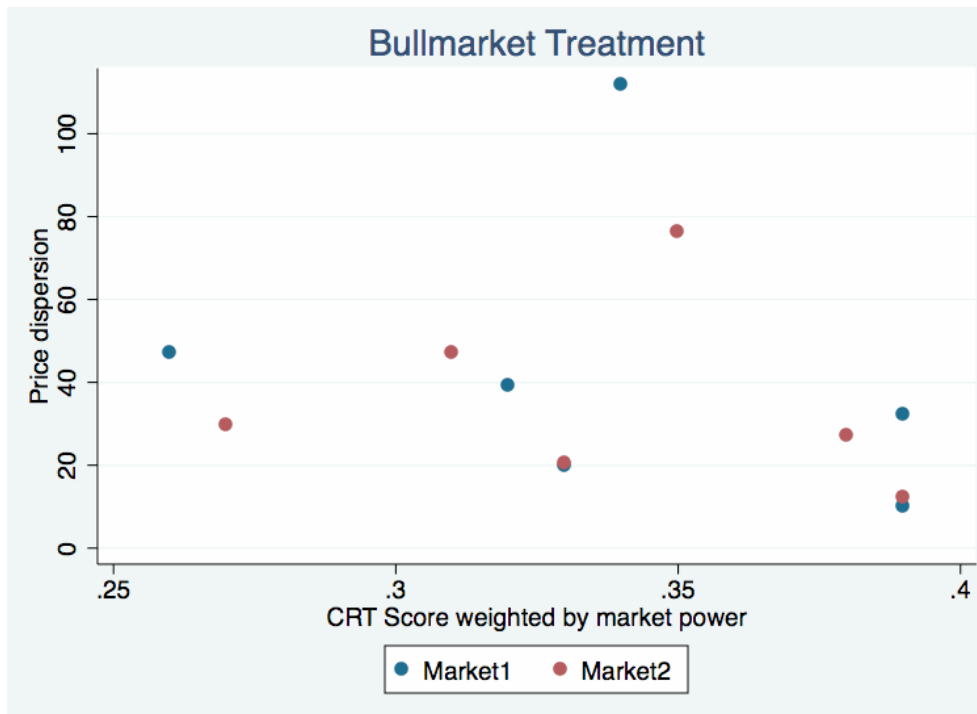


Figure 6: Final Individual Asset Holdings and Risk Aversion

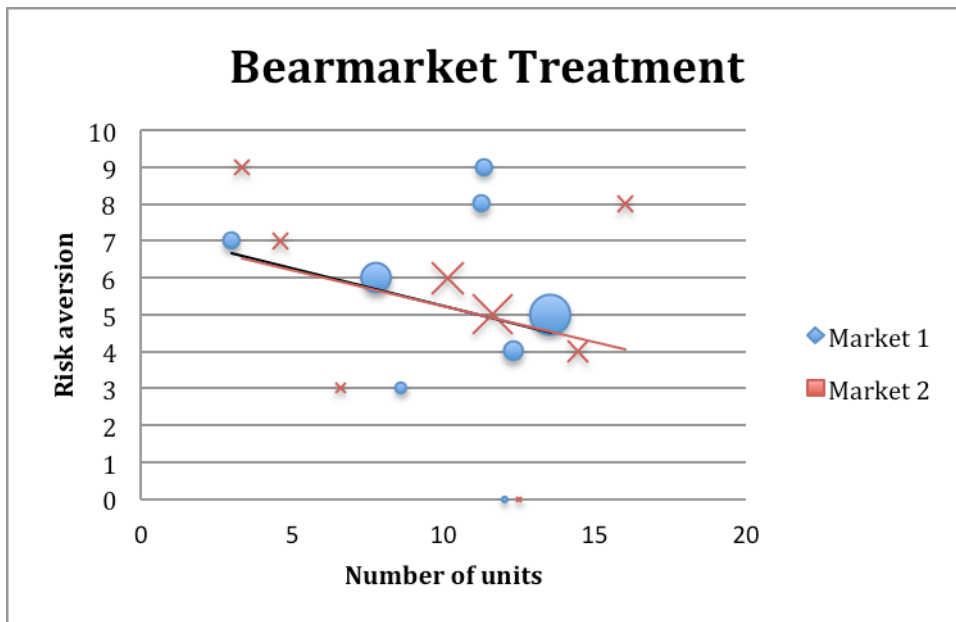
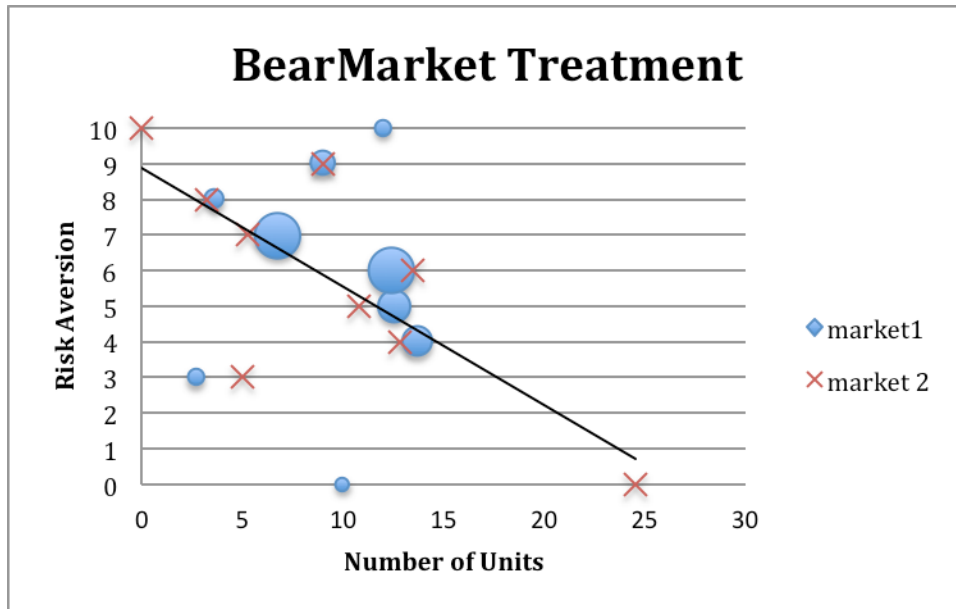


Figure 7: Total number of trades individuals conclude and their loss aversion level

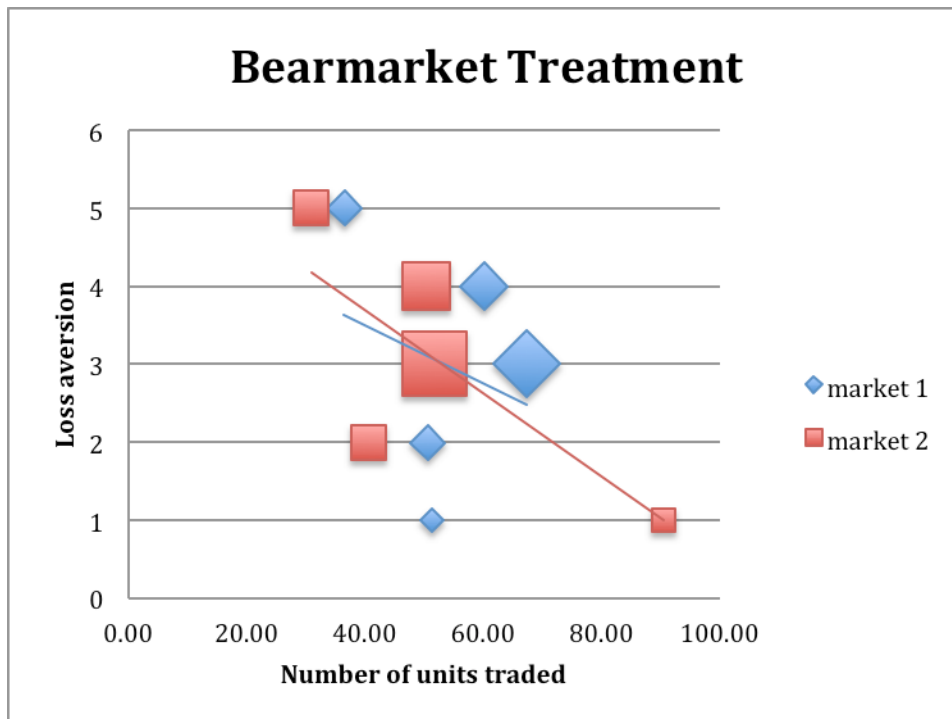
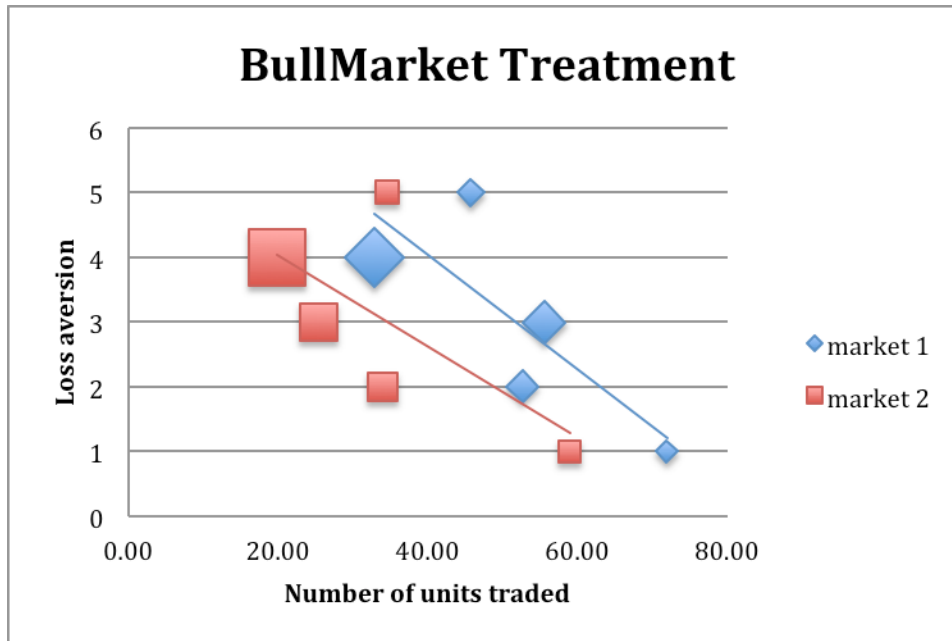
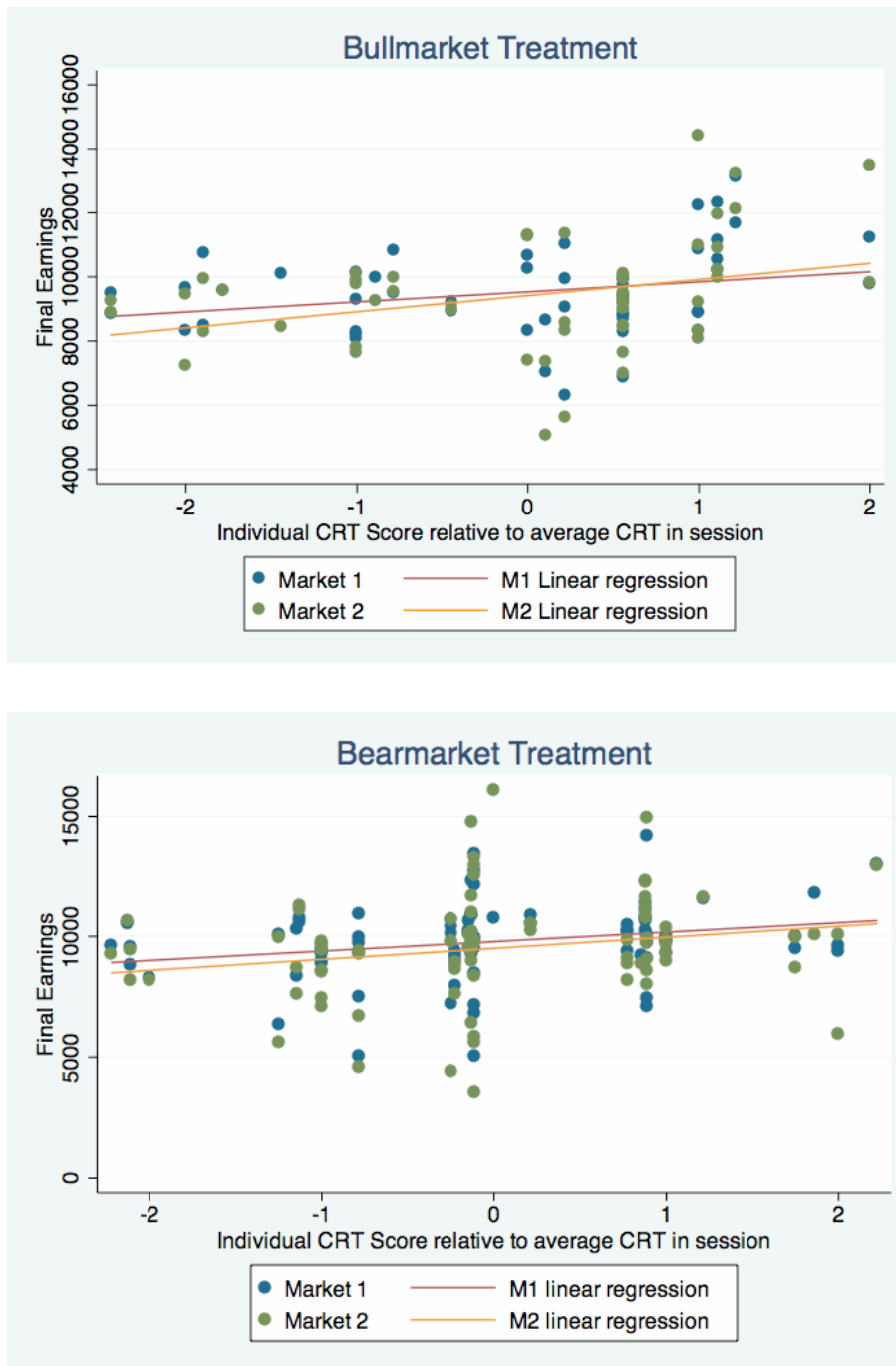


Figure 8: CRT Score and final earnings at an individual level



Appendix: This appendix contains histograms of the distributions of Loss Aversion, Risk Aversion and Cognitive Reflection Test Scores among our subjects.

