# The effect of price magnitude on analysts' forecasts: evidence from the lab

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CENTER FOR ENVIRONMENTAL ECONOMICS - MONTPELLIER

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CEE-M Working Paper 2018-24

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

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October 29, 2018

**Abstract**

Recent research in 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 of the participants in a continuous double auction market act as analysts and forecast future prices. Participants engage in two successive markets: one in which the fundamental value is a small price and one in which the fundamental value is a large price. Our results indicate that analysts' forecasts are more optimistic in small price markets compared to large price markets. We also find that analysts strongly anchor on past price trends when building their price forecasts. Overall, our findings support the existence of a small price bias.

*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., 2014). 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.

Roger et al. (2018) find evidence that analysts' optimism is influenced by stock price magnitude. Analysts exhibit a small price bias; their 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. The authors also find that analysts become more optimistic after stock splits (which only impact stock price magnitude, but not the firms' fundamentals).

According to standard finance theory, stock price magnitude should influence neither portfolio choices nor implied returns. However, the empirical evidence contradicts this view. Green and Hwang (2009) show that the returns of small (large) price stocks comove more together than with the returns of large (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 low-price stocks. Baker et al. (2009) find that firms manage nominal prices through forward stock splits when investors are willing to pay a premium for low-price stocks. Finally, Roger et al. (2017) show, in an experiment based on continuous double auction market, that stock price magnitude plays an important role in explaining the deviations of traded prices from the fundamental value.

In this paper, we conduct a novel experiment where some participants in a continuous double auction market act as analysts and forecast future prices. As in Roger et al. (2017), each session is broken down into two markets of ten periods each: one market in which the fundamental value is a small price and one in which the fundamental value is a large price. Following the empirical evidence in Roger et al. (2018), we investigate whether the analysts in our experiment exhibit differences in optimism, in small price markets compared to large price markets, when forecasting future prices. Evidence of differential optimism in the controlled environment of an experiment would indicate that differences in optimism between small price stocks and large price stocks are indeed driven by a small price bias and not by unobservable economic factors.

The results of our experiment, based on 8 sessions with a total of 82 analysts, indicate that analysts 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 fundamental value and when optimism is assessed with respect to past prices. We also observe a strong anchorage on former-period trading prices which yields an under-reaction to the eventual convergence of trading prices to the fundamental value.

Overall, our results are consistent with the findings of Roger et al. (2018) on financial analysts in the U.S. market. Analysts are more optimistic on small price stocks than on large price stocks. In addition, the analysts in our experiment fail to anticipate the eventual convergence of prices towards the fundamental value. This observation is consistent with the results of Haruvy et al. (2007) and Duclos (2015) on traders' elicitation. Interestingly, we show that the adaptation of individuals' beliefs about prices also occur when participants who are not the traders are asked to predict future prices. Similarly to traders' predictions in previous studies, analysts' forecasts in our experiment can largely be explained by past price trends.

# 2 Theoretical framework

## 2.1 Bubbles and the fundamental value process

The literature 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) (SSW hereafter), characterized by a decreasing FV process, has been replicated and extended by an expanding literature.[1] When the fundamental value (hereafter FV) 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 under-

[1] *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).

pricing 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 would like 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 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 traders and analysts. 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 market.[2]

A unit of the risky asset is a vector of *i.i.d.* random cash-flows, denoted $CF = (CF_{j,t}, t = 1, ..., T)$. 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

[2]See Roger et al. (2017) for a detailed description of the market design.

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 our small price market[3], 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 $[1.2; 10.8]$. In the large price market, 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 the small price market.

Due to the progressive revelation of *i.i.d.* cash-flows[4], the standard deviation of the final payoff decreases linearly with the square root of the time remaining until $T$.[5] As a consequence, the price range compatible with the absence of arbitrage opportunities in period $t$ is

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

with $S_t^{min}$ ($S_t^{max}$) the minimum (maximum) possible redemption value seen from period $t$.

The dual mental system the brain uses to make assessments, called System 1-System 2 by Daniel Kahneman in his book (Kahneman, 2011), starts with an initial estimate by System 1, adjusted (or not) in a second step by System 2. Anchoring refers to the fact that the adjustment System 2 applies is typically insufficient (Kahneman and Tversky, 1974). For example, Duclos (2015) finds in experimental markets that the last closing price has a disproportionate influence on investment behavior, a phenomenon he calls *end-anchoring*. Li and Yu (2012) show that the nearness of the 52-week high, which is largely reported in the financial press, influences forecasts and investment decisions. Barberis et al. (2016) illustrate that retail investors have a tendency to base their choices on first impressions because their System 1 gives an immediate idea of what to do when they look at the chart

[3] The experimental design is described in the next section

[4] The progressive revelation of information over time avoids inducing an anchor in the minds of participants 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.

[5] 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.

of past prices. Our experimental design does not impose a salient anchor; nevertheless, subjects can easily calculate $E(FV_t)$ and the range of arbitrage-free prices, using their System 2.

# 3 Experimental design

The experiment was realized in the computerized laboratory of the University of Montpellier (LEEM) with z-Tree (Fischbacher, 2007). The experiment involved 155 subjects (8 sessions with 9 traders by session and 6 to 11 analysts per session); the subjects were randomly selected from a pool of approximately 5,000 volunteers from the Universities of Montpellier.[6] Each participant took part to one and only one session.

In the first part of the experiment, subjects completed an effort task to earn real money, to avoid the house money effect. They were informed that successfully fulfilling the real effort task is a necessary condition to participate in the second part of the experiment. In case of failure, students would only receive a show up fee. Subjects earned 30 euros in the first part, then converted into units of asset and experimental currency for the remainder of the experiment. The real effort task consisted of a series of counting exercises (lasting approximately 15 minutes). Subjects had to count the number of "ones"in matrices of various sizes containing either zeros or ones.

Subjects received written instructions and participated to one trial period at the beginning of the second part of the experiment. They were assigned to a group of 9 traders and up to 11 analysts.[7] Subjects were informed that they would participate in two successive markets. They did not receive any specific information about the second market before the end of the first market.

[6] 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 results that could be caused by the difficulties of subjects to deal with numbers.

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

## 3.1 The risky asset

In each market, 9 subjects trade a risky asset that lives ten periods. At the end of each trading period, a cash-flow is randomly drawn from a discrete uniform distribution and displayed to all subjects. The support of the cash-flow distribution is $\{0.0,\ 0.3,\ 0.6,\ 0.9\ , 1.2\}$ in the small price market, and $\{0.0,\ 3.6,\ 7.2,\ 10.8, 14.4\}$ in the large price market. There are no intermediate dividends. The risky asset is simply repurchased in the end of the market by the experimenter. Instructions clearly stated that the asset redemption value is equal to the sum of the 10 cash-flows.[8] 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) .[9] 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.

In our within-subject design, each session contains two consecutive treatments: a small price and a large price treatments. Four sessions start with the small price treatment and four with the large price treatment. As mentioned above, cash-flows are scaled up by 12 in the large price treatment, compared to the small price treatment.[10]

## 3.2 Price forecasts

At the beginning of period $t$, each analyst $i$ is asked to provide three forecasts, denoted $(L_{i,t}, M_{i,t}, H_{i,t})$. $L_{i,t}, t = 0, ..., T-1$ is the anticipated price level such that $Q_{i,t}(S_{t+1} \leq L_{i,t}) = 10\%$ where $Q_{i,t}$ is analyst $i$ subjective probability distribution of future price $S_{t+1}$. $M_{i,t}, t = 0, ..., T-1$ is the anticipated median price such that $Q_{i,t}(S_{t+1} \leq M_{i,t}) = Q_{i,t}(S_{t+1} \geq M_{i,t}) = 50\%$. Finally, $H_{i,t}, t = 0, ..., T-1$ is the anticipated price such that $Q_{i,t}(S_{t+1} \geq H_{i,t}) = 10\%$. $L_{i,t}$ is then the lower bound of the 80% confidence interval of analyst $i$ regarding the stock price at time $t+1$ while $H_{i,t}$ is the upper bound.

We use formulas introduced by Kieffer and Bodily (1983)[11] to estimate the expected

[8]The cash-flows, though drawn from a uniform distribution, are determined in advance.

[9]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).

[10]A scaling factor of 12 (instead of 10 for example), is used to prevent subjects from easily perceiving that the second market is simply a scaled version of the first market.

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

future price ($E_{Q_{i,t}}(S_{t+1})$) and the variance of the future price ($V_{Q_{i,t}}(S_{t+1})$), implicit in the vector $(L_{i,t}, M_{i,t}, H_{i,t})$.

$$E_{Q_{i,t}}(S_{t+1}) = 0.63 \times M_{i,t} + 0.185 \times (L_{i,t} + H_{i,t}) \tag{2}$$

$$V_{Q_{i,t}}(S_{t+1}) = 0.63 \times M_{i,t}^2 + 0.185 \times (L_{i,t}^2 + H_{i,t}^2) - E_{Q_{i,t}}(S_{t+1})^2 \tag{3}$$

## 3.3 Earnings

A measure of analysts' performance should be built so that it rewards a forecast interval that contains the observed next period stock price and penalizes analysts who take no risks (by providing large intervals $[L_{i,t}; H_{i,t}]$). Equations 2 and 3 provide a way to define the performance function. As our cash-flow distributions are symmetric, we can assume that $M_{i,t} = (L_{i,t} + H_{i,t})/2$. We then obtain

**Proposition 1** *If $M_{i,t} = (L_{i,t} + H_{i,t})/2$, then*

$$E_{Q_{i,t}}(S_{t+1}) = \frac{L_{i,t} + H_{i,t}}{2} \tag{4}$$

$$V_{Q_{i,t}}(S_{t+1}) = \frac{0.185}{2} \times (L_{i,t} - H_{i,t})^2 \tag{5}$$

We then propose 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 $[L_{i,t}; H_{i,t}]$.

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

$PERF$ is a payoff function that provides analysts with incentives to propose a probability distribution compatible with their perceived knowledge of the pricing process. The maximum performance an analyst 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 $S_{t+1}$). The last term in the $PERF$ function penalizes analysts if they choose a distribution with a large coefficient of variation, equivalent here to a large (relative) difference between the high and the low forecast. We used the following parametrization: $\alpha_1 = 10$ and $\alpha_2 = 24$. The interesting property of $PERF$ is that it is a homogeneous function of degree 0. It is therefore perfectly suited to our problem. The performance of the analyst thus does not depend on the cash-flow magnitude (as long as they are scaled up by a unique factor from the small price market to the large price market).

In the written instructions, analysts receive complete information about performance evaluation. They were also instructed that their earnings would be function of their performance. They were also told that only one of the two markets would be randomly selected to be evaluated. The conversion rule from performance to earnings was

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

where $\lambda$ was a constant which value was undisclosed to participants. In practice, the constant was set equal to the average global performance of all the analysts in the session (and the selected market).

# 4 Empirical study

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. 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 ($IR\_FV_{i,t} = F_{i,t}/FV_{t-1} - 1$); and, (2) the implied return with respect to the previous median price ($IR_{i,t} = F_{i,t}/S_{t-1} - 1$).

Table 2 gives the average level of implied returns for small price and large price markets. In each session, analysts provide 9 forecasts (periods 2 to 10) in a small price market and 9 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 2 indicate that analysts' 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 optimism simply shows that analysts take into account the differential optimism of traders across markets, that is, small price markets versus large price markets (Roger et al., 2017). However, analysts are asked to forecast future trading prices, not the future FV. 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.

To confirm these results, we perform a multivariate analysis in which we control for the information held by analysts when they issue their forecasts. Contrary to real financial markets, the framework of experimental markets allows participants to easily compute the fundamental value of the traded asset. As a consequence, a given analyst $i$ who issues a price forecast $F_{i,t}$ at the beginning of period $t$ builds her forecast on 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, 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 difference between the median transaction price and the end-of-period FV in period $t-1$, $RD_{t-1} = \frac{S_{t-1} - FV_{t-1}}{FV_{t-1}}$.[12]

We estimate a linear model with random effects where analysts' implied return ($IR\_FV$ or $IR$) in a given period are regressed on our treatment dummy (*i.e.*, a small price dummy) and different control variables. In addition to $\Delta FV_{t-1}$ and $RD_{t-1}$, we introduce a dummy variable equal to 1 when the forecast was 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 because the final payoff is the sum of $T$ *i.i.d.* random variables at date 0 and becomes the sum of $T-t$ random variables and a constant at the end of period $t$.

The regression results appear in Table 3. Panel A (Panel B) gives 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 panels. As explained above, the result in Panel A ($IR\_FV$) is not surprising since traders deviate more in small price markets compared to large price markets (Roger et al., 2017). As a consequence, analysts take into account traders' deviations in the two market types. This interpretation is confirmed by the signs of the coefficients of the control variables $FV$

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

*Trend* and *Lag RD*. These coefficients are positive (although non significant for *FV Trend*) because analysts include in their forecast the deviation of the realized cash-flow with respect to the expected cash-flow. Regarding *Lag RD*, the coefficient is highly significant because trading prices deviate more in small price markets than in large price markets. Analysts integrate, in their forecasts, the errors made by traders. In other words, analysts strongly anchor on previous prices when making their forecasts. The results in Panel B ($IR$) confirm our previous findings that analysts are more optimistic in small price markets than in large price markets. The *small price dummy* is positive and significant. The coefficient of *Lag RD* is negative and significant, indicating that while analysts mitigate the mispricing of traders in the preceding period, a difference remains between small and large price markets.

# 5 Concluding remarks

Our results, obtained in the controlled environment of an experiment, confirm the empirical findings of Roger et al. (2018). Analysts' forecasts are more optimistic on small price stocks than on 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.

# Appendix

**Proof.** We only develop the proof for equation 5. To simplify we denote $p = 0.185$. Equation 3 allows to write

$$
\begin{aligned}
V_{Q_{i,t}}(S_{t+1}) &= (1-2p)M_{i,t}^2 + p(L_{i,t}^2 + H_{i,t}^2) - M_{i,t}^2 && (7)\\
&= p(L_{i,t}^2 + H_{i,t}^2 - 2M_{i,t}^2) && (8)\\
&= p(L_{i,t}^2 + H_{i,t}^2 - \frac{1}{2}(L_{i,t}^2 + H_{i,t}^2 + 2L_{i,t}H_{i,t}) && (9)\\
&= \frac{p}{2}(L_{i,t}^2 + H_{i,t}^2 - 2L_{i,t}H_{i,t}) && (10)\\
&= \frac{p}{2}(H_{i,t} - L_{i,t})^2 && (11)
\end{aligned}
$$

■

# References


Baker, M., Greenwood, R., Wurgler, J., 2009. Catering through nominal share prices. Journal of Finance 64, 2559–2590.

Barberis, N., Mukherjee, A., Wang, B., 2016. Prospect theory and stock returns: An empirical test. Review of Financial Studies 29, 3068–3107.

Birru, J., Wang, B., 2016. Nominal price illusion. Journal of Financial Economics 119, 578–598.

Boening, M. V. V., Williams, A. W., LaMaster, S., 1993. Price bubbles and crashes in experimental call markets. Economics Letters 41, 179–185.

Bradshaw, M. T., Brown, L. D., Huang, K., 2013. Do sell-side analysts exhibit differential target price forecasting ability? Review of Accounting Studies 18, 930–955.

Bradshaw, M. T., Huang, A. G., Tan, H., 2014. Analyst target price optimism around the world. Working paper, Boston College.

Brav, A., Lehavy, R., 2003. An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics. Journal of Finance 58, 1933–1967.

Caginalp, G., Porter, D., Hao, L., 2010. Asset market reactions to news: An experimental study. Working paper, Economic Science Institute, Chapman University.

Duclos, R., 2015. The psychology of investment behavior: (de)biasing financial decision-making one graph at a time. Journal of Consumer Psychology 25, 317–325.

Fischbacher, U., 2007. z-tree: Zurich toolbox for ready-made economic experiments. Experimental Economics 10, 171–178.

Gillette, A. B., Stevens, D. E., Watts, S. G., Williams, A. W., 1999. Price and volume reactions to public information releases: An experimental approach incorporating traders' subjective beliefs. Contemporary Accounting Research 16, 437–479.

Giusti, G., Jiang, J. H., Xu, Y., 2012. Eliminating laboratory asset bubbles by paying interest on cash. Working paper, Munich Personal RePEc Archive, Munich.

Green, C. T., Hwang, B.-H., 2009. Price-based return comovement. Journal of Financial Economics 93, 37–50.

Haruvy, E., Lahav, Y., Noussair, C. N., 2007. Traders' expectations in asset markets: Experimental evidence. American Economic Review 97, 1901–1920.

Haruvy, E., Noussair, C. N., 2006. The effect of short selling on bubbles and crashes in experimental spot asset markets. Journal of Finance 61, 1119–1157.

Johnson, D., Joyce, P., 2012. Bubbles and crashes revisited. Review of Economics 2, 29–42.

Kahneman, D., 2011. Thinking, fast and slow. New York: Farrar, Straus and Giroux.

Kahneman, D., Tversky, A., 1974. Judgment under uncertainty: Heuristics and biases. Science 185, 1124–1131.

Kieffer, D. L., Bodily, S. E., 1983. Three-point approximations for continuous random variables. Management Science 29, 595–609.

King, R., Smith, V., Williams, A., Van Boening, M., 1993. The robustness of bubbles and crashes in experimental stock markets. In: Day, R., Ping Chen, e. (eds.), *Non Linear Dynamics and Evolutionary Economics*, Oxford University Press, Oxford, pp. 183–200.

Kirchler, M., 2009. Underreaction to fundamental information and asymmetry in mispricing between bullish and bearish markets: An experimental study. Journal of Economic Dynamics and Control 33, 491–506.

Lei, V., Noussair, C., Plott, C., 2001. Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality. Econometrica 69, 831–859.

Li, J., Yu, J., 2012. Investor attention, psychological anchors, and stock return predictability. Journal of Financial Economics 104, 401–419.

Noussair, C., Richter, G., Tyran, J.-R., 2012. Money illusion and nominal inertia in experimental asset markets. Journal of Behavioral Finance 13, 27–37.

Noussair, C., Robin, S., Ruffieux, B., 2001. Price bubbles in laboratory asset markets with constant fundamental values. Experimental Economics 4, 87–105.

Noussair, C. N., Tucker, S., 2016. Cash inflows and bubbles in asset markets with constant fundamental values. Economic Inquiry 54, 1596–1606.

Noussair, C. N., Tucker, S., Xu, Y., 2016. Futures markets, cognitive ability, and mispricing in experimental asset markets. Journal of Economic Behavior & Organization 130, 166–179.

Pearson, E. S., Tukey, J., 1965. Approximate means and standard deviations based on distances between percentage points of frequency curves. Biometrika 52, 533–546.

Ramnath, S., Rock, S., Shane, P. B., 2008. The financial analyst forecasting literature: A taxonomy with suggestions for further research. International Journal of Forecasting 24, 34–75.

Roger, T., Bousselmi, W., Roger, P., Willinger, M., 2017. Another law of small numbers: Patterns of trading prices in experimental markets. Conference paper, ASFEE.

Roger, T., Roger, P., Schatt, A., 2018. Behavioral bias in number processing: Evidence from analysts' expectations. Journal of Economic Behavior & Organization 149, 315–331.

Smith, V., Suchanek, G., Williams, A., 1988. Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica 56, 1119–1151.

Stöckl, T., Huber, J., Kirchler, M., 2010. Bubble measures in experimental asset markets. Experimental Economics 13, 284–298.

Stöckl, T., Huber, J., Kirchler, M., 2015. Multi-period experimental asset markets with distinct fundamental value regimes. Experimental Economics 18, 314–334.

**Table 1**
Sequences of cash-flows

| | Time series of cash-flows | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 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 |

This table 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.

**Table 2**
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 presents the within-analysts comparison between small price markets and large price markets. For each analyst and each market, we compute the average of $IR\_FV$ (and $IR$). $IR\_FV$ is the implied return with respect to fundamental value ($IR\_FV = F_t/FV_{t-1} - 1$) and $IR$ is the implied return with respect to previous median transaction price (($IR = F_t/S_{t-1} - 1$)). 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 3**
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 | 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 ] |
| Periods 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 | -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 ] |
| Periods 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 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 $RD_{t-1} = \frac{S_{t-1}-FV_{t-1}}{\overline{FV}}$, *Periods 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. Standard errors are in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

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