ALGORITHMIC TRADING, WHAT IF IT IS JUST AN ILLUSION? EVIDENCE FROM EXPERIMENTAL FINANCIAL MARKETS

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Algorithmic trading, what if it is just an illusion? Evidence from experimental financial markets

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Abstract

This work investigates whether and how the potential presence of algorithmic trading in financial markets can influence humans' trading activities, and ultimately price dynamics and market liquidity. We consider two different types of trading strategies commonly employed by high-frequency traders, spoofing and market making. The former has been associated with market manipulation, and the latter is often seen as providing liquidity to markets. We run artificial trading experiments to examine the effect of their potential presence. From these experiments, we find that the potential presence of algorithmic trading induces (1) larger initial price forecasts deviations from the fundamental value, (2) more volatile forecasted prices, and (3) delayed initial orders.

Keywords: Market volatility, Market efficiency, Computer trader, Experiment, Asset market.

JEL codes: C90, G14, D84, G01

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1 Introduction

This work investigates whether and how the potential presence of algorithmic trading (AT) in financial markets can influence the trading activity of human participants and ultimately market dynamics.

Over the past decade, high-frequency trading (HFT), AT at high speed, has sharply increased in US and European equity exchanges (AFM, 2010; SEC, 2010, 2014) and represents a major financial innovation. However, as expressed by O'Hara (2015), "[...] viewing the advent of HFT as being only about speed misses the revolution that has happened in markets" (O'Hara, 2015, p.1). In fact, besides the sharp increase in immediacy, the rapid and radical transformation of financial markets has created new players and a more complex trading environment, modified the way information is shared and integrated among participants, altered the way interactions take place; and increased the interconnectedness of markets (Pardo et al., 2011; Cliff and Northrop, 2012; Lo, 2015).

Furthermore, this radical transformation has created new challenges for financial market regulators (Lenglet, 2011; Pardo et al., 2011; Prewitt, 2012; Goldstein et al., 2014). Creating a level playing field for all market participants, reinforcing market integrity and transparency, and guaranteeing equal treatment of market participants are examples of new priorities set by regulators to account for the possible threats that the presence of computer traders might represent for current financial markets.

Above all, this evolution has transformed the very nature of real financial markets moving away from only-human markets to hybrid markets, where human participants have to interact with computer traders. However, the increased complexity and the wide variety of HFT strategies employed in real markets (see, for instance, Aldridge, 2013; Goldstein et al., 2014; SEC, 2014) have made market behaviors more puzzling (Lo, 2015) and have complexified the effects of human computer interactions on humans.

However, little research has been conducted about how human traders react and adapt to this complexification of real financial markets, the increased trading speed and the presence of algorithms as new players. How does the presence of computer traders influence human trader behavior? How do human participants behave in such a more complex trading environment? How do they respond to these more fuzzy and unreliable market behaviors?

Several experimental works have introduced computer traders. These earlier works have mainly focused on the analysis of (1) the effect of AT strategies on human traders' performance, market dynamics and efficiency (Das et al., 2001; Cartlidge et al., 2012; Cartlidge and Cliff, 2013, 2015); (2) the effect of computer traders on price dynamics (Veiga and Vorsatz, 2009, 2010); (3) how their presence might affect subjects' learning (Cason and Friedman, 1997); or (4) the effect of perception of others' rationality on mispricing (Fehr and Tyran, 2001, 2005; Akiyama et al., 2017). However, only few attempts have been made to account for the effect of the potential presence of computer traders on human trading behavior and market dynamics. Farjam and Kirchkamp (2018) is an exception. Specifically, they study whether and how the expected presence of algorithmic traders can influence humans' trading speed as well as market dynamics in an experimental asset market. Farjam and Kirchkamp (2018) show that the mere possibility of the presence of algorithmic traders in the market reduces the magnitude of mispricing in markets consisting only of human traders compared to the same markets where human traders can rule out the presence of algorithmic traders. While the results of Farjam and Kirchkamp (2018) are very interesting, they did not specify the type of trading strategies employed by algorithmic traders. Would these results still hold if subjects are informed that algorithmic traders employ market making strategies or manipulative strategies? This is the question we aim to address in this paper.

This work therefore aims to enrich the recent debate on the actual effect of human computer interactions on humans and market dynamics (Akiyama et al., 2017; Farjam and Kirchkamp, 2018) by providing additional evidence from a controlled laboratory experiment. We believe our work also helps to shed new light on the actual impact of AT, and more generally HFT, on financial markets (Kirilenko and Lo, 2013; Haldane, 2014).

To this end, we consider two different types of strategies commonly employed by high frequency (HF) traders: layering/spoofing and market making in our experiment. While the former is one of the trading strategies that has been identified as a deceptive activity and associated with market manipulation (IIROC, 2013), the latter is a trading strategy that may have a beneficial effect on market quality (Menkveld, 2013). The aim of this work is to examine whether the potential presence of such traders in the market, having either detrimental or beneficial effects on market quality, can affect human trading behavior and as a result price dynamics and market liquidity.

Using a framework similar to Farjam and Kirchkamp (2018), we consider three treatments in our experiments: **HO**, **MM**, and **SP**. In all treatments, we consider markets where only human traders participate. These treatments differ, however, in terms of how subjects are informed about the nature of other participants in the markets. In **HO**, subjects are told that computer traders are not present in their market. In **MM** and **SP**, subjects are informed that there could be computer traders that employ, respectively, market-making strategy (MM) and layering/spoofing strategy (SP) in the market. By comparing elicited price forecasts, trading behavior, and ultimately price dynamics and market liquidity across these three treatments, we aim to disentangle the effect of the potential presence of computer traders on human trading behavior.

Our experimental results suggest that the potential presence of computer traders (1) makes subjects' initial price forecasts to deviate from the fundamental value and be more volatile; (2) makes subjects to initially postpone submitting their orders.

The remaining of the paper is organized as follows. Section 2 presents the design of the experiment. In Section 3, we present and discuss the results of the experiment. Section 4 provides a summary and concluding remarks.

2 Experimental Design

We employ an electronic continuous double auction market (Bostian and Holt, 2009; Smith et al., 2014) consisting of eight traders. Using a framework similar to Farjam and Kirchkamp (2018), we consider three treatments: **HO**, **MM**, and **SP**. In all the treatments, eight traders participate in one market, and all the eight traders are in fact human participants. These treatments differ, however, in terms of how subjects are informed about the nature of other participants in the markets. In **HO**, they were explicitly told that traders were participants to the experiment. In **MM** and **SP**, participants were informed that there could be computer traders in the market. Participants were further told that these computer traders *"can facilitate trading by frequently placing new buy or sell orders"* in **MM**, or *"try to influence prices by frequently placing new buy or sell orders and canceling them"* in **SP**.

Uncertainty about the presence of computer traders in **MM** and **SP** was introduced by (1) constructing two types of markets within an experimental session just as in Farjam and Kirchkamp (2018), (a) markets where only human traders interact (*i.e.,* only-human markets) and (b) markets where human traders interact with computer traders (*i.e.,* hybrid markets), and (2) explicitly telling our subjects the following: *"Some of you will be assigned to a market in which some traders are computer traders and the remaining traders are participants in this room. Some of you will be assigned to a market in which all traders are participants in this room. You will not be informed which type of market you are assigned to."* There was no deception because some subjects indeed participated in only-human markets while others participated in hybrid markets. To be able to gauge whether and how the potential presence of computer traders, employing market-making or spoofing strategy, can influence human traders' price forecasts, trading activity, and ultimately price dynamics and market liquidity, we solely focus on and compare only-human markets wherein subjects receive differing information about the possible composition of the population of traders in the market.

In each market, each trader is initially endowed with $A = 10$ units of risky asset and $C = 1,500$ units of cash in experimental currency (ECU) and repeatedly trades over $T = 10$ periods. Each trading period lasts for 60 seconds.[1] Cash is assumed to be a safe asset and earns interest r ($r = 0.05$). At the end of each period, the asset pays dividends d_t that are uniformly randomly drawn from a pre-specified set of possible dividend values D ($D \in \{0, 10\}$) (see Appendix A3). All the cash and asset held at the end of a period, except for the final one, are carried over to the next period for further trading (see Appendix A3).

At the end of period T, after interest and dividend payments are made, each unit of asset owned will be converted to cash for $ECU100$ and the game ends. The risk-neutral fundamental value of the asset (FV) in this setting is $FV_t = ECU100$ for all t.[2]

[1] The experiment was implemented using z-Tree (Fischbacher, 2007). Screenshots are shown in Appendix A.

[2] Suppose that, at the beginning of period $T = 10$, a trader buys a unit of asset at a price of FV_T, then its expected value at the end of the period will be $5 + 100 = ECU105$. If the trader kept the same amount of cash until the end, then, it will become $1.05FV_T$ after interest payment. Since these two outcomes have to be the same in equilibrium for the risk neutral traders, we have $1.05FV_T = ECU105$, *i.e.,* $FV_T = 100$. Now, consider the beginning of period $T - 1$. If a trader buys a unit of asset at FV_{T-1}, its expected value at the end of the period is $5 + FV_T = ECU105$. If the same amount of cash is held until the end of the period, it will become

Treatment	Number of Participants	Number of Markets
HO	64	8
MM	72	9
SP	56	7
Total	192	24

Table 1: Number of participants and markets per treatment.

Assets are traded using limit orders. Traders can buy or sell 1 unit of the asset in continuous time in each transaction (see Appendix A1), but can make multiple transactions within each period. Orders are classified by price and then by arrival time. Cancellation is allowed for both human and computer traders. Traders participate in two consecutive stock trading games. Traders are encouraged to earn as much money as possible and that they can earn money in four ways: (1) trading stocks; (2) holding stocks and receiving dividend; (3) holding cash and receiving interest; (4) accurately predicting future stock prices.

At the beginning of each trading period, traders are asked to forecast the average prices for each of the remaining trading periods. Namely, at the beginning of period 1, they forecast average trading prices of periods $p = 1, 2, ..., 10$, at the beginning of period 2, they forecast prices of periods $p = 2, 3, ..., 10$, and so on (See Appendix A2 for the screen shot). Subjects are given 0.5% of their final cash holding (of the game) for each forecast that was between 90% and 110% of the realized average price. Because subjects are making a total of 55 forecasts, if all these forecasts fall within the specified range, then they receive 27.5% of their final cash holding as the bonus for their forecasting performance. This way of eliciting long-run price forecasts have been first employed by Haruvy et al. (2007). The specific incentive scheme employed in our experiment follows that of Akiyama et al. (2014, 2017).

Subjects were told that they would be paid in real currency (EUR) based on the final holding of one of the stock trading games, randomly drawn at the end of the second trading game.[3] The final cash is converted into euros for ECU200 = EUR1. Traders also receive a participation fee of 5 euros.

3 Results

The experiment was conducted at Laboratory of Experimental Economics in Nice (LEEN), University of Nice-Sophia Antipolis (France) between November 2016 and October 2017. A total of 192 subjects have participated in the experiment. Number of participants per treatment vary because of the variation in show-up rate across experimental sessions. See Table 1 for the number of participants and markets in each treatment. These subjects had never participated in a similar experiment before and each subject participated in only one experiment session. The experiment lasted about 2 hours including instructions and the post-experimental questionnaire.

$1.05FV_{T-1}$. Since these two outcomes have to be equivalent, $1.05FV_{T-1} = 105$, *i.e.,* $FV_{T-1} = 100$. One can apply the same reasoning for all the remaining periods to obtain $FV_t = 100$ for all $t = 1, ..., T$.

[3]The randomly drawn game is used for all subjects of the session.

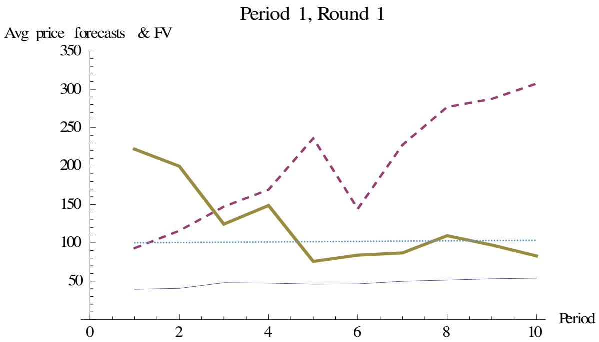

Figure 1: Average price forecasts dynamics in period 1 and round 1 of three treatments: **HO** (thin line), **MM** (dashed line), **SP** (thick line). Fundamental value of the asset over the 10 periods is also displayed (dotted line).

Subjects were paid in addition to the show up fee of 5 euros, 21.8 euros on average.

The presentation of our results is organized as follows. We first report the results regarding elicited price forecasts (Section 3.1) and orders (Section 3.2), and then present the results regarding market prices (Section 3.3) and market liquidity (Section 3.4).

Furthermore, given that, in all of the aforementioned dimensions, we do not observe any statistically significant differences between **MM** and **SP** (see all the details in Appendix C), in what follows, we mainly present results pooling data from the markets of these two treatments in **AT** and comparing it to **HO** when conducting statistical analyses.[4]

3.1 Price forecasts

We start our investigation of the impact of the possible presence of computer traders on humans by comparing the elicited price forecasts between markets wherein subjects can rule out the presence of computer traders (**HO**) and markets wherein humans know they could interact with computer traders (**MM** and **SP**). In particular, we ask the following questions:

Can the mere possibility of interacting with computer traders modify the price forecasts made by subjects? If so, how?

To answer these questions, we explore successively price forecasts dynamics, price forecasts deviation from the asset fundamental value (FV), and price forecasts volatility.

Figure 1 shows the dynamics of the average *initial* price forecasts, elicited in period 1 of round 1, in three treatments: **HO** (thin line), **MM** (dashed line), **SP** (thick line).

Preliminary observation reveals that subjects expect prices to evolve differently in these three treatments, merely based on the information about the potential presence of computer traders. In particular, initial price forecasts tend to be lower in **HO** than in **MM** and **SP** (see Figure 1). In **HO**, subjects expect prices to stay below FV. Furthermore, from Figure 1, one notices that subjects' price forecasts tend to be more erratic in **MM** and **SP** than in **HO**. When humans can rule out the presence of computer traders in **HO**, they expect prices to be

[4]When relevant, we present detailed results of **MM** and **SP** compared to **HO**.

more stable over the periods than when computer traders could be present. Moreover, Figure 1 suggests that, when informed that they could interact with computer traders, subjects expect prices to evolve differently over time depending on the type of strategy employed by computer traders. In **MM**, they initially forecast prices to depart from FV over time. Instead, in **SP**, subjects appear to initially expect prices to converge to FV as time passes.

We further this investigation by analyzing the deviations of initial price forecasts from FV. We focus only on initial price forecasts because this is where we should observe the pure effect, if any, of our experimental manipulation regarding the potential presence of computer traders and the strategies these traders employ. This is because, as Haruvy et al. (2007), Hanaki et al. (2018a) and Carlé et al. (2019) demonstrate, forecasts elicited after period 2 tend to be heavily influenced by the realized prices in the past, and thus, any differences we may observe may simply be a result of differences in realized prices across markets and treatments.

In particular, we investigate the extent of the deviations of initial price forecasts from the fundamentals by computing the Relative Absolute Forecasts Deviation ($RAFD$) and the Relative Forecasts Deviation (RFD) for each subject in period 1 and round 1 (see Akiyama et al., 2014, 2017; Hanaki et al., 2018b), as well as a measure of forecast volatility based on Noussair et al. (2016). These three measures for forecasts elicited in period t of round r are defined as follows:

$$\mathrm{RAFD}^i_{t,r} = \frac{1}{T-t+1}\sum_{p=t}^{T}\frac{\left|f^i_{t,p,r} - \mathrm{FV}_p\right|}{\left|\overline{\mathrm{FV}}\right|} \tag{1}$$

$$\mathrm{RFD}^i_{t,r} = \frac{1}{T-t+1}\sum_{p=t}^{T}\frac{f^i_{t,p,r} - \mathrm{FV}_p}{\left|\overline{\mathrm{FV}}\right|} \tag{2}$$

$$\mathrm{VolPF}^i_{t,r} = \frac{1}{T-t+1}\sum_{p=t}^{T-1}\left|(f^i_{t,p+1,r} - \mathrm{FV}_{p+1}) - (f^i_{t,p,r} - \mathrm{FV}_p)\right| \tag{3}$$

where $T = 10$ is the number of periods per round. $f^i_{t,p,r}$ is the elicited price forecast in period t of round r for the period $p \in \{t, t+1, ..., 10\}$ price. FV_p is the fundamental value of the asset in period p. $\left|\overline{\mathrm{FV}}\right| = \left|\frac{1}{T}\sum_{k=1}^{T}\mathrm{FV}_k\right|$.

We then compare these three measures across treatments by running linear regressions with treatment dummies (without constant term) using individual as a unit of observation. We correct standard errors for within market clustering effect.[5]

Table 2 reports the results. First, from the values of the estimated coefficients of the two treatment dummies, one notices that $RAFD^i_{1,1}$, $RFD^i_{1,1}$, and $VolPF^i_{1,1}$ are all significantly larger, although only marginally so for $RFD^i_{1,1}$ and $VolPF^i_{1,1}$, in **AT** as compared to **HO**. Thus the mere potential presence of computer traders, in **SP** and **MM** (pooled into **AT**), is sufficient to modify subjects' initial price forecasts. In particular, the threat of computers

[5]As noted above, because we do not observe statistically significant differences between **MM** and **SP** for most of the measures of our interest (see Appendix C1), we pool the observations from these two treatments and call them **AT**.

Period 1 of Round 1	$RAFD^i_{1,1}$	$RFD^i_{1,1}$	$VolPF^i_{1,1}$
HO	0.727***	-0.530***	21.811***
	(0.064)	(0.077)	(2.809)
AT	1.807***	0.556	67.219***
	(0.487)	(0.532)	(22.787)
p-value (HO=AT)	0.038	0.055	0.060

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 2: OLS regression results of $RAFD^i_{1,1}$, $RFD^i_{1,1}$, $VolPF^i_{1,1}$ on treatment dummies.

presence makes subjects' initial price forecasts depart more from FV and more volatile in **AT** than in **HO** *i.e.,* when humans can rule out their presence. However, although market making and spoofing are two different strategies, subject initial price forecasts do not differ in terms of these three measures. Subjects do not appear to predict differing effects of these two strategies on price dynamics.

3.2 Orders

We continue our investigation of the impact of the potential presence of computer traders on humans by comparing subject trading behavior, *i.e.,* orders, between markets wherein subjects can rule out the presence of computer traders (**HO**) and markets wherein humans know they could interact with computer traders (**MM** and **SP**). In other words:

Can the potential presence of computer traders alter subject trading behavior? If so, how?

To address these questions, we investigate first the timing and the price of *initial* orders submitted by subjects, and then subjects' order price over time.

We first analyze the very first orders subjects submit in period 1 of round 1 because these orders are not influenced by what subjects observe during the earlier periods. Analyzing initial orders enables us to grasp the effect, if any, of the possible presence of computer traders on subjects' orders. Our treatment comparison is based on linear regressions with treatment dummies (without constant) using individual as a unit of observation while correcting standard errors for within market clustering effect.

Table 3 shows the results. We observe that subjects submit their initial orders, both bids and asks, significantly later in **AT** than in **HO**. Our subjects, who expect more erratic prices due to the potential presence of computer traders, appear to be more reluctant to trade. Table 3 also reveals that, while there is no significant difference in the price of initial bids between **AT** and in **HO**, the initial asks in the latter are marginally significantly higher than those in the former.

Thus the mere potential presence of computer traders, whatever the type of strategy employed,[6] is sufficient to make subjects postpone their initial orders. This result might be ex-

[6] See further details in Table 9 of Appendix C2.

Period 1 of Round 1	Bids time stamp	Asks time stamp	Bids	Asks
HO	262.997***	261.812***	22.317***	64.534***
	(13.890)	(14.338)	(3.615)	(16.030)
AT	376.496***	371.809***	19.602***	35.265***
	(24.492)	(21.674)	(3.775)	(5.657)
p-value (HO=AT)	0.000	0.000	0.608	0.098

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 3: OLS regression results of initial bids and initial asks time stamps and order size on treatment dummies.

plained by the aforementioned evidence on elicited initial forecasts. Subjects might be more cautious to trade or might prefer to wait more before submitting their orders when they know they could interact with computers.

Is this evidence true over time? We now turn to examine whether subjects' orders are influenced over time by the potential presence of these computer traders by taking into account all orders in all periods of round 1 and round 2. To do so, we calculate the average bids and average asks submitted by each subject in each period and we compare the order price between **HO** and **AT**.[7] We do so by taking the effect of past realized prices observed by subjects into account.

Table 4 shows the results of panel regressions (using random-effects estimators). **HO** is the baseline in this regression. As one can observe, both average bids and average asks are positively related to the observed price in the previous period in all the treatments. However, we do not observe any statistically significant treatment differences in average bids and average asks. In this case, we find that subjects do not modify the price of their orders due to the potential presence of computer traders. As suggested earlier, this might be explained by the fact that, in our experiment, markets are only populated by human traders. Hence, subjects do not observe any computer activity and might be able to recognize that computer traders are not present in the markets as they gain experience. As a result, subject order submission behavior is the same between **HO** and **AT**. Thus, although the threat of the presence of computer traders makes subjects postpone their initial orders, this effect is not long lasting due to subjects' ability to recognize as time passes that computers are not present in these markets.

In Appendix D2a, we also compare the outcomes between only-human **MM** and **SP** treatments and the corresponding hybrid markets.[8] This analysis suggests that, when computer traders are present in markets, subjects demonstrate different order dynamics compared to only-human markets. Furthermore, the effect of past realized prices on average bids and average asks differs across treatments when computer traders are present (see Table 15 in Appendix D2a). As a result, we confirm that our subjects are able, with experience, to recognize when computer traders are absent in the market and behave accordingly.

[7] See details of treatment comparisons of average order price between **MM** and **SP** in Table 10 of Appendix C2.

[8] As noted in Section 2, uncertainty about the presence of computer traders were introduced by running two types of markets, only-human and hybrid, within each experimental sessions.

	Average bids		Average asks	
	Round 1	Round 2	Round 1	Round 2
p_{t-1}	0.656***	0.757***	2.080**	1.347***
	(0.168)	(0.030)	(0.991)	(0.402)
AT	-2.733	-7.372	7.256	-42.885
	(7.370)	(4.957)	(56.765)	(36.545)
$p_{t-1}AT$	0.122	0.158**	0.944	-0.115
	(0.180)	(0.067)	(1.941)	(0.477)
$constant$	7.184	7.418*	-9.827	63.894*
	(6.958)	(3.896)	(39.480)	(34.418)
p-value p_{t-1}=$p_{t-1}AT$	0.119	0.000	0.661	0.083

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 4: Panel regression results of average bids and average asks on realized price in previous period, treatment dummies, accounting for interaction effects in round 1 and round 2.

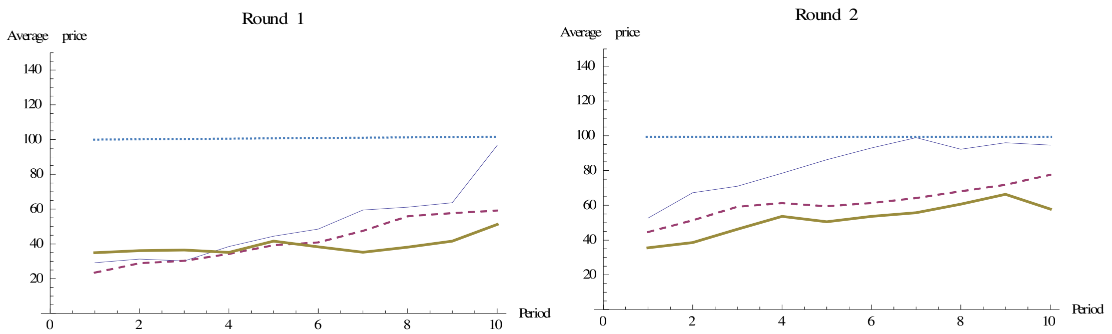

Figure 2: Average price dynamics for two rounds of three treatments: **HO** (thin line), **MM** (dashed line), **SP** (thick line). Fundamental value of the asset over ten periods is also displayed (dotted line).

3.3 Prices

We now turn to examine the impact of the possible presence of computer traders on realized prices. In this section, we compare successively price dynamics, mispricing, *i.e.,* size and direction, and price volatility, that emerge from markets wherein subjects can rule out the presence of computer traders (**HO**) with markets wherein subjects know they could interact with computer traders (**MM** and **SP**). In particular, we ask the following question:

Can the mere potential presence of computer traders modify prices?

Figure 2 shows the dynamics of average realized prices across markets in three treatments: **HO** (thin line), **MM** (dashed line) and **SP** (thick line) in round 1 (left panel) and round 2 (right panel).

Preliminary observations unveil that average realized prices in these three treatments tend to likewise diverge from the FV, especially in round 1. Indeed, left panel of Figure 2 reveals

	RAD_r^m		RD_r^m		Vol_r^m	
	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2
HO	0.551***	0.326***	-0.497***	-0.170	18.318***	13.952***
	(0.091)	(0.110)	(0.098)	(0.121)	(2.428)	(2.553)
AT	0.602***	0.456***	-0.595***	-0.425***	13.464***	11.682***
	(0.064)	(0.078)	(0.069)	(0.091)	(1.717)	(1.805)
p-value	0.652	0.345	0.419	0.112	0.117	0.476

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 5: Regression estimates for RAD_r^m, RD_r^m and Vol_r^mon treatment dummies in round 1 and round 2.

that, in round 1, the asset price is far below FV in all three treatments. Instead in round 2 (right panel), average realized prices tend to converge more quickly towards FV in **HO** than in **MM** and **SP**. Therefore, the mere possibility of the presence of computer traders, regardless of the strategy type employed, seems to prevent prices from converging towards FV over time. This seems in contrast with the result reported in Farjam and Kirchkamp (2018) that showed that the potential presence of computer traders made prices to deviate less from FV.

We put above observation into a statistical test by measuring the degree of mispricing, *i.e.*, the deviation of realized prices from FV, by the Relative Absolute Deviation (RAD) and the Relative Deviation (RD), proposed by Stöckl et al. (2010), as well as price volatility following Noussair et al. (2016). For each market m and round r, RAD_r^m, RD_r^m and $VolP_r^m$ are defined as follows:

$$\mathrm{RAD}_r^m = \frac{1}{T}\sum_{t=1}^{T}\frac{\left|P_{r,t}^m - \mathrm{FV}_t\right|}{\left|\overline{\mathrm{FV}}\right|} \tag{4}$$

$$\mathrm{RD}_r^m = \frac{1}{T}\sum_{t=1}^{T}\frac{P_{r,t}^m - \mathrm{FV}_t}{\left|\overline{\mathrm{FV}}\right|} \tag{5}$$

$$\mathrm{Vol}_r^m = \frac{1}{T}\sum_{t=1}^{T-1}\left|(P_{r,t+1}^m - \mathrm{FV}_{t+1}) - (P_{r,t}^m - \mathrm{FV}_t)\right| \tag{6}$$

where $T = 10$ is the number of periods per round. $P_{r,t}^m$ is the average realized price in period t of round r in market m. FV_t is the fundamental value of the asset in period t. $\left|\overline{\mathrm{FV}}\right| = \left|\frac{1}{T}\sum_{t=1}^{T}\mathrm{FV}_t\right|$.

We then compare these three measures across treatments by running linear regressions with treatment dummies (without constant term) using market as a unit of observation. Table 5 reports the estimation results of linear regressions of RAD_r^m, RD_r^m and Vol_r^m on treatment dummies HO and AT.[9]

Consistent with the aforementioned preliminary observations of price dynamics (see Figure 2), column 3 and 4 of Table 5 (dependent variable RD_r^m) unveils that average realized prices are significantly lower than FV in all the treatments of our experiment in both round 1 and round

[9]See further evidence about **MM** and **SP** in Appendix C3.

2, except for **HO** in round 2. However, we do not observe any significant treatment effects on either the magnitude (RAD_r^m) or the direction (RD_r^m) of the mispricing. Thus contrary to Farjam and Kirchkamp (2018), we do not observe that the potential presence of computer traders has any significant impact on mispricing in both rounds. As suggested earlier, the effect of the mere threat of computer traders might not be strong and long-lasting enough to markedly modify prices over time. Table 16 in Appendix D2b confirms that the lack of treatment effect in only-human markets, observed in Table 5, is likely to be explained by the absence of computer traders in these markets.[10]

Moreover, results reported in Table 11 of Appendix C3 suggest that the information about the specific type of strategy employed by computer traders has no significant effect on the magnitude (RAD_r^m) and the direction (RD_r^m) of the mispricing.

Lastly, from the value of the estimated coefficients of the treatment dummies in Table 5, we notice that the mean of Vol_r^m is larger in **HO** as compared to **AT** in both rounds. However, these differences are not statistically significant. Consistent with Farjam and Kirchkamp (2018), we find that the mere possibility of interacting with computer traders is not sufficient to modify price volatility in markets where only humans intervene. Furthermore, we find that computer traders' strategy type has no significant impact on price volatility (see Table 11 in Appendix C3). Prices do not seem to evolve differently depending on the type of computer traders humans could interact with.

To summarize, our investigation of prices reveals that the mere threat of the presence of computer traders is not sufficient to alter price dynamics, mispricing and price volatility. However, this is likely to be explained by the ability of our subjects to recognize, as time passes, that computer traders are not present in the market (see Appendix D2b for further details about the comparison between only-human and hybrid markets).

3.4 Market liquidity

We now turn to examine the effect of the potential presence of computer traders on market liquidity. In other words:

Can the potential presence of computer traders modify market liquidity?

To address this question, we focus successively on two commonly employed indicators of market liquidity namely trading volumes, using a measure of share turnover (ST) proposed by Kirchler et al. (2012) and Corgnet et al. (2014) (see eq. 7), and bid-ask spreads, computing the Absolute Bid-Ask Spread (ABAS) (see eq. 8). These measures for market liquidity in market m and round r are defined as follows:

$$\mathrm{ST}_r^m = \frac{TV_r^m}{TSO_r^m} \tag{7}$$

[10]We checked whether the magnitude of the mispricing over time would differ between only-human markets and hybrid markets. However, although we do not observe any treatment effect in only-human markets (*i.e.,* **HO** and **AT**), we do observe differences in mispricing size over time between only-human markets and hybrid markets (see all details in Table 16 in Appendix D2b).

	ST_r^m	
	Round 1	Round 2
HO	1.564***	1.519***
	(0.157)	(0.247)
AT	1.417***	1.634***
	(0.111)	(0.175)
p-value	0.454	0.708

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 6: Regression estimates for ST_r^m on treatment dummies in round 1 and round 2.

where TV_r^m is the total number of transactions in market m and round r, $TSO_r^m = 80$ is the number of shares outstanding in market m and round r.[11]

$$\text{ABAS}_{t,r}^m = \left|\text{Pa}_{t,r}^m - \text{Pb}_{t,r}^m\right| \tag{8}$$

where $Pb_{t,r}^m$ is the best available bid at the end of period t and round r and $Pa_{t,r}^m$ is the best available ask at the end of period t and round r.

We then compare these measures across treatments **HO** and **AT**[12] by running linear regressions with treatment dummies (without constant) using market as a unit of observation.

Table 6 reports the results of regressing ST_r^m on treatment dummies HO and AT that take value 1 in the relevant treatment and 0 otherwise in round 1 and round 2.

From the value of the estimated coefficients of the two treatment dummies in Table 6, one notices that trading volumes (ST_r^m) do not differ between these treatments, whatever the round. Indeed, we do not observe any treatment effect on ST_r^m. Subjects do not trade less when they participate in markets where computer traders *could* be present, but are not. This holds regardless of the strategy type.[13] The mere possible presence of computer traders hence is not sufficient to modify trading volumes or reduce the number of transactions in these markets, although subjects in **AT** delay submission of orders in Period 1 of round 1.

We now turn to the analysis of bid-ask spreads and comparing it across treatments **HO** and **AT**.[14] Specifically, we run linear regressions with treatment dummies (without constant) using market as a unit of observation. Table 7 reports the results across ten periods in round 1 (top panel) and round 2 (bottom panel).

From the value of the estimated coefficients of the two treatment dummies in Table 7, we do not observe any significant treatment effects on bid-ask spreads across most of the periods.[15] This finding holds for both rounds. Therefore, we find that the effect of the potential presence of computer traders on observed initial forecasts and initial orders submission timing is not

[11] In our setting, in each market and round, each of the eight traders receives ten assets at the beginning of the trading game.

[12] See all the details about **MM** and **SP** treatment comparisons in Table 12 of Appendix C4.

[13] This finding is no longer true when computer traders are present in markets (see Table 17 in Appendix D2c).

[14] See detailed analysis of treatment comparisons between **MM** and **SP** in Table 13 of Appendix C4.

[15] We also performed this analysis computing the Relative Bid-Ask Spread ($\text{RBAS}_{t,r}^m = \frac{\left|\text{Pa}_{t,r}^m - \text{Pb}_{t,r}^m\right|}{\text{Pa}_{t,r}^m}$) and obtained similar results.

Round 1

Coef. $ABAS_t^m$	1	2	3	4	5	6	7	8	9	10
HO	70.25*** (15.322)	47.25** (21.309)	61.625* (32.164)	41** (18.032)	62.125 (36.223)	193.25*** (46.287)	211.75** (91.75)	76.5*** (23.359)	164*** (44.101)	170.875* (98.469)
AT	40.312*** (10.834)	56.937*** (15.068)	74.437*** (22.744)	58.375*** (12.750)	75.625*** (25.614)	52.437 (32.730)	92 (64.883)	56.562*** (16.517)	69.312** (31.184)	144.75** (69.628)
p-value	0.125	0.714	0.748	0.440	0.764	0.021	0.298	0.493	0.093	0.830

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Round 2

Coef. $ABAS_t^m$	1	2	3	4	5	6	7	8	9	10
HO	82*** (10.366)	113.75*** (27.313)	72.125* (37.135)	57.875** (24.880)	275.125*** (85.23)	237.5** (86.223)	89.5** (34.039)	117.75*** (38.289)	163* (81.940)	76.125*** (20.490)
AT	52.625*** (7.330)	51.125** (19.313)	77.437*** (26.258)	69.562*** (17.593)	92.562 (60.267)	120.5* (60.969)	77.125*** (24.069)	63.875** (27.075)	102.375 (57.940)	52.687*** (14.489)
p-value	0.030	0.074	0.908	0.705	0.094	0.280	0.769	0.263	0.552	0.360

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: OLS regression results of $ABAS_t^m$ on treatment dummies.

strong enough to have any significant impact on bid-ask spreads. This result is consistent with Farjam and Kirchkamp (2018)'s findings.

Furthermore, when comparing the effect of the specific type of strategy employed by computer traders on bid-ask spreads, we realize that the strategy used by computer traders does not matter. Indeed, we do not observe any statistically significant differences in $ABAS_t^m$ between **MM** and **SP** in most of the periods of both rounds (see estimated coefficients in Table 13 in Appendix C4).

Overall, our findings provide evidence that the potential presence of computer traders, employing spoofing or market-making strategies, is not sufficient to impact market liquidity.

4 Concluding Remarks

We run an artificial trading experiment to explore whether and how the information about the potential presence of algorithmic trading (AT) can alter subjects price forecasts, trading behavior and ultimately price dynamics and market liquidity. We tested the effect of two opposite HFT strategies, namely: layering/spoofing strategy that has been identified as a deceptive activity and associated with market manipulation (IIROC, 2013) and market making strategy that may have a beneficial effect on market quality (Menkveld, 2013).

In particular, we consider three treatments. **HO**: markets where only human traders participate and they know that computer traders are not present in these markets; **MM**: markets wherein human traders could trade with computer traders that employ market making strategy; **SP**: markets wherein human traders could interact with computer traders that employ manipulative layering/spoofing strategy. In this work, we focused on analyzing data from markets populated with human subjects only.

On the one hand, we use subjects' price forecasts elicited at the beginning of each trading period and the initial bids and initial asks submitted by our subjects at the very beginning of the trading experiment. On the other hand, we analyze price dynamics and mispricing over time as well as market liquidity. Treatment comparisons enable us to analyze the effect of the potential presence of computer traders on human trading activity and disentangle the effect of the specific type of strategy employed by computer traders.

Our experimental results suggest that the potential presence of computer traders, regardless of the type of strategy employed, can alter our subjects initial price forecasts and order timing. Namely, first, subjects' initial price forecasts deviate more from the fundamental value and are more volatile when computer traders could be present in the market than when they are known to be absent. Subjects initially expect that, in presence of computer traders, prices will differ compared to interacting only with human traders. Second, subjects' response to the potential presence of computer traders was to postpone their initial orders. Our work provides evidence that the mere threat of computer traders presence, regardless of the strategy employed, is sufficient to modify human initial expectations and order submission. In particular, we show that when subjects expect computer traders to make prices to deviate from the fundamental value of the asset and fluctuate more than when computers are not present, they tend to postpone their initial orders.

However, contrary to Farjam and Kirchkamp (2018), the information about the potential presence of computer traders had no significant effect on mispricing in our experiment. This difference may be due to the difference in the experimental procedure between ours and Farjam and Kirchkamp (2018). In Farjam and Kirchkamp (2018), subjects are shown a colored word cloud created based on participants' writing (in earlier sessions) about how algorithms would act in the experimental market. This picture based priming may have resulted in stronger experimental manipulation than our experiment. Another possibility is the difference in the FV process. Farjam and Kirchkamp (2018) uses declining FV which has been shown to result in larger mis-pricing than constant FV in our experiment (Stöckl et al., 2014).

At the same time, consistent with Farjam and Kirchkamp (2018), we show that information about the potential presence of computer traders has no significant effect on price volatility as well as market liquidity. In fact, whilst humans knew they could interact with computer traders, price dynamics and market liquidity were similar in **HO** and **AT**. This is likely to be explained by subjects' ability to recognize, over time, that computer traders are absent in these markets. Indeed, we suggest that the effect of the potential presence of computer traders observed on subjects' initial price forecasts and initial orders is not long-lasting or strong enough to generate noteworthy differences in subject and market behavior over time *i.e.,* modify prices dynamics and/or alter market liquidity. Alternatively, experiencing only human-human interactions, subjects had no motives to modify their trading behavior over time that then translated in the observed similar market behavior across treatments.

Furthermore, although we implemented and tested the effect of two opposite HFT strategies, namely market making and spoofing, we find that the specific type of trading strategy employed by computer traders does not influence human trading activity and market dynamics. This evidence seems in opposition with earlier evidence about human-computer interactions that suggest that humans tend to rely on scripts and habits when they interact with computers (Moon and Nass, 1996; Parise et al., 1999; Posard and Rinderknecht, 2015). However, this difference might be simply explained by the effect of the uncertainty about the presence of computer trader in our experiment on human behavior.

Overall, besides providing a human-human baseline for future comparisons to human-computer relations, our findings help to better understand how humans react to the presence of, and the uncertainty surrounding, new players in real financial markets and ultimately the consequences of the human-computer interactions on human and market behavior. An understanding of the way humans respond to interacting with algorithmic trading and the implications of hybrid markets on human behavior and market dynamics is important. Such a knowledge can help regulators to design more effective and relevant policy measures.

Although the presentation of computer traders are not the same between our experiment and that of Farjam and Kirchkamp (2018), the differences in the results reported in these two studies invite further studies to better understand how subject expectations, trading behavior, and thus market dynamics would be influenced by the way human traders perceive the trading strategies and the presence of computer traders in the market.

This work can be extended along the following lines (1) by investigating how subjects behave when they know they could interact with computer traders in hybrid markets; (2) by examining how subjects respond if they know they interact with computer traders; (3) by studying the consequences of enduring process of interactions with computers.

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Appendix A. Trading interfaces

A1. Order submissions

Subjects used the following interface to buy and sell the asset (see Figure 3).

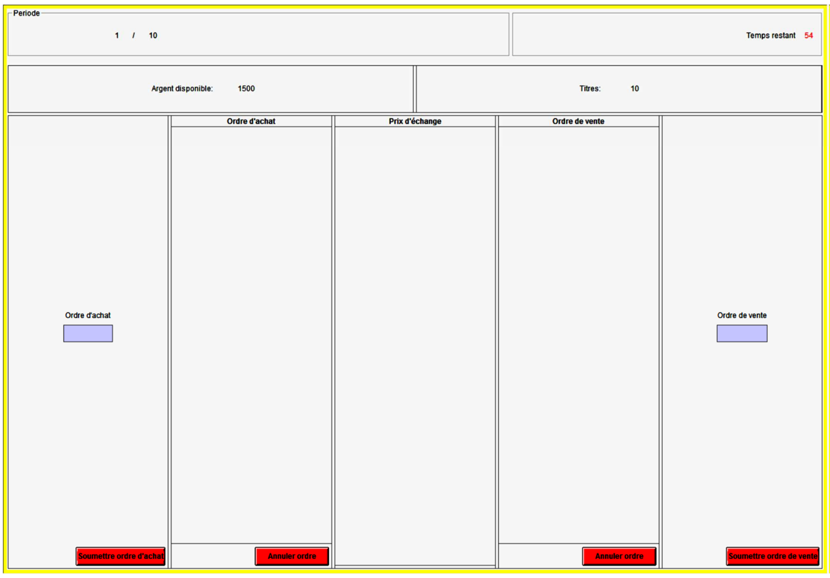


Figure 3: Order submission interface.

A2. Price forecasts

Subjects used the following interface to forecast prices at the beginning of each trading periods for the remaining periods (see Figure 4).

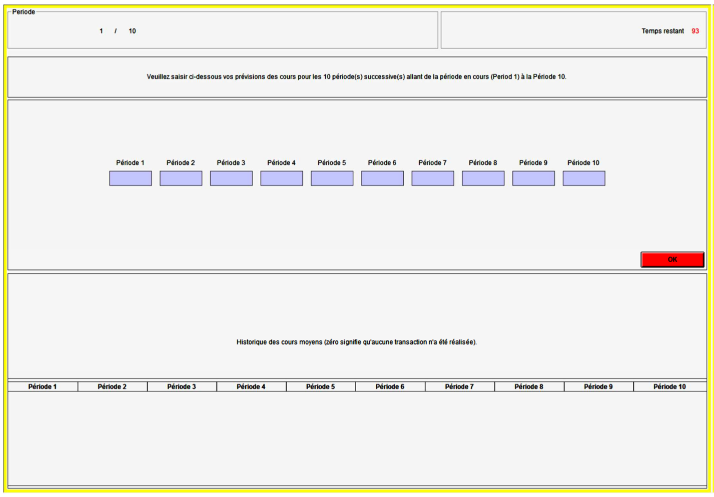


Figure 4: Price forecasts interface.

A3. End of period

At the end of each trading session, the following screen is shown to each subject (see Figure 5).

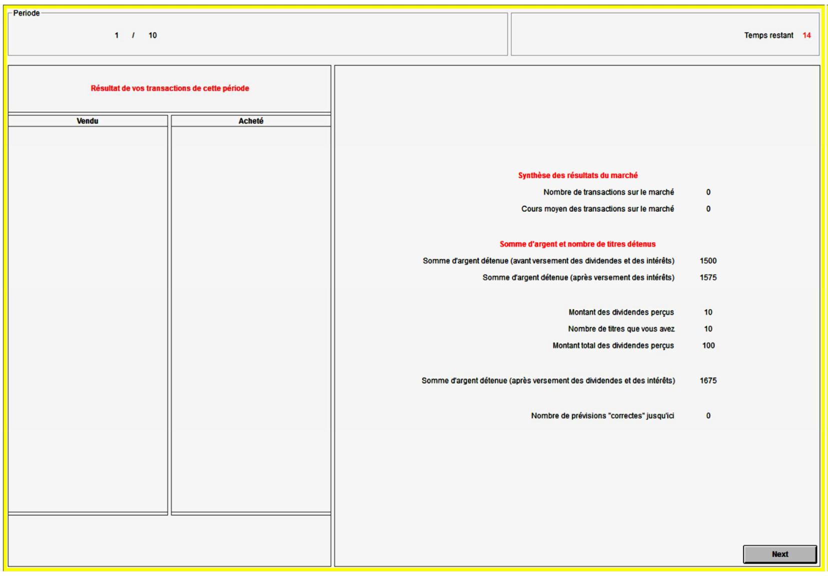


Figure 5: End of period interface.

On this screen, subjects can see a synthesis of their trading activity in the last period *i.e.,* number of transactions made, average price, price of each unit bought and sold, of the amount of cash hold, the amount of dividends and interest earned, and the number of correct forecasts. Subjects can also see, in this screen, a synthesis of the amount of cash and the number of units hold, the final amount they earned and the number of correct forecasts they made during the last round.

Appendix B. Treatment comparisons: Price dynamics per market.

Figure 6 shows the dynamics of the average realized price in period $t\epsilon 1, 2, ..., 10$ in m markets for two rounds in the baseline (**HO**) when computer traders are not present in the market and subjects are informed that only subjects will participate in the market.

When there is uncertainty about the presence of computer traders, regardless of the type, price dynamics seem less erratic and less far away from the fundamental value of the asset than in the baseline (**HO**). Prices also seem to exhibit stronger convergence towards the fundamental value when subjects might trade with computer traders using MM strategy, compared to treatments **HO** and **SP**. Furthermore, Figure 7 shows that bubble-and-crash patterns might emerge only when computer traders employ spoofing strategy (**SP**).

Preliminary inspection reveals that average price dynamics seem to differ from the asset fundamental value. The asset price apparently converges towards the fundamental value in some markets in round 1. Instead, in round 2, the convergence towards the fundamental value seems stronger in some markets and bubble-and-crash patterns emerge in some markets.

Results for treatment **MM** and treatment **SP** are shown separately in the two rows of Figure 7 1^{st} row, when computer traders employ MM strategy and 2^{nd} row, when computer traders

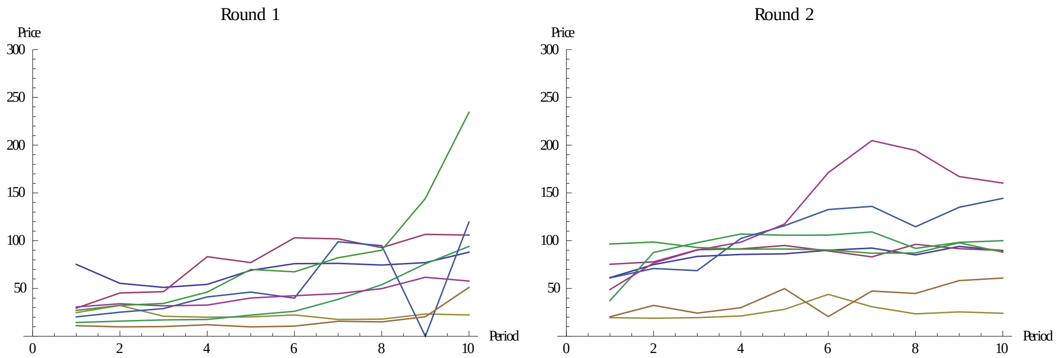
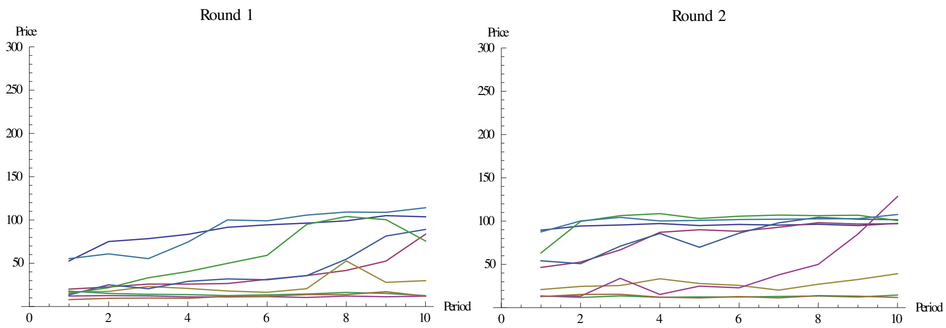
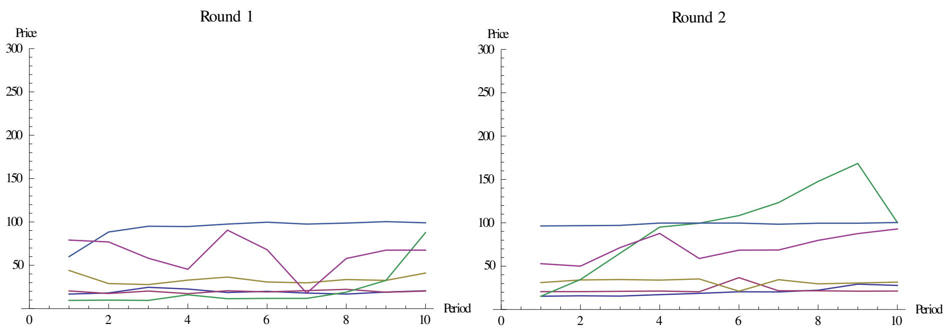


Figure 6: Price dynamics in eight markets for two rounds in treatment **HO** *i.e.*, subjects knowing that computer traders are absent.



(a) Treatment **MM**: potential presence of MM



(b) Treatment **SP**: potential presence of SP

Figure 7: Price dynamics in nine markets for two rounds in two treatments: (a) **MM** potential presence of MM, (b) **SP** potential presence of SP.

employ SP strategy.

Period 1 of Round 1	$RAFD^i_{1,1}$	$RFD^i_{1,1}$	$VolPF^i_{1,1}$
HO	0.727***	-0.530***	21.811***
	(0.064)	(0.077)	(2.816)
MM	2.122**	0.872	71.778**
	(0.770)	(0.804)	(27.254)
SP	1.403***	0.150	61.357
	(0.470)	(0.610)	(38.602)
p-value HO=MM=SP	0.095	0.146	0.137
p-value MM=SP	0.433	0.480	0.827
p-value HO=MM	0.083	0.095	0.080
p-value HO=SP	0.167	0.278	0.316

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 8: OLS regression results of $RAFD^i_{1,1}$, $RFD^i_{1,1}$, $VolPF^i_{1,1}$ on treatment dummies.

Appendix C. Treatment comparisons only-human markets, MM *versus* SP, and measures of interest.

C1. Price forecasts

Table 8 reports the results of regressing $RAFD^i_{1,1}$, $RFD^i_{1,1}$, and $VolPF^i_{1,1}$ on treatment dummies, HO, MM and SP that take value of 1 in the relevant treatment and 0 otherwise. Standard errors are corrected for within market clustering effect.

First, from the p-value for the test of the equality of the coefficients of MM and SP treatment dummies in Table 8, we do not observe any statistically significant differences in the aforementioned indicators. Thus the type of strategy computer traders employ has no impact on either the price forecast deviation from FV, *i.e.,* magnitude ($RAFD^i_{1,1}$) and direction ($RFD^i_{1,1}$), nor price forecast volatility ($VolPF^i_{1,1}$). The type of strategy employed by computer traders does not influence subjects' initial price forecasts.

Second, closer inspection reveals that the treatment effect on $RAFD^i_{1,1}$, presented in Section 3.1 (see 1^{st} column in Table 2), is due to the potential presence of computer traders employing market-making strategies. Indeed, we observe significant differences in $RAFD^i_{1,1}$ between **HO** and **MM**. p-value=0.083 for the test of the equality of the coefficents of two treatment dummies HO and MM. We can therefore confirm that the potential presence of computer traders employing market-making strategies widens the magnitude of price forecast deviations from the fundamentals. Instead, we do not observe any statistical differences in $RAFD^i_{1,1}$ between **HO** and **SP** (p-value=0.167 for the test of the equality of the coefficients of two treatment dummies HO and SP).

Lastly, although we noticed that subjects expect prices to be rather volatile when they know they could interact with computer traders (see Section 3.1 3^{rd} column in Table 2), careful examination unveils that subjects expect prices to be more volatile especially when they know they could interact with computer traders employing market making strategy (p-value $= 0.080$ for the test of the equality of the coefficients of HO and MM treatment dummies). Instead, p-value $= 0.316$ for the test of the equality of the coefficients of HO and SP treatment dummies.

Period 1 of Round 1	Coef. Bids time stamp	Coef. Asks time stamp	Coef. Bids	Coef. Asks
HO	262.997***	261.812***	22.317***	64.534***
	(13.940)	(14.380)	(3.626)	(16.077)
MM	354.846***	356.567***	15.379***	30.379***
	(21.273)	(21.908)	(2.991)	(5.413)
SP	406.899***	393.212***	25.532	42.128
	(48.241)	(41.449)	(0.238)	(10.669)
p-value HO=MM=SP	0.001	0.001	0.238	0.126
p-value MM=SP	0.332	0.441	0.220	0.335
p-value HO=MM	0.001	0.001	0.152	0.055
p-value HO=SP	0.009	0.006	0.702	0.256

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 9: OLS regression results of initial bids and initial asks time stamps and size on treatment dummies.

C2. Orders

Table 9 shows the results of regressing initial orders timing and size on treatment dummies, HO, MM and SP, that take value of 1 in the relevant treatment and 0 otherwise, in period 1 and round 1. Standard errors are corrected for within market clustering effect.

One notices, from the p-value for the test of the equality of the coefficients of MM and SP treatment dummies in Table 9, that we do not observe any statistically significant differences in the timing and the size of initial orders. The timing and the size of subjects' initial orders, both asks and bids, do not depend on the strategy employed by computer traders. We therefore decide to pool the observations from these two treatments into **AT** and compare it to **HO** (see Table 3).

Moreover, further investigation of initial asks reveals that subjects tend, on average, to submit significantly lower asks when computer traders employing market-making strategy could be present in the market, *i.e.,* **MM**, than when subjects can rule out the presence of computer traders, *i.e.,* **HO** (p-value = 0.055 for the test of the equality of the coefficients of HO and MM treatment dummies).[16]

Lastly, when analyzing subjects' orders, both bids and asks, over time, we do not observe any statistically significant differences between **MM** and **SP**. Table 10 shows the results of panel regressions (using random-effects estimators) of average bids and average asks on realized price in previous period, treatment dummies, accounting for interaction effects in round 1 and in round 2. **HO** is the baseline in this regression.

One observes from Table 10 that, except for the average bids in **MM** in round 2, we do not observe statistically significant differences in average bids and average asks. As a result, we pool the data from these two treatments into **AT** and compare it to **HO** (see Table 4) and only present the results of the pooled data from **MM** and **SP** *i.e.,* **AT** in Section 3.2.

C3. Prices

Table 11 reports the estimation results of linear regressions of RAD_r^m, RD_r^m and Vol_r^m on treatment dummies MM and SP that take value of 1 in the relevant treatment and 0 otherwise in round 1 and round 2.

[16]These differences in initial ask size between MM and SP compared to HO are not easy to explain, given the lack of differences for the pooled data AT.

	Average bids		Average asks	
	Round 1	Round 2	Round 1	Round 2
p_{t-1}	0.656***	0.756***	2.081**	1.347***
	(0.169)	(0.030)	(0.985)	(0.402)
MM	-3.642	-9.871**	51.037	-52.606
	(7.244)	(4.278)	(52.375)	(37.865)
SP	1.662	-4.949	-108.372	-33.902
	(8.656)	(5.363)	(113.119)	(37.799)
$p_{t-1}MM$	0.212	0.238***	-0.801	0.138
	(0.174)	(0.053)	(1.060)	(0.553)
$p_{t-1}SP$	-0.088	0.052	4.875	-0.420
	(0.211)	(0.066)	(3.898)	(0.431)
$cons$	7.191	7.427*	-9.871	63.896*
	(6.981)	(3.897)	(39.871)	(34.421)
p-value MM=SP	0.332	0.228	0.153	0.400

NB: Std. Err. adjusted for 24 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 10: Panel regression results of average bids and average asks on realized price in previous period, treatment dummies, accounting for interaction effects in Round 1 and Round 2.

	RAD_r^m		RD_r^m		Vol_r^m	
	Round 1	Round 2	Round 1	Round 2	Round 1	Round 2
MM	0.594***	0.404***	-0.583***	-0.381***	13.249***	10.907***
	(0.140)	(0.122)	(0.136)	(0.123)	(4.335)	(3.687)
SP	0.611***	0.524***	-0.611***	-0.481***	13.741**	12.679***
	(0.159)	(0.138)	(0.154)	(0.139)	(4.916)	(4.181)
p-value	0.935	0.524	0.890	0.595	0.941	0.753

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 11: Regression estimates for RAD_r^m, RD_r^m and Vol_r^mon treatment dummies in round 1 and round 2.

When comparing RAD_r^m, RD_r^m and Vol_r^m between **MM** and **SP**, we do not observe any statistically significant differences in both rounds. In round 1, p-value=0.935 (0.890) for the test of the equality of the coefficients of MM and SP treatment dummies of RAD_r^m (RD_r^m). In round 2, p-value=0.524 (0.595) for the test of the equality of the coefficients of the two treatment dummies of RAD_r^m (RD_r^m).

Furthermore, when comparing the effect of the specific type of strategy employed by computer traders (*i.e.,* **MM** *vs.* **SP**) on price volatility, we find that computer traders' strategy type has no significant impact. p-value=0.941 (0.753) for the tests of the equality of the coefficients of MM and SP treatment dummies in round 1 (round 2). We therefore pool the observations from these two treatments into **AT** and compare it to **HO** (see Table 5). Thus, in Section 3.3, we only present the results of the pooled data from **MM** and **SP** *i.e.,* **AT**.

	ST_r^m	
	Round 1	Round 2
MM	1.372***	1.493***
	(0.347)	(0.381)
SP	1.475***	1.814***
	(0.394)	(0.432)
p-value	0.847	0.583

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 12: Regression estimates for ST_r^m on treatment dummies in round 1 and round 2.

Round 1

Coef. $ABAS_t^m$	1	2	3	4	5	6	7	8	9	10
MM	34.222 (20.105)	74.444*** (21.494)	102.556*** (31.478)	61.889*** (18.859)	35.778 (34.019)	35.333 (58.163)	120.444 (95.977)	56.667** (26.860)	76.556 (53.010)	215.444** (96.329)
SP	48.143** (22.797)	34.429 (24.372)	38.286 (35.693)	53.857** (21.384)	126.857*** (38.574)	74.429 (65.951)	55.429 (108.828)	56.429* (30.456)	60 (60.107)	53.857 (109.227)
p-value	0.651	0.231	0.191	0.781	0.090	0.661	0.658	0.995	0.838	0.279

* p < 0.1, ** p < 0.05, *** p < 0.01.

Round 2

Coef. $ABAS_t^m$	1	2	3	4	5	6	7	8	9	10
MM	60*** (19.014)	57.556 (34.375)	102.222** (37.042)	66.444** (26.164)	128.667 (96.850)	178* (92.433)	71.111* (36.740)	68.889 (43.136)	145.333* (82.764)	43* (24.446)
SP	43.143* (21.560)	42.857 (38.977)	45.571 (42.002)	73.571** (29.668)	46.143 (109.818)	46.571 (104.809)	84.857* (41.659)	57.429 (48.912)	47.143 (93.846)	65.143** (27.719)
p-value	0.564	0.780	0.323	0.859	0.579	0.357	0.807	0.862	0.441	0.555

* p < 0.1, ** p < 0.05, *** p < 0.01.

Table 13: OLS regression results of $ABAS_t^m$ on treatment dummies.

C4. Market liquidity

First, Table 12 reports the results of regressing ST_r^m on treatment dummies MM and SP that take value 1 in the relevant treatment and 0 otherwise in round 1 and round 2.

The comparison of ST_r^m between **MM** and **SP** confirms that the type of strategy employed by computer traders, *i.e.,* market making or spoofing, has no significant effect on trading volumes (ST_r^m) either in round 1 or in round 2 (see 5^{st} row of Table 12). As a result, in Section 3.4, we only present the results of regressing ST_r^m on **AT** and **HO** treatment dummies.

Furthermore, while market making is often associated with liquidity provision, improves market quality, mediates transactions and facilitates trading (Brogaard, 2010; Menkveld, 2013), the mere possible presence of computer traders employing market making strategies is not sufficient, or reassuring enough, to foster subjects to trade. Furthermore, although spoofing strategies are often associated with price manipulation (Prewitt, 2012; IIROC, 2013), our results suggest that the mere possible presence of computer traders employing spoofing strategies is not sufficient to drive human traders out of the market.

Second, Table 13 reports the results of regressing $ABAS_t^m$ across ten periods on treatment dummies MM and SP that take value of 1 in the relevant treatment and 0 otherwise in round 1 (top panel) and round 2 (bottom panel).

One notices that we do not observe any statistically significant differences in $ABAS_t^m$ be-

Treatment	Number of Subjects	Number of Computer traders	Number of Markets
MM_{hyb}	28	28	7
SP_{hyb}	28	28	7
Total	56	56	14

Table 14: Number of participants and markets per treatment.

tween **MM** and **SP**. The type of strategy employed by computer traders hence does not make any difference in the extent of bid-ask spreads. As a result, in Section 3.4, we pool the observations from these two treatments into **AT** (see Table 7).

Appendix D. Hybrid markets $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$.

Although in this work, we solely focus on and compare only-human markets, in our experiment, in order to introduce uncertainty about the presence of computer traders and avoid deception (see Section 2), some subjects participated in hybrid markets $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$ knowing they could interact with computer traders employing market-making strategy and spoofing, respectively.[17] Table 14 shows the number of participants, *i.e.,* human subjects and computer traders, as well as the number of markets in each treatment with hybrid markets (*i.e.,* $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$).

This appendix therefore provides additional information about price dynamics in hybrid markets (Section D1) and treatment comparisons between only-human *versus* hybrid markets and measures of interest (Section D2).

D1. Price dynamics in hybrid markets

Figure 8 shows the dynamics of realized prices over 10 periods that emerge in hybrid markets *i.e.,* in two treatments: $\mathbf{MM}_{hyb}$ (top panel) and $\mathbf{SP}_{hyb}$ (bottom panel) and in round 1 (left panel) and round 2 (right panel).

Visual inspection reveals that price dynamics seem less erratic when computer traders employ SP strategy than MM strategy, at least in round 1. Furthermore, when computer traders are present, we observe that, in some markets, price dynamics exhibit bubble-and-crash patterns that vanish over one period.

Figure 9 compares the dynamics of average realized prices across markets in three treatments: **HO** (thin line), $\mathbf{MM}_{hyb}$ (dashed line) and $\mathbf{SP}_{hyb}$ (thick line) as well as the fundamental value (FV) of the asset (dotted line).

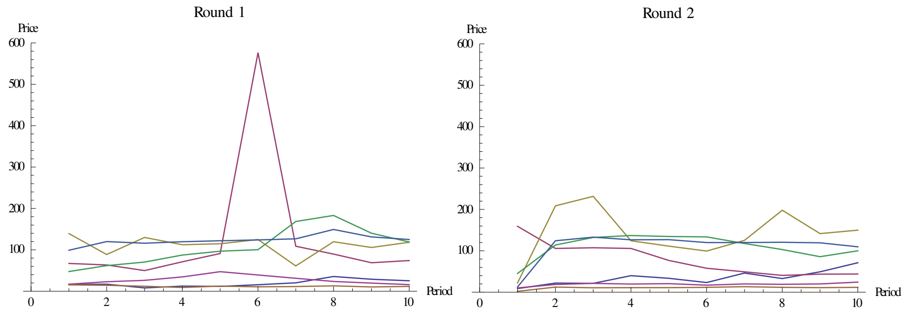
Preliminary observations unveils that prices seem to converge more markedly towards FV when subjects can rule out the presence of computer traders in **HO** than when computer traders are present in markets $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$. In round 2, prices seem to depart further away from FV when computer traders, regardless of the strategy type, participate in the market.

D2. Treatment comparisons, only-human markets (*i.e.,* HO, MM and SP) *versus* hybrid markets ($\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$), and measures of interest.

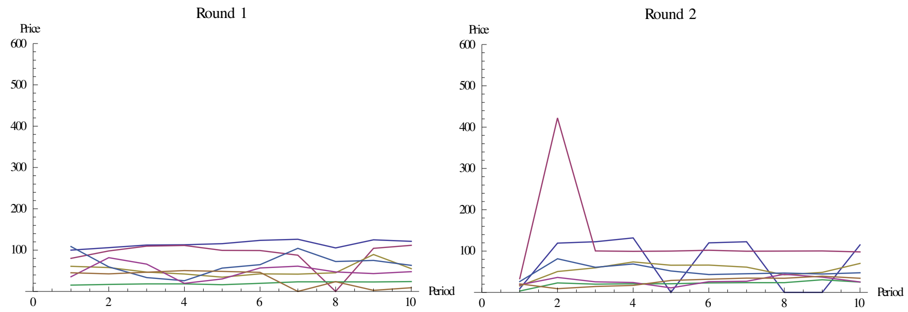
D2a. Orders

Table 15 shows the results of panel regressions (using random-effects estimators) of average bids and average asks on realized price in previous period, treatment dummies of hybrid markets

[17]The details of these algorithms are available upon request.



(a) Treatment MM_{hyb}: presence of MM



(b) Treatment SP_{hyb}: presence of SP

Figure 8: Price dynamics in hybrid markets in two treatments: (a) $\mathbf{MM}_{hyb}$ presence of MM, (b) $\mathbf{SP}_{hyb}$ presence of SP, and two rounds.

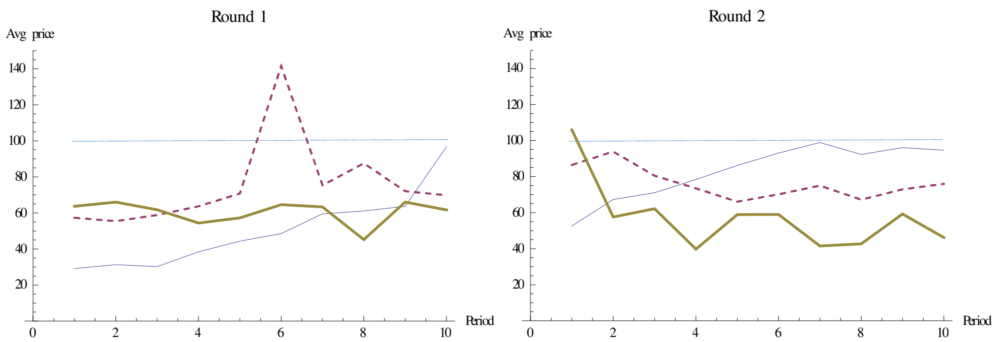


Figure 9: Average price dynamics of three treatments: **HO** (thin line), MM_{hyb} (dashed line), SP_{hyb} (thick line). Fundamental value of the asset over the 10 periods is also displayed (dotted line).

$\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$, accounting for interaction effects in round 1 and in round 2. **HO** is the baseline in this regression. Note that we only account for orders submitted by human subjects.

Contrary to our findings when computer traders are not present (see Section 3.2), we observe that the presence of computer traders, except for average asks in round 2, has a significant effect on average bids and average asks and modifies the influence of past realized prices on average bids and average asks (see Table 15). We suggest that the presence of computer traders in $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$ tends to lessen the observed realized price and average orders relationship

	Average bids		Average asks	
	Round 1	Round 2	Round 1	Round 2
p_{t-1}	0.660***	0.742***	2.112***	1.346***
	(0.158)	(0.030)	(0.787)	(0.402)
MM_{hyb}	37.206**	5.603	100.629**	-18.671
	(16.008)	(10.601)	(49.970)	(40.826)
SP_{hyb}	21.554**	29.765***	61.546*	21.657
	(9.283)	(8.837)	(35.721)	(42.700)
$p_{t-1}MM_{hyb}$	-0.483**	-0.141	-1.745**	-0.443
	(0.188)	(0.108)	(0.820)	(0.433)
$p_{t-1}SP_{hyb}$	-0.467***	-0.750***	-1.674**	-1.150***
	(0.174)	(0.084)	(0.816)	(0.426)
$cons$	7.016	8.679**	-11.243	63.924*
	(6.493)	(3.805)	(29.603)	(34.325)
p-value MM_{hyb}=SP_{hyb}	0.330	0.057	0.385	0.231
p-value p_{t-1}=$p_{t-1}MM_{hyb}$=$p_{t-1}SP_{hyb}$	0.002	0.000	0.053	0.000

NB: Std. Err. adjusted for 22 clusters in market in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 15: Panel regression results of average bids and average asks on realized price in previous period and treatment dummies of hybrid markets MM_{hyb} and SP_{hyb}, accounting for interaction effects in Round 1 and Round 2.

compared to when computer traders are not present in **HO**, **MM** and **SP**. This evidence hint at the ability of our subjects, as they gain experience, to recognize the presence of computer traders in the market and behave accordingly. We therefore suggest that the non-significant results presented in Section 3.2 when comparing only-human markets is explained by the absence of computer traders in these markets.

D2b. Prices

We also checked whether mispricing size (measured as $P_t^m - FV_t^m$) over time would differ across treatments. Table 16 reports the estimation results of linear regressions of $mispricing_t^m$ on treatment dummies MM, SP, MM_{hyb}, SP_{hyb} that take value of 1 in the relevant treatment and 0 otherwise in round 1 and round 2. **HO** is the baseline in this regression.

As one can observe, mispricing is positively related to time (independent variable *Period* in Table 16) *i.e.,* it shrinks, or becomes less negative, over time. However, although we do not observe any treatment effect in only-human markets (*i.e.,* **MM** and **SP** or **AT**), we do observe differences in mispricing size over time when computer traders, regardless of the strategy type, are present in $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$, especially in round 1. Furthermore, while mispricing decreases with time, such an improvement is significantly lower when computer traders are present in the market. The coefficient of the interaction effect $PeriodAT_{hyb}$ is negative and significant in both rounds. Moreover, the differences in the interaction terms $PeriodAT$ and $PeriodAT_{hyb}$ is significant in both rounds. p-value=0.023 (0.002) for the test of the equality of the coefficients of $Period$, $PeriodAT$ and $PeriodAT_{hyb}$. This finding further confirms that, when present, computer traders have an influence on price dynamics which may enable our subjects are able to recognize, with experience, that computer traders are present in hybrid markets. Instead the absence of computer traders, in only-human markets, is likely to explain the non-significant

	$mispricing_t^m$	
	Round 1	Round 2
$Period$	6.402***	4.566**
	(1.976)	(1.794)
MM	3.538	-12.533
	(10.476)	(15.994)
SP	17.400	-21.893
	(13.839)	(14.342)
MM_{hyb}	44.192**	28.189
	(18.655)	(27.481)
SP_{hyb}	40.393***	-8.759
	(11.163)	(16.565)
$PeriodMM$	-2.204	-1.568
	(2.311)	(2.129)
$PeriodSP$	-5.246**	-1.684
	(2.147)	(2.492)
$PeriodMM_{hyb}$	-3.505	-6.375**
	(2.604)	(2.445)
$PeriodSP_{hyb}$	-6.980***	-5.636**
	(2.211)	(2.089)
$cons$	-84.901***	-42.081***
	(8.010)	(9.584)
p-value $MM = SP$	0.299	0.578
p-value $MM_{hyb} = SP_{hyb}$	0.839	0.212
p-value $Period = PeriodMM = PeriodSP$	0.007	0.264
p-value $Period = PeriodMM_{hyb} = PeriodSP_{hyb}$	0.004	0.026
$Period$	6.402***	4.566**
	(1.966)	(1.784)
AT	9.602	-16.628
	(10.244)	(12.851)
AT_{hyb}	42.292***	9.715
	(12.202)	(18.040)
$PeriodAT$	-3.535	-1.619
	(2.144)	(2.040)
$PeriodAT_{hyb}$	-5.243**	-6.006***
	(2.246)	(2.040)
$cons$	-84.901***	-42.081***
	(7.967)	(9.533)
p-value $AT = AT_{hyb}$	0.006	0.142
p-value $Period = PeriodAT = PeriodAT_{hyb}$	0.021	0.002

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 16: Regression estimates for $mispricing_t^m$ on treatment dummies of only-human markets **MM** and **SP** and the corresponding hybrid markets $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$ in round 1 and round 2.

	ST_r^m	
	Round 1	Round 2
MM_{hyb}	1.452***	1.682***
	(0.162)	(0.228)
SP_{hyb}	0.789***	0.912***
	(0.162)	(0.228)
p-value MM_{hyb}=SP_{hyb}	0.013	0.034

$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

Table 17: Regression estimates for ST_r^m on treatment dummies in round 1 and round 2.

results presented in this work (see Section 3.3). Indeed, when computer traders, regardless of the type of strategy employed, are not present in **AT**, we observe that prices converge more rapidly towards the fundamental value of the asset compared to hybrid markets $\mathbf{AT}_{hyb}$.

D2c. Market liquidity

Table 17 reports the results of regressing ST_r^m on treatment dummies MM_{hyb} and SP_{hyb} that take value 1 in the relevant treatment and 0 otherwise.

One notices that, contrary to the evidence on share turnover in **MM** and **SP** *i.e.,* when computer traders *could* be present but are not, the presence of computer traders in $\mathbf{MM}_{hyb}$ and $\mathbf{SP}_{hyb}$ has a significant impact on share turnover in both round 1 and round 2. p-value = 0.013 (0.034) for the test of the equality of the coefficients of the two treatment dummies.

Furthermore, we observe that share turnover is significantly lower when computer traders, employing spoofing strategy, are present in the market compared to market-making strategy, especially in round 1. This evidence might be explained by the fact that in presence of potentially adverse computer traders, because of the fear of price manipulation, subjects may be driven out of the market (Prewitt, 2012). This evidence hint at the ability of our subjects to recognize when computer traders are present in the market.

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