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Trading fast and slow: 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 studied both the determinants of bubbles and institutional measures to prevent them. Within the framework of the dual-process theory, we experimentally investigate whether traders under higher time pressure (*Fast* condition) behave differently than traders under lower time pressure (*Slow* condition). Relative to the *Fast* condition, the *Slow* condition dampens market price volatility, dramatically reduces the spread between ask and bid limit orders, and leads to higher equality in payoffs.

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1. Introduction

The ubiquitous diffusion of online trading platforms offers opportunities to trade in (almost) real-time to many non-professional traders. Platforms often advertise their transaction speed to win consumers in this intensely competitive market. Speed in the execution of trades might be prompted by the fear of missing out, a relevant decision driver, especially when individuals are connected through social networks (Buglass et al., 2017). The pressure for humans to perform fast trades might be further exacerbated by the diffusion of fast-trading algorithms in the financial markets (Aït-Sahalia and Saglam, 2013).

Human fast trading might increase capital markets' short-termism and its potential distortions (Davies et al., 2014). Furthermore, faster trading could induce misallocation due to the formation of financial bubbles, possibly connected with herding behavior (Hott, 2009). Two additional downfalls are that excessively speculative and volatile markets might contribute to raising inequality (Brei et al., 2018) and could bias the valuation of listed enterprises aiming at long-term and sustainable objectives (Orlitzky, 2013).

We focus on the possible implications that human fast trading has on market outcomes. Specifically, we explore the hypothesis that orders of traders who are given less time to ponder are more erratic than those of traders who are given more time to deliberate. Although financial theory largely relies on the assumption that traders are fully rational decision-makers, behavioral finance has long been questioning this assumption (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. Time pressure is generally acknowledged as one of the key factors that induce decision-makers to rely more on System 1 than on System 2.

In the face of this evidence, addressing the following questions becomes paramount: Does the increased speed of trades affect the way decisions are made in financial markets? Are quick and

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smooth financial markets producing better allocative decisions, or is speed deteriorating the decision-making process and favoring the formation of financial bubbles? Does more reliance on speed lead financial markets to increase inequality?

In this paper, we study the formation of financial bubbles in the context of a double-auction 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 s 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. This simple manipulation is sufficient to curb highly volatile and extreme price realizations that are present in the *Fast* condition: Average prices become consistently aligned with the expected fundamental value once risk-aversion is considered. The high volatility observed in the *Fast* condition is explained by the larger bid/ask spreads observed here relative to the *Slow* condition, and these larger spreads mainly originate from an upward biased evaluation by potential sellers. A further noticeable effect concerns the distribution of wealth at the end of the experiment, which is more egalitarian in the *Slow* condition. Our lab experiment puts the predictions of the standard efficient-market hypothesis to test and suggests that a small variation in the time span of the trader's decision may have a sizable impact on prices in financial markets with possible effects on fairness considerations as well.

2. Surveying the literature

The experimental literature on financial bubbles mostly builds on the landmark paper by Smith et al. (1988) (SSW). 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 a 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 a market did produce large bubbles followed by sudden crashes. A large experimental literature has since then been built on the original SSW design in order to test whether such bubbles and crashes depend on institutional market characteristics and/or on behavioral biases (for a survey see Palan, 2013).

In terms of the impact of behavioral states on market outcomes, Hargreaves-Heap and Zizzo (2011) show that markets with subjects in a state of excitement produce substantially larger bubbles. Andrade et al. (2015) and Lahav and Meer (2012) show that inducing a positive mood in subjects prior to trading produces significantly higher prices. Breaban and Noussair (2018) gather traders' emotions in a double-auction market with dedicated software detecting facial expressions. A strong connection between emotions and market outcomes emerges from their data. Specifically, positive emotions are associated with bubbles, while negative emotions are associated with negative price changes. In addition, several works show that overconfidence is likely to inflate bubbles (Kirchler and Maciejovsky, 2002; Michailova and Schmidt, 2016; Oechssler et al., 2011; Deck and Jahedi, 2015).

Our experiment intentionally manipulates the time frame of the trade in order to study how this affects the quality of the decision under the hypothesis that quicker decisions are more affected by cognitive biases (Kahneman, 2002). On how speed is related to cognitive biases, an established theory based on the dual-process paradigm (Epstein, 1994; Kahneman, 2002) suggests that decisions are the outcome of the interaction between an impulsive/reactive mechanism (System 1) and a reasoned/reflective mechanism (System 2). Alós-Ferrer and Strack (2014) highlight the opportunity the dual-process perspective offers to economists as a "theoretical scaffolding" to generate hypotheses that can be tested in the lab. Notice that the theory suggests that the human brain can at times elaborate the very same decisions by means of either one of the two systems, depending on the circumstances. In particular, by reducing the cognitive resources available for System 2, the decision-making process might be shifted to System 1. The two most common controlled manipulations used to obtain this shift are *cognitive load* and *time pressure*. In the former, individuals are asked to make the decision while they perform a cognitive-intensive task; in the latter, individuals are exogenously limited in the time available to make their decision. The intuition is that under higher time pressure and/or higher cognitive load the impulsive/reactive mechanism becomes prominent over the reasoned/reflective mechanism. While our paper explores the time-pressure manipulation, Kocher et al. (2019) instead manipulate cognitive load through a laboratory task (a standard Stroop task) and shows that depleting self-control prior to trading inflates market bubbles and undermines profits for those subjects with depleted self-control. The work of Kocher et al. (2019) is complementary to ours.

Several studies highlighted the relevance of the impulsive/reasoned tension for decisions having an explicit financial meaning. Kirchler et al. (2017) show how time pressure strengthens the asymmetry in risky preferences typical of Prospect Theory (reflection effect): Individuals choosing among risky prospects under tighter time constraints are more risk-averse in gains and more risk-seeking in losses than individuals choosing under looser time constraints. Even more interesting for our study is the fact that stronger time pressure generates more noise in observed choices. As an example, Kocher and Sutter (2006) demonstrate that, in a beauty contest game, convergence toward equilibrium outcomes is faster when more time is given to choose. These results are generally taken as evidence supportive of the conjecture that time pressure leads to higher reliance on System 1.

Our inquiry into the impact of time pressure on the overall performance of financial markets must be read within a broader stream of literature investigating the relevance of the cognitive dimension in financial markets. Hirshleifer (2015) offers an extensive survey of the many implications of behavioral finance, arguing that cognitive biases can help explain most of the observed anomalies in financial markets. Among recent works investigating the role that one's own cognitive abilities have on trading behavior, Corgnet et al. (2018) focus on three main constituents of one's cognitive endowment: Fluid intelligence, cognitive reflection, and theory of mind. In a nutshell, fluid intelligence is a measure of computational skills, cognitive reflection captures the ability to engage System 2 in making decisions, and theory of mind is the ability to infer others' intentions. Data collected in experimental double-auction markets show that all three constituents positively affect traders' earnings. The authors also highlight the importance of the interaction between alternative resources, with cognitive reflection fostering the positive impact of theory of mind. Weitzel et al. (2020) compare the behavior of students and financial professionals in a lab-in-the-field experiment and show that in both populations mispricing is present, but in markets with professionals, deviations from rational predictions are smaller in magnitude. Among possible explanations for this difference, the authors also consider the role of cognitive abilities, ruling out the hypothesis that the higher efficiency of markets populated by professionals is due to

better cognitive skills. Differently, Bosch-Rosa et al. (2018) report that when market participants are sorted into markets according to a (high and low) cognitive sophistication index, which measures cognitive reflection, strategic sophistication, and backward induction ability, experimental markets with low-scoring participants often experience bubbles, while markets with high-scoring participants trade around fundamental values. Overall, recent contributions confirm the relevance of the cognitive dimension in experimental financial markets.

The relevance of the dual-process approach for the understanding of financial markets is not uncontroversial (e.g., Shleifer, 2012). However, the experimental evidence reviewed above suggests that when individuals are given more time to deliberate, choices are closer to rational outcomes. As we detail in Section 3.2, we start from this evidence to formulate a series of research questions investigating the impact that our controlled manipulation, altering time to deliberate on trades, has on market outcomes and individual trading behavior.

3. Method

3.1. 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 1000 ECUs. We allow participants to trade in 2-minute-long sessions for 10 consecutive periods, 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 showing the 10 best 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.[2]

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 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 lower (higher) than the risk-neutral one (see also Appendix A).

We compare the behavior of participants in two different experimental conditions, *Slow* and *Fast*. The treatment labels refer to the time given to a participant to deliberate on an inputted order. In the *Slow* condition, the participant who "closes" a transaction, either by buying or selling virtual stocks, is given 10 s to either confirm or cancel the trade. In more detail, after a market order, a blank screen is shown for the first 5 s, and then the buttons to confirm or to cancel the order appear on the screen. The participants have 5 s to press the button and cannot return to the market before the 5 s are over. 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 market order but waits for 10 s before returning to the market. As in *Slow*, the market keeps working on existing orders during the 10 s. In both conditions, the traders cannot follow the market dynamics or input any new order during the 10 s following the input of the order. This design feature aims to prevent the possible strategic use of the waiting time, similar to what happens when traders sign option contracts.

3.2. Research questions

Our research questions rely on the starting assumption that experimental subjects rely more on the (impulsive/reactive) System 1 than on the (reasoned/reflective) System 2 to make their decisions when they play in condition *Fast* and less so when they play in condition *Slow*. The contributions reviewed above suggest that factors prompting System 1 are likely to trigger deviations from rational outcomes in markets and games which, in the domain of financial markets, translates into the emergence of substantial deviations from fundamental values, taking the form of bubbles. Based on this, the following main research question will guide our analysis.

RQ 1. *Does the* Slow *condition promote smaller deviations from fundamental values than the* Fast *condition?*

Furthermore, we will also explore additional questions that descend from our RQ1. Moving from market outcomes to individual behavior, we investigate the impact that our experimental manipulation has on trading styles. Specifically, we will inquire whether our manipulation affects the distance between demand and supply of stocks as captured by the bid/ask spread in limit orders. An established strand of experimental literature demonstrated that sellers and buyers tend to have diverging perceptions of their assets. In particular, sellers' willingness to accept is generally upward biased relative to market values (on the WTP/WTA spread see, among others, Kahneman et al., 1990). Based on this solid evidence, we inquire whether more reliance on System 1 might promote a larger bid/ask spread in limit orders.

RQ 2a. *Does the* Slow *condition promote a smaller bid/ask spread than the* Fast *condition?*

Based on market orders, traders can be classified into different types (e.g. Haruvy et al., 2014). We will focus on the presence of fundamental traders and speculators in the two conditions. The former tend to trade around the fundamental values, buying stocks when they are undervalued and selling them when they are overvalued. The latter can be divided into two types, momentum and rational speculators. Momentum speculators choose on feedback and tend to inflate bubbles; rational speculators aim at anticipating bubble dynamics and start to offload their stocks when momentum traders still buy, initiating the downward spiral of prices. Our research question relies on the assumption that higher time pressure will foster the emergence of blind momentum speculation at the expense of forward-looking speculation.

RQ 2b. *Does the* Slow *condition favor the emergence of rational speculators relative to the* Fast *condition?*

Finally, we will explore the impact that our experimental manipulation has on the earnings distribution of those participating in the market. The starting consideration is that markets that deviate more from fundamental values offer more opportunities for speculators. In particular, when sophisticated traders can anticipate the burst of a bubble, large profits can be made. This should translate into more inequality in traders' earnings.

[2] A screenshot of the trading screen is reported in Appendix D.

RQ 3. *Does the* Slow *condition induce a more equal distribution of final earnings than the* Fast *condition?*

3.3. Participants and procedures

The experimental sessions were run at the Cognitive and Experimental Economics Laboratory (CEEL) of the University of Trento (Italy). A total of 210 participants took part in the experiment, 104 participants in the *Slow* condition and 106 in the *Fast* condition. Each participant could take part in only one session of the experiment. Participants were students 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 min and a total of 23 independent market observations (12 *Fast* and 11 *Slow*) were collected.[3] 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 periods, participants were given the opportunity to familiarize themselves with the trading platform in a practice period.

4. Results

The presentation of our results follows the structure of our research hypotheses: First, we focus on market outcomes, with several measures of deviations from fundamental values; second, we highlight potential patterns in the behavior of traders across the two experimental conditions; third, we assess the impact of alternative experimental conditions on final earnings, with a special focus on the equity of allocations.

4.1. Market outcomes

Fig. 1 provides a depiction of the markets in the two experimental conditions, *Fast* and *Slow*.

Fig. 1 shows that, at the session level, average prices in the *Fast* condition are much more dispersed than in the *Slow* condition. For 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 in each period. Furthermore, relative standard deviations (RSD) are reported to ease comparison across treatments.

In the *Fast* condition, average prices start largely above the risk-neutral in the first two periods. In contrast, in the *Slow* condition, average prices are consistently below the FV in all periods. 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 the *Fast* than in the *Slow* conditions throughout trading periods, with larger differences in the first periods. Concerning trading volumes, on average, 17.6 units per period are exchanged in the *Fast* and 16.6 in the *Slow* condition. In both conditions, trades tend to increase over time, with the last four periods recording more trades than the average.

Fig. 1 highlights differences across the two conditions and a visual representation of deviations from FVs. Evidence gathered from Fig. 1 is corroborated by a series of measures of deviations from the risk-neutral fundamental price (Stöckl et al., 2010).[4] Prices observed in the *Slow* condition are consistently below the FV, with an overall RD $= -0.35$, significantly different from zero (p-value $= 0.005$). In contrast, in the *Fast* condition, we observe a RD $= -0.04$, not significantly different from zero (p-value $= 0.519$). This is mainly due to a "composition effect" obtained by aggregating initial over-pricing and later under-pricing. Differently, the RAD measure, which takes deviations in absolute terms, shows that deviations from the FV are significantly different from zero in both conditions, with RAD $= 0.29$ in *Fast* and RAD $= 0.35$ in *Slow* (p-values< 0.001).[5]

Table 1
Prices: Descriptive statistics.

Period	Fast			Slow		
	Mean	SD	RSD	Mean	SD	RSD
1	74.69	119.21	1.60	42.41	13.88	0.33
2	52.38	67.18	1.28	32.91	15.81	0.48
3	36.78	44.95	1.22	27.79	15.66	0.56
4	30.91	47.06	1.52	22.27	14.85	0.67
5	21.19	20.75	0.98	19.19	12.60	0.66
6	16.67	15.58	0.93	14.20	8.42	0.59
7	12.30	13.63	1.11	11.73	7.08	0.60
8	9.01	7.81	0.87	6.99	4.22	0.60
9	6.01	4.79	0.80	4.57	3.64	0.80
10	3.58	2.82	0.79	2.26	1.86	0.83

The table provides a few summary statistics of market orders in the two experimental conditions in the 10 trading periods. RSD is the ratio between SD and Mean.

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; Dohmen et al., 2011). In Appendix A, we explore the implications of risk aversion for our market. As shown by Table 7 in the Appendix, in *Slow* the estimated coefficients of relative risk aversion display a consistent distaste for risk in each period. Differently, in *Fast* risk aversion emerges only from period 3 on. Adopting the overall estimates of risk aversion reported in Table 7, one can re-estimate the RD and RAD coefficients for the risk-adjusted fundamental value (see Appendix A for more details). As shown by Table 8 in the Appendix, the RD value in *Slow* condition is close to zero (RD $= -0.05$) and smaller than that estimated under the conventional assumption of risk neutrality. Differently, in the *Fast* condition, the RD value increases from -0.04 to 0.12. The risk-adjusted RAD measures are equal to 0.26 in both conditions. Overall, the risk-adjusted estimate shows that trading patterns in *Slow* condition are compatible with risk-averse attitudes in trading. Instead, in *Fast* traders are not consistently risk-averse and are more erratic over trading periods.

To corroborate the evidence emerging from our descriptive analysis, in Table 2 we also report the outcome of linear mixed model estimations, with random effects at the individual and market level. The dependent variable is *Price*, which refers to the prices of closed market transactions. As explanatory variables, we employ the minutes elapsed from the beginning of the trading

[3] In the *Fast* condition, 4 markets had 8 participants, 6 markets 9 participants and 2 markets 10 participants. In the *Slow* condition, 2 markets had 8 participants, 2 markets had 9 participants, and 7 markets had 10 participants.

[4] The Relative Absolute Deviation (RAD) captures average mispricing and is computed as $RAD = \frac{1}{N}\sum_{t=1}^{N}\frac{|P_t^M - FV_t|}{FV^M}$, where t stands for trading periods, N is the total number of periods, and P_t^M and FV_t stand for volume-weighted average price in period t and FV in period t, respectively. The absolute difference between these two terms is normalized with the mean fundamental value in the market FV^M. Unlike the RAD, the Relative Deviation (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: $RD = \frac{1}{N}\sum_{t=1}^{N}\frac{(P_t^M - FV_t)}{FV^M}$.

[5] The reported p-values are obtained from Wilcoxon signed rank tests on session-level data.

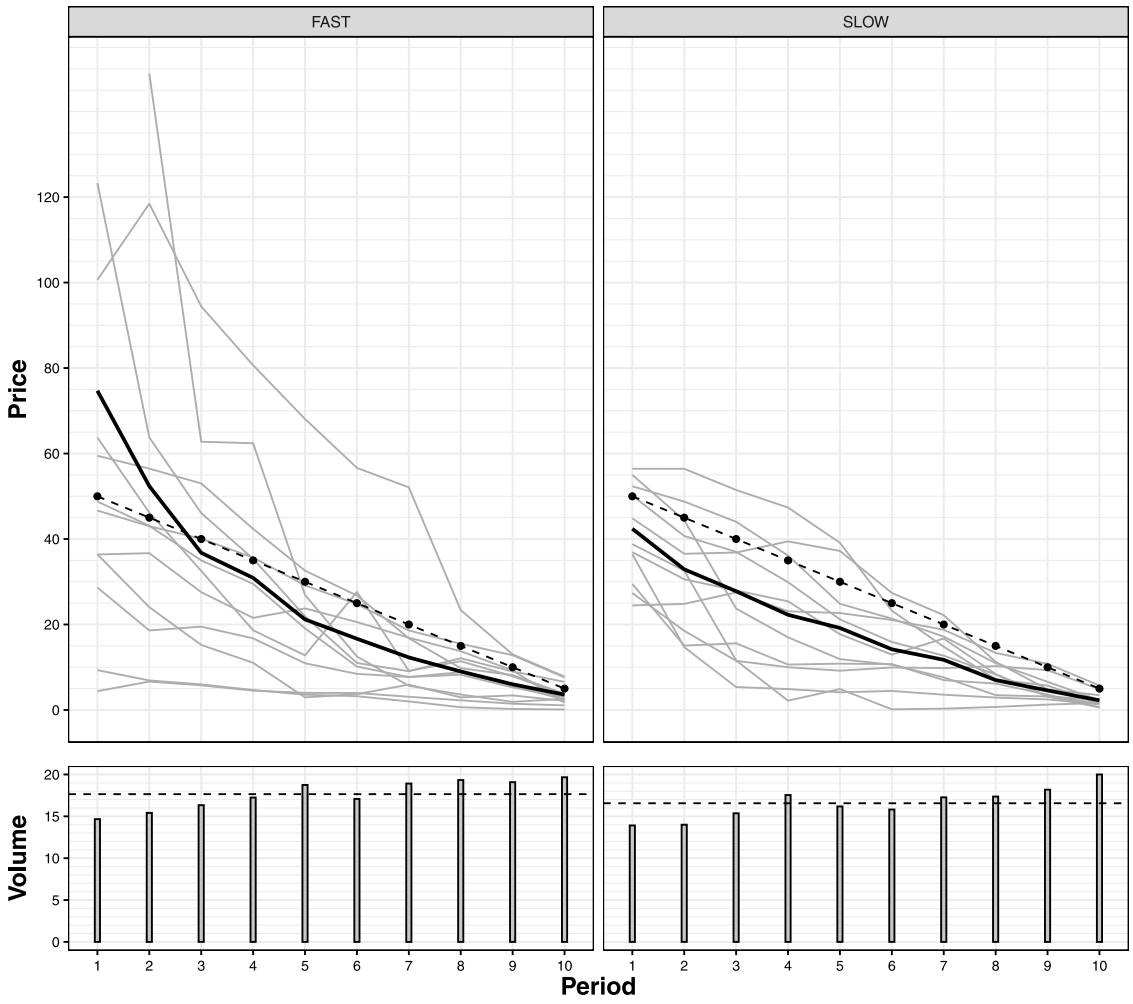


Fig. 1. Market outcomes. The upper panels capture the price dynamics of market orders in the two experimental conditions. The gray lines show average prices in each period for each market. The bold black line shows the mean price in each period obtained by pooling all markets together. The dashed line captures the risk-neutral FV. The lower panels illustrate market volumes per period (bars) and average volumes across periods (dashed lines).

session (*Time*); a treatment dummy (*Slow*), equal to 1 when the transaction happens in the *Slow* condition and equal to zero when in the *Fast* condition. In Model 2, we also control for the potential impact of past dividends, with a dummy variable coding whether a dividend was paid in the previous period (Div_{t-1}).[6] We also consider the impact of the interaction between the dividend payment and the treatment dummy.

The regression estimates in Model 1 show that in the *Slow* condition, prices start significantly lower than in the *Fast* condition (*SLOW* coeff $= -24.382$). However, the decrease in prices observed as trading periods progress (*Time* coeff. $= -3.447$) is much more sustained in the *Fast* condition than in the *Slow* condition (*Time* : *SLOW* coeff. $= 1.422$). When adding a control for past dividends (2), the statistical quality of the estimation increases sharply, as shown by information criteria. Interestingly, obtaining a dividend in the previous period inflates prices (Div_{t-1}); however, as shown by the interaction term, the effect

Table 2
Prices — Regression analysis ().

	(1)	(2)
(Intercept)	67.237 (4.358)***	54.296 (3.547)***
Time	−3.447 (0.125)***	−2.781 (0.097)***
Slow	−24.382 (6.310)***	−14.490 (5.144)**
Time:Slow	1.422 (0.183)***	0.925 (0.142)***
Div_{t-1}		0.463 (0.102)***
Slow: Div_{t-1}		−0.401 (0.150)**
AIC	38539.197	32494.923
BIC	38583.149	32550.649
Num. obs.	3940	3611
IDs	194	192
Sessions	23	23

The table reports the outcomes of a Linear Mixed Model regression (LMM). The *dependent variable* is the price of a closed market transaction. The *explanatory variables* are: *Time*, capturing the minutes elapsed from the beginning of the trading session; *Slow*, a treatment dummy; Div_{t-1}, a dummy variable capturing whether a dividend was paid in the previous period. Significance levels: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$.

[6] 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.

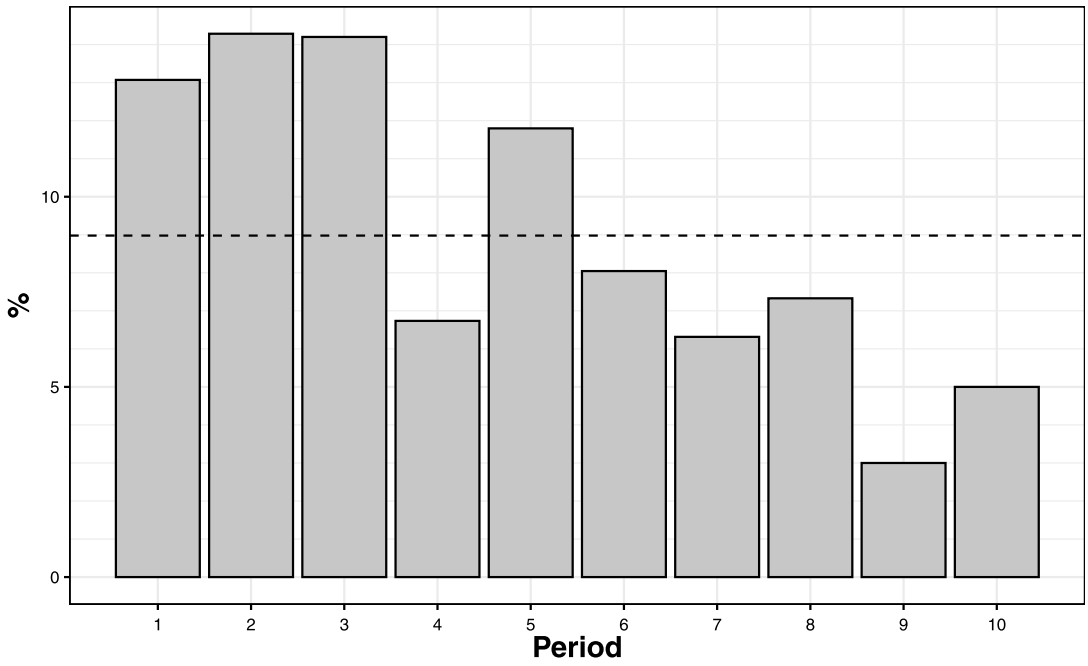


Fig. 2. Market orders' withdrawal (*Slow* condition). Bars provide a representation of the percentage ratio of orders that are withdrawn to orders that are actively executed in different periods.

is statistically significant only in the *Fast* condition.[7] Thus, the *Fast* condition seems to promote biased beliefs about positively correlated dividend payments.

The evidence collected about outcomes at the market level leads us to formulate our main result:

Result 1. *Overall, market prices are less volatile in the* Slow *than in the* Fast *condition. Positive deviations from fundamental values are generally observed only in the early periods of the* Fast *condition.*

4.2. 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 specific aspects of individual trading behavior, namely the spread between ask and bid offers and trading styles. Before moving to this analysis, we provide a description of order choices in trading.

4.2.1. Order choices

We compute here a few measures of order choices following Stöckl and Kirchler (2014). In particular, we focus on *limit orders (LO), limit trades (LT), and market orders (MO)* made by a trader. Limit orders capture the number of orders inputted to the market at a given execution price by a trader, limit trades capture the number of trades that originate in a limit order inputted by the trader, and market orders measure the number of trades executed by a trader on others' limit orders. Given these order choices, we compute three indexes of traders' activity, namely *Submission Rate (SR), Execution Rate (ER), and Taking Rate (TR)*: SR captures the propensity to post limit orders relative to overall trading activity; ER is a measure of the likelihood that limit orders end up in actual trades; TR is a measure of the propensity to engage in market activity with own liquidity.[8]

Table 3
Order Choice Indexes.

Condition	SR	ER	TR
Fast	0.631 (0.215)	0.438 (0.243)	0.519 (0.203)
Slow	0.638 (0.210)	0.409 (0.246)	0.500 (0.190)

SR: Submission Rate; ER: Execution Rate; TR: Taking Rate. Averages and standard deviations (within parentheses) are reported in the table.

The overall share of traders who do not post limit orders is equal to 9.7% and 9.3% in conditions *Fast* and *Slow*, respectively. On average, 7.0 and 7.1 limit orders are inputted in each period by active traders in conditions *Fast* and *Slow*, respectively. Limit trades are equal to 2.9 and 2.7, and market orders are 2.8 and 2.5, respectively. Table 3 reports on the average and the standard deviation (in parentheses) for the three indexes, across the two experimental conditions.

As Table 3 shows, both ER and TR are slightly higher in the *Fast* than in the *Slow* condition. However, a series of non-parametric tests on average indexes at the individual level do not detect any significant difference across the two conditions (Wilcoxon rank sum test, all p-values > 0.140).

Participants in condition *Slow* are given the opportunity to withdraw a market order within a given time span, while limit orders can never be withdrawn from the book. Fig. 2 shows the percentage of withdrawn market orders relative to actively

[7] The linear hypothesis test $Div_{t-1} + Div_{t-1} : SLOW = 0$ returns a Chisq = 0.324 (p-value = 0.569).

[8] Given that in our market only unit trades are accepted, the number of shares traded and the number of orders match. For a trader j in period k of market m, the measures are computed as follows: $SR_{m,j,k} = \frac{LO_{m,j,k}}{LO_{m,j,k}+MO_{m,j,k}}$; $ER_{m,j,k} = \frac{LT_{m,j,k}}{LO_{m,j,k}}$; $TR_{m,j,k} = \frac{MO_{m,j,k}}{MO_{m,j,k}+LT_{m,j,k}}$.

Table 4
Bid/Ask orders — Regression analysis.

	(1) Ask	(2) Bid
(Intercept)	117.711 (21.167)***	32.405 (2.910)***
Slow	−76.435 (30.522)*	−9.660 (4.201)*
Time	−0.049 (0.003)***	−0.022 (0.000)***
Time:Slow	0.032 (0.005)***	0.010 (0.001)***
Num. obs.	9326	4227
IDs	206	194
Sessions	23	23

The table reports the outcomes of a Linear Mixed Model regression (LMM). The *dependent variable* in (1) is a price order posted by a potential seller. The *dependent variable* in (2) is a price order posted by a potential buyer. The *explanatory variables* are: *Time*, capturing the minutes elapsed from the beginning of the trading session; *Slow*, the treatment dummy. Significance levels: $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$.

executed orders (i.e., confirmed orders in the waiting stage), in condition *Slow*.

On average, withdrawn market orders are 9% of the actively executed orders. The relative share of withdrawn orders is well-sustained in the first periods and then tends 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 the *Fast* condition, where the withdrawn option is not available.[9]

4.2.2. Bid/ask spread

Fig. 3 provides a representation of the distance between average demand and supply in the two experimental conditions, over periods.

As Fig. 3 shows, both ask and bid prices tend to decrease over time, following the evolution of fundamental values. 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 differ markedly from those 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*.

Table 4 corroborates, with the support of a regression analysis, the qualitative evidence delivered by Fig. 3. When the dependent variable is *Ask*, we refer to the price of orders posted by those ready to sell. When the dependent variable is *Bid*, we refer to the price of orders posted by those ready to buy. As explanatory variables, we adopt the same variables as in Model 1 of Table 2.

In qualitative terms, the regression estimate for *Ask* confirms the effects highlighted for closed contracts. Offers are significantly lower in the *Slow* than in the *Fast* condition and decrease over time. A similar pattern emerges for bids, though the differences between the two conditions are less dramatic.

Result 2a. *Overall, a smaller bid/ask spread is observed in the* Slow *compared to the* Fast *condition. This is mainly due to the disproportionately large limit orders posted by potential sellers in the* Fast *condition.*

[9] As a robustness check, we run a few additional sessions based on the *Slow* condition, but with a different default rule: orders not withdrawn are automatically executed. In these sessions, we also keep track of the price of withdrawn orders. A detailed description is available in Appendix B. From these sessions, we gather that the default execution rule in condition Slow has no major impact on trading prices and that the value of withdrawn orders is similar to that of actively executed orders.

Table 5
Distribution of types.

Condition	Fundamental	Momentum	Speculators	Others
Fast	30.6%	16.4%	39.6%	13.4%
Slow	30.3%	13.1%	46.7%	9.8%

The table shows the distribution of types in percentage terms. Details about classification criteria are provided in footnote 10.

Table 6
Earnings (EUR).

Condition	Mean	SD	Median	Range
Fast	10.223	2.485	9.981	3.833–18.667
Slow	9.923	1.680	10.023	4.484–14.743

The table shows summary statistics of earnings in the two experimental conditions.

4.2.3. Trading style

Following the traders' taxonomy of Haruvy et al. (2014), we identify three main types of traders: *Fundamental* traders who purchase stocks when they are below their fundamental value and sell stocks when they are above it; *momentum* traders who trade following a momentum strategy, i.e. buy after an increase in prices and sell after a decrease; *rational speculators* who correctly anticipate future price movements and if the price movement is upward (downward) they increase (decrease) their holdings. The distribution of types is reported in Table 5.[10]

The share of fundamental traders is quite similar across conditions, while the composition of other types shows some differences in *Fast* and *Slow*. Notably, the share of rational speculators is larger in *Slow*, while the share of momentum traders and the residual type is larger in *Fast*. However, a Pearson's Chi-squared test detects no significant difference in the distribution of types in the two conditions (p-value = 0.585).

Result 2b. *In qualitative terms, more rational speculators and fewer momentum traders are present in the* Slow *than in the* Fast *condition. However, the difference in types distribution is not significantly different across conditions.*

4.3. Earnings distribution

The analysis above highlighted differences in trading patterns across experimental conditions, with higher price volatility in the *Fast* condition than in the *Slow* condition. Here, we investigate how this reflects into the final earnings of the participants. Table 6 presents a few summary statistics of the earnings in the two experimental conditions.

As expected, central measures of earnings are pretty similar across the two conditions. This is a direct consequence of our design, featuring a fixed number of shares and stochastic dividends.

[10] $\Delta_S = S_t - S_{t-1}$ captures the change in stocks holding from period t to $t-1$, FV_t the stock's fundamental value in period t, and $\overline{P}_t$ the average trading price in period t. A trader is classified as fundamental if $\Delta_S > 0$ and $FV_t - \overline{P}_t > 0$ or $\Delta_S < 0$ and $FV_t - \overline{P}_t < 0$. A trader is classified as momentum trader if $\Delta_S > 0$ and $\overline{P}_{t-1} - \overline{P}_{t-1} > 0$ or $\Delta_S < 0$ and $\overline{P}_{t-1} - \overline{P}_{t-1} < 0$. A trader is classified as rational speculator if $\Delta_S > 0$ and $\overline{P}_{t+1} - \overline{P}_t > 0$ or $\Delta_S < 0$ and $\overline{P}_{t+1} - \overline{P}_t < 0$. For each trading period, traders who fall in one of the categories obtain a score. There are 7 periods for which we have all the pieces of information needed to classify a subject, when traders obtain the majority of scores (> 3) for a type, they are classified as belonging to that type. Those who do not report a score larger than 3 are classified as Others.

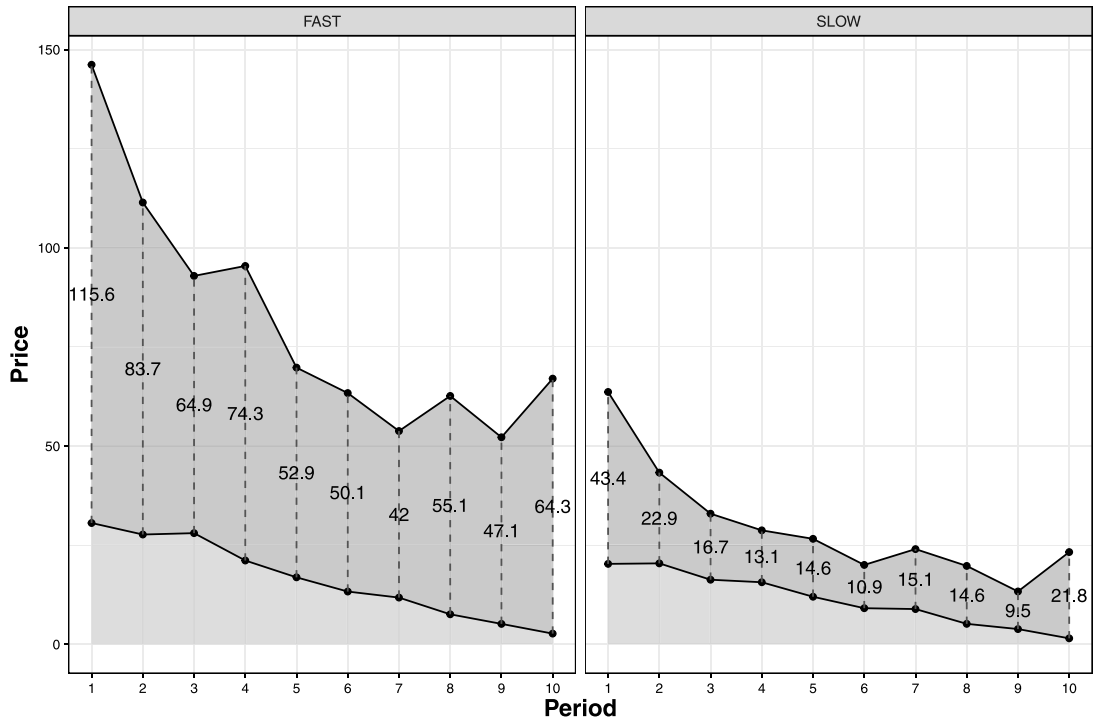


Fig. 3. Bid/ask spread. The upper line captures average ask prices. The lower line captures average bid prices posted by traders. Numbers measure the distance between the two lines.

However, both the range of values and the standard deviation differ across conditions, with earnings significantly more dispersed in the *Fast* than in the *Slow* condition (Levene's Test, p-value = 0.001).

To obtain a direct measure of differences in the distribution of earnings across the two conditions, we provide a representation of earnings deciles in Fig. 4.

As shown by the figure, larger differences across income deciles are observed in condition *Fast* than in condition *Slow*. Common measures of inequality in income distribution provide us with a direct measure of differences across the two conditions: The interdecile ratio 90–10 is equal to 1.8 and 1.454 in conditions *Fast* and *Slow*, respectively; the Gini Index is equal to 0.131 and to 0.086 in conditions *Fast* and *Slow*, respectively. Thus, the *Slow* condition results in higher equality in terms of income distribution, while the *Fast* condition seems to foster a polarization of earnings, with a few participants able to capitalize on the higher volatility induced by faster decision making. This can be summarized as follows:

Result 3. *Less inequality in final earnings is observed in the* Slow *than in the* Fast *condition.*

5. Discussion and conclusions

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). In these markets, where algorithms and naive and sophisticated human traders interact, studying the impact of cognitive biases on the efficient working of financial markets has become of paramount importance.

As speed in transactions is becoming ubiquitous, dual-process theory predicts more and more trading decisions to lean toward intuition rather than deliberation and this increases even further the quest for more studies on how speed affects finance via its effect on behavioral biases. Our own contribution to this inquiry is based on the study of a continuous double auction experimental market, modeled after Smith et al. (1988). We have characterized our two treatments as either the *Fast* condition or the *Slow* condition; in the former, trading decisions are taken quickly and cannot be reversed while in the latter decisions must be confirmed within 10 s before being implemented. Our conjecture is that traders in the *Fast* condition have to rely more on System 1 decision making and, thus, may trade quite differently than individuals in the *Slow* condition that could, instead, rely more heavily on System 2.

Our experiment shows that *Fast* markets experience huge volatility and price dispersion relative to *Slow* markets and the most extreme realizations always happen in the *Fast* condition. Traders in *Fast* are more likely to induce inconsistent market patterns that begin well above fundamental values, then collapse quickly to very low values (well below FV). 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. Moreover, we show that *Slow* trading produces final allocations which are consistently more equally distributed than in *Fast*, thus engendering a sense of market fairness. Interestingly, the regression analysis of Table 2 highlights that under the *Fast* condition individuals are more prone to wrongly believe there exists a positive auto-correlation of stock dividends (Huber et al., 2010; Xu and Harvey, 2014). This is compatible with the well-known "hot-hand fallacy" (Gilovich et al., 1985), a biased belief in

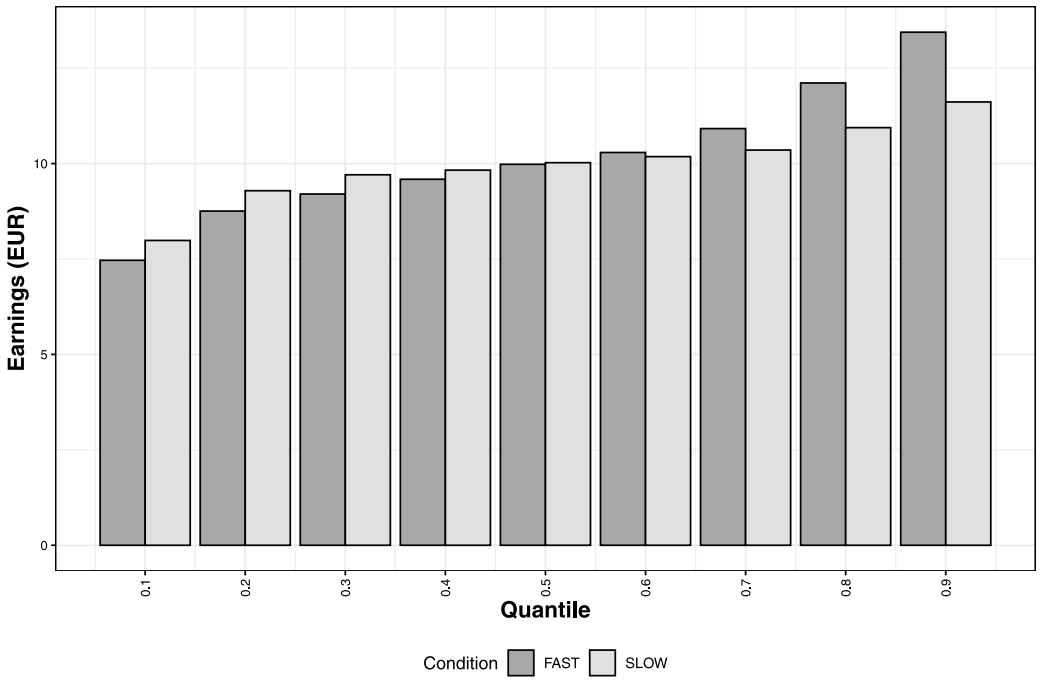


Fig. 4. Earnings deciles. Bars provide a representation of the earnings deciles of participants in the experiment. Lighter bars identify the *Slow* condition, darker bars the *Fast* condition.

series continuation of independent stochastic events. This further corroborates the hypothesis that when less time is available to deliberate, choices rely more on instinctive-heuristic reasoning.

Previous experimental evidence about continuous double-auctions consistently documents the emergence of speculative bubbles (e.g. Smith et al., 1988; Kirchler et al., 2012). In contrast, our markets are characterized by "conservative" trading, with market prices often below the risk-neutral fundamental value. This difference might be potentially due to several ancillary conditions in experimental settings (e.g., unobservable characteristics of the sample). However, it should be noticed that, unlike previous contributions, both our experimental conditions impose a waiting time of 10 s on active traders (the only difference being the possibility of confirming/canceling the order in the slow condition). Future research may study whether the mere existence of the waiting time is enough to curb positive deviations from fundamental values. Another interesting extension to the present framework would be to implement mixed markets where fast and slow traders interact. This design could capture an essential feature of real-world markets, namely that traders exposed to different time pressure in decision-making interact in the same market.

Market equilibrium prices under *Fast* and *Slow* differ, especially in early periods, but where does this difference come 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. This result is in line with previous findings on the WTA–WTP gap (Kahneman et al., 1990), which show that the overly high requests of sellers mainly drive the difference in the price asked by sellers and buyers. Interestingly, Nadler et al. (2018) report that testosterone-treated traders in experimental double-auction markets post higher ask prices than placebo-treated traders. Coincidentally, in the *Slow* condition we observe relatively more withdrawals of orders in the first periods, exactly when ask limit orders and market prices skyrocket in the *Fast* condition. The evidence collected suggests that the possibility to withdraw orders may reduce deviations from the fundamental because it decreases the number of inflationary inputs to the markets.

Several contributions called for a revision of the continuous-time trading protocol of modern financial markets to contrast the arms race for speed of High-Frequency Trading. Aquilina et al. (2021) estimate that the latency arbitrage due to such arms race imposes a roughly 0.5 basis point tax on trading, while suggesting that market designs that eliminate latency arbitrage would reduce the market's cost of liquidity by 17%, and that the total sums at stake are on the order of $5 billion per year in global equity markets alone. Harris (2013) suggests delaying the processing of all orders by a trivially short, random period of between 0 and 10 ms, which would ensure that high-frequency traders always provide markets with very low transaction costs. Budish et al. (2015) illustrate how moving from a continuous limit order book to discrete-time trading with frequent batch auctions will limit the profitability of algorithmic mechanical arbitrage. In the same spirit, Kyle and Lee (2017) put forward a mechanism based on continuous scaled limit order that jointly defines for each order a price range, the maximum quantity, and the speed of execution over time.

With all the usual disclaimers about external and ecological validity which apply to any experimental work, we do not resist the temptation to speculate about the policy implications of our

work. If our results would prove to be robust to further analysis, they might suggest that slowing down financial trading might be an effective course in reducing price volatility and making financial markets more efficient. How this slowing down should take place is beyond the scope of the present work, but some hints can be taken – for instance – from consumer protection legislation guaranteeing the right of withdrawal to informed consent procedures in medical decisions. Among the various difficulties, it is hard to envisage how High-Frequency Trading may be made consistent with a waiting time to prompt System 2 investment decisions. Another approach to relieving investors from time pressure would be to organize financial markets more as call auction mechanisms (such as the ones that happen at the opening and closing of most major stock markets) and less like continuous double-auctions.[11]

All the same, we shall recall that fifty years ago Nobel Prize laureate James Tobin proposed the introduction of a tax on financial transactions to curb the very same financial speculation and bubbles that still worry policymakers today. Our paper puts forward the idea that there might be another way of putting "sand in the wheels of finance" (Tobin, 1978) and this would be through the introduction of a non-monetary transaction cost in the form of waiting time. Our paper provides the first evidence that this intuition actually may produce more desirable market outcomes.[12] Can this intuition be transferred to financial markets? Hardly, to say the least, but so it was said for the Tobin tax until it has actually been implemented in several countries.

Appendix A. Risk-averse fundamental

Here we explore the possibility that transactions prices are affected by risk aversion by estimating coefficients of risk aversion inferred from transaction prices. 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 $t \in \{1, 2..., 10\}$, $EU(D_t)$ 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 have 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 $P_t = \left(\sum_{k=0}^{t} Pr(\overline{X} = k) \cdot (\overline{D} \cdot k)^{(1-r)}\right)^{1/(1-r)}$.

Table 7 reports the estimated coefficients of risk aversion (r) of the constant relative risk aversion function (CRRA). Risk neutrality, commonly assumed to compute FVs, is captured by coefficients not differing from zero, while risk aversion (seekingness) is captured by positive (negative) values.

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.

Table 7
Estimates of coefficient of relative risk aversion.

Period	*ast*	*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.

Table 8
Relative deviations from risk-averse FVs.

	RAD	RD
Fast	0.26	0.12
Slow	0.26	−0.05

We are now ready to re-estimate RD and RAD coefficients reported in Table 8, assuming that traders are risk averse and therefore using the parameters specification of the overall estimation in Table 7 ($r = 0.760$ and $r = 0.944$ in *Fast* and *Slow*, respectively).

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.

Appendix B. Robustness check

To improve our understanding of the nature of withdrawn orders in the main experiment, we conducted a few additional sessions, labeled *Slow_exec*. These additional sessions replicate the *Slow* condition reported above, with a significant difference: orders not withdrawn are executed by default rather than canceled. Furthermore, traders started trading immediately after reading the instructions without going through a practice period.

A total of 86 participants took part in 10 distinct market sessions. Fig. 5 shows the average market prices during the sessions, similar to Fig. 1 above.

Fig. 5 displays an overall "conservative" pattern in trading, similar to what happens in condition *Slow*. This is confirmed also by measures of deviations from the risk-neutral fundamental price: the RD is equal −0.28 and the RAD is equal to 0.35. A

[11] Previous experimental works show that call markets tend to produce lower deviations from fundamental than continuous double auctions but not to eliminate them (e.g., Cason and Friedman, 2008; Van Boening et al., 1993).

[12] Previous experiments investigating the impact of the Tobin tax show that the tax has little effect in producing the desired results (see Hanke et al., 2010; Kirchler et al., 2011; Huber et al., 2012).

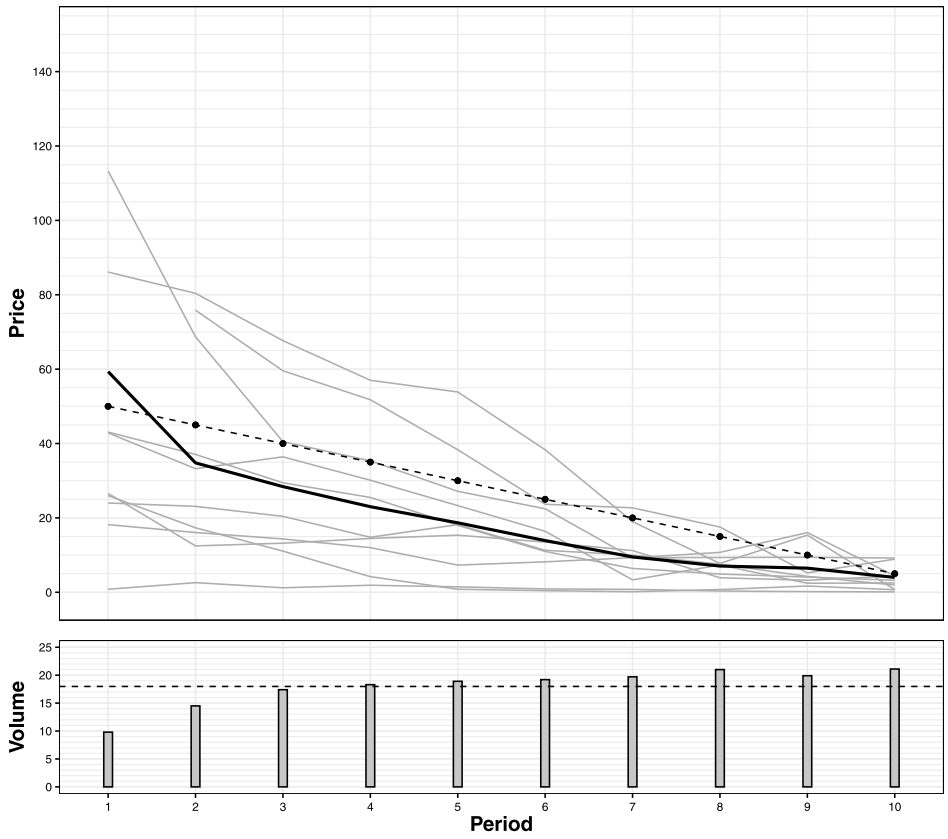


Fig. 5. *Slow_exec*: Market outcomes.

Wilcoxon rank sum test shows that deviation measures computed at the session level for *Slow* and *Slow_exec* are not significantly different at the conventional 5% level (RAD, p-value $= 0.051$; RD, p-value $= 0.973$).

In the additional sessions, we collect more pieces of information than in the main *Slow* condition, as we also keep track of prices associated with withdrawn orders and of orders that are neither confirmed nor withdrawn during the waiting time. Accordingly, we distinguish between three types of orders: *actively executed*, that get confirmed during the waiting time; *automatically executed*, that are neither confirmed nor withdrawn during the waiting time, but given the default rule adopted, are automatically executed; *withdrawn*, that get canceled during the 10 s waiting time. On average, 30.7% of orders submitted to the book are actively executed, while only 1.1% and 2.5% are withdrawn and automatically executed, respectively. The largest share of actively executed orders is observed in Period 3 (33.6%), while the largest share of withdrawn and automatically executed is observed in Period 1 (2.9% and 3.6%, respectively).

A declining pattern in withdrawn orders relative to actively executed orders is observed in *Slow_exec*, similar to what happens in *Slow* (see Fig. 2). However, the share of withdrawn orders is generally smaller in condition *Slow_exec* than in *Slow*, probably because traders just exploit the default execution as a way to automatically-implemented transactions.

In *Slow_exec*, the average price equals 17.9, 14.29, and 19.2 for actively executed, automatically executed, and withdrawn orders, respectively. A series of Wilcoxon signed-rank tests on individual-level data does not highlight any statistically significant difference between the prices of different order types (all p-values ≥ 0.087).

Outcomes from the *Slow_exec* condition show that the default execution rule has not a major impact on trading prices. This is probably due to the limited impact of automatically executed orders on total orders. Furthermore, the value of automatically executed orders is similar to that of withdrawn and actively executed orders.

Appendix C. 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 experimenter 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 min.

Trade is accomplished in the 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 cannot 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 s. After 10 s 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 s to confirm or withdraw your order. If you do not make any decision, your order will be automatically withdrawn. After 10 s 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 following 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 Payment 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.

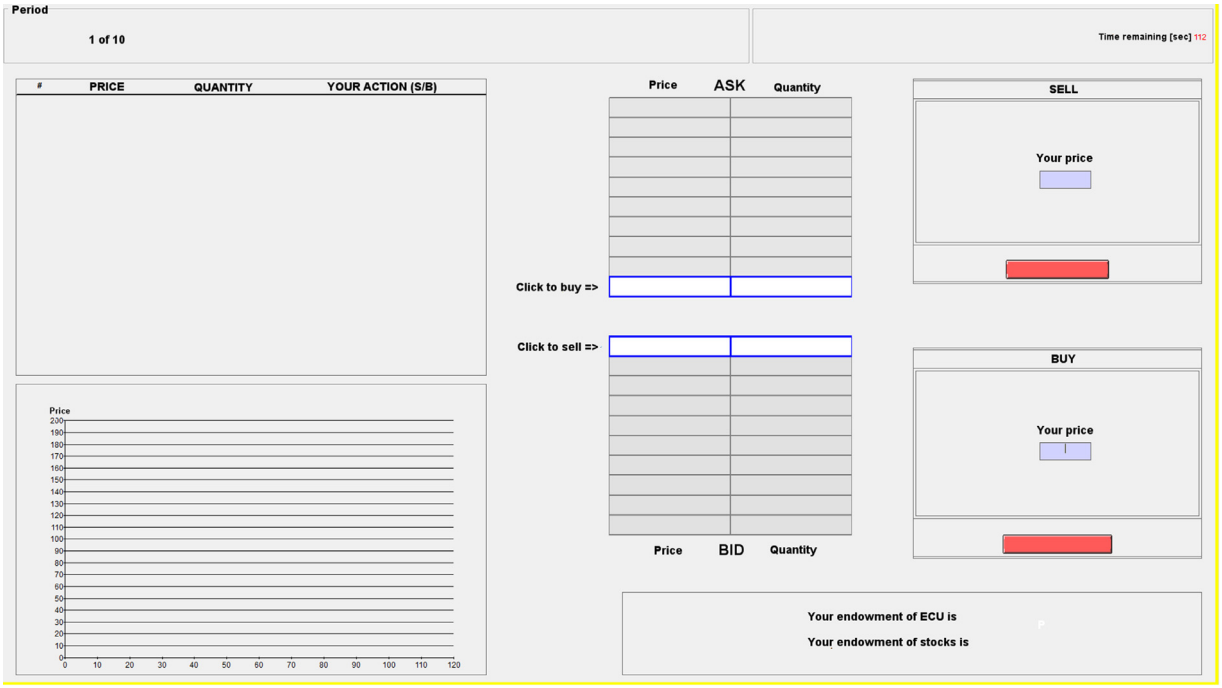
Your total earnings in this experiment are converted into Euro at a rate of 400 ECU = 1 Euro.

Important information

- No interest is paid for ECU holdings.
- Each trading period lasts for 2 min.
- 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.

Appendix D. Trading screen



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