Count to ten before trading
The Role of Deliberation in Experimental Financial Markets

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Abstract

Experimental finance has long studied both the determinants of bubbles and institutional measures to prevent them. Within the framework of the dual process theory, we experimentally investigate whether the behavior of traders who are given time to ponder about their orders differs from that of traders given less time to ponder. At this aim, we distinguish between submission of an order to the market and its execution. In one condition (INST), the order and its execution are simultaneous, while in another condition (DEL) the execution is delayed relative to the order submission and the trader can ponder about the order and even withdraw it. We show that the DEL condition heavily dampens market volatility relative to the INST condition and that the former generates prices that are overall consistent with market's fundamental values, once risk aversion is accounted for. We also observe that traders in the INST condition are prone to the gambler's fallacy, while those in the DEL condition are not.

Keywords: Rational vs. emotional choice, Dual process theory, Speculative bubbles, Experimental and Behavioral Finance.

1 Introduction

From fast trading algorithms to ever expanding financial platforms allowing all types of traders to be only 1-click away from every type of financial product, making profitable decisions in financial transactions is increasingly becoming a matter of speed. The ubiquitous diffusion of online trading platforms offers opportunities to trade in (almost) real-time to many non-professional traders. To win consumers in this intensely competitive market, platforms often highlight their speed of transactions. Speed in the execution of trades, captured by the time proximity between order's input and its execution, seems to be perceived as quintessential to successful trading.

Although much of financial theory relies on the assumption that traders are rational decision makers, behavioral finance has long been putting this assumption to question (Shiller, 2003; Lo, 2004). The influential contribution of

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Kahneman (2011) that builds on the well established dual process theory in psychology envisages the coexistence of two parallel decision-making processes: System-1, dominated by heuristics, emotional factors and instinct, is at work whenever individuals are prompted to decide quickly or under cognitive load; System-2 instead relies on rational and conscious thought and intervenes whenever individuals have the time and cognitive resources to make more deliberative decisions. In this perspective, higher speed in trading may induce decision makers to rely more on the instinctive System 1.

Recent experimental evidence shows that the origin of financial bubbles can largely be attributed to the emotional status of agents and to cognitive limitations (see Palan, 2013). Historical evidence suggests that financial bubbles cause misallocation and even systemic crises (e.g. Kindleberger and Aliber, 2011). This has justified the long held tenet that "putting sand in the wheels" of finance may be desirable, a view behind the European Union's decision to establish a Tobin tax on financial transactions. However, some recent experimental evidence suggests that such Tobin tax has little effect in producing the desired results (Hanke et al., 2010; Kirchler et al., 2011; Huber et al., 2012) in the context of experimental financial markets, and the question whether introducing this type of transaction tax is the most effective way of preventing the formation of financial bubbles remains unsolved.

On the face of this evidence, addressing the following questions becomes paramount: Is increased reliance on speed affecting the way decisions are made in financial markets? Are quick and smooth financial markets producing better allocative decisions or is speed deteriorating the decision making process and favoring the formation of financial bubbles?

In this paper we study the formation of financial bubbles in the context of a lab experiment and we manipulate the way in which orders are executed on the market, inducing either more or less deliberation in the choices of traders. This is obtained simply by forcing traders in the DEL(ayed) condition to face a waiting time of 10 seconds before transactions can be confirmed and finalized. Instead, traders in the INST(antaneous) condition make their decisions final the very same moment they input their bid/ask prices into the market. Condition DEL provides the traders with the opportunity to withdraw "instinctive" orders, while this is not possible in condition INST. This simple manipulation is sufficient to curb the high volatility and extreme realizations that are present in the INST condition; moreover average prices become consistently aligned with the expected fundamental value once risk-aversion is considered. Our lab experiment puts the predictions of the standard efficient-market hypothesis to test and proves that a small variation in the time span of the trader's decision may have sizable impact on the efficiency of financial markets.

2 Surveying the literature

In the last twenty years, financial trading has gone through some major changes in trading technologies. The advent of online and mobile trading platforms has deeply affected the costs of transacting in capital markets, thus inducing a significant decline in institutional commissions and a sharp increase in liquidity (Chakravarty et al., 2005; French, 2008). In turn, these phenomena have caused an explosion in trading volumes that are the results of more frequent but smaller trades, which have progressively formed a larger fraction of total trading volumes over time (Chordia et al., 2011). Although institutional trading (and in particular trading by hedge funds) accounts for a large part of this increase, retail investors are also participating to a greater extent because of enhanced access to online trading (Barber and Odean, 2000).

In these markets where naive and sophisticated traders interact, studying the impact of cognitive biases on the efficient working of financial markets has become of paramount importance. Hirshleifer (2015) offers an updated extensive survey of the many implications of behavioral finance, arguing that cognitive biases can help explain most of the observed anomalies in financial markets.

In a dual system perspective (Epstein, 1994; Kahneman, 2002), decisions are the outcome of the interaction between an instinctive-affective mechanism (System1) and a deliberative-cognitive mechanism (System 2). A direct implication of this approach to cognitive architecture is that reducing the cognitive resources available for one of the systems fosters the other system's impact in the decision making process. Experimental evidence provides support to this conjecture. As an example, Sutter et al. (2003) find that under higher time pressure individuals are more likely to reject unfair offers in a ultimatum game than under lower time pressure. Furthermore, Grimm and Mengel (2011) show that when more time is given to deliberate about offers in the ultimatum game, individuals are more likely to accept unfair offers. When jointly taken, these pieces of evidence suggest that time pressure impedes the working of System 2 and fosters instinctive behavior leading to inefficient outcomes at least for a relevant proportion of traders (Kandasamy et al., 2016 show that occasionally some traders are particularly good at exploiting System 1 "gut feelings" to succeed on a real high frequency trading floor).

If one follows this framework, behavioral finance can take us can very often take us very far away from rational choice and, thus, severely questions financial markets efficiency. In just two cited examples this is made obvious: in the first example, Soufian et al. (2014) argues in favor of an Adaptive Market Hypothesis (AMH) where AMH would be able to better represent financial markets dynamics than does the standard Efficient Market Hypothesis. In the second example, conscious that cognitive biases are intrinsic to individual choices, Etzioni (2014) proposes what he calls an "Humble Decision-Making Theory" to render a less emotional and more rational choice. In it, among the others, Etzioni (2014) suggests that, "decision-making should have built-in delays".

Oddly enough, to our knowledge, no one has so far experimentally addressed what happens to financial markets if we build in waiting times for trading. The experimental literature on financial bubbles mostly builds on the landmark paper by Smith et al. (1988). In their financial market, participants in the experiment could buy and sell assets over a finite number of periods in a single closed book continuous double auction market. After each period the assets traded paid a random, discretely and uniformly distributed dividend with positive expected value. The assets had no terminal value; therefore the assets' risk-neutral fundamental value declined monotonically with the number of periods. There were no transaction costs, no interest on money holdings and no short selling or possibility of buying assets on the margin. To the surprise of the authors, such market did produce large bubbles followed by sudden crashes. A large experimental literature has since then built on the original design (see Palan, 2013 for a recent survey) in order to test whether such bubbles and crashes depend on institutional market characteristics and or on behavioral biases. Close to our research question, Hanke et al. (2010), Kirchler et al. (2011), and Huber et al. (2012) test whether the introduction of a Tobin tax in the experimental setting can reduce the frequency and magnitude of bubbles and crashes, but find no evidence in this regard. Angerer et al. (2014) find that computerized agents, who trade according to an active information processing strategy, outperform human subjects trading in the same market in most of the information conditions implemented in the experiment. Hargreaves-Heap and Zizzo (2011) focus on the role played by the four basic emotions (excitement, anger, anxiety and joy) and find that markets with subjects in a state of excitement exhibit substantially larger bubbles. Andrade et al. (2015) and Lahav and Meer (2012) show that inducing some positive mood in subjects prior to trading produces significantly higher prices. In addition, several works show that overconfidence is likely to inflate bubbles (Kirchler and Maciejovsky, 2002; Michailova and Schmidt, 2011; Oechssler et al., 2011; Deck and Jahedi, 2015).

The paper that is most closely related to ours is the one by Kocher et al. (2015), showing that depleting self-control through a laboratory task (a standard Stroop task) prior to trading significantly inflates market bubbles and undermines profits for those subjects with depleted self-control. Their manipulation of self-control can be related to the dual system perspective of decision making: System-1 decisions (impulsive, largely automatic) are typically those with low self-control, whereas System-2 decisions (deliberate, largely controlled albeit effortful) need full control of self.

The relevance of the dual system approach for the understanding of financial markets is not uncontroversial (e.g., Shleifer, 2012). However, previous experimental evidence suggests that introducing forced waiting times could prompt traders to revise instantaneous choices made on the basis of an emotional drive. If that happens, then would market outcomes less likely depart from fundamentals? Checking this proposition is exactly the main task of our experimental approach.

3 Experimental Design

We observe trading behavior in a classical continuous double auction market following Smith et al. (1988). Half of the participants are endowed with 20 stocks and 3,000 Experimental Currency Units (ECU; 400 ECU = 1 Euro); the other half are given 60 stocks and 1,000 ECUs. We allow participants to trade in 2-minutes-long sessions for 10 consecutive periods and with 8 to 10 people in each market. Investment on margin and short selling are not allowed.

Participants trade a virtual stock and may act as sellers and buyers. Exchanges happen on an open book containing a maximum of 10 limit orders by potential buyers (bid) or sellers (ask). Each order is limited to the exchange of 1 stock and the book is cleared at the end of each period.

In each period each stock pays either 0 or 10 ECUs and both outcomes have a 50% realization probability. Thus, we rely on a declining fundamental value (FV), with an increasing cash to asset ratio specification (see T1 in Kirchler et al. 2012). To elaborate, the FV is equal to 50 ECUs during the first period of trading and its value decreases linearly to 5 ECUs during the last period. Needless to say, this evaluation is obtained under the assumption of risk neutrality. When one allows for risk-aversion (risk-seekingness) the value of the stocks is smaller (larger) than the risk-neutral one.

We compare the behavior of participants in two different conditions, DEL(ayed) and INST(antaneous). In the DEL condition, the participant who "closes" a transaction, either by buying or selling an amount of virtual stocks, is given ten seconds to either confirm or cancel the trade. During the 10 "quarantine" seconds the order is withdrawn from the market, but the market keeps working on existing orders. If the order is not confirmed, the order goes back to the book; if it is confirmed, it becomes effective and the balance sheets of the two parties are adjusted accordingly. In the INST condition, the trader has no opportunity to cancel the order, but waits 10 seconds before returning to the market. Like in DEL, the market keeps working on existing orders during the 10 seconds.

In light of previous evidence in the economic and psychological literature, we expect INST traders to have a stronger reliance on the emotional-instinctive system. We hypothesize that deviations from fundamental-value trading in experimental asset markets is largely due to the prevalence of emotional instinctive reasoning over deliberative reasoning. Accordingly, we expect to observe larger deviations from FV in the INST condition than in the DEL condition.

4 Participants and Procedures

The experimental sessions were run at the University of Trento's Cognitive and Experimental Economics Laboratory (CEEL) between May and October of 2015. A total of 210 participants took part in one session of the experiment, 104 participants in the DEL condition and 106 in the INST condition. Participants were students of the University of Trento, and the average payment in the experiment was 13.07 Euro, including a show-up fee of 3.00 Euro.

The experiment took between 50 and 60 minutes and a total of 23 independent market observations (12 INST and 11 DEL) were collected.[1] The experiment was programmed and conducted with the Z-tree software (Fischbacher, 2007).

Upon entering the laboratory, participants were given a few minutes to read the instructions privately and then the instructions were read aloud by the experimental staff. Individuals were then allowed to privately ask clarifying questions. Before beginning the 10 trading rounds, participants were given the opportunity to familiarize with the trading platform in a practice round.

5 Results

Figure 1 provides a description of markets in the two experimental conditions, INST and DEL.

[1] In the INST condition, 4 markets had 8 participants, 6 markets 9 participants and 2 markets 10 participants. In the DEL condition, 2 markets had 8 participants, 2 markets had 9 participants, and 7 markets had 10 participants.

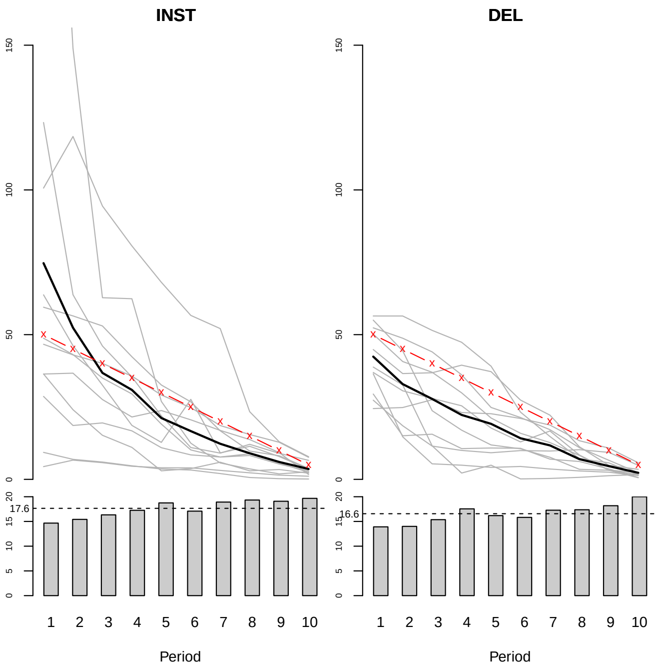

Figure 1: **Prices**
The gray lines show average prices in each period for each market. The darker line shows the mean price in each period obtained by pooling all markets together. The "X" symbols show the risk-neutral FVs. The bars in the lower panel are the average market volumes in each period.

Figure 1 shows that, at the session level, average prices in the INST condition are much more dispersed than in the DEL condition. As an example, the distance between average prices in the most extreme markets in the first period is 320 in the INST and 32 in the DEL condition.

Table 1 reports average prices and their standard deviations (within brackets), in each period. Furthermore, relative standard deviations (RSD) are reported to ease comparison across treatments.

Table 1: **Prices: Descriptive statistics**

	INST		DEL	
	Mean (SD)	RSD	Mean (SD)	RSD
1	74.69 (119.21)	1.6	42.41 (13.88)	0.3
2	52.38 (67.18)	1.28	32.91 (15.81)	0.5
3	36.78 (44.95)	1.22	27.79 (15.66)	0.6
4	30.91 (47.06)	1.52	22.27 (14.85)	0.7
5	21.19 (20.75)	0.98	19.19 (12.60)	0.7
6	16.67 (15.58)	0.93	14.20 (8.42)	0.6
7	12.30 (13.63)	1.11	11.73 (7.08)	0.6
8	9.01 (7.81)	0.87	6.99 (4.22)	0.6
9	6.01 (4.79)	0.80	4.57 (3.64)	0.8
10	3.58 (2.82)	0.79	2.26 (1.86)	0.8

Treatment comparison of means and relative standard deviations (RSD) in each period.

In the INST condition, prices begin largely above the risk-neutral FV, but only for the first two periods. In contrast, in the DEL condition average prices are consistently below the FV in all sessions. Table 1 also highlights the huge difference in price volatility across the two treatments. The standard deviations relative to the mean (RSD) are higher in INST than in DEL throughout trading periods, with larger differences in the first periods. Concerning trading volumes, on average, 17.6 units are exchanged in INST and 16.6 in DEL. In both conditions, trades tend to increase over time, with the last four periods recording more trades than the average.

5.1 Deviations from the Fundamental Value

Figure 1 highlights differences across the two conditions and a visual representation of deviations from FVs. Evidence gathered from Figure 1 is corroborated by a series of measures of deviations from the risk-neutral fundamental price (Stöckl et al., 2010). In Table 2, we compute the relative deviation (RD) and the relative absolute deviation (RAD) from risk-neutral FVs.[2]

[2] The RAD measure captures average mis-pricing and is computed as $RAD = \frac{1}{N}\sum_{p=1}^{N}\frac{|P_p^M - FV_p|}{FV^M}$, where p stands for periods, N is the total number of periods and P_p^M and FV^M stands for volume-weighted average price in period p and FV in period p, respectively. Unlike RAD, RD discriminates between over- under- pricing, with a $RD < 0$ signaling under-pricing and a $RD > 0$ signaling over-pricing. The measure is computed as: $RD = \frac{1}{N}\sum_{p=1}^{N}\frac{(P_p^M - FV_p)}{FV^M}$.

Table 2: **Relative deviations from risk-neutral FVs**

	RAD	RD
INST	0.29	-0.04
DEL	0.35	-0.35

As shown by RD, prices observed in the DEL condition are consistently below the FV, with an overall RD=-0.35. In contrast, in the INST condition, prices are largely above the FV in the first two trading periods and then move below the FV in later periods. In condition INST, we observe an RD=-0.04, substantially smaller than the one observed in DEL but this is explained by the two effects (initial over-pricing and later under-pricing) almost entirely canceling out. The RAD values that take measures in absolute terms show that deviations from the FV are positive and substantial in both conditions.

The FV taken as a reference in the analysis above is implicitly based on the assumption of risk neutrality. However, evidence gathered in previous experiments suggests that individuals are generally risk-averse Holt and Laury (2002). Here we explore the hypothesis of risk aversion by estimating coefficients of risk aversion inferred from transaction prices.[3] In the next paragraph we then recompute both RD and RAD using the FVs inferred from empirically estimated risk aversion at the population level. This identification strategy seems to provide a fair account of deviations from fundamental values, when individuals are not risk neutral.

Table 3 reports the estimated coefficients of risk aversion (r) of a constant relative risk aversion function (CRRA).[4] Risk neutrality, commonly assumed to compute FVs, is captured by coefficients not differing from zero, while risk aversion (propensity) is captured by positive (negative) values.

[3] To estimate the degree of risk aversion we start from the assumption that $u(P_t) = EU(D_t)$, where P_t is the price paid for a stock at time t, $EU(D_t)$ is the expected utility of the cash flow generated by the stock at time t. The expected utility at time t, is computed as $EU(D_t) = \sum_{k=0}^{T-t+1} Pr(X = k) \cdot u(\overline{D}k)$, where $\overline{D} = 10$ is the monetary value of the high dividend and T is the total number of trading periods. $Pr(X = k)$ is the probability of obtaining k times the high outcome in the remaining periods. Given that the random variable X follows a binomial distribution $X \sim B(t,p)$ we conclude that $Pr(X = k) = \binom{t}{k} p^k (1 - p)^{(t-k)}$. In our estimate, we assume a constant relative risk aversion (CRRA) specification for the utility function, i.e. $u = \frac{x^{(1-r)}}{1-r}$. Then, parameters of risk aversion r are estimated via a non-linear least squares (NLS) procedure from $P_t = \left(\sum_{k=0}^{t} Pr(\overline{X} = k) \cdot (\overline{D} \cdot k)^{(1-r)}\right)^{1/(1-r)}$.

[4] The CRRA function has the following standard specification $u(x,r) = \frac{x^{(1-r)}}{1-r}$

Table 3: **Estimates of coefficient of relative risk aversion**

Period	INST	DEL
1	-19.270 (12.52)	0.991 (0.002)***
2	-3.575 (2.594)	0.992 (0.001)***
3	0.854 (0.329)*	0.987 (0.002)***
4	0.875 (0.179)***	0.979 (0.003)***
5	0.944 (0.013)***	0.958 (0.005)***
6	0.910 (0.016)***	0.938 (0.005)***
7	0.863 (0.021)***	0.875 (0.010)***
8	0.769 (0.022)***	0.838 (0.008)***
9	0.622 (0.025)***	0.720 (0.015)***
10	0.326 (0.034)***	0.534 (0.017)***
Overall	0.760 (0.076)***	0.944 (0.004)***

Signif. codes: $*** < 0.001$; $** < 0.01$; $* < 0.05$

Coefficients estimated in the DEL condition consistently display a distaste for risk, with the magnitude of the estimated coefficients slightly decreasing as trading periods progress. In the INST condition, coefficients for the first two trading periods are negative, signaling positive attitudes to risk. However, the huge variance of prices in these periods does not allow us to reject the hypothesis that estimated coefficients are null. Attitudes then rapidly flip against risk and risk aversion increases up to the fifth period when the values are very similar to the DEL condition. Thereafter the estimated coefficients decrease rapidly again over the remaining periods. When pooling data across periods, traders are characterized by substantial risk aversion, with higher risk aversion observed among traders in the DEL condition than in the INST condition.

We are now ready to re-estimate RD and RAD coefficients reported in Table 4, assuming that traders are risk averse and therefore using the parameters specification of the overall estimation in Table 3.

Table 4: **Relative deviations from risk-averse FVs**

	RAD	RD
INST	0.26	0.12
DEL	0.26	-0.05

We obtain that the RAD is equal to 0.26 in both conditions and the RD is equal to -0.05 in DEL and to 0.12 in INST. Overall, prices are in line with the risk-averse FV in the DEL condition, but are higher than expected in the INST condition. This result derives directly from the higher consistency of behavior in the former condition than in the latter.

5.2 Trading behavior

So far, the analysis highlights the differences between the two trading conditions in terms of market prices. In order to improve our understanding of the determinants of such observed differences, we investigate two specific aspects of trading behavior: the spread between ask and bid offers and the dynamics of order withdrawals in the DEL condition.

Figure 2 provides a representation of the distance between demand and supply in the two experimental conditions.

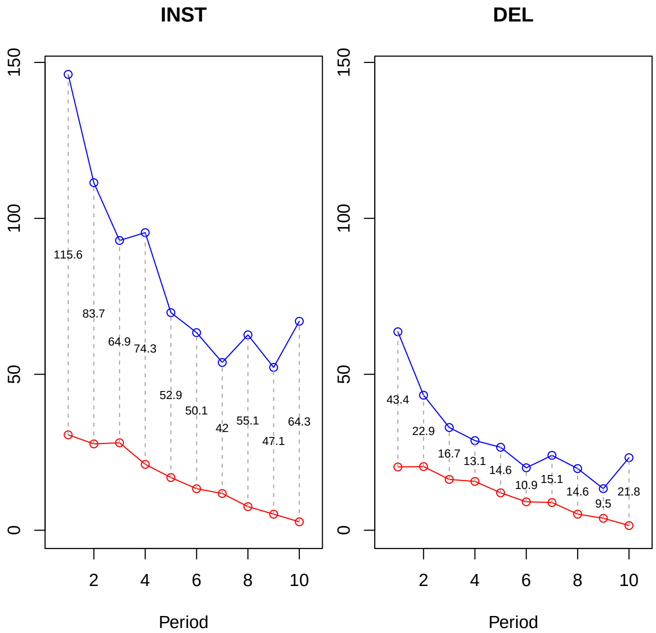

Figure 2: **Bid-Ask Spread**
The upper line captures average ask prices, while the lower line captures average bid prices posted by traders. The numbers capture the distance between the two lines.

As Figure 2 shows, both ask and bid prices tend to decrease over time, following the evolution of dividend payments. The dynamics of the average bid prices are quite similar in both conditions, with values below the risk-neutral FVs. In contrast, ask prices radically differ across the two conditions. In the INST condition, ask prices are much higher than in the DEL condition, for all trading periods. It follows that the average spread between listed selling and buying prices is much larger in the INST condition than in the DEL one.

It is important to remember that in the DEL condition traders are given the opportunity to withdraw their orders after a few seconds. Figure 3 shows the percentage of withdrawn orders over total orders.

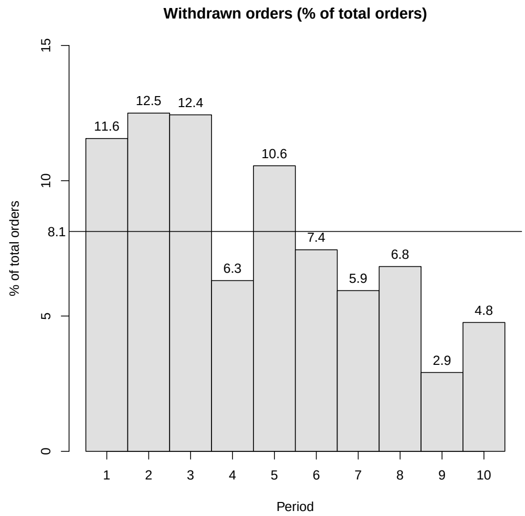

Figure 3: **Orders withdrawal in DEL condition**

On average, 8.1% of the orders are withdrawn from the system. The relative share of withdrawn orders is quite sustained in the first periods and tends then to decrease over time (albeit not consistently). Interestingly, the initial periods are those in which the two experimental conditions differ the most, with overly inflated values observed in INST condition, where the withdrawn option is not available.

5.3 Regressions Analysis

Table 5 reports results of linear mixed model estimations, controlling for repeated choices of individuals nested within a market. Three alternative estimates are reported, differing in the dependent variable adopted. When the dependent variable is $Price$, we refer to prices of closed transactions. When the dependent variable is Ask, we refer to the price orders posted by those ready to sell at this price. When the dependent is Bid, we refer to price orders posted by those ready to buy at this price.

As explanatory variables, we employ the minutes elapsed from the beginning of each trade ($Time$); a treatment dummy (DEL) equal to 1 when the transaction happens in condition DEL and equal to zero when in condition INST, and a dummy variable coding whether a dividend was paid in the previous period (Div_{t-1}).[5] The latter is a direct measure of the impact of biased beliefs on price formation. When individuals wrongly maintain the idea that dividends are auto-correlated, prices may reflect the dividend outcome of previous rounds. Individuals could both believe that dividends were positively auto-correlated - this is the so-called hot-hand fallacy (Gilovich et al., 1985) - or they may believe that dividends were negatively auto-correlated and thus they would withstand the gamblers' fallacy (Huber et al., 2010; Xu and Harvey, 2014). We also consider the impact of the interaction between the time measure, the dividend payment, and the treatment dummy.

Table 5: **Regression Analysis (Linear mixed model)**

	Price	Ask	Bid
(Intercept)	54.061 (1.899)***	108.719 (10.064)***	32.325 (1.222)***
DEL	-14.338 (2.765)***	-66.604 (14.315)***	-9.402 (1.719)***
Time	-2.788 (0.100)***	-0.048 (0.003)***	-0.022 (0.000)***
Div_{t-1}	0.455 (0.103)***	1.042 (0.274)***	0.053 (0.039)
$Time : DEL$	0.930 (0.146)***	0.032 (0.005)***	0.010 (0.001)
$Div_{t-1} : DEL$	-0.364 (0.150)*	-1.142 (0.380)**	-0.097 (0.052)

Signif. codes: $*** < 0.001$; $** < 0.01$; $* < 0.05$

For closed contracts (Price), regression estimates show that in condition DEL prices start lower than in condition INST (DEL coeff=-14.338). However, the decrease in prices observed as trading periods progress ($Time$ coeff.=-2.788) is much more sustained in condition INST than in condition DEL ($Time : DEL$ coeff.=0.930). Interestingly, obtaining a dividend in the previous round inflates prices (Div_{t-1}) thus providing evidence of the existence of the hot-hand fallacy; however, the effect is statistically significant only in the INST condition.[6] Thus, the INST condition seems to promote biased beliefs about positively correlated dividend payments.

In qualitative terms, the regression estimate for Ask confirms the effects highlighted for closed contracts. Offers are significantly lower in the DEL condition than in INST and decrease over time. The impact of dividends in the previous period is positive, but only in condition INST. Concerning Bid, offers of purchase are lower in INST than in DEL and decrease over time. However,

[5] The introduction of Div_{t-1} in the regression model implies that observations of the dependent variable in the first period are dropped from the analysis.

[6] The linear hypothesis test $Div_{t-1} + Div_{t-1} : DEL = 0$ returns a Chisq=0.675 (p-value=0.411).

in contrast to what is highlighted for ask offers and closed contracts, previous dividends have no significant impact on offers, neither in the INST condition nor in the DEL condition.

6 Discussion and Conclusions

The speed of modern financial markets is further amplified by the widespread presence of algorithmic trading: up to 70% of stock trading by 2013 – and the figure may have further increased thereafter – materialize via High Frequency Trading (HFT) (Aït-Sahalia and Saglam, 2013) and the presence of HFT has pushed the execution speed of trades to microseconds (Economist, 2014). If, on one hand, HFT may increase market efficiency by lowering bid-ask spreads and by favoring market liquidity (see, Chordia et al. 2013), on the other hand it exacerbates the pressure on the human traders towards speeding up trading. This might not trouble those believing in the EMH and in investors' rational behavior. However we believe that the assessment of whether speed helps or hinders financial markets efficiency is an open, legitimate and very relevant question for policy making.

As speed in transactions is becoming ubiquitous, dual-system theory predicts more and more trading decisions to lean toward intuition rather than deliberation. We have begun to address this issue by using a standard experimental financial market, modeled after Smith et al. (1988). We have characterized our two treatments as either the INST condition or the DEL condition: in the former, trading decisions cannot be reversed and traders are given no time to ponder about their choice between input and execution, while in the latter decisions must be confirmed within 10 seconds before being executed. Our conjecture was that orders in the INST condition lean more on System-1 than those in condition DEL, as in INST it is not possible to withdraw "instinctive" orders.

Our experiment delivers unambiguous results. INST markets experience huge volatility and price dispersion relative to DEL markets and the most extreme realizations always happen while under the INST condition. INST traders are more likely to induce inconsistent market patterns that begin well above fundamental values, then collapse quickly to very low values (well below FV), and then rise again. In contrast, DEL traders tend to trade much more conservatively, in a way compatible with a risk-averse assessment of the market FV all the way through.

In this paper we also made a methodological contribution. All the standard measures of financial market efficiency used in the literature (we use RD and RAD in particular) rely on the fundamental value intended as the expected value of the underlying bet under risk-neutrality. However the predominance of risk aversion is well established both in laboratory (e.g., Holt and Laury, 2002) and field experiments (e.g., Andersen et al., 2008). We thus first estimated the coefficients of risk aversion (r) of a constant relative risk aversion function (CRRA) in each period under both conditions (see table 3), and then used these estimated coefficients to compute the new empirically based FVs as well as the new indexes of deviance (RD and RAD). These new measures show that the DEL condition produces prices that are indeed very close to the predicted FV with risk-aversion, while in the INST condition the relative deviation is substantial and positive.

Market equilibrium prices under INST and DEL surely differ, but where does this difference derive from? We have shown that there exists a huge distance between average ask and bid prices in the INST condition and a much smaller price difference in the DEL condition. The difference is mainly driven by the difference in the ask prices that range far higher in the INST condition. Coincidentally, in the DEL condition, we observe relatively more withdrawals of orders in the first periods, exactly when ask and final prices skyrocket in the INST condition. This evidence suggests that System-2 reasoning in the DEL condition induces subjects to withdraw extreme offers before they reach the market.

Finally we also demonstrated that under the INST condition individuals are more prone to believe there exists a positive auto-correlation of stock dividends; this evidence is compatible with the "hot-hand fallacy" (Gilovich et al., 1985). This further corroborates the hypothesis that when less time is available to deliberate, choices rely more on instinctive-heuristic reasoning.

With all usual disclaimers applied to any lab experiment, we do not resist the temptation to derive some policy implications from this work which would sound simple, although detonating. Our results clearly suggest that slowing down financial trading would be an effective course in avoiding bubbles and making financial markets more efficient. This would demand drastic revisions of current trading rules with vast implications for the same architecture of many financial markets. For instance: it is hard to envision how High Frequency Trading — which covers the bulk of trades nowadays and relies on computerized algorithms that trade in matter of milliseconds — may be made consistent with the waiting time to prompt System-2 investment decisions in human traders. Furthermore our results are also at odds with the Tobin tax approach. James Tobin suggested to put "sand in the wheels" of financial markets in the form of a small transaction tax which has proven, in the meanwhile, not to be that much effective at least in experimental settings (see literature cited above). Our alternative approach aims at the same goal of slowing down the financial transaction machinery but by mean of a direct braking of the wheels.

There is no need to mention that additional evidence and argumentation will be needed to make such policy implications more forceful. However, if the literature will make progress in this direction, it will become difficult to dismiss the implications for the optimal trading rules derived from the simple intuition that rationality demands time in order for System-1 to step up to System-2 decision-making.

References

Aït-Sahalia, Y. and Saglam, M. (2013). High frequency traders: Taking advantage of speed. Technical report, National Bureau of Economic Research.

Andersen, S., Harrison, G. W., Lau, M. I., and Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3):583–618.

Andrade, E. B., Odean, T., and Lin, S. (2015). Bubbling with excitement: an experiment. *Review of Finance*, page rfv016.

Angerer, M., Huber, J., and Kirchler, M. (2014). Trader performance in a market experiment with human and computerized traders. *Schmalenbach Business Review: ZFBF*, 66(3):224.

Barber, B. M. and Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance*, pages 773–806.

Chakravarty, S., Panchapagesan, V., and Wood, R. A. (2005). Did decimalization hurt institutional investors? *Journal of Financial Markets*, 8(4):400 – 420.

Chordia, T., Roll, R., and Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. *Journal of Financial Economics*, 101(2):243–263.

Chordia, T., Subrahmanyam, A., and Tong, Q. (2013). Trends in capital market anomalies. *Unpublished working paper, Emory University, UCLA, Singapore Management University.*

Deck, C. and Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, 78:97–119.

Economist, T. (2014). Frequent but inefficient. high-frequency trading might reduce liquidity, not boost it as its defenders claim. *Free exchange November 29th.*

Epstein, S. (1994). Integration of the cognitive and the psychodynamic unconscious. *American psychologist*, 49(8):709.

Etzioni, A. (2014). Humble decision-making theory. *Public Management Review*, 16(5):611–619.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental economics*, 10(2):171–178.

French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, 63(4):1537–1573.

Gilovich, T., Vallone, R., and Tversky, A. (1985). The hot hand in basketball: On the misperception of random sequences. *Cognitive psychology*, 17(3):295–314.

Grimm, V. and Mengel, F. (2011). Let me sleep on it: Delay reduces rejection rates in ultimatum games. *Economics Letters*, 111(2):113–115.

Hanke, M., Huber, J., Kirchler, M., and Sutter, M. (2010). The economic consequences of a tobin tax—an experimental analysis. *Journal of Economic Behavior & Organization*, 74(1):58–71.

Hargreaves-Heap, S. P. and Zizzo, D. J. (2011). Emotions and chat in a financial markets experiment. *Available at SSRN 1783462*.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, 7(1).

Holt, C. and Laury, S. (2002). Risk aversion and incentive effects. *The American Economic Review*, 92(5):1644–1655.

Huber, J., Kirchler, M., and Stöckl, T. (2010). The hot hand belief and the gambler's fallacy in investment decisions under risk. *Theory and Decision*, 68(4):445–462.

Huber, J., Kleinlercher, D., and Kirchler, M. (2012). The impact of a financial transaction tax on stylized facts of price returns—evidence from the lab. *Journal of Economic Dynamics and Control*, 36(8):1248–1266.

Kahneman, D. (2002). Maps of bounded rationality. Technical report, Nobel Prize Committee.

Kahneman, D. (2011). *Thinking, fast and slow*. Macmillan, New York.

Kandasamy, N., Garfinkel, S. N., Page, L., Hardy, B., Critchley, H. D., Gurnell, M., and Coates, J. M. (2016). Interoceptive ability predicts survival on a london trading floor. *Scientific Reports*, 6.

Kindleberger, C. and Aliber, R. Z. (2011). *Manias, Panics, and Crises. A History of Financial Crises.* Palgrave Macmillan, sixth edition.

Kirchler, E. and Maciejovsky, B. (2002). Simultaneous over-and underconfidence: Evidence from experimental asset markets. *Journal of Risk and Uncertainty*, 25(1):65–85.

Kirchler, M., Huber, J., and Kleinlercher, D. (2011). Market microstructure matters when imposing a tobin tax—evidence from the lab. *Journal of economic behavior & organization*, 80(3):586–602.

Kirchler, M., Huber, J., and Stöckl, T. (2012). Thar she bursts: Reducing confusion reduces bubbles. *The American Economic Review*, 102(2):865–883.

Kocher, M. G., Lucks, K. E., and Schindler, D. (2015). Unleashing animal spirits-self-control and overpricing in experimental asset markets. *workingpaper.*

Lahav, Y. and Meer, S. (2012). The effect of induced mood on prices in asset markets-experimental evidence. *Available at SSRN 2050299.*

Lo, A. W. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management*, 30(5):15–29.

Michailova, J. and Schmidt, U. (2011). Overconfidence and bubbles in experimental asset markets. *Kiel Working Papers*, (1729).

Oechssler, J., Schmidt, C., and Schnedler, W. (2011). On the ingredients for bubble formation: informed traders and communication. *Journal of Economic Dynamics and Control*, 35(11):1831–1851.

Palan, S. (2013). A review of bubbles and crashes in experimental asset markets. *Journal of Economic Surveys*, 27(3):570–588.

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of economic perspectives*, pages 83–104.

Shleifer, A. (2012). Psychologists at the gate: A review of daniel kahneman's" thinking, fast and slow". *Journal of Economic Literature*, pages 1080–1091.

Smith, V. L., Suchanek, G. L., and Williams, A. W. (1988). Bubbles, crashes, and endogenous expectations in experimental spot asset markets. *Econometrica: Journal of the Econometric Society*, pages 1119–1151.

Soufian, M., Forbes, W., and Hudson, R. (2014). Adapting financial rationality: Is a new paradigm emerging? *Critical Perspectives on Accounting*, 25(8):724–742.

Stöckl, T., Huber, J., and Kirchler, M. (2010). Bubble measures in experimental asset markets. *Experimental Economics*, 13(3):284–298.

Sutter, M., Kocher, M., and Strauß, S. (2003). Bargaining under time pressure in an experimental ultimatum game. *Economics Letters*, 81(3):341–347.

Xu, J. and Harvey, N. (2014). Carry on winning: The gamblers' fallacy creates hot hand effects in online gambling. *Cognition*, 131(2):173–180.

Instructions

Dear participant, please do not talk to other participants for the duration of the experiment. We ask you to turn off your cell phone or other mobile devices. If you need to ask questions, raise your hand and an experiment will come to you.

General information In this experiment a financial market is reproduced where traders can exchange shares of a fictitious listed company for the duration of the experiment which lasts 10 periods. The unit of measure of wealth is the ECU (Experimental Currency Unit) that will be suitably exchanged in Euros at the end of the experiment at the exchange rate of 400 ECU = 1 EUR.

Market Overview

Each market involves ten subjects, also called operators. Five of the ten operators will have an initial wealth equal to 20 shares and 3000 ECU. The other five will have a starting wealth of 60 shares and 1000 ECU. At the beginning the share has a fundamental value (FV) of 50 ECU.

If you evaluate the share at its initial FV, each operator then has an initial wealth equal to 4000 ECU. In each period, you can sell or buy shares using the ECU at your disposal, and both the shares and the ECU you accumulate are transferred to the following period. Each period ends automatically after 2 minutes.

Trade is accomplished in form of a double auction, i.e., each trader can appear as buyer and seller at the same time. You can submit any quote of shares with prices ranging from 0 to a maximum of 999 ECU (with at most two decimal places). Every bid is intended for one share. You can never sell more shares than you own and you can not buy shares for an amount higher than the number of ECU in your possession.

The screen will show the 10 best bid and ask prices. Offers to sell (ask) will be sorted from lowest to highest, while the purchase offers (bid) will be ordered from highest to lowest. Offers that do not fit within the 10 best deals are deleted.

In every moment you can enter a bid at the lowest price among the offers to sell and enter an order to sell at the highest price among the bids.

[INST] Once the purchase/sale order is entered action will be bought / sold and you will need to take a break of 10 seconds. After 10 seconds you can operate again on the market

[DEL] Once the purchase/sale order is entered, you will need to take a break for five seconds at the end of which you will have 5 seconds to confirm or withdraw your order. If you do not take any

decision, your order will be automatically withdrawn. After 10 seconds you can operate again on the market

At the end of each trading period, every share pays a dividend (profit) which gets summed up to your ECU holding. The dividend (for one share) amounts either to 0 or 10 ECU, given equal probability. So the average dividend per share is 5 ECU. You will learn the actual value at the end of each period and not during the period. The shares have a duration of 10 periods; after the last dividend payment at the end of the tenth period their value in ECU is 0.

The subsequent table might help you to make your decisions. The first column, labeled "Ending Period", indicates the last trading period of the market. The second column, labeled "Current Period", indicates the period during which the FV is being calculated. The third column gives the number of holding periods from the period in the second column until the end of the market. The fourth column, labeled "Average Dividend Value Per Period", gives the average amount that the dividend will be in each period for each unit held in your inventory. The fifth column, labeled "Fundamental Value Per Unit of Inventory", gives the expected total dividend earnings (per share) for the remainder of the experiment. That is, for each unit you hold in your inventory for the remainder of the market, you receive in expectation the amount listed in column 5, which is defined as the FV of the current period. The number in column 5 is calculated by multiplying the numbers in column 3 and 4. Suppose for example that there are 4 periods remaining in a market. Since the dividend on a unit of share has a 50% chance of being 0 and a 50% chance of being 10, the dividend is in expectation 5 ECU (per period for each share). If you hold one share for 4 periods, the total dividend paid on the unit over 4 periods is in expectation 4 * 5 = 20.

Ending Period	Current period	Number of Holding Periods	Average Payment per Period (0 or 10 with equal probability)	Fundamental Value per Unit of Inventory
10	1	10	5	50
10	2	9	5	45
10	3	8	5	40
10	4	7	5	35
10	5	6	5	30
10	6	5	5	25
10	7	4	5	20
10	8	3	5	15
10	9	2	5	10
10	10	1	5	5

Share trading

If you buy shares, your ECU holding is diminished by the respective expenditures. Inversely, if you sell shares, your ECU holding will be increased by the respective revenues.

Calculate Your Earnings

At the end of the market (after 10 periods), shares have a value of zero. Solely your ECU holdings serve for the determination of your total earnings.

Your total earnings in this experiment are converted into Euro at a rate of 400 ECU = 1 Euro

Important information

- No interest is payed for ECU holdings.
- Each trading period lasts for 2 minutes.
- The experiment ends after 10 periods.
- Use the full stop (.) as decimal place.

Trading screen: By means of the following figure, the procedure of trading (buying and selling) will be illustrated.

Trading screen