Another law of small numbers: patterns of trading prices in experimental markets

Tristan Roger* Wael Bousselmi† Patrick Roger‡ Marc Willinger§

October 12, 2017

Abstract

Studies in neuropsychology show that the human brain processes small and large numbers differently. Small numbers are processed on a linear scale, while large numbers are processed on a logarithmic scale. In this paper, we report the results of an experiment showing that trading prices on experimental markets are processed differently by participants, depending on their magnitude. Deviations from fundamental values are larger in small price markets than in large price markets. Our experimental design allows us to confirm the result at the individual level. For a given participant, the deviation from the fundamental value is 27.27% on average when she trades on a small price market compared to about 0% on a large price market. Our results show that price magnitude influences the way people perceive the distribution of future returns. This result is at odds with standard finance theory but is consistent with: (1) a number of observations in the empirical finance and accounting literature; and, (2) the use of different mental scales for small and large prices.

*DRM Finance, Université Paris-Dauphine, PSL Research University – Mailing address: Place du Maréchal de Lattre de Tassigny, 75775 Paris Cedex 16 FRANCE – Tel: +33 (0) 1 44 05 44 90 – Email: tristan.roger@dauphine.fr

†Université de Montpellier, LAMETA, UFR d'Economie, – Mailing address: Avenue Raymond Dugrand, CS79606, 34 960 Montpellier Cedex 2, France – Tel: – Email:waelbousselmi@yahoo.fr

‡LaRGE Research Center, EM Strasbourg Business School, University of Strasbourg – Mailing address: 61 avenue de la Forêt Noire, 67085 Strasbourg Cedex FRANCE – Tel: +33 (0) 3 68 85 21 56 – Email: proger@unistra.fr

§Université de Montpellier, LAMETA, UFR d'Economie, – Mailing address: Avenue Raymond Dugrand, CS79606, 34 960 Montpellier Cedex 2, France – Tel: – Email: willinger@lameta.univ-montp1.fr

1 Introduction

Normative decision theory assumes that expectations are not sensitive to changes in the way information is presented. For instance, the magnitude of a stock price should not influence portfolio choices, return expectations or future realized returns. Empirical evidence on financial markets, however, indicates that stock price levels have an impact on stock returns, analysts' forecasts and investors' portfolio choices. For instance, Schultz (2000) finds that: (1) retail investors hold lower-priced stocks than institutions; and, (2) the number of retail investors among shareholders of a firm, increases after a forward stock split that decreases the stock price without changing the fundamentals of the firm. Green and Hwang (2009) show that the returns on small (large) price stocks comove more together, than with the returns of large (small) price stocks. Birru and Wang (2016) argue that investors overestimate the "room to grow" of small price stocks. Baker, Greenwood, and Wurgler (2009) find that firms manage nominal prices through forward stock splits when investors are willing to pay a premium for small price stocks.

None of the aforementioned papers, however, provides an explanation for the influence of price magnitude. In this paper, we aim at filling this gap. Our study draws on research in neuropsychology on the mental representation of numbers (Dehaene, 2011, for a review) and specifically, on the existence of different mental scales for small and large numbers. We investigate, using an economic experiment, whether people behave differently when trading small price stocks compared to large price stocks. Our experiment has two treatments, one in which the fundamental value of the traded asset is a small number (*i.e.*, the small price market), and a second treatment in which the fundamental value is a large number (*i.e.*, the large price market). We find that the participants of our experiment are more optimistic in small price markets than in large price markets. In addition to the between-participants comparison, we conduct a within-participants analysis. The results indicate that the average participant deviates by 27.27% from the fundamental value in small price markets and by about 0% in large price markets.

The main model of number representation in the human brain is Weber's law (Nieder, 2005). In short, this law states that the brain uses a logarithmic scale to represent numbers: increasingly larger numbers are subjectively closer together. This theoretical framework is in line with finance theory: people select stocks on the distribution of future returns (logarithmic scale), not on price expectations (linear scale). In other words, under Weber's law, investors should expect returns that are independent of the stock price magnitude.

Recent papers (Dehaene, Izard, Spelke, and Pica, 2008; Hyde and Spelke, 2009) have shown, however, that Weber's law is not satisfied for small numbers. People tend to use a linear scale for small numbers and they compress large numbers on a logarithmic scale (Viarouge, Hubbard, Dehaene, and Sackur, 2010). The use of different scales for small and large numbers is likely to impact market participants' expectations of future prices, leading to larger deviations from fundamental values.

The use of a linear scale for small numbers means that people correctly evaluate absolute distances between small numbers. On the contrary, using a logarithmic scale for large numbers leads to a compressed mental number line. People underrepresent absolute distances between large numbers. A corollary can be derived for relative distances. Relative distances between large numbers are correctly assessed (as a result of the use of a logarithmic scale) while relative distances between small numbers are exaggerated. Since the norm in finance is to work with relative distances (*i.e.*, stock returns), we expect market participants to process small prices incorrectly. More precisely, we know since Smith, Suchanek, and Williams (1988) that there is a tendency to observe bubbles, that is an overvaluation of risky assets, in experimental markets. As a consequence, if a small price effect exists, due to the mental representation of numbers, we expect a larger overvaluation in small price markets (with respect to fundamental values), compared to large price markets.

Empirical evidence of the existence of two mental scales by financial market participants can be found in Roger, Roger, and Schatt (2016). They show that financial analysts exhibit a small price bias when they issue one-year ahead price forecasts (target prices). Forecasts are more optimistic for small price stocks compared to large price stocks. The returns implied by analysts' price forecasts are greater for small price stocks than for large price stocks. In addition, this difference in implied returns remains on a risk-adjusted basis. In the accounting literature, studies on earnings forecasts (which are essentially small numbers) also support the use of a linear scale. Graham, Harvey, and Rajgopal (2005) show that market participants focus on earnings per share (EPS) in absolute terms (*i.e.*, in cents, not in percentages of the share price). Cheong and Thomas (2011) find that neither analysts' unscaled forecast errors, nor the dispersion of these errors, depend on the EPS magnitude.

In this paper, therefore, we test whether market prices deviate more from fundamental values in small price markets compared to large price markets.[1] We run eight sessions with two successive experimental markets per session with the same participants in the two markets of a given session. One market is a small price market and the other is a large price market where cash-flows and endowments are multiplied by a fixed number (12 in our study).

In four sessions, the first experimental market is the "small price" market and the following market is the "large price" market. In the four other sessions, the order of the two successive markets is reversed. Overall, we find that these two different experimental markets generate different price processes. Consistent with the linear vs. logarithmic scales in processing numbers, we find that participants' optimism is greater in small price markets compared to large price markets. At the aggregate level, we find an average deviation from the fundamental value which is about 22 points larger in small price markets than that in large price markets. This result is obtained over 2,118 trades executed in the 2×8 markets. The significance of the result remains when we control for a number of potential confounding effects. For example, when we restrict the sample to the first market of each session (neutralizing experience of trading), the difference is still about 11 points. A similar result is obtained at the participant level with a difference of about 27 points between the optimism in small price markets compared to large price markets.

The paper is organized as follows. Section 2 presents the related research. Section 3 describes the cash-flow and fundamental value processes used in the experiment. Section 4 outlines the experimental design. Section 5 presents the results from the experiment. The last section concludes.

2 Related research

Numerous experiments have shown that bubbles may be amplified or attenuated depending on various characteristics, in particular the choice of the fundamental value (FV hereafter) process. It is, therefore, useful to review and discuss some of the processes implemented in previous studies. The seminal result of Smith, Suchanek, and Williams (1988) (SSW hereafter) has been replicated and extended by an expanding literature (*e.g.*, King, Smith, Williams, and Van Boening, 1993; Boening, Williams, and LaMaster, 1993; Lei, Noussair,

[1] In an experimental market, we aim at controlling all risk factors usually present on stock markets, to focus on the potential effect of price magnitude.

and Plott, 2001; Noussair, Robin, and Ruffieux, 2001; Haruvy and Noussair, 2006; Caginalp, Porter, and Hao, 2010; Noussair, Richter, and Tyran, 2012; Noussair and Tucker, 2016; Noussair, Tucker, and Xu, 2016; Stöckl, Huber, and Kirchler, 2015). This literature showed that the formation of bubbles in experimental asset markets is robust to the availability of short-selling (Haruvy and Noussair, 2006; King, Smith, Williams, and Van Boening, 1993) and non-speculative markets (Lei, Noussair, and Plott, 2001). Even when the fundamental value (hereafter FV) process is constant, bubbles still arise (Lei, Noussair, and Plott, 2001). Yet, when the FV is increasing over time (Giusti, Jiang, and Xu, 2012; Johnson and Joyce, 2012; Stöckl, Huber, and Kirchler, 2015), bubbles disappear and underpricing is observed. Furthermore, in markets with randomly fluctuating fundamentals, Stöckl, Huber, and Kirchler (2015) observed overvaluation when FVs predominantly decline and undervaluation when FVs are mostly upward-sloping. Similar observations were made earlier by Gillette, Stevens, Watts, and Williams (1999) and Kirchler (2009). Therefore, allowing for randomness in the FV process seems to have a tempering effect on the price deviation 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 an amplification effect is conditional on the magnitude of the fundamental value, asymmetric reactions could either exaggerate or diminish the type of effect we are studying. Given the above reported experimental evidence, relying on a stochastic FV process, therefore, seems to be recommended.

Stöckl, Huber, and Kirchler (2015) implement a very simple rule for the fundamental value, defined as $F_t = F_{t-1} + \widetilde{\epsilon}$, with different specifications for $\widetilde{\epsilon}$. In one of their treatments, the FV process is a random walk with $\widetilde{\epsilon}$ drawn from a normal distribution with $\mu = 0$ and $\sigma = 2.5$. A similar process was implemented by Gillette, Stevens, Watts, and Williams (1999) and by Kirchler (2009).

In our experiment, we also rely on this type of process but we do not impose a deterministic fundamental value at the start of the market. Instead, all along the experiment, the fundamental value is the sum of the per period cash-flows progressively revealed to participants. Such a process is realistic, by allowing a random FV from the start of the market but it should also mitigate bubbles. Again, the kind of mispricing we are studying is not driven by speculative behavior but by human beings processing small and large numbers differently. We now discuss the key properties of our cash-flow process and the resulting predicted equilibrium price process.

3 The cash-flow and fundamental value processes

In this section, we briefly describe the cash-flow and fundamental value processes (a detailed description can be found in Appendix 2). In our experimental market (described in the next section), a unit of asset is a vector of *i.i.d.* random cash-flows, denoted $CF = (CF_t, t = 1, ..., T)$. These cash-flows are progressively revealed over time. The asset does not pay any dividend until the market ends. Only the final owner of the asset receives the sum of the $T = 10$ cash-flows. At the end of each period t, a realization of the random variable CF_t (denoted cf_t) is drawn and made public. The expected fundamental value of the asset at the beginning of the market is equal to $T\mu$ where $\mu = E(CF_t)$.

Such a cash-flow process without intermediate dividend payments keeps the magnitude of prices stable during a given market. In fact, we use a small per-period variance of cash-flows to ensure that the so-called small price market is actually a market with trading prices below 10 in most cases.[2] In the small price market, 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 at 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, even though the initial range is $[0; 144]$, this range shrinks quickly to keep potential prices greater than 12. Overall, the price ranges are distinct in small price markets and in large price markets.

At the end of period t, the expected fundamental value $E(FV_t)$ is given by:

$$E(FV_t) = \sum_{s=1}^{t} cf_s + (T - t)\mu \tag{1}$$

Due to the progressive revelation of *i.i.d.* cash-flows, the standard deviation of the final payoff shrinks over time: it decreases linearly with the square root of the time remaining until the end of the market.[3]

[2] Of course, we cannot prevent the existence of irrational trades because participants are free to post any price at which they are ready to buy.

[3] More technically, the stochastic process of the fundamental value is a martingale with respect to the information given by the cash-flow process. In other words, the conditional expectation of the redemption value is constant.

Finally, the cash-flow and payoff processes induce, at any date t, a price range compatible with the absence of arbitrage opportunities. (cf_{min}, cf_{max}) denote the two extreme cash-flows at a given date (remember that cash-flows are *i.i.d.*). In period t, the rational price range is

$$\{S_t^{min}, S_t^{max}\} = \{\sum_{s=1}^{t-1} cf_s + (T-t) \times cf_{min}, \sum_{s=1}^{t-1} cf_s + (T-t) \times cf_{max}\} \tag{2}$$

with S_t^{min} (S_t^{max}) the minimum (maximum) possible redemption value in a given period t.

In addition to keeping the magnitude of prices stable, our design, which includes a progressive revelation of information over time, has another advantage. It 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. In general, when people assess a quantity, they often start with an initial estimate, and then adjust away from it. This process comes from the dual mental system the brain uses to make assessments, usually called System 1-System 2 (Kahneman, 2011). 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, Mukherjee, and Wang (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 of past prices. Our experimental design does not impose a salient anchor; nevertheless, participants can easily calculate $E(FV_t)$ and the range of rational prices, using their System 2.

4 Experimental design

The experiment was conducted at the LEEM, the computerized laboratory of the University of Montpellier, with the software z-Tree (Fischbacher, 2007). Seventy two participants were randomly selected from a student subject pool containing over 5,000 volunteers from the Universities of Montpellier.[4] No participant took part in more than one experiment. The data for this study were gathered across eight sessions. Each session involved two consecutive markets of ten periods each. Each market corresponds to a distinct treatment. The difference between the two treatments resides in the price magnitude of the asset traded by participants.[5] In the small price treatment, the fundamental value of the asset is scaled by 12 compared to the large price treatment.[6] To keep the Cash/Asset ratio constant, the total allotment of cash (*i.e.*, experimental currency) is also divided by 12. Four sessions started with the small price treatment and the remaining four started with the large price treatment.

Each market involved nine participants endowed with heterogeneous portfolios consisting of several units of asset and some amount of experimental currency (ECU). Participants were only informed that three portfolio types were available and that three participants would be assigned to each type. The specific composition of each portfolio was not revealed. Only the total number of outstanding asset units (*i.e.*, 54) was common knowledge. Details about portfolio composition and cash-flow processes are provided in Table 1.

The traded asset has a finite life of ten periods and is traded in a continuous double auction. After each period of trading, one cash-flow is drawn from a uniform distribution with five potential outcomes and displayed to all participants. 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 traded asset does not pay any dividend until the market ends, at which point it is bought back by the experimenter. The redemption value is equal to the sum of the ten cash-flows. Thus, the unconditional expected fundamental value of the asset is equal to 6 in the small price treatment and is equal to 72 in the large price treatment.

Participants were instructed that only one of the two consecutive markets would be randomly selected at the end to be paid out for real. Experimental currency accumulated during this market (including the redemption value of the asset) would be converted into euros to calculate their earnings for the experiment.

[4]We have selected only students who are comfortable in mathematics: third year of Mathematics, School of Engineering, Medicine, Physics, Biology and Master's Degree in Economics, Computer Science and Pharmacy.

[5]Participants were not told about the specifics of the second market until the end of the first market.

[6]The purpose of choosing a scaling factor $k = 12$, an integer that is not a round number, was to prevent participants from perceiving immediately that the second market is simply a scaled version of the first market.

In order to limit the house-money effect, participants first earned money by completing a real effort task. The real effort task lasted 15 minutes and consisted of a series of counting exercises. Participants were made aware that they would not be allowed to participate in the subsequent parts of the experiment if they were unable to successfully fulfill the preliminary task. After completion of the real effort, participants were awarded 30 euros, converted into units of asset and experimental currency.[7]

5 Results

5.1 Descriptive statistics

Let us recall that our main objective is to provide experimental evidence about how people exhibit greater optimism when dealing with small price assets compared to large price assets. We measure the optimism of a trade as the relative deviation of the price with respect to the expected fundamental value. Let us define the measure of optimism as follows:

$$O_{t,k} = \frac{P_{t,k} - V_{t-1}}{V_{t-1}} \tag{3}$$

where $P_{t,k}$ is the price at which the k-th trade in period t was executed and V_{t-1} is the conditional expected fundamental value at the end of period $t-1$ (after the announcement of the cash-flow).

Table 2 provides descriptive statistics on trades executed by participants in the eight sessions. We characterize trades as rational (irrational) if they are realized within (outside) the range of possible redemption values. Among irrational trades, we distinguish between trades realized at a price $S_t > S_t^{max}$ (see equation 2) and trades realized at a price $S_t < S_t^{min}$. We call the former *overvalued trades* and the latter *undervalued trades*.

Panel A of Table 2 provides statistics on the number of trades in each category of trades (All trades, rational trades, overvalued and undervalued trades). 1,822 trades were realized in the rational range and 296 outside this range. Among the 296 irrational trades, 204 were overvalued and 92 undervalued. The larger number of overvalued trades, compared to undervalued trades, is consistent with the evidence of bubbles in the literature on

[7] All participants successfully completed the real effort task.

experimental markets. The number of trades is roughly the same for small price markets and large price markets. We note, however, that the proportion of irrational trades for small price markets (20.75%) is nearly three times the proportion for large price markets (7.37%).

Panel B of Table 2 gives a measure of average optimism in each category of trades. At the aggregate level (first column), we find a difference of 22.25% between optimism in small price markets (21.29%) and optimism in large price markets (−0.96%). This difference is about 14% for rational trades. The average optimism of overvalued trades ranges from 33.58% for large price markets to 93.41% for small price markets. Overvalued trades are realized at prices that greatly exceed the maximum possible terminal fundamental value (which is the final payment made to the owner of the asset). Participants who buy at this price make almost surely a loss, except if they later find another irrational participant willing to pay a larger price to buy the asset.

In Table 3, we provide the same statistics as in Table 2 but we restrict our analysis to the first market of each session. The results of the second markets can be influenced by factors such as experience or past gain and losses. On the contrary, these effects do not impact the results of the first markets. Approximately 50% of trades were realized in the first markets (1,132 trades in the first markets compared to a total of 2,118 trades). Trades in the small price markets represent approximately 60% of the first markets' trades. The proportion of irrational trades is similar to the one in Table 2. Overall, optimism is greater in the first markets (13.07% compared to 10.03% for both type of markets). This difference with the results in Table 2 comes essentially from the large price markets (optimism in large price markets is 6.31% for the first markets compared to approximately 0% at the aggregate level in Table 2).

Figure 1 provides descriptive statistics at the participant level. There are eight sessions with nine participants in each session. Participants in the first session are numbered from 1 to 9, participants in the second session are numbered from 10 to 18, and so on. Panel A of Figure 1 gives the number of trades initiated by each participant. Panel B (respectively, Panel C) shows the number of buy (sell) trades executed by each participant. These graphs show that participants exhibit heterogeneous trading patterns. Some participants initiate a large proportion of trades (participant 14 for instance) while others mainly respond to posted orders. For instance, in Panel A, participant 18 is the most active with a total of 298 trades. This participant, however, only initiated five of these 298 trades. The heterogeneity in trading activity and trading initiation may simply reveal differences in herding behavior among participants.

We also distinguish between trades initiated by buyers from trades initiated by sellers. We intuitively expect that, as trade initiators, sellers post higher prices than buyers. Indeed, sellers are likely to post orders at large prices to test whether overly optimistic buyers are willing to buy at such prices. Following the same logic, buyers are likely to post orders at small prices. We thus expect trades initiated by sellers to be more optimistic than trades initiated by buyers. Our interest here is if the difference in optimism between small price markets and large price markets is influenced by whether trades are initiated by buyers or by sellers. Table 4 provides statistics on buyer initiated and seller initiated trades. About 40% of executed trades were initiated by buyers. This proportion is roughly the same in small price markets and large price markets. As expected, trades initiated by sellers are more optimistic than the ones initiated by buyers. The optimism of trades initiated by sellers is about 18% while trades initiated by buyers are executed at prices close to the fundamental value. For the matter at hand, we find that optimism is greater in small price markets compared to large price markets both for buyer-initiated and for seller-initiated trades. For seller-initiated trades, the difference in optimism between small and large price markets is approximately 28%. It is close to 15% for buyer-initiated trades. Using a nonparametric Mann-Whitney statistical test, we find that these differences in optimism between small and large price markets are all significant at the 1% significance level.

5.2 Difference in optimism between small price and large price markets

5.2.1 Between-participants analysis

Figure 2 illustrates the time series of average optimism in the small price markets and the large price markets. Optimism is substantially greater in the small price markets than that in the large price markets in all ten periods. A Mann-Whitney statistical test (unreported) indicates that the differences in optimism are statistically significant (at the 1% significance level) for periods 1 to 5. The differences are not statistically significant (at a 10% significance level) for periods 6 to 10. The first periods are characterized by large deviations from the fundamental value; participants are optimistic in the small price markets and mainly pessimistic in the large price markets. The deviation (and therefore the difference in optimism) decreases over time. This trend can be explained by two features of our experiment. First, the uncertainty regarding the terminal fundamental value decreases over time. The standard deviation of cumulated cash-flows decreases with the square root of time. Thus, the range of possible terminal payoffs gets smaller as time passes. Rational participants, therefore, exhibit lesser optimism or pessimism. Second, there may exist a restart effect at the beginning of second markets. When the first market is the small (large) price market, it is likely that one or several trades in the first period of the second market are realized at a small (large) price. This typically happens when participants do not pay sufficient attention to the change of the cash-flow process.

Figure 3 provides pooled average optimism in the first market of each session. In this between-participants design, we find that optimism is greater in the small price markets compared to the large price markets (except in period 6). A Mann-Whitney statistical test (unreported) indicates that the differences in optimism are statistically significant (at a 10% significance level) for all periods except periods 5, 8 and 9.

5.2.2 Within-participants analysis

In our experiment, each of the 72 participants was involved in two markets, a small price market and a large price market. We can, thus, evaluate the average optimism of a given participant in each market and test the null hypothesis of a zero difference between a participant's optimism in the small price market versus the large price market. The within-participants design of our experiment allows us to neutralize individual differences in optimism. Table 5 reports the results of our paired difference test. A Wilcoxon signed-rank test indicates that optimism is significantly larger (at a 1% significance level) for small price markets compared to large price markets. The difference in optimism is about 27%. We consider the influence of the restart effect and test whether our results are robust to excluding the first period of second markets. The results provided in the last column of Table 5, show that the observed difference in optimism between small price and large price markets is not a by-product of a potential restart effect.

Overall, univariate results indicate a significant difference in optimism between small price and large price markets. This difference is obtained both at aggregate and individual levels. We also find this result both between and within-participants. We now turn to the multivariate analysis of the experiment results.

5.3 Multivariate analysis

The descriptive statistics and univariate analyses of the previous subsections show that participants behave as if they were willing to pay more (with respect to the fundamental value) in the small price market than in the large price market. The evolution of average optimism over time can, however, mask different effects. Firstly, as uncertainty decreases over time (*i.e.*, the standard deviation of cumulated cash-flows decreases with the square root of time), smaller deviations from the fundamental values are expected in the last periods of a given market. Secondly, larger deviations are expected to be more likely to be observed at the beginning of the different periods. In particular, if irrational prices are offered by a participant, other participants will exploit the arbitrage opportunity and the following prices are more likely to come back to the rational range and stay in this range. Thirdly, trend followers could become excessively optimistic (pessimistic) after a sequence of high (low) cash-flows, a kind of hot hand fallacy. Fourthly, some participants could suffer from the gambler's fallacy, which is the expectation of low (high) cash-flows to follow a sequence of high (low) cash-flows.

To test the small price effect and control for the effects listed above, we consider the following regression specification

$$\begin{aligned} O_{j,k,l,t} = \alpha &+ \beta_1 SMALLPRICE_{j,l} + \beta_2 TIME_t + \beta_3 TRANSAC_k \\ &+ \beta_4 PCF_{j,l,t} + \beta_5 O_{j,k-1,l,t} + \beta_6 RATIONAL_{j,k,l,t} + \epsilon_{j,k,l,t} \end{aligned} \quad (4)$$

where $O_{j,k,l,t}$ is the optimism of the k-th trade executed in period t of market l in session j (optimism is calculated as in equation 3), $SMALLPRICE_{j,l}$ is a dummy variable that equals 1 if market l in session j is a small price market, $TIME_t$ is the square root of the period number t and $TRANSAC_k$ is the logarithm of the transaction number k within a period t, $PCF_{j,l,t}$ is the normalized per period cumulated cash-flow[8], $O_{j,k-1,l,t}$ is the optimism of the previous trade (lagged optimism) and $RATIONAL_{j,k,l,t}$ is a dummy variable that equals 1 if the transaction price is in the range of rational prices.

[8] This normalized per period cumulated cash-flow aims at controlling for gambler fallacy and hot hand fallacy.

By convention, we set the lagged optimism $O_{j,k-1,l,t}$ equal to zero when $k = 1$ since there are no previous existing trades in the period under consideration (we also consider the alternative of deleting observations when $k = 1$). The square root of the period number $\sqrt{t}$ ($TIME_t$) aims at taking into account the effect of time. Indeed, because successive cash-flows are *i.i.d.*, the standard deviation of the fundamental value decreases linearly in $\sqrt{t}$.

Table 6 reports the results of the regressions. In model (1), we consider all executed trades. Model (2) is the same specification as model (1) but standard errors are clustered at the order initiator level. In model (3), we remove trades that took place in the first period of second markets to account for a potential restart effect. In model (4), we delete the first trade of each period. Model (5) includes only the first market of each session. Finally, model (6) considers only rational trades, that is, trades executed in the range of possible terminal payoffs.

The coefficient of the dummy variable $SMALLPRICE$ is highly significant at the 1% significance level in all models. The regression coefficient is 0.0925 in the baseline regression specification. It ranges from a minimum value of 0.0790, when the first period of second markets is excluded from the regression to a maximum of 0.0999 when only rational trades are taken into account.

6 Conclusion

This paper investigates the impact of price magnitude on trading prices observed on experimental markets. We show the existence of a small price effect. Participants are more optimistic and prices deviate more from fundamental values in small price markets compared to large price markets. On a small (large) price market with an initial expected fundamental value of 6 (respectively 72), the average trading price is approximately 21% (0%) above the fundamental value. This result is in line with recent empirical literature in finance and accounting, showing that market participants behave differently with small and large price assets. In particular, Roger, Roger, and Schatt (2016) use recent research in neuropsychology to justify more optimistic analysts' price forecasts on small price stocks than on large price stocks. The main reason is the existence of two mental scales, a linear one for small numbers and a logarithmic one for large numbers.

Our experimental setting allows us to test this "two mental scales" hypothesis. We are able to measure between-participants and within-participants effects of price magnitude. In the within-participants analysis, we find that the average participant trades in small price markets at an average deviation of fundamental value, which is 27 points larger than the corresponding deviation on a large price market. The result is striking because the two types of markets are identical, except that cash-flows in the large price market are 12 times the cash-flows in the small price-market.

Our results make significant contributions in different domains. First, we show that the price magnitude is not a neutral choice in experimental studies; bubbles are larger in small price markets, a result that has not been shown before. Second, our paper contributes to the finance literature because the controlled environment of our experiments eliminates the "usual suspects"explaining the small price effect, such differences in perceived risk, differential information and analysts' coverage or behavioral biases like the 52-week bias. Finally, our paper also contributes to the literature on the perception of numbers. To the best of our knowledge, the literature in neuropsychology does not consider numbers in the context of financial markets. Our paper shows that the peculiarity of small numbers can also be found in an economic environment.

References

Baker, Malcolm, Robin Greenwood, and Jeffrey Wurgler, 2009, Catering through nominal share prices, *Journal of Finance* 64, 2559–2590.

Barberis, Nicholas, Abhiroop Mukherjee, and Baolian Wang, 2016, Prospect theory and stock returns: An empirical test, *The Review of Financial Studies* 29, 3068–3107.

Birru, Justin, and Baolian Wang, 2016, Nominal price illusion, *Journal of Financial Economics* 119, 578–598.

Boening, Mark V. Van, Arlington W. Williams, and Shawn LaMaster, 1993, Price bubbles and crashes in experimental call markets, *Economics Letters* 41, 179–185.

Caginalp, Gunduz, David Porter, and Li Hao, 2010, Asset market reactions to news: An experimental study, Working paper Economic Science Institute, Chapman University.

Cheong, Foong Soon, and Jacob Thomas, 2011, Why do EPS forecast error and dispersion not vary with scale? Implications for analyst and managerial behavior, *Journal of Accounting Research* 49, 359–401.

Dehaene, Stanislas, 2011, *The number sense: How the mind creates mathematics.* (Oxford University Press).

Dehaene, Stanislas, Véronique Izard, Elizabeth Spelke, and Pierre Pica, 2008, Log or linear? Distinct intuitions of the number scale in Western and Amazonian indigene cultures, *Science* 320, 1217–1220.

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

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

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

Giusti, Giovanni, Janet H. Jiang, and Yiping Xu, 2012, Eliminating laboratory asset bubbles by paying interest on cash, Working paper Munich Personal RePEc Archive, Munich.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal, 2005, The economic implications of corporate financial reporting, *Journal of Accounting and Economics* 40, 3–73.

Green, Clifton T., and Byoung-Hyuon Hwang, 2009, Price-based return comovement, *Journal of Financial Economics* 93, 37–50.

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

Hyde, Daniel C., and Elizabeth S. Spelke, 2009, All numbers are not equal: an electrophysiological investigation of small and large number representations, *Journal of Cognitive Neuroscience* 21, 1039–1053.

Johnson, Dean, and Patrick Joyce, 2012, Bubbles and crashes revisited, *Review of Economics* 2, 29–42.

Kahneman, Daniel, 2011, *Thinking, fast and slow.* (New York: Farrar, Straus and Giroux).

Kahneman, Daniel, and Amos Tversky, 1974, Judgment Under Uncertainty: Heuristics and Biases, *Science* 185, 1124–1131.

King, Ronald R., Vernon L. Smith, Arlington W. Williams, and Mark Van Boening, 1993, The robustness of bubbles and crashes in experimental stock markets, in Richard Day, and ed. Ping Chen, eds.: *Non Linear Dynamics and Evolutionary Economics* (Oxford University Press, Oxford).

Kirchler, Michael, 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, Vivian, Charles N. Noussair, and Charles R. Plott, 2001, Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality, *Econometrica* 69, 831–859.

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

Nieder, Andreas, 2005, Counting on neurons: The neurobiology of numerical competence, *Nature Reviews* 6, 177–190.

Noussair, Charles N., Gregers Richter, and Jean-Robert Tyran, 2012, Money illusion and nominal inertia in experimental asset markets, *Journal of Behavioral Finance* 13, 27–37.

Noussair, Charles N., Stephane Robin, and Bernard Ruffieux, 2001, Price bubbles in laboratory asset markets with constant fundamental values, *Experimental Economics* 4, 87–105.

Noussair, Charles N., and Steven Tucker, 2016, Cash Inflows and Bubbles in Asset Markets with Constant Fundamental Values, *Economic Inquiry* 54, 1596–1606.

Noussair, Charles N., Steven Tucker, and Yilong Xu, 2016, Futures markets, cognitive ability, and mispricing in experimental asset markets, *Journal of Economic Behavior & Organization* 130, 166–179.

Roger, Patrick, Tristan Roger, and Alain Schatt, 2016, Behavioral Biases in Number Processing: Evidence from analysts' expectations, Conference paper Helsinki Finance Summit.

Schultz, Paul, 2000, Stock splits, tick size, and sponsorship, *Journal of Finance* 55, 429–450.

Smith, Vernon L., Gerry L. Suchanek, and Arlington W. Williams, 1988, Bubbles, crashes, and endogenous expectations in experimental spot asset markets, *Econometrica* 56, 1119–1151.

Stöckl, Thomas, Jürgen Huber, and Michael Kirchler, 2015, Multi-period experimental asset markets with distinct fundamental value regimes, *Experimental Economics* 18, 314–334.

Viarouge, Arnaud, Edward M. Hubbard, Stanislas Dehaene, and Jérôme Sackur, 2010, Number line compression and the illusory perception of random numbers, *Experimental Psychology* 57, 446–454.

Appendix 1 – Instructions to participants

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.

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.

After the practice round [...].

Generalities

There are 9 participants in the session.

A. 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 2 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.

B. 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 3 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: 3 traders will get P1, 3 other traders P2 and the remaining 3 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 after his role will be revealed to him.

C. 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 traders 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.

D. 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:

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

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

E. 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.

F. 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 7.6 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.*

G. 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 cash.

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

A. 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.

B. 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, 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+...+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.*

C. 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.

Appendix 2

The progressive revelation of information to participants is as follows. A realization cf_t of CF_t is drawn (and publicly released) at the end of period $t, t = 1, ..., 10$ in a set of 5 equally likely values. Let μ and σ denote the expectation and the standard deviation of CF_t. The *i.i.d.* assumption implies that μ and σ do not depend on t. The date-0 theoretical price is the expected fundamental value, that is the sum of the unconditional expectation of future cash-flows.

$$E(FV_0) = \sum_{t=1}^{T} E(CF_t) = T\mu \qquad (5)$$

The cumulated cash-flows are paid at the end of the market, therefore, at any date, buying (selling) the asset is equivalent to acquiring (selling) the complete sequence of T cash-flows, including those that are already known. In fact, at the end of any intermediate period t, traders know for sure the past cash-flows $cf_s, s = 1, ..., t$ but future cash-flows $CF_s, s > t$ remain random. The expected fundamental value at the beginning of period t

is therefore equal to

$$FV_t = \sum_{s=1}^{t-1} cf_s + \sum_{u=t}^{T} E(CF_u) = \sum_{s=1}^{t-1} cf_s + (T - t + 1)\mu \tag{6}$$

In this model, the variations of the expected fundamental value between two dates $t-1$ and t come from the partial resolution of uncertainty at the end of period $t-1$ when the cash-flow of period $t-1$ is revealed. If cf_{t-1} is larger (lower) than μ, the fundamental value increases (decreases) by $cf_{t-1} - \mu$. In such a framework, the process of the fundamental value $FV = FV_t, t = 0, ..., T$ is a martingale with respect to the information generated by the cash-flow process (I_t denotes the information available at date t).

$$FV_t = E(FV_{t+1} \,|I_t) \tag{7}$$

It turns out that, seen from date 0, the fundamental value has a constant expectation (by the law of iterated expectations). During the session, the conditional expectation of a future fundamental value can be higher or lower than the initial value, depending on the past (and, thus, is already known) sequence of cash-flows.

The *i.i.d.* assumption also implies that the variance of the terminal payoff of the asset, $FV_T = \sum_{t=1}^{T} CF_t$ is equal to $T \times \sigma^2$. Combined with equation 5, it means that the variance of the gross return $\frac{FV_T}{FV_0}$ over the entire period is equal to

$$Var(\frac{FV_T}{V_0}) = \frac{Var(FV_T)}{V_0^2} = \frac{T\sigma^2}{T^2\mu^2} = \frac{1}{T}\frac{\sigma^2}{\mu^2} \tag{8}$$

It could seem counter-intuitive that the variance of returns decreases with maturity. The average price, however, increases linearly with maturity (simply because more cash-flows are added when the number of periods increases), being given a per period cash-flow probability distribution. This result should not be misinterpreted. It does not mean that the variance of returns increases as time passes. The reason is simple. At date t, the variance of the gross return until date T is written

$$Var(\frac{FV_T}{V_t}|I_t) = \frac{Var(FV_T|I_t)}{FV_t^2} = \frac{(T-t)\sigma^2}{(\sum_{t=1}^{t} cf_t + (T-t)\mu)^2} \tag{9}$$

Most of the time, this quantity decreases when t increases. In fact, when the date-t cash-flow is greater or equal to μ, the denominator of the right hand side of equation 9 increases between $t-1$ and t. Simultaneously, the numerator decreases. It may, however, happen that this conditional variance increases between two dates when the realized cash-flow is very low. In this situation, the denominator can decrease more than the numerator (which decreases by σ^2 per period). This special case can only occur in the first periods, when the amount of cash-flows already paid is low.

To sum up, everything else being equal, the variance of the global return decreases as the maturity of the asset increases[9] but, being given a maturity date, the conditional variance of returns decreases as time passes.

[9]This phenomenon is called time-diversification by finance professionals.

Figure 1
Frequency of trades

Figure 2
Time series of average optimism in small price and large price markets (all markets)

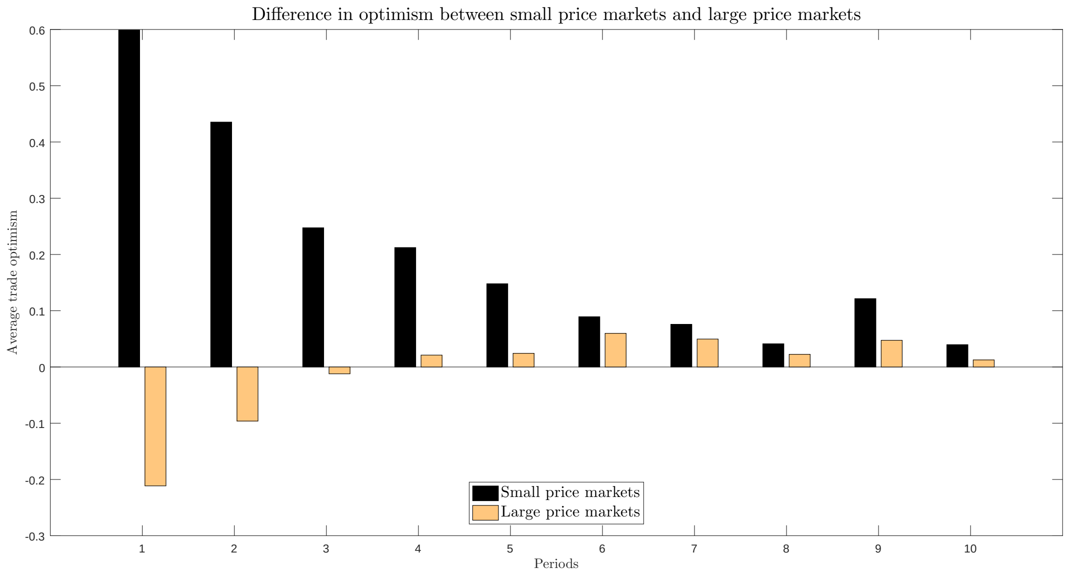

Figure 3

Time series of average optimism in small price and large price markets (first markets only)

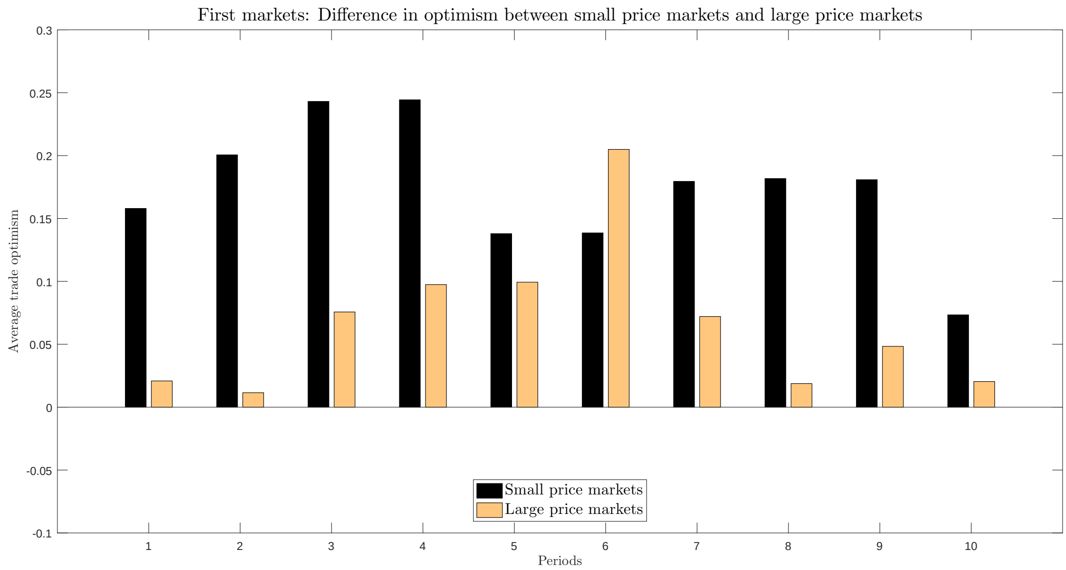

Table 1

Composition of portfolios

Panel A: 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 cash	82	64	46	984	768	552

Panel B: 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

The first (second) line of Panel A 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 market. Quantities are determined to have a theoretical portfolio value in the large price market equal to 12 times the theoretical portfolio value in the small price market. The four lines of Panel B give the basic sequences of cash-flows used in the experiment. The cash-flows realizations used in the experiment are randomly generated but determined in advance to ensure comparability. Sequences S3 and S4 are obtained by "mirroring "sequences S1 and S2.

Table 2
Descriptive statistics on trades

	Panel A: Number of trades			
	All trades	Rational trades	Overvalued trades	Undervalued trades
All trades	2,118	1,822	204	92
Small price markets	1,046	829	155	62
Large price markets	1,072	993	49	30
	Panel B: Average optimism			
	All trades	Rational trades	Overvalued trades	Undervalued trades
All trades	0.1003	0.0521	0.7904	-0.4769
Small price markets	0.2129	0.1291	0.9341	-0.4696
Large price markets	-0.0096	-0.0121	0.3358	-0.4921

Panel A provides statistics on the number of trades for each category (All trades, rational trades, overvalued trades and undervalued trades). Rational trades are the trades realized within the range of possible terminal payoffs $\{S_t^{min}, S_t^{max}\}$. Overvalued trades are trades that were realized at a price above the maximum rational price S_t^{max}. Undervalued trades are trades that were realized at a price below the minimum rational price S_t^{min}. Panel B gives a measure of the average optimism for each category of trades. Average optimism is calculated as the average of the relative variations of the trading price with respect to the fundamental value.

Table 3
Descriptive statistics on trades (first markets)

	Panel A: Number of trades (first markets)			
	All trades	Rational trades	Overvalued trades	Undervalued trades
All trades	1,132	984	119	29
Small price markets	677	576	90	11
Large price markets	455	408	29	18
	Panel B: Average optimism (first markets)			
	All trades	Rational trades	Overvalued trades	Undervalued trades
All trades	0.1307	0.1061	0.4586	-0.3791
Small price markets	0.1762	0.1312	0.5387	-0.4323
Large price markets	0.0631	0.0708	0.2098	-0.3467

This table presents descriptive statistics on trades realized in the first market of the different sessions. Panel A provides statistics on the number of trades for each category of trades (All trades, rational trades, overvalued trades and undervalued trades). Rational trades are the trades realized within the range of possible terminal payoffs $\{S_t^{min}, S_t^{max}\}$. Overvalued trades are trades that were realized at a price above the maximum rational price S_t^{max}. Undervalued trades are trades that were realized at a price below the minimum rational price S_t^{min}. Panel B gives a measure of the average optimism for each category of trades. Average optimism is calculated as the average of the relative variations of the prices with respect to the fundamental value.

Table 4
Optimism as a function of the order initiator

Panel A: Number of trades			
	Buyer initiated	Seller initiated	All orders
All markets	873	1,245	2,118
Small price markets	438	608	1,046
Large price markets	435	637	1,072

Panel B: Optimism			
	Buyer initiated	Seller initiated	All orders
All markets	−0.0197	0.1844	0.1003
Small price markets	0.0565	0.3255	0.2129
Large price markets	−0.0965	0.0497	−0.0096
Difference Small-Large	0.1530***	0.2758***	0.2225***
	(7.7779)	(12.6960)	(13.7863)

Mann-Whitney test. z-statistics in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

Table 5
Within-participants analysis – Differences in optimism between small price and large price markets

	All periods	Excluding the first period of second markets
Small price markets	0.2727	0.1950
Large price markets	−0.0020	0.0376
Difference Small-Large	0.2747***	0.1573***
	(6.5492)	(5.1821)

Wilcoxon signed-rank test. z-statistics in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.

Table 6
Multivariate analysis

	(1) All trades	(2) Clustering at order initiator level	(3) Excluding first period of second markets	(4) Excluding first trade of each period	(5) First markets only	(6) Rational trades
INTERCEPT	0.7808***	0.7808***	0.7360***	0.6928***	0.9032***	0.3971***
	(8.14)	(3.52)	(9.00)	(7.11)	(8.45)	(5.94)
SMALLPRICE	0.0925***	0.0925***	0.0790***	0.0799***	0.0944***	0.0999***
	(6.10)	(3.78)	(6.15)	(5.19)	(6.25)	(9.65)
TIME	-0.0599***	-0.0599**	-0.0345***	-0.0594***	-0.0250**	0.0256***
	(-5.46)	(-2.60)	(-3.33)	(-5.34)	(-2.19)	(3.39)
TRANSACTION	-0.0021**	-0.0021*	-0.0030***	-0.0015	-0.0037***	-0.0024***
	(-2.10)	(-1.96)	(-3.44)	(-1.47)	(-3.81)	(-3.55)
PCF	-0.0704***	-0.0704**	-0.0897***	-0.0592***	-0.1104***	-0.0718***
	(-4.61)	(-2.29)	(-7.00)	(-3.81)	(-6.05)	(-6.46)
LAGGED OPTIMISM	0.4444***	0.4444***	0.3784***	0.4578***	0.2709***	0.2589***
	(22.76)	(6.88)	(17.53)	(23.77)	(9.26)	(16.07)
RATIONAL	-0.2171***	-0.2171***	-0.0775***	-0.2011***	-0.1181***	
	(-9.74)	(-3.51)	(-3.98)	(-8.83)	(-5.01)	
Observations	2,118	2,118	1,987	1,958	1,132	1,822
Adjusted R^2	34.93%	34.93%	25.81%	37.04%	23.8%	24.23%

The regression specification is

$$O_{j,k,l,t} = \alpha + \beta_1 SMALLPRICE_{j,l} + \beta_2 TIME_t + \beta_3 TRANSAC_k + \beta_4 PCF_{j,l,t} + \beta_5 O_{j,k-1,l,t} + \beta_6 RATIONAL_{j,k,l,t} + \epsilon_{j,k,l,t}$$

where $O_{j,k,l,t}$ is the optimism of the k-th trade executed in period t of market l for session j (optimism is calculated as in equation 3), $SMALLPRICE_{j,l}$ is a dummy variable that equals 1 if market l of sessions j is a small price market, $TIME_t$ is the square root of the period number t and $TRANSAC_k$ is the logarithm of the transaction number k within a period t, $PCF_{j,l,t}$ is the normalized per period cumulated cash-flow, $O_{j,l,k-1,t}$ is the optimism observed in the previous trade (lagged optimism), and $RATIONAL_{j,k,l,t}$ is a dummy variable that equals 1 if the transaction price is in the range of rational prices. $O_{t,k-1}$ is the value of the optimism of the preceding trade $k-1$. When $k=1$, $O_{j,k-1,l,t}=0$ by convention. t-statistics in parentheses. ***/**/* correspond to 1%/5%/10% significance levels.