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# Speed Traps: Algorithmic Trader Performance Under Alternative Market Structures

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# Speed Traps: Algorithmic Trader Performance Under Alternative Market Structures

## Comments

ESI Working Paper 20-39

# Speed traps: Algorithmic trader performance under alternative market structures

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*November 10, 2020*

## Abstract

Using laboratory experiments, we illustrate that trading algorithms that prioritize low latency pose certain pitfalls in a variety of market structures and configurations. In hybrid double auctions markets with human traders and trading agents, we find superior performance of trading agents to human traders in balanced markets with the same number of human and Zero Intelligence Plus (ZIP) buyers and sellers only, thus providing a partial replication of Das et al. (2001). However, in unbalanced markets and extreme market structures, such as monopolies and duopolies, fast ZIP agents fall into a speed trap and both human participants and slow ZIP agents outperform fast ZIP agents. For human traders, faster reaction time significantly improves trading performance, while Theory of Mind can be detrimental for human buyers, but beneficial for human sellers.

*Keywords:* Trading agents, Speed, Algorithmic trading, Laboratory experiment.

*JEL Classifications:* C78, C92, D40

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## 1. Introduction

As automated electronic markets have become ubiquitous, speed in both decisions and actions has become an important factor in a wide variety of markets. Algorithmic traders (ATs) and particularly high-frequency traders (HFTs), a subgroup of ATs, rely heavily on their speed advantage to respond to market opportunities faster than other participants. HFTs achieve high speed by reducing latency, the length of time required to receive and send information to market exchanges, and the use of simple a computationally efficient decision rules that transform market information into market actions. In doing so, they realize substantial trading profits and outperform other slower participants (cf. Baron et al., 2019; Biais et al., 2015).

However, market conditions can be an important effect in HFTs' trading behavior and market impact. Examples of extreme market conditions include the thin and volatile markets around the occurrence of flash crashes. Flash Crashes are a conspicuous example of the market anomalies facilitated by the increase in speed and automation.<sup>1</sup> While the first Flash Crash in 2010 (Kirilenko et al., 2017) was treated as an isolated extreme event at the time, flash crashes have become more frequent in recent years. Prominent examples of “regular” flash crashes include the Japanese Yen in foreign exchange markets, which are in part caused by liquidity droughts around Japanese holidays when markets are closed<sup>2</sup> and positional skews of retail traders.<sup>3</sup> To understand

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<sup>1</sup> In their experimental asset market, Asparouhova et al. (2019) show that flash crashes occur primarily in markets where automated trading is present.

<sup>2</sup> See, for example, “Yen flash crash: what happened and why”, Financial Times, Jan 3, 2019 (<https://www.ft.com/content/45d3807a-0f5b-11e9-a3aa-118c761d2745>, accessed 11-11-2020), and “To avoid a 'flash crash', FX traders drop yen shorts and run bare”, Reuters, April 24, 2019 (<https://www.reuters.com/article/us-asia-markets-flashcrash-idUSKCN1S00YY>, accessed 11-11-2020).

<sup>3</sup> Cf. “Flash-Crash Risks Are Back as Japan Shuttters for Six-Day Holiday”, Bloomberg, Dec 30, 2019 (<https://www.bloomberg.com/news/articles/2019-12-30/flash-crash-risks-are-back-as-japan-shuttters-for-six-day-holiday>, accessed 11-11-2020).

the role of speed in financial markets, it is thus vital to include market conditions with extreme imbalances of volume and market power.

An important evidential basis for the trading fast conjecture was Das et al. (2001). These researchers first demonstrated that robot traders, following simple adaptive trading rules and reacting quickly, could outperform human traders while contemporaneously participating in a continuous double auction (CDA). This study marked a turn in research objectives and methodologies.

The seminal work of Smith (Smith, 1962; Smith, 1981) empirically established that coupling buyers and sellers with decentralized private information regarding individual preferences and costs with a CDA robustly generated competitive equilibrium market outcomes. There were subsequent efforts to develop accurate models of trader behavior (such as Wilson (1986)), Friedman (1991), and Easley and Ledyard (1993)). The literature was pivoted by Gode and Sunder (1993) who demonstrated through simulations that Zero Intelligence (ZI) traders, who randomly make welfare improving trade proposals, participating within a CDA robustly realized social welfare maximizing allocations.<sup>4</sup>

Their study triggered the development of incrementally more sophisticated trading agents to establish the lower bounds of rationality, at which ATs could reproduce the trading patterns of humans or even outperform them. Cliff and Bruten (1997) developed the prominent type of Zero Intelligence Plus (ZIP) agents which augmented ZI traders with the ability to learn from market events. Gjerstad and Dickhaut (1998) developed a trading agent that determines its actions based

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<sup>4</sup> In these ZI simulations, while the allocation of units generally coincides with the competitive equilibrium one, prices only approached equilibrium ones during the latter stages of trading activity within trading periods. This results from the probabilistic Marshallian order of trades induced by the ZI strategies.

on “belief” functions of the probability whether their bid or offer will be rejected; these functions are updated using observed market data. Both studies used computer simulations to demonstrate that their respective models are able to generate price dynamics and allocative efficiency (the percentage of potential gains of trade that are realized) similar to those generated in pure human experiments.

A subsequent wave of studies, in addition to Das et al. (2001), examined the interaction of human subjects and AT’s in hybrid experiments, and the relative performance of humans and AT naturally arose. Gjerstad (2007) found that impatient versions of the Gjerstad and Dickhaut agents performed similarly to humans, and surprisingly patient versions of these agents performed the best. Grossklags and Schmidt (2003, 2006) conducted hybrid experiments in a more complex environment and agents who follow an arbitrage strategy. However, they found that the interaction of trading agents and human participants lowered efficiency. Cartlidge et al. (2012) further conduct human-agent experiments using the OpEx experimental economics system. They vary the speed of the agents and find that including agents that are too fast can have negative effects on market efficiency. While Cartlidge et al. (2012) focus on agent speed in their study, our study focuses on the role of speed in markets with different market structures.

We suggest that the results of Das et al. (2001) are knife-edged and crucially rely upon different factors, such as market balance and structure. In particular, we replicate the hybrid experimental markets of this study and further test the robustness of results in unbalanced markets – those in which all ATs are either buyers or sellers with all human traders taking the opposite role – as well as more in extreme market structures, such as a monopoly or duopoly.<sup>5</sup> We further

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<sup>5</sup> Smith and Williams (2000) showed duopoly markets with human traders converge towards the competitive equilibrium rather than prices and quantities associated joint profit maximizing, or monopoly, outcomes.

analyze human trading performance by evaluating which individual characteristics can predict human trading performance in different market settings.

We find that fast-ZIP agents, who seek to submit market orders on average every one second, outperform human participants only as buyers in a balanced market. However, human participants outperform fast-ZIP agents as sellers in balanced markets and generally in other unbalanced and uncompetitive market structures, such as monopolies and duopolies. These results are novel and reveal that market balance and market structure are important prerequisites in achieving the previous findings of Das et al. (2001). We further find that slow ZIP agents, who seek to submit market orders on average every five seconds, outperform fast agents and in some cases even human traders under alternative market structures, providing further evidence that patience can lead to superior trading performance in certain market conditions. Our paper illustrates the market conditions in which speed can trap fast traders and lead to inferior results compared to more patient traders.

The analysis of individual characteristics of human subjects reveals that the performance of human traders largely depends on their reaction time in competitive fast-paced markets. We find measures of the Theory of Mind (ToM) has mixed effects on a subjects' performance; it is detrimental for human buyers but beneficial for human sellers. Furthermore, individual assessments of whether there is AT activity in markets is strongly influenced by cognitive reflection abilities.

Our analysis of market surplus and individual surplus in unbalanced and uncompetitive market structures is particularly relevant for trading participants as well as market operators and regulators to understand the role of trading speed in these market conditions. In financial markets,

unfavorable market conditions, such as thin and/or imbalanced markets, can contribute to the occurrence of flash crashes and thus deteriorate market quality and stability.

## **2. Experimental Design**

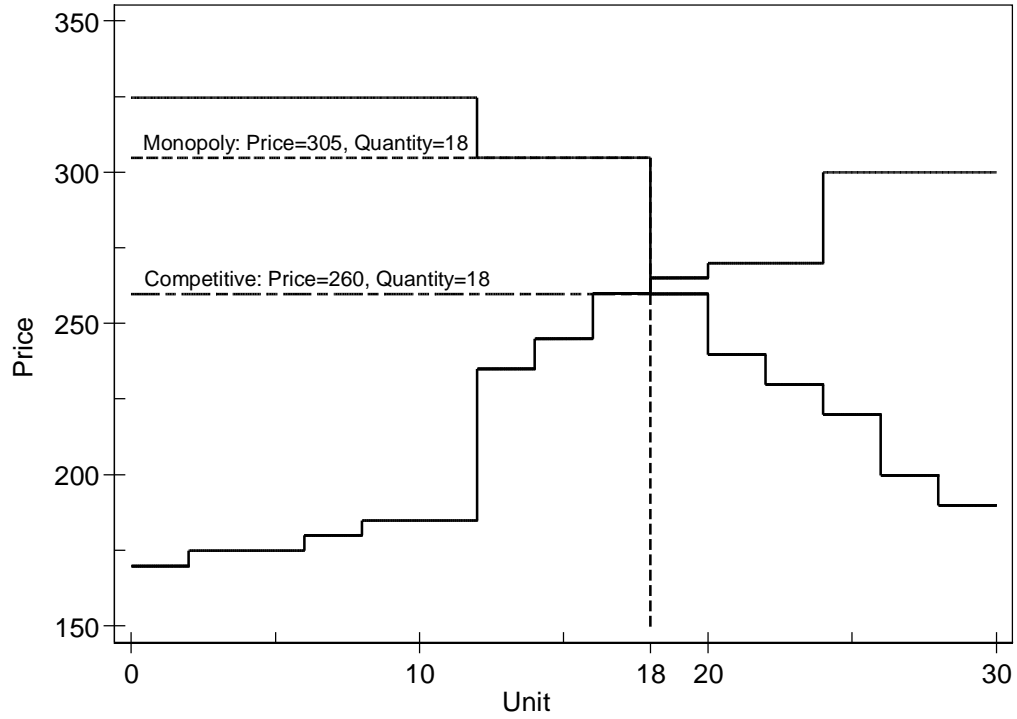
Our experimental design consists of a series of individual tasks that measure individual abilities, a survey instrument to record individual socio-economic characteristics, and participation in a CDA with induced supply and demand (Smith (1976)). We first provide the details of the CDA task as its results are of primary interest, and it is where we implement our experimental treatments.

### **2.1 Market Environment and Treatments**

We adopt a common induced market supply and demand pair in all treatments, which Figure 1 depicts. In the competitive equilibrium, the equilibrium price is 260 and the number of units traded in equilibrium is 18. In the monopoly solution, the price is 305 and the number of traded units is, again, 18. The Cournot duopoly equilibrium prices and total quantity traded are the same as in the Monopoly solution. We choose a configuration in which the alternative solutions yield the same quantity traded, to focus on the AT's ability to capture surplus through effective price negotiation rather than its ability to withhold units from the market. The total achievable surplus, or gains from exchange, is 2,110 in the alternative solutions. In the competitive equilibrium, the supply side receives 1,060, and the demand side 1,050. In the monopoly and duopoly solutions, the seller(s) surplus amounts to 1,870 and the buyer surplus is 240.



**Figure 1** Supply-Demand Curve



**Table 1** Experimental Treatment Design - (H-Human, FZ-Fast ZIP, SZ-Slow ZIP; S-Seller, B-Buyer)

Speed			Market Structure		
			Competitive	Duopoly	Monopoly
<b>Balanced Markets</b>	Baseline: Human only		6HS-6HB	2HS-6HB	1HS-6HB
	Mixed: 3 ZIP Buyers, 3 ZIP Sellers	Slow	H-SZ		
		Fast	H-FZ		
<b>Unbalanced Markets</b>	ZIP Buyers	Slow	6HS-6SZB	2HS-6SZB	1HS-6SZB
		Fast	6HS-6FZB	2HS-6FZB	1HS-6FZB
	ZIP Sellers	Slow	6SZS-6HB	2SZS-6HB	1SZS-6HB
		Fast	6FZS-6HB	2FZS-6HB	1FZS-6HB

We establish a baseline with all human interactions for the competitive structure, and the monopoly and duopoly structure. In addition to the 3 human-only baseline treatments, there are 14 different treatments in total as shown in Table 1. In all treatments, the instructions state that there might be computer agents present on the market. We conduct 8 sessions for each treatment except for treatment 2HS-6SZB, for which we conduct 9 sessions due to over-recruitment of participants.

### *Trading Agents*

Cliff and Bruten (1997) developed ZIP agents which augmented ZI traders with adaptive price expectations based on previously accepted or rejected bids and offers. In particular, agents start with an initial expectation of transaction price and a latent surplus demand. Price expectations are adjusted every time a bid or offer is submitted to the market and either accepted (resulting in a trade) or rejected (resulting in an addition to the order book). In particular, if a trade occurs at a price  $q$  which is greater than the expected price  $p_i$  for unit  $i$  of a seller (buyer), the seller (buyer) increases (decreases) his latent surplus demand  $\mu$ . Otherwise, if  $q$  is less than  $p_i$ , the seller (buyer) decreases (increases) his latent surplus demand  $\mu$ . The algorithm constrains the latent surplus demand to be non-negative. The size of the adjustment of the latent surplus demand is proportional to a learning rate parameter  $\beta$ . We provide further details of the ZIP algorithm in Appendix B.

Our experimental treatments study two ZIP types defined by differential speed, i.e. fast-ZIP and slow-ZIP. The agents' speed relates to their specific sleep-wake cycles. Agents are only allowed to submit or update their orders after a specific time interval. Fast-ZIP agents that have a sleep/wake cycle that is a random variable with a uniform probability distribution over the interval 0.75 to 1.25 seconds; slow-ZIP agents' sleep/wake cycle that is a random variable with a uniform probability distribution over the interval 3.75 to 6.25 seconds.

### *Trading Process*

Each participant participates in a single treatment and session. Each market setting is run for 8 consecutive trading periods, each lasting 2.5 minutes. A participant is privately informed of the redemption value for buyers (or costs for sellers)  $v_i$  for unit  $i$ ,  $i = 1, \dots, 5$ , which is drawn from the specified supply and demand functions. The information about the private values of the units is given to the trader at the beginning of each period. Each limit order and each transaction is valid for a single unit and a crossing of bid and ask prices leads to a transaction price equal to the earlier submitted of the two. See Appendix A for the full set of instructions and screen captures.

## **2.2 Experimental Procedures, Individual Abilities Assessments, and Individual Characteristics Survey**

The experiment was conducted at the laboratory of the Center for Behavioral and Experimental Research at Wuhan University and in accordance with its ethics guidelines. Participants were recruited using the Ancademy System (<https://www.ancademy.org/>). A total of 746 students (mean age = 20.2; Gender: 436 female; 309 male, this data is missing is for one subject) participated in 24 sessions. Participants were almost exclusively students from Wuhan University and enrolled in a broad cross-section of majors. An experimental session lasted no more than 120 minutes. The minimum payoff was a show-up fee of 20 Chinese Yuan. Depending on their trading behavior in the experiment, the average payoff per participant was 82.7 Chinese Yuan (Min=35.3, Max=137.2).

At the beginning of the experiment, participants completed three tasks: the eye gaze test (ET), the extended cognitive response test (CRT), and the reaction test (RT). All three tasks are rewarded on a piece-rate basis.

The eye gaze test is a task to measure ToM skills based on the assessment of eye gaze (Baron-Cohen et al., 1997; see Appendix C for a description of the survey). We reward subjects for correct answers, as is common in the literature (see for example Bruguier et al., 2010). The average rate of correct answers is 25.69 (N=745, SD=2.92, Min=14, Max=34).

The second task is the CRT, a common test to measure skills of cognitive reflection and thus their ability to avoid common behavioral biases. We use the test version by Frederick (2005) which consists of 7 questions that have an intuitive but incorrect answer (e.g., “A bat and a ball cost \$1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost?”, Frederick, 2005). While the intuitive answer (“10¢”) is incorrect, reflection will help to choose the correct one (“5¢”). We again reward subjects for correct answers in this task. The average number of correct answers is 5.70 (N=746, SD=1.52, Min=1, Max=7).

The third task is the RT, a test in which subjects are repeatedly asked to choose the highest of three listed numbers during a fixed time period of 2 minutes. We measure the number of correct answers for this task and offer a reward proportional to the performance in the task. The average number of correct answers is 31.08 (N=746, SD=5.98, Min=16, Max=54).

After completing all three tasks, participants are provided with a hard copy of the participant instructions for the trading game, which are also conveyed verbally to participants by reading them out loud. The translated instructions can be found in Appendix A. We further conduct 1 trial period before the actual experiment, so that the participants can get used to the trading interface.

We implemented the above-described market design using a market platform on the Ancademy System. The trading interface is depicted in Figure A1 in Appendix A. At the end of the experiment, the participants have to complete a questionnaire with general questions about their age, gender, and background. In addition, they are asked to complete an assessment of the market with respect to the number of active computer agents and the number of buyers and sellers. All the questions in the questionnaire are not compulsory for subjects.

### **3. Results**

In the first part of this section, we present the results of a balanced competitive market design which is a partial replication of the study by Das et al. (2001) which also employs mixed markets with the same number of human and ZIP buyers and sellers. The two sections on unbalanced markets focus on competitive markets in which buyers and sellers have the same market power, and non-competitive markets in which there are either duopolist or monopolist sellers.

#### **3.1. Balanced Competitive Markets**

In this section, we present the results of a balanced competitive market design with 3 human and 3 ZIP buyers, and 3 human and 3 ZIP sellers, focusing on the overall market surplus, the surplus distribution as well as the determinants of human surplus.

##### *Trade Prices and Market Surplus*

Table 2 shows average prices and the realized surplus for the overall market as well as each trader group H(uman) Buyers, H(uman) Sellers, ZIP Buyers and ZIP Sellers for the 3 treatments, human traders only (HH), and mixed markets with human traders and fast ZIP agents (H-FZ) and slow ZIP agents (H-SZ). While these results provide a general overview of our results, we establish

the statistical significance of these results in our analysis of surplus distribution in Table 4 of this section.

The H-FZ treatment achieves a 0.54% higher efficiency than the slow ZIP treatment. In the fast ZIP treatment, fast ZIP agents realize a total surplus of 49.96%, while human traders achieve 48.97%. In the H-SZ treatment, slow ZIPs realize 47.34% of the surplus, while human traders achieve 51.05%.

Therefore, we find that fast ZIPs outperform human traders, confirming previous findings of Das et al. (2001). In contrast, slow ZIPs perform worse than human traders in the slow ZIP treatment, confirming the notion that agent speed is an important factor for the differences in performance. Comparing the buyer and seller surplus for trader groups shows that only fast ZIP sellers perform better than human sellers, while fast ZIP buyers perform worse than human buyers. The better ZIP seller performance comes at the expense of human buyers who perform worse in the fast ZIP treatment compared to the slow ZIP treatment.

**Table 2** Average Trade Prices, Market Surplus and Surplus Distribution of Balanced Competitive Markets by Treatment and Trader Group (H-Human, FZ-Fast ZIP, SZ-Slow ZIP); standard deviations are in parentheses.

Treatment	Average Price	Market Surplus	H Seller Surplus	H Buyer Surplus	ZIP Seller Surplus	ZIP Buyer Surplus
Theory Bench	260	100%	50.24%	49.76%	--	--
Baseline: Pure Human	259 (21.642)	98.95% (0.015)	48.73% (0.103)	50.22% (0.103)	--	--
Balanced H-FZ	254 (19.444)	98.93% (0.014)	24.15% (0.029)	24.82% (0.022)	20.01% (0.069)	29.95% (0.071)
Balanced H-SZ	245 (20.622)	98.39% (0.028)	18.99% (0.061)	32.06% (0.064)	17.89% (0.059)	29.45% (0.055)

**Figure 2** Example Trading Session for Balanced Competitive Treatment with Humans only (HH), mixed treatments with Fast ZIP agents (H-FZ) and Slow ZIP agents (H-SZ)

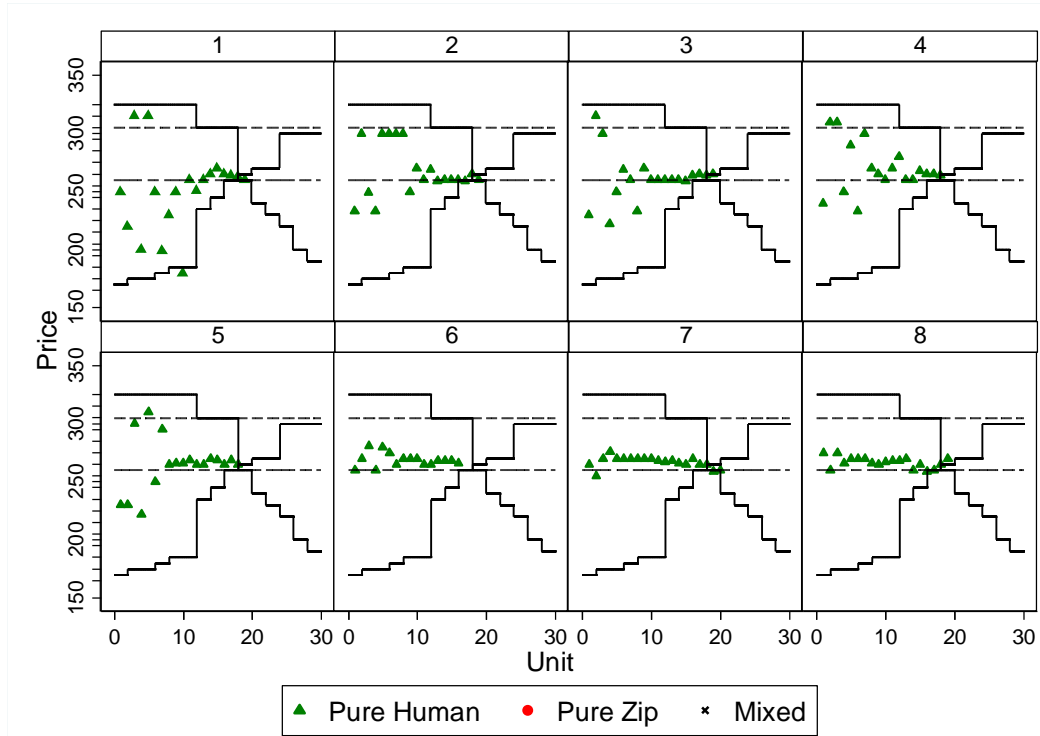


Figure 2A: Example Trading Session for HH Treatment

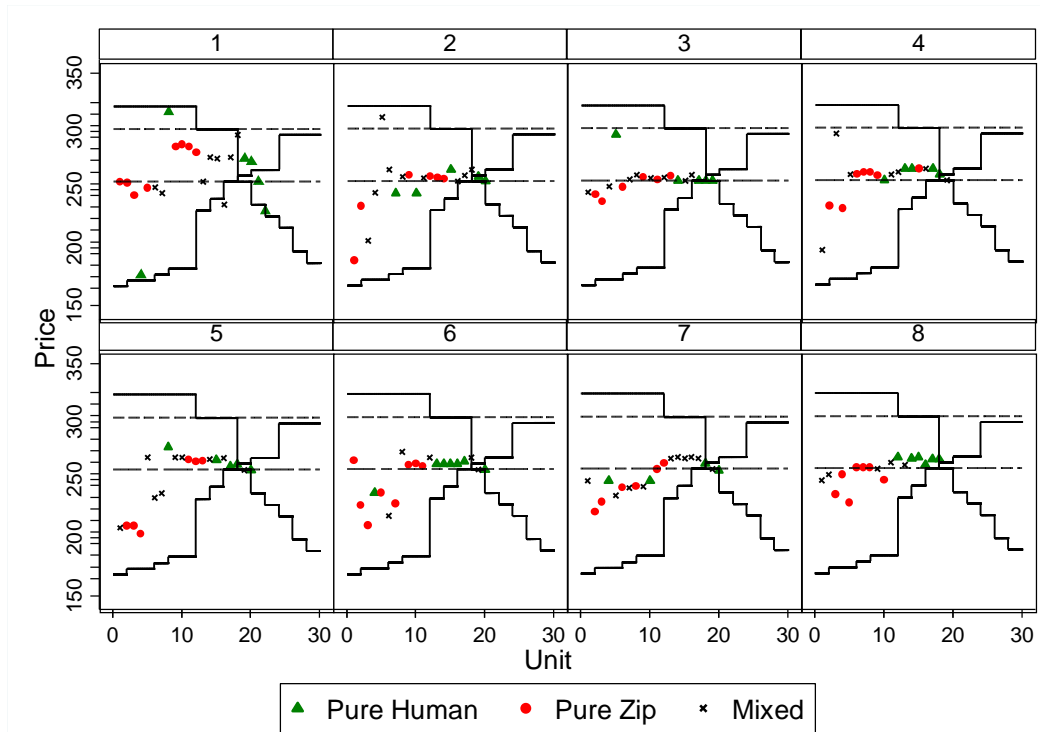


Figure 2B: Example Trading Session for H-FZ Treatment

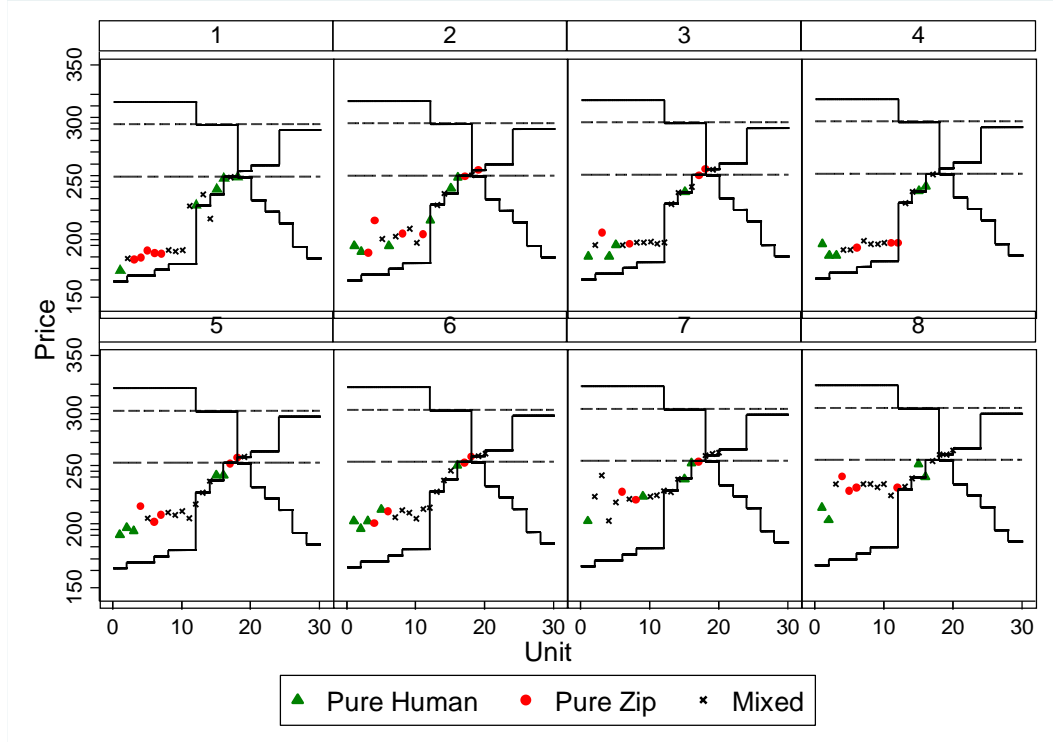


Figure 2C: Example Trading Session for H-SZ Treatment

Figure 2 shows trading prices for three example sessions for each of the balanced competitive treatments. In Figure 2A, the example HH session shows a large variance of trade prices at the beginning of the session, but a strong convergence towards the equilibrium price, implying strong learning effects of human traders. In the H-FZ session in Figure 2B, the majority of trades, particularly at the start of the session, are ZIP-ZIP (Z-Z) trades, implying that fast agents trade with each other first, followed by human-human (H-H) and human and ZIP agent (H-Z) trades. In contrast, the H-SZ session in Figure 2C shows H-H trades at the beginning of each period which results in much lower trade prices compared to the equilibrium price. Furthermore, trades between humans and agents in the H-SZ session are more evenly distributed throughout the trading period compared to the H-FZ session. This result implies that human traders and slow ZIPs trade at a comparable speed, while the clustering of fast Z-Z trades implies that fast ZIPs operate at a faster speed than human traders. This is in line with the “robot phase transition” concept found by



Cartlidge and Cliff (2013) which states that trading robots that act on a super-human timescale tend to trade more with each other rather than with slower human traders. We further study this phenomenon by analyzing the trades between different trader types.

### *Trading Volume*

Table 3 provides detailed statistics on the percentage of trades between different trader types. We generally expect 50% of all trades to be between human and ZIP agents (H-Z) in theory and the remainder split evenly between H-H trades and Z-Z trades, due to the trader population in the market (see e.g., Cartlidge and Cliff (2013)). In the fast agent treatment, the numbers of Z-Z trades and H-Z trades are roughly equal to 35%, while H-H trades represent around 29%. The deviation from expected values shows a bias towards H-H and Z-Z trades in the market, similar to the results of Cartlidge and Cliff (2013). In contrast, the H-Z trades represent 48% of the conducted trades in the slow agent treatment and H-H and Z-Z trades around 26%, thus close to the expected value in theory. This confirms that biases towards Z-Z and H-H trades in the fast agent treatment are mostly due to agent speed.

**Table 3** Statistics of Trading Volume in Balanced Markets and Trade Distribution by Treatment and Trader Types (H-Human, FZ-Fast ZIP, SZ-Slow ZIP)

	Average Volume	Std Dev. Volume	H-H Trades	H-Z Trades	Z-Z Trades
Balanced H-H	18.59	0.750	100%		
Balanced H-FZ	19.59	0.921	28.73%	35.75%	35.52%
Balanced H-SZ	18.70	0.885	25.75%	48.36%	25.89%

### *Determinants of Surplus*

To analyze the determinants of market surplus for different groups of traders, we conduct a regression analysis using individual period level data of surplus in experimental currency units (ECU). The dependent variable is the paired difference between the realized surplus of a human participant ( $\text{Surplus}^H$ ) and his ZIP agent counterpart with the same private values ( $\text{Surplus}^Z$ ). We use three sets of regressors: role (*Buyer* or *Seller*) in *Fast* or *Slow* agent treatment, individual characteristics, measured by the scores achieved in the three tasks (reaction test – *RT*, cognitive reflection test – *CRT*, and eye test – *ET*), and learning effects, measured by the interaction effects of *Period* and role in treatment variables. The dependent variable ( $\text{Surplus}^H - \text{Surplus}^Z$ ) is regressed on treatment and role variables in Model (1), and additionally on individual characteristics in Model (2) and further adding learning effects in Model (3).

The results are presented in Table 4. The coefficients of role-treatment variables show the paired difference in performance between a human trader and his agent counterpart. A human seller realizes 7.8 ECU more surplus than a slow ZIP seller and a human buyer realizes 18.4 ECU more than a small ZIP buyer. We can infer that humans generally outperform slow ZIP agents in the role of both buyer and seller, as the difference in performance is positive for both roles. Compared to fast ZIP agents, human sellers outperform fast ZIP sellers by 29.2 ECU, but perform worse as buyers by -36.1 ECU. These observations confirm the previous results of superior performance of fast ZIP agents to human traders in Table 2 and Das et al. (2001) but also highlight that the difference in performance crucially relies on the role of the traders.

**Table 2** Determinants of Difference in Surplus between Human and Agent Trader Pairs (Surplus<sup>H</sup> – Surplus<sup>Z</sup>) for Balanced Markets

	(1)	(2)	(3)
<i>Treatment Variables</i>			
Fast Buyer	-36.1*** (3.9)	-23.3 (20.0)	-54.8*** (20.3)
Slow Buyer	18.4*** (4.8)	31.7 (20.2)	27.6 (21.6)
Fast Seller	29.2*** (4.0)	41.2** (20.1)	39.7* (20.9)
Slow Seller	7.8*** (2.4)	21.1 (19.2)	13.6 (18.9)
<i>Individual Characteristics</i>			
ET		-1.8*** (0.7)	-1.8*** (0.7)
CRT		0.8 (1.0)	0.8 (1.0)
RT		0.9*** (0.3)	0.9*** (0.3)
<i>Learning Effects</i>			
Fast Buyer*Period			9.0*** (1.6)
Slow Buyer*Period			1.2 (2.4)
Fast Seller*Period			0.4 (1.8)
Slow Seller*Period			2.1** (1.0)
Obs.	768	768	768
R-squared	0.2	0.2	0.2
F-statistic	41.2***	25.7***	21.33***

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1 Robust standard errors are in parentheses.

We find that ZIP speed is beneficial in the buyer role and detrimental in the seller role. We conjecture that on the one hand, early order submissions by fast ZIP sellers might be underpriced and thus get picked off by other traders, whereas slower, more “patient” sellers would not suffer from these losses. On the other hand, fast ZIP buyers are better able to pick off these low-priced orders by “impatient” sellers. This results in a higher surplus for fast ZIP buyers and a negative

difference in surplus between human and fast ZIP surplus. Figure 3 confirms that trade prices often start from a low level, implying underpriced orders from impatient sellers (as is common in these types of experiments) and converge to the competitive price level over time.

The positive significant coefficient of RT score implies that faster reaction time is related to better performance of human traders. However, the negative coefficient for ET score shows a negative effect of ToM on human trader performance. The CRT score does not have a significant influence on the difference in trading performance. We argue that fast reaction is particularly important for buyers to match against low-priced sell orders quickly, similar to the previous discussion on fast ZIP agents. The positive coefficients of learning effects show that human traders improve their performance quickly over time. Particularly the advantage of fast ZIP buyers over human buyers decreases significantly over time, as human buyers adapt quickly to the market conditions and their fast ZIP competitors.

### **3.2. Unbalanced Competitive Markets**

In this section, we report on the differences in results for unbalanced competitive markets where human traders and ZIP agents exclusively occupy the buyer or seller roles. In section 3.3, we further show how non-competitive markets with duopolists and monopolists yield significantly different results from competitive markets.

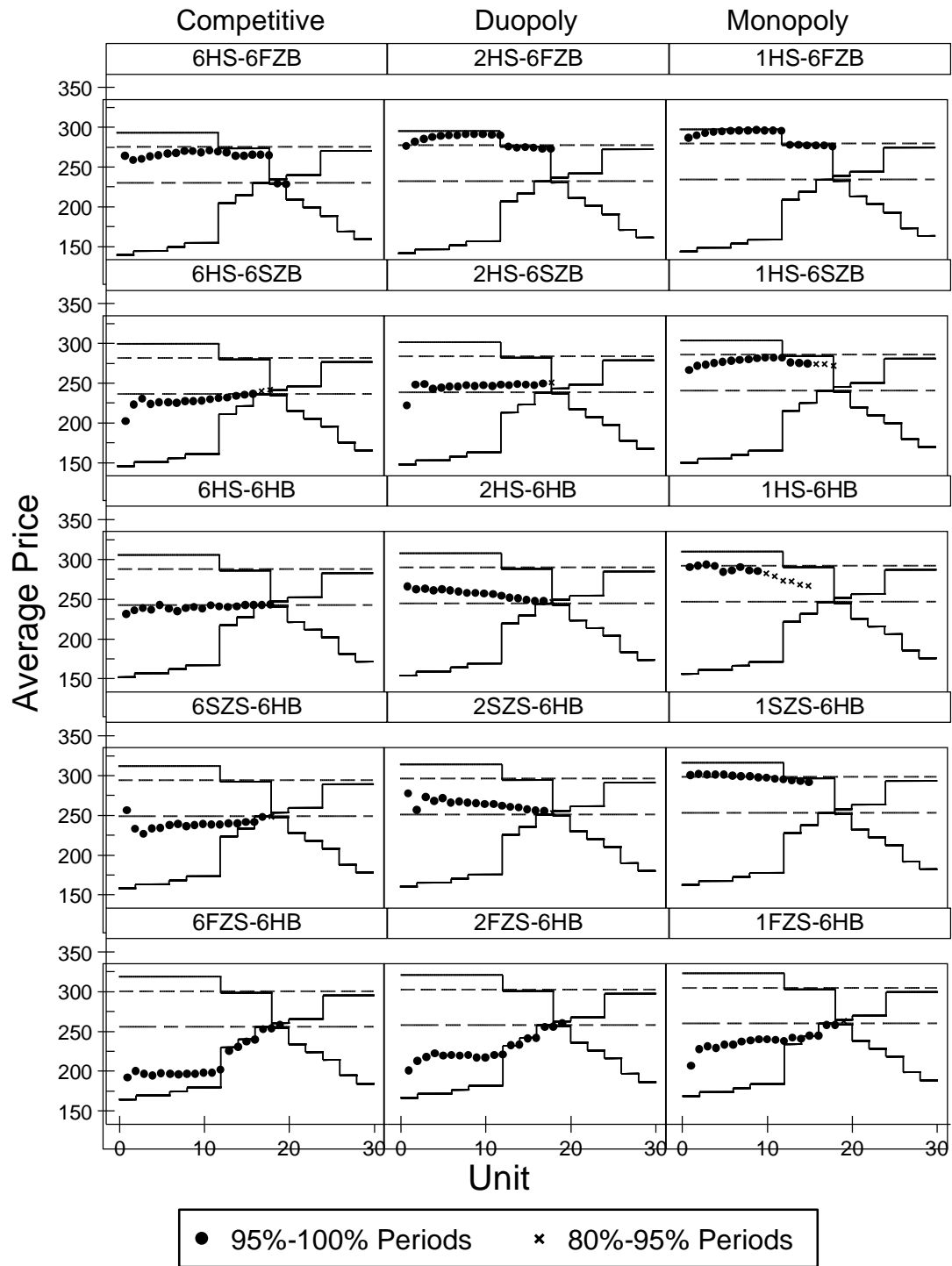
Figure 3 presents the trade price dynamics for unbalanced competitive markets and unbalanced non-competitive duopoly and monopoly structures. Each subfigure time series in the graph represents the graph of the  $n$ th transaction of a period, averaged across all periods. The dots in the graphs represent average prices for the transactions which occur in 95%-100% of all periods,

while the crosses represent average prices for the transactions which occur in 80%-95% of all periods.

The human baseline is the balanced 6HS-6HB treatment in the middle on the left, which shows a strong price convergence towards the competitive equilibrium price. Comparing the human-only treatment to the slow ZIP buyer and slow ZIP seller treatment, the price dynamics are similar to the human-only treatment. Fast ZIPs perform worse than slow ZIPs as both buyers and sellers, as they lose surplus to their human counterparts. Human sellers achieve almost the monopoly equilibrium price, and human buyers achieve close to first-degree price discrimination.

Table 5 shows the average surplus realized in the unbalanced treatments and the distribution of surplus for each trader group. In unbalanced competitive markets, slow ZIP buyers realize a greater surplus (53.36%) than human buyers (50.22%), but slow ZIP sellers realize a lower surplus (43.47%) than human sellers (48.73%). Surprisingly, slow ZIP agents realize higher surplus as duopolist sellers and monopolist sellers than human sellers in the same role. Thus, slow ZIP agents have an advantage due to their slow speed and patience in unbalanced uncompetitive markets. Fast ZIPs perform consistently worse in both buyer and seller roles in these unbalanced markets, realizing 17.47% and 14.31% in surplus as buyers and sellers respectively. We can conclude that the balanced design is indeed vital for achieving the result of superior fast ZIP performance compared to human traders and that unbalanced markets do not yield the same result.

**Figure 3** Average Trade Prices across Periods by Treatment (H-Human, FZ-Fast ZIP, SZ-Slow ZIP; S-Seller, B-Buyer)



**Table 3** Trade Price Statistics and Surplus Distribution in Unbalanced Market Structures (H-Human, FZ-Fast ZIP, SZ-Slow ZIP; S-Seller, B-Buyer)

Market Composition	Average Price	Std Dev. Price	Average Volume	Eff(Total)	Eff(Seller)	Eff(Buyer)
<b>Panel A: Competitive Market Structure</b>						
Theory Bench.	260	--	18	100%	50.24%	49.76%
6HS-6HB	259	21.64	18.59	98.95%	48.73%	50.22%
6HS-6FZB	293	19.11	20.38	96.38%	78.91%	17.47%
6HS-6SZB	255	18.42	18.64	98.45%	45.09%	53.36%
6FZS-6HB	223	30.77	20.02	98.12%	14.31%	83.81%
6SZS-6HB	253	17.47	19.00	98.69%	43.47%	55.21%
<b>Panel B: Duopoly Market Structure</b>						
Theory Bench.	305	--	18	100%	88.63%	11.37%
2HS-6HB	273	19.12	18.19	98.36%	61.22%	37.14%
2HS-6FZB	307	19.93	19.89	96.96%	92.29%	4.67%
2HS-6SZB	269	25.15	18.76	98.60%	57.12%	41.48%
2FZS-6HB	233	25.99	19.67	98.50%	25.02%	73.48%
2SZS-6HB	274	19.28	18.39	99.31%	62.28%	37.03%
<b>Panel C: Monopoly Market Structure</b>						
Theory Bench.	305	--	18	100%	88.63%	11.37%
1HS-6HB	295	25.55	16.50	94.45%	76.21%	18.25%
1HS-6FZB	316	9.99	17.67	98.91%	96.96%	1.95%
1HS-6SZB	298	18.98	17.56	98.74%	81.34%	17.41%
1FZS-6HB	242	19.03	19.22	98.67%	33.30%	65.38%
1SZS-6HB	306	9.17	16.63	96.82%	86.00%	10.81%

## Trading Performance

We further compare the trading performance of human sellers (buyers) trading against human, fast ZIP, and slow ZIP buyers (sellers) in Table 6. Similar to Table 4 in Section 3.1, we regress the aggregate surplus of 6 human traders in a session on treatment variables *SlowZIP* and *FastZIP* (Model 1), on the average test scores within their cohort (*ET*, *CRT*, *RT*) (Model 2), and learning effects (Model 3). The intercept reflects the baseline H-H treatment.

**Table 4** Determinants of Aggregate Human Surplus for Unbalanced Competitive Markets

Dependent Variable	Aggregate Human Surplus					
	6 Sellers			6 Buyers		
Theoretical Benchmark	Seller Surplus: 1060			Buyer Surplus: 1050		
Intercept	1028.1*** (27.1)	172.6 (385.9)	135.8 (351.7)	1059.7*** (27.2)	983.6*** (340.9)	1024.6*** (303.3)
<i>Treatment Variables</i>						
FastZIP	636.8*** (33.4)	683.0*** (42.3)	859.5*** (68.6)	708.7*** (36.4)	705.6*** (32.3)	851.7*** (59.7)
SlowZIP	-76.7* (39.6)	-89.5** (38.4)	-277.6*** (73.6)	105.3*** (34.6)	80.4** (32.9)	49.6 (76.6)
<i>Individual Characteristics</i>						
ET		45.4*** (17.4)	45.4*** (15.5)		-25.9** (12.3)	-25.9** (11.5)
CRT		-1.4 (22.5)	-1.4 (19.6)		-4.9 (19.7)	-4.9 (18.0)
RT		-9.7 (6.7)	-9.7* (5.4)		25.2*** (5.1)	25.2*** (4.8)
<i>Learning Effects</i>						
Period			10.5 (11.3)			-11.7 (10.9)
FastZIP*Period			-50.4*** (13.9)			-41.8*** (13.9)
SlowZIP*Period			53.7*** (14.9)			8.8 (15.1)
Obs.	192	192	192	192	192	192
R-squared	0.7	0.7	0.8	0.7	0.8	0.8
F-statistics	295.3***	131.0***	133.1***	243.2***	121.1***	157.2***

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1 Robust standard errors are in parentheses.



The intercepts in Model 1 for aggregate human sellers and buyers respectively show that in H-H treatments, seller surplus is slightly lower on average than the theoretical benchmark (1028.1 ECU compared to 1060), while buyer surplus is slightly higher. The positive coefficients for *FastZIP* show that the surplus realized by human traders is greater when trading against fast ZIP traders than against other human traders. This again highlights that superior fast ZIP performance found by Das et al. (2001) can only be replicated in balanced market structures, but not in unbalanced markets. The difference in performance between human-only and H-SZ treatments depends largely on the trader role. When trading against slow ZIP agents, human sellers generate less surplus than against other human traders on average, whereas human buyers realize more surplus.

The treatment effects are robust to the inclusion of individual characteristics in the model. The ET score has a significant positive effect on human sellers' surplus, but a negative effect on human buyers' surplus. The RT score has a negative effect on human sellers' surplus, but a positive effect on human buyers' surplus. The CRT does not have significant effects on human buyer or seller surplus. These results confirm again that reaction time is particularly important for buyers to quickly pick off low-priced sell orders. Additionally, a positive ET coefficient shows a significantly positive effect of ToM skills on human seller performance. The learning effects show that the higher surplus achieved against fast ZIP traders decreases over the course of the session. In comparison, human losses to slow ZIPs decrease as well as human traders learn about the equilibrium price and possibly also to be more patient.

### 3.3. Unbalanced Non-competitive Markets

#### *Duopoly*

Table 5 shows that human duopolist sellers are able to achieve approximately first-degree price discrimination when trading with fast ZIP buyers, capturing most of the duopoly surplus. In contrast, when trading against slow ZIP buyers, their surplus is lower than trading against other human traders. In comparison, slow ZIP duopolist sellers obtain higher prices and a greater surplus compared to their human counterparts whereas fast ZIP duopolist sellers are not able to exert their market power such as slow ZIPs and human traders and realize prices well below the competitive equilibrium. Generally, slow ZIP traders capture a higher surplus compared to their human counterparts as both buyers and sellers in unbalanced uncompetitive markets, which can be primarily ascribed to their patience.

To analyze the different determinants of human surplus, the aggregate surplus of human buyers and sellers in a session is regressed on treatment variables (Model 1), average test scores of their buyer/seller cohort (Model 2), and learning effects (Model 3). The results are reported in Table 7.

The treatment effects in Table 7 again show that human traders generally realize more surplus when trading against fast ZIP traders than trading against other human traders, but lower surplus when trading against slow ZIP traders. From the previous sections on individual characteristics, we concluded that reaction time is vital for human buyers to pick off low-priced sell orders, which is also the case in this treatment. There is also a slightly significant positive effect of RT on human duopolist sellers, possibly due to the competition effects between the two sellers which make reaction time more important.

**Table 5** Determinants of Aggregate Human Surplus in Duopoly Markets

Dependent Variable	Aggregate Human Surplus					
	2 Sellers			6 Buyers		
Theoretical Benchmark	Seller Surplus: 1870			Buyer Surplus: 240		
Intercept	1291.8*** (31.2)	1028.8** (400.5)	1228.8*** (387.8)	783.6*** (30.8)	-187.0 (618.3)	-394.9 (472.8)
<i>Treatment Variables</i>						
FastZIP	655.4*** (34.3)	661.9*** (37.7)	485.5*** (62.7)	766.8*** (39.8)	747.1*** (39.2)	1079.8*** (71.2)
SlowZIP	-86.6 (53.4)	-135.9*** (50.4)	-404.8*** (89.4)	-2.3 (45.9)	61.5 (61.5)	17.3 (81.1)
<i>Individual Characteristics</i>						
ET		-5.2 (11.2)	-5.2 (10.1)		2.0 (16.0)	2.0 (11.9)
CRT		-5.3 (15.9)	-5.3 (15.9)		-9.8 (28.3)	-9.8 (23.3)
RT		14.9* (9.0)	14.9* (8.4)		30.6*** (9.8)	30.6*** (8.1)
<i>Learning Effects</i>						
Period			-57.1*** (12.0)			59.4*** (11.5)
FastZIP*Period			50.4*** (13.4)			-95.0*** (15.1)
SlowZIP*Period			76.8*** (21.7)			12.6 (16.1)
Obs.	200	200	200	192	192	192
R-squared	0.6	0.6	0.6	0.7	0.7	0.8
F-statistics	279.0***	126.2***	118.8***	255.1***	117.0***	102.0***

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1 Robust standard errors are in parentheses.

### *Monopoly*

With the increase in market power in the monopoly structure, Figure 3 shows that human monopolist sellers achieve the monopoly equilibrium price for the first traded units on average when trading against human buyers. In comparison, the human monopolist seller achieves lower prices for units traded early when trading against slow ZIP buyers, but he is more successful in negotiating higher trade prices for units traded later. Similar to the duopoly structure, the human

monopolist seller achieves approximately first-order price discrimination when trading against fast ZIPs. Acting as a monopolist, slow ZIPs are surprisingly better able to utilize their market power in achieving higher prices compared to human monopolists. Fast ZIP monopolist sellers perform better than in the duopoly setting, but trade prices are still well below the competitive equilibrium price.

Panel C of Table 5 shows that slow ZIP monopolist sellers achieve a higher surplus (86%) than human monopolist sellers (76.21%), whereas slow ZIP buyers achieve a slightly lower surplus (17.41%) compared to their human counterparts (18.25%). Fast ZIP buyers lose most of their surplus to the human monopolist seller. However, the fast ZIP monopolist seller is able to capture more of the monopolist profit compared to the duopoly setting (33.30% compared to 25.02%), possibly due to the absence of competition in the monopoly structure.

We conclude that patience is key in unbalanced and uncompetitive market structures as slow ZIP monopolist sellers consistently achieve better results than “impatient” human monopolists. Furthermore, “impatient” fast ZIP duopolists and monopolists are trapped into perverse market outcomes due to their speed, leading to poorer performance compared to their human and slow ZIP counterparts.

To analyze the determinants of human trading performance, the aggregate human surplus is regressed on treatment variables, the individual characteristics of the human seller or cohort, respectively, and learning effects.

The results in Table 8 show that human monopolist sellers capture on average more surplus (1608 ECU) when trading against human buyers compared to human duopolists (1291.8 ECU). In contrast to the duopoly structure, human monopolists gain 108.2 ECU more surplus on average when trading against slow ZIPs than against human traders, possibly due to the absence of duopoly

competition. Similar to previous market settings, human traders consistently realize higher profits when trading against fast ZIPs compared to trading against human traders as both buyers and sellers, but surprisingly realize fewer profits when trading against slow ZIPs. This could be again due to the positive effects of patience on trading performance, which leads to higher trade prices and thus a greater surplus of slow ZIP monopolists.

**Table 6** Determinants of Aggregate Human Surplus in Monopoly Treatment

Dependent Variable	Aggregate Human Surplus					
	1 Seller			6 Buyers		
Theoretical Benchmark	Seller Surplus: 1870			Buyer Surplus: 240		
Intercept	1608.0*** (40.7)	1435.3*** (167.4)	1529.7*** (177.4)	385.0*** (44.1)	977.2*** (356.2)	848.9** (338.5)
<i>Treatment Variables</i>						
FastZIP	437.9*** (43.3)	456.0*** (45.1)	328.2*** (75.0)	994.4*** (46.8)	1007.4*** (47.9)	1152.0*** (74.3)
SlowZIP	108.2* (54.9)	148.7*** (51.2)	-30.2 (94.3)	-156.8*** (46.1)	-141.3*** (53.4)	-77.6 (70.4)
<i>Individual Characteristics</i>						
ET		-1.2 (6.5)	-1.2 (6.4)		-20.3* (12.0)	-20.3* (11.7)
CRT		-35.2*** (12.3)	-35.2*** (12.0)		8.9 (30.1)	8.9 (29.3)
RT		12.8*** (3.3)	12.8*** (3.3)		-4.2 (7.8)	-4.2 (7.6)
<i>Learning Effects</i>						
Period			-27.0 (17.3)			36.6** (18.5)
FastZIP*Period			36.5* (18.8)			-41.3** (20.0)
SlowZIP*Period			51.1** (22.7)			-18.2 (19.6)
Obs.	192	192	192	192	192	192
R-squared	0.3	0.4	0.4	0.8	0.8	0.9
F-statistics	75.9***	42.4***	27.3***	1555.3***	613.7***	453.0***

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1 Robust standard errors are in parentheses.

Interestingly, the RT score has a positive influence on human monopolist seller surplus, but no significant effect on human buyers' surplus. The positive RT effect can be explained by Figure 4 which shows that trade prices in the monopoly settings are mostly adjusted downwards (except for the fast ZIP monopolist treatment 1FZS-6HB) over the course of a trading period, in contrast to the upward price adjustment in other market structures. Therefore, monopolists need to act quickly and realize higher trade prices before prices decrease towards the equilibrium price. The insignificant negative RT effect on human buyer surplus can be affected by impatient buyers who are willing to accept higher prices rather than wait for prices to drop towards the end of the period. However, this effect would be counteracted by the high market power exerted by the monopolist which renders the individual reaction time insignificant. Surprisingly, CRT has a negative effect on human monopolist seller surplus, while the ET score again has a negative effect on human buyer surplus. We speculate that similar to the negative effects of the eye test in other market structures, CRT and ET might impair reaction to market events which is the main determinant of market surplus across different treatments and market structures.

### **3.4. Individual Market Assessments**

In this section, we analyze the assessment of the human participants about agent presence in different treatment groups. Table 7 shows the average percentage of correct answers to the question of whether computer agents are present in the market.

Participants are significantly worse at correctly assessing markets with only humans compared to markets with fast or slow robots, for all types of market structures. Due to different reaction times of fast and slow robots, we expect that it is easier for human participants to detect robot presence in fast robot markets. Indeed, the difference between market assessments in fast and slow robot treatments in competitive markets is positive and significant (12%), but the

difference is negative albeit insignificant in uncompetitive treatments. We speculate that the superior performance of slow robots could lead to the assumption by the participants that the counterparty must be a computer agent, leading to a better assessment in the slow ZIP treatment.

**Table 8** Correct Rates of Market Assessment (Q6) by Treatment Group

Panel A: Mean and Binomial Test for correct rate of market assessment				
Treatment Subsamples	All Markets	Competitive	Duopoly	Monopoly
Pure Human	0.43**	0.44	0.45	0.38*
Pure Robots	0.62***	0.61***	0.66***	0.58
FastZIP	0.64***	0.67***	0.66**	0.54
SlowZIP	0.59***	0.55	0.67***	0.63*

Notes: The values in this table are the correct rate of Q6 in corresponding subsample. The stars indicate the significance of the binomial two-tailed test. (P0=0.5)

Panel B: Wilcoxon Test for correct rate of market assessment				
Z-value (p-value)	All Markets	Competitive	Duopoly	Monopoly
Human vs Robots	-0.19*** (0.00)	-0.17*** (0.00)	-0.21*** (0.01)	-0.21** (0.01)
Fast vs. Slow	0.04 (0.32)	0.12** (0.04)	-0.01 (0.90)	-0.09 (0.34)
Human vs Fast	-0.21*** (0.00)	-0.23*** (0.00)	-0.20** (0.02)	-0.16* (0.09)
Human vs. Slow	-0.17*** (0.00)	-0.11* (0.09)	-0.21** (0.02)	-0.25*** (0.01)

Notes: The p-value is result of two-tailed Wilcoxon test.

The analysis of the influence of individual characteristics on correct market assessment in Table 10 suggests that CRT has a positive influence on the correct response rates. Surprisingly, the ET score does not have any meaningful effect on market assessment. These results imply that cognitive reflection abilities, or the avoidance of behavioral biases, can help with detecting robot activity in markets, but that ToM does not have an effect on this task. We argue that cognitive reflection is indeed necessary to avoid any biases (similar to findings of Corgnet et al. (2018)), such as algorithm aversion (see Farjam and Kirchkamp (2018) and Angerer et al. (2019)), which might lead human participants to wrongly blame robots for bad trading performance or trading difficulties.

**Table 9** Determinants of Correct Market Assessment

	(1) Whole Sample	(2) Pure Human Subsample	(3) Robot Subsample	(4) Robot Subsample
Intercept	-0.74 (0.82)	2.06 (1.40)	-1.18 (1.04)	-0.81 (1.02)
ET	0.01 (0.03)	0.01 (0.05)	0.00 (0.03)	0.00 (0.03)
CRT	0.09* (0.05)	-0.12 (0.10)	0.16*** (0.06)	0.16*** (0.06)
RT	-0.01 (0.01)	-0.07*** (0.02)	0.02 (0.02)	0.02 (0.02)
Fast ZIP				-0.37 (0.45)
Obs.	745	216	529	529
Pseudo R2	0.0358	0.0402	0.0319	0.0319
Wald chi2	34.11**	11.30**	22.47	22.47
Correctly classified	61.61%	61.57%	62.57%	62.57%



#### **4. Discussion and Concluding Remarks**

In this work, we conducted laboratory experiments to demonstrate potential pitfalls of high speed for trading performance. While previous research has focused on the benefits of speed, we challenge the notion that speed is always good for trader performance and present alternative market structures in which speed can be disadvantageous. In particular, we show that speed can be detrimental to trading performance in unbalanced and uncompetitive market conditions.

Previous research focuses on the benefits of speed for individual trading performance (e.g. Das et al., 2001). We confirm previous results and show that fast ZIP buyers outperform human buyers in balanced CDA markets with the same number of human and ZIP buyers and sellers. For unbalanced markets with only human traders on one side of the market, fast ZIPs perform comparably worse than their human counterparts and slow ZIPs. In more extreme market conditions, such as duopoly and monopoly, human and slow ZIP monopolist sellers are better able to exert their market power than fast ZIP sellers. In fact, slow ZIP duopolists and monopolists capture even more surplus than human duopolists and monopolists, due to their slower reaction time and thus greater patience. In the buyer role, fast ZIPs lose more of their surplus to human duopolists or monopolists compared to their human and slow ZIP counterparts. Our result is in line with the arguments of Gjerstad (2007) who argues that the “relative performance of sellers and buyers is significantly affected by a difference between the pace of asks and the pace of bids, with an advantage to the more patient side of the market” (Gjerstad, 2007, p.1756).

We further find that reaction time is vital particularly for human buyers to pick off underpriced sell orders of impatient sellers, while ToM skills can help sellers in unbalanced markets to understand and maintain their market power. Finally, we find that assessment of algorithmic activity in markets is mainly influenced by cognitive reflection abilities which help

avoid behavioral biases of erroneously detecting algorithmic activity on markets where there is none. Our results are novel and provide important insight into the role of speed in different market conditions.

In a high-frequency world where speed is crucial for trading performance and co-location services and optic fiber connections are commonly used to shave microseconds off latency, this result is particularly relevant. Our study highlights the risks of speed and presents example market conditions where speed can trap traders into perverse market outcomes. During extreme market conditions such as the Flash Crash on May 6, 2010, high-speed algo traders can be especially vulnerable as they might be incapable to adapt to non-standard market conditions. These considerations also highlight the importance of appropriate risk management for AT systems.

Our future work will explore the role of speed in more opaque markets. Other important avenues for possible future research include the analysis of different types of trading agents, such as trading agents which can be employed by human traders to execute orders (cf. Asparouhova et al., 2019), and the influence of different behavioral biases (such as algorithm aversion) on trading behavior and learning effects.

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## **Appendix A: Instructions (Translated)**

Welcome to this experiment! Before the experiment starts, please read the experimental instructions carefully. If you follow the experimental instructions and make the right decisions, you will receive additional income. The extra income is determined by your decisions and that of other experimental participants. Before you make a decision, you will read the experimental instructions to help you understand how to make decisions and how your income is determined.

Please remain quiet during the experiment. Please do not talk to other participants or exchange information in other ways during the experiment. Please do not use communication tools such as mobile phones. If you have any questions or need any help, please give the experimenter a hand signal. Otherwise, if we find someone whispering or making loud noises, and using communication tools such as cell phones during the experiment, we will ask you to leave the lab without paying any compensation.

### **Experimental Structure**

There are a total of 8 trading periods in today's experiment. There is a short break between each trading period, so trading is not continuous. The current trading period and the remaining time of the phase will be displayed directly above the screen (→①).

In the experiment, each transaction period is divided into three phases: the "Preview phase" at the beginning of each period and the "Trading Phase", and "Review phase". During the "Preview phase", you can check the "Unit Value" of each unit of product.

There are other human buyers and sellers in each market, as well as computer trading agents which assume the role of buyer or seller. Each experimental participant has a fixed role in the market as either a buyer or a seller. You can find your assigned role in the status bar (→①).

You will anonymously trade with other experimental participants (including buyers and sellers). The identities of you and other experimental participants will never be disclosed. All the other buyers are reading exactly the same experimental instructions.

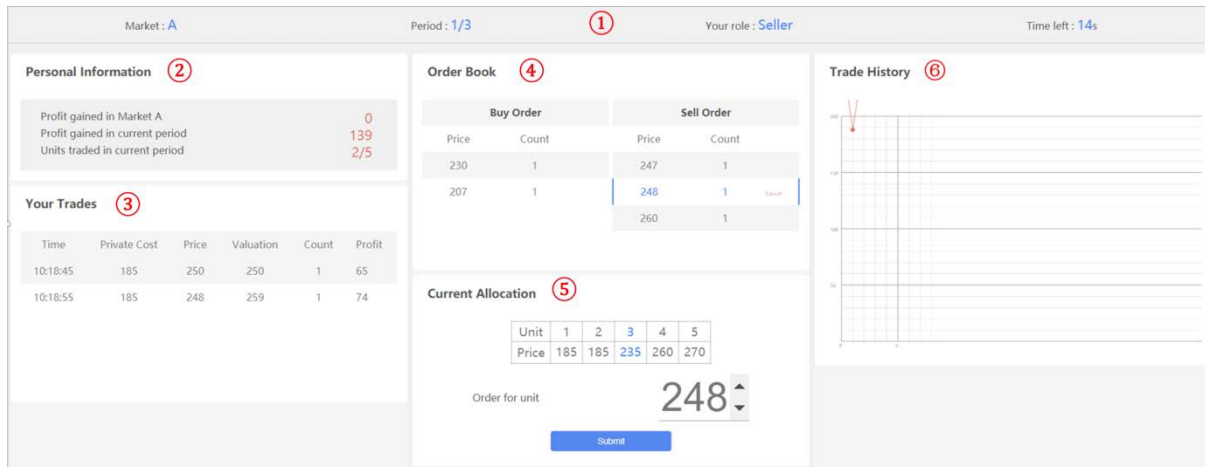


Figure A1: User Interface

In the section “**Personal Information**” (→②), you can find your profits earned in the current market scenario, in the current period and the number of units traded in the current period.

### **Your Payoff**

Your final income is determined by the total revenue you earn in the experiment. The conversion rate from ECU to Chinese Yuan is:

- For all buyers: 1 CNY=35 ECU;
- For sellers in competitive markets: 1 CNY=35 ECU;
- For sellers in duopoly markets: 1 CNY=105 ECU;
- For sellers in monopoly markets: 1 CNY=210 ECU.

[The exchange rate is private information and it will only be displayed on one's own screen.]

Your extra income earned in the experiment plus a participation fee of 10 yuan is the total income of your experiment. At the end of today's experiment, everyone will be paid individually in cash.

In the section “**Your Trades**” (→③), you can find information on the individual “Costs”/“Values” of your traded units, the transaction “Price” that you achieved for each unit and the realized “Profit”.

### **Buyer payoff:**

The buyer's bid (Bid) is the price he/she is willing to pay for buying a certain product. In each stage of the trading phase, you can enter your bid in the blank box to the right of the label “**Order Per unit**” (→⑤).

As a buyer, you can bid for the good during each period. A bid represents the price a buyer is willing to pay for the good. In a transaction, only the highest bid is taken into account. In order to achieve the **highest bid**, your bid price has to **exceed the currently highest bid price** in the market. In case of a transaction, you realize a **profit** of the difference of your private valuation and the transaction price.

$$\text{Unit Profit} = \text{Unit Value} - \text{Unit Price}$$

Example: Your private value of unit #2 is 60 ECU and you buy it at a price of 45 ECU, therefore you realize a profit of 15 ECU:  $60 \text{ ECU} - 45 \text{ ECU} = 15 \text{ ECU}$ .

### **Seller Payoff:**

The seller's ask (Ask) is the price he/she is willing to sell a certain product. In each stage of the trading phase, you can enter your ask in the blank box to the right of the label “**Order Per unit**” (→⑤).

As a seller, you can make offers for the good during each period. An offer represents the price a seller is willing to sell the good. In a transaction, only the lowest offer is taken into account. In order to achieve the **lowest offer**, your offer price has to be lower than the **currently lowest offer price** in the market. In case of a transaction, you realize a **profit** of the difference of the transaction price and your private costs.

$$\text{Unit Profit} = \text{Unit Price} - \text{Unit Value}$$

Example: Your private cost of unit #2 are 75 ECU and you sell at a price of 75 ECU, therefore you realize a profit of 0 ECU:  $75 \text{ ECU} - 75 \text{ ECU} = 0 \text{ ECU}$ .

### **Total Payoff**

After the end of each trading period, your "Total Profit" equals the sum of the unit profits you have realized from purchasing each item.

**Cumulative Total Profit = Sum of the Total Profit realized for each trading period.**

Example: There are 3 phases in the experiment, the total income in period 1 is 100, the total income in period 2 is 120, and the total income in period 3 is 80, then the total cumulative profit =  $100 + 120 + 80 = 300$ .

### **Matching bids and offers**

You can find your active orders in the section “**Order Book**” (→④), where your order will be highlighted in blue and appear with the orders of other participants. Orders are ordered by their prices and submission time. You can cancel your order by clicking on “Cancel” next to your order. Newly submitted bid prices must be strictly greater than the highest bid in the current buyer's bid list. Newly submitted ask prices must be strictly less than the lowest ask in the current seller's ask list.

**A trade is executed, if**

- a) a buyer submits a **bid higher than or equal to the currently lowest offer**
- b) a seller submits an **offer being lower than or equal to the currently lowest bid**.

When they can agree on a price, a transaction takes place. In case of a transaction, the transaction price is executed at the order price already placed in the market, **not** at the newly made order

*Example: You are a buyer. There is an existing sell order with ask price for 40 ECU.*

- *You enter an offer for 30 ECU → No trade takes place*
- *You enter an offer for 40 ECU → A trade is executed. You gain 40 ECU for the unit bought.*
- *You enter an offer for 50 ECU → A trade is executed. You gain 40 ECU for your unit bought.*

In the lower part of the screen, there is a chart labeled “**Trade History**” (→⑥), which shows the prices of all the units that were traded during the current period. On the horizontal axis is the number of units (Quantity), on the vertical axis is the transaction price (Price).



## Appendix B: ZIP Agent Description (Cliff and Bruten, 1997)

### 1. Notation

- $i$ : buyer or seller agent  $i$
- $j$ : the unit the agent buyer (seller)  $i$  is attempting to buy(sell).  $j=1,2,3,\dots,N$
- $k$ : number of sleep cycles of agent  $i$  followed by order submissions or updates upon waking of agent  $i$
- $s$ : sequence number for accepted market actions (transactions and accepted limit prices)
- $t$ : market time  $t$
- $t_i^k$ : the real time when trader  $i$  submits its order value  $p_{i,j}$  to the market
- $\Delta t_i^k = \text{fixed time interval} \times (1 + \alpha_i^k)$  for  $\forall i, k$ , where the fixed time interval for fast ZIP is 1 second, and for slow ZIP is 5 seconds.  $\alpha_i^k$  is drawn at random from a uniform distribution over the interval  $[-0.25, 0.25]$  for  $\forall i, k$ .
- $p_{i,j}(t)$ : The current limit price of trader  $i$  for unit  $j$ .
- $q_s(t)$ : last limit price accepted by the market
- $\mu_i(t)$ : latent surplus demand of agent  $i$
- $\lambda_{i,j}(t)$ : agent  $i$ 's value or cost of unit  $j$

### 2. Overview

At a given time  $t$ , a ZIP agent  $i$  calculates the shout-price  $p_i(t)$  for unit  $i$  with value/cost  $\lambda_{i,j}$  using the latent surplus demand  $\mu_i(t)$  according to the equation

$$p_{i,j}(t) = \lambda_{i,j}(1 + \mu_i(t))$$

At market opening  $t = 0$ ,  $\mu_i(0)$  is drawn randomly a uniform distribution over the interval  $[0.05, 0.35]$  for sellers and  $[-0.35, -0.05]$  for buyers. Every agent  $i$  will calculate an initial latent order  $p_{i,1}(t)$  and its 1<sup>st</sup> sleep time  $\Delta t_i^1$  which determines the time  $t_i^1$  when it should submit its first order of  $p_{i,1}$  to the market.

A market action triggers a response from agent  $i$ . We distinguish between 4 types of market actions. Depending on the relationship between its current latent order price  $p_{i,j}(t)$  and last shout-price  $q(t)$ , the ZIP agents will take action depending on their role and latent order price.

*Market action 1: A new limit buy order ( $q_s(t)$  = new BID price) is added to the order book.*

1. Agent buyer  $i$ 's latent order  $p_{i,j}(t) \geq q_s(t)$ : Agent  $i$  does not respond to market action.
2. Agent buyer  $i$ 's latent order  $p_{i,j}(t) \leq q_s(t)$ : Agent  $i$  should lower its profit margin, i.e. increase its latent order price.
3. Agent sellers do not respond to market action

*Market action 2: A new limit sell order ( $q_s(t)$  = new ASK price) is added to the order book.*

1. Agent seller  $i$ 's latent order  $p_{i,j}(t) \geq q_s(t)$ : Agent  $i$  should lower its profit margin, i.e. decrease its latent order price.
2. Agent seller  $i$ 's latent order  $p_{i,j}(t) < q_s(t)$ : Agent  $i$  does not respond to market action.
3. Agent buyers do not respond to market action

*Market action 3: A new buy order triggers a transaction with a latent sell order at price  $q_s(t)$*

1. Agent buyer  $i$ 's latent order  $p_{i,j}(t) \geq q_s(t)$ : Agent  $i$  should raise its profit margin, i.e. decrease its latent order price.
2. Agent buyer  $i$ 's latent order  $p_{i,j}(t) < q_s(t)$ : Agent  $i$  does not respond to market action.
3. Agent seller  $i$ 's latent order  $p_{i,j}(t) \leq q_s(t)$ : Agent  $i$  should increase its profit margin, i.e. increase its latent order price.
4. Agent seller  $i$ 's latent order  $p_{i,j}(t) > q_s(t)$ : Agent  $i$  should lower its profit margin, i.e. decrease its latent order price.

*Market action 4: A new sell order triggers a transaction with a latent buy order at price  $q_s(t)$*

1. Agent buyer  $i$ 's latent order  $p_{i,j}(t) \geq q_s(t)$ : Agent  $i$  should raise its profit margin, i.e. decrease its latent order price.
2. Agent buyer  $i$ 's latent order  $p_{i,j}(t) < q_s(t)$ : Agent  $i$  should lower its profit margin, i.e. increase its latent order price.
3. Agent seller  $i$ 's latent order  $p_{i,j}(t) \leq q_s(t)$ : Agent  $i$  should raise its profit margin, i.e. increase its latent order price.
4. Agent seller  $i$ 's latent order  $p_{i,j}(t) > q_s(t)$ : Agent  $i$  does not respond to market action.

*NOTE:* Fast ZIP agents will respond to all the 4 kinds of market actions  $q_s(t)$ , while slow ZIP agents will only respond to Market action 3 & Market action 4.

### 3. Different agent actions are reflected through different formulas

For every ZIP agent, there are 3 types of actions: don't respond (the agent's latent order  $p_{i,j}$  will remain the same.), increase its latent order and decrease its latent order. The update rule of increasing or decreasing a latent order is described below.

(we suppress subscript t below for the sake of readability and use the sequence variables k and s)

The target price is set based on a relative price change and an absolute price change

$$(1) \tau_i^k = R_i^k * q_s + A_i^k$$

$\tau_i^k$ : target price determined by  $R_i^k$ ,  $A_i^k$  and price  $q_s$

$R_i^k$ : randomly generated *relative* price change, uniformly distributed over [1.0, 1.05] for price increases, and [0.95, 1.0] for price decreases

$A_i^k$ : randomly generated *absolute* price change, uniformly distributed over [0.0, 0.05] for price increases and [-0.05, 0.0] for price decreases

Based on the new target price, the change in price is calculated using the Widrow-Hoff rule and the learning characteristic of the individual agent.

$$(2) \Delta_i^k = \beta_i (\tau_i^k - p_{i,j})$$

$\Delta_i^k$ : Widrow-Hoff delta rule based on target price  $\tau_i^k$  and latent order  $p_{i,j}$

$\beta_i$ : learning characteristic of agent i. For every agent i in a period,  $\beta_i$  is randomly generated from the uniform distribution [0.1, 0.5] at the beginning of this period and remains fixed for the whole period.

The learning system requires a dampening factor  $(1 - \gamma_i)$  to prevent price oscillations:

$$(3) \Gamma_i^k = \gamma_i * \Gamma_i^{k-1} + (1 - \gamma_i) * \Delta_i^k, \text{ where } \Gamma_i^0 = 0$$

$\Gamma_i^k$ : new price change based on Widrow-Hoff delta and previous price change  $\Gamma_i^{k-1}$

$\gamma_i$ : momentum coefficient. For every agent i,  $\gamma_i$  is randomly generated from the uniform distribution over [0, 0.1] at the beginning of this period and remains fixed for the whole period.

$$(4) \mu_i^{k+1} = \frac{p_{i,j}^k + \Gamma_i^k}{\lambda_{i,j}^k} - 1$$

$\mu_i^{k+1}$ : new latent surplus demand of trader i based on previous latent order  $p_{i,j}^k$ , new price change  $\Gamma_i^k$ , and private value/cost  $\lambda_{i,j}^k$

$$(5) p_{i,j}^{k+1} = \lambda_{i,j}^{k+1} (1 + \mu_i^{k+1})$$

$p_{i,j}^{k+1}$ : new latent order price

Notes: When an agent modify its latent order at time t, its latent order and its current item may have a sudden gap over the time. So we use  $t^+$  to represent the tiny change in time t.

## Appendix C: Pre- and Post-experiment Survey

### C.1 Eye Gaze Test

We administered the eye gaze test in order to measure ToM skills, developed by Baron-Cohen et al. (1997) and applied by Bruguier et al. (2010) and Corgnet et al. (2018) among others. 36 photographs of eye gazes are shown and subjects are asked to pick the mental state from a list of four adjectives that best describe the mental state of the person.

Adult Eyes Instructions: For each set of eyes, choose which word best describes what the person in the picture is thinking or feeling. You may feel that more than one word is applicable but please choose just one word, the word which you consider to be most suitable. Before making your choice, make sure that you have read all 4 words. If you really don't know what a word means you can look it up in the definition handout.

**Figure C1:** Practice eye test question

jealous

panicked



arrogant

hateful

## C.2 Extended CRT

We administered the extended (seven-question) version of the CRT, which includes the original three questions (Frederick (2005)) and four additional questions developed by Toplak, West, and Stanovich (2014).

1. A bat and a ball cost \$1.10 in total. The bat costs a dollar more than the ball. How much does the ball cost? \_\_\_\_ cents [Correct answer: 5 cents; intuitive answer: 10 cents]
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? \_\_\_\_ minutes [Correct answer: 5 minutes; intuitive answer: 100 minutes]
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? \_\_\_\_ days [Correct answer: 47 days; intuitive answer: 24 days]
4. If John can drink one barrel of water in 6 days, and Mary can drink one barrel of water in 12 days, how long would it take them to drink one barrel of water together? \_\_\_\_ days [Correct answer: 4 days; intuitive answer: 9]
5. Jerry received both the 15th highest and the 15th lowest mark in the class. How many students are in the class? \_\_\_\_\_ students [Correct answer: 29 students; intuitive answer: 30]
6. A man buys a pig for \$60, sells it for \$70, buys it back for \$80, and sells it finally for \$90. How much has he made? \_\_\_\_ dollars [Correct answer: \$20; intuitive answer: \$10]
7. Simon decided to invest \$8,000 in the stock market one day early in 2008. Six months after he invested, on July 17, the stocks he had purchased were down 50%. Fortunately for Simon, from July 17 to October 17, the stocks he had purchased went up 75%. At this point, Simon has: a. broken even in the stock market, b. is ahead of where he began, c. has lost money [Correct answer: c; intuitive answer: b]

### **C.3 General Survey**

1. How old are you? \_\_\_\_\_ years
2. Are you \_\_\_\_\_ [male/female]
3. Are you enrolled in an economics-related study programme? [yes/no]
4. Have you ever participated in a double auction experiment (in a laboratory or classroom)?  
[yes/no]
5. How would you rate your knowledge about double auctions? [expert/basic knowledge/none]

### **C.4 Market Assessment Survey**

1. Do you think that computer traders were active in the market? [yes/no]

If you answer yes, then go to 2, otherwise go to 3.

2.

- a. If yes, How many buyers and sellers do you think were participating in the market?

\_\_\_\_\_ buyers, \_\_\_\_\_ of which were computer traders

\_\_\_\_\_ sellers, \_\_\_\_\_ of which were computer traders

- b. how would you describe the computer traders' strategies? [max 350 characters]

3.

- a. If no, How many buyers and sellers do you think were active?

\_\_\_\_\_ buyers

\_\_\_\_\_ sellers

- b. How would you describe the other traders' strategies? [max 350 characters]