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

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Abstract

This paper studies the influence of allowing borrowing and short selling on market prices and traders' forecasts in an experimental asset market. We verify, although not statistically significantly so, that borrowing tends to increase asset overvaluation and price forecasts, while short selling tends to reduce these measures. We also show that a number of results on beliefs, traders' types, cognitive sophistication, and earnings obtained in earlier experimental studies in which borrowing and short selling are not possible, generalize to markets with borrowing and short sales.

keywords: Experimental asset market, bubble, short sales, margin buying
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1 Introduction

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

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 (Boehmer et al., 2013; Beber and Pagano, 2013).

Because there are 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. King et al. (1993) found no effect of short selling on market prices and that 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 is prohibited, allows prices to better track the fundamental value for both assets. Conversely, borrowing, when short selling is banned, increases overpricing of the lottery asset, but not of the standard asset. Haruvy and Noussair (2006) found that the greater the short-selling capacity that traders possessed, the lower were prices. If the short-sale constraints were sufficiently loose, assets would trade at below fundamental values. However, the experimental literature has not investigated how borrowing and short-selling possibilities influence dynamics of traders' expectations. 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 experiment reported here has two objectives. The first is to investigate the effect of borrowing and short selling on dynamics of traders' expectations and market outcomes. Specifically, we consider the effect of short selling and borrowing on (1) price patterns, (2) expectation dynamics, and (3) the trading strategies employed, as well as their relationships with market outcomes and earnings. We also verify whether borrowing increases prices and short selling lowers prices, and measure which effect is stronger.

The second objective is to consider whether the relationship between cognitive ability, measured by the Cognitive Reflection Test (CRT, Frederick et al., 2005), and earnings as well as market outcomes reported in recent studies (Corgnet et al., 2015; Breaban and Noussair, 2015; Noussair et al., 2016; Akiyama et al., 2017), generalize to markets with borrowing and short selling.

To do so, we conduct a set of laboratory experiments in which traders make forecasts of the future price trajectory, as in Haruvy et al. (2007) and Carle et al. (2017). Each trader participates in two consecutive markets, allowing us to gauge the effect of experience. There are four treatments organized in a 2x2 design. The factors are whether or not margin buying is allowed, and whether short selling is permitted or not.

We confirm that borrowing increases, and short selling reduces, market prices. Nonetheless, the differences are not statistically significant because of large within-treatment variations in the outcomes. Some of the difference is explained by the differences in the median CRT scores of subjects across each market. We also find that more frequent use of a passive (or fundamentalist) trading strategy is negatively related to the magnitude of mispricing, and positively associated with earnings. The relationships between CRT scores, trading strategies and market dynamics, as well as the dynamics of expectations, observed in our data is 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 (subsection 3.1), traders' expectations (subsection 3.2) and traders' strategies (subsection 3.3). Section 4 summarizes the results and concludes.

2 Experimental design

2.1 Procedures common to all treatments

A set of computerized experiments were conducted at the LEEM at the University of Montpellier, France, between February and March, 2016.[1] A total of 210 student and non-student subjects registered in LEEM's subject database, who have never 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.

Our experimental design is similar to those of Haruvy et al. (2007), Carle et al. (2017) and Akiyama et al. (2014, 2017). In each market, traders can buy and sell an asset with a lifetime of 10 periods. At the end of each period, each unit of asset pays a dividend of either 24 or 48 ECU (experimental currency units) with an equal probability. Thus, the expected dividend per

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

period is 36 ECU per asset. After the final dividend payment in period 10, the asset loses its value. Accordingly, at the beginning of period t, the asset's (risk neutral) fundamental value is $FV_t = 36(11 - t)$. At the beginning of period 1 of each market, each subject is endowed with 10 units of the asset and 3600 ECU. The exchange rate between ECU and Euros is 1 euro = 360 ECU.

We employ a call market to trade the asset, as in Akiyama et al. (2014, 2017), Haruvy et al. (2007) and Carle et al. (2017). The call market rule facilitates the elicitation of price forecasts, because there is a unique and unambiguous price in each period. 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).[2] Once all orders have been submitted, they are aggregated to calculate a market clearing price.[3] Transactions are realized for those orders for which the bid (ask) is greater (less) than or equal to the market clearing price.[4]

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.[5]

The pre-recorded instructions were played while subjects followed it along on their own

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

[3]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)).

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

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

printed copy. The instructions were available to the subjects throughout the experiment.[6]

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 Finucane 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.[7] In the Baseline treatment (hereafter BL), no short selling and no borrowing is allowed. In the Borrowing treatment (BW), borrowing is allowed but short selling is not. In addition to the 3600 ECU given at the beginning of each market, 3600 ECU are lent to each trader.[8] This additional cash lent must be repaid entirely by the end of each market.[9]

In the Short Selling treatment (SS), short selling is allowed but borrowing is not. Any trader can 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 has to pay the dividend randomly selected by the computer. The dividend paid for each stock sold short is automatically deducted from the trader's available cash. The initial total value of stocks available for short sale, 360*10=3600 ECU, is equal to the amount of cash lent in the borrowing treatment. This perfect symmetry facilitates comparisons between these two treatments. Finally, in the fourth treatment (BWSS), short selling and borrowing are both allowed. As in the SS treatment, each trader can hold a short position of up to 10 units. As in the BW treatment, 3600 ECU are lent to each trader and must be returned at the end of each market.[10]

[6] The experiment was conducted in French. An English translation is provided in the appendix.

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

[8] 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.

[9] 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.

[10] One subject went bankrupt in this treatment, the only one to do so in all the four treatments.

3 Results

3.1 Market behavior

Figure 1 shows the time series of observed prices in the four treatments in Markets 1 and 2. The price charts for Market 1 show the tendency for overpricing 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. Secondly, the markets of the BW and BWSS treatments are characterized by a larger variability of the first period prices. Volatility also appears to be greater in BW and BWSS than in the other treatments.

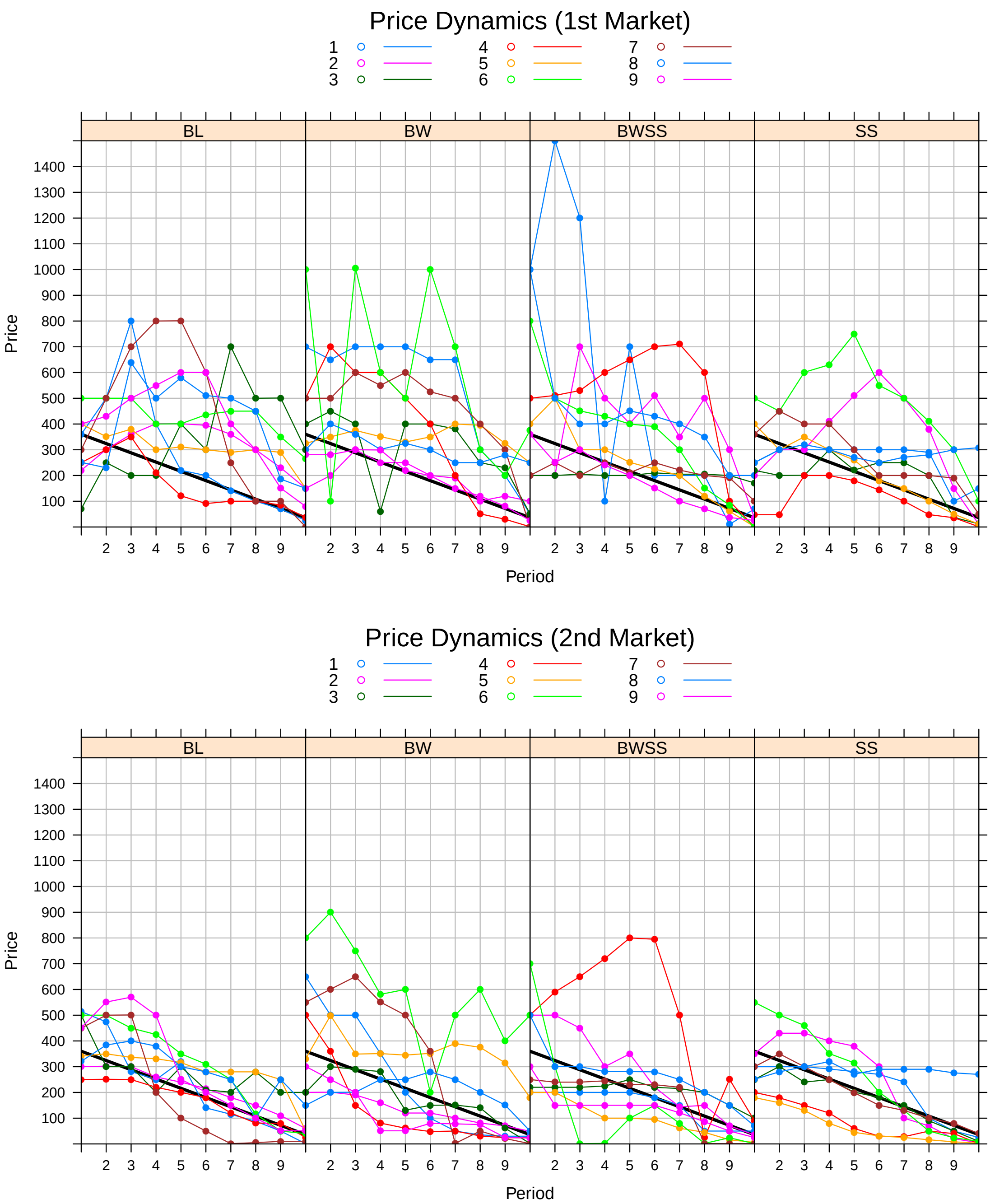
In Market 2, prices track the fundamental value more closely than in Market 1 in all treatments. The BW treatment displays the largest mispricing, with a tendency toward overvaluation in almost half of the markets and undervaluation in 3 others. BW and BWSS continue to have a large variability of the 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 and market, the averages of various measures characterizing price dynamics proposed in the literature.[11] It also reports the p-values from Kruskal-Wallis (KW) tests for between-treatments comparisons. As one can see from these p-values, except for the volatility in Market 2, none of the measures of price dynamics we have considered is statistically significantly different across the four treatments. This is presumably at least partly because of the large within-treatment variations in the price dynamics we observe in our data.

For each treatment, most measures related to the magnitude of mis-pricing become significantly smaller in Market 2 compared to Market 1. See the bottom panel of Table 1 for p-values. Thus, regardless of the treatment, we observe that subjects trade at prices closer to FV after gaining some experience in trading in the same environment with the same group of subjects,

[11] We consider measures proposed by King et al. (1993); Porter and Smith (1995); Haruvy and Noussair (2006); Haruvy et al. (2007); Stöckl et al. (2010), and Powell (2016). See Appendix B for the definitions of these measures.

Figure 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, numbered from 1 to 9, corresponds to a market.

Table 1: The average characteristics of market outcomes 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 signed-rank test.

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

in agreement with the previous literature.

The relationship between the CRT scores of market participants and mis-pricing 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 volatility and six of our mis-pricing measures. Such relationships, however, are not observed in Market 2, where prices consistently track fundamentals more closely. In the next subsection, we analyze the dynamics of forecasts.

3.2 Traders' forecasts

Figures 2 and 3 display the average forecasted prices submitted by all the 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 panel PoE 1 of Figure 2, we observe that, for Market 1, the average forecasts are initially 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 FV either. Moreover, we can clearly see that the predictions under BW tend to be above the others, while in SS they tend to be below. These results indicate that there can be a treatment effect regarding forecasts at the outset of market.

Contrasting the dynamics of forecasts shown in Figure 2 with the dynamics of prices shown in Figure 1, we note 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 for all periods of

Table 2: 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

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

Figure 2: Average Forecasts made during Market 1 for each period of elicitation.

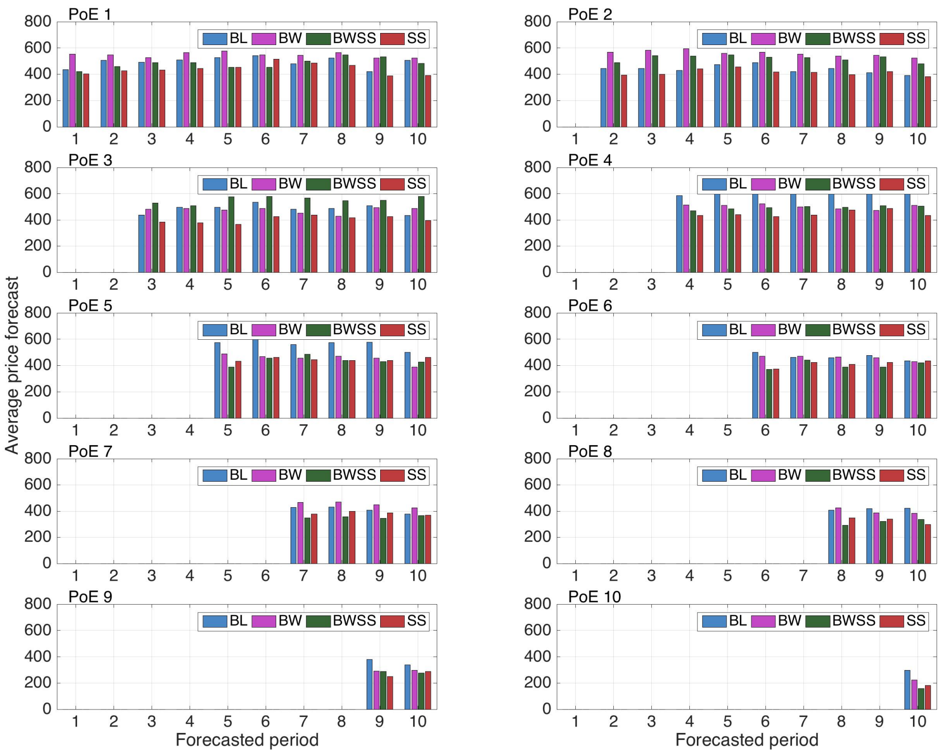
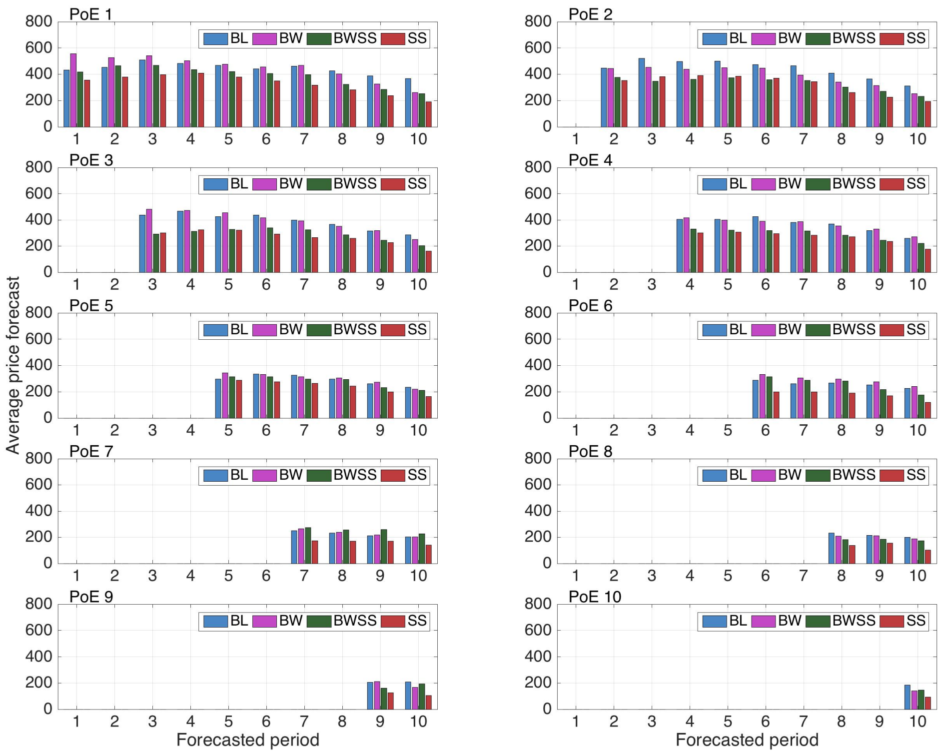


Figure 3: Average Forecasts made during Market 2 for each period of elicitation.



elicitation and for all treatments, 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 the traders' inclination to use both prices of Market 1 and past prices of Market 2 to define their forecasts.

We now proceed to further analyze the forecast dynamics by extending the framework proposed by Haruvy et al. (2007) to allow for comparison across four treatments as follows:

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

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.

$Periodtrend_{m,t}$ corresponds to the movement of the last prices and expectations of the current market between $t+k-2$ and $t+k-1$. This indicator catches the concept 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. This implies 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.[12]

Finally, FV_t is the component which measures the extent to which a trader integrates the FV of the asset in the formation of his beliefs.

[12]The definitions of $Periodtrend_{m,t}$ and $Markettrend_{m,t}$ are presented in Appendix B.

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 regressions (MLM) for Markets 1 and 2 (the two left hand columns) and the random effects (RE) regressions (the two right hand columns).[13] While we will mainly discuss the results of the MLM regressions, we report the standard RE approach in the same table to show how divergent conclusions might be drawn. We consider the MLM approach to be relevant, since it allows the separation of the variance at many levels and exploration of variations in effects across and within various clusters. Thus, it enables us to evaluate variables both within and between clusters.[14]

In Market 1, *Periodtrend* is significant. This result confirms the influence of past prices in the current market in the formation of traders' expectations. Moreover the interaction coefficients between *Periodtrend* and dummy treatment variables are not significant, which confirms that the process of expectation formation is common 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,

[13]To analyse this regression, we offer two statistical methodologies. First, we run a random effects regression (RE) in a panel data framework to account for dependencies at the subject level. 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. As it is proposed with random effects models in a panel data framework, which identify 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 $f^{t+k}_{i,m,t}$) 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 C. Treatment effects are captured by dummy treatment variables, through differences in intercepts and interaction coefficients of these dummy variables with the explanatory variables.

[14]Here, our MLM selection procedure selected the model with random slopes for both subject and market clusters, because of a better fit. Besides, 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 (in red) are significantly different from zero, which implies that there are large heterogeneities across markets and subjects.

demonstrating the lack of a connection between beliefs and the fundamental value. Finally, in the RE (random-effect) regression, all coefficients are significant (except β_{15}). This result is in contrast with the MLM approach and shows how the impact of identifying clusters and their variance 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.

In Market 2, *Periodtrend* and *Markettrend* are both significant, while FV is not. These results are 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 between treatments in any intercept or interaction term at the 5% level, indicating a common expectation formation rule in the four treatments in Market 2.

Table 3: Forecasts as a function of Treatments, Periodtrend, Markettrend, and FV

	Market 1 MLM	Market 2 MLM	Market 1 RE	Market 2 RE
(Intercept)	300.29728***	97.45534**	410.7913***	88.7104***
	(65.41692)	(42.51203)	(37.71727)	(26.5301)
BW	−114.97198	3.00103	−130.4065**	8.65860
	(92.53810)	(60.12138)	(53.36331)	(37.53207)
BWSS	−142.04766	11.96244	−201.1948***	41.37383
	(92.49816)	(60.16877)	(53.36189)	(37.52237)
SS	−119.20819	−56.80329	−114.4298**	−41.09470
	(95.45765)	(62.053923)	(54.99364)	(38.68557)
Markettrend	*NA*	0.41677***	*NA*	0.4681***
	NA	(0.08632)	*NA*	(0.0122)
Periodtrend	0.3393***	0.25364***	−0.0008*	0.0085***
	(0.05855)	(0.04861)	(0.0004)	(0.0017)
FV	0.07737	0.14691	0.3177***	0.4162***
	(0.20278)	(0.10837)	(0.0658)	(0.0414)
BW ∗ *Markettrend*	*NA*	0.05686	*NA*	−0.3709***
	NA	(0.12167)	*NA*	(0.0133)
BWSS ∗ *Markettrend*	*NA*	0.06893	*NA*	−0.3994***
	NA	(0.12449)	*NA*	(0.0130)
SS ∗ *Markettrend*	*NA*	0.03801	*NA*	0.07110***
	NA	(0.12794)	*NA*	(0.0230)
BW ∗ *Periodtrend*	0.05102	−0.09937	0.0583***	0.0518***
	(0.08326)	(0.06782)	(0.0039)	(0.0039)
BWSS ∗ *Periodtrend*	0.04163	−0.11577*	0.0736***	−0.0063***
	(0.08383)	(0.06841)	(0.0044)	(0.0017)
SS ∗ *Periodtrend*	0.02028	−0.04197	0.0207***	0.0163***
	(0.08731)	(0.07403)	(0.0029)	(0.0049)
BW ∗ *FV*	0.37759	0.05074	0.3482***	0.3064***
	(0.28696)	(0.15321)	(0.0930)	(0.0573)
BWSS ∗ *FV*	0.43780	0.01192	0.5145***	0.1254**
	(0.28722)	(0.15262)	(0.0931)	(0.0569)
SS ∗ *FV*	0.27421	0.04749	0.0881	−0.1395**
	(0.29572)	(0.15792)	(0.0959)	(0.0611)
AIC	151329.9	140075.8	156421.4	144585.8
BIC	151512.3	140345.6	156523.6	144717
Log Likelihood	-75639.96	-70000.91	-78196.72	-72274.88
Num. obs.	10904	10904	10904	10904
Number of markets	35	35	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	246.76/60889.56	180.10/32437.49
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	92553.22	32231.60

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

Coefficients with standard errors in parentheses of MLM and RE regressions for Markets 1 and 2.

3.3 Trading strategies

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 et al. (2006, 2014) and Breaban and Noussair (2015). We consider three types of trading behavior: passive traders, feedback traders, and rational speculators. We modify, however, the classification of Haruvy et al. (2006, 2014) and Breaban and Noussair (2015), to take advantage of the fact that we have belief data.

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:

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

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 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 on them, looking specifically at the difference between the next period price and the current period price. They try to buy in the current period, if they believe that the next period's price will be higher than the current one, and try to sell if they believe that the price for the next period will be lower. A trader is considered as a rational speculator in period t if

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

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

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

If a subject is considered as 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 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. Therefore, at period t, if a subject's behavior is consistent with more than one strategy, we weight them less, compared to a situation where it is consistent with a single strategy. 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.

Figure 4 and 5 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 feedback strategies. These two scores are shown separately in the scatter plots in the bottom panel. Each point in the simplex and scatter plot represents a subject. In the simplex plots, the height of a point from the edge of the triangle that is opposite of the apex labeled R+F represents the joint score of rational speculation and feedback strategies. Thus, if a point is on R+F 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. Similarly, if a point is located on N apex, then the score for no-type for this subject is one, thus, this subject did not demonstrate behavior consistent with the passive, feedback and rational speculation strategies in any of the seven periods. The score for the passive strategy can be read in a similar manner by the height of a point from the edge that is opposite of the Apex P.

We investigate the relationships between average normalized scores of market participants and market outcomes. Table 4 reports the results of regressing various measures of price dynamics on the average normalized score of feedback, passive, and rational speculation strategies for Markets 1 and 2. We pool the data from the four treatments.

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 mis-pricing. 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). There is, however, no statistically significant relationship between the average score of the feedback strategy and mis-pricing in Market 1.

We now consider the relationship between the normalized score of a subject and the profit obtained. Table 5 shows, both for pooled data and for each of four treatments separately, the result of regressing the end of market profit from trading[15] on score of passive, feedback, and rational speculation strategy.

We observe that a higher score for the passive strategy is associated with a greater profit in both Markets 1 and 2. In Market 1, a higher score of rational speculation is also weakly asso-

[15]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 of strategies.

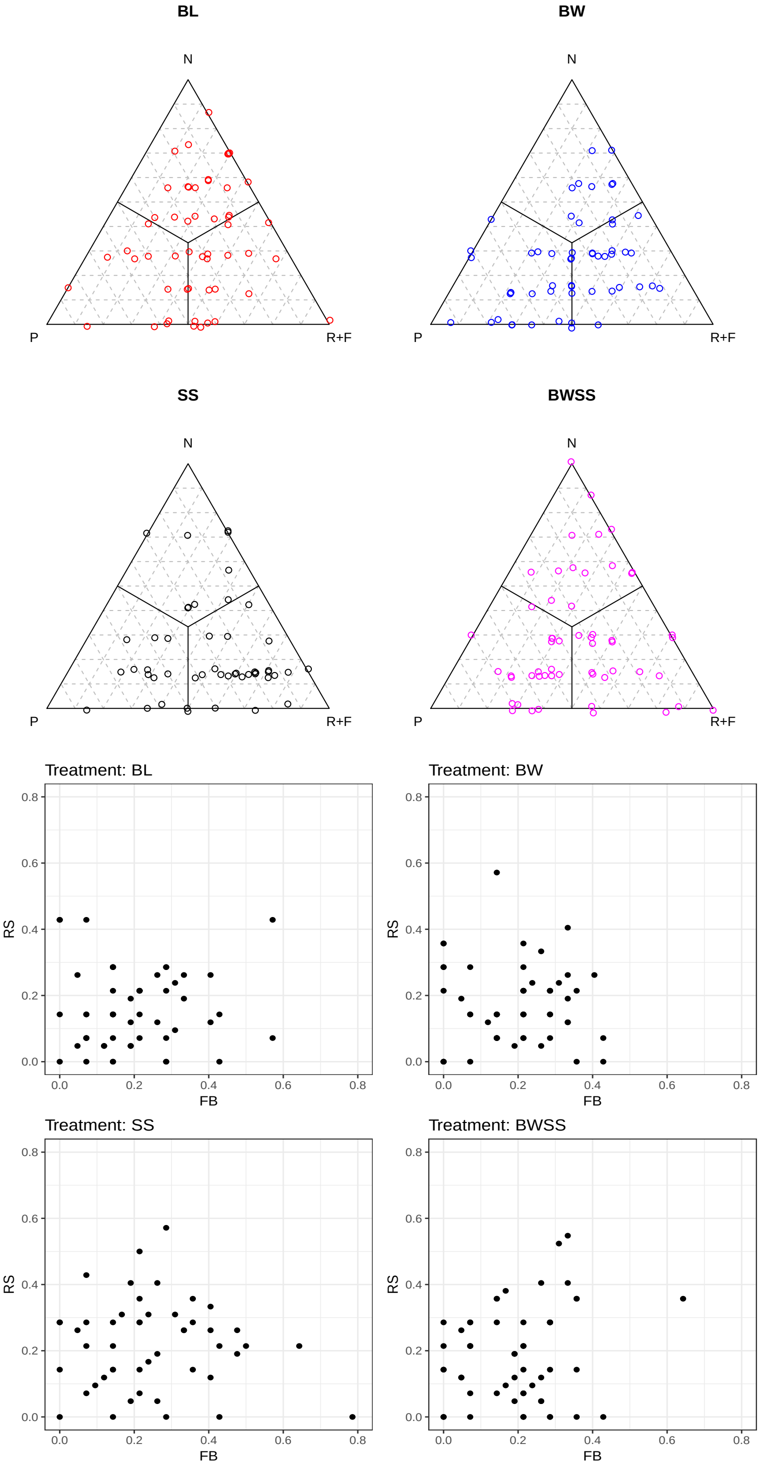


Figure 4: Distribution of normalized scores in Market 1

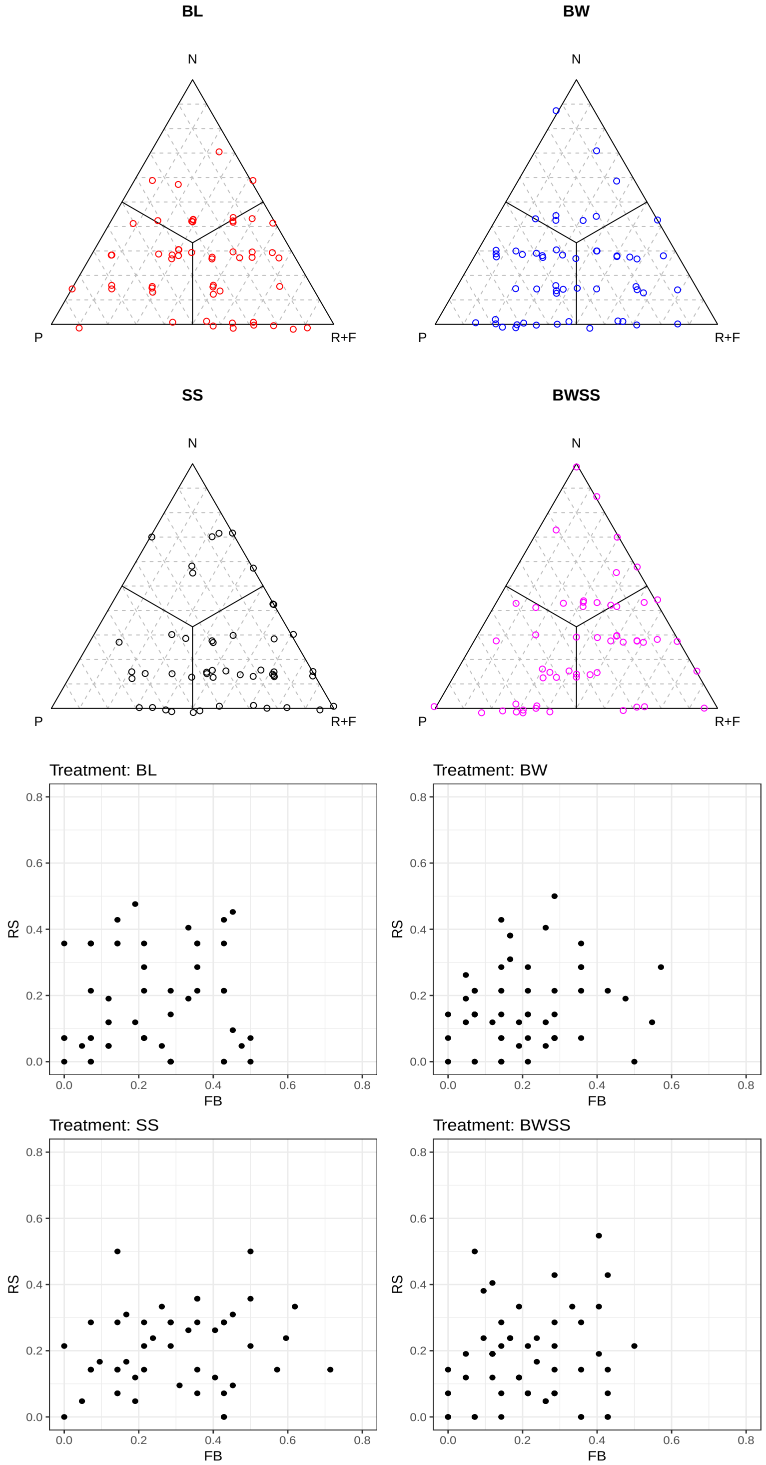


Figure 5: Distribution of normalized scores in Market 2

Table 4: 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 Speculator	−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 Speculator	−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

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

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

Market 1					
	Pooled	BL	BW	BWSS	SS
(Intercept)	5352.8111***	5591.2816***	5477.0671***	4669.5018***	5989.1982***
	(502.0638)	(734.0249)	(1460.3212)	(1048.8939)	(974.8799)
Score Speculator	2968.1418**	2485.9158	−120.9329	7394.9383***	961.4005
	(1181.4783)	(2125.2720)	(3053.0957)	(2531.8936)	(1953.4988)
Score Feedback	1960.1316*	2305.9557	2031.3276	1138.5641	1643.0083
	(1108.0575)	(1869.8754)	(3253.0958)	(2684.2857)	(1590.2542)
Score Passive	3127.6093***	2953.6649**	3883.4101**	3164.5725*	2494.7622*
	(737.1111)	(1185.2004)	(1832.2726)	(1618.7186)	(1395.2275)
AIC	3761.3773	907.3376	939.1453	939.0925	793.0477
BIC	3781.4599	919.2715	951.0792	951.0264	804.2749
Log Likelihood	-1874.6886	-447.6688	-463.5726	-463.5463	-390.5238
Num observations	210	54	54	54	48
Num. groups	35	9	9	9	8
Between group variance/Sd (Intercept)	0.00/0.0965	0.00/0.0949	0.00/0.1161	0.00/0.1242	0.00/0.0957
Residual variance	4474456.0768	3203070.0778	6100699.7920	6010534.7214	2716975.5428
Market 2					
	Pooled	BL	BW	BWSS	SS
(Intercept)	5896.7656***	5424.7277***	5059.2302***	6524.6261***	6655.7069***
	(421.1300)	(751.8024)	(1121.0320)	(868.0986)	(521.0691)
Score Speculator	805.1172	871.1378	1121.8314	1380.3555	−332.6211
	(873.3448)	(1326.1675)	(2275.8729)	(1909.2992)	(1208.0996)
Score Feedback	450.0404	2415.1925*	−554.6717	−2414.2063	1111.1305
	(819.9437)	(1370.4170)	(2213.2531)	(2040.9023)	(904.7225)
Score Passive	2428.3305***	2487.6561**	4509.0174***	2241.3172**	258.4163
	(581.8368)	(1092.8414)	(1486.1992)	(1137.4071)	(759.8185)
AIC	3638.0039	873.3494	912.9784	909.6786	743.6579
BIC	3658.0865	885.2833	924.9123	921.6125	754.8851
Log Likelihood	-1813.0019	-430.6747	-450.4892	-448.8393	-365.8290
Num observations	210	54	54	54	48
Num. groups	35	9	9	9	8
Between group variance/Sd (Intercept)	0.00/0.0732	0.00/0.0656	0.00/ 0.1044	0.00/0.0982	0.00/0.0508
Residual variance	2457284.3593	1616963.2915	3600627.3636	3327428.2655	886419.5882

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

ciated with the higher profit in pooled data (which is mainly coming from the strong positive relationship between this score and profit in BWSS treatment). We do not observe statistically significant relationship 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 pooled data. Therefore, this result shows the interest of studying these strategies.

4 Conclusion

This experiment allowed us to explore the relationships between market price dynamics and traders' forecasts and strategies, in an experimental asset market featuring short selling and/or borrowing. We observe that short selling alone reduces, although not in a statistically significant manner, price levels, price deviations from the fundamental value, volatility and price fluctuations. Conversely, borrowing increases overvaluation, deviations from the fundamental value, volatility and price fluctuations, though not significantly. The effects of the combination of these two types of leverage are are not systematic and depend on the variables and the periods that are being considered.

We believe the absence of statistically significant treatment effects on market outcomes are due to large within-treatment variation in the outcome. We show, through multi-level modeling, that the dynamics of forecasts depend strongly on subjects and markets, and less so on whether short selling and borrowing are possible.

We have also shown that a number of results that have been reported in markets without short selling and borrowing generalize to settings in which these types of leverage are permitted. Namely, we observe negative relationships between the cognitive ability of market participants and mispricing and volatility. We also find that greater use of the passive strategy is associated with smaller market mispricing and greater individual earnings. These results lead us to believe that these patterns are general relationships that apply to a broad class of asset markets.

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Appendix

A Cognitive Reflection Test

(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]

(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 $8,000$ € in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon:
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 $7,000$ €; intuitive response b].

B Definitions of various measures

Table 6 summarizes the definitions of the measures of market mispricing that we use in our analysis.

Table 6: Definition of various measures

Measure	Definition
Volatility	$Vol = \frac{1}{9}\sum_{p=2}^{10} \lvert(p_p - FV_p) - (p_{p-1} - FV_{p-1})\rvert$
Boom Duration	max number of consecutive periods for which price is above the FV
Bust Duration	max number of consecutive periods for which price is below the FV
Turnover	$Turn = \frac{\sum_{p=1}^{10} Q_p}{TSU}$
Amplitude	$Amp = \max_p(\frac{p_p - FV_p}{FV_p}) - \min_p(\frac{p_p - FV_p}{FV_p})$
Normalized Deviation	$ND = \sum_{p=1}^{10} \frac{Q_p \lvert p_p - FV_p\rvert}{TSU}$
Average bias	$AB = \sum_{p=1}^{10} \frac{p_p - FV_p}{10}$
Total dispersion	$TD = \sum_{p=1}^{10} \lvert p_p - FV_p\rvert$
Relative absolute deviation	$RAD = \frac{1}{10}\sum_{p=1}^{10} \frac{\lvert p_p - FV_p\rvert}{\lvert \overline{FV}\rvert}$
Geometric absolute deviation	$GAD = exp(\frac{1}{N}\sum_{p=1}^{10} \lvert \ln(\frac{p_p}{FV_p})\rvert) - 1$
Relative deviation	$RD = \frac{1}{10}\sum_{p=1}^{10} \frac{p_p - FV_p}{\lvert \overline{FV}\rvert}$
Geometric deviation	$GD = (\prod_{p=1}^{10} \frac{p_p}{FV_p})^{\frac{1}{10}} - 1$
Period Trend[a]	$Periodtrend = f_{i,m,t}^{t+k-1} + f_{i,m,t}^{t+k-1} \frac{f_{i,m,t}^{t+k-1} - f_{i,m,t}^{t+k-2}}{f_{i,m,t}^{t+k-2}}$
Market Trend[a]	$Markettrend = f_{i,m,t}^{t+k-1} + f_{i,m,t}^{t+k-1} \frac{p_{m-1,t+k} - p_{m-1,t+k-1}}{p_{m-1,t+k-1}}$

Note. (a) For Period Trend and Market Trend. $f_{i,m,t}^{t+k-1}$ 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 $p_{m,t-1}$.

C Multi-level Modelling

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

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

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 between subjects (For example the CRT score or the Treatments), and t is the period variable. Further, u and v are random coefficients, and $\sigma^2_{u_{0i}}$, $\sigma^2_{u_{1i}}$, and $\sigma^2_{u_{3i}}$ respectively represent the between-subject variances of their distributions in the intercepts, in the slopes, and in time; while $\sigma^2_{v_{0m}}$, $\sigma^2_{v_{1m}}$ and $\sigma^2_{v_{3m}}$ 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, andα_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 based onHaruvy et al. (2007). 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 with 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 (in the same way as 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 rejected 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.

D Instructions of the experiment

The instructions are available online at:
http://www.sebastien-duchene.fr/wp-content/uploads/2018/07/Instructions-borrowing-and-short-selling-T-LAMETA-english-finale-version.pdf