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The effect of short selling and borrowing on market prices and traders' behavior

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ABSTRACT

This paper studies the effect of allowing borrowing and short selling on market prices and traders' forecasts in an experimental asset market. There are four treatments, organized in a 2×2 design based on whether or not margin buying is allowed, and whether short selling is permitted or not. We observe that borrowing and short selling do not have significant effects on prices and forecasts due to extensive within-treatment heterogeneity. Beliefs are based on past prices of the current and previous markets, regardless of borrowing or short selling possibilities. Traders who have greater cognitive abilities tend to make more use of short selling and borrowing. A number of relationships regarding traders' types, cognitive sophistication, and earnings observed in earlier experimental studies in which borrowing and short selling are not possible, generalize to markets with borrowing and short sales.

1. Introduction

The relationship between trading with leverage and overpricing has been extensively debated (Acharya and Viswanathan, 2011; Adrian and Shin, 2010; Geanakoplos, 2009; Mertens and Ravn, 2011). While some claim that borrowing does not exacerbate market volatility (Hsieh and Miller, 1990; Kupiec, 1989; Reserve, 1984; Schwert, 1989), others have highlighted the negative correlations between stock volatilities and margin requirements (Douglas, 1967; Hardouvelis and Theodossiou, 2002; Moore, 1966; Officer, 1973; Salinger, 1989).

Similarly, the effect of short selling is also the subject of some contention. Some authors argue that it improves market efficiency and price adjustment (Miller, 1977), and reduces the probability of bubbles, as it enables speculation on downward trends (Jarrow, 1980). Others claim that short selling has a destabilizing effect (Allen and Gale, 1991), because it leads to negative skewness in market returns (Bris et al., 2007). Alternatively, Battalio and Schultz (2006) claim that short selling constraints would not have modified prices during the internet bubble, or during the SEC restrictions on short selling in 2008 (Beber and Pagano, 2013; Boehmer et al., 2013).

In view of the various confounding factors that may influence market dynamics, experimental research has tried to isolate the effects of borrowing and short selling on market outcomes under controlled and stylized environments. The literature considering these issues has almost exclusively employed the asset market environment first constructed and studied by

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Smith et al. (1988). King et al. (1993) reported no effect of short selling on market prices while borrowing increased bubble magnitudes. However, they only allowed small short positions and did not require short sellers to pay dividends on borrowed stocks. Ackert et al. (2006) constructed a market with two assets (a standard one, and a lottery asset with positively skewed returns) and found that short selling, when borrowing was prohibited, allowed prices to better track the fundamental value for both assets. Conversely, borrowing, when short selling was banned, increased overpricing of the lottery asset, but not of the standard asset. Haruvy and Noussair (2006) reported that the greater the short-selling capacity that traders possess, the lower prices were. If the short-sale constraints were sufficiently loose, assets tended to be traded at below fundamental values. However, the number of observations in all of these studies is too low to test for statistically significant differences between treatments, under the now widely-accepted assumption that each session is to be taken as the unit of observation.

In this paper, we report a new experiment intended to evaluate the impact of short selling, borrowing, and the interaction of these two techniques on prices and expectations in the asset market environment *a la* Smith et al. (1988). We do so with a relatively large dataset of 35 sessions and two markets per session. The prior literature suggests the following two hypotheses regarding the effect of trading constraints on market activity. The hypotheses presume the existence of price bubbles, a pattern that is well-established in the type of markets we study. The first, Hypothesis 1a, is a statement about average prices; that permitting borrowing would increase, and that allowing short-selling would decrease, average prices. While these patterns do not require the presence of irrational traders, they do require that the rationality of traders is not common knowledge. If rationality were common knowledge, prices would adhere to a risk-adjusted fundamental value trajectory that would be independent of trading restrictions. The weakening of the common knowledge assumption generates the belief that speculation in the pursuit of trading profits is beneficial. If speculation is occurring, a relaxation of a short-sale constraint allows more speculation on price decreases and lower prices, while a relaxation of borrowing constraints allows larger long positions to be taken, pushing up prices.

Hypothesis 1b asserts that traders anticipate these relationships before the start of trading, and thus that initial beliefs about future prices have the properties that they are higher when margin buying is possible, and lower when short-selling is permitted. This hypothesis also requires that rationality of traders not to be common knowledge, as such expectations require a belief that at least some traders intend to speculate.

H1a. Short selling lowers prices while borrowing increases prices.

H1b. Before the market opens, traders' beliefs in period 1 are that prices would be higher when borrowing is permitted and lower when short selling is allowed.

The second purpose of this paper is to investigate whether individuals trading in markets in which short-selling and borrowing are permitted behave in a similar manner as in markets in which they are not allowed. Traders' behaviors in markets with no borrowing and short selling have been studied extensively. The three aspects of behavior that we consider here are: (1) the manner in which beliefs are formed, (2) the relationship between trader types and pricing, and (3) correlations between cognitive sophistication and trading behavior.

The experimental literature has not investigated how borrowing and short-selling possibilities influence traders' expectations. Indeed, Palan (2013), in his extensive survey of the experimental literature, calls for more research on the dynamics of expectations to better understand the effect of introducing of new financial instruments or policies. The results that are available are from markets with no borrowing or short sales. Smith et al. (1988) asked subjects to predict, at the end of each trading period, the mean contract price for the upcoming period and showed that although better forecasters obtained higher profits, forecasts generally failed to predict future price movements. Ackert and Church (2001) observed that forecasts were biased and serially correlated. Haruvy et al. (2007) elicited trader's price forecasts in four successive and identical markets.[1] They showed that forecasts are based on extrapolation of trends in past prices in the current and previous markets. Deck et al. (2014) concluded that traders used past prices, and experienced traders also employed fundamental values, in making their forecasts. Akiyama et al. (2014) observed that only one half of experienced traders have beliefs that react to inflows of inexperienced traders. Based on this literature, we hypothesize that:

H2. Beliefs are formed based on past prices in the current and any previous markets in which traders have participated, regardless of whether or not borrowing and short selling are possible.

Some previous authors have tried to identify specific strategies traders are using, and have related these trader types to market outcomes. Using the theoretical model of De Long et al. (1990), who proposed interactions among three types of trading strategies – passive traders, rational speculators, and momentum traders – to account for asset price bubbles (the types are described in detail in Section 3.3), Haruvy and Noussair (2006) replicated, through computer simulations of the model, the main empirical patterns detected in their experiment, which included treatments with short-selling and margin-buying. Haruvy et al. (2014) used the same simulation model to study asset repurchases and issues. Breaban and Noussair (2015) used the same strategies to classify traders and observed that the proportions of each type were very similar to those in the studies mentioned above. Hypothesis 2 is compatible with the presence of each of these types. Passive traders

[1] At the beginning of each period, subjects were asked to predict prices for all the remaining periods. This method allowed the observation of long term forecasts — for distant periods as well and not only for the next period.

trade based on fundamentals regardless of the expectations that they hold. Momentum traders are backward-looking, and their behavior does not depend on their beliefs about the future. Rational speculators use beliefs to determine their trading strategies, and these beliefs could well be rooted in prior market activity, as proposed in Hypothesis 2.

In each of these studies, the greater the percentage of passive traders and rational speculators, and consequently the smaller the percentage of momentum traders, the closer that markets adhered to fundamentals. We hypothesize that the same would be the case in our experiment.

H3. The greater the use of Passive and/or Rational Speculator strategies, the more closely prices adhere to fundamental values.

We also expect that CRT scores to be correlated with the abilities to identify and adopt these two strategies, which are rational. Indeed, previous authors have identified a strong relationship between cognitive ability, measured by the Cognitive Reflection Test (CRT, Frederick et al., 2005), and individual earnings as well as market outcomes (Akiyama et al., 2017; Breaban and Noussair, 2015; Corgnet et al., 2015; Noussair et al., 2016). We consider here whether these correlations generalize to markets with borrowing and short selling.[2] The CRT is intended to distinguish spontaneous from deliberate reasoning.[3] In experimental asset markets with no borrowing or shorting, CRT score is positively correlated with earnings (Breaban and Noussair, 2015; Corgnet et al., 2015; Noussair et al., 2016), less confusion (Akiyama et al., 2017), and a trader's tendency to employ the fundamentalist passive strategy more often and the momentum strategy less frequently (Breaban and Noussair, 2015). Studying professional traders, Thoma et al. (2015) find that higher CRT scores were associated with more years of experience and greater salaries. At the aggregate level, Breaban and Noussair (2015) and Noussair et al. (2016) showed that markets in which traders' CRT scores are on average higher display smaller deviations from the fundamental value and a lower volatility.[4] We hypothesize that the same patterns would appear in our experiment.

H4. Markets composed of traders with higher CRT scores display smaller deviations of prices from fundamental values.

In this paper, we report a laboratory experiment consisting of 35 sessions, in which traders make forecasts of the future price trajectory, as in Haruvy et al. (2007). Each trader participates in two consecutive markets, allowing us to gauge the effect of experience on beliefs and behavior. We do not detect a significant effect of borrowing or short selling on prices, which is mainly due to the existence of large within-treatment heterogeneity. Some of the heterogeneity is explained by the differences in the median CRT scores of subjects across markets. We also find that more frequent use of a passive (or fundamentalist) trading strategy is negatively related to the magnitude of market mispricing, and positively associated with earnings at the individual level. The relationships between CRT scores, trading strategies and market dynamics, as well as the dynamics of expectations, observed in our data are consistent with what has been reported in the literature on markets without short-selling and borrowing possibilities. Thus, we conclude that these findings generalize to markets where borrowing and short selling are possible.

The rest of the paper is organized as follows. The experimental protocol is described in Section 2. Section 3 presents the results of the effects of borrowing and short selling on market prices (Section 3.1), traders' expectations (Section 3.2), and traders' strategies (Section 3.3). Finally, Section 3.4 studies the characteristics of traders who use borrowing and short selling to trade assets. Section 4 summarizes the results and concludes.

2. Experimental design

2.1. Procedures common to all treatments

The experimental sessions were conducted at the LEEM at the University of Montpellier, France, between February and March, 2016.[5] A total of 210 individuals, registered in LEEM's subject database, who had never previously been in similar asset market experiments, participated. Each session consisted of two identical, independent and sequential 10-period markets. Each subject could participate in only one session. Sessions lasted about two and a half hours. Subjects earned on average 25 euros, in addition to a show up fee of 5 Euros. The pre-recorded instructions were played while subjects followed along on their own printed copy. The instructions were available to the subjects throughout the experiment.

Our experimental design was based on those of Haruvy et al. (2007) and Akiyama et al. (2014, 2017). In each market, traders could buy and sell an asset with a lifetime of 10 periods. At the end of each period, each unit of asset paid a dividend of either 24 or 48 ECU (experimental currency units) with an equal probability. Thus, the expected dividend per period was 36 ECU per asset. Dividends received by the subjects during the 10 periods of the market could be used to purchase assets.

[2] CRT scores correlate with the Wonderlic Personnel Test (WTP), the Scholastic Achievement Test (SAT), the American College Test (ACT), the Wechsler abbreviated scales of intelligence (WASI) and Belief Bias in Syllogistic Reasoning (BBSR).The WTP measures the person's intellectual abilities, ACT and SAT measure academic achievement such as mathematics, science, critical reading and writing, and are used for college admissions in the USA. WASI is used to measure intelligence and BBSR to gauge an individual's rationality of thinking.

[3] Higher CRT scores are correlated with skills such as patience, intelligence, and a good calculation capacity. These include lower incidences of the conjunction fallacy and conservatism in updating probabilities (Oechssler et al., 2009).

[4] CRT scores, and cognitive ability more generally, is a distinct concept from that of the trading strategies a participant employs.

[5] The experiment was computerized with z-Tree (Fischbacher, 2007).

After the final dividend payment in period 10, the asset had no value.[6] Accordingly, at the beginning of period t, the asset's (risk neutral) fundamental value was $FV_t = 36(11 - t)$. Though Kirchler et al. (2012) note that the dividend structure of an asset with a constant fundamental value over time is better understood than one in which the fundamental value is decreasing, our choice of a decreasing fundamental value was made because it is the dominant setup in the literature, and in particular in the prior studies of short-selling and borrowing. This facilitates the comparison of our results to those in the existing literature. Subjects received a table indicating the fundamental value of the asset in each period in the instructions, as well as on a separate sheet of paper, and instructed subjects about how to calculate the fundamental value.[7] At the beginning of period 1 of each market, each subject was endowed with 10 units of the asset and 3600 ECU. The exchange rate between ECU and Euros was 1 euro = 360 ECU.

We employed a call market to trade the asset, as in Akiyama et al. (2014, 2017) and Haruvy et al. (2007). The call market rule facilitates the elicitation of price forecasts, because there is a unique and unambiguous price in each period. Therefore, whether an agent is thinking about the mean, median, initial or last trading price in a period when making their price prediction is irrelevant. In a call market, all traders simultaneously submit their buy and/or sell orders. If trader i submits a buy order in period t, she must specify the highest price at which she is willing to buy (b_t^i for bid) and the maximum quantity she is willing to buy at that price (d_t^i for quantity demanded). If she submits a sell order, she must specify the lowest price at which she is willing to sell (a_t^i for ask) and the maximum quantity to sell at that price (s_t^i for quantity supplied).[8] Once all orders have been submitted, they are aggregated to calculate a market clearing price.[9] Transactions are realized for those orders for which the bid (ask) is greater (less) than or equal to the market clearing price.[10]

At the beginning of each period, subjects were asked to predict market prices for all of the remaining periods before submitting their orders, as in Haruvy et al. (2007) and Akiyama et al. (2014, 2017). Thus, in period t, each subject had to forecast $11 - t$ prices, which corresponded to a total of 55 predictions over the 10 periods. Each forecast that was between 90% and 110% of the realized market price in the period predicted yielded a bonus of 36 ECU.[11]

At the end of the two consecutive 10-period markets, subjects answered a 7-question version of the CRT (Frederick, 2005). We selected the 3 first questions of Finch and Gullion (2010) and the last 4 questions of Toplak et al. (2014). No monetary incentive was provided for correct answers.

2.2. The treatments

There are four treatments. Nine sessions, each involving six traders, were run under each treatment.[12] In the Baseline treatment (hereafter BL), no short selling and no borrowing was allowed. In the Borrowing treatment (BW), borrowing cash was permitted but short selling was not. In addition to the 3600 ECU given at the beginning of each market, 3600 ECU were lent to each trader.[13] This additional cash lent had to be repaid entirely by the end of each market.[14]

In the Short Selling treatment (SS), short selling (borrowing stock) was allowed but borrowing cash was not. Any trader could hold a short position of up to 10 shares (a position equal to −10 shares). For every asset sold short at the end of each period, the trader had to pay the dividend for the period. The dividend paid for each stock sold short was automatically deducted from the trader's available cash. The initial total value of stocks available for short sale, $360 \times 10 = 3600$ ECU, was equal to the amount of cash lent in the borrowing treatment. This symmetry at the beginning of the market facilitates comparisons between these two treatments. However, it is not possible to preserve this symmetry for the duration of the market. Due to the declining fundamental value of the asset, the borrowing limit for stocks ($10 \text{ stocks} * FV_t \leq 3600$) decreases over time, while the borrowing limit for cash (3600) remains constant. In other words, the largest number of shares that can be purchased on margin at the fundamental value, and thus the greatest possible long position, increases over time, while the largest short-position possible stays the same.[15]

In the fourth treatment (BWSS), short selling and borrowing were both permitted. As in the SS treatment, each trader could hold a short position of up to 10 units. As in the BW treatment, 3600 ECU were lent to each trader and had to be

[6] Therefore, the cash-to-asset value ratio is increasing over time.

[7] The experiment was conducted in French. An English translation of the instructions is provided in Appendix I.

[8] The admissible price range that a trader can offer must respect the following conditions: If $d_t^i > 0$ ($s_t^i > 0$), $b_t^i \in \{1, 2, \ldots, 2000\}$ ($a_t^i \in \{1, 2, \ldots, 2000\}$). If $d_t^i > 0$ and $s_t^i > 0$, then $a_t^i \geq b_t^i$. The budget constraint in effect depended on the treatment. See Section 2.2.

[9] If there are multiple market-clearing prices, the lowest among them is chosen (as in Haruvy et al. (2007) and Akiyama et al. (2014, 2017)).

[10] In the case of ties among buy and sell orders, the computer randomly chooses which ones will be executed.

[11] See Hanaki et al. (2018) for a discussion of the effects that this method of incentivizing forecasting performance may have on market dynamics and trading behavior.

[12] The exception is the Short Selling treatment, in which only eight sessions were conducted.

[13] By allowing a borrowing leverage of 2:1, equivalent to a 50% margin requirement., we have deliberately chosen to follow the margin requirement set up by the Federal Reserve Board in the United States since 1974.

[14] If a trader cannot repay the borrowed funds at the end of the market, he is considered to be bankrupt. In this case, the amount he can not repay is automatically deducted from the show-up fee of 5 Euros.

[15] Indeed, since the fundamental value of the asset decreases from 360 at the beginning of period 1 to 36 at the beginning of period 10, the overall difference at the end of the market between the borrowing limit for stocks and the borrowing limit for cash is substantial. For example, in the last period (when $FV = 36$), the borrowing limit for stocks is $10 \times 36 = 360$ ECU, which is 10% of the borrowing limit for cash. According to a measure called the *Relative Borrowing Limit* (*RBL*), defined in Appendix C, the average *RBL* over 10 periods in our market is −0.79. We thank an anonymous referee for suggesting this measure.

Table 1
Average values (standard deviations) of market mispricing measures for each treatment in Markets 1 and 2.

	RAD	GAD	RD	GD	RAD	GAD	RD	GD
	M1				M2			
BL	0.87	1.14	0.71	0.73	0.39	0.82	0.24	0.15
	(0.38)	(0.59)	(0.42)	(0.56)	(0.15)	(0.98)	(0.25)	(0.46)
SS	0.59	0.94	0.35	0.37	0.39	1.13	−0.04	−0.16
	(0.40)	(0.56)	(0.56)	(0.69)	(0.22)	(1.19)	(0.40)	(0.47)
BW	0.95	1.31	0.82	0.72	0.69	1.27	0.26	0.14
	(0.65)	(0.82)	(0.69)	(0.70)	(0.52)	(0.88)	(0.76)	(0.96)
BWSS	0.86	1.14	0.67	0.39	0.53	1.79	0.07	−0.08
	(0.60)	(0.63)	(0.67)	(0.51)	(0.41)	(2.35)	(0.61)	(0.64)
p-values (KW)	*0.56*	*0.80*	*0.41*	*0.35*	*0.62*	*0.42*	*0.42*	*0.55*

M1 and M2 comparisons

Treatment	RAD	GAD	RD	GD
BL	0.00	0.25	0.01	0.01
BW	0.10	0.65	0.02	0.02
BWSS	0.25	1	0.02	0.03
SS	0.31	0.74	0.01	0.01

(p-values of Wilcoxon paired signed-rank tests)

returned at the end of each market.[16] In order to simplify the experimental design as much as possible and to avoid adding difficulties to the subjects, the interest rates on the borrowing of cash and assets were set at zero in all treatments.[17]

3. Results

3.1. Market behavior

Fig. 1 shows the time series of observed prices in the four treatments in Markets 1 and 2. Each price displayed in the figures corresponds to the market clearing price in a period. The price charts for Market 1 show some overpricing on average in the BL, BW and BWSS treatments. The SS treatment displays lower prices than the other three treatments, with 4 of 8 markets tracking the fundamental value closely. However, the markets of the BW and BWSS treatments are characterized by a larger variability of period 1 prices, and greater volatility over time.

In Market 2, prices track the fundamental value more closely than in Market 1 in all treatments. The BW treatment displays the largest mispricing on average, with a tendency toward overvaluation in almost half of the markets and undervaluation in three others. BW and BWSS continue to have a large variability of the first period prices. Markets that have high first period prices in Market 1 also have a strong tendency to do so in Market 2.

Table 1 reports, for each treatment, the averages over all the sessions of four mispricing measures: *RAD, GAD, RD* and *GD* (Stöckl et al., 2010 and Powell, 2016), as well as *p*-values from Kruskal-Wallis (KW) tests for treatment differences.[18] The *p*-values reveal that none of the four measures is statistically significantly different across the four treatments.[19]

To compensate for the increase over time in the number of units that can be bought with leverage compared to the quantity that can be sold short, we have also corrected the mispricing indicators using the RBL measure (see footnote [15]) as follows. When testing BL against SS, we multiply (divide) the positive (negative) mispricing indicators for the SS treatment by 0.79, which is equal to the average RBL, so as to amplify the decrease of the mispricing phenomenon observed in SS. Mann-Whitney pairwise comparisons between the SS and BL treatments, for each of the four mispricing indicators did not result in any significant treatment effect in either market 1 or market 2 after making this *RBL* correction, in addition to the Bonferroni correction for multiple hypotheses testing.

In each treatment, *RD* and *GD* are significantly smaller in Market 2 than in Market 1. This is also the case for *RAD* for BL and for BW at the 10% level. See the bottom panel of Table 1 for *p*-values. This lower market mispricing in Market 2 is confirmed by the various measures introduced in Appendix B. Thus, regardless of the treatment, we observe that subjects

[16] One subject went bankrupt in this treatment, the only one to do so in any of the four treatments.

[17] Adding a positive interest rate could yield quite different results, as it may lead subjects to borrow less. However, Giusti et al. (2016) find that increasing the opportunity cost of speculation by introducing interest payments on cash holdings "has limited effect on containing price inflation."

[18] Relative Absolute Deviation (RAD) and Geometric Absolute Deviation (GAD) are absolute measures of mispricing. Relative Deviation (RD) and Geometric Deviation (GD) are measures of price level relative to fundamentals. See Appendix C for definitions. We also report a number of other measures of mispricing in Appendix B, that are defined in Appendix C.

[19] We have also conducted OLS regressions with cluster-robust estimates at the session level ($Price_t - FV_t$ as a function of treatments), to test for differences between treatments. In addition, we have run Mann–Whitney pairwise comparisons of the four mispricing indicators for all the possible treatment combinations, with and without Bonferroni corrections. Neither analysis yields any statistically significant treatment differences.

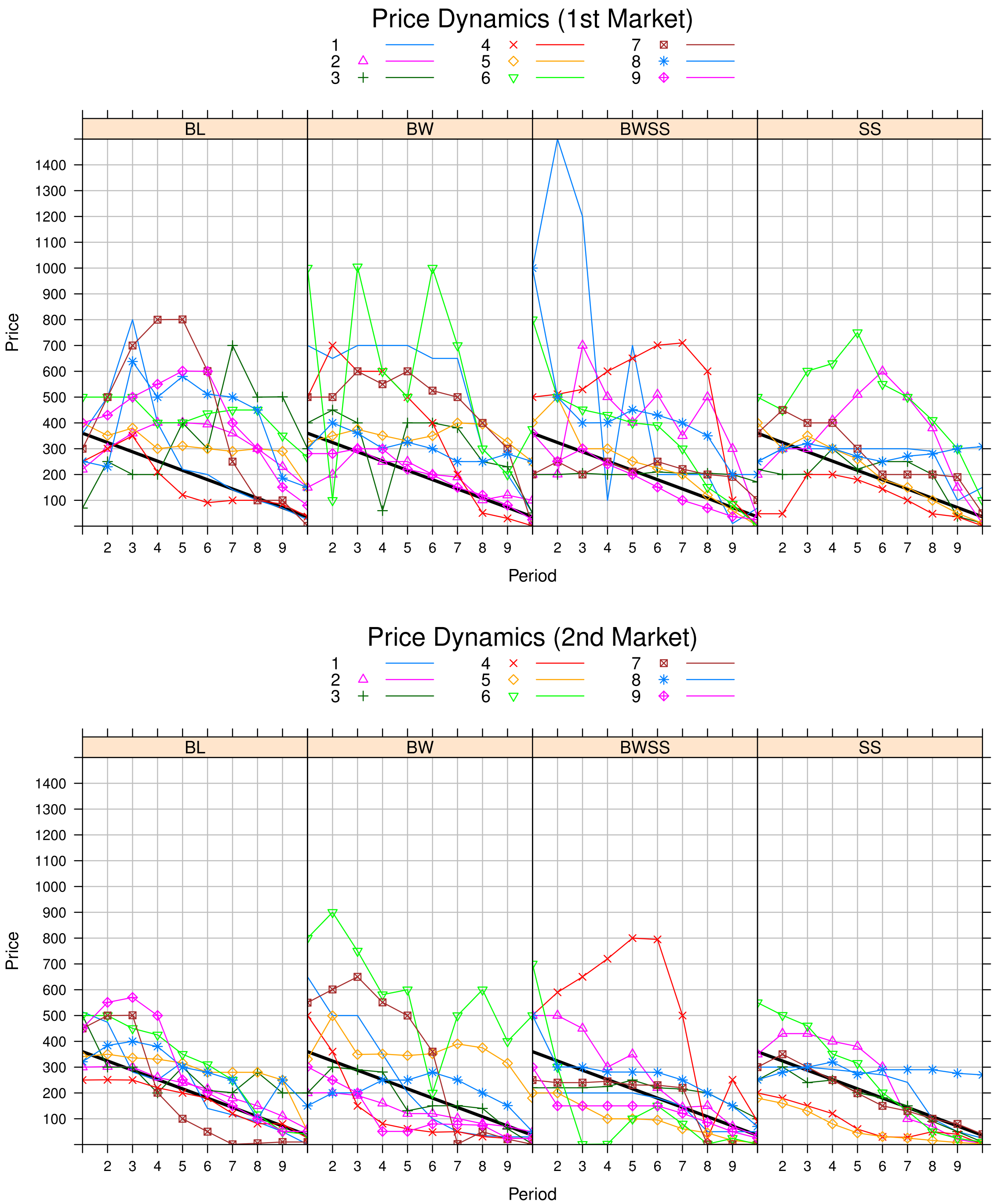

Fig. 1. Price dynamics in the Market 1 and 2. Note:The four treatments are displayed. Baseline treatment (BL) is on the left, Borrowing treatment (BW) is in the middle to the left, Borrowing and Short Selling treatment (BWSS) is in the middle to the right, and Short Selling treatment (SS) is on the right. Each line, with a different color, corresponds to a market. The black straight line is the fundamental value of the asset over time.

trade at prices closer to fundamentals after gaining some experience in the same environment with the same group of subjects, in agreement with the previous literature.[20]

Fig. 1, as well as Table 1, are the basis of our first result, which shows that our data fail to support Hypothesis 1a.

[20] In Table 1, and in Appendix B for the other mispricing measures, the Wilcoxon Signed Rank tests are statistically significant for many indicators, showing that the distributions are statistically different between Markets 1 and 2. Considering these tests in conjunction with the direction of the average changes between Markets 1 and 2, we conclude that market prices are generally closer to the FV in Market 2.

Table 2
Mispricing indicators as a function of median CRT.

	Market 1				Market 2			
	RAD	GAD	RD	GD	RAD	GAD	RD	GD
(Intercept)	1.21***	1.39***	1.09***	1.15***	0.50***	0.54	0.45	0.55*
	(0.25)	(0.33)	(0.29)	(0.29)	(0.18)	(0.74)	(0.27)	(0.32)
med CRT	−0.17*	−0.12	−0.18*	−0.21*	−0.05	0.13	−0.10	−0.19
	(0.09)	(0.12)	(0.10)	(0.11)	(0.06)	(0.27)	(0.10)	(0.12)
BW	0.16	0.22	0.19	0.09	0.32*	0.39	0.07	0.07
	(0.24)	(0.31)	(0.28)	(0.28)	(0.17)	(0.72)	(0.26)	(0.31)
BWSS	−0.08	−0.05	−0.11	−0.42	0.11	1.02	−0.21	−0.31
	(0.24)	(0.31)	(0.27)	(0.28)	(0.17)	(0.72)	(0.26)	(0.31)
SS	−0.36	−0.26	−0.45	−0.46	−0.02	0.38	−0.33	−0.40
	(0.25)	(0.32)	(0.28)	(0.29)	(0.18)	(0.74)	(0.27)	(0.32)
R^2	0.16	0.07	0.17	0.19	0.13	0.07	0.09	0.12
Adj. R^2	0.05	−0.05	0.06	0.08	0.01	−0.06	−0.03	0.01
Num. obs.	35	35	35	35	35	35	35	35
RMSE	0.51	0.66	0.58	0.59	0.36	1.50	0.54	0.65

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Result 1: Short selling and borrowing do not significantly affect prices.

The relationship between the CRT scores of market participants and mispricing replicates the findings by Breaban and Noussair (2015) and Noussair et al. (2016). As reported in Table 2, we observe, in Market 1, statistically significant negative relationships between median CRT scores of market participants and *RAD, RD* and *GD* (at 10%). These relationships are also confirmed with the other mispricing indicators analyzed in Appendix D, Table 11. The relationships are not observed in Market 2, however, where prices track fundamentals more closely and there is less variation. These relationships are summarized in Result 2, which indicates that Hypothesis 4 is supported.

Result 2: Markets composed of traders with higher CRT scores display lower deviations from the FV in Market 1, but not in Market 2.

3.2. Traders' forecasts

3.2.1. Initial forecasts

In our analysis of trader forecasts, we first evaluate Hypothesis 1b, and consider the extent to which initial forecasts made at the beginning of period 1 in Market 1 before any transactions and prices occur, are affected by the possibility for traders to borrow and sell short. Fig. 2 displays the average initial forecast by treatment (left panel). Forecast trajectories are constant for all periods and for each treatment, which confirms and generalizes results of Haruvy et al. (2007). Initial forecasts do not reflect an expectation that prices will follow the fundamental value. The BW curve tends to be above the others, while the SS one tends to be below — with BL and BWSS in the middle. While these first impressions suggest that there might be a treatment effect regarding forecasts, before any market activity has taken place, based only on the description of the environment, the average depicted in the Fig. 2 masks the considerable heterogeneity in beliefs within each treatment.

To consider the deviation of the initial forecast from fundamentals, we use a measure called the relative absolute forecast deviation, or *RAFD* (Akiyama et al., 2014; 2017).[21] The right panel in Fig. 2 displays the empirical cumulative distribution function (ECDF) of the *RAFD* computed for the first period of Market 1 ($RAFD_{1,1}$). Although the ECDF for the BW treatment is to the right of the other three, and SS is slightly to the left of BL and BWSS, the differences are not statistically significant. This lack of difference forms the basis of support for our third result.

Result 3: Traders' initial predictions are not significantly different when borrowing and/or short selling are allowed.

3.2.2. Forecast dynamics

Figs. 3 and 4 display the average price forecasts submitted by all traders in each treatment at the beginning of each period of Markets 1 and 2, respectively. Each figure shows ten bar charts, each displaying price forecasts in one of the four treatments (shown in four different colors) made for each period of elicitation (PoE). The horizontal axis indicates the forecasted period, and the vertical axis indicates the average forecast.

In the first bar charts of Fig. 3 (PoE 1 to 6), we observe that, for Market 1, the average forecasts are constant for all periods in all the treatments. This is similar to the finding of Haruvy et al. (2007). Traders initially do not anticipate the increasing prices in the first few periods of the market nor the decreasing prices in the later periods. They do not expect that prices will follow the Fundamental Value (FV) either. The predictions under BW tend to be above the others, while in SS they tend to be below, giving the impression that there might be a treatment effect.

[21] The definitions and formula are given in Appendix C.

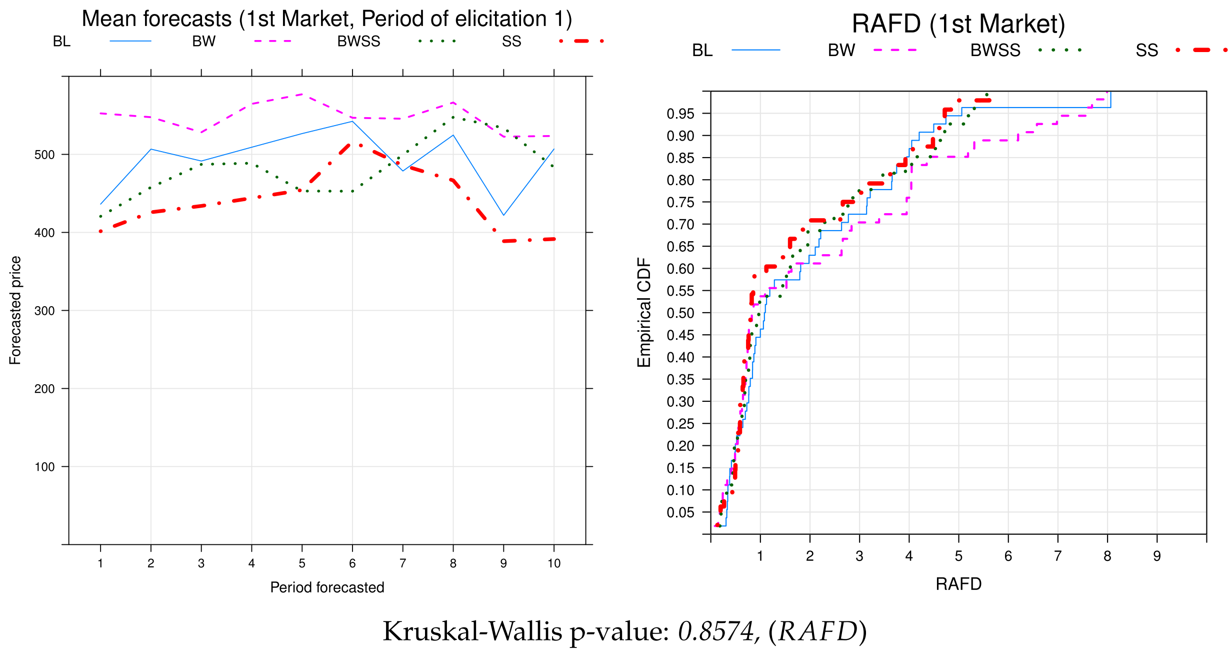

Fig. 2. Mean forecasts made during the 1st period of Market 1 (left), ECDF of *RAFD* (right).

Considering Figs. 1 and 3 together reveals that forecasts made in period t tend to anticipate constant prices at the level of those of period $t-1$, which indicates that traders simply adjust their forecasts based on the previous price. In Market 2, traders' expectations are generally lower than in Market 1, except at the very beginning of the market. Moreover, in all treatments, successive price forecasts submitted during a period t gradually decrease as the period forecasted moves away from the elicitation period. However, price forecasts decline less rapidly than actual prices. This pattern is consistent with the results of Haruvy et al. (2007) and, as is shown below, reflects traders' inclination to use both prices of Market 1 and past prices of Market 2 to define their forecasts.

Haruvy et al. (2007) observed that beliefs anticipated a continuation of trends in the current market, as well as the price patterns observed in prior markets. We consider here an extension of their model that allows for multiple treatments and for beliefs to depend on fundamentals.

$$\begin{aligned} f_{i,m,t}^{t+k} = {} & \beta_0 + \beta_1 BW + \beta_2 BWSS + \beta_3 SS + \beta_4 (Markettrend_{m,t}) + \beta_5 (Periodtrend_{m,t}) \\ & + \beta_6 FV_t + \beta_7 (Markettrend_{m,t} * BW) + \beta_8 (Markettrend_{m,t} * BWSS) \\ & + \beta_9 (Markettrend_{m,t} * SS) + \beta_{10} (Periodtrend_{m,t} * BW) + \beta_{11} (Periodtrend_{m,t} * BWSS) \\ & + \beta_{12} (Periodtrend_{m,t} * SS) + \beta_{13} (FV_t * BW) + \beta_{14} (FV_t * BWSS) + \beta_{15} (FV_t * SS) \end{aligned} \tag{1}$$

where $f_{i,m,t}^{t+k}$ is the price forecast submitted in period t for the period $t+k$ of market m by trader i. *BW*, *BWSS* and *SS* are treatment dummy variables.

$Periodtrend_{m,t}$ is the change in prices or expectations in the current market between $t+k-2$ and $t+k-1$. This variable captures the idea that a trader will anticipate the same percentage price change between $t+k-1$ and $t+k$ as the one between $t+k-2$ and $t+k-1$. $Markettrend_{m,t}$ incorporates the idea that a trader takes into account the price dynamics that occurred during the same periods of the previous market to form his expectations in the current market. It assumes that a trader will anticipate the same percentage price change between $t+k-1$ and $t+k$ in the current market as the one which occurs between $t+k-1$ and $t+k$ in the previous one. This is defined for Market 2 in our data.[22] Finally, FV_t measures the extent to which a trader integrates the current fundamental value of the asset in the formation of his beliefs.

This regression allows us to isolate the effects directly related to treatments and those related to the price dynamics of the current market ($Periodtrend_{m,t}$) and of the previous market ($Markettrend_{m,t}$). Table 3 reports the results of multilevel

[22] The precise definitions of $Periodtrend_{m,t}$ and $Markettrend_{m,t}$ are given in Appendix C.

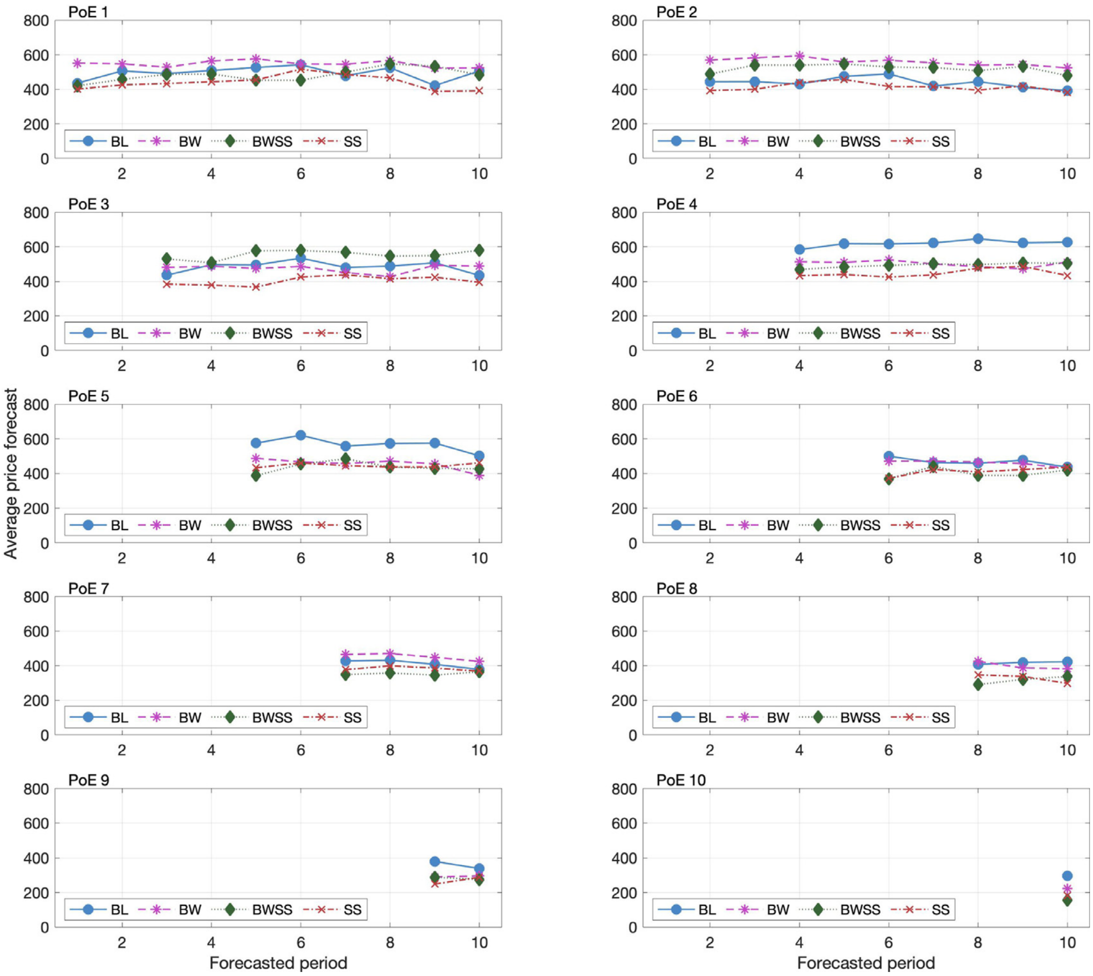

Fig. 3. Average forecasts made during Market 1 for each period of elicitation.

regressions (MLM) for Markets 1 and 2.[23] The MLM approach allows the separation of the variance at many levels and exploration of variations in effects both between and within clusters.[24]

In Market 1, *Periodtrend* is significant. This result confirms the influence of past price trends in the current market in the formation of traders' expectations. Moreover the interaction coefficients between *Periodtrend* and dummy treatment variables are not significant, indicating that the prior trend influences expectation formation in a similar manner in all four treatments. The difference in expectations between treatments results from differences in price histories, rather than any differences in the expectation formation process itself. The coefficients for *FV* are not significant, demonstrating the lack of a connection between beliefs and the fundamental value.

[23] To conduct this regression specification, we use two statistical methodologies. First, we ran a random effects regression (RE) in a panel data framework to account for dependencies at the subject level (displayed in Appendix F). The second approach is new in experimental finance and consists of building multilevel models (MLM). This technique is an extension of random and mixed effects models. Since it is proposed with random effects models in a panel data framework, which identifies each subject as a cluster, multilevel modeling allows many levels of clusters and their inter-dependencies to be considered, so as to better determine where the statistical effects come from. Moffatt (2016) highlights how some significant treatment effects can be reduced or even eliminated when some clusters are identified and taken into account. Using multilevel modeling, we first consider the subjects' cluster, since there are 55 observations (here $f_{i,m,t}^{t+k}$) for each of the 210 subjects. We then look at the market cluster, as there are 35 markets in which subjects' forecasts can be dependent on each other (correlated), which could imply a significant variance at the market-level. These two clusters are identified through a subject-specific random effect and a market-specific random effect. The theoretical presentation of the multilevel model, the procedures, and the selection criteria of the MLM regressions are summarized in Appendix E. Treatment effects are captured by dummy variables for each treatment, through differences in intercepts and interaction coefficients of these dummy variables with the explanatory variables. We present here the results of the MLM regressions, but we report the estimates from the more standard RE approach in Appendix F to show how divergent conclusions might be drawn.

[24] Here, our MLM selection procedure selected the model with random slopes for both subject and market clusters, because of a better fit. This procedure confirms that the intercepts and the slopes of the explanatory variables vary across subjects and markets, because of dependencies within clusters. Moreover, all standard deviations at the subject and market levels are significantly different from zero, which implies that there are large heterogeneities across markets and subjects.

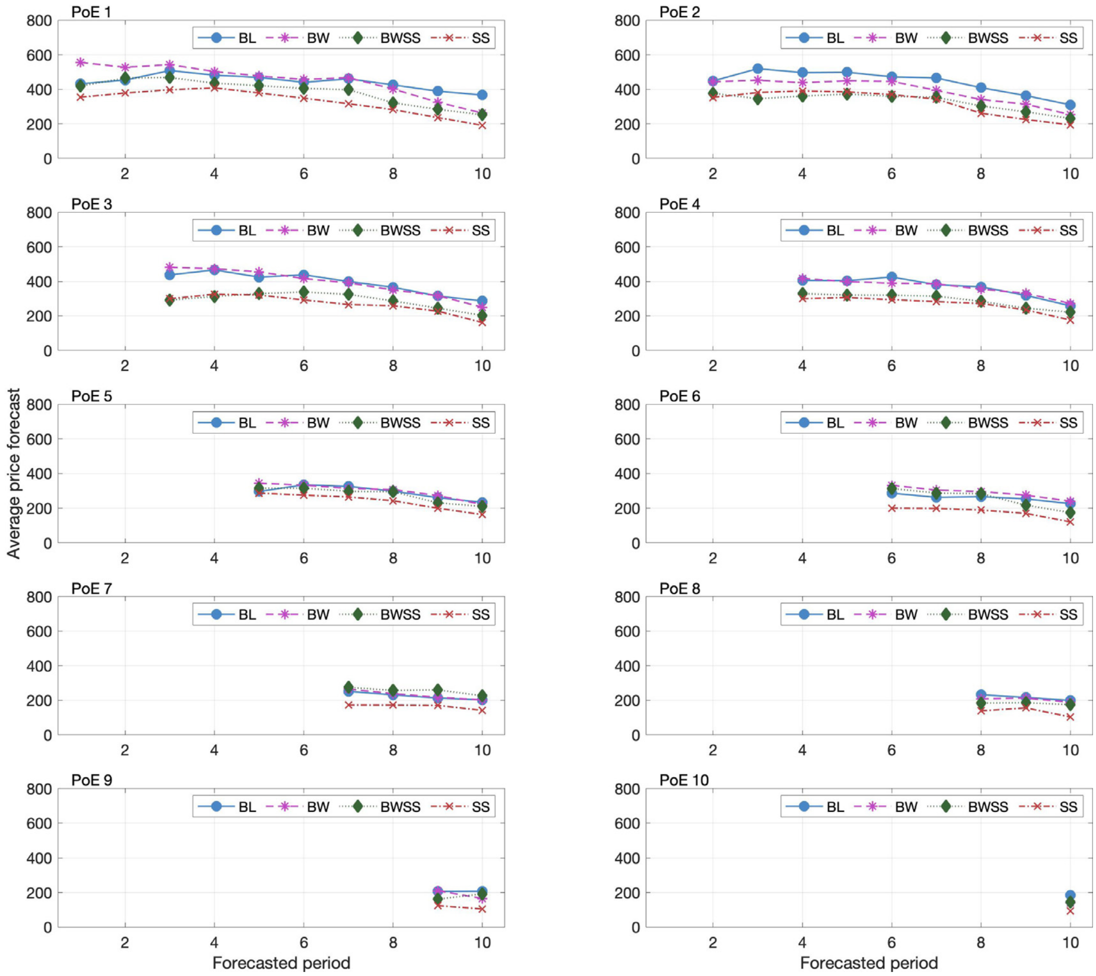

Fig. 4. Average forecasts made during Market 2 for each period of elicitation.

In Market 2, *Periodtrend* and *Markettrend* are both significant, while *FV* is not. These results are also very close to those in Haruvy et al. (2007), indicating that expectations are formed adaptively based on observed past prices in the previous and current markets. Moreover, there is no statistical significance of treatments in any intercept or interaction term at the 5% level, indicating a common expectation formation rule in the four treatments in Market 2. We summarize these results on expectation formation, which show strong support for Hypothesis 2, as follows:

Result 4: Beliefs are formed based on past prices of the current and previous markets and therefore do not directly depend on borrowing and short selling possibilities.

3.3. Trading strategies

We now study whether the tendency to use different strategies varies by treatment and correlates with market outcomes. We classify traders based on their trading behavior, following the typology proposed in the theoretical model of De Long et al. (1990) and implemented by Haruvy and Noussair (2006); Haruvy et al. (2014) and Breaban and Noussair (2015). There are three types of trader: passive traders, feedback traders, and rational speculators. We modify the classification algorithm from those used in these prior studies to take advantage of the fact that we have belief data available.

Passive traders offer bid (ask) prices below (above) the fundamental value in the current period. A trader is considered as following a passive trading strategy in the current period if:

$$b^i_{t,m} \leq FV_{t,m} \leq a^i_{t,m} \tag{2}$$

with the index i for the trader, t for the period and m for the market, a (b) is the ask (bid) and *FV* is the fundamental value of the asset.

Feedback traders trade on momentum, trying to buy if they observe increasing past prices, as they expect prices will continue to rise. Conversely, they try to sell if they note decreasing past prices, as they expect prices will keep falling. We

Table 3
Forecasts as a function of Treatment, Periodtrend, Markettrend, and Fundamental Value.

	Market 1 MLM	Market 2 MLM
(*Intercept*)	300.30***	97.46**
	(65.42)	(42.51)
BW	−114.97	3.00
	(92.54)	(60.12)
BWSS	−142.05	11.96
	(92.50)	(60.17)
SS	−119.21	−56.80
	(95.46)	(62.05)
Markettrend	*NA*	0.42***
	NA	(0.09)
Periodtrend	0.34***	0.25***
	(0.06)	(0.05)
FV	0.08	0.15
	(0.20)	(0.11)
*BW**Markettrend*	*NA*	0.06
	NA	(0.12)
*BWSS**Markettrend*	*NA*	0.07
	NA	(0.12)
*SS**Markettrend*	*NA*	0.04
	NA	(0.13)
*BW**Periodtrend*	0.05	−0.10
	(0.08)	(0.07)
*BWSS**Periodtrend*	0.04	−0.12*
	(0.08)	(0.07)
*SS**Periodtrend*	0.02	−0.04
	(0.09)	(0.07)
*BW**FV*	0.38	0.05
	(0.29)	(0.15)
*BWSS**FV*	0.44	0.01
	(0.29)	(0.15)
*SS**FV*	0.27	0.05
	(0.30)	(0.16)
AIC	151329.9	140075.8
BIC	151512.3	140345.6
Log Likelihood	-75639.96	-70000.91
Num. obs.	10904	10904
Number of markets	35	35
Bet group SD/Variance (Int)	133.42/17800.63	77.70/6036.84
Bet group SD/Variance (MT)	NA	0.23/0.05
Bet group SD/Variance (PT)	0.14/0.018	0.10/0.01
Bet group SD/Variance FV	0.32/0.10	0.20/0.04
Bet subject SD/Variance (Int)	336.53/113255.22	239.43/57326.92
Bet subject SD/Variance (MT)	NA	0.18/0.03
Bet subject SD/Variance (PT)	0.25/0.06	0.18/0.03
Bet subject SD/Variance (FV)	1.21/1.45	0.56/0.32
Residual variance	228.96	138.26

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Coefficients with standard errors in parentheses of MLM regressions for Markets 1 and 2.

classify a trader as following a feedback strategy in period t, if :

$$p_{t-1,m} > p_{t-2,m} \text{ and } f^t_{i,m,t} > p_{t-1,m} \text{ and } d^i_{t,m} \geq s^i_{t,m} \text{ or} \tag{3}$$

$$p_{t-1,m} < p_{t-2,m} \text{ and } f^t_{i,m,t} < p_{t-1,m} \text{ and } d^i_{t,m} \leq s^i_{t,m} \text{ or} \tag{4}$$

$$p_{t-1,m} = p_{t-2,m} \text{ and } f^t_{i,m,t} = p_{t-1,m} \tag{5}$$

with $p_{t-k,m}$ equals to the price in period $t-k$ of market m, $d^i_{t,m}$ and $s^i_{t,m}$ are the quantity demanded and supplied by subject i in period t of market m, and $f^t_{i,m,t}$ is the forecasted period t price submitted by subject i in period t for market m.

Finally, rational speculators anticipate the prices in the next period and trade based on the difference between next period's price and the current price. They try to buy (sell) in the current period, if they believe that the next period's price will be higher (lower) than the current level. A trader is considered as a rational speculator in period t if

Table 4
Mispricing indicators as a function of the normalized score for each strategy.

	Market 1				Market 2			
	RAD	GAD	RD	GD	RAD	GAD	RD	GD
(Intercept)	2.47^{***}	3.08^{***}	2.35^{***}	2.16^{**}	1.82^{***}	2.48	2.11^{**}	2.77^{***}
	(0.68)	(0.83)	(0.78)	(0.80)	(0.60)	(2.48)	(0.85)	(0.99)
Score Feedback	−1.46	−1.70	−1.22	−1.20	−1.44	1.52	-2.53^{*}	-3.84^{**}
	(1.41)	(1.73)	(1.62)	(1.67)	(1.02)	(4.23)	(1.45)	(1.70)
Score Passive	-2.57^{**}	-3.33^{***}	-2.87^{**}	-3.07^{**}	-1.83^{**}	−3.37	-1.98^{*}	-2.69^{*}
	(0.95)	(1.17)	(1.09)	(1.12)	(0.82)	(3.41)	(1.17)	(1.37)
Score Rat Spec	−2.66	−2.61	−2.71	−1.84	-1.90^{*}	−2.33	-3.82^{**}	-5.04^{***}
	(1.71)	(2.11)	(1.98)	(2.03)	(1.07)	(4.43)	(1.51)	(1.78)
R^2	0.20	0.21	0.19	0.20	0.15	0.08	0.20	0.26
Adj. R^2	0.12	0.13	0.11	0.12	0.06	-0.00	0.13	0.19
Num. obs.	35	35	35	35	35	35	35	35
RMSE	0.49	0.60	0.56	0.57	0.35	1.46	0.50	0.59

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

$$p_{t+1,m} > p_{t,m} \text{ and } f_{i,t,m}^{t+1} > f_{i,t,m}^{t} \text{ and } d_{t,m}^{i} \geq s_{t,m}^{i} \text{ or} \tag{6}$$

$$p_{t+1,m} < p_{t,m} \text{ and } f_{i,t,m}^{t+1} < f_{i,t,m}^{t} \text{ and } d_{t,m}^{i} \leq s_{t,m}^{i} \text{ or} \tag{7}$$

$$p_{t+1,m} = p_{t,m} \text{ and } f_{i,t,m}^{t+1} = f_{i,t,m}^{t} \tag{8}$$

If a subject is following none of these three strategies in period t, then she is classified as “No-type” for this period.

We check if a subject is following one of the four trading strategies (including “No type”) in each period t (from period 3 to 9). We attribute a score of 1 for a strategy in a period if the player is compliant with the definition of the strategy, otherwise 0. We then normalize these strategy points by period among the four strategy types so that they sum up to one. For each subject, we then normalize the scores over the seven periods considered (3–9) for each strategy to determine the normalized strategy score for each trading strategy for the market.

Figs. 5 and 6 show the distribution of normalized strategy scores in each of the four treatments in Markets 1 and 2, respectively. Because the normalized scores of the four classifications add up to one for each subject, we use a simplex plot by adding the scores of rational speculation and passive strategies. These two scores are shown separately in the scatter plots in the bottom panel. We divide subjects into 134 Low-CRT subjects who scored 0, 1 or 2 on the CRT test and 76 high-CRT subjects scored above 2. Each empty square (black triangle) in the simplex and scatter plot represents a subject with a low (high) CRT. In the simplex plots, the height of a point from the edge of the triangle that is opposite of the apex labeled RS+P represents the joint score of rational speculation and passive strategies. Thus, if a point is on RS+P apex, the joint score of these two strategies for this subject is one, meaning that this subject has followed the behavior consistent with either of these two strategies throughout the market session.

The figures show that traders have higher scores for, and thus are most likely to employ, the passive strategy in both Markets 1 and 2, and for all treatments. We do not observe clear differences between treatments, though participants have slightly higher scores for the feedback strategy in SS treatment.

We investigate the relationships between average normalized scores of market participants and market outcomes. Table 4 reports the results of regressing *RAD, GAD, RD* and *GD* on the average normalized score of feedback, passive, and rational speculation strategies for Markets 1 and 2.[25] We pool the data from the four treatments as we did not find any significant treatment effects.

For Market 1, we clearly observe that a higher average score for the passive strategy significantly reduces the magnitude of mispricing for the four measures. This is intuitive because of their strategy consisting of selling when prices are above the FV and buying when prices are below. This result shows the stabilizing role of this type of trader, whatever the market rules and leverage available. This significant negative relationship between the score of the passive strategy and mispricing is also observed for Market 2. Moreover, rational speculation trading is correlated with lower mispricing in Market 2. As rational traders anticipate that prices will converge toward the fundamental value, they tend to push prices toward that value. There is no statistically significant relationship between the average score of the feedback strategy and mispricing in Market 1, though a negative one exists in Market 2 for *RD* and *GD*. Our results regarding the relationship between trader types and market behavior, which provide some support for Hypothesis 3, are summarized as follows.

[25] The regressions of the other various measures of mispricing are displayed in Appendix G, Table 13.

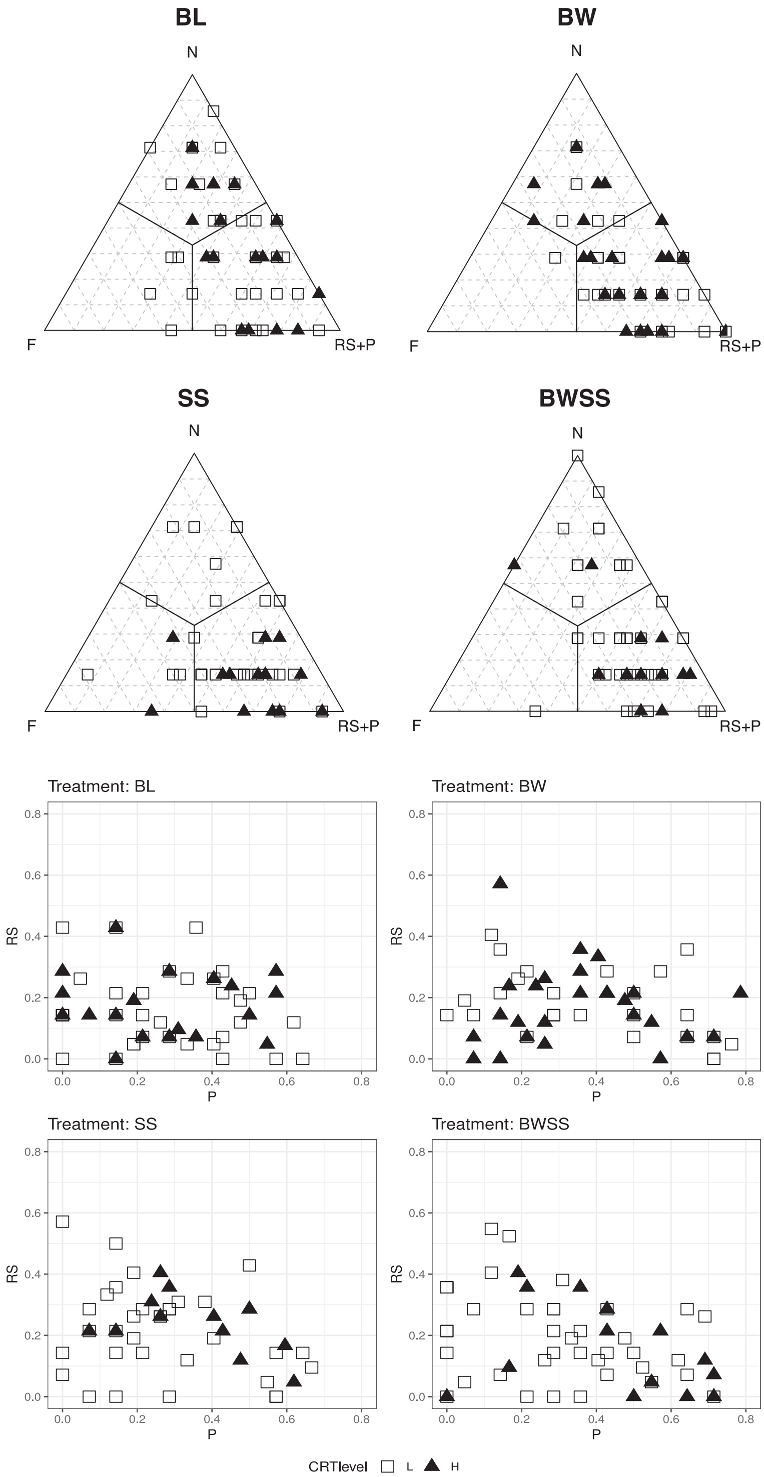

Fig. 5. Distribution of normalized scores in Market 1.

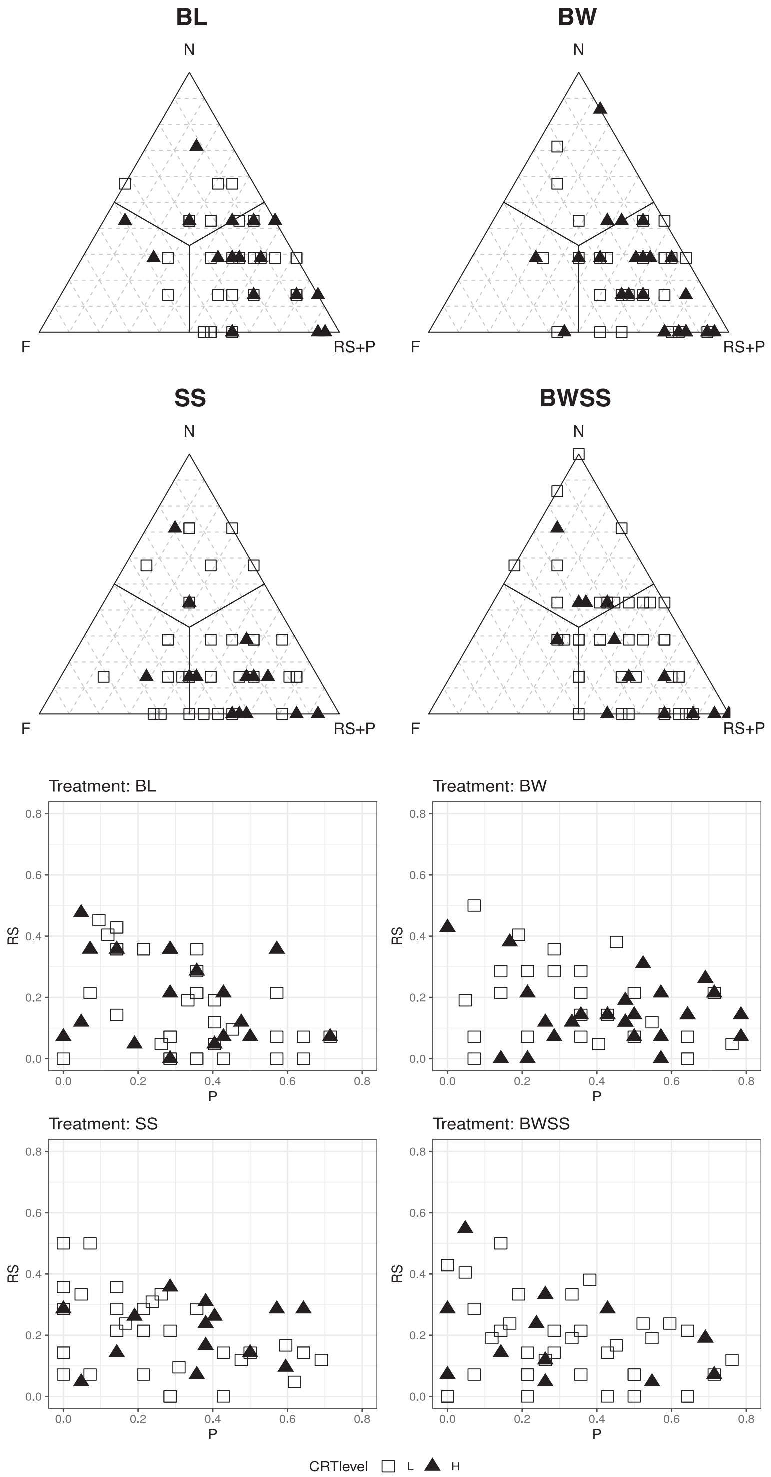

Fig. 6. Distribution of normalized scores in Market 2.

Table 5
Profit from trading as a function of the normalized score for each strategy.

Market 1					
	Pooled	BL	BW	BWSS	SS
(Intercept)	5352.81***	5591.28***	5477.07***	4669.50***	5989.20***
	(502.06)	(734.02)	(1460.32)	(1048.89)	(974.88)
Score Rat Spec	2968.14**	2485.92	−120.93	7394.94***	961.40
	(1181.48)	(2125.27)	(3053.10)	(2531.89)	(1953.50)
Score Feedback	1960.13*	2305.96	2031.33	1138.56	1643.01
	(1108.06)	(1869.88)	(3253.10)	(2684.29)	(1590.25)
Score Passive	3127.61***	2953.66**	3883.41**	3164.57*	2494.76*
	(737.11)	(1185.20)	(1832.27)	(1618.72)	(1395.23)
AIC	3761.38	907.34	939.15	939.09	793.05
BIC	3781.46	919.27	951.08	951.03	804.27
Log Likelihood	−1874.69	−447.67	−463.57	−463.55	−390.52
Num observations	210	54	54	54	48
Num. groups	35	9	9	9	8
Between group variance/Sd (Intercept)	0.00/0.10	0.00/0.09	0.00/0.12	0.00/0.12	0.00/0.10
Residual variance	4474456.08	3203070.08	6100699.79	6010534.72	2716975.54
Market 2					
	Pooled	BL	BW	BWSS	SS
(Intercept)	5896.77***	5424.73***	5059.23***	6524.63***	6655.71***
	(421.13)	(751.80)	(1121.03)	(868.10)	(521.07)
Score Rat Spec	805.12	871.14	1121.83	1380.36	−332.62
	(873.34)	(1326.17)	(2275.87)	(1909.30)	(1208.10)
Score Feedback	450.04	2415.19*	−554.67	−2414.21	1111.13
	(819.94)	(1370.42)	(2213.25)	(2040.90)	(904.72)
Score Passive	2428.33***	2487.66**	4509.02***	2241.32**	258.42
	(581.84)	(1092.84)	(1486.20)	(1137.41)	(759.82)
AIC	3638.00	873.35	912.98	909.68	743.66
BIC	3658.09	885.28	924.91	921.61	754.89
Log Likelihood	−1813.00	−430.67	−450.49	−448.84	−365.83
Num observations	210	54	54	54	48
Num. groups	35	9	9	9	8
Between group variance/Sd (Intercept)	0.00/0.07	0.00/0.07	0.00/ 0.10	0.00/0.10	0.00/0.05
Residual variance	2457284.36	1616963.29	3600627.36	3327428.27	886419.59

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Result 5: The greater the use of the passive strategy, the lower is the level of mispricing in both Markets 1 and 2. The greater the use of the rational speculation strategy, the lower is the level of mispricing in Market 2.

We now consider the relationship between the normalized score of a subject for each strategy and the earnings she obtains. Table 5 shows, both for pooled data from all treatments and for each of the four treatments separately, the result of regressing total profit from trading[26] on the scores of the passive, feedback, and rational speculation strategies.

We observe that a higher score for the passive strategy is associated with a greater profit in both Markets 1 and 2, with the strongest effect in the BW treatment in both Markets 1 and 2. This is to be expected since passive traders by definition take positions that are on average profitable over the lifetime of the asset. In Market 1, a higher score of rational speculation is also weakly associated with greater profit in the pooled data. This mainly arises from the strong positive relationship between this score and profit in BWSS treatment. It may be that, in BWSS, the larger uncertainty about future prices generated by the combination of the two speculative techniques offers a particular advantage for rational traders who succeed in anticipating the next price. We do not observe any statistically significant relationships between the profit and the score of the feedback strategy (except at 10% in Market 1). Finally, we find that getting a high score as "No type", which means that traders do not follow any of the three strategies identified, generates significantly lower profits in Market 1, in the pooled data. Those who fail to behave in a consistent manner typically do poorly.

3.4. Who are the short sellers and borrowers?

We conclude this section by considering which traders tend to exercise the right to sell short and to borrow cash. Do many traders use leverage? Is the use of leverage correlated with cognitive ability and/or the use of specific trading strategies? To answer these questions, we apply two different definitions of a short seller and a borrower. The more conservative definition is to define a short seller (borrower) as an individual who has a negative asset (cash) position for at least one

[26] Here we do not include the bonus obtained from the forecasting performance. We did not find any statistically significant relationship between the forecasting bonus and the score for any of the strategy types.

Table 6
Percentage of short sellers and borrowers in each treatment.

Treatment	SS (# 48)		BWSS (# 54)		BW (# 48)	
Market	1	2	1	2	1	2
% short sellers	4%	13%	13%	19%		
% potential short sellers	8%	23%	19%	24%		
% borrowers			11%	7%	9%	9%
% potential borrowers			22%	17%	19%	17%
% borrowers or short sellers			20%	26%		
% potential borrowers or short sellers			31%	35%		

Table 7
Percentage of short sellers and borrowers among high and low CRT traders.

Treatment	Tested condition		CRT scores	
			% among high CRT	% among low CRT
SS (# 48)	SS position $\geq$ 1	M1	7%	3%
		M2	14%	12%
	Potential SS position $\geq$ 1	M1	21%	3%
		M2	43%	15%
BW(# 54)	BW position $\geq$ 1	M1	4%	15%
		M2	4%	15%
	Potential BW position $\geq$ 1	M1	15%	22%
		M2	19%	15%
BWSS (# 54)	SS position $\geq$ 1	M1	27%	8%
		M2	27%	15%
	Potential SS position $\geq$ 1	M1	47%	8%
		M2	33%	21%
	BW position $\geq$ 1	M1	20%	8%
		M2	20%	3%
	Potential BW position $\geq$ 1	M1	47%	13%
		M2	33%	10%
	SS or BW position $\geq$ 1	M1	33%	15%
		M2	47%	18%
	Potential SS or BW position $\geq$ 1	M1	60%	21%
		M2	53%	28%

period during the 10 periods of the market. As a second measure, we also consider a trader's willingness to sell short or to borrow cash. We compute the maximum number of units a trader is willing to sell (comparing with the maximum number of assets she wishes to buy) and observe if she could potentially have a negative asset (cash) position if her transactions were realized. Thus, we define a potential short seller (potential borrower) as a trader who intends to sell short (to borrow) based on her net buy and sell orders.[27]

Table 6 reports the percentage of traders who are short sellers (borrowers) and potential short sellers (potential borrowers). In Market 1, we observe a low proportion of short sellers, with a higher proportion in the BWSS treatment compared to the SS treatment. The percentages are larger for potential short sellers, especially in BWSS (19%). For a short sale to occur, there is need for a counterparty to buy at the sale price, that can explain (i) why there are more effective short selling trades in BWSS than in SS and (ii) why there are more potential short sellers than effective ones. The percentage of borrowers is about 10% in BW and BWSS, and is approximately twice as high for potential borrowers (22% in BWSS). Finally, those using either of these two techniques in BWSS are at higher proportions of 20% and 31% for potential. In Market 2, all of the measures increase, indicating greater use of leverage than in market 1. The proportion of short sellers reaches 19% in BWSS and that of potential short selllers climbs to 24%. The percentage of borrowers remains stable in BW and decreases slightly in BWSS. Finally, the percentages of individuals who are borrowers or short sellers (potential borrowers or short sellers) increase to reach 26% (35%) in BWSS.

In Table 7, we consider how the propensity to sell short or to borrow varies with CRT score. The table displays the percentage of short sellers (borrowers) and potential short sellers (potential borrowers) among those traders with high and low CRT scores. It shows that short-selling is more common for more sophisticated agents. The tendency to borrow is less consistent: it is more likely among those with high CRT scores in BWSS but less common in BW. Table 8 reports estimates of the likelihood of being a (potential) borrower or a (potential) short seller as a function of trader type and CRT score. It shows that there is no systematic relationship between trader type and the tendency to use leverage. This means that

[27] The algorithm is given in Appendix H.

Table 8
Probability of being a short seller (SP)/borrower (BP) as a function of the normalized score for each strategy, and cognitive sophistication.

	Effective				Potential			
	Market 1		Market 2		Market 1		Market 2	
	SP	BP	SP	BP	SP	BP	SP	BP
(Intercept)	−1.53*	−1.32	−1.00	−1.71	−1.91*	−0.10	−0.15	−1.11
	(0.78)	(1.30)	(0.92)	(1.20)	(0.93)	(0.87)	(0.77)	(1.01)
High CRT	1.73	0.11	0.57	0.45	2.51**	0.78	1.25*	0.87
	(0.96)	(0.96)	(0.48)	(0.94)	(0.68)	(0.66)	(0.49)	(0.47)
Score Passive	−2.87	−3.59	−0.74	−2.12	−1.88	−3.01**	−1.93	−0.83
	(1.88)	(2.03)	(1.13)	(1.98)	(1.55)	(1.01)	(1.34)	(1.40)
Score Speculator	−2.69***	0.16	−0.39	−0.81	−2.59	−1.24	−1.20	−0.09
	(1.03)	(1.95)	(1.65)	(1.90)	(2.45)	(1.51)	(2.02)	(1.93)
Score Feedback	−0.48	0.52	−2.29	−0.11	0.18	−2.03	−2.61**	−2.79
	(2.10)	(2.73)	(1.88)	(0.94)	(2.38)	(2.13)	(1.14)	(2.65)
Observations	102	108	102	108	102	108	102	108

Adjusted clustered standard errors with respect to markets (groups) in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

leverage does not make any of the types more active compared to the others. If passive traders had made more use of leverage than others, it might have moved prices toward fundamentals. In contrast, if feedback traders had made more use of leverage, mispricing might have been more severe. Finally, we observe that subjects with higher CRT scores have a significantly higher probability of being potential short sellers in both Markets 1 and 2.

4. Conclusion

This experiment was designed to study two sets of issues. The first is whether allowing traders to sell short lowers asset prices, and whether permitting them to borrow to finance purchases increases prices. While we observe that markets with short-selling have lower prices on average, while those with borrowing exhibit higher prices, none of the differences are statistically significant despite our relatively large data set. There are similar effects of treatment on other measures of market outcomes. There are no significant effects of borrowing and short-selling on absolute deviations in prices from the fundamental value, price volatility and price fluctuations. The heterogeneity in market behavior within each treatment is very substantial and means that any treatment effect is likely to be very small compared to the variation in market outcomes within individual treatments. Thus, it is important to study the sources of within-treatment heterogeneity in price levels and to continue the search for correlates of individual market outcomes.

The second set of issues concerns whether a number of patterns regarding beliefs, cognitive sophistication, and trader strategies, that have been documented in prior experimental studies in which short-selling and borrowing were not possible, generalize to markets in which these types of leverage are allowed. We show, through multi-level modeling, that the rules individuals use in formulating their forecasts are similar, regardless of whether or not short selling and borrowing are possible. We also observe negative relationships between the cognitive ability of market participants and mispricing as well as volatility. We find that greater use of the passive strategy is associated with smaller market mispricing and greater individual earnings. Finally, we observe that traders who have greater cognitive ability tend to make more use of short selling. The appearance of similar results in our various treatments leads us to believe that the patterns we document are general relationships that apply to a broad class of asset markets.

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Appendix A. Cognitive reflection test administered to our participants

(1) If it takes 2 nurses 2 minutes to measure the blood pressure of 2 patients, how long would it take 200 nurses to measure the blood pressure of 200 patients? ___ minutes. [Correct answer: 2 minutes; intuitive answer: 200 minutes]

Table 9
Average values (standard deviations) of market mispricing measures for each treatment in Markets 1 and 2.

	Treat	Volatility	Boom duration	Bust duration	Turnover	Amplitude	Norm.Dev	Average bias	Total dispersion	RAD	GAD	RD	GD
M1	BL	89.65	7.22	2.00	0.88	3.66	129.23	140.72	1720.33	0.87	1.14	0.71	0.73
		(43.98)	(2.73)	(1.94)	(0.31)	(2.21)	(61.42)	(83.93)	(753.19)	(0.38)	(0.59)	(0.42)	(0.56)
	SS	61.06	6.25	2.75	0.85	2.78	97.57	68.73	1172.75	0.59	0.94	0.35	0.37
		(30.27)	(3.37)	(3.15)	(0.30)	(2.29)	(56.27)	(111.63)	(789.27)	(0.40)	(0.56)	(0.56)	(0.69)
	BW	103.30	7.56	1.33	0.79	4.18	149.16	162.49	1881.78	0.95	1.31	0.82	0.72
		(118.16)	(2.13)	(0.87)	(0.23)	(2.85)	(113.44)	(136.19)	(1294.58)	(0.65)	(0.82)	(0.69)	(0.70)
	BWSS	107.80	6.44	2.67	0.84	3.22	150.27	132.94	1693.00	0.86	1.14	0.67	0.39
		(108.32)	(2.92)	(2.40)	(0.30)	(1.65)	(137.13)	(131.87)	(1187.71)	(0.60)	(0.63)	(0.67)	(0.51)
	p-values (KW)	*0.67*	*0.80*	*0.65*	*0.97*	*0.61*	*0.79*	*0.41*	*0.56*	*0.56*	*0.80*	*0.41*	*0.35*
M2	BL	47.02	5.56	2.78	0.80	1.92	63.06	46.71	776.22	0.39	0.82	0.24	0.15
		(21.53)	(2.88)	(2.28)	(0.24)	(1.38)	(25.28)	(49.66)	(300.65)	(0.15)	(0.98)	(0.25)	(0.46)
	SS	29.46	3.50	5.38	0.84	1.59	63.81	−7.61	778.38	0.39	1.13	−0.04	−0.16
		(10.31)	(2.93)	(3.02)	(0.20)	(2.16)	(35.75)	(79.08)	(430.89)	(0.22)	(1.19)	(0.40)	(0.47)
	BW	67.30	4.44	4.89	0.68	2.90	99.96	51.93	1356.22	0.69	1.27	0.26	0.14
		(44.58)	(3.54)	(3.59)	(0.22)	(3.84)	(95.78)	(151.19)	(1034.16)	(0.52)	(0.88)	(0.76)	(0.96)
	BWSS	60.38	3.56	5.11	1.09	1.49	103.02	13.98	1038.67	0.53	1.79	0.07	−0.08
		(50.53)	(3.21)	(3.69)	(0.50)	(1.19)	(83.63)	(120.41)	(810.94)	(0.41)	(2.35)	(0.61)	(0.64)
	p-values (KW)	*0.06*	*0.39*	*0.31*	*0.29*	*0.40*	*0.70*	*0.42*	*0.62*	*0.62*	*0.42*	*0.42*	*0.55*

Differences between Market 1 and Market 2. p-values of Wilcoxon paired signed-rank tests.

Treatment	Volatility	Boom duration	Bust duration	Turnover	Amplitude	Norm. Dev	Average bias	Total dispersion	RAD	GAD	RD	GD
BL	0.00	0.02	0.39	0.65	0.00	0.00	0.01	0.00	0.00	0.25	0.01	0.01
BW	0.20	0.02	0.02	0.21	0.13	0.04	0.02	0.10	0.10	0.65	0.02	0.02
BWSS	0.50	0.02	0.11	0.04	0.00	0.25	0.02	0.25	0.25	1	0.02	0.03
SS	0.01	0.03	0.04	1	0.01	0.25	0.01	0.31	0.31	0.74	0.01	0.01

(2) Soup and salad cost 5.50 € in total. The soup costs one € more than the salad. How much does the salad cost? ___ (in cents of €). [Correct answer: 225 cents; intuitive answer: 250 cents]
(3) Sally is making sun tea. Every hour, the concentration of the tea doubles. If it takes 6 hours for the tea to be ready, how long would it take for the tea to reach half of the final concentration? ___ hours. [Correct answer: 5 hours; intuitive answer: 3 hours]
(4) If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? ___ days. [correct answer: 4 days; intuitive answer: 9]
(5) Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? ___ students. [correct answer: 29 students; intuitive answer: 30]
(6) A man buys a pig for 60 €, sells it for 70 €, buys it back for 80 €, and sells it finally for 90 €. How much has he made? ___ €. [correct answer: 20 € ; intuitive answer: 10 €]
(7) Simon decided to invest 8000 € in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17, to October 17, the stocks he had purchased went up 75%. At this point, Simon:

a. has broken even in the stock market,
b. is ahead of where he began,
c. has lost money.
[correct answer: c, because the value at this point is 7000 € ; intuitive response b.]

Appendix B. Average values of market outcome measures of mispricing for each treatment in Markets 1 and 2

The various measures reported in Table 9 have been proposed by Haruvy et al. (2007); Haruvy and Noussair (2006); King et al. (1993); Porter et.al (1995); Stöckl et al. (2010), and Powell (2016). Volatility, Amplitude, Normalized Deviation, Total Dispersion, Relative Absolute Deviation (RAD), Geometric Absolute Deviation (GAD) are absolute measures of mispricing. Average Bias, Relative Deviation (RD), Geometric Deviation (GD), Boom Duration and Bust Duration are measures of price level relative to fundamentals. See Appendix C just below for the precise definitions of these measures.

Appendix C. Definitions and explanations of variables

Table 10 presents the definitions of a number of variables that we use in our analysis. The notes subsequent to the table explain the purpose of each variable.

Table 10
Definition of various measures.

Measure	Definition
Volatility[a]	$Vol = \frac{1}{9}\sum_{p=2}^{10} \lvert (p_p - FV_p) - (p_{p-1} - FV_{p-1}) \rvert$
BoomDuration	max number of consecutive periods for which price is above the FV
BustDuration	max number of consecutive periods for which price is below the FV
Turnover[b]	$Turn = \frac{\sum_{p=1}^{10} Q_p}{TSU}$
Amplitude[c]	$Amp = \max_p(\frac{p_p - FV_p}{FV_p}) - \min_p(\frac{p_p - FV_p}{FV_p})$
NormalizedDeviation[d]	$ND = \sum_{p=1}^{10} \frac{Q_p \lvert p_p - FV_p \rvert}{TSU}$
Averagebias[e]	$AB = \sum_{p=1}^{10} \frac{p_p - FV_p}{10}$
Totaldispersion[f]	$TD = \sum_{p=1}^{10} \lvert p_p - FV_p \rvert$
Relativeabsolutedeviation[g]	$RAD = \frac{1}{10}\sum_{p=1}^{10} \frac{\lvert p_p - FV_p \rvert}{\lvert \overline{FV} \rvert}$
Geometricabsolutedeviation[h]	$GAD = \exp(\frac{1}{N}\sum_{p=1}^{10} \lvert \ln(\frac{p_p}{FV_p}) \rvert) - 1$
Relativedeviation[i]	$RD = \frac{1}{10}\sum_{p=1}^{10} \frac{p_p - FV_p}{\lvert \overline{FV} \rvert}$
Geometricdeviation[j]	$GD = (\prod_{p=1}^{10} \frac{p_p}{FV_p})^{\frac{1}{10}} - 1$
PeriodTrend[k]	$Periodtrend = f_{i,m,t}^{t+k-1} + f_{i,m,t}^{t+k-1} \frac{f_{i,m,t}^{t+k-1} - f_{i,m,t}^{t+k-2}}{f_{i,m,t}^{t+k-2}}$
MarketTrend[l]	$Markettrend = f_{i,m,t}^{t+k-1} + f_{i,m,t}^{t+k-1} \frac{p_{m-1,t+k} - p_{m-1,t+k-1}}{p_{m-1,t+k-1}}$
RelativeBorrowingLimit[m]	$RBL = \frac{1}{10}\sum_{p=1}^{10} RBL_p$ with $RBL_p = \log \frac{Borrowing\ limit_p^{asset}}{Borrowing\ limit_p^{cash}}$
Relative absolute forecast deviation[n]	$RAFD_{t,m}^{i} = \frac{1}{10-t+1}\sum_{p=t}^{10} \frac{\lvert f_{t,p,m}^{i} - FV_p \rvert}{\overline{FV}}$

Notes, explanations and definitions used in the paper:

[a] The *Volatility* (with p_p and p_{p-1} the respective prices and FV_p and FV_{p-1} the respective Fundamental Values in periods p and $p-1$) measures the variability of prices relative to the FV. The more instability and fluctuations there are from the FV, the higher this indicator will be.

[b] *Turnover* is a normalized measure of trading activity during the 10 periods of the market (with Q_p as the quantity of units exchanged in period p and *TSU* equals to the number of the total units of stocks in the market). High transaction volume is interpreted as disagreement among traders about expected future prices and a high *Turnover* is usually associated with pricing away from fundamentals.

[c] *Amplitude* (where p_p and FV_p are the respective price and FV in period p) allows the identification of large bubbles or crashes. A high *Amplitude* means that low and high extreme prices relative to the FV are very different, and typically indicates high and volatile mispricing.

[d] *Normalized Deviation* considers the quantities and the prices jointly and can identify large trading quantities and deviations from the FV. It weights a difference from fundamentals by the size of the price difference and the transaction volume, and thus is a good measure of the extent of the departure and intensity of trading activity at variance from fundamental values.

[e] *Average bias* indicates the average difference between prices and fundamentals. As a measure of price level, both positive and negative values are possible, and because it is an average, a negative (positive) value away from zero indicates an aggregate tendency to be below (above) the fundamental value.

[f] *Total dispersion* is the sum of the absolute difference for each period between the price and the FV. Thus, a high (low) total dispersion indicates large (small) price deviations from the FV and is consequently a measure of departure of prices from FV.

[g] *RAD* captures the sum of the absolute differences for each period between price and FV. This indicator is then normalized by the absolute mean of the FV over all the periods and the number of periods. Thus, *RAD* measures mispricing, i.e. price deviations either above and below the FV in a normalized manner that can be compared to other studies. A high *RAD* indicates that prices do not track the FV, allowing the identification of either bubbles and/or crashes. For example, a *RAD* of 0.2 means that prices differ on average per period by 20% from the average FV.

[h] Using the geometric mean, *GAD* allows measurement of absolute price differences from fundamentals, while having the property of being numeraire independent.

[i] *RD* measures the extent to which prices exceed fundamentals. A negative (positive) *RD* indicates prices are on average below (above) the FV. This indicator is therefore complementary to *RAD*. For example, a high *RAD* with a zero *RD* would mean that prices largely differ from the FV but that are at times below and at other times above it.

[j] *GD* measures the extent to which prices exceed fundamentals using the geometric mean. A negative (positive) *GD* indicates prices are on average below (above) the FV. This indicator is therefore complementary to *GAD*. For example, a high *GAD* with a zero *GD* would mean that prices largely differ from the FV but are at times below and at other times above.

[k] *Upward Trend* has been proposed by Haruvy et al. (2007). It indicates the strength of a sustained boom in prices. In markets where fundamental values are decreasing over time, it is a measure of mispricing.

[l] *Periodtrend* and *Markettrend* are measures of price trends. The Periodtrend is the change in forecast or in price between two periods before and the period immediately preceding the period of interest. Marlettrend is the change in forecast or price from the immediately preceding to the period of interest in the prior market the same traders participated in. $f_{i,m,t}^{t+k-1}$

is the forecast for period $t+k-1$ price submitted by subject i in period t of market m. For $k=0$, $f_{i,m,t}^{t+k-1}$ is substituted by $p_{m,t-1}$ and $f_{i,m,t}^{t+k-2}$ by $p_{m,t-2}$, for $k=1$, $f_{i,m,t}^{t+k-2}$ by $p_{m,t-1}$.

[m] *Relative Borrowing Limit* is the measure of the capacity to borrow shares and cash.

Borrowing limit$_p^{asset}$ corresponds to the value of the maximum quantity of shares, evaluated at the FV, that a trader can sell short in period p. *Borrowing limit*$_p^{cash}$ corresponds to the maximum amount of cash that a trader can borrow in period p.

[n] *Relative Absolute Forecast Deviation*: For a period of elicitation t, the relative absolute forecast deviation (*RAFD*) computes the sum of the absolute differences between each price forecast of a future period p and the FV of the same period. Thus, RAFD measures the "misforecasting" from FV (where 10 is the number of periods in the market, $f_{t,p,m}^{i}$ is the forecasted price in period p submitted in period t of market m by subject i, FV_p is the FV of period p, and finally $\overline{FV}$ is the average FV of the asset for all periods).

Appendix D. Mispricing indicators as a function of median CRT

The relationship between the CRT scores of market participants and mispricing replicates the findings by Breaban and Noussair (2015) and Noussair et al. (2016). As reported in Table 11, we observe, in Market 1, statistically significant negative relationships between median CRT scores of market participants and volatility, as well as six of our mispricing measures. Such relationships are not observed in Market 2, however, where prices consistently track fundamentals more closely.

Table 11
Mispricing indicators as a function of median CRT.

Market 1

	Volatility	Boom duration	Bust duration	Turnover	Amplitude	Norm.Dev	Average bias	Total dispersion	RAD	GAD	RD	GD
(Intercept)	157.07***	7.58***	1.27	0.84***	5.35***	151.41***	215.33***	2404.65***	1.21***	1.39***	1.09***	1.15***
	(39.81)	(1.41)	(1.10)	(0.14)	(1.08)	(49.72)	(56.47)	(496.36)	(0.25)	(0.33)	(0.29)	(0.29)
med CRT	−32.80**	−0.17	0.35	0.02	−0.82**	−10.79	−36.29*	−332.91*	−0.17*	−0.12	−0.18*	−0.21*
	(14.33)	(0.51)	(0.40)	(0.05)	(0.39)	(17.89)	(20.33)	(178.66)	(0.09)	(0.12)	(0.10)	(0.11)
BW	28.22	0.41	−0.82	−0.09	0.89	24.72	37.90	309.40	0.16	0.22	0.19	0.09
	(38.40)	(1.36)	(1.06)	(0.14)	(1.04)	(47.97)	(54.48)	(478.87)	(0.24)	(0.31)	(0.28)	(0.28)
BWSS	5.39	−0.84	0.80	−0.03	−0.76	16.84	−21.89	−156.80	−0.08	−0.05	−0.11	−0.42
	(38.28)	(1.35)	(1.06)	(0.14)	(1.04)	(47.81)	(54.30)	(477.33)	(0.24)	(0.31)	(0.27)	(0.28)
SS	−44.77	−1.06	0.92	−0.02	−1.29	−36.99	−89.89	−711.73	−0.36	−0.26	−0.45	−0.46
	(39.67)	(1.40)	(1.10)	(0.14)	(1.07)	(49.55)	(56.28)	(494.69)	(0.25)	(0.32)	(0.28)	(0.29)
R^2	0.19	0.04	0.09	0.02	0.18	0.06	0.17	0.16	0.16	0.07	0.17	0.19
Adj. R^2	0.08	−0.08	−0.03	−0.11	0.07	−0.07	0.06	0.05	0.05	−0.05	0.06	0.08
Num. obs.	35	35	35	35	35	35	35	35	35	35	35	35
RMSE	80.34	2.84	2.22	0.29	2.17	100.34	113.97	1001.78	0.51	0.66	0.58	0.59

Market 2

	volatility	boom duration	bust duration	turnover	amplitude	Norm.Dev	average bias	total dispersion	RAD	GAD	RD	GD
(Intercept)	51.50***	6.85***	1.65	0.76***	3.05**	73.37**	89.24	982.02***	0.50***	0.54	0.45	0.55*
	(18.23)	(1.56)	(1.59)	(0.16)	(1.17)	(34.16)	(53.43)	(356.43)	(0.18)	(0.74)	(0.27)	(0.32)
med CRT	−2.18	−0.63	0.55	0.02	−0.55	−5.02	−20.69	−100.12	−0.05	0.13	−0.10	−0.19
	(6.56)	(0.56)	(0.57)	(0.06)	(0.42)	(12.30)	(19.23)	(128.29)	(0.06)	(0.27)	(0.10)	(0.12)
BW	21.24	−0.83	1.87	−0.13	1.22	39.13	14.42	624.50*	0.32*	0.39	0.07	0.07
	(17.59)	(1.50)	(1.53)	(0.15)	(1.13)	(32.96)	(51.55)	(343.87)	(0.17)	(0.72)	(0.26)	(0.31)
BWSS	12.51	−2.25	2.55	0.29*	−0.65	38.01	−40.78	223.51	0.11	1.02	−0.21	−0.31
	(17.54)	(1.50)	(1.53)	(0.15)	(1.13)	(32.85)	(51.38)	(342.76)	(0.17)	(0.72)	(0.26)	(0.31)
SS	−18.64	−2.37	2.87*	0.05	−0.61	−1.72	−64.53	−47.21	−0.02	0.38	−0.33	−0.40
	(18.17)	(1.55)	(1.58)	(0.16)	(1.17)	(34.05)	(53.25)	(355.22)	(0.18)	(0.74)	(0.27)	(0.32)
R^2	0.15	0.11	0.13	0.21	0.11	0.09	0.09	0.13	0.13	0.07	0.09	0.12
Adj. R^2	0.04	−0.01	0.02	0.10	−0.01	−0.04	−0.03	0.01	0.01	−0.06	−0.03	0.01
Num. obs.	35	35	35	35	35	35	35	35	35	35	35	35
RMSE	36.80	3.14	3.20	0.32	2.37	68.95	107.84	719.36	0.36	1.50	0.54	0.65

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

Appendix E. Multi-level modeling

The three level model, in its extended version, is specified as:

$$Y_{t,m}^{i}=\alpha_0+u_{0i}+v_{0m}+\alpha_1 x_{it}+u_{1i}x_{it}+v_{1m}x_{it}+\alpha_2 z_i+\alpha_3 t+u_{3i}t+v_{3m}t+\epsilon_{imt} \tag{9}$$

with $i=1...,210$ then $m=1...,35$ and $t=1...,10$. Here x_{it} corresponds to the vector of variables which vary between periods and subjects, and z_i contains the variables which are fixed over time but differ among subjects (For example the CRT score or the Treatments), and t is the period variable. Further, u and v are random coefficients, and $\sigma_{u_{0i}}^2$, $\sigma_{u_{1i}}^2$, and $\sigma_{u_{3i}}^2$, respectively, represent the between-subject variances of their distributions in the intercepts, in the slopes, and in time. $\sigma^2_{\upsilon_{0m}}$, $\sigma^2_{\upsilon_{1m}}$ and $\sigma^2_{\upsilon_{3m}}$, respectively, represent the between-market variances of their distributions in the intercepts, in the slopes, and in time. Finally, ϵ_{imt} is the equation error term, and α_0, α_1, α_2, and α_3 are coefficients of the equations.

We use the "bottom up" procedure when we do not specifically know which is the best model to select and thus which clusters and random effects to choose as in our analyses of forecast dynamics. In this case, to choose our model, we use: 1) the likelihood ratio (LR) test, a conservative procedure for testing the goodness of fit of two nested models, with at least one random effect model (Moffatt, 2016), and 2) the comparisons of Akaike information criteria (AICs), which are also widely employed to compare the quality of two models (Finch et al., 2014).

We follow a step-by-step approach (as in Moffatt, 2016) to identify and validate the number of clusters and the random effects on intercepts and slopes. First, it consists of testing the simplest model against the model with one more cluster, thus testing one restriction at a time. We stop our procedure if the null is not rejected and when the AICs confirm the LR test results. Then, after having tested all intercept terms, we test the restricted model (random intercepts) versus the random slopes model.

In our analyses of forecast dynamics, the LR test always rejects the null hypothesis that there is no significant difference between the two models, and the AICs confirmed the LR test procedure. Thus, the unrestricted model (with more parameters), here with random slopes on subjects and markets, provides a better fit than the restricted model.

Appendix F. Random effects regression of dynamic forecasts

In the RE (random-effect) regression for Market 1, all coefficients are significant (except β_{15}). This result is in contrast with the MLM approach presented in the main text and shows how the impact of identifying clusters and their variance

Table 12
Forecasts as a function of Treatments, Periodtrend, Markettrend, and FV.

	Market 1 RE	Market 2 RE
(*Intercept*)	410.79***	88.71***
	(37.72)	(26.53)
BW	−130.41**	8.66
	(53.36)	(37.53)
BWSS	−201.19***	41.37
	(53.36)	(37.52)
SS	−114.43**	−41.09
	(54.99)	(38.69)
Markettrend	*NA*	0.47***
	NA	(0.01)
Periodtrend	−0.00*	0.01***
	(0.00)	(0.00)
FV	0.32***	0.42***
	(0.07)	(0.04)
*BW*Markettrend*	*NA*	−0.37***
	NA	(0.01)
*BWSS*Markettrend*	*NA*	−0.40***
	NA	(0.01)
*SS*Markettrend*	*NA*	0.07***
	NA	(0.02)
*BW*Periodtrend*	0.06***	0.05***
	(0.00)	(0.00)
*BWSS*Periodtrend*	0.07***	−0.01***
	(0.00)	(0.00)
*SS*Periodtrend*	0.02***	0.02***
	(0.00)	(0.00)
*BW*FV*	0.35***	0.31***
	(0.09)	(0.06)
*BWSS*FV*	0.51***	0.13**
	(0.09)	(0.06)
*SS*FV*	0.09	−0.14**
	(0.10)	(0.06)
AIC	156421.4	144585.8
BIC	156523.6	144717
Log Likelihood	-78196.72	-72274.88
Num. obs.	10904	10904
Number of markets	35	35
Bet subject SD/Variance (Int)	246.76/60889.56	180.10/32437.49
Residual variance	92553.22	32231.60

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ Coefficients with standard errors in parentheses of RE regressions for Markets 1 and 2.

can change coefficients and significance, and thus the interpretation of the results. We can also note that AIC, BIC and log likelihood are better in the MLM models.

Appendix G. Mispricing indicators as a function of the normalized score for each strategy

In Table 13, for Market 1 (shown in the top panel), we clearly observe that a higher average score for the passive strategy significantly reduces the magnitude of mispricing for a number of our measures. We also observe that the average score for rational speculator is negatively correlated with the magnitude of volatility. These significant relationships between the score of passive and rational speculation strategies are also observed for Market 2 (shown in the bottom panel). Moreover, rational speculation trading is correlated with lower mispricing in Market 2. There is no statistically significant relationship between the average score of the feedback strategy and mispricing in Market 1, though a negative one exists in Market 2.

Table 13
Mispricing indicators as a function of the normalized score for each strategy.

Market 1												
	Volatility	Boom duration	Bust duration	Turnover	Amplitude	Norm.Dev	Average bias	Total dispersion	RAD	GAD	RD	GD
(Intercept)	317.43***	11.38***	−0.83	1.49***	11.78***	422.46***	465.06***	4885.12***	2.47***	3.08***	2.35***	2.16**
	(114.04)	(3.67)	(3.09)	(0.37)	(2.90)	(130.25)	(154.99)	(1344.73)	(0.68)	(0.83)	(0.78)	(0.80)
Score Feedback	−349.34	0.05	1.77	−0.19	−9.78	−270.81	−241.22	−2896.44	−1.46	−1.70	−1.22	−1.20
	(236.65)	(7.62)	(6.42)	(0.78)	(6.02)	(270.30)	(321.64)	(2790.63)	(1.41)	(1.73)	(1.62)	(1.67)
Score Passive	−174.43	−11.02**	6.23	−0.75	−11.05**	−410.24**	−568.04**	−5081.23**	−2.57**	−3.33***	−2.87**	−3.07**
	(159.51)	(5.14)	(4.33)	(0.52)	(4.06)	(182.19)	(216.79)	(1880.93)	(0.95)	(1.17)	(1.09)	(1.12)
Score Rat Spec	−520.95*	−4.62	3.06	−1.97**	−14.13*	−530.84	−536.26	−5262.39	−2.66	−2.61	−2.71	−1.84
	(287.83)	(9.27)	(7.81)	(0.94)	(7.33)	(328.76)	(391.20)	(3394.17)	(1.71)	(2.11)	(1.98)	(2.03)
R^2	0.13	0.16	0.07	0.14	0.22	0.16	0.19	0.20	0.20	0.21	0.19	0.20
Adj. R^2	0.05	0.07	-0.02	0.06	0.15	0.08	0.11	0.12	0.12	0.13	0.11	0.12
Num. obs.	35	35	35	35	35	35	35	35	35	35	35	35
RMSE	81.62	2.63	2.21	0.27	2.08	93.22	110.93	962.42	0.49	0.60	0.56	0.57
Market 2												
	Volatility	Boom duration	Bust duration	Turnover	Amplitude	Norm.Dev	Average bias	Total dispersion	RAD	GAD	RD	GD
(Intercept)	195.69***	14.37***	−2.80	2.49***	12.33***	428.25***	417.31**	3599.71***	1.82***	2.48	2.11**	2.77***
	(57.47)	(5.08)	(5.13)	(0.52)	(3.59)	(101.61)	(167.64)	(1184.02)	(0.60)	(2.48)	(0.85)	(0.99)
Score Feedback	−164.75	−10.48	11.62	−2.09**	−12.84**	−407.53**	−500.96*	−2852.60	−1.44	1.52	−2.53*	−3.84**
	(98.31)	(8.70)	(8.77)	(0.89)	(6.13)	(173.80)	(286.75)	(2025.30)	(1.02)	(4.23)	(1.45)	(1.70)
Score Passive	−142.61*	−11.01	3.58	−2.20***	−11.16**	−469.21***	−392.26*	−3627.90**	−1.83**	−3.37	−1.98*	−2.69*
	(79.25)	(7.01)	(7.07)	(0.72)	(4.95)	(140.11)	(231.17)	(1632.69)	(0.82)	(3.41)	(1.17)	(1.37)
Score Rat Spec	−310.73***	−21.20**	18.51*	−2.14**	−19.20***	−481.26**	−756.78**	−3765.49*	−1.90*	−2.33	−3.82**	−5.04***
	(102.82)	(9.09)	(9.17)	(0.93)	(6.42)	(181.78)	(299.92)	(2118.31)	(1.07)	(4.43)	(1.51)	(1.78)
R^2	0.25	0.16	0.20	0.25	0.26	0.28	0.20	0.15	0.15	0.08	0.20	0.26
Adj. R^2	0.18	0.08	0.12	0.17	0.19	0.21	0.13	0.06	0.06	-0.00	0.13	0.19
Num. obs.	35	35	35	35	35	35	35	35	35	35	35	35
RMSE	34.00	3.01	3.03	0.31	2.12	60.12	99.18	700.52	0.35	1.46	0.50	0.59

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Appendix H. Algorithm to classify traders as potential short sellers and potential borrowers

H.1. Potential short sellers

We look at the trader position (asset holding) at the beginning of period t and at her orders in period t. We compute the quantity she wishes to sell during period t minus the quantity she wishes to buy in period t. Consequently, we look at her net sell and buy orders :

Then, if her asset holding at the beginning of period t - (her quantity to sell - her quantity to buy) is negative, then she is a potential short seller.

H.2. Potential borrowers

We look at the trader's cash on hand at the beginning of period t and at her orders in period t. We compute (i) the maximum amount she is willing to pay multiplied by the number of assets she is willing to buy, minus (ii) the minimum price at which she is willing to sell an asset multiplied by the number of assets she is willing to sell :

Then, if her cash at the beginning of period t + (her quantity to sell * the minimum amount she is willing to sell an asset) - (her quantity to buy * the number of assets she is willing to buy) is negative, then she is a potential borrower.

Appendix I. Instructions of the experiment

The instructions are available online at:
http://www.sebastien-duchene.fr/wp-content/uploads/2019/03/Instructions-borrowing-and-short-selling-T-LAMETA-english-finale-version.pdf

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