The effect of price magnitude on analysts' forecasts: Evidence from the lab*

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December 8, 2020

Accepted for publication in *Revue Economique*

Abstract

Recent empirical research in accounting and finance shows that the magnitude of stock prices influences analysts' price forecasts (Roger et al., 2018). In this paper, we report the results of a novel experiment where some subjects are asked to forecast future prices in a continuous double auction market. In this experiment, two successive markets take place: one where the fundamental value is a small price and one where the fundamental value is a large price. Although market prices are higher (compared to fundamental value) in small price markets than in large price markets, our results indicate that analyst subjects' forecasts are more optimistic in small price markets compared to large price markets. Analyst subjects strongly anchor on past price trends when building their price forecasts and do not mitigate subject traders' bias. Overall, our experimental findings support the existence of a small price bias deeply rooted in the human brain.

*Patrick Roger acknowledges the financial support of the Chair in Behavioral Finance at EM Strasbourg Business School. Marc Willinger acknowledges the financial support of the BEAM project - Behavioral and Experimental Analyses in Macro-finance - (ANR-15-ORAR-0004-02).

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1 Introduction

Financial analysts produce reports on a regular basis. These reports contain earnings forecasts and target prices (*i.e.*, price forecasts) among other information. The literature shows that target prices issued by analysts are too optimistic (Ramnath et al., 2008; Bradshaw et al., 2019). For instance, the yearly average return implied by analysts' target prices on U.S. stocks was 28% for the 1997-1999 period (Brav and Lehavy, 2003) and 24% for the 2000-2009 period (Bradshaw et al., 2013). Similarly, Roger et al. (2018) find an implied return of 21.55% over the 2000-2014 period. These figures, estimated on the U.S market, are well above the yearly return on the S&P500 over the corresponding periods.

Nominal stock prices should not be relevant for portfolio allocation or firm valuation since stock prices can be managed through corporate actions such as stock splits. However, a large body of literature provides evidence that investors care about nominal stock prices (Baker and Gallagher, 1980; Baker et al., 2009; Weld et al., 2009). In addition, nominal stock prices have been shown to influence stock returns. Green and Hwang (2009) show that the returns on small price stocks comove more together than with the returns on large price stocks. Symmetrically, returns on large price stocks comove more together than with the returns on small price stocks. The authors interpret their results as an overestimation by investors of the room to grow for small price stocks, compared to large price stocks. In the same vein, Birru and Wang (2016) state that investors overestimate the expected skewness of small price stocks. A recent paper by Shue and Townsend (2019) indicates that, controlling for size, low-priced stocks have higher volatility and market betas. The authors also find that small price stocks exhibit a stronger response to firm-specific news events.

Using price forecasts (*i.e.*, target prices) issued by financial analysts in the U.S., Roger et al. (2018), find evidence of a small price bias. Their results indicate that target prices are more optimistic for small price stocks (price below \$10) compared to large price stocks (price above \$40). The difference in optimism between small price stocks and large price stocks remains significant on a risk-adjusted basis. While the results in Roger et al. (2018) are robust and not likely explained by alternative economic factors, one cannot totally exclude that their findings are in fact driven by some unobservable factors or by some form of endogeneity (since analysts' forecasts can influence stock prices). Additionally, the finance and accounting literature provides extensive evidence that financial analysts face conflicts of interest (Lin and McNichols, 1998; Michaely and Womack, 1998; O'Brien et al., 2005; Cowen et al., 2006; Ljungqvist et al., 2006). Thus, the differential optimism between small price stocks and large price stocks could also be the result of distorted incentives.

The goal of our paper is twofold. First, we study the small price bias found in (real markets) price forecasts by Roger et al. (2018) in the controlled environment of a market experiment. Second, we analyze, in the context of a market experiment, the behavior of subjects whose task is to forecast future prices (analyst subjects hereafter) and who are distinct from subjects who trade (trader subjects hereafter). To the best of our knowledge, our paper is the first, with the contemporaneous article by Giamattei et al. (2020), to do so.[1]

To approach our main research question, that is whether stock price magnitude influence price forecasts, we conduct a novel experiment where some subjects in a continuous

[1]However, our paper and the one of Giamattei et al. (2020) address different issues. Giamattei et al. (2020) study how forecasting influences mispricing. Additionally, a key difference is that, in Giamattei et al. (2020), analysts and traders interact while, in our paper, traders do not observe analysts' forecasts.

double auction market act as analysts and forecast future prices.[2] Contrary to financial markets, the price forecasts, in our experiment, are not available to trader subjects. Thus, analyst subjects cannot influence prices. Moreover, a major advantage of experimental markets over real financial markets is the existence of a FV whose expected value can be easily computed. Finally, in a market experiment, the forecasts of subjects who act as analysts are not influenced by conflict of interests and other bad incentives.

In each of the eight sessions of our experiment, subjects are divided into two groups. In the first group, nine subjects act as traders and are endowed with a portfolio of experimental currency and units of a risky asset. These subjects trade the risky asset in two successive continuous double auction markets which last 10 periods each. In the second group, up to 11 subjects act as analysts and are asked to forecast the price of the risky asset at the beginning of each period. Overall, there were 72 trader subjects and 83 analyst subjects. While we provide summary statistics on transaction prices, the focus of this paper is on subjects acting as analysts.[3] Each session is composed of two successive markets: a market where the FV is a small price and a market where the FV is a large price. Four sessions begin with a small price market and the four remaining sessions begin with a large price market.

Our results indicate that analyst subjects are more optimistic in small price markets than in large price markets. These findings are obtained both when optimism is assessed with respect to the FV and when optimism is assessed with respect to past market prices. Price forecasts are on average 32.70% greater than the FV in small price markets and only 3.22% greater in large price markets. These price forecasts are set, on average, 8.10% above

[2]The design of the experiment is the same as in Roger et al. (2020). Roger et al. (2020) study the behavior of the subjects acting as traders while the present article analyzes the behavior of subjects acting as analysts.

[3]Detailed results on subject traders can be found in Roger et al. (2020).

the median transaction price of the previous period for small price markets. This figure decreases to 2.55% in large price markets. Since analyst subjects are asked to forecasts future prices and transaction prices tend to exceed FV, it is not surprising to observe a large deviation of forecasts from FV. However, the greater deviation of forecasts from past prices on small price markets compared to large price markets indicate that the small price bias observed among trader subjects by Roger et al. (2020) is exacerbated among analyst subjects. Overall, our results are in line with the findings of Roger et al. (2018) on financial analysts in the U.S. market. Akin to financial analysts issuing price forecasts on real financial markets, the analyst subjects in our experiment exhibit greater optimism when issuing price forecasts on small price stocks than on large price stocks.

In addition to the small price bias, our results also highlight that subjects anchor their forecasts on former-period trading prices and fail to anticipate the eventual convergence of prices towards the FV. This observation is consistent with the results of Haruvy et al. (2007) and Duclos (2015) on trader subjects' elicitation. Interestingly, we show that the adaptation of individuals' beliefs about prices also occurs when passive subjects who act as analysts, and not as traders, are asked to predict future prices. Similarly to trader subjects' forecasts in previous studies (Kirchler et al., 2015; Razen et al., 2017), we find that forecasts, in our experiment, are largely determined by past price trends. This reliance on trend extrapolation by subjects acting as analysts is also found in Giamattei et al. (2020).

2 Theoretical framework

2.1 Bubbles and the fundamental value process

The literature in experimental finance shows that the size of bubbles depends, among other characteristics, on the fundamental value (FV hereafter) process. The seminal result of Smith et al. (1988), characterized by a decreasing FV process, has been replicated and extended by an expanding literature.[4] When the fundamental value process is constant, bubbles still arise (Lei et al., 2001). However, when the FV increases over time (Giusti et al., 2012; Johnson and Joyce, 2012; Stöckl et al., 2015), bubbles disappear and underpricing is observed. Furthermore, in markets with randomly fluctuating fundamentals, Stöckl et al. (2015) observe overvaluation when FVs predominantly decline and undervaluation when FVs are mostly upward-sloping. Similar observations were made earlier by Gillette et al. (1999) and Kirchler (2009). Therefore, allowing for randomness in the FV process seems to have a tempering effect on the price deviations from the FV, limiting therefore the extent of bubbles and crashes.

The latter observation is important with respect to the choice of our experimental design. We want to prevent amplification effects that might be built in the FV process as in the case of a declining FV. If such amplification effect is conditional on the magnitude of the fundamental value, asymmetric reactions could either exaggerate or fade away the type of effect we are studying. Given the above reported experimental evidence, relying on a stochastic FV process seems therefore recommended.

Stöckl et al. (2015) implement a very simple rule $FV_t = FV_{t-1} + \widetilde{\epsilon}$ with different

[4] *e.g.*, King et al. (1993), Boening et al. (1993), Lei et al. (2001), Noussair et al. (2001), Haruvy and Noussair (2006), Caginalp et al. (2010), Noussair et al. (2012), Noussair and Tucker (2016), Noussair et al. (2016) and Stöckl et al. (2015).

specifications for $\widetilde{\epsilon}$. A similar process was implemented by Gillette et al. (1999) and by Kirchler (2009). In our experiment, we rely on the same type of process as the multimodal distribution in Stöckl et al. (2015). We do not impose a deterministic fundamental value at the start of the market. Instead, all along the experiment, the fundamental value is equal to the sum of the per period cash-flows progressively revealed to both trader subjects and analyst subjects. We briefly discuss hereafter the properties of our cash-flow process and the resulting equilibrium price process.

2.2 The cash-flow and fundamental value processes

Subjects trade a single risky asset over T periods. We denote $j = 0, 1$ the market type; $j = 0$ ($j = 1$) corresponds to the large (small) price treatment.[5]

A unit of the risky asset, in market j, is a vector of *i.i.d.* random cash-flows, denoted $CF_j = (CF_{j,t}, t = 1, ..., T)$. These cash-flows are progressively revealed over time. At the end of each period t, a realization of the random variable $CF_{j,t}$ (denoted $cf_{j,t}$) is drawn at random and made public. The expected fundamental value of the asset at the beginning of the market is then equal to $T\mu_j$ where $\mu_j = E(CF_{j,t})$. The experimenter pays the sum of the T cash-flows to the final holder of the risky asset at the end of the market. No dividend is paid during the market.

Such a cash-flow process keeps the magnitude of prices stable during a given market, provided the variance of cash-flows is not too large. For example, in small price markets, the distribution of cash-flows is uniform over the set $\{0; 0.3; 0.6; 0.9; 1.2\}$. The range of potential terminal payoffs, seen from date 0 is $[0; 12]$. After two draws, equal for example to 0.3 and 0.9 respectively, the range of possible terminal payoffs is restricted to $[1.2; 10.8]$.

[5] See Roger et al. (2020) for a detailed description of the market design.

In large price markets, cash-flows are scaled up by 12. Though the terminal range, seen from date 0, is $[0; 144]$, this range shrinks quickly to keep potential prices greater than the maximum price of small price markets.

Due to the progressive revelation of *i.i.d.* cash-flows[6], the standard deviation of the final payoff decreases linearly with the square root of the time remaining until T.[7] As a consequence, the price range compatible with the absence of arbitrage opportunities in period t is

$$\{S_t^{min}, S_t^{max}\} = \{\sum_{s=1}^{t-1} cf_s + (T-t) \times cf_{min}, \sum_{s=1}^{t-1} cf_s + (T-t) \times cf_{max}\} \quad (1)$$

with S_t^{min} (S_t^{max}) the minimum (maximum) possible redemption value seen from period t, and cf_s the realization of the cash-flow in period s.

3 Experimental design

The experiment was run at the computerized laboratory of the University of Montpellier (LEEM) with z-Tree (Fischbacher, 2007). 155 subjects (8 sessions with 9 trader subjects by session and 6 to 11 analyst subjects per session)[8] were involved, randomly selected from a pool of approximately 5,000 volunteers from the Universities of Montpellier.[9] Each

[6]The progressive revelation of information over time avoids inducing an anchor in the minds of subjects at the start of the market, contrary to designs where zero-mean dividends are paid at each date and a fixed redemption value is paid at the end of the market.

[7]Our choice not to distribute dividends during the market implies that the stochastic process $FV_{j,t}, t = 0, ..., T$ of the fundamental value is a martingale with respect to the information given by the cash-flow process.

[8]At times, some students did not show up. As a result, we reduced the number of subjects acting as analysts. The number of subjects acting as traders was always 9.

[9]Only students comfortable in mathematics (3rd year in School of Engineering, Mathematics, Physics, Biology, Medicine, and Master's Degree in Economics, Computer Science and Pharmacy) participated in order to prevent our results for being driven by subjects' difficulties in dealing with numbers.

subject took part to one session only.

In the first part of the experiment, subjects completed a real effort task to earn real money, to avoid the house money effect. The real effort task consisted of a series of counting exercises (lasting approximately 15 minutes): Subjects were asked to count the number of ones in matrices composed of zeros and ones, a task used previously in Abeler et al. (2011) and Beaud and Willinger (2014). Subjects were informed[10] that successfully fulfilling the real effort task was a necessary condition to participate in the second part of the experiment. In case of failure, subjects only received the show up fee. Subjects were first provided with written general instructions about the market design. They were then selected to act either as traders or as analysts. Specific written instructions were provided for each role. Subjects were assigned to two different groups: a group of 9 trader subjects and a group of up to 11 analyst subjects. Subjects were informed that they would participate in two successive markets. However, they did not receive any specific information about the second market before the end of the first market.

3.1 Experimental market

We implemented a within-subject design. In each session, trader subjects were involved in two consecutive ten-period markets. Each market corresponds to a distinct treatment. The difference between the two treatments lies in the magnitude of the fundamental value (FV) of the risky asset. In the large price treatment, the FV of the risky asset is 12 times the FV of the small price treatment. To keep the cash-to-asset ratio constant[11], the total allotment of cash (*i.e.*, experimental currency) is also scaled up by 12. Four sessions

[10]Complete instructions can be found in the Appendix

[11]The ratio between total cash and total value of assets, in experimental markets, has been shown to influence asset prices (Caginalp et al., 1998, 2001).

started with the small price treatment and the remaining four started with the large price treatment.

The risky asset has a finite life of ten periods and is traded in a standard continuous double auction. At the end of each trading period, a cash-flow is drawn from a uniform distribution with five potential outcomes and displayed to all subjects. These five potential outcomes are 0, 0.3, 0.6, 0.9 and 1.2 in the small price treatment, and 0.0, 3.6, 7.2, 10.8 and 14.4 in the large price treatment. The unconditional FV is thus equal to 72 in large price markets and equal to $\frac{72}{12} = 6$ in small price markets. The traded asset does not pay any dividend until the market ends, at which point it is bought back by the experimenter. Instructions clearly stated that the asset redemption value is equal to the sum of the 10 cash-flows.

Panel A of Table 1 gives the sequences of cash-flows used in the experiment. Sequences S3 and S4 are "mirrored" versions of sequences S1 and S2 (with respect to the unconditional fundamental value).[12] We follow Stöckl et al. (2015) in using sequences S1 and S2 in the four first sessions and their mirrored counterpart S3 and S4 in the following four sessions. While these different sequences yield slightly different average FV[13], their unconditional FV at the beginning of the market are the same (72 for large price markets and 6 for small price markets). Panel B provides the different portfolio composition. There were three different initial endowments. In large price markets, the endowments were the same but the cash positions were multiplied by 12. Finally, Panel C of Table 1 summarizes the information for the different sessions.

[12] As discussed previously, Stöckl et al. (2015) indicate that a trend in the FV process may influence mispricing. Gillette et al. (1999) and Kirchler (2009) find that a decreasing (increasing) FV tends to generate overvaluation (undervaluation).

[13] These cash-flows sequences were drawn at random so that the unconditional FV were the same for all small price markets and large price markets. The random draw, however, yielded cash-flows sequences with slightly different FV trajectories and thus slightly different average FV.

3.2 Price forecasts

Each analyst subject had to provide three forecasts at the beginning of each period: an upper bound, the median price, and a lower bound. More precisely, at the beginning of period t, each analyst subject i is asked to provide $(L_{i,t}, M_{i,t}, H_{i,t})$. $L_{i,t}, t = 1, ..., T$ is the anticipated price level such that $Q_{i,t}(S_t \leq L_{i,t}) = 10\%$ where $Q_{i,t}$ is analyst subject i's subjective probability distribution of future price S_t. $M_{i,t}, t = 1, ..., T$ is the anticipated median price such that $Q_{i,t}(S_t \leq M_{i,t}) = Q_{i,t}(S_t \geq M_{i,t}) = 50\%$. Finally, $H_{i,t}, t = 1, ..., T$ is the anticipated price such that $Q_{i,t}(S_t \geq H_{i,t}) = 10\%$. $L_{i,t}$ is then the lower bound of the 80% confidence interval of analyst subject i regarding the stock price at time t while $H_{i,t}$ is the upper bound.

We use formulas introduced by Kieffer and Bodily (1983)[14] to estimate the expected future price $(E_{Q_{i,t}}(S_t))$ and the variance of the future price $(V_{Q_{i,t}}(S_t))$, implicit in the vector $(L_{i,t}, M_{i,t}, H_{i,t})$.

$$E_{Q_{i,t}}(S_t) = 0.63 \times M_{i,t} + 0.185 \times (L_{i,t} + H_{i,t}) \tag{2}$$

$$V_{Q_{i,t}}(S_t) = 0.63 \times M_{i,t}^2 + 0.185 \times (L_{i,t}^2 + H_{i,t}^2) - E_{Q_{i,t}}(S_t)^2 \tag{3}$$

Equations 2 and 3 provide a way to define the performance function. In a framework of symmetric cash-flow distribution, the median is assumed equal to the mean, with $M_{i,t} =$

[14]These formulas are an extension of the three-point approximation of Pearson and Tukey (1965).

$(L_{i,t} + H_{i,t})/2$.[15] In this case, equations 2 and 3 become:[16]

$$E_{Q_{i,t}}(S_t) = \frac{L_{i,t} + H_{i,t}}{2} \tag{4}$$

$$V_{Q_{i,t}}(S_t) = \frac{0.185}{2} \times (L_{i,t} - H_{i,t})^2 \tag{5}$$

[15]This assumption is backed by the data. The ratio of the distance between the median and the 10th percentile and the distance between the 90th percentile and the 10th percentile ($\frac{M_{i,t}-L_{i,t}}{H_{i,t}-L_{i,t}}$) has a mean of 45.40% and a median of exactly 50%.

[16]Proofs are provided in the Appendix.

Table 1
Sequences of cash-flows

Panel A: Time series of cash-flows (for small price markets)

Periods	1	2	3	4	5	6	7	8	9	10
Basic sequence 1 (S1)	0.6	0.3	0.6	0.9	0.6	1.2	0.9	0.3	0.0	0.6
Basic sequence 2 (S2)	0.9	0.6	0.6	0.6	0.6	1.2	0.9	0.0	0.3	0.6
Mirrored sequence 1 (S3)	0.6	0.9	0.6	0.3	0.6	0	0.3	0.9	1.2	0.6
Mirrored sequence 2 (S4)	0.3	0.6	0.6	0.6	0.6	0	0.3	1.2	0.9	0.6

Panel B: Portfolio composition

	Small price market			Large price market		
Portfolios	P1	P2	P3	P4	P5	P6
Units of asset	3	6	9	3	6	9
Amount of experimental currency (ECU)	82	64	46	984	768	552

Panel C: Characteristics of sessions

	Type of market		Cash-flow sequence		Average FV	
	Market 1	Market 2	Market 1	Market 2	Market 1	Market 2
Session 1	Small price	Large price	S1	S2	6.15	77.4
Session 2	Large price	Small price	S1	S2	73.8	6.45
Session 3	Small price	Large price	S1	S2	6.15	77.4
Session 4	Large price	Small price	S1	S2	73.8	6.45
Session 5	Small price	Large price	S3	S4	5.85	66.6
Session 6	Large price	Small price	S3	S4	70.2	5.55
Session 7	Small price	Large price	S3	S4	5.85	66.6
Session 8	Large price	Small price	S3	S4	70.2	5.55

Panel A gives the basic sequences of cash-flows used in the experiment. They are randomly generated but pre-determined to ensure comparability. Sequences S3 and S4 “mirror”(at the unconditional expected value of 6) sequences S1 and S2. Sequences are scaled up by 12 in large price markets. The first (second) line of Panel B gives the number of units of asset (cash) in the different portfolios. Portfolios P1 to P3 (P4 to P6) correspond to the small (large) price markets. Quantities are determined to have a theoretical portfolio value in large price markets equal to 12 times the theoretical portfolio value in small price markets. Panel C summarizes the information for the different sessions.

3.3 Earnings

A measure of predictive success satisfying axioms 1 to 5 of Selten (1991) should reward successful predictions and penalize overly accomodating predictions. We therefore choose a performance function, based on equations 4 and 5, that penalizes distributions with a large variance (compared to the mean) and rewards a forecast falling in the 80% confidence interval $[L_{i,t}; H_{i,t}]$.

$$PERF_{i,t}(L_{i,t}, H_{i,t}, S_t) = \alpha_1 \mathbf{1}_{S_t \in [L_{i,t}; H_{i,t}]} - \alpha_2 (\frac{H_{i,t} - L_{i,t}}{H_{i,t} + L_{i,t}}) \tag{6}$$

The payoff function $PERF$ gives an incentive to analyst subjects to propose a probability distribution compatible with their perceived knowledge of the pricing process. $PERF$ refers explicitly to L and H in its two terms but $PERF$ also refers implicitly to the median M because of the symmetry of the cash-flow distribution (the denominator of $PERF$ is $H + L$). The maximum performance an analyst subject can achieve is $T \times \alpha_1$ if: (1) the three predictions L, M, H satisfy $H_{i,t} = M_{i,t} = L_{i,t}$ for any date t; and, (2) the common prediction is perfect (equal to S_t). The last term in the $PERF$ function penalizes analyst subjects who choose a distribution with a large coefficient of variation, equivalent here to a large (relative) difference between the upper bound and the lower bound of the forecast interval. We use the following parametrization: $\alpha_1 = 10$ and $\alpha_2 = 24$. The interesting property of the $PERF$ function is its homogeneity of degree 0, *i.e.*, the performance of an analyst subject does not depend on the cash-flow magnitude (since the cash-flows are scaled up by a unique factor from the small price treatment to the large price treatment).

In the written instructions, analyst subjects received complete information about the determination of their earnings. They were instructed that their earnings depended on their performance. They were also told that only one of the two markets would be randomly selected to be paid out for real.

The conversion rule from performance to earnings was

$$Earnings_i \text{ (in €)} = 30 + 0.1 \times \left(\sum_{t=1}^{10} PERF_{i,t} - \lambda \right) \tag{7}$$

where λ was a constant whose value was undisclosed to subjects. The 30 euros were earned in a real-effort task that took place during the first part of the experiment. In practice, the constant was set equal to the average global performance of all the analyst subjects in the session (and the selected market). Payoffs to analyst subjects (including show-up fees) totaled 2473,37 euros and an average of 30,16 euros per person, with a minimum of 20,84 euros and a maximum of 34,56 euros.

The motivation for calculating subjects' earnings as a function of their own performance relative to the average performance was to control the total cost of the experiment and to provide exactly the same monetary incentives in both treatments. Indeed, a fixed conversion rate between forecast accuracy and euros could have resulted in very large earnings for a few subjects. In addition, this tournament structure is coherent with the kind of incentives financial analysts have (Yin and Zhang, 2014). However, tournaments incentives have been shown to enhance risk-taking and mispricing (James and Isaac, 2000; Berlemann and Vöpel, 2012; Cheung and Coleman, 2014). We thus decided to adopt the procedure of Keser and Willinger (2000) and Keser and Willinger (2007) who hide the tournament structure from subjects. By not disclosing the value of the constant λ until the end of the experiment, this payoff procedure provides a clear incentive to maximize PERF.

4 Results

4.1 Descriptive statistics on trades

We first present some descriptive statistics on market dynamics. Figure 1 provides charts on the evolution of transactions prices. Since there are four different cash-flow sequences and two different FV magnitudes, we show a total of 8 charts. Overall, price charts indicate that transactions take place at prices that are mainly above FV. The mispricing seems, at first glance, more severe for small price markets than for large price markets. Table 2 gives summary statistics on trader subjects' activity. The results in Table 2 indicate that trader subjects complete transactions at prices that are further away from (and above) FV in small price markets than in large price markets.[17] The number of transactions is roughly the same in both types of markets and appears independent from FV magnitude.

4.2 Univariate results on analyst subjects' forecasts

We follow Roger et al. (2018) and investigate whether analysts' optimism is influenced by stock price magnitude. In the literature on financial analysts' target prices, optimism is measured by the return implied by the target price with respect to the current stock price (Bradshaw et al., 2019). We adapt this measure to the context of experimental markets and define optimism in two ways. We consider: (1) the implied return with respect to the FV denoted $IR_{i,t}^{FV}$ and defined by $IR_{i,t}^{FV} = \frac{E_{Q_{i,t}}(S_t)-FV_{t-1}}{FV_{t-1}}$; and, (2) the implied return with respect to the previous median price (*i.e.*, the median of the transaction prices in the previous period), denoted $IR_{i,t}$ and defined by $IR_{i,t} = \frac{E_{Q_{i,t}}(S_t)-S_{t-1}}{S_{t-1}}$ where S_{t-1} is the median traded price in period $t-1$ and $E_{Q_{i,t}}(S_t)$ is the expected future price as defined

[17] See Roger et al. (2020) for a more detailed analysis of subject traders' behavior.

Table 2
Descriptive statistics on trades

	Small price markets	Large price markets
Unconditional FV	6	72
Median Price	7.30	74.00
Relative Absolute Deviation (RAD)	32.58%	18.75%
Relative Deviation (RD)	20.90%	-1.44%
Number of transactions	1,046	1,072

This table provides summary statistics on transactions in small price and large price markets. Relative Absolute Deviation (RAD) and Relative Deviation (RD) are defined as in Stöckl et al. (2010). We have

$$RAD = \frac{1}{N} \sum_{t=1}^{N} \frac{\left|\overline{P_t} - FV_t\right|}{\overline{FV}} \text{ and } RD = \frac{1}{N} \sum_{t=1}^{N} \frac{\left(\overline{P_t} - FV_t\right)}{\overline{FV}}. \tag{8}$$

where t denotes the period number in a given market and N is the total number of periods in a given market ($N = 10$ in our experiment). $\overline{P_t}$ is the period-t average transaction price and FV_t is the beginning of period-t fundamental value. $\overline{FV}$ is the average fundamental value over the N periods.

in equation 4.[18]

Table 3 gives the average level of implied returns for small price and large price markets.[19] In each session, analyst subjects provide 9 sets of forecasts (periods 2 to 10) in a small price market and 9 sets of forecasts in a large price market. Since we have paired observations, we use a Wilcoxon matched-pairs signed-rank test to assess the significance of the difference in implied returns between small price markets and large price markets. The results in Table 3 indicate that analyst subjects' forecasts are more optimistic in small price markets than in large price markets regardless of the measure of optimism that is used. When measured with respect to the FV, the difference in implied returns between

[18]Since analyst subjects are also asked to provide a median forecast in order to estimate the future price, we also tested our model with $M_{i,t}$, the median forecast, instead of the expected future price $E_{Q_{i,t}}(S_t)$. The results can be found in Tables D1 and D2 in the Appendix.

[19]Time series of median price forecasts can be found in Figure C1 of the Appendix.

Table 3
Wilcoxon matched-pairs signed-ranks tests

	IR^{FV}	IR
Small price markets	0.3270	0.0810
Large price markets	0.0322	0.0255
Difference	0.2948***	0.0555***
	(14.70)	(6.12)

This table presents the within analyst subjects comparison between small price markets and large price markets. For each subject analyst and each treatment, we compute the average of IR^{FV} (and IR). IR^{FV} is the implied return with respect to fundamental value ($IR_{i,t}^{FV} = \frac{E_{Q_{i,t}}(S_t)-FV_{t-1}}{FV_{t-1}}$) and IR is the implied return with respect to previous median transaction price ($IR_{i,t} = \frac{E_{Q_{i,t}}(S_t)-S_{t-1}}{S_{t-1}}$). Statistical significance is assessed with a Wilcoxon matched-pairs signed-ranks test. z-statistics are reported in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

small price and large price markets is equal to 0.2948 and is significant at the 1% level. This difference in optimism shows that analyst subjects take into account the differential optimism of trader subjects across markets, that is, small price markets versus large price markets (Roger et al., 2020). However, analyst subjects are asked to forecast future trading prices, not future FVs. When we measure implied returns with respect to the previous median price (IR), we also find a significant difference in optimism between small price markets and large price markets. The average implied return is equal to 8.10% in small price markets compared to 2.55% in large price markets. This result suggests that analyst subjects do not mitigate the small price bias of trader subjects. Our results in Table 3 show that analyst subjects' forecasts are anchored on past prices which are inflated with respect to FVs.[20]

[20]The small price bias is not limited to the initial periods. Table E1 in the Appendix shows that these differences in implied returns between small price markets and large price markets remain significant if only periods 6 to 10 are considered.

Figure 1
Fundamental value (*bold line*) and median prices for individual markets (*gray lines with circles and squares*). The x-axis represents the different periods.

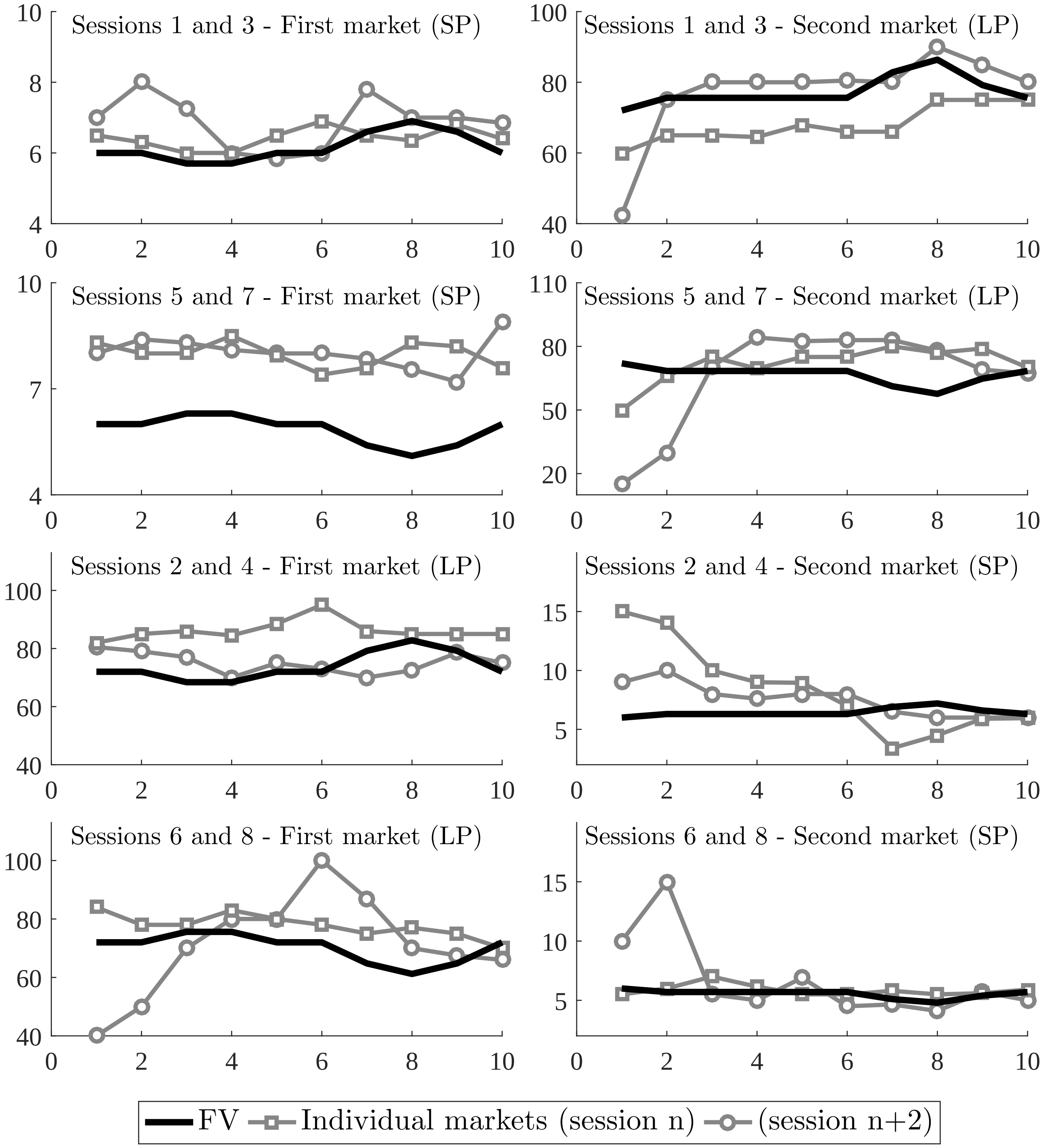

Table 4
Random effect panel data estimation

Panel A: Implied return with respect to fundamental value (IR^{FV})			
	(1)	(2)	(3)
	All forecasts	First markets only	Second markets only
Intercept	0.3186***	0.0726*	1.0080***
	[3.80]	[1.68]	[6.18]
Small price dummy	0.1834***	0.0419**	0.3011***
	[3.99]	[2.18]	[3.32]
Lag RD (RD_{t-1})	0.6610***	0.8696***	0.6389***
	[8.34]	[11.99]	[9.12]
FV Trend	-0.7740	-0.7632***	-0.7972***
	[-6.17]	[-8.31]	[-2.95]
Period square root	-0.1966***	-0.0110	-0.3883***
	[-5.95]	[-0.82]	[-6.14]
Market dummy	0.1445***		
	[2.68]		
R^2	0.2377	0.5181	0.2623
Number of observations	1476	738	738

Panel B: Implied return with respect to previous median transaction price (IR)			
	(1)	(2)	(3)
	All forecasts	First markets only	Second markets only
Intercept	0.0944	0.0183	0.4068***
	[0.96]	[0.44]	[3.64]
Small price dummy	0.0907*	0.0319**	0.1486*
	[1.94]	[2.09]	[1.71]
Lag RD (RD_{t-1})	-0.1757***	-0.1671*	-0.1776***
	[-3.26]	[-1.88]	[-2.92]
FV Trend	0.4257**	0.3968***	0.4510
	[2.30]	[4.00]	[1.09]
Period square root	-0.0830***	-0.0059	-0.1602***
	[-3.91]	[-0.48]	[-4.12]
Market dummy	0.0779*		
	[1.71]		
R^2	0.0395	0.0471	0.0407
Number of observations	1476	738	738

This table reports the results of random effects regressions of IR^{FV} (Panel A) and IR (Panel B) on our treatment dummy (*i.e.*, a small price dummy) and different control variables. *FV Trend* is defined as $\Delta FV_{t-1} = \frac{FV_{t-1}-FV_{t-2}}{FV_{t-2}}$, *Lag RD* is $RD_{t-1} = \frac{S_{t-1}-FV_{t-1}}{FV}$, *Period square root* is equal to $\sqrt{t}$ and *Market dummy* is a dummy variable equal to 1 for the first market and 0 for the second. t-statistics are in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

To reinforce our results, we perform a multivariate analysis in which we control for the information held by analyst subjects when they issue their forecasts. Contrary to real financial markets, the framework of experimental markets allows subjects to easily compute the fundamental value of the traded asset. As a consequence, a given analyst subject i who forecasts future prices at the beginning of period t uses two types of information: (1) the end-of-period fundamental value of the risky asset (after cash-flow of period $t-1$ has been revealed); and, (2) the trading prices in preceding periods. To keep things simple[21], we summarize past information by: (1) the relative change in end-of-period FV between period $t-2$ and period $t-1$, $\Delta FV_{t-1} = \frac{FV_{t-1}-FV_{t-2}}{FV_{t-2}}$; and, (2) the relative deviation between the median traded price and the end-of-period FV in period $t-1$, $RD_{t-1} = \frac{S_{t-1}-FV_{t-1}}{FV_{t-1}}$.[22]

We estimate a linear model with random effects where analyst subjects' implied return (IR^{FV} or IR) in a given period is regressed on our treatment dummy (*i.e.*, a small price dummy) and different control variables. In addition to ΔFV_{t-1} and RD_{t-1}, we introduce a dummy variable equal to 1 when forecasts were issued during the first market of a session and 0 otherwise. Also, we introduce a variable equal to the square root of the period number to take into account that the standard deviation of the FV decreases as the square root of time. As shown previously, the variance of the final payoff decreases linearly over time (the final payoff is the sum of T *i.i.d.* random variables at date 0, but the sum of $T-t$ random variables and a constant at the end of period t).

The regression results appear in Table 4. Panel A (Panel B) shows the results when implied returns are calculated with respect to the FV (with respect to the former period median price). The *small price dummy* is significant in all specifications and in both

[21]We could also consider more lags but the markets cover only 10 periods. As a consequence, introducing more lags would generate an important loss of information. Moreover, our choice is consistent with the private information possessed by analyst subjects who only know their own forecast errors.

[22]This measure is adapted from Haruvy and Noussair (2006), Haruvy et al. (2007) and Stöckl et al. (2010).

panels. As explained above, the results in Panel A (IR^{FV}) are not entirely surprising since trader subjects deviate more in small price markets compared to large price markets (Roger et al., 2020). As a consequence, analyst subjects take into account trader subjects' deviations in both market types. This interpretation is confirmed by the coefficients of the control variable *Lag RD* (RD_{t-1}) which are positive and highly significant. Analyst subjects integrate, in their forecasts, the errors made by trader subjects. In other words, analyst subjects strongly anchor on previous prices when making their forecasts. In panel B (IR), the *small price dummy* is positive and significant. These results confirm our previous findings that analyst subjects are more optimistic in small price markets than in large price markets.

5 Conclusion

Our paper makes two important contributions. First, we introduced a new type of agent in traditional asset market experiments, namely analyst subjects. To the exception of the contemporaneous paper by Giamattei et al. (2020), this is the first experiment where subjects other than traders are tasked to provide forecasts. Our results highlight that analyst subjects suffer from anchoring bias and trend extrapolation. This finding echoes previous results on traders' elicitation (Haruvy et al., 2007; Duclos, 2015) and traders' forecasts (Kirchler et al., 2015; Razen et al., 2017). Second, our paper contributes to the literature on the importance of nominal prices. Our results, obtained in the controlled environment of an experiment, confirm the empirical findings of Roger et al. (2018). Analyst subjects' forecasts are more optimistic for small price stocks than for large price stocks, even after controlling for the deviation of trading prices with respect to the fundamental value and the evolution of the uncertainty of the fundamental value over time. Our two experimental markets differ only by the scale of cash-flows. As a consequence, usual arguments of the finance literature (such as lottery-like features of some small price stocks) are not at work in the experimental framework. Our results are a strong indicator that a deeply rooted behavioral bias in number processing explains the differences in forecast optimism between small price markets and large price markets.

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A Proofs

Proof for equation 4.

Since we assume that $M_{i,t} = (L_{i,t} + H_{i,t})/2$, we have:

$$\begin{aligned}
E_{Q_{i,t}}(S_t) &= 0.63 \times M_{i,t}^2 + 0.185 \times (L_{i,t} + H_{i,t}) \\
&= 0.63 \times \frac{L_{i,t} + H_{i,t}}{2} + 0.185 \times (L_{i,t} + H_{i,t}) \\
&= \left(\frac{0.63}{2} + 0.185\right) \times (L_{i,t} + H_{i,t}) \\
&= \frac{L_{i,t} + H_{i,t}}{2} \qquad (9)
\end{aligned}$$

■

Proof for equation 5.

To simplify, we denote $p = 0.185$. Equation 3 allows to write:

$$\begin{aligned}
V_{Q_{i,t}}(S_t) &= (1 - 2p)M_{i,t}^2 + p(L_{i,t}^2 + H_{i,t}^2) - M_{i,t}^2 \\
&= p(L_{i,t}^2 + H_{i,t}^2 - 2M_{i,t}^2) \\
&= p(L_{i,t}^2 + H_{i,t}^2 - \frac{1}{2}(L_{i,t}^2 + H_{i,t}^2 + 2L_{i,t}H_{i,t}) \\
&= \frac{p}{2}(L_{i,t}^2 + H_{i,t}^2 - 2L_{i,t}H_{i,t}) \\
&= \frac{p}{2}(H_{i,t} - L_{i,t})^2 \qquad (10)
\end{aligned}$$

■

B Instructions to participants (translated from French)

[These instructions correspond to a session that starts with a small price market. Instructions for the part 1 (real effort task) of the experiment are not reported.]

General instructions

I. Sequence 1

At this stage, you own the 30 Euros that you won in part 1. During part 2, you will use your 30 Euros to participate in experimental markets, in which you can make gains or losses. If you make gains they will be added to your 30 Euros and if you make losses, they will be deducted from your 30 Euros. Details about the calculation of your final gains (losses) are provided at the end of the instructions.

There are two different roles in part 2 of the experiment: **traders** and **analysts**. The main body of instructions is common to both roles. We first present the instructions that are common to both roles. Then, specific instructions will be communicated to traders on the one hand, and analysts on the other hand.

You will participate in two consecutive experimental markets in which you will be able to make transactions by buying and selling assets. All transactions are realized in Ecus. After reading the instructions, you will be invited to answer a brief questionnaire in order to assess your understanding of the tasks. Then, you will participate in a practice round to be trained with the transaction software. Eventual gains or losses during the practice round will not be counted in your final balance.

[A practice round takes place...]

Generalities

There are nine participants in the session.

1. Duration of a market and random draws

   You will be involved in two consecutive markets. Each market consists of a sequence of 10 periods. Each period lasts two minutes during which you are able to make transactions. At the end of the session, only one of the two markets will be randomly selected to be paid in Euros. Your score for this market will be converted into Euros according to a conversion rule that will be given at the end of the instructions. The computer program will post your final score for the selected market.

   The remainder of these instructions applies only to market 1. Once market 1 is closed you will receive new instructions, specific to market 2.

2. Portfolios

   Before the market opens, each trader receives a portfolio containing a number of units of asset and an amount of Ecus. A total of 54 units of asset can be traded in the market.

   There are three types of portfolios, noted P1, P2 and P3. They differ by the number of units of asset and the amount of Ecus. A portfolio that contains more units of asset contains less Ecus, and vice versa, a portfolio that contains more Ecus contains less units of asset. The division of these portfolios among the traders is the following: three traders will get P1, three other traders P2 and the remaining three get P3.

The assignment of a portfolio to a trader is made on a random basis. Each trader will be the only one to know exactly his portfolio.

3. Lifetime of assets and redemption value

   In each period, traders can buy and sell units of asset. Each unit has a lifetime of 10 periods. After each period, the computer program selects randomly the cash-flow (in Ecu) attached to each unit of asset (see below the determination of cash-flows). At the end of the 10 periods, the market closes. All units of asset held by a trader are bought back by the experimenter at the same unit price for all traders, called the redemption value. The redemption value is equal to the sum of the 10 cash-flows randomly drawn during the market.

4. Cash-flows

   Five cash-flow values (in Ecus) can occur, $\{0; 0.3; 0.6; 0.9; 1.2\}$. At the end of each period, the computer randomly selects the value of the cash-flow for the period. Each of the five possible values is equally likely, i.e. one chance out of five. The selected cash-flow is posted on participants' screens and is identical for all units of asset. The computer screen also displays the sum of the cash-flows revealed since the beginning of the market. Note that the selected cash-flow in any given period is not distributed to the asset owners. Therefore, it does not affect the amount of Ecus available in the traders' portfolios. Cash-flows are only used to determine the redemption value of each unit of asset at the end of period 10. As mentioned before, this redemption value is equal to the sum of all cash-flows revealed over the 10 periods.

   Example 1 Consider the following sequence of cash-flows:

   The redemption value of each unit of asset is equal to the sum of the cash-flows over the 10 periods: $0.3 + 0.0 + 0.9 + 0.9 + \ldots + 1.2 + 0.6 = 6.0$ *Ecus. In this example,*

Period	1	2	3	4	5	6	7	8	9	10
Cash-flow	0.3	0.0	0.9	0.9	0.6	0.3	0.3	0.9	1.2	0.6
Cumulated cash-flow	0.3	0.3	1.2	2.1	2.7	3.0	3.3	4.2	5.4	6.0

each unit of asset would be bought back by the experimenter at a price of 6 *ecus at the end of period 10.*

5. Carrying over portfolios

   The portfolio of each trader is carried over from one period to the next without changing its content.

   Example 2

   At the end of period 5, a trader's portfolio contains 5 units of asset and 67 Ecus. At the beginning of period 6 the composition of his portfolio will be identical: 5 units of asset and 67 Ecus.

6. Losses and profits

   The value of a portfolio can change from one period to the next, even if its composition is unchanged because the value of a portfolio depends on the price of the asset.

   Example 3

   At the end of period 7, your portfolio contains 80 Ecus and 3 units of asset. The last traded price was 7.2 Ecus. At the beginning of period 8, the value of each unit of asset is equal to 7.2 Ecus and the value of your portfolio is equal to 80 + (3×7.2*) = 101.6 Ecus. At the end of period 8, the asset price is equal to 7.6 Ecus. If you did not trade during period 8, the value of your portfolio is equal to 80 + (*3×7.6*) = 102.8 Ecus, that is an increase of 1.2 Ecus corresponding to* $3 \times \ (7,6 - 7,2) = 1.2$ *Ecus.*

Example 4

At the end of period 7, your portfolio contains 80 Ecus and 3 units of asset. The last traded price was 7.2 Ecus. At the beginning of period 8, the value of each unit of asset is equal to 7.2 Ecus and the value of your portfolio is equal to 80 + (3×7.2*) = 101.6 Ecus. At the end of period 8, the asset price is equal to 5.7 Ecus. If you did not trade during period 8, the value of your portfolio is equal to 80 + (*3×5.7*) = 97.1 Ecus, that is a decrease of 4.5 Ecus corresponding to* $3\times\ (5.7 - 7.2) = -4.5$ *Ecus.*

7. Conditions for transactions

   In any given period, a trader cannot sell more units than he owns in his portfolio. Equivalently, a trader cannot buy a unit of asset if he does not own the corresponding amount of Ecus.

Analyst specific instructions

a) Forecasts

   Recall that a market consists of a sequence of 10 periods. Each period lasts 2 minutes during which traders carry out transactions. At the beginning of each period, we will ask you to forecast transaction prices for the coming period. Concretely, you will have to choose a lower bound, an upper bound and a median price defined as follows:

   Lower bound = You think the average transaction price in the coming period has a nine in ten chance of being above your lower bound.

   Upper bound = You think the average transaction price in the coming period has a nine in ten chance of being below your upper bound.

   Median price = You think that the average transaction price in the coming period has a one-in-two chance of being above your median price and a one-in-two chance of being below your median price.

The forecast interval is defined by: I = [lower bound; upper bound]

b) Forecast quality

At the end of each period, the computer will calculate the points you have earned by measuring the quality of your forecast. This measurement depends on your forecast interval, and is calculated as follows:

$$\text{Quality of the forecast} = \text{Forecast achievement} - \text{Forecast inaccuracy}$$

* Forecast achievement: it is equal to 10 points or 0 points. 10 points if the average transaction price for the period belong to the forecast interval I, and 0 points if the average transaction price is outside the forecast interval I.
* The forecast inaccuracy is measured as follows:

$$24 \times (\text{upper bound} - \text{lower bound})/(\text{upper bound} + \text{lower bound})$$

Note that the quality of the forecast can be positive or negative. Table 1 gives some examples of forecasts and the corresponding forecast quality for each forecast.

Table 1. Example of forecast quality calculation

Forecast interval	Upper bound - Lower bound	Average transaction price	Forecast achievement	Forecast inaccuracy	Forecast quality
(a)	(b)	(c)	(d)	(e)	(f = d - e)
[43 - 81]	38	57	10	$24 \times \frac{38}{124} = 7.35$	2.65 points
[63 - 73]	10	77	0	$24 \times \frac{10}{136} = 1.76$	-1.76 points
[46 - 50]	4	51	0	$24 \times \frac{4}{96} = 1.00$	-1.00 point
[57 - 75]	18	69	10	$24 \times \frac{18}{132} = 3.27$	6.73 points

Your overall performance is equal to the sum of the points obtained with respect to the quality of your forecasts from period 2 to period 10.

c) Conversion to euros

At the end of the experiment, one of the two markets (market 1 or market 2) will be drawn at random to be paid in euros. The conversion rule for converting your points into euros is:

$$\text{Payment (in €)} = 30 + 0.1 \times [\text{Overall performance} - \text{Constant}]$$

The level of the constant is determined by the experimental procedure. It will not be communicated to you before the end of the experiment. If your overall performance is greater than the value of the constant, gains will be added to the 30 euros you held at the end of the first part of the experiment. If your overall performance is less than the value of the constant, losses will decrease the amount of the 30 euros you held at the end of the first part of the experiment. The amount that will be added or subtracted to the 30 euros depends on the difference between your overall performance and the value of the constant. The overall sum redistributed to all 11 analysts cannot be less than $30 \times 11 = 330$ euros.

II. Sequence 2

The instructions below are specific to market 2. The group of traders remain the same as in market 1 and the functioning of market 2 is identical to market 1, with two exceptions:

- new portfolios will be assigned to traders
- cash-flow values are different

Changes are detailed below.

Generalities

1. Portfolios

   As for market 1, the total number of available units of asset in market 2 is equal to 54. In market 2, new starting portfolios will be assigned to the traders, noted P4, P5 and P6. As in market 1, 3 traders will receive P4, 3 other traders will receive P5 and the 3 remaining traders will receive portfolio P6. The assignment will be made on a random basis. Each trader will be the only one to know exactly his portfolio.

2. Cash-flows

   In market 2, five cash-flow values can occur : $\{0, 3.6, 7.2, 10.8, 14.4\}$. Each of the five possible values is equally likely, i.e. each one has one chance out of five to be drawn. At the end of each period, the selected cash-flow will be posted on all participants' screens (traders and analysts), as well as the sum of the realized cash-flows since the beginning of the market. The selected cash-flow in any given period is not distributed to asset owners and, therefore, does not affect the amount of Ecus available to a trader. The cash-flows are only used to determine the redemption value of each unit of asset at the end of period 10. This redemption value is equal to the sum of all cash-flows revealed over the 10 periods.

   Example 1

   The sequence of cash-flows for market 2 is as follows:

Period	1	2	3	4	5	6	7	8	9	10
Cash-flow	3.6	0	10.8	10.8	7.2	3.6	3.6	10.8	14.4	7.2
Cumulated cash-flow	3.6	3.6	14.4	25.2	32.4	36	39.6	50.4	64.8	72

The redemption value in this example is equal to: $3.6+0+10.8+10.8+\ldots+14.4+7.2 =$ 72 *Ecus. Each unit of asset held by a trader at the end of the 10 periods is bought back by the experimenter at a price of* 72 *Ecus.*

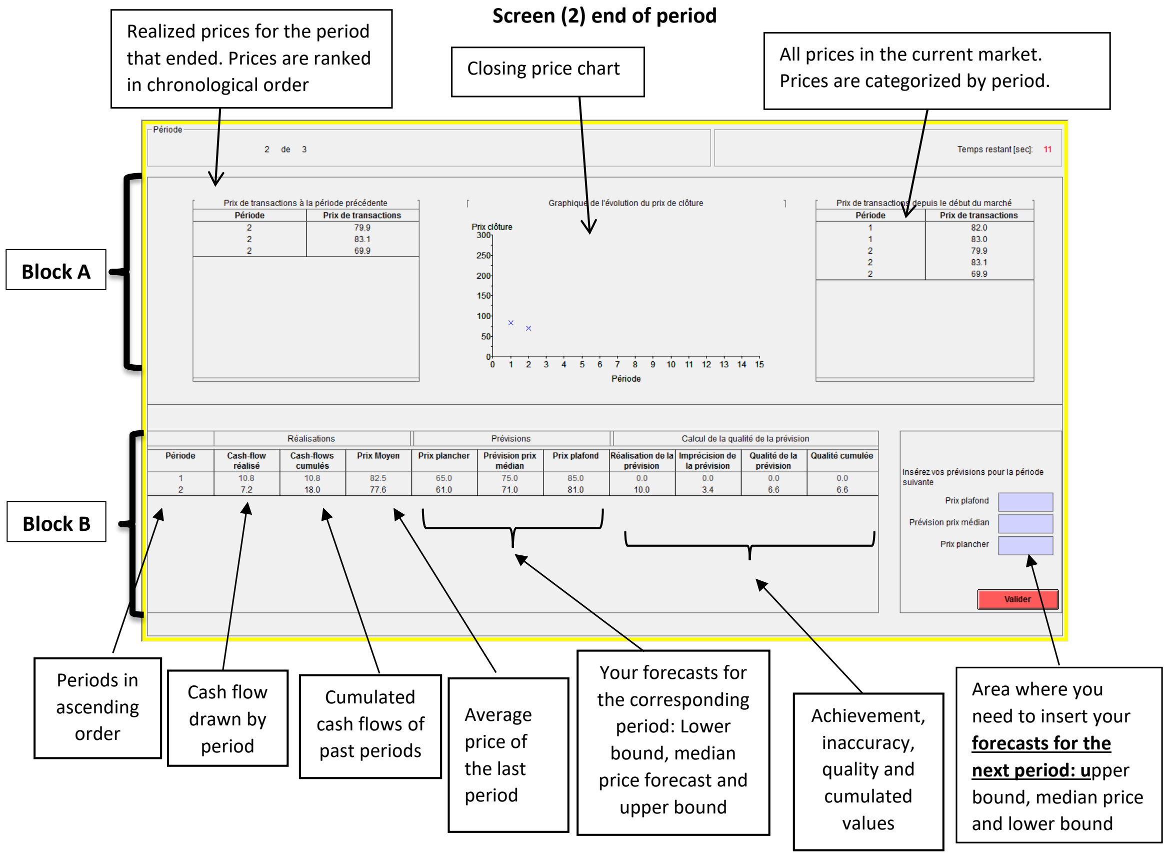
3. Rules of market 2

   The rules of market 2 are identical to those of market 1. As for market 1, market 2 is divided into 10 periods. Each period lasts 2 minutes. Traders will therefore have 20 minutes for realizing their transactions. Remember that at the end of part 2, one of the two markets (market 1 or market 2) will be randomly selected to be paid for real. The computer will calculate your earnings for the selected market, for traders on the one hand and for analysts on the other hand.

III. Z-tree user-guide for analysts

End-of-period screen: analysts

This screen appears at the end of each period (for 15 seconds).



Block A represents a display area of 3 types of information:

1- The history of prices in the period that ended
2- The evolution of the closing prices in past periods
3- Complete price history since the beginning of the market

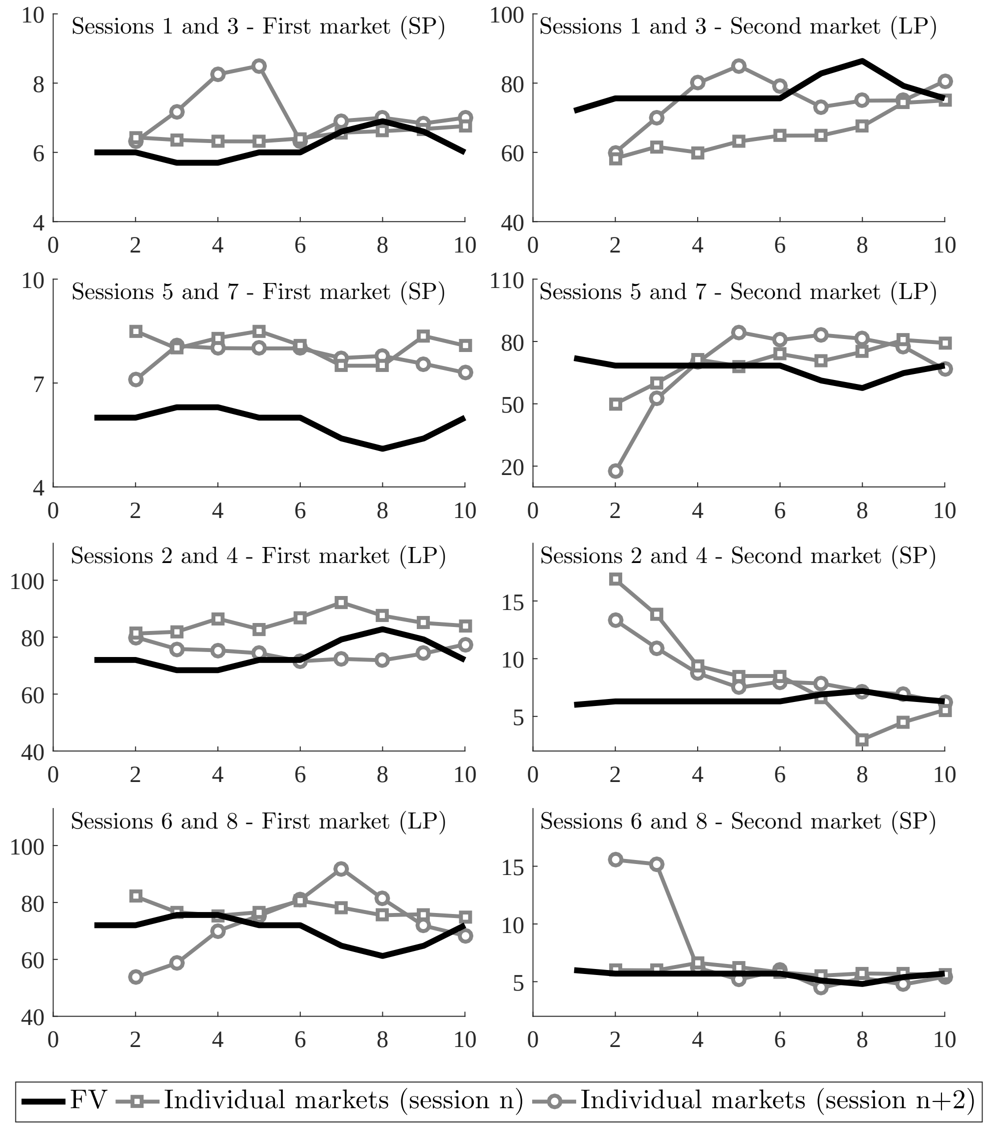
Block B represents the history of the past periods.

Block C is the area where you need to insert your forecasts for the next period.

Important: **After entering your forecasts for the next period, you need to press the "Validate" button to move on to the next period.**

C Fundamental value and median price forecasts

Figure C1
Fundamental value (*bold line*) and median forecasts for individual markets (*gray lines with circles and squares*). The x-axis represents the different periods.



D Robustness test: Results obtained with median forecasts, instead of the expected future prices

Table D1
Wilcoxon matched-pairs signed-ranks tests

	IR^{FV}	IR
Small price markets	0.3000	0.0582
Large price markets	0.0122	-0.0036
Difference	0.2878***	0.0617***
	(14.36)	(5.15)

This table corresponds to Table 3 where implied returns are computed with the median forecast $M_{i,t}$ instead of the expected future price $E_{Q_{i,t}}$. This table presents the within analyst subjects comparison between small price markets and large price markets. For each analyst subject and each treatment, we compute the average of IR^{FV} (and IR). IR^{FV} is the implied return with respect to fundamental value ($IR^{FV}_{i,t} = \frac{M_{i,t}-FV_{t-1}}{FV_{t-1}}$) and IR is the implied return with respect to previous median transaction price ($IR_{i,t} = \frac{M_{i,t}-S_{t-1}}{S_{t-1}}$). Statistical significance is assessed with a Wilcoxon matched-pairs signed-ranks test. z-statistics are reported in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

Table D2
Random effect panel data estimation

Panel A: Implied return with respect to fundamental value (IR^{FV})			
	(1)	(2)	(3)
	All forecasts	First markets only	Second markets only
Intercept	0.1834***	-0.0520**	0.3423***
	[3.42]	[-2.25]	[3.41]
Small price dummy	0.0903***	0.0389**	0.1798**
	[3.92]	[2.07]	[2.07]
Lag RD (RD_{t-1})	1.0362***	0.7893***	1.0323***
	[26.40]	[23.79]	[19.82]
FV Trend	0.1731	0.0040	0.1478
	[0.91]	[0.05]	[0.45]
Period square root	-0.0666***	0.0215***	-0.1509***
	[-3.39]	[2.69]	[-4.43]
Market dummy	-0.0909***		
	[-4.17]		
R^2	0.3655	0.5859	0.3641
Number of observations	1476	738	738

Panel B: Implied return with respect to previous median transaction price (IR)			
	(1)	(2)	(3)
	All forecasts	First markets only	Second markets only
Intercept	0.1945***	-0.0119	0.3402***
	[3.82]	[-0.54]	[3.55]
Small price dummy	0.0906***	0.0448**	0.1584**
	[4.09]	[2.52]	[2.00]
Lag RD (RD_{t-1})	-0.1300***	-0.2470***	-0.1492***
	[-3.45]	[-7.83]	[-2.94]
FV Trend	0.2220	0.0251	0.3604
	[1.21]	[0.32]	[1.13]
Period square root	-0.0667***	0.0065	-0.1406***
	[-3.53]	[0.85]	[-4.24]
Market dummy	-0.0744***		
	[-3.54]		
R^2	0.0274	0.0743	0.0316
Number of observations	1476	738	738

This table corresponds to Table 4 where implied returns are computed with the median forecast $M_{i,t}$ instead of the expected future price $E_{Q_{i,t}}$. This table reports the results of random effects regressions of IR^{FV} (Panel A) and IR (Panel B) on our treatment dummy (*i.e.*, a small price dummy) and different control variables. *FV Trend* is defined as $\Delta FV_{t-1} = \frac{FV_{t-1}-FV_{t-2}}{FV_{t-2}}$, *Lag RD* is $RD_{t-1} = \frac{S_{t-1}-FV_{t-1}}{FV}$, *Period square root* is equal to $\sqrt(t)$ and *Market dummy* is a dummy variable equal to 1 for the first market and 0 for the second. t-statistics are in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

E Robustness test: Wilcoxon matched-pairs signed-ranks tests using only periods 6 to 10

Table E1
Wilcoxon matched-pairs signed-ranks tests using only periods 6 to 10

	IR^{FV}	IR
Small price markets	0.1453	0.0476
Large price markets	0.0735	-0.0281
Difference	0.0718***	0.0757***
	(5.20)	(4.69)

This table presents the within analyst subjects comparison between small price markets and large price markets using only periods 6 to 10. Results for periods 1 to 10 can be found in Table 3. For each subject analyst and each treatment, we compute the average of IR^{FV} (and IR). IR^{FV} is the implied return with respect to fundamental value ($IR^{FV}_{i,t} = \frac{E_{Q_{i,t}}(S_t) - FV_{t-1}}{FV_{t-1}}$) and IR is the implied return with respect to previous median transaction price ($IR_{i,t} = \frac{E_{Q_{i,t}}(S_t) - S_{t-1}}{S_{t-1}}$). Statistical significance is assessed with a Wilcoxon matched-pairs signed-ranks test. z-statistics are reported in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.