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Trading Fast and Slow
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experimental financial
markets**

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Count to Ten Before Trading
Evidence on the Role of Deliberation
in Experimental Financial Markets*

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Abstract

Financial bubbles cause misallocation of resources and even systemic crises. Experimental finance has long tested both the determinants of the formation of financial bubbles and institutional designs meant at solving such bubbles. We explore whether the dual process theory proposed by Kahneman (2011) can explain bubbles' formation. As compared with our benchmark FAST treatment, we deliberately slow down the decision making process in our SLOW treatment, and thus we induce more System-2 type reasoning. We show that high volatility and extreme realizations are greatly reduced and average prices remain consistently aligned with the expected fundamental value once risk-aversion is considered. We also show that the main differences are driven by abnormal ask prices in the FAST treatment that are consistently withdrawn in the SLOW treatment. We also show that the SLOW condition clears out the hot-hand fallacy. Finally, we derive some tentative policy implications concerning slowing down finance.

Keywords: Rational vs. emotional choice; Slow vs. fast trading; Dual process theory; System-1 and System-2; Speculative bubbles; Behavioral finance.

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1 Introduction

From fast trading algorithms to ever expanding financial platforms allowing all type 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 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 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. Speed is certainly a key factor that induces decision makers to use System-1 over System-2.

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), 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 thus favoring the formation of financial bubbles?

In this paper we study the formation of financial bubbles with 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 SLOW condition to face a waiting time of 10 seconds before transactions can be confirmed and finalized. Traders in the FAST condition instead make their decisions final the very same moment they post their bid/ask prices .

2 Surveying the literature

In the last 20 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).

“Time is money”; this popular saying appears to be even truer nowadays in a financial world dominated by High Frequency Trading (HFT). Up to 70% of stock trading by 2013 – and the figure may have further increased thereafter – materialize via HFT (Aït-Sahalia and Saglam, 2013). HFT is performed through computerized trading systems and competition seems to be so fierce to push the execution of trades from milliseconds to microseconds (Economist, 2014). If one believes in investors’ rational behavior, anything that speeds up (slows down) trades should in theory improve (worsen) financial markets efficiency. Indeed, according to various scholars, HFT helps market efficiency by lowering bid-ask spreads and by favoring market liquidity (see, Chordia et al. 2013).

Here we do not neglect the importance of HFT or other kinds of algorithmic trading for modern financial markets. However, we focus on the human side of trading and on the impact that cognitive biases may have on the efficient working of financial markets. 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.

If one follows this framework, behavioral finance can take us very often and 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 EMH. 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 students 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); 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. 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 excited subjects 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). It shows 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.

In spite of the fact that some pundits find the dual system approach to be oversimplifying (Shleifer, 2012), one could expect 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 sessions 2 minute 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. Ex-

changes happen on an open book containing a maximum of 10 limit orders from 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% 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, SLOW and FAST. In the SLOW 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 FAST condition, the trader has no opportunity to cancel the order, but waits 10 seconds before returning to the market. Like in SLOW, the market keeps working on existing orders during the 10 seconds.

In light of previous evidence in the economic and psychological literature, we expect FAST 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 FAST condition than in the SLOW 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 SLOW condition and 106 in the FAST 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 FAST and 11 SLOW) 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, FAST and SLOW.

¹In FAST condition, 4 markets had 8 participants, 6 markets 9 participants and 2 markets 10 participants. In SLOW condition, 2 markets had 8 participants, 2 markets had 9 participants, and 7 markets had 10 participants.

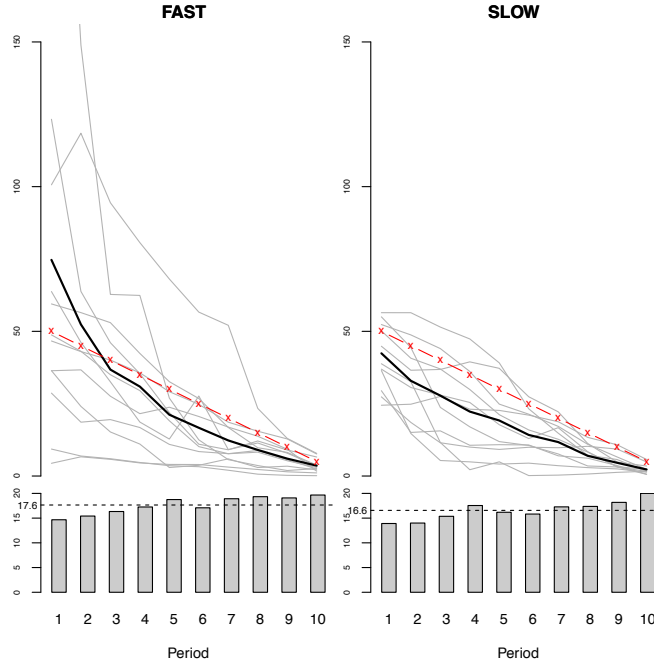


Figure 1: **Prices**

The gray lines show average prices in each period for each market. The darker line signifies the average (not weighted by volume) of the average prices in each market. 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 FAST condition are much more dispersed than in the SLOW condition. As an example, the distance between average prices in the most extreme markets in the first period is 320 in the FAST and 32 in the SLOW 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**

	FAST		SLOW	
	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 FAST condition, prices begin largely above the risk-neutral FV, but only for the first two periods. In contrast, in the SLOW 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 FAST than in SLOW throughout trading periods, with larger differences in the first periods. Concerning trading volumes, on average, 17.6 units are exchanged in FAST and 16.6 in SLOW. 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

²The 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:

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

	RAD	RD
FAST	0.29	-0.04
SLOW	0.35	-0.35

As shown by RD, prices observed in the SLOW condition are consistently below the FV, with an overall RD=-0.35. In contrast, in the FAST condition, prices are largely above the FV in the first two trading periods and then move below the FV in later periods. In condition FAST, we observe an RD=-0.04, substantially smaller than the one observed in SLOW but this is explained by the two effects (initial over-pricing and later under-pricing) almost entirely cancelling 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.

$$RD = \frac{1}{N} \sum_{p=1}^N \frac{(P_p^M - FV_p)}{FV^M}$$

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 $EU(D_t) = \sum_{k=0}^{T-t+1} Pr(X = k) \cdot u(\bar{D}k)$, where $\bar{D} = 10$ 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 $P_t = (\sum_{k=0}^t Pr(\bar{X} = k) \cdot (\bar{D} \cdot k)^{(1-r)})^{1/(1-r)}$.

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

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

	RAD	RD
FAST	0.26	0.12
SLOW	0.26	-0.05

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

Period	FAST	SLOW
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 SLOW condition consistently display a distaste for risk, with the magnitude of the estimated coefficients slightly decreasing as trading periods progress. In the FAST 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 SLOW 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 SLOW condition than in the FAST 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.

We obtain that the RAD is equal to 0.26 in both conditions and the RD is equal to -0.05 in SLOW and to 0.12 in FAST. Overall, prices are in line with the risk-averse FV in the SLOW condition, but are higher than expected in the FAST 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 SLOW condition.

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

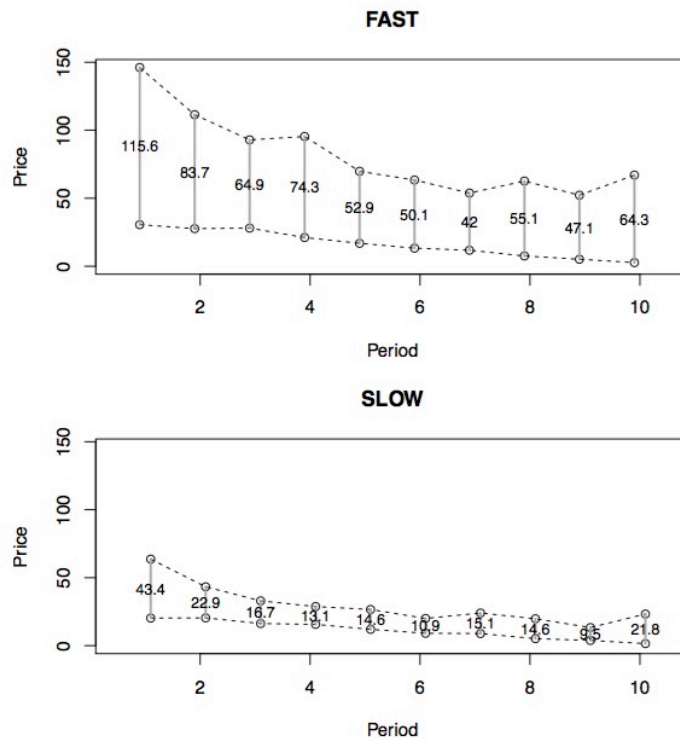


Figure 2: **Bid-Ask Spread**

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 FAST condition, ask prices are much higher than in the SLOW condition, for all trading periods. It follows that the average spread between listed selling and buying prices is much larger in the FAST condition than in the SLOW one. It is important to remember that in the SLOW 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.

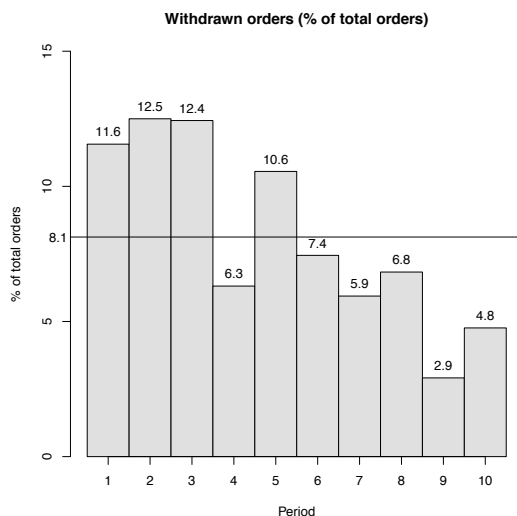


Figure 3: **Orders withdrawal in SLOW condition**

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 FAST 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 esti-

mates 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 (*SLOW*) equal to 1 when the transaction happens in condition SLOW and equal to zero when in condition FAST, 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)***
SLOW	-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)
<i>Time</i> : <i>SLOW</i>	0.930 (0.146)***	0.032 (0.005)***	0.010 (0.001)
Div_{t-1} : <i>SLOW</i>	-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 SLOW prices start lower than in condition FAST (*SLOW* coeff=-14.338). However, the decrease in prices observed as trading periods progress (*Time* coeff.=-2.788) is much more sustained in condition FAST than in condition SLOW (*Time* : *SLOW* coeff.=0.930). Interestingly, obtaining a dividend in the previous round inflates prices (Div_{t-1}) thus providing evidence of the existence

⁵The 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.

of the hot-hand fallacy; however, the effect is statistically significant only in the FAST condition.⁶ Thus, the FAST 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 SLOW condition than in FAST and decrease over time. The impact of dividends in the previous period is positive, but only in condition FAST. Concerning *Bid*, offers of purchase are lower in FAST than in SLOW and decrease over time. However, in contrast to what is highlighted for ask offers and closed contracts, previous dividends have no significant impact on offers, neither in condition FAST nor in condition SLOW.

6 Conclusions

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 be made within System-1; therefore without relying on rational decision making as mainstream financial theory assumes that trading decisions are made. We have begun to address this issue by using a standard experimental financial market, modeled after Smith et al. (1988). We have characterized two treatments as FAST and SLOW: in the former, trading decisions are taken quickly and cannot be reversed while in the latter and decisions had to be confirmed within 10 seconds before being enforced. Our conjecture was that individuals in the FAST condition had to rely more on System-1 decision making; and thus these individuals may trade quite differently than individuals in the SLOW condition that could instead rely on System-2.

Our experiment delivers unambiguous results. FAST markets experience huge volatility and price dispersion relative to SLOW markets and the most extreme realizations always happen while under the FAST condition. FAST 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, SLOW traders tend to trade much more conservatively, in a way compatible with a risk-averse assessment of the market FV all the way through.

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

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 measure show that the SLOW condition produces prices that are indeed very close to the predicted FV with risk-aversion, while in the FAST condition the relative deviation is substantial and positive.

Market equilibrium prices under FAST and SLOW 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 FAST condition and a much smaller price difference in the SLOW condition. The difference is mainly driven by the difference in the ask prices that range far higher in the FAST condition. Coincidentally, in the SLOW condition, we observe relatively more withdrawals of orders in the first periods, exactly when ask and final prices skyrocket in the FAST condition. This evidence suggests that System-1 reasoning in the SLOW condition induces subjects to withdraw extreme offers before they reach the market.

Finally we also demonstrated that under the FAST 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 experimental work, we do not resist the temptation to derive some policy implications from this work which would sound simple, although detonating. Our results suggest that slowing down finance trading would be an effective course in avoiding bubbles and making financial markets more efficient. This would demand drastic revisions of current trading rules, and we are aware this proposal will sound unpalatable to various parties. First, it is hard to envision how High Frequency Trading – which covers the bulk of trades nowadays and relies on computerized algorithms – may be made consistent with a waiting time to prompt System-2 investment decisions.

Secondly, our results are also at odds with the Tobin tax approach. For us, in fact, what makes financial markets outcomes more rational is not a transaction tax but a waiting time. In other words, we do not need “to put sand in the wheels” of finance, but need to “use the right wheels”.

In the event, we might appeal to a “Fabian strategy” instead of a “Tobin tax”. Tangentially, in fact, we can remind that Roman general Quintus Fabius Maximus dealt with Hannibal’s military superiority through the first application of the war of attrition strategy. Detractors of his time debased Fabius Maximus to ‘Cunctator’, the delayer. But history recognizes that waiting was the most rational choice for the Roman general, for he eventually managed to defeat Hannibal. There is no need to mention that additional evidence and argumentations 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 our (better, Kahneman’s) simple intuition that rationality demands time in order for System-1 to step up to System-2 decision-making.

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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 $400 \text{ ECU} = 1 \text{ EUR}$.

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.

[FAST] 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

[SLOW] 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.

