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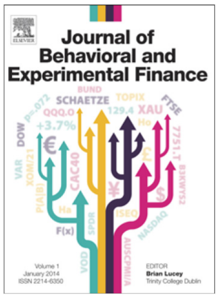

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How do markets react to (un)expected fundamental value shocks? An experimental analysis

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ABSTRACT

We study experimentally the reaction of asset markets to fundamental value (FV) shocks. The pre-shock and post-shock FV are both constant, but after the shock the FV is either higher or lower than before. We compare treatments with expected shocks (the date and the magnitude are known in advance, but not the direction) to treatments with unexpected shocks (subjects only know that a shock may occur but are unaware of the date and the magnitude). We observe mispricing in markets without shocks and in markets with shocks. Shocks tend to reduce the post-shock price deviation and to increase the difference of opinions (DO), whatever the type of the shock (expected or unexpected) and its direction (upwards or downwards). In contrast to standard predictions, the larger DO after a shock is not accompanied by an increase in transaction volumes, but by sharp depression of share turnover.

Keywords: Experimental asset market, shocks, price bubble, difference of opinions.

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I. Introduction

Financial markets are inherently noisy and asset prices convey only partial information to the traders (Grossman, (1976), Grossman and Stiglitz, (1980)). One of the fundamental reasons is that financial markets are affected by exogenous shocks (Subrahmanyam and Titman, (2013)) which move prices away from their equilibrium path, leading to bubbles and crashes.

The experimental literature on financial markets has provided ample evidence about the relevance of price bubbles in laboratory asset markets. The seminal findings of Smith et al., (1988) (SSW (1988) hereafter) have been replicated and extended by a growing literature (e.g., King et al., (1993), Van Boening et al., (1993), Lei et al., (2001), Noussair et al., (2001), Haruvy and Noussair, (2006), Caginalp et al., (2011), Noussair and Richter, (2012), Noussair and Tucker, (2014), Noussair et al., (2014) and Stöckl et al., (2015))[1].

So far, most experiments relied on a deterministic process of fundamental value (FV thereafter). While such an assumption is useful for identifying and isolating the characteristics of speculative behavior in the lab, it may lead to particular behavioral insights that are valid only for rather unrealistic contexts. For instance, a deterministic FV may encourage speculation by traders who are over-confident in their ability to buy low and sell high. Introducing randomness in the FV process may therefore temper experimental traders' speculative expectations and, as a consequence, prevent the formation of price bubbles. Compared to a situation where the FV is deterministic, and therefore perfectly anticipated,

1 For detailed reviews on experimental asset markets we refer to Palan, (2013) and Powell and Shestakova, (2016). In addition, the review of Nuzzo and Morone, (2017) is of particular interest as it is focused on diffusion of information.

when traders are exposed to a stochastic FV process, they face both strategic uncertainty and background uncertainty, providing therefore a more important role for expectations.

The purpose of this paper is to study experimentally the formation of asset price bubbles in experimental markets where the FV can be affected by an exogenous shock, which is either expected or non-expected by traders. More specifically, we compare markets in which traders are perfectly aware that a shock will occur, i.e. they know the period in which the shock will occur and its magnitude but not its direction, to markets in which traders only know that a shock may occur, but ignore the period, the magnitude and the direction.

The empirical relevance of expected shocks is illustrated by political events such as the Brexit referendum vote in UK in 2016. Similarly, the recent history provides numerous examples of unexpected exogenous shocks that affected financial markets, e.g. the subprime crisis and more generally shocks that are provoked by events such as natural hazard, civil wars, popular uprising, political scandals or other reasons. Although most of these shocks have an indisputable impact on the FV, their magnitude and exact timing (when they are unexpected), cannot be measured precisely. Furthermore, in real financial markets, several shocks of different timings and magnitude, often arise in a given time period. In contrast, experiments allow us to manipulate the FV process, and the timing and magnitude of the shocks.

In our framework a shock consists in an upwards or a downwards shift of the FV path. We consider binary symmetric shocks, i.e. the upwards shift is of the same magnitude than the downwards shift with uniform probability. We compare markets with shocks to markets without shocks by considering mean-zero shocks, keeping thereby constant the expected FV before the outcome of the shock applies. In markets without shocks we implement a constant FV path as in Noussair et al., (2001).

Introducing a mean zero perturbation of the FV path is similar to adding an *unfavorable background risk,* i.e. a risk with a null or negative mean, to a preexisting risk. Such increase in risk may affect negatively risk-taking for decreasingly risk-averse agents as shown in Gollier and Pratt (1996), a conjecture which is experimentally supported Beaud and Willinger, (2015). We therefore expect that the introduction of a binary symmetric shock in an experimental asset market is likely to increase the demand for the risk-free asset before the occurrence of the shock and therefore to mitigate the formation of a price bubble. On the other hand, after the shock, as the risk is resolved we expect risk-averse traders to take more risk, i.e. a higher demand for the risky asset.

We are also interested in how the volume of trading is affected by such shocks. The answer depends on how shocks affect the difference of opinions (DO thereafter), i.e. the dispersion of beliefs. We expect that before an expected shock traders' DO increases. In contrast, once the shock is realized and uncertainty has vanished beliefs converge. Relying on the theoretical and empirical literature about the relation between the DO and trading volume, we expect trading volume to respond positively to the increase in the DO: high trading volume before the realization of the shock and low trading volume after it.

We implemented a within-subject design for which each subject was involved in a market without a shock followed by a market with a shock. Subjects were endowed with different types of portfolios and their main task was to submit bids and asks for trading units of a financial asset. We elicited individual price expectations at the opening of each market round in order to measure the traders' difference of opinions (DO) in each independent group.

Our main findings are the following. First, we observe overpricing with respect to the FV in markets without shocks as well as is in markets with (expected or unexpected) shocks. However, mispricing is attenuated following a shock. Second, after a shock we observe an increase in the DO, whatever the type of the shock (expected or unexpected) and whatever its direction (upwards or downwards). Third, there is a sharp drop in transaction volume after a shock whatever its type and direction.

Our experiment is closely related to Weber and Welfens (2009) who studied the impact of new information about the FV. Following the arrival of new information they observed a clear pattern for trading volume in their data: the frequency of transactions drops sharply, whether the new information increases or decreases the FV. A similar result was established by Nosic and Weber (2009), but Marquardt et al. (2019) found that turnover increases after the announcement of new information. Additional evidence is therefore needed. Although our experimental design involves strong methodological differences, several of our findings agree with those of Weber and Welfens (2009) and Nosic and Weber (2009). Our experimental design is based on the standard SSW setup but with a constant FV as in Noussair et al., (2001): 9 traders per market, 3 types of initial portfolios of equal expected value, 3 traders assigned to each portfolio type, 15 trading rounds and all rounds paid. A shock consists in moving upwards or downwards the FV in round 8. In contrast, in Weber and Welfens, (2009) and in Nosic and Weber, (2009), groups have different sizes and are randomly reformed during the 4 first rounds (out of 10). There is only one portfolio type which is reset at the beginning of each round, and a single round is randomly selected to be paid. A positive (negative) shock consists in announcing in the middle of a round that the two low (high) payout states are discarded. Despite all these differences several results are remarkably similar: a sharp drop in turnover after a shock, an increase in the DO, and a positive correlation between DO and turnover.

The rest of the paper is organized as follows. In section 2 we review the main findings of the experimental literature on asset markets with deterministic FV. Section 3 describes our experimental design. In section 4 we discuss the theoretical predictions of FV shocks on prices, transactions and the DO. Section 5 presents our results and Section 6 discusses our findings.

II. Literature review

Most of the literature on experimental financial markets has focused on a single asset with a deterministic FV, i.e. subjects know in advance the time path of the FV. Moreover, until recently this literature also assumed a monotonic (non-stochastic) FV process. Recent exceptions are Noussair and Powell, (2010), Kirchler et al., (2012), Breaban and Noussair, (2015) and Stöckl et al., (2015). A few papers also introduced a stochastic FV "random-walk FV-processes" (Weber and Welfens, (2009), Nosic and Weber (2009), Kirchler, (2009), Nosic et al., (2011), Kirchler et al., (2011), Stöckl et al., (2015)). There is therefore limited knowledge with respect to one of the key components of real financial markets, namely stochasticity. An important reason is that in real asset markets, the FV process is not only stochastic but it is also unobservable. Experimental asset markets provide therefore a valuable source of knowledge because the experimenter is able to observe the FV process and traders' behavior and expectations when markets are affected by controlled FV shocks. While the identification of the reactions of market prices and transaction volumes to such shocks is a challenging issue with real market data, it becomes much more easy with experimental data. We next briefly discuss some of the findings of experimental asset markets that will be relevant to our study, with respect to price bubbles (II.1) and trading volumes (II.2).

II.1 Price bubbles

Following SSW (1988), most of the later literature relied on a deterministic and monotonic FV process. Many of these later papers (e.g., Noussair et al., (2001), Noussair and Richter, (2012) Smith et al., (2000), Haruvy et al., (2013), Huber and Kirchler, (2012), Kirchler et al., (2012)[2], Ikromov and Yavas, (2011), Giusti et al., (2012) and Straznicka and Weber, (2011)) established that price bubbles are frequently observed and robust to various market mechanisms, e.g. short-selling (Haruvy and Noussair, (2006) and King et al., (1993)) lack of common knowledge (Lei et al., (2001)), availability of non-speculative markets (Lei et al., (2001)) and constant FV process (Noussair et al., (2001)). However experimental papers which implemented an increasing FV over time (e.g., Giusti et al., (2012), Johnson and Joyce, (2012) and Stöckl et al., (2015)) did not find significant evidence for bubbles, confirming the conjecture of Smith, (2010) and Oechssler, (2010) that bubbles are less likely under increasing FV patterns, which correspond to the market experience of most individual traders.

A few papers examined the case where the FV is non-monotonic (Noussair and Powell, (2010), Breaban and Noussair, (2015) and Kirchler, (2009)). Noussair and Powell, (2010) investigated how the FV's trajectory affects price discovery in an experimental asset market and transaction prices behavior facing downwards and upwards variation of FV. In their *Peak* treatment, the FV first rises and then falls, while in their *Valley* treatment the FV follows the

2 The authors show that adding a "gold mine" context to the standard declining FV process considerably abates bubbles.

opposite pattern. They found that both *Peak* and *Valley* treatments generate bubbles when traders are inexperienced. Breaban and Noussair, (2015) studied how the time path of the FV trajectory affects the level of adherence to the FV, by comparing the level of mispricing for decreasing and increasing FV trajectories. They observed closer adherence to FVs when the trajectory follows a decreasing rather than an increasing trend.

In experiments where the FV fluctuates randomly (e.g. Gillette et al., (1999), Kirchler, (2009)), market prices tend to underreact to changes in FV leading to lower prices when the FV is predominantly increasing and to higher prices when the FV is predominantly decreasing. In other words there seems to be a tempering effect of random shocks on the price deviation from the FV. Finally, Hussam et al., (2008) observed that bubbles are rekindled after an increase in liquidity or an increase of the variance of the dividends, even with experienced subjects.

II.2 Trading volume

Fewer papers examined the impact on trading volume (e.g., Gillette et al., (1999), Lei et al., (2001)) compared to those who studied mispricing and bubbles. In our experiment, we concentrate on the impact of shocks on turnover.

Our set up is closely related to Weber and Welfens (2009)'s design. At the beginning of their experiment it is common knowledge to subjects that each unit of stock can take one of four different values, with equal probability. After 2 minutes of trading new information is provided in the following way: with equal probability, either the two higher values are discarded (negative FV shock) or the two lower values are discarded (positive FV shock), the remaining values being equally likely. Following such a shock, Weber and Welfens, (2009) observed that the frequency of transactions drops sharply, whether the FV increases or decreases. They also observed a similar effect for order placements which are significantly reduced after the shock.

The drop in transaction volume following the arrival of new information is not well understood, but seems to be related to a change in the DO. In the periods preceding an expected shock the DO is larger than in the absence of shocks, an in the periods following the shock beliefs seem to converge which tends to depress turnover. Note also that the negative impact of a FV shock on trading volume can be compared to the impact of the unexpected introduction of a Tobin tax in an experimental asset market. Hanke et al., (2010) and Kirchler et al., (2011) observe a significant drop in trading volume in each market where a Tobin tax is introduced. Furthermore, without surprise, if only one market is taxed, the drop in trading is amplified in the taxed market while trading is intensified in the untaxed market (the tax haven).

Our brief overview of the literature points out the knowledge gap about the impact on mispricing and trading volumes of FV shocks. Our experiment contributes to fill in this gap.

III. Experimental Design

A total of 270 student subjects[3] from various disciplines of the University of Montpellier (France) participated in the experiment. They were recruited from a large subject-pool (with over 5000 volunteers) with ORSEE (Greiner, (2004)). They were inexperienced with experimental asset markets and could participate only in one session. The experiment was programmed with the z-Tree software (Fischbacher, (2007)). In each session, two independent groups[4] of nine subjects were involved in two consecutive markets: market 1 and market 2.

3 Most of our subjects are graduate student from scientific, economic and business administration disciplines. Descriptive statistics about our sample are available upon request. Haigh and List, (2005) showed that professional traders do not better (and partly worse) than university students in an investment task that examined myopic loss aversion.

4 In one of the sessions we had only one group due to the absence of several subjects.

Each market consisted of 15 periods, during which individuals could trade units of an asset. It was common knowledge that the asset's lifetime was equal to the 15 periods. The numeraire in the experiment consisted of "Experimental Currency Units" (ecus), which were converted into euros at the end of a session at a predetermined, publicly known, conversion rate *(1 euro = 337.5 ecus)*. Each session lasted approximately 3 hours, including instructions and payment of subjects. Subjects earned on average 28 euros.

The experiment was broken into three treatments: **T1** *"Expected FV shock"*, **T2** *"Unexpected FV shock"* and **T0** *"No-shock"*. Market 1 is the same in all treatments and similar to the market studied by Noussair et al., (2001) and Kirchler et al., (2012) in which the FV of the asset is constant over the entire life of the asset. In treatment T1 and T2, we introduce a FV shock in a way similar to Weber and Welfens, (2009), Bao et al., (2012)[5], Corgnet et al., (2013) and Marquardt et al., (2019)). More precisely, market 2 involved a shock in period 8 on the FV which becomes either larger or lower compared to the pre-shock value. In T1 subjects are informed that a random shock will arise at the end of period 8. In treatment T2 the shock was the same as in T1 but subjects ignored that a random shock would arise at the end of period 8[6]. Treatment T0 is our control treatment: subjects participate in two consecutive identical markets with constant FV (two markets without shock). Table 1 summarizes our experimental design and the parametric setting. The instructions provided to subjects are available in appendix 2.

Our experimental setting is close to the following studies. Weber and Welfens, (2009) consider a single trading period with an interruption in the middle to announce new

5 One of our treatments involves unexpected shocks as in the learning-to-forecast experiment of Bao et al., (2012).

6 T2 is the closest to the real stock market, where traders have often good or bad unexpected news about the value of their stock. To prevent deception we used a design characterized by an unexpected news, knowing that the news in our design are related to the terminal value of stocks (buyout).
Two experimental market studies used a design characterized by an unexpected Tobin tax news (Kirchler et al., (2011) and Hanke et al., (2010)). In both studies subjects do not get any information about the potential implementation of transaction taxes before the main experiment starts and they are not informed whether and when the tax regime is changed again. Furthermore, the tax rate is also placed on the trading screen once a tax has been introduced. By contrast in the following studies (Bloomfield et al., (2009) and Cipriani and Guarino, (2008)) subjects know in advance that Tobin tax will be levied.

information about the possible states of the world. In their experimental design, the new information "shifted" the FV upwards or downwards, and subjects had only 120 seconds for trading before and after the shock. Corgnet et al., (2013) studied the effects of ambiguous public news. They consider an experimental market with three trading periods and four minutes for each period. In their design, subjects know that they will have news at the end of each of the three periods. In the Marquardt et al., (2019) design, subjects participate to two markets with 12 two-minute periods each, where an expected shock (either good or bad business conditions) is announced after the first two periods and the business activities are neutral again in the two last periods (such in the first two periods). The particularity of our design is that we rely on the SSW asset market with a constant FV. Participants were involved in 15 trading periods of 2 minutes each. The shock always happened in period 8. This allows us to have a reasonable number of periods both before and after the shock to observe eventual price bubbles and to detect changes in prices, volumes and expectations. Our design allows for 8 periods of 120 seconds each before the shock and 7 periods of 120 seconds after the shock. This design allows for more feedback information (e.g. closing prices after each round) and more rounds to allow for the eventual mispricing and adjustments in turnover.

Each session was divided into three parts: part one was a real effort task, part two consisted in two consecutive experimental markets and part three in a risk preference questionnaire.

IV.1 - Part one: real effort task

In part 1 subjects had to perform a real effort task in order to accumulate *private money*. The task consisted to count the number of "1's" in a grid containing a sequence of "0's" and "1's". The reason of part 1 was to avoid the house-money effect (De Bondt and Thaler, (1990), Thaler and Johnson, (1990) and Ackert et al., (2006)) that is likely to favor speculative behavior. In particular, in treatment T1 for which the shock was expected, speculative behavior could have been over-amplified if subjects would have played with the experimenter's money. The money earned in part 1 was available to subjects for participating in the second part of the experiment. Subjects received a flat rate for task completion. Precisely, all subjects who had succeeded in achieving the task received 6,750 ecus (which corresponds to 20 euros) to participate in the second part of the experiment. Subjects who failed in part 1 earned only the show-up fee and where asked to leave the room[7] before we started part 2.

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INSERT TABLE 1

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IV.2 - Part two: Experimental markets

In this part, subjects participated in two consecutive markets. Before market 1 began subjects were randomly assigned to a group of nine traders. The groups remained identical for the two markets. In each group subjects were randomly assigned to one of three types: P1 trader, P2 trader or P3 trader. Each group consisted of 3 traders of each type. Each trader type was defined according to the composition of its portfolio. However the expected value of a portfolio was equal to 6,750 ecus for all types (P1, P2 and P3). Table 1 describes the portfolio composition of each type.

Before starting the first market, subjects were involved in a training phase for two minutes to allow them to become comfortable with the interface. Gains and losses of the training phase were not counted as accumulated wealth for cash payment.

7 This happened only once over all sessions.

a) Market One

After the training phase, subjects participated in the fifteen market periods of market 1. Each trading period lasted 2 minutes, during which subjects could buy and/or sell units of a single stock. Prices were quoted in terms of experimental currency units (ecus), and gains were converted into euros at the end of the session. The traded asset had a fifteen period lifetime.

At the end of each period, the asset paid a dividend of either 45 or 15 ecus, or incurred a holding cost of either -15 or -45 ecus. A random draw determined at the end of each period the dividend or the holding cost for that period, with uniform probability (according to the roll of a four-sided die). The expected value of the dividend/holding cost equals therefore zero in each period. Dividends and holding costs were accumulated in a separate account and were added and subtracted from the final market gain (accumulated and distributed at the end of the session). The separate account was introduced in order to keep constant the liquidity and the number of stock over time. However, subjects were informed after each period about the realized level of dividend/holding cost of that period.

Each unit of the asset paid a terminal value (buyout) of 300 ecus to its owner at the end of market 1. Thus the FV for each unit of the asset is equal to 300 ecus at any period[8] of market 1. The dividend process, the number of periods and the terminal value were common knowledge.

8 The FV of a unit of asset in period t equals $f_t = Buyout + (T - t) \times E(d_t), t = 1, 2, \ldots, T$, where f_t correspond to the FV in period t, T the total number of periods, t the current period and $E(d_t)$ the expected value of the dividend payment in period t. In our markets $E(d_t) = 0$ for all t, so $f_t = Buyout$ for all t.

At the beginning of each period, subjects were required to make a price forecast about the current period contract prices. We asked them to provide a forecast in interval form, by setting a lower bound and an upper bound in the beginning of each period. In order to incentivize the forecasting task, we introduced a variant of Selten's measure of predictive success (Selten, (1991)). According to our predictive success rule the payoff of a forecast increases in the number of correctly predicted transaction prices and decreases in the size of the forecasting interval. The forecast profit of subject $i=1,..,9 \in period\ t$ was defined as follows: $\pi_{i,t}=Max(G_{i,t};0)$, where $G_{i,t}$ equals[9] :

$$G_{i,t}=\begin{cases} 10\frac{h}{h^{¿}_{t}}-5\frac{(a_i-a^{¿}_{t})}{a^{¿}_{t}};\ if\ a_i-a^{¿}_{t}>0 \\ 10\frac{h}{h^{¿}_{t}};\ if\ a_i-a^{¿}_{t}\leq 0 \end{cases}$$

$where\ a^{¿}_{t}$ is the size of the realized price interval, i.e. $a^{¿}_{t}=\{max_t(P_t)-min_t(P_t)+1\}$, a_i is the size of the predicted interval, i.e. a_i $¿\{upper\ bound-lower\ bound+1\}$ for subject i , $h^{¿}_{t}$ is the total number of transactions in period t, h is the number of transaction prices which fall into the forecasted interval[10]. Note that we constrained the forecast payoff in order to avoid losses: the maximum possible forecast payoff was 10 ecus and the minimum 0 ecus.

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9 We used the following forecast profit formula only in the first two sessions, $G_{i,t}=5\frac{h}{h^{¿}_{t}}-2.5\frac{(a_i-a^{¿}_{t})}{a^{¿}_{t}};\ if\ a_i-a^{¿}_{t}>0$ and $G_{i,t}=5\frac{h}{h^{¿}_{t}};\ if\ a_i-a^{¿}_{t}\leq 0$. For the remaining sessions we used $G_{i,t}=10\frac{h}{h^{¿}_{t}}-5\frac{(a_i-a^{¿}_{t})}{a^{¿}_{t}};\ if\ a_i-a^{¿}_{t}>0$ and $G_{i,t}=10\frac{h}{h^{¿}_{t}};\ if\ a_i-a^{¿}_{t}\leq 0$.

10 A referee pointed out that our method for eliciting forecasts was complex and therefore could have generated confusion. Even though it might have generated some noise in the prediction data, there is no reason why it could have created more noise in the test treatments (with shocks) than in the baseline treatment. Moreover, test treatments were always introduced in sequence 2, therefore subjects became more accurate in the prediction task because they were once experienced and learned to make better predictions. We provide support for this claim by comparing the relative prediction error, i.e. |median forecast -FV|/FV, between sequence 1 and sequence 2. The relative prediction error is significantly lower in the first half of sequence 2 than in the first half of sequence 1 for all our treatments with one exception (sign-rank tests, 5%).

b) *Market 2*

There is only one difference between market 1 and market 2 (in treatments T1 and T2): the presence of a FV shock in market 2 at the end of period 8. Let us describe precisely each treatment.

T1: *Expected fundamental value shock*:

Two final buyout values are possible after the shock: 200 or 400 ecus with equal probability. Hence, the expected value of the buyout in the pre-shock periods was equal to 300 ecus as in market 1. All subjects knew that at the end of period 8, one of the two possible buyout values would be randomly selected and publicly announced to all members of their group. The shock could be upwards if the selected value was equal to 400 ecus or downwards if the selected value was equal to 200 ecus. After the shock, the final buyout was displayed on the subject's screens and the FV was equal to the selected buyout.

T2: *Unexpected fundamental value shock*

In treatment T2, although subjects were aware that a FV change was possible, they had no clue about the possible amplitudes of the changes nor about the period in which such a change could occur. At the beginning of market 2, they were simply told that the initial FV was equal to 300 ecus as in market 1 but that possibly new information regarding the terminal value could be provided during the market.

At the end of period 8, a warning message was displayed on their screens, in which they could read that the final buyout was no longer equal to 300 ecus but to 400 ecus in the upwards case or to 200 ecus in the downwards case. In addition to the displayed message, the experimenter announced aloud that a new redemption value was set.

At the end of the session one of the two markets was randomly selected to be paid out. Subjects were aware of this rule before starting market 1. The final gain/loss in ecus for the selected market was determined as follows:

$$Final\,gain = Final\,cash\,balance \quad + \\ (Final\,buyout \times Inventory\,of\,asset) + Savings\,account\,balance$$

Note that the savings account consisted of the accumulated net dividends and forecasts profits. The cash balance could evolve with successive transactions, in particular by capital gains (losses) due to differences between selling and buying prices of units of stock.

Subjects' final earning was equal to their final gain for the selected market plus their participation fee.

IV.3 - Part three: Risk aversion and demographic questionnaires

Subjects were asked a series of questions about their self-declared risk attitudes. Following the questionnaire of Vieider et al. (2015), we asked each participant about her willingness to take risks in general and in specific contexts (driving, financial matters, health domain, occupational risks, sports, and social risks). They had to indicate their answer on a scale ranging from 0 to 10: *0 if extremely risk averse and 10 if fully prepared to take risks.* In a final short questionnaire we collected data about subjects' individual characteristics.

The next section exposes the theoretical predictions of FV shock effects.

IV. Predictions

In this section we state our key predictions about the impact of a FV shock. Our statements rely both on theoretical arguments as well as on empirical regularities reported by the financial literature. We break the predictions into two categories: predictions about changes in asset prices and predictions about changes in trading volumes.

IV.1 Impacts of shocks on asset prices

According to the Efficient Market Hypothesis (EMH) competition among investors clears all positive net present value trading opportunities (Fama, (1970)), implying that securities are fairly priced, based on their FV and the information that is available to investors. Therefore, following an exogenous shock, stock prices should convergence quickly to their new FV. There are many cases against EMH (see Robert A. Haugen, (1999)). Market can overreact to news (De Bondt and Thaler, (1985)) and deviations from the FV can be persistent creating momentum and favorable conditions for the appearance of bubbles (Jegadeesh and Titman, (1993)). Barberis et al., (1998) and Daniel et al., (1998) identified many cognitive biases favorable to such outcomes: conservatism, herding, overconfidence, the confirmation bias and the disposition effect. Bubbles driven by such cognitive biases are sometimes called "behavioral bubbles" (De Grauwe and Grimaldi (2004)). How such bubbles are affected by FV shocks is unknown.

In our experiment we consider a single asset that is exposed to a mean-zero FV shock. Some traders may become more risk-averse if they anticipate such shocks. They may react by reducing their exposure to such risk by selling shares of the risky stock. Gollier and Pratt, (1996) and Huang and Stapleton, (2017) identified the conditions under which an expected utility maximizer, exposed to an independent unfavorable[11] background risk, becomes more risk-averse. This property, called *risk-vulnerability*, implies that agents treat independent risks as substitutes. Therefore, if a mean-zero (or unfavorable) shock is introduced, such an agent adjusts downwards his level of risk-taking. Symmetrically, if the risk represented by the shock is removed he adjusts upwards his level of risk-taking. In short, a risk-vulnerable agents is a net seller before the shock and a net buyer after the shock.

In contrast to the risk-vulnerability conjecture that is based on expected utility theory, non-expected utility agents may treat independent risks as complements (Quiggin, (2003)), suggesting exactly the opposite prediction: the presence of a mean-zero shock increases the demand for the risky asset before the shock and reduces it after the shock.

Prediction 1*: In markets with anticipated shocks mispricing is attenuated (amplified) before the shock and amplified (attenuated) after the shock if traders are risk-vulnerable (non-vulnerable).*

Prediction 1 applies only to expected shocks. We conjecture therefore that the traders who are unware about the occurrence of a shock in the future will behave as the traders in markets without shocks. Therefore before the shock arises, similar mispricing will be observed in markets with unexpected shocks than in markets without shocks. However, following an unexpected shock, the extent of mispricing will depend on traders' beliefs revision and its impact on trading volume. We discuss this issue in the next sub-section.

IV.2 Impacts of shocks on the difference of opinion (DO) and the trading volume

Before discussing how shocks affect the DO and the trading volume, we provide an overview of the financial literature about the relation between the DO and trading volume. The

11 A risk is unfavorable if its expected value is negative or null.

standard view of the EMH is best expressed in the no trade theorem. Some authors (e.g., Milgrom and Stokey (1982)) argue that if agents have rational expectations no trade should occur even in the wake of new private information. This view was challenged by several important contributions, e.g. Harrison and Kreps, (1987), Tirole, (1982) and Varian, (1989) among others. Their key argument is that if traders have different priors they will have different expectations about market prices even if all information is common knowledge. In other words, heterogeneity of beliefs generates trade (Varian, (1989), M. Harris and Raviv, (1993), Kandel et al., (1995), Cao and Ou-Yang, (2009) and Banerjee, (2011)).

Most of the theoretical work that focused on the relation between the dispersion of opinions and the volume of trade identified a positive interaction: increasing the variance of expectations increases the volume of trades. Such a prediction is derived from a variety of assumptions. Following the arrival of new public information, such as earnings announcements, traders' can have disagreements (Copeland, (1976), Kandel et al., (1995) and Banerjee and Kremer, (2010), heterogeneous reactions (Karpoff, (1986)), different opinions (Varian, (1985) and M. Harris and Raviv, (1993)), heterogenous priors (Kim and Verrecchia, (1991)), information asymmetries (Kim and Verrecchia, (1994)), differential interpretations (Kim and Verrecchia, (1997)) or a combination of some or all of these (Banerjee, (2011)). The common idea is that public information is processed differently by different traders (or analysts), thereby creating information asymmetries and diversity of opinion leading to higher trading. In Kim and Verrecchia, (1991)'s model, investors have private signals of different precisions before the public announcement. Investors with a more precise signal put more weight on their private information and less on the public information, generating ex post heterogeneity. In Milton Harris and Raviv, (1993) traders have common priors and observe the same public information, but have different interpretations of it.

Empirical support of a positive relation between the difference of opinion and trading volume[12] was provided by the accounting research community (see Bamber et al., (2011) for a review): Comiskey et al., (1987), Ziebart, (1990), Ajinkya et al., (1991), Terpstra and Fan, (1993), Bildersee and Ronen, (1996), Bamber et al., (1997), Roulstone, (2003) and Antweiler and Frank, (2004)). The standard empirical measure of forecast dispersion is the standard deviation of analysts' forecasts normalized by the absolute value of the average forecast[13]. Trading volume is usually measured as the percentage of shares traded relative to the number of shares outstanding. We rely on similar measures in our experiment. To our knowledge, Gillette et al., (1999) and Nosic and Weber (2009) are the only experimental paper that addressed the relation between dispersion of expectations and trading volume. While Gillette et al., (1999) found a negative relation between the dispersion of traders' price expectations and trading volume, in contradiction to the theoretical literature, Nosic and Weber (2009) observed a positive relation. Interestingly, Nosic and Weber (2009) investigated two competing hypotheses about higher trading volumes: differences in risk attitudes and differences of opinion. They find that only differences of opinions are significantly and positively related to trading volume. Given the mixed evidence there is a need for additional data about this relation.

We summarize the previous discussion as prediction 2.

Prediction 2: *The volume of transactions increases in traders' difference of opinions.*

We can now discuss how trading volume and the difference of opinions might be affected by shocks. Two experimental studies have provided evidence that shocks have a negative impact

12 Recently Siganos et al., (2017) found a similar pattern for the divergence of investors' sentiments, i.e. trading volume is increasing in investors' divergence of sentiments.

13 Note that several authors interpret high trading volume as an indicator of the difference of opinions, e.g. Kandel et al., (1995).

on trading volume. Nosic and Weber (2009) observed a larger number of transactions before subjects received a signal, than after receiving it. Similarly, Weber and Welfens, (2009) found substantially lower levels of trading following a FV shock. Hanke et al., (2010) and Kirchler et al., (2011) also observed that trading volume drops after the introduction of a "surprise" Tobin tax[14]. Introducing suddenly such a tax is similar to an unexpected negative FV shock. Supporting evidence about the negative impact of tax shocks on trading volume is also provided by simulation results (Mannaro et al., (2008)). Based on this evidence we state prediction 3 as follows:

Prediction 3: *Trading volumes drop after the realization of a shock.*

Finally we expect that the presence of an expected shock increases the dispersion of beliefs before its realization and leads to convergence of beliefs after it, because once the shock is realized, information asymmetry is reduced.

Prediction 4: *The presence of an expected shock increases the difference of opinion before the shock occurs, and reduces it afterwards.*

Prediction 4 does not apply to unexpected shocks. We conjecture however, that if traders are unware about the shock, the DO should not be affected, neither before, nor after the realization of the shock.

V. Results

The results section is organized as follows. In subsection 1, we provide an overview of the price patterns in markets with and without shocks. We investigate the effects of shocks on bubbles in subsection 2 and on transaction volumes in subsection 3. In subsection 4 we

14 In both experiments, the introduction of the Tobin tax was unexpected by the participants.

discuss our main hypothesis about the positive relation between the difference of opinions and turnover. For all tests, we set a 5% threshold level for rejecting the null hypothesis.

V.1 Descriptive results

In this subsection we provide an overview of the data. Figure 1 shows the time series of the median transaction price by treatment and direction of the shock in first and second markets.[15] It can be seen that on average median prices are substantially above the FV in most periods. Mispricing is visible in our experimental markets with and without shocks whatever the direction (upwards or downwards) and the type (expected or unexpected) of the shock.

We summarize these observations as result 1.

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INSERT FIGURE 1 ABOUT HERE

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Result 1. *Mispricing arises in all markets, with and without shocks.*

With respect to market 1, result 1 is in line with the findings of Noussair et al., (2001) that *"A constant FV is not sufficient to remove the tendency for bubbles and crashes to form in experimental markets"*. However, when subjects replicate the market without shock, bubbles are clearly attenuated in market 2 (see figure 1, T0). The attenuation effect is probably due to subjects' experience as observed in previous studies (Peterson, (1993), Van Boening et al., (1993) and Dufwenberg et al., (2005)). By contrast, when market 2 is affected by a shock,

15 We opted for the median rather than the closing price or the mean price in order to avoid the problem of single outliers.

over-pricing remains persistent whatever the direction and the type of the shock. The presence of shocks seems therefore to fuel over-pricing and the formation of bubbles.

Visual inspection of figure 1 provides further insights about the effects of a shock on prices. On average the median price remains above the FV before and after the shock in all treatments. There seems to be a different price reaction for upwards and downwards shocks. While the latter seem to trigger under-reaction[16], no specific bias appears in the case of upwards shocks.

V.2 Mispricing

In this subsection we provide evidence about mispricing, based on standard bubble measures of the traditional experimental literature and the more recent measures proposed by Stöckl et al., (2010). The various measures and their definitions are summarized in table A of appendix 1).

Market 1 serves as a benchmark with respect to which we assess the impact of the shocks on prices and volumes. We first check whether the benchmark behavior of markets is the same across treatments. Table B of appendix 1 reports bubble measures for each session of market 1. Although there is some variance across treatments, for none of the bubble measures there is a significant difference across treatments for market 1. This is stated as result 2.

Result 2. *There is no significant difference in asset mispricing and trading volumes across 1st markets.*

<u>Support for result 2</u>: (rank-sum tests, see table B appendix)

16 In Bousselmi et al., (2018) we document that prices underreact only after a negative shock, but not after a positive shock.

As expected bubble measures do not differ across treatments for 1st market. In particular, no difference is detected in 1st market between treatments for which shocks are expected and unexpected. We can therefore assume that in all treatments subjects gained similar market experience at the end of 1st market and that the remaining differences observed in 2nd market are only due to treatment effects.

Let us turn now to markets with shocks. Table C of appendix 1 displays the bubble measures for 2nd market broken down by sequence: "before" and "after" the shock. First, note that in the "No-shock" treatment (T0), the bubble measures do not differ between the first half (periods 2-8) and the second half of the 2nd market (periods 9-15). In treatments with shocks, several patterns emerge[17]: after a shock price amplitude (PA) and volatility (Vol) tend to increase, independently of the type and the direction of the shock. Considering the type of the shock, we also observe a fall in transaction volume (ST) just after the shock which is significant in the case of expected shocks. We also observe a depression in the transaction volume independently of the direction of the shock. The decrease is however significant only in the case of an upwards shock. Sign-rank test results for these observations are provided in table D (appendix 1). We summarize our observations about the impact of shocks on mispricing as result 3.

Result 3. *After a shock, price deviation tends to decrease.*

<u>Support for result 3:</u>

We provide additional support for the impact of shocks on mispricing by focusing on the determinants of price deviation (*PD* thereafter), based on panel regressions (table 2). In contrast to other bubble measures (e.g. *PA*, *ND*, *D* and others[18]), the *PD* measure is available

17 Support is provided in appendix (Table D), based on Wilcoxon signed-rank tests.

18 *PA*: Price amplitude, *ND*: Normalized absolute FV deviation and *D*: Duration. (See Appendix 1)

for each period. The estimates reported in table 2 show that after a shock (dummy *Post*), the price deviation tends to decrease. The decrease is however significant only if we control for the *Type* of the shock (equal to 1 if the shock is unexpected) and for the interaction variable *Post* × *Type*. The direction of the shock (upwards or downwards) and the type of the shock (Expected or Unexpected) have no significant impact on price deviation.

Result 3 seems to reject the *risk-vulnerability hypothesis* (prediction 1), according to which, when the shock is anticipated, over-pricing is attenuated before the shock and amplified after it.

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INSERT TABLE 2 ABOUT HERE

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V.3 transaction volumes

In accordance with prediction 3, we observe a sharp drop in trading volume after a shock. Neither the direction nor the type of shock does affect the magnitude of the depression of the volume of trades. The reduction in share turnover between positive and negative shocks is not significantly different (WMW, p-value = 0.165). Similarly, we find that the reduction in transaction volume after the shock does not depend on the type of shock, expected or unexpected (WMW, p-value = 0.165)[19]. Further support is provided by the regressions of table 3: the variable *Post* (= 1 after the shock) has a negative impact on share turnover.

Result 4: *Shocks depress equally the volume of transactions, whatever the direction of the shock (upwards or downwards) and the type of shock (expected or unexpected).*

19 These tests are based on *diff turnover = average share turnover before the shock (period 2-8) – average share turnover after the shock (period 9-15).*

Figure 2 supports this result, and shows clearly that share turnover decreases after a shock, whatever the direction and the type of shock.

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INSERT TABLE 3 AND FIGURE 2 ABOUT HERE

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<u>Support for result 4</u>:

In accordance with the results of the non-parametric tests, the regressions reported in table 3 confirm that the variable *Post* has a significant negative impact on share turnover in regressions (1) – (3). Furthermore, the interaction variable *Post* × *Dir* is not significant. *Post* × *Type* has an insignificant attenuation effect on the shock, meaning that the negative effect of the shock on turnover is attenuated when the shock is unexpected. Note that one of the key variables that affects share turnover is the difference of opinions (DO) which is captured by the variable SF, a normalized measure of the dispersion of forecasts. The next sub-section will be dedicated to the analysis of this variable and its relation to share turnover. Note that result 4 supports prediction 3 according to which "trading volumes drop after the realization of a shock".

V.4 Share turnover and difference of opinions

We now discuss our key observation: the sharp drop in trading volume after a shock and its relation to the difference of opinions (DO). We focus on a possible change in the DO after a shock. According to prediction 2, transaction volume and the DO are positively correlated: an increase (decrease) in the difference of opinion leads to more (less) intensive trade, a conjecture supported by the literature (Copeland, (1976), Varian, (1985), Karpoff, (1986), Kim and Verecchia (1991, 1994, 1997), M. Harris and Raviv, (1993), Kandel et al., (1995) and Banerjee and Kremer, (2010)). Since after a shock we observe a drop in share turnover we also expected to see a reduction in the DO. However as shown below, our data exhibits a clear increase in the DO, (see also Figure 3).

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INSERT FIGURE 3 ABOUT HERE

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We consider the following possible measures for the DO: (i) the difference between the most optimistic and the most pessimistic forecast in each trading period, i.e. $max f_t - min f_t$, the normalized dispersion of forecasts (ii) $SF_t = \sigma_{ft} / MF_t$, where σ_{ft} is the standard deviation of the subjects' forecasts in period t and MF_t is the mean of the median forecasts in period t, and (iii) the relative absolute forecast deviation, $RAFD = \frac{1}{N}\sum_{i=1}^{N}\frac{|f_i^t - FV_t|}{\acute{FV}}$, where f_i^t is the median forecast of subject i in period t and $\acute{FV}$ the mean FV[20], (see Akiyama et al., (2014), Akiyama et al., (2017) and Hanaki et al., (2018)). $SF_t \wedge the\ max f_t - min f_t$ indicator are almost perfectly correlated (Spearman rank > 0.90, p = 0.000) in all periods. Therefore, we shall rely exclusively on SF_t (noted *SF* hereafter and in the tables) in the remainder of the paper and test for robustness with the *RAFD* measure. Note that *SF* is also one of the most widely used measure for the DO in empirical research

20 FV = 300 without shock, FV = (1/15×((300*8)+(400*7)) for an upwards shock and FV = (1/15×((300×8)+(200×7))) for a downwards shock.

(Comiskey et al., (1987), Ziebart, (1990), Ajinkya et al., (1991), Terpstra and Fan, (1993), Bildersee and Ronen, (1996), Bamber et al., (1997) and Roulstone, (2003)).

Prediction 2 (*the volume of transactions increases with the DO*), is tested on the basis of panel regressions (table 3) with dependent variable *share turnover*. Independent variables are $Post$ (equal to 1 if t > 8), $Type$ (equal to 1 if the shock is unexpected), and Dir (equal to 1 if the direction of the shock is downwards). We also take into account all the possible interactions among these variables. *SF* has a significant and positive impact on turnover as predicted. The effect of SF is however tempered by the negative impact following a shock (*Post*) which is amplified by the type of shock (*SF* × *Type*) and further accentuated when the direction of the shock is downwards (*Post* × *SF* × *Dir*). The post-shock effect seems to reflect a negative trend in turnover: as the final period gets closer fewer transactions are realized. We summarize these findings as result 5.

Result 5: *An increase in the difference of opinion increases turnover.*

Support for result 5: (see table 3)

Does the combination of result 4 (shocks depress share turnover) and result 5 (larger DO increases share turnover) imply that shocks also affect negatively the DO? We answer this question by identifying the variables that affect the DO. Table 4 reports panel regressions with dependent variable SF, which clearly show that shocks affect positively the dispersion of forecasts. The effect is mainly due to downwards shocks as shown by regressions (3) and (5): when the interaction variable $Post \times Dir$ is included in the list of regressors, the variable *Post* is no longer significant. Note also that when the shock is unexpected there is a negative impact on *SF* in all periods. In other words, when the shock is expected there is an additional positive influence on *SF*, that is probably due to the uncertainty about its direction.

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INSERT TABLE 4 ABOUT HERE

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Result 6: *Following a shock the difference of opinion increases whatever the type and the direction of the shock.*

Result 6 clearly rejects prediction 4 that after a shock we should observe a convergence of opinions, and a larger DO before than after the shock.

V.5 Robustness check

In this section we address two potential concerns with our data analysis. First, does the impact of the shock on share turnover depend on the type of measure of the DO? Second, is there an endogeneity issue with share turnover and the DO?

We test for the robustness of the impact of shocks on the DO by substituting *RFAD* to *SF* as dependent variable (the results are reported in appendix 1, table E). After the shock *RFAD* increases significantly as for *SF*. Similar to *SF*, we also find that when the shock is unexpected there is a negative effect. However, the interaction variable $Post \times Dir$ is not significant, but its inclusion in the regression does not alter the significance of the variable

Post. Therefore, we conclude that our findings a robust with respect to a substitution of the measure of the DO.

The fact that shocks affect the DO (result 6) suggests that the dispersion of forecasts (SF) is an endogenous variable. This may be problematic for result 5 which was established on the basis of the assumption that SF is an exogenous variable. To control for the potential endogeneity of share turnover and the DO we rely on instrumental variables using a two-stage least squares (2SLS) approach. The binary variable *Type* is uncorrelated with turnover, and we therefore chose it as an instrumental variable (IV). Our results (see appendix 1 table F) show that the 2SLS estimates are very close to the OLS estimates. In addition we compare the OLS and the 2SLS model coefficients using the Durbin-Wu-Hausman test (p-value = 0.5330), which allows us to claim that the difference of opinion can be considered as an exogenous regressor.

VI. Discussion and concluding remarks

The main question investigated in this paper is whether FV shocks affect bubbles and asset mispricing, trading volume and the difference of opinions in experimental asset markets. We found strong evidence that shocks affect negatively the volume of transactions, positively the difference of opinions and that they tend to mitigate mispricing. However, there is no general impact of shocks on bubble measures.

Mispricing appears in almost all markets, with and without FV shocks. More precisely prices remain above the FV even after the shock, independently of the type of shock (expected or unexpected) and the direction of the shock (upwards and downwards). Overall shocks do not seem to have a clear effect on most of the bubble measures. We tentatively conclude that shocks do not affect the formation of bubbles, despite a tempering effect on price deviation. We thereby provide additional support to the hypothesis that the formation of bubbles is a quite general phenomenon in experimental asset markets, whether the FV is decreasing or constant, whether alternative activities are available or not, and whether shocks affect the FV or not. It seems therefore that the bubble phenomenon is rather driven by the institutional design of the stock market. For instance, Haruvy and Noussair, (2006) showed that short-selling reduces sharply the prices leading to frequent trades below the FV.

Concerning trading volume, we found that shocks depress equally the volume of transactions whatever the direction of the shock (upwards or downwards) and whatever the type of the shock (expected or unexpected). We also found strong evidence that after a shock the difference of opinions increases. Taken together these two facts seem to contradict both the theoretical predictions and previous experimental findings about a positive correlation between trading volume and the DO. However, our data remains compatible with the hypothesis that traders' DO affects positively trading volume.

Some of our results agree with earlier findings in the literature. Result 5 agrees with the findings of Weber and Welfens, (2009) and Nosic and Weber, (2009) who reported a drop in turnover after new information about the FV became available. The nature of the shock that we consider in our experiment is similar to the provision of new information about the FV. Results 5 and 6 are also in line with earlier findings by Nosic and Weber (2009) who observed a positive relation between the difference of opinion and turnover, as well as a positive relation between the variation of the difference of opinion and the variation of turnover before and after a shock.

An alternative explanation for the drop in turnover after a shock is the heterogeneity in risk attitudes among the population of traders. Unfortunately, our data does not allow to test this hypothesis, because we elicited subjects' risk aversion only once (at the end of the market) and therefore we are unable to measure how the distribution of risk-aversion was eventually affected by the shock. Note however, that Nosic and Weber, (2009) found that transaction volume is not affected by the disparity in risk-aversion, but only by the DO. It could nevertheless be interesting to investigate changes in risk-attitudes in future work.

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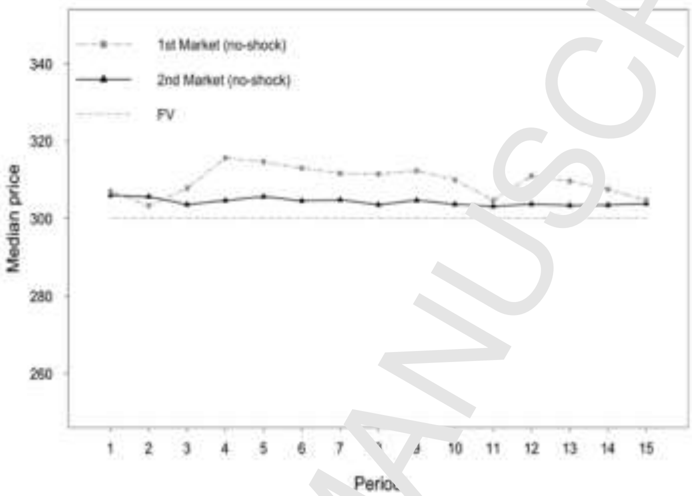
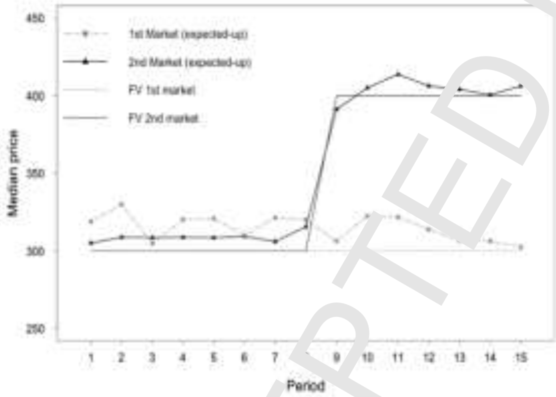
Figure 1: Time series of median prices

Figure 1 plots the time series of the mean of median transaction price by treatment and direction of the shock in first and second markets. The horizontal axis shows the period and the vertical axis indicates the median transaction price. The dashed dotted line indicates the mean of median price in first market and the bold dotted line indicates the mean of median price in second market. The FV is equal to 300 ecus in markets without shock and in the 8 first periods of markets with shock. In periods 9 -15 of markets with shock, the FV is either equal to 200 (downwards shock) or 400 (upwards shock).

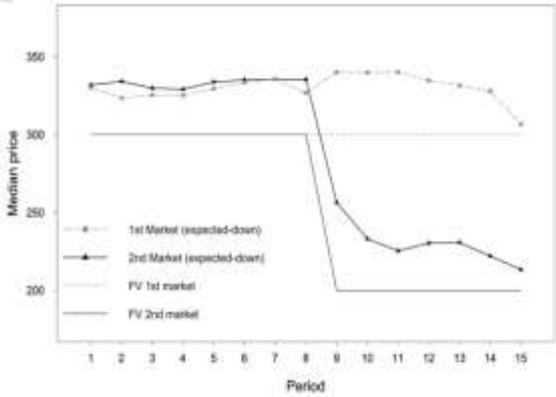
No-shock



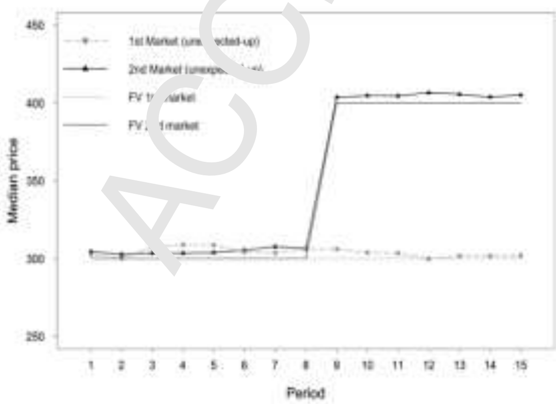
Expected Up



Expected Down



Unexpected Up



Unexpected Down

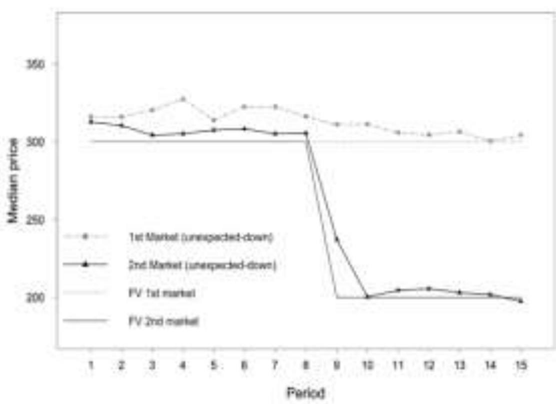
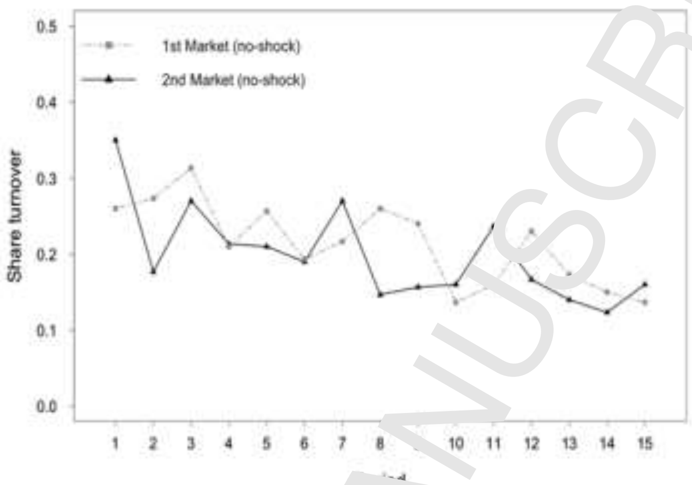


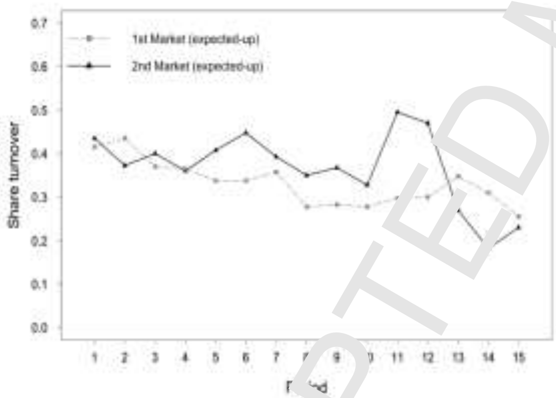
Figure 2: Time series of share turnover

Figure 2 shows the mean share turnover by treatment and direction of the shock in first and second markets. The horizontal axis shows the period and the vertical axis indicates the mean of share turnover. The dashed dotted line indicates the mean share turnover in first market and the bold dotted line indicates the mean share turnovers in second market.

No-shock



Expected Up



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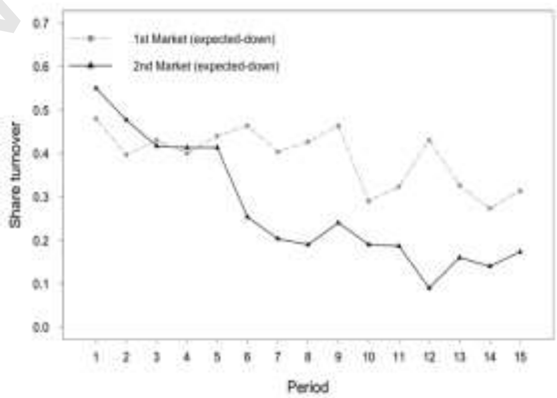

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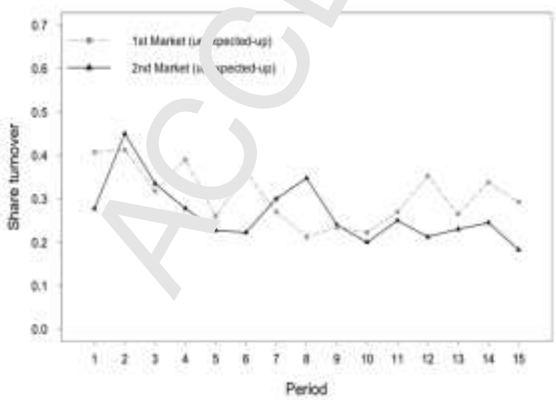

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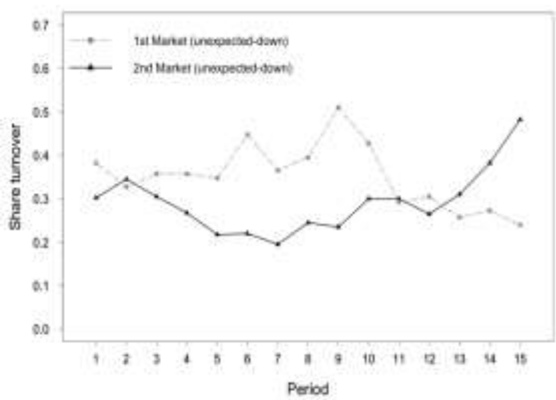
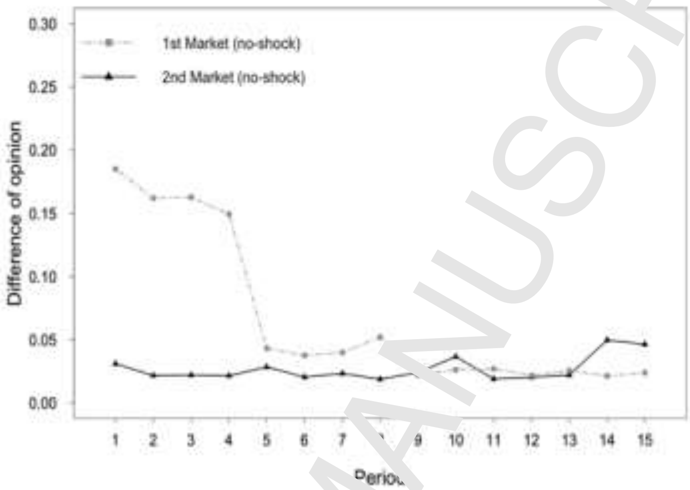


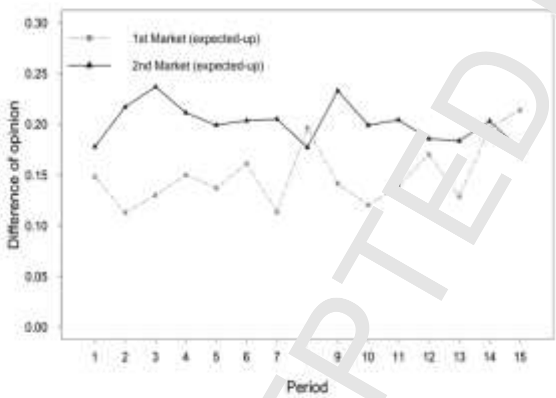
Figure 3: Time series of the difference of opinions (DO)

Figure 3 represents the mean DO by treatment and direction of the shock in first and second markets. The DO is measured by the normalized standard deviation of traders' forecasts: $SF_t = \sigma_{f_t} / MF_t$, where σ_{f_t} and MF_t represent the standard deviation of the traders' forecasts at period t and the mean of median forecasts at period t, respectively. The horizontal axis shows the period and the vertical axis indicates the SF. The dashed dotted line indicates the mean SF in first market and the bold dotted line indicates the mean SF in second markets. Note that we eliminated outliers by adding the condition: σ_f < 190.

No-shock



Expected Up



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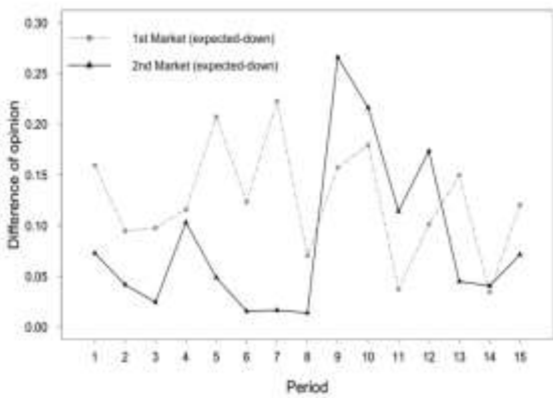
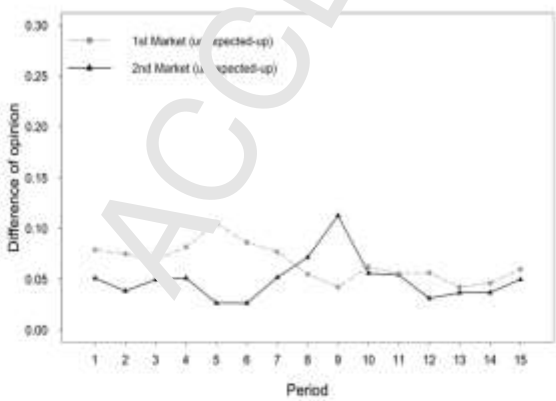


Unexpected Up



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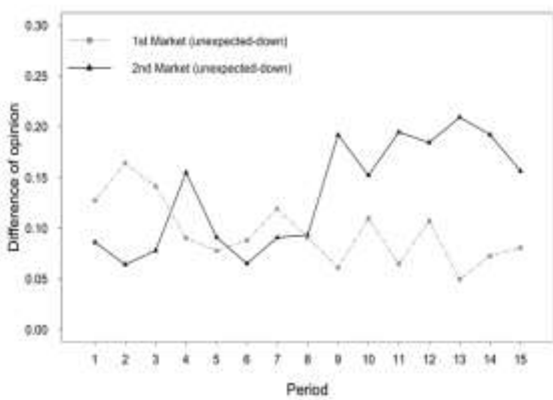


Tables

Table 1: Experimental design

<table>
<tr><th>Markets</th><th>Type[a]</th><th>Direction[b]</th><th>Groups</th><th>Portfolio type: endowments (ecus, shares)/ portfolio value (ecus)[c]</th><th>Dividend distribution (ecus), probabilities, expected value and variance[d]</th><th>FV from period 1 to 8[e]</th><th>FV from period 9 to 15[f]</th></tr>
<tr><td>Market 1</td><td></td><td colspan="2">All groups: G1, G2, G3, G5, G6, G7, G8, G17, G18, G19, G20, G21, G22, G23, G24, G25, G26, G27</td><td rowspan="6">P1: (5850, 3) / 6,750
P2: (4950, 6) / 6,750
P3: (4050, 9) / 6,750</td><td rowspan="6">D = (-45, -15, 15, 45)
P(D)= (1/4, 1/4, 1/4, 1/4)
E(D) = 0
$\sigma^2(D)$= 1125</td><td rowspan="6">FV = 300</td><td>FV = 300</td></tr>
<tr><td rowspan="5">Market 2</td><td>T0: No-shock</td><td colspan="2">G17, G18, G19</td><td>FV = 300</td></tr>
<tr><td rowspan="2">T1: Expected</td><td>Up</td><td>G1, G3, G5, G7</td><td rowspan="4">FV = 200
Or
FV = 400</td></tr>
<tr><td>Down</td><td>G2, G6, G8</td></tr>
<tr><td rowspan="2">T2: Unexpected</td><td>Up</td><td>G20, G21, G24, G25</td></tr>
<tr><td>Down</td><td>G22, G23, G26, G27</td></tr>
</table>

Note: Each market had 15 transactions periods of two minutes. Each subject participated in two consecutive markets: 1st market without shock followed by 2nd market (with shock in T1 and T2 and without shock in T0).

[a] T0: 1st market and 2nd are without shock, T1: 1st market is without shock and 2nd market with an expected shock, T2: 1st market is without shock and 2nd market with an unexpected shock.

[b] Direction is upward or downward (T1 and T2).

[c] 9 traders per group. The groups remained identical for the two markets. In each group subjects were randomly assigned to one of three portfolio types: P1, P2 or P3. Each group consisted of 3 traders of each type. The expected value of a portfolio is equal to 6,750 ecus for all types.

[d] Each dividend outcome occurs with probability 1/4 in each period.

[e,f] The expected buyout value for market 1 is constant and equal to 300 ecus. For market 2, the expected buyout value in the pre-shock periods (1-8) was equal to 300 ecus. In the post-shock periods (9-15) the expected buyout value was equal to 300 ecus in T0, to 400 ecus in the upward case and to 200 ecus in the downward case.

Table 2: Variables affecting price deviation (*median price – FV*)

Table 2 summarizes the results of seven panel regressions (fixed effects) for 2nd market, where *Price deviation = (median price – FV)* is the dependent variable. Independent variables are the binary variables *T0* (equal to 1 if the treatment is T0), *Post* (equal to 1 for periods 9-15 and to 0 for periods 1-8), *Type* (equal to 1 if the shock is unexpected and to 0 otherwise), *Dir* (equal to 1 if the shock is downwards and to 0 otherwise). Several interaction variables are included: $Post \times T0$ captures the post-shock effect whatever the direction or the type of the shock, $Post \times Dir$ captures the post-shock effect of the downward shock, $Post \times Type$ captures the post-shock effect of the unexpected shock and $Dir \times Type$ captures the additional effect of a downward shock that is unexpected. $Post \times Dir \times Type$ captures the post-shock effect of a downward unexpected shock (after knowing the direction of the shock).

Dependent variable = Price Deviation

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Post	-1.767	-1.896	-1.767	-2.415	-1.767	-4.023*	-4.924*
	(0.154)	(0.164)	(0.154)	(0.195)	(0.154)	(0.043)	(0.062)
T0	-6.954	-7.315	-13.407	-13.407	-1.709	-1.709	-2.986
	(0.565)	(0.548)	(0.301)	(0.301)	(0.894)	(0.894)	(0.829)
$Post \times T0$		0.774					
		(0.817)					
Dir			12.098	11.555			24.135*
			(0.213)	(0.238)			(0.084)
$Post \times Dir$				1.165			2.103
				(0.64[illegible])			(0.601)
Type					-11.239	-12.962	-4.094
					(0.251)	(0.189)	(0.752)
$Post \times Type$						3.691	5.019
						(0.146)	(0.178)
$Dir \times Type$							-21.269
							(0.264)
$Post \times Dir \times Type$							-2.773
							(0.594)
_cons	12.078**	12.138**	6.432	6.734	18.072**	19.125***	8.781
	(0.015)	(0.015)	(0.335)	(0.315)	(0.012)	(0.008)	(0.337)
N	270	270	270	270	270	270	270
chi2	2.360	2.407	3.920	4.131	3.685	5.806	9.569
r2_o	0.0[illegible]8	0.018	0.088	0.089	0.079	0.081	0.223

* p < 0.10. ** p < 0.05. *** p < 0.01

N: number of observations, *chi2:* Pearson's χ^2, *r2_o:* overall R-squared.

Table 3: Variables affecting share turnover

Table 3 summarizes the results of four panel regressions (fixed effects) for 2nd market, where *Share turnover* is the dependent variable. Independent variables are, *SF* corresponding to $SF_t = \sigma_{f_t} / MF_t$ where σ_{f_t} and MF_t represent the standard deviation of the traders' forecasts at period t and the mean median forecast at period t, respectively. Independent variables are the dummies *Post* (equal to 1 for periods 9-15 and to 0 for periods 1-8), *Type* (equal to 1 if the shock is unexpected), *Dir* (equal to 1 if the shock is downwards). Several interaction variables between these variables are included. $Post \times SF$ represents the interaction between the two variables $Post$ and SF. $Type \times SF$ represents the interaction between the two variables $Type$ and SF. $Dir \times SF$ represents the interaction between the two variables Dir and SF. $Post \times Type$ captures the post-shock effect of the unexpected shock. $Dir \times Type$ captures the additional effect of the downward and unexpected shock. $Post \times SF \times Type$ represents the interaction between the three variables Post, SF and $Type$, which captures the post-shock effect of the downward and unexpected shock (after knowing the direction of the shock). $Post \times SF \times Dir$ represents the interaction between the three variables $Post$, SF and Dir. $Post \times Type \times Dir$ represents the interaction between the three variables $Post$, $Type$ and Dir. $Post \times SF \times Type \times Dir$ represents the interaction between the three variables $Post$, SF, $Type$ and Dir.

Dependent variable = Share turnover

	(1)	*(2)*	*(3)*	*(4)*
Post	-0.067**	-0.123***	-0.071**	0.038
	(0.019)	(0.003)	(0.032)	(0.514)
SF	0.504***	0.281	0.4[illegible]**	0.821***
	(0.004)	(0.174)	(0.050)	(0.010)
Type		-0.091		0.106
		(0.114)		(0.366)
Dir			-0.043	0.025
			(0.415)	(0.846)
$Post \times SF$	-0.012	0.102	-0.007	-0.091
	(0.947)	(0.586)	(0.970)	(0.712)
$Type \times SF$		0.330		-1.471***
		(0.289)		(0.005)
$Dir \times SF$			0.118	1.110**
			(0.708)	(0.033)
$Post \times Type$		0.071*		-0.081
		(0.[illegible])		(0.277)
$Dir \times Type$				-0.138
				(0.372)
$Post \times Dir$			0.003	-0.025
			(0.940)	(0.773)
$Post \times SF \times Type$				0.885
				(0.223)
$Post \times SF \times Dir$				-1.879***
				(0.001)
$Post \times Type \times Dir$				0.120
				(0.330)
$Post \times SF \times Type \times Dir$				1.325
				(0.112)
_cons	0.272***	0.333***	0.296***	0.229**
	(0.000)	(0.000)	(0.000)	(0.016)
N	214	214	214	214
chi2	18.538	25.329	19.203	53.165
r2_o	0.110	0.139	0.133	0.168

* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$

N: number of observations, *chi2:* Pearson's χ^2, *r2_o:* overall R-squared.

Note : For all regressions we eliminated outliers by adding the condition : $\sigma_f < 190$.

Table 4: Variables affecting the difference of opinions (SF)

Table 4 summarizes the results of five panel regressions (fixed effects) for 2nd market, where the dependent variable is SF. *SF* equals to $SF_t = \sigma_{f_t} / MF_t$, where σ_{f_t} *and* MF_t represent the standard deviation of the traders' forecasts at period t and the mean of median forecasts at period t, respectively. Independent variables are the dummies *Post* equals to 1 for periods 9-15 and to 0 for periods 1-8, *Type* equals to 1 if unexpected shock and to 0 otherwise and *Dir* equals to 1 if downward shock and to 0 otherwise. Several interaction variables between these variables are included. $Post \times Type$ captures the post-shock effect of the unexpected shock. $Post \times Dir$ captures the post-shock effect of the downward shock. $Dir \times Type$ captures the additional effect of the downward and unexpected shock. $Post \times Type \times Dir$ represents the interaction between the three variables $Post, Type$ and Dir. *N*, *chi2 and r2_o* represent the number of observations, Pearson's χ^2 and the overall R-squared, respectively.

Dependent variable = SF

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$Post$	0.040***	0.027**	0.001	0.040***	-0.006
	(0.000)	(0.011)	(0.894)	(0.000)	(0.634)
$Type$	-0.076	-0.086*		-0.151**	-0.158**
	(0.138)	(0.081)		([illegible])	(0.010)
Dir	0.009		-0.039	-0.080	-0.125*
	(0.865)		(0.457)	(0.224)	(0.061)
$Post \times Type$		0.023			0.014
		(0.111)			(0.420)
$Post \times Dir$			0.089***		0.093***
			(0.000)		(0.000)
$Dir \times Type$				0.164*	0.169*
				(0.067)	(0.062)
$Post \times Type \times Dir$					-0.008
					(0.753)
_cons	0.144***	0.154***	0.125***	0.182***	0.203***
	(0.001)	(0.000)	([illegible])	(0.000)	(0.000)
N	214	214	214	214	214
chi2	34.041	36.983	86.603	37.895	92.758
r2_o	0.137	[illegible]	0.081	0.310	0.355

* $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$

N: number of observations, *chi2:* Pearson's χ^2, *r2_o:* overall R-squared.

Note : For all regressions we eliminated outliers by adding the condition : $\sigma_f < 190$.

Appendix 1

Table A: Definition and computation of bubble measures

Measure	***Computation***
Share turnover (ST)	$ST = q_t / TSU$
Price amplitude (PA)	$PA = max_t\{(P_t - f_t)/f_1\} - min_t\{(P_t - f_t)/f_1\}$
Price deviation (PD)	$PD_t = \mathrm{P_t} - \mathrm{f_t}$
Normalized absolute FV deviation (ND)	$ND = \sum_t \sum_i \lvert \mathrm{P_{it}} - \mathrm{f_t} \rvert / \mathrm{TSU}$
Duration (D)	$D = Max\{T: P_t - f_t < P_{t+1} - f_{t+1} < \cdots < P_{t+(T-1)} - f_{t+(T-1)}\}$
Total dispersion (TD)	$TD = \sum_{t=1}^{T} \lvert P_t - f_t \rvert$
Average bias (AB)	$AB = \frac{1}{T} \sum_{t=1}^{T} (P_t - f_t)$
Relative absolute deviation (RAD)	$\mathrm{RAD} = \frac{1}{T} \sum_{t=1}^{T} \lvert P_t - f_t \rvert / \lvert f_t \rvert$
Relative deviation (RD)	$\mathrm{RD} = \frac{1}{T} \sum_{t=1}^{T} (P_t - f_t) / \lvert f_t \rvert$
Volatility (Vol)	$\mathrm{Vol} = \frac{1}{T} \sum_{t=1}^{T} \lvert (P_t - f_t) - (P_{t-1} - f_{t-1}) \rvert$
Geometric absolute deviation (GAD)	$\mathrm{GAD} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} \left\lvert \ln\left(\frac{P_t}{f_t}\right) \right\rvert\right) - 1$
Geometric deviation (GD)	$\mathrm{GD} = \left(\prod_{t=1}^{T} \left(\frac{P_t}{f_t}\right)\right)^{\frac{1}{T}} - 1$
Boom Duration (BoomD)	Max number of consecutive periods for which P_t is above FV
Bust Duration (BustD)	Max number of consecutive periods for which P_t is below FV

Where: q_t represents the quantity of units of the asset exchanged in period t and TSU is the total stock of units that subjects hold. P_t is the median transaction price in period t and $\mathrm{f_t}$ is the FV in period t. T stands for the total number of periods and $\mathrm{P_{it}}$ is the price of the ith transaction in period t and

- ST: Share Turnover is equal to the total trading volume over a market divided by the number of shares outstanding (the total number of shares). The number of shares outstanding is always equal to 54 in our experiment. Usually, a high turnover is associated with bubbles.

- PA: Price Amplitude: A high amplitude means that extreme prices depart strongly from the FV.

- ND: Normalized Absolute FV Deviation: considers the quantities and the prices jointly and can identify large trading quantities and deviations from the FV.

- D: The *duration (D)* is the number of periods for which one observes an increase in market prices relative to the FV of the asset (Porter and Smith (1995)).

- TD: Total Dispersion is the sum of the absolute difference for each period between the price and the FV. Thus a high (low) total dispersion indicates large (small) price deviations from the FV and is consequently a measure of price variability.

- AB: Average Bias indicates the average gap from the FV. Since there are both positive and negative values depending on the periods, and because it is an average, a negative (positive) value indicates an aggregate tendency to be below (above) the FV.

- PD: Price deviation captures the difference for each period between price and FV.

- RAD: Relative absolute deviation captures the sum of the absolute differences for each period between price and FV. This indicator is then normalized by the absolute mean of the FV over all the periods and the number of periods. Thus RAD measures mispricing, i.e. price deviations both above and below the FV. A high RAD indicates prices do not track the FV, allowing the identification of either bubbles and/or crashes. For example, a RAD of 0.3 means that prices differ on average per period of 30% from the average FV.

- RD: Relative deviation measures the over or underpricing. Since there is no absolute value, a negative (positive) RD indicates prices are on average below (above) the FV. This indicator is therefore very complementary to the RAD. For example, a high RAD with a zero RD (Stöckl, Huber, and Kirchler (2010)) would mean that prices largely differ from the FV but are equally below and above it.

- Vol: The Volatility (with P_t and P_{t-1} the respective prices and f_t and f_{t-1} the respective FV in periods t and t−1) measures the variability of prices in relation to the FV. The more instability and fluctuations there are from the FV, the higher this indicator will be.

- GAD: Using the geometric mean, GAD allows to measure price deviations while having the property of being numeraire independent.

- GD: Geometric deviation allows over- and undervaluation to be measured by using geometric mean.

***Table B*: Bubble measures for 1st market (without shock)**

Bubble measures for 1st market for each group by treatment (T1 = expected shock, T2 = unexpected shock and T0 = no-shock). ST: share turnover, PA: price amplitude, ND: normalized absolute FV deviation, TD: total dispersion, AB: Average bias, RAD: Relative absolute deviation, RD: Relative deviation, Vol: Volatility, GAD: Geometric absolute deviation, GD: Geometric deviation, D: duration, BoomD: Boom Duration and BustD: Bust Duration. p-values for the Wilcoxon rank-sum test are reported at the bottom of the table * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	1st Markets	*ST*	*PA*	*ND*	*TD*	*AB*	*RAD*	*RD*	*Vol*	*GAD*	*GD*	*D*	*BoomD*	*BustD*
T1: Expected Shock	G1	[illegible]	0.08	3.61	190.00	13.57	0.05	0.05	8.71	0.04	0.04	2	13	0
	G2	[illegible]	[illegible]	4.22	198.00	14.14	0.05	0.05	2.86	0.05	0.04	2	13	0
	G3	[illegible]	0.17	5.00	250.00	17.86	0.06	0.06	15.71	0.06	0.05	2	4	0
	G5	5.20	0.27	4.63	230.00	12.86	0.05	0.04	21.36	0.05	0.04	1	4	1
	G6	4.87	[illegible]	[illegible]	1045.00	74.64	0.25	0.25	10.43	0.25	0.23	3	15	0
	G7	5.43	0.13	[illegible]	[illegible]	14.79	0.05	0.05	6.57	0.05	0.05	1	14	0
	G8	7.96	0.12	1.24	[illegible]	0.93	0.01	0.00	5.86	0.01	0.00	1	3	1
	Mean	***5.35***	***0.16***	***6.20***	[illegible]	[illegible]	***0.07***	***0.07***	***10.21***	***0.07***	***0.06***	***2***	***9***	***0***
	Median	***5.20***	***0.13***	***4.39***	[illegible]	[illegible]	***0.05***	***0.05***	***8.71***	***0.05***	***0.04***	***2***	***13***	***0***
T2: Unexpected Shock	G20	4.02	0.02	0.17	4.14	[illegible]	0.00	0.00	0.81	0.00	0.00	2	2	7
	G21	3.41	0.06	3.69	198.00	[illegible]	[illegible]	0.05	4.86	0.05	0.04	3	15	0
	G22	5.59	0.06	2.41	120.00	8.57	0.03	0.03	4.86	0.03	0.03	2	15	0
	G23	4.76	0.13	3.62	165.52	11.82	0.04	0.04	[illegible]	0.04	0.04	2	8	0
	G24	5.26	0.10	2.84	123.50	8.82	0.03	[illegible]	[illegible]	0.03	0.03	2	12	0
	G25	5.72	0.12	2.31	99.50	-6.39	0.02	[illegible]	[illegible]	[illegible]	-0.02	2	1	5
	G26	4.76	0.10	1.89	97.50	2.18	0.02	0.01	5.82	[illegible]	0.01	2	8	2
	G27	6.02	0.16	8.06	415.00	29.64	0.10	0.10	[illegible]	0.10	0.09	2	15	0
	Mean	***4.94***	***0.09***	***3.12***	***152.90***	***8.59***	***0.04***	***0.03***	***6.39***	[illegible]	[illegible]	***2***	***10***	***2***
	Median	***5.01***	***0.10***	***2.63***	***121.75***	***8.70***	***0.03***	***0.03***	***6.02***	[illegible]	[illegible]	***2***	***10***	***0***
T0: No-shock	G17	1.98	0.10	3.53	190.50	12.89	0.05	0.04	7.14	0.05	[illegible]	[illegible]	[illegible]	1
	G18	3.69	0.07	1.92	83.75	5.98	0.02	0.02	1.79	0.02	0.02	1	14	0
	G19	3.94	0.05	2.77	148.51	10.61	0.04	0.04	2.07	0.04	0.03	3	15	[illegible]
	Mean	3.20	0.07	2.74	140.92	9.83	0.03	0.03	3.67	0.03	0.03	2	[illegible]	0
	Median	3.69	0.07	2.77	148.51	10.61	0.04	0.04	2.07	0.04	0.03	3	14	[illegible]
Mean (T1 + T2 + T0)		***4.81***	***0.12***	***4.25***	***212.38***	***13.72***	***0.05***	***0.05***	***7.42***	***0.05***	***0.04***	***2***	***10***	***1***
Median (T1+T2+T0)		***4.81***	***0.10***	***3.57***	***177.76***	***12.34***	***0.04***	***0.04***	***6.39***	***0.04***	***0.04***	***2***	***13***	***0***
rank-sum (p-value) (T1 vs T2)		***0.772***	***0.091****	***0.121***	***0.105***	***0.105***	***0.111***	***0.128***	***0.224***	***0.143***	***0.124***	***0.188***	***1.000***	***0.490***
rank-sum (p-value) (T1 vs T0)		***0.067****	***0.051****	***0.117***	***0.183***	***0.183***	***0.224***	***0.161***	***0.117***	***0.345***	***0.194***	***0.398***	***0.356***	***1.000***
rank-sum (p-value) (T2 vs T0)		***0.052***	***0.470***	***0.921***	***1.000***	***0.776***	***0.756***	***0.757***	***0.412***	***0.756***	***0.917***	***0.550***	***0.673***	***0.723***

Table C: **Bubbles measures for 2nd market (with shock)**

Bubble measures for 2nd market for each group by treatment (T1 = expected shock. T2 = unexpected shock and T0 = no-shock) and by the direction of the shock (upward or downward): "before" and "after" the shock for treatments T1 and T2; "periods 2 – 8" and "periods 9 - 15" for treatment T0. Period 1 is not considered in order to have the same number of periods before (sequence 1) and after (sequence 2) the shock. ST: share turnover. PA: price amplitude. ND: normalized absolute FV deviation. TD: total dispersion. AB: Average bias. RAD: Relative absolute deviation. RD: Relative deviation. Vol: Volatility. GAD: Geometric absolute deviation. GD: Geometric deviation. D: duration. BoomD: Boom Duration and BustD: Bust Duration. p-values for the Wilcoxon rank-sum test are reported at the bottom of the table * *p < 0.10. ** p < 0.05. ***p < 0.01.*

		2nd Markets	*ST*		*PA*		*ND*		*TD*		*AB*		*RAD*		*RD*	
			Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
T1: Expected shock	**Upward**	G1	[illegible]	[illegible]	0.01	0.05	2.61	1.57	141.00	85.00	20.14	12.14	0.07	0.03	0.07	0.03
		G3	[illegible]	2.06	0.03	0.01	0.33	0.50	18.00	27.00	2.57	3.86	0.01	0.01	0.01	0.01
		G5	2.70	[illegible]	[illegible]	0.19	1.65	1.76	89.00	95.00	12.71	0.71	0.04	0.03	0.04	0.00
		G7	3.44	[illegible]	[illegible]	0.02	0.24	0.20	13.00	11.00	1.86	-1.29	0.01	0.00	0.01	0.00
	Downward	G2	1.61	1.02	[illegible]	[illegible]	1.37	1.31	74.00	71.00	10.57	10.14	0.04	0.05	0.04	0.05
		G6	1.39	1.35	[illegible]	0.45	11.89	9.72	642.00	525.00	91.71	75.00	0.31	0.38	0.31	0.38
		G8	4.09	1.19	0.03	0.29	0.39	1.15	21.00	62.00	-3.00	5.14	0.01	0.04	-0.01	0.03
	Mean up		**2.73**	**2.35**	**0.04**	[illegible]	[illegible]	**1.01**	**65.25**	**54.50**	**9.32**	**3.86**	**0.03**	**0.02**	**0.03**	**0.01**
	Mean down		**2.36**	**1.19**	**0.04**	**0.28**	[illegible]	[illegible]	**245.67**	**219.33**	**33.09**	**30.09**	**0.12**	**0.16**	**0.11**	**0.15**
T2: Unexpected shock	**Upward**	G20	3.13	1.78	0.03	0.01	0.32	[illegible]	17.50	8.00	2.50	1.14	0.01	0.00	0.01	0.00
		G21	1.09	0.50	0.03	0.03	1.90	[illegible]	[illegible]	119.00	14.64	17.00	0.05	0.04	0.05	0.04
		G24	2.17	2.30	0.02	0.01	0.16	[illegible]	8.50	8.90	1.21	1.27	0.00	0.00	0.00	0.00
		G25	2.24	1.70	0.03	0.03	0.25	0.33	[illegible]	[illegible]	0.50	-0.29	0.01	0.01	0.00	0.00
	Downward	G22	1.37	1.87	0.04	0.25	1.10	1.71	[illegible]	[illegible]	8.50	13.21	0.03	0.07	0.03	0.07
		G23	1.61	1.81	0.05	0.50	1.39	2.37	[illegible]	[illegible]	10.73	12.00	0.04	0.09	0.04	0.06
		G26	1.35	1.87	0.03	0.08	0.72	1.10	39.00	59.50	[illegible]	8.50	0.02	0.04	0.02	0.04
		G27	2.83	3.54	0.05	0.04	0.37	0.64	20.00	[illegible]	[illegible]	-4.93	0.01	0.02	0.01	-0.02
	Mean up		**2.16**	**1.57**	**0.03**	**0.02**	**0.66**	**0.71**	**35.50**	**38.48**	[illegible]	[illegible]	**0.02**	**0.01**	**0.02**	**0.01**
	Mean down		**1.79**	**2.27**	**0.04**	**0.22**	**0.90**	**1.46**	**48.40**	**78.63**	**6.59**	**7.20**	[illegible]	**0.06**	**0.03**	**0.04**

		ST		*PA*		*ND*		*TD*		*AB*		*RAD*		*RD*	
		p2-p8	p9-p15	p2-p8	p9-p15	p2-p8	p9-p15	p2-p8	p9-p15	p2-p8	p9-p15	p2-p8	p9-p15	p2-p8	p9-p15
T0: No-shock	G17	0.72	1.48	0.02	0.01	0.43	0.15	23.00	8.00	3.29	1.14	0.01	0.00	0.01	0.00
	G18	1.41	0.61	0.01	0.00	0.07	0.03	3.60	1.64	0.29	-0.23	0.00	[illegible]	0.00	0.00
	G19	2.33	1.33	0.01	0.00	1.35	1.32	72.75	71.34	10.39	10.19	0.03	0.03	0.03	0.03
Mean		**1.49**	**1.14**	**0.01**	**0.00**	**0.62**	**0.50**	**33.12**	**26.99**	**4.66**	**3.70**	**0.01**	**0.01**	**0.01**	**0.01**

		2nd Markets	*Vol* Before	*Vol* After	*GAD* Before	*GAD* After	*GD* Before	*GD* After	*D* Before	*D* After	*BoomD* Before	*BoomD* After	*BustD* Before	*BustD* After
T1: Expected shock	**Upward**	G1	0.71	4.17	0.07	0.03	0.07	0.03	1	1	7	5	0	0
		G3	3.71	1.83	0.01	0.01	0.01	0.01	1	1	1	6	0	0
		G5	8.43	20.83	0.04	0.03	0.04	0.00	1	2	5	1	0	1
		G7	1.14	1.17	0.01	0.00	0.01	0.00	1	1	4	1	0	2
	Down-ward	[illegible]	3.00	4.00	0.04	0.05	0.04	0.05	4	1	7	6	0	0
		G6	8.29	22.67	0.31	0.37	0.31	0.37	3	2	7	7	0	0
		G8	[illegible]	11.50	0.01	0.04	-0.01	0.02	1	2	0	1	3	3
	Mean up (T1)		**3.50**	**7.00**	**0.03**	**0.02**	**0.03**	**0.01**	**1.00**	**1.25**	**4.25**	**3.25**	**0.00**	**0.75**
	Mean down (T1)		[illegible]	**12.72**	**0.12**	**0.15**	**0.11**	**0.15**	**2.67**	**1.67**	**4.67**	**4.67**	**1.00**	**1.00**
T2: Unexpected shock	**Upward**	G20	1.43	[illegible]	[illegible]	0.00	0.01	0.00	3	3	4	3	0	0
		G21	2.79	3.33	0.05	0.04	0.05	0.04	1	2	7	7	0	0
		G24	2.07	1.12	0.00	[illegible]	0.00	0.00	1	1	4	5	0	0
		G25	3.57	5.83	[illegible]	0.01	0.00	0.00	2	1	3	1	1	1
	Down-ward	G22	3.71	12.50	0.03	[illegible]	[illegible]	0.06	2	1	7	6	0	0
		G23	4.11	23.83	0.04	0.08	[illegible]	0.05	2	1	7	2	0	3
		G26	3.86	5.00	0.02	0.04	[illegible]	0.04	1	2	4	6	0	0
		G27	3.43	1.33	0.01	0.03	0.01	-0.02	1	1	3	0	1	7
	Mean up (T2)		**2.47**	**2.78**	**0.02**	**0.01**	**0.02**	**0.01**	**1.75**	**1.75**	**4.50**	**4.00**	**0.25**	**0.25**
	Mean down (T2)		**3.78**	**10.67**	**0.03**	**0.05**	**0.03**	[illegible]	[illegible]	**1.25**	**5.25**	**3.50**	**0.25**	**2.50**

			Vol p2-p8	*Vol* p9-p15	*GAD* p2-p8	*GAD* p9-p15	*GD* p2-p8	*GD* p9-p15	*D* p2-p8	*D* p9-p15	*BoomD* p2-p8	*BoomD* p9-p15	*BustD* p2-p8	*BustD* p9-p15
T0: No-shock		G17	2.57	1.25	0.01	0.00	0.01	0.00	2	2	5	2	0	0
		G18	0.53	0.21	0.00	0.00	0.00	0.00	2	2	2		2	7
		G19	0.57	0.24	0.03	0.03	0.03	0.03	1	2	7	7	0	0
	Mean		**1.22**	**0.57**	**0.01**	**0.01**	**0.01**	**0.01**	**1.67**	**2.00**	**4.67**	[illegible]	**0.67**	**2.33**

Table D: Difference between bubble measures before and after the shock in markets with shocks

D1.Significance of differences before and after (p-values, Wilcoxon signed-rank test)

Before vs after (p-values)	ST	PA	ND	TD	AB	RAD	RD	Vol	GAD	GD	D	BoomD	BustD
All 2nd markets (with shocks)	0.201	0.025*	0.315	0.303	0.524	0.238	0.637	0.030**	0.195	0.844	0.608	0.17	0.100
By type of shock													
Expected	0.047**	0.059*	[illegible]	[illegible]	0.297	0.752	0.916	0.078*	0.752	1.000	0.850	0.599	0.371
Unexpected	0.945	0.402	0.052*	[illegible]	[illegible]	0.248	0.675	0.313	0.142	0.833	0.766	0.233	0.371
By direction of the shock													
Upward	0.039**	0.786	0.933	0.844	0.250	[illegible]	0.058*	0.461	0.057*	0.058*	0.773	0.396	0.371
Downward	0.938	0.031**	0.375	0.375	0.938	[illegible]	[illegible]	[illegible]	0.022**	0.147	0.374	0.396	0.371

* p<0.10. ** p<0.05. *** p<0.01

D2: Mean values before and after the shock (overall)

M (2nd)	***ST***		***PA***		***ND***		***TD***		***AB***		***RAD***		***RD***	
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
Mean all	2.25	1.89	0.04	0.14	1.65	1.66	88.91	89.63	12.12	10.24	0.04	[illegible]	0.04	0.05
(p-value)	0.201		0.025**		0.315		0.303		0.524		0.238		0.637	
M (2nd)	***Vol***		***GAD***		***GD***		***D***		***BoomD***		***BustD***			
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*		
Mean All	3.86	8.00	0.04	0.05	0.04	0.04	1.67	1.47	4.67	3.80	0.33	1.13		
(p-value)	0.030**		0.195		0.844		0.608		0.17		0.1			

* p<0.10. ** p<0.05. *** p<0.01

D3: Mean values before and after the shock by type of shock (expected vs unexpected)

	ST		PA		ND		TD		AB		RAD		RD	
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
Mean T1	[illegible]	1.85	0.04	0.16	2.64	2.32	142.57	125.14	19.51	15.10	0.07	0.08	0.07	0.07
(p-value)	[illegible]		*0.059**		*0.813*		*0.813*		*0.297*		*0.752*		*0.916*	
Mean T2	[illegible]	[illegible]	0.04	0.16	2.44	2.24	131.75	120.79	17.96	13.92	0.06	0.08	0.06	0.07
(p-value)	*0.945*		*0.402*		*0.052**		*0.039***		*0.641*		*0.248*		*0.675*	

	Vol		GAD		GD		D		BoomD		BustD	
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
Mean T1	4.71	9.45	[illegible]	[illegible]	0.07	0.07	1.71	1.43	4.43	3.86	0.43	0.86
(p-value)	*0.078**		[illegible]		[illegible]		*0.85*		*0.599*		*0.371*	
Mean T2	3.12	6.72	0.02	0.03	[illegible]	0.02	1.63	1.50	4.88	3.75	0.25	1.38
(p-value)	*0.313*		*0.142*		[illegible]		*0.766*		*0.233*		*0.371*	

* p<0.10. ** p<0.05. *** p<0.01

D4: Mean values before and after the shock by direction of the shock (upper vs down)

	ST		PA		ND		TD		AB		RAD		RD	
	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After	Before	After
Mean up M (2nd)	2.45	1.96	0.03	0.04	0.93	0.86	50.38	46.49	[illegible]	4.32	0.03	0.02	0.02	0.01
(p-value)	*0.039***		*0.786*		*0.933*		*0.844*		*0.25*		*0.057**		*0.058**	
Mean down M (2nd)	2.04	1.81	0.04	0.24	2.46	2.57	132.94	138.93	[illegible]	[illegible]	0.07	0.10	0.06	0.09
(p-value)	*0.938*		*0.031***		*0.375*		*0.375*		[illegible]		*0.016***		*0.109*	

	Vol		GAD		GD		D		BoomD		BustD	
	Before	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*	*Before*	*After*
Mean up M (2nd)	2.98	4.89	0.03	0.02	0.02	0.01	1.38	1.50	4.38	3.63	[illegible]	[illegible]
(p-value)	*0.461*		*0.057**		*0.058**		*0.773*		*0.396*		[illegible]	
Mean down M (2nd)	4.87	11.55	0.07	0.10	0.06	0.08	2.00	1.43	5.00	4.00	0.57	[illegible]
(p-value)	*0.078**		*0.022***		*0.147*		*0.374*		*0.396*		*0.371*	

* p<0.10. ** p<0.05. *** p<0.0

***Table E*: Variables affecting the difference of opinions (RFAD)**

Table E summarizes the results of five panel regressions (fixed effects) for 2nd market, where the dependent variable is RFAD (relative absolute forecast deviation from prices) Hanaki, Akiyama, and Ishikawa (2018). RAFD equals to $RAFD_t = \frac{1}{N} \sum_{s=1}^{N} \frac{|f_s^t - FV_t|}{\overline{FV}}$, where T is the number of periods (T = 15), f_i^t is the forecast of median transaction price submitted by subject s in period t, N is the total number of subjects in each group, FV_t is the fundamental value of the asset in period t, and $\overline{FV}$ is the average fundamental value of the asset over all periods (= 300 if no-shock, = $1/15 \times ((300 \times 8) + (400 \times 7))$ if the shock is upwards, = $1/15 \times ((300 \times 8) + (400 \times 7))$ if the shock is downwards). Independent variables are the dummies *Post* equals to 1 for periods 9-15 and to 0 for periods 1-8, *Type* equals to 1 if unexpected shock and to 0 otherwise and *Dir* equals to 1 if downward shock and to 0 otherwise. Several interaction variables between these variables are included. $Post \times Type$ captures the post-shock effect of the unexpected shock. $Post \times Dir$ captures the post-shock effect of the downward shock. $Dir \times Type$ captures the additional effect of the downward and unexpected shock. $Post \times Type \times Dir$ represents the interaction between the three variables $Post$, $Type$ and Dir. *N, chi2 and r2_o* represent the number of observations, Pearson's χ^2 and the overall R-squared, respectively.

Dependent variable = RFAD

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
$Post$	0.013***	0.012**	0.011**	0.013***	0.012*
	(0.000)	(0.022)	(0.021)	(0.000)	(0.070)
$Type$	-0.047**	-0.046**		-0.046	-0.044
	(0.017)	(0.035)		(0.108)	(0.121)
Dir	0.035*		0.029	0.037	0.037
	(0.079)		(0.216)	(0.228)	(0.236)
$Post \times Type$		0.002			-0.002
		(0.819)			(0.792)
$Post \times Dir$			0.005		0.000
			(0.460)		(0.979)
$Dir \times Type$				-0.004	-0.008
				(0.924)	(0.855)
$Dir \times Type \times Post$					0.008
					(0.574)
_cons	0.066***	0.081***	0.043***	0.065***	0.065***
	(0.000)	(0.000)	(0.007)	(0.001)	(0.001)
N	214	214	214	214	214
chi2	22.153	18.355	16.285	21.424	22.144
r2_o	0.343	0.210	0.108	0.344	0.345

* p<0.10, ** p<0.05, *** p<0.01

N: number of observations, *chi2:* Pearson's χ^2, *r2_o:* overall R-squared.

***Table F*: Comparison of OLS and 2SLS regression coefficients**

Column 1 summarizes the results of OLS regression for 2nd market, where the dependent variable is share turnover ($Y1 = Turnover$). Column 2 summarizes the results of 2SLS regression (first stage) for 2nd market, where the dependent variable is the difference of opinion measure (Y2 = SF). SF equals to $SF = \sigma_{f_t} / MF_t$, where σ_{f_t} and MF_t represent the standard deviation of the traders' forecasts at period t and the mean of median forecasts at period t, respectively. Column 3 summarizes the results of 2SLS regression (second stage) for 2nd market, where the dependent variable is share turnover (Y1 = $Turnover$). Independent variables are SF (endogenous variable to test), $Post$ equals to 1 for periods 9-15 and to 0 for periods 1-8 (exogenous variable) and $Type$ equals to 1 if unexpected shock and to 0 otherwise (instrumental variable). *N and* R-sq represent the number of observations and R-squared, respectively.

	OLS regression for (Y1 = Turnover)	*2SLS: first stage for (Y2 = SF)*	*2SLS: second stage for (Y1 = Turnover)*
	(1)	***(2)***	***(3)***
SF	0.458***		0.64[illegible]**
	(0.000)		(0.038)
$Post$	-0.066***	0.042***	-0.073***
	(0.003)	(0.003)	(0.003)
$Type$		-0.070***	
		(0.000)	
_cons	0.273***	0.142***	0.255***
	(0.000)	(0.000)	(0.000)
N	214	214	214
R-sq	0.11	0.14	0.10

* p<0.10, ** p<0.05, *** p<0.01

N: number of observations and R-sq: R-squared.

Note : For all regressions we eliminated outliers by adding the condition : $\sigma_f < 190$.

The null hypothesis that the regressors are exogenous is not rejected (Durbin (score), p = 0.529, Wu-Hausman p = 0.5330)
The null hypothesis that the OLS and 2SLS coefficients are equal is not rejected (Durbin-Wu-Hausman, p = 0.5330)

APPENDIX 2

Instructions

Appendix 2 provides a translation (from French) of Part 2 of the instructions in the case of an *Expected shock.*

MARKET 1

For this part you have the 20 euros you have won in Part 1 and are now yours. In Part 2 you can use all or part of your 20 euros to carry out transactions. For this purpose your 20 euros will be converted into experimental currency (ecus), with the exchange rate: **1 euro = 337.5 ecus**. You will therefore have an endowment of **6750 ecus** (20 euros × 337,5 ecus). The same exchange rate will be applied at the end of the experiment to convert ecus into euros.

In Part 2 you will participate in two experimental financial markets on which you can trade securities. In concrete terms, you will have the opportunity to buy and sell securities. When you have finished reading the instructions, you will participate in a trial period to familiarize yourself with the transaction software.

At the end of the trial period you will be assigned to a group of **nine people** with whom you will interact for the whole of part 2. The composition of your group will be determined randomly by the computer program. Once formed, your group will remain unchanged until the end of part 2. If you follow the instructions below carefully, you can make significant monetary gains.

I. Background

a) Duration of the market and Part 2 earnings

Part 2 is composed of ***two successive markets***. Each market is divided into 15 consecutive periods. Each period lasts 2 min. You will have 30 min to carry out transactions for each market.

At the end of Part 2, one of the two markets will be drawn at random to be paid out for real. The computer program will then calculate your final earnings for this market. The remainder of these instructions are for market 1 only. Specific instructions for market 2 will be provided after market 1 is completed.

b) Portfolios

Before the opening of market 1, your endowment of 6750 ECUSwill be allocated to a portfolio. In concrete terms, part of your allocation will be available in the form of **Securities** and the remainder in the form of **Experimental Currency** (ecus). The value of your portfolio before market opening 1 will be 6750 ecus, whatever its composition. The initial value of each security is 300 ecus.

There are three types of portfolio (Table 1) called P1, P2 and P3. The three types of portfolios all have the same initial value, equal to 6750 ecus.

Type	**Composition (securities , ecus)**	Value of securities (number of units × 300)	Initial portfolio value
P1	**(3 , 5850)**	900	6750
P2	**(6 , 4950)**	1800	6750
P3	**(9 , 4050)**	2700	6750

Table 1: composition and initial values of portfolios (in ecus)

Before the opening of market 1, the software will randomly assign you one of the three types of portfolios: P1, P2 or P3. Subsequently, you will receive the same portfolio composition for market 2. The 9 members of your group will not all have the same portfolio. 3 members will receive a portfolio of type P1, 3 other members a portfolio of type P2 and the remaining 3 members a portfolio of type P3.
Example: The computer program assigns you portfolio P1. Your portfolio at the beginning of each of the two markets will consist of 3 units of title and 585 ecus.

c) **Lifetime of a security and buyout value**

In each period, you can buy or sell securities. Each security has a lifetime equal to 15 periods (duration of the market).

At the end of the 15 periods the market will be closed. Units of securities that you will hold in your final portfolios will be redeemed by the experimenter. The redemption value of each unit of security is set at 300 ecus.

d) **Deferral of the portfolio**

Your portfolio is carried over from period to period without change in composition.

Example: At the end of period 5 your portfolio is composed of 5 securities and 5500 ecus. The composition of your portfolio at the beginning of period 6 will be the same: 5 securities and 5500 ecus.

e) **Losses and profits**

In addition to transaction gains and losses you have two sources of additional losses and profits: dividends and forecasts.

i) Dividends

At the end of each period, each unit of security you hold in your portfolio will generate a dividend that may be positive or negative. The dividend value at the end of each period will be randomly selected by the computer program. Four dividend values are possible: 45, 15, -15 and

-45 ecus (Table 2). Each value has a one-in-four chance of achieving each period (a probability of 0.25). Note that the expected dividend is equal to zero. (45 + 15 – 15 - 45) / 4 = 0 (see Table 3). The dividend value selected for a period will apply to all securities and participants.

Distribution of the unit dividend	
Ecus	Probability
45	0.25
15	0.25
-15	0.25
-45	0.25

Table 2: possible dividend values

Your dividends will be paid in each period into a savings account. The savings account cannot be used to make transactions. You will receive the accumulated amount on the savings account only at the end of the experiment.

ii) Forecasts

At the beginning of each period, we will ask you to forecast the transaction prices for the next period in the form of an interval. Concretely you will have to choose the interval in which you think the realized prices for the period will be located. This task will allow you to earn ecus. At the end of the period the profit of your forecast will be calculated as follows:

Forecast Profit = Forecast Gain - Cost of Forecasting

* The **profit of the forecast** varies between 0 and 5.
* The **Forecast Gain** depends on the number of prices correctly predicted. The number of correctly predicted prices is equal to the number of transactions whose prices fall within the range you have chosen. This gain varies between 0 and 5. Forecast gain = 5 ecus if all transaction prices realized fall within the forecast range.
* The **Cost of the forecast** depends on the size of the interval you have chosen.
This cost is increasing with the size of the interval.
Table 3 shows, by way of example, different winning possibilities that can be realized.

Example: In period 4, three transactions were carried out at the following prices: **340**, **350** and **360** ECU. Column (a) of Table 3 illustrates several examples of forecasts. Column (b) corresponds to the size of the interval (upper bound - lower bound + 1), column (c) indicates the number of transactions falling within the predicted range, column (d) Forecast and column (e) the cost of the forecast. The last column corresponds to the profit of the forecast, that is to say the difference between column (d) and column (e).

	Forecast interval (a)	Interval size (b)	Number of prices in the interval (c)	**Forecast gain (d)**	**Forecast cost (e)**	**Profit of the forecast (d) - (e)**
1	340 - 360	21	3	**5.00**	**0.00**	**5**
2	335 - 365	31	3	**5.00**	**1.20**	**3.80**
3	330 - 370	41	3	**5.00**	**2.39**	**2.61**
4	320 - 370	51	3	**5.00**	**3.58**	**1.42**
5	300 - 400	101	3	**5.00**	**5.00**	**0.00**
6	335 - 355	21	2	**3.33**	**0.00**	**3.33**
7	320 - 355	36	2	**3.33**	**1.78**	**1.55**
8	300 - 355	56	2	**3.33**	**4.16**	**0.00**
9	335 - 342	7	1	**1.66**	**1.54**	**0.12**
10	330 - 342	13	1	**1.66**	**0.95**	**0.71**
11	330 - 335	6	0	**0.00**	**1.78**	**0.00**
12	341 - 349	9	0	**0.00**	**1.42**	**0.00**

Table 3: Examples of prediction profit calculation

N.B. For examples 8, 11 and 12, the cost of the forecast is greater than the gain of the forecast. In these cases the profit of the forecast is equal to 0. The general rule is that if the cost is greater than the forecast gain, the forecast profit is equal to 0.

The profits of your forecasts will be paid into your savings account. As for dividends, you will not be able to use the amount of profits from your forecasts to make transactions and you will receive the accumulated amount the end of the experiment.

f) Transaction conditions

You cannot sell more securities during a period than those you hold in your portfolio. Equivalently, you can buy a security only if you hold the amount corresponding to its sale price in ecus.

Market Gain

Your total gain at the end of the market is calculated as follows:
Experimental currency in your portfolio (ecus)
+ Redemption value of securities (number of securities in your portfolio × 300)
+ Balance of the savings account (cumulative dividends and forecast profits).

Trial period

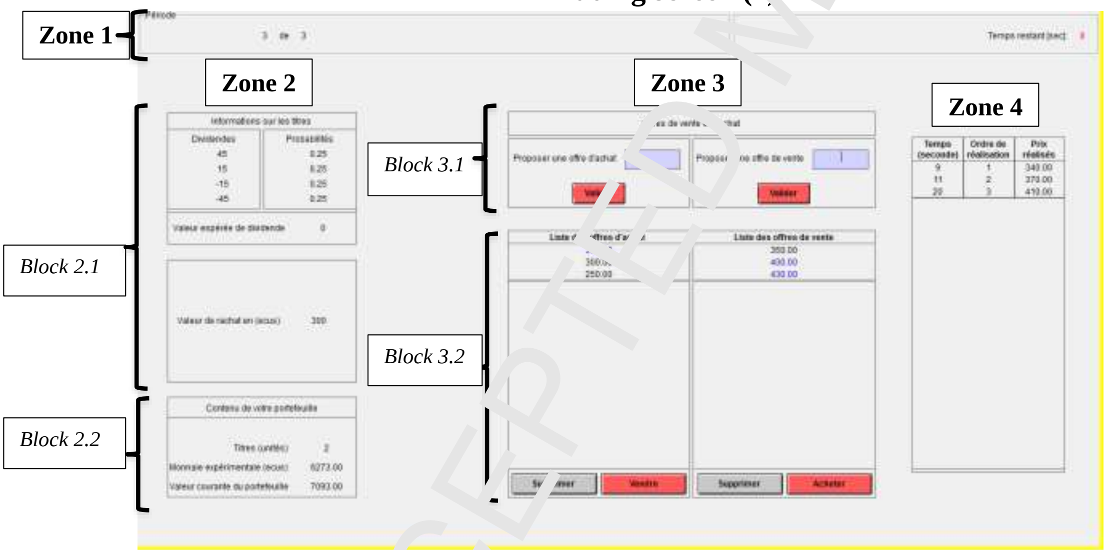
The trial period lasts **two minutes** and you will learn how to:

- Make a bid
- Make an ask
- Buy a security (accept an ask)
- Sell a security (accept a bid)

Gains and losses realized during this period will not be recognized in your final gain.

• **How to use the computer program?**

Trading screen (1)



In each period, a screen similar to this one will appear on your computer. Different types of information are displayed on this screen. For ease of description, the information is split into 4 zones.

Zone 1

On the left is the number of the current period.
On the right the remaining time in the current period appears (number of seconds remaining).

Zone 2

Zone 2 has two blocks:

Block 2.1, entitled " Securities Information ", details the different possible dividend values for the period and the corresponding probabilities as well as the possible redemption values (*case: Market 2*). Note that the information of this block is common to all members of the group.
Block 2.2, " Content of your portfolio " shows the current composition of your portfolio, i.e. the number of securities, your cash holding and the current value of your portfolio.

Zone 3

Zone 3 of your screen corresponds to the transaction area.
Block 3.1 allows you to make offers to buy and sell
Block 3.2 corresponds to the order book. This is the display area of all offers to buy and sell. Your offers appear in blue and those of other members in black.
Note that the order book is visible by all members of the group.

How do you make an offer (bid or ask)?

Enter in block 3.1 the price at which you are willing to buy or sell in the appropriate space: on the left for the bids and on the right for the asks. Then click on "Validate" to validate your offer. Once validated, your offer will appear in blue in block 3.2, in the column " list of offers to buy " if it is a bid or in the column " list of offers to sell " it it is an ask.
- If your bid is the highest in the list of offers to buy (ie at the top of the list), it will be more likely to be accepted by another player.
- If your ask is the lowest in the list of offers (ie if it is at the top of the list), it will be more likely to be accepted by another player.

How can you delete one of your offers?

Select the offer you want to delete from the list of bids (or asks), then click on "Delete". You can only delete your offers that appear in Blue.

How do you sell a security?

Select the price you are interested in in the column " list of offers to buy ", then click on 'Sell'

How do you buy a security?

Select the price you are interested in in the column " list of offers for sale ", then click on 'Buy it'

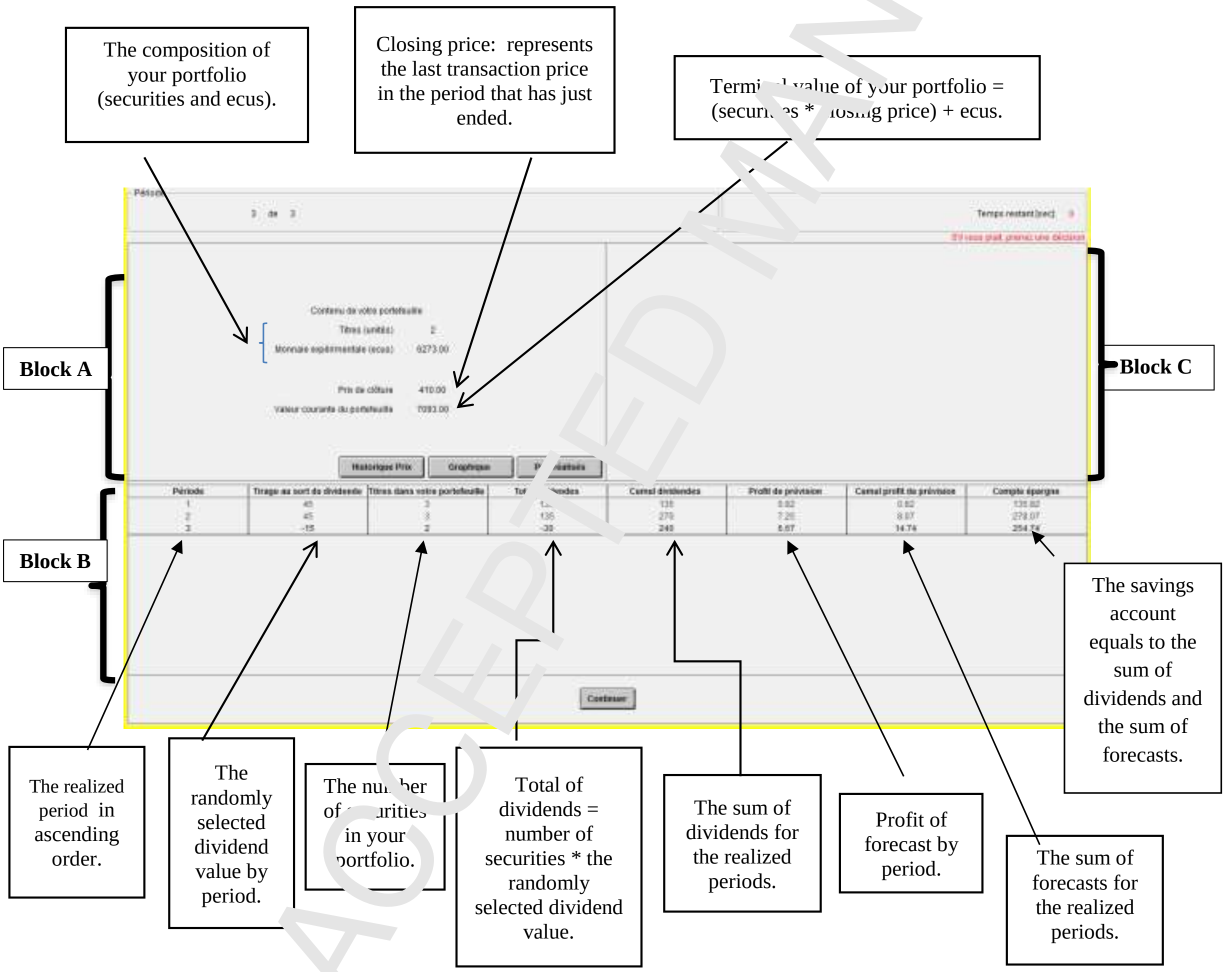
Zone 4

As transactions are completed during the period, the price of each transaction will be displayed in the order of execution in the "Realized Price" panel.
The realization time in seconds is displayed in the column " Time (seconds) " and the order of execution is displayed in the column " Completion order ".
Note that the information table in Zone 4 is common to all members of the group.

• Other important screens in the market:

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

Screens (2) end of period



Block C displays 3 types of information:

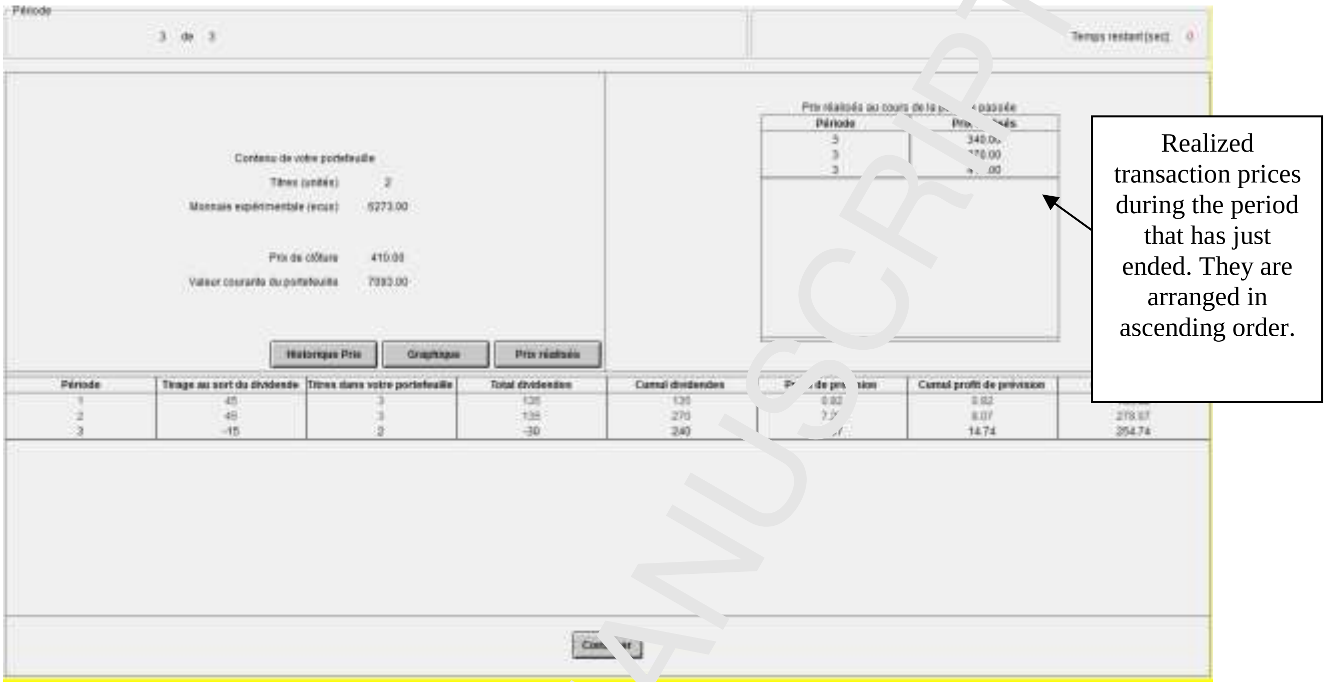
1- The history of prices realized in the period just ended (display 1).

2- The evolution of the closing price during the past periods (display 2).

3- All the price history since the beginning of the market (display 3).

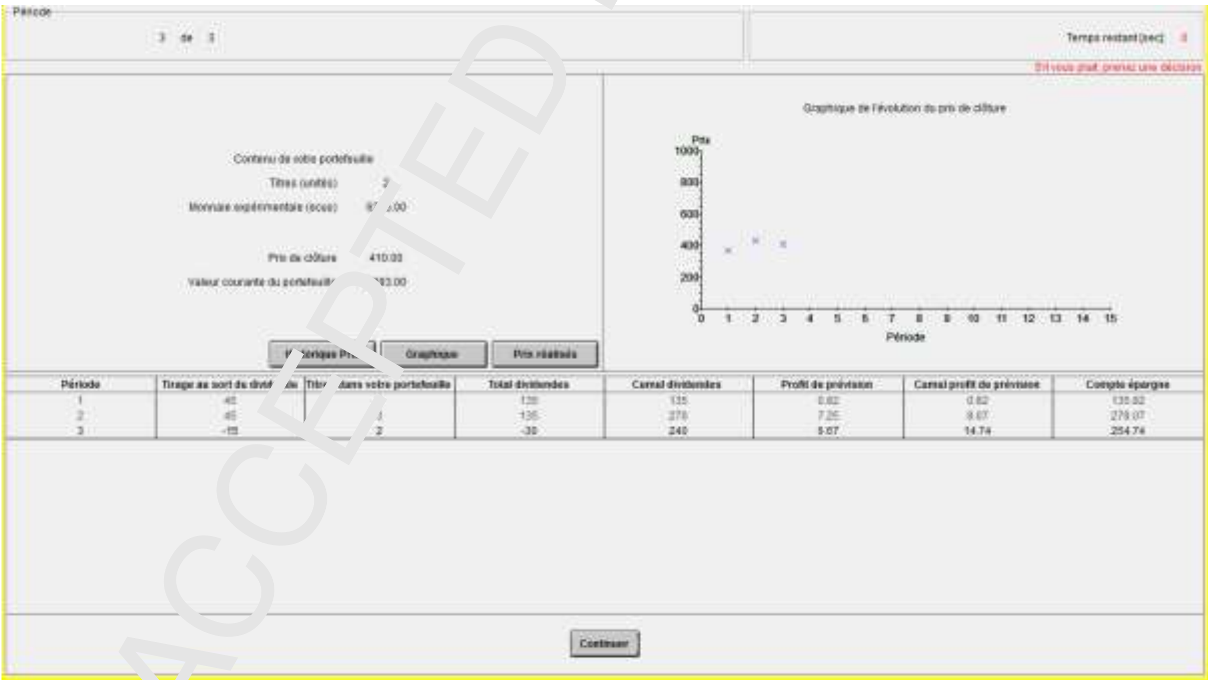
Display 1:

Result after pressing the button " Realized prices ".



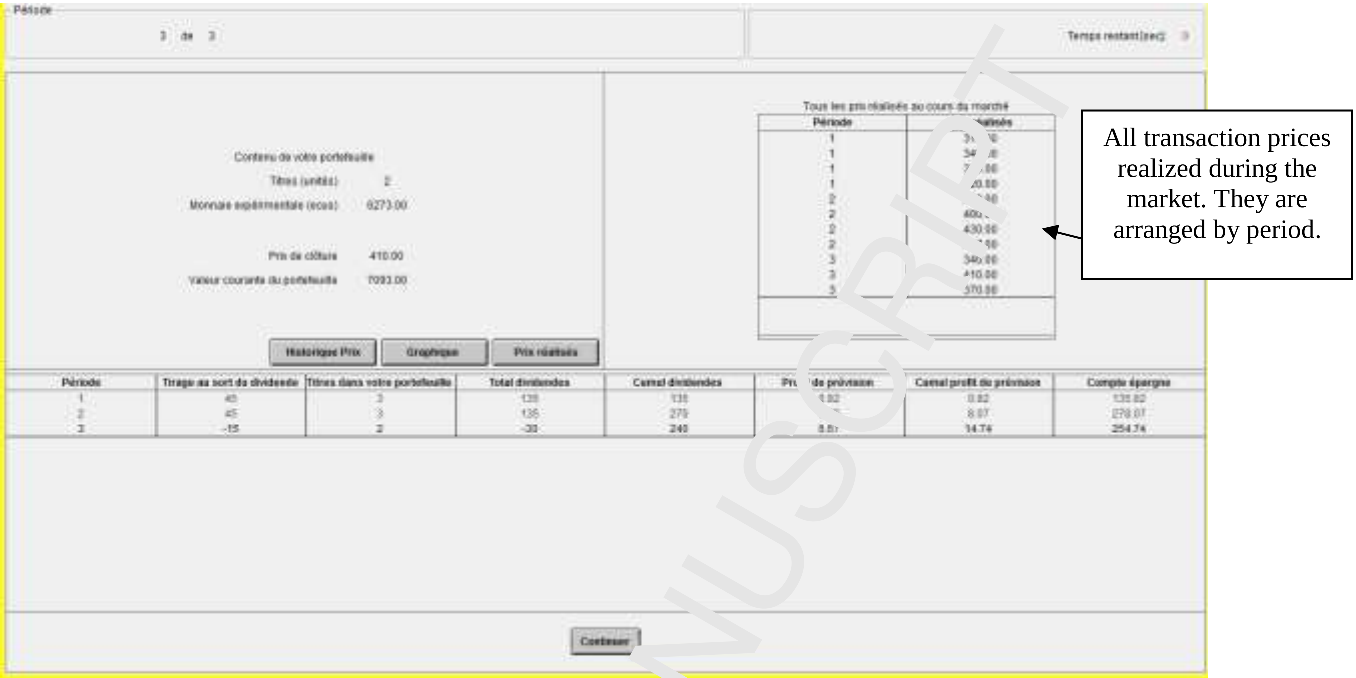
Display 2:

Result after pressing the "Graphic" button.



Display 3:

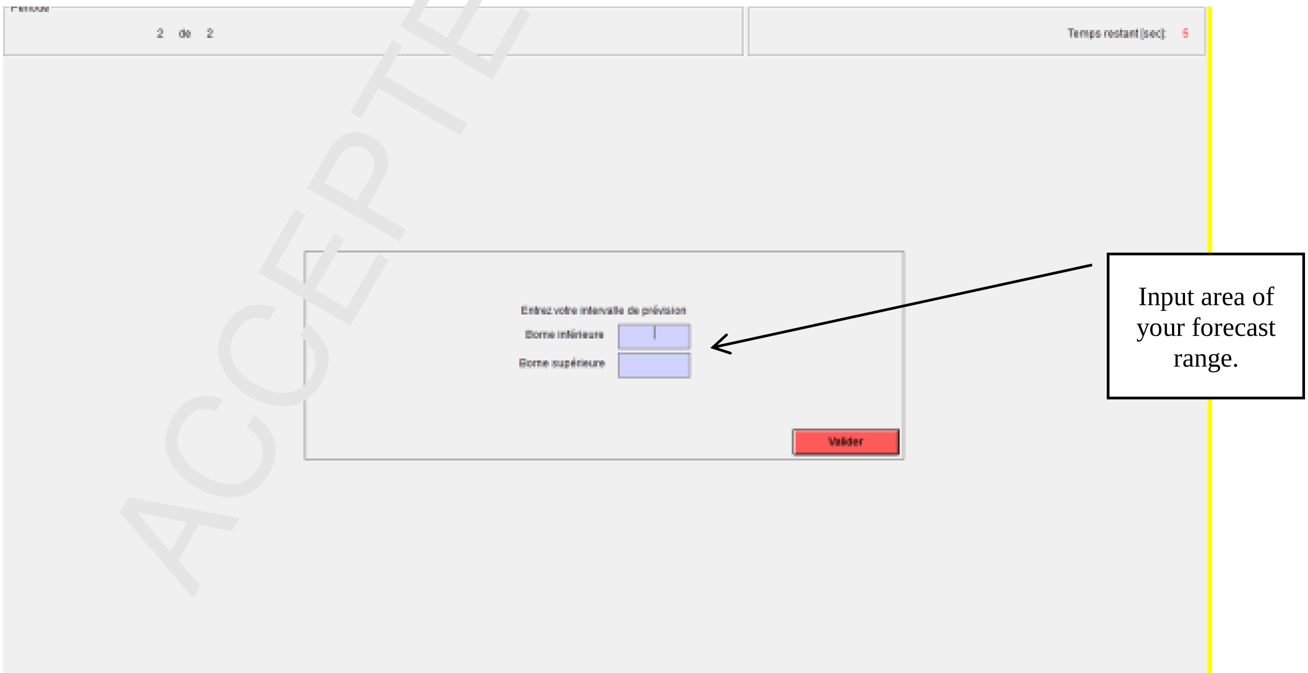
Result after pressing the "History Price" button.



Forecast screen

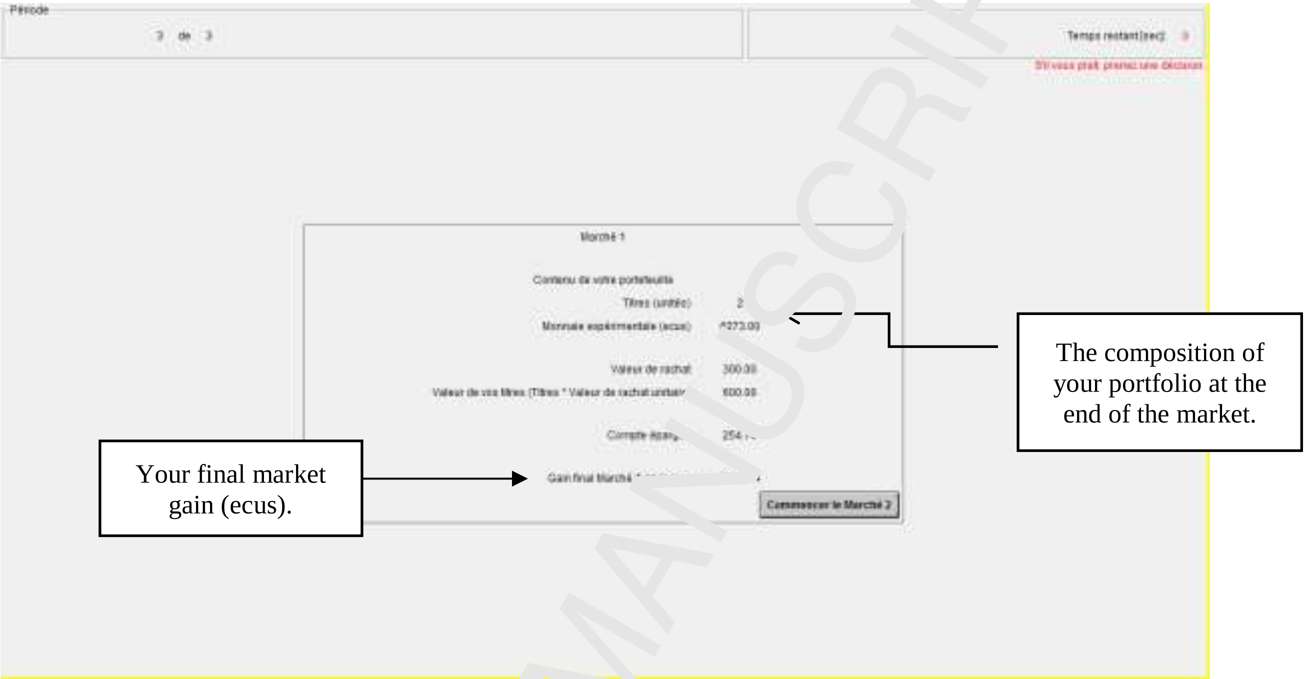
This screen appears at the beginning of each period to enter your forecast interval. Enter your interval then press << Confirm >>.

Important: If you do not press "OK" the market will be blocked.



Final screen at end of the market

This screen displays at the end of the market, it summarizes what you have in your portfolio and your final market gain.
The last line represents your market gain in ECU.
Important: You must press "Start Market 2" to avoid blocking the experiment and to be able to proceed to the other stages of the session.



MARKET 2

The paragraph below was included in the instructions for market 2 in the case of an expected shock.
[…]

Unlike Market 1, for which the redemption value of the shares was equal to 300 ecus, for market 2 the redemption value will be equal to **either 200 or 400 ecus** with one chance out of 2. At the end of period 8 the program will randomly select the cash value (Table 2). The final redemption value will then be displayed on your screen **at the end of period 8**. The selected value will apply to all securities and all participants.

Distribution of redemption values for market 2	
Redemption value	Probability
200	0.5
400	0.5

Table 2: Possible redemption values for *market 2*
NB Please note that the expected redemption value is 300 ecus (200 + 400) / 2.

[…]