

TOO FAST TOO FURIOUS

Faster Financial-Market Trading Agents Can Give Less Efficient Markets

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Abstract: For many of the world's major financial markets, the proportion of market activity that is due to the actions of "automated trading" software agents is rising: in Europe and the USA, major exchanges are reporting that 30%–75% of all transactions currently involve automated traders. This is a major application area for artificial intelligence and autonomous agents, yet there have been very few controlled laboratory experiments studying the interactions between human and software-agent traders. In this paper we report on results from new human-agent experiments using the *OpEx* experimental economics system first introduced at ICAART-2011. Experiments explore the extent to which the performance of the traders, and of the market overall, is dependent on the speed at which the agents operate. Surprisingly, we found that slowing down the agents increased the markets overall ability to settle to a competitive equilibrium, and that slow-agent markets were more efficient.

1 INTRODUCTION

For many of the world's major financial markets, in the past quarter of a century or less, the traditional scene of a central exchange's "trading floor" populated by large numbers of human traders interacting with each other to buy and sell blocks of financial instruments has been replaced by electronic markets. Traders still interact with each other to discover counterparties and agree a price for a transaction, but they do so via trader-interface client computers that attach to the exchange's server, which may be many kilometres away. For many of the world's major exchanges, there is now no physical trading floor; instead everything happens via electronic interaction.

As this shift has taken place, so it has enabled software agents with various degrees of artificial intelligence (AI) to replace human traders. The proportion of market activity that is due to the actions of "automated trading" software agents is rising: in Europe and the USA, major exchanges are reporting that 30%–75% of all transactions currently involve automated traders (Foresight Project, 2011). Many investment banks, hedge funds, and money-management firms are now so dependent on technology involving sophisticated and computationally intensive analysis of financial data combined with high-speed au-

tomated trading systems, that these financial-sector businesses have in reality become technology companies. AI techniques are used to analyse large financial data-sets of both numeric and non-numeric information, to generate trading signals that are fed to autonomous software-agent "algorithmic trading" or "automated execution" systems which perform roles that ten years ago would have been the responsibility of a human trader.

As algorithmic trading has become common over the past decade, automated trading systems have been developed with truly super-human performance, assimilating and processing huge quantities of data, making trading decisions, and executing them, on sub-second timescales. This has enabled what is known as *high-frequency trading*, where algorithmic trading systems will take positions in the market (e.g., by buying a block of shares) for perhaps one or two seconds or less, before reversing the position (e.g., selling the block of shares); each such transaction generates only a few cents worth of profit, but by doing this constantly and repeatedly throughout the day, steady streams of significant profit can be generated. For accounts of recent technology developments in the financial markets, see: Angel, Harris, and Spratt (2010), Gomber, Arndt, Lutat, and Uhle (2011), Lein-

weber (2009), Perez (2011).

Clearly, the current financial markets are a major application area for research in AI and autonomous agents, and the present-day markets are populated by a mix of human and software-agent traders. Given the huge economic significance of the financial markets in most advanced economies, it seems reasonable to expect that there would be a well-established body of research that studies the interaction of human traders with autonomous software-agent trading systems. Surprisingly, this is not the case: in fact, the number of scientific studies of human-agent interactions in electronic marketplaces is staggeringly small. The entire research literature includes only six papers: we discuss each in Section 2.

The main contribution of this paper is our demonstration of new results from controlled laboratory studies of human and software-agent traders interacting in electronic marketplaces. Our new results indicate something that is perhaps counterintuitive: when automated trader-agents are slowed down to operate on human time-scales, the efficiency of the overall market dynamics *increases*. We demonstrate this by detailed reporting and analysis of results from new human-agent experiments using the *OpEx* experimental economics system that was first introduced by De Luca and Cliff (2011a). We explore the extent to which the performance of traders, and of the market overall, is dependent on the speed at which the agents operate: we ran one set of experiments where the “reaction time” of agents was faster than human traders can realistically be expected to operate at, and another set where agents were slowed to operate at human-like timescales. Perhaps counter-intuitively, we found that slowing down the agents increased the market’s overall ability to settle to a competitive equilibrium, and that slow-agent markets were more efficient. We describe our methods in Section 3, present results in Section 4, and discuss those results in Section 5.

2 BACKGROUND

2.1 Economics, Experiments, & Agents

In the academic economics literature, the mechanism within which buyers and sellers interact on almost all of today’s electronic financial markets is known as the *continuous double auction* (CDA). In this mechanism, buyers are free to announce (or “quote”) bid-prices at any time, and sellers are free to quote offer-prices (also commonly referred to as “asks”) at any time. Also, at any time, any seller is free to accept (or “hit”) any buyer’s bid, and any buyer is free to

hit any seller’s offer. When Trader A hits Trader B’s quote, whatever price B quoted is the agreed price of the transaction. There may be a clock running, indicating for how much longer the market will remain open, but there is no central auctioneer or coordinator: the exchange’s central server exists to receive bids and offers, to display a summary (commonly known as the order-book) of the current outstanding quotes to all market participants, and to remove orders when they are hit, passing the details of the transaction to appropriate clearing and settlement systems.

The order book will typically show quote data in two columns or lists: one for bids, the other for asks. Both lists will be ordered best-to-worst, so bid prices will appear in descending numerical order (highest-first) and ask-prices will appear in ascending numerical order (lowest-first). Very often, next to each price will be an indication of the quantity available at that price. In liquid markets, the number of orders and price-points in the order book may be very large, and the order-book displayed on a trader’s screen may only show the best ten or twenty prices.

The CDA is the auction mechanism that underlies most of the world’s financial markets: the many electronic markets and the few remaining ones that use a physical trading floor. Every hour of every working day, trillions of dollars-worth of orders flow through CDA markets. Understanding the dynamics of such markets, how they behave under varying circumstances, is an endeavour that can be pursued by observation of real-world market activity, or by controlled experimentation in laboratory settings with traders interacting in artificial markets. This second approach is known as *experimental economics*, a field established in a seminal sequence of papers published by Vernon Smith in the early 1960’s, a contribution for which he was awarded the Nobel Prize in Economics in 2002 (for further details, see Smith, 2006).

In his landmark first paper, Smith (1962) reported on experiments in which he took a number of human subjects and randomly assigned them to be traders, either buyers or sellers. Each buyer was given a quantity of money and a private (known only to that seller) *limit price*, the maximum they should pay for a unit of the “stock” being traded in the market. Each seller was given one or more units of stock to sell (all sellers’ units of stock were each identical and carried no real-world value) along with a private limit price, the price below which they should not sell that unit of stock. The experimental CDA market then opened for a “trading-day” and the traders were allowed to quote bids and offers and to hit each other’s quotes. If a buyer had used up all her money, or a seller had sold all her units, she dropped out of the market for

the rest of that day. This continued until either no traders were able or interested in trading, or a time-limit expired for that “day”. In reality, each “day” lasted five or ten minutes. At the end of each “day”, any unused assignments of money or units of stock were returned to the experimenters. Subjects were rewarded in proportion to how much “profit” or “utility” they had generated, calculated as the differences between transaction prices and their private limit prices. So, for example, if a buyer with a limit price of \$2.00 hit the order of a seller who had quoted \$1.80, where the seller’s limit price was \$1.50, the buyer’s utility would be \$0.20 and the seller’s would be \$0.30.

Smith’s experiments typically ran for several (five to ten) trading “days”, with fresh assignments of stock and money being made at the start of each “day”. The set of buyers’ limit prices defined a market demand schedule (conventionally plotted as a *demand curve* on a graph illustrating the relationship between quantity and price) and the sellers’ limit prices defined a market supply schedule (commonly plotted as a *supply curve*). As any student of elementary economics is aware, the point at which the supply and demand curve intersect, where the quantity demanded equals the quantity supplied, defines the market’s *equilibrium price* which we denote by P_0 and its equilibrium quantity which we denote Q_0 . If transactions take place at P_0 then the allocation of resources from sellers to buyers can be optimal, for a particular definition of optimality. One of the very attractive features of the CDA that Smith’s experiments helped to illuminate is that it can reliably, rapidly, and robustly “discover” the underlying equilibrium price, with transaction prices converging on P_0 even with only small numbers of traders, and where each trader is acting only out of self-interest and without any trader disclosing their private limit-prices.

Smith measured the equilibration (equilibrium-finding) behaviour of his experimental CDA markets using a metric that he referred to as α , the root mean square difference between each transaction price, p_i , over some period, and the P_0 value for that period, expressed as a percentage of the equilibrium price:

$$\alpha = \frac{1}{P_0} \sqrt{\frac{1}{n} \sum_{i=1}^n (p_i - P_0)^2} \quad (1)$$

As we discuss at length in De Luca, Szostek, Cartlidge, and Cliff (2011), this design—the one that Smith (1962) chose for his first set of experiments—has proven to be extremely influential and its influence has been very long-lasting. Experimental economics became a well-established field, with many researchers around the world exploring various types of market mechanism under various types of circum-

stances. Initially, all work in experimental economics involved human subjects, but as the computing power fell in cost so some academic economists (such as Arthur, 1993) suggested that computer programs, autonomous software agents, could be written to simulate the human subjects and could operate as substitutes for those humans, thereby allowing for large numbers of experiments to be conducted without the time and monetary costs of running experiments with rooms full of humans. At much the same time, the notion of working on software agents, for a wide variety of purposes, was gaining popularity in the AI research community, and a sizeable research community grew up around the area of agent-mediated electronic commerce (AMEC: see, e.g., Noriega & Sierra, 1999). However the focus in the AI/agents/AMEC research communities was almost exclusively on studies of software agents interacting with other software agents in various market scenarios: there are so few papers in the literature that study the interactions of human traders with software-agent traders that we can discuss all of them here.

2.2 IBM 2001

The first ever scientific study of the interactions between human and robot traders in experimental CDA markets was published in 2001 by a team of researchers working at IBM’s Research Labs (Das, Hanson, Kephart, & Tesauro, 2001). The IBM team tested several software-agent strategies, including “Zero-Intelligence-Plus” (ZIP: Cliff & Bruten, 1997) and a version of the “GD” algorithm introduced by Gjerstad and Dickhaut (1998), which IBM had modified and re-named as MGD. Both ZIP and MGD had originally been tested only in CDA markets populated by copies of the same algorithm, which could hence be simulated at great speed. However, to run these algorithms against human traders, the IBM researchers introduced a *sleep-wake cycle* for the trading-agents, where on each loop of the cycle they would be prevented from trading by going into a dormant ‘sleep’ mode for s seconds, then ‘wake up’, issue quotes and potentially enter into transactions, and then go back to sleep. Most of IBM’s results came from ‘fast’ agents where $s = 1.0$, but they also provided a brief discussion of results from ‘slow’ agents where $s = 5.0$.

IBM’s results showed that both ZIP and MGD could consistently out-perform human traders, an outcome that generated worldwide press coverage. They also found, curiously, that the efficiency of the markets (a measure that we define formally later in this paper) reduced when the traders in the markets were

mixtures of humans and agents: purely human markets, and purely agent markets, each had better efficiency scores than did the human-agent ones.

The new results that we present in this paper give a more detailed exploration of the effects of varying the ‘reaction speed’ s , but for a more recent trading-agent strategy that has been shown in previous papers to outperform both ZIP and MGD.

2.3 Grossklags & Schmidt 2003/2006

Grossklags & Schmidt (G&S) performed a set of human-agent experiments that they describe in two papers (Grossklags & Schmidt, 2003, 2006). This work was clearly inspired by Das et al. (2001), and they duly cited that paper. However, G&S used their own trader-agent algorithm rather than any of the ones employed by IBM, in order to explore a different issue: the effect of knowledge/ignorance of the presence of trader-agents on the behaviour of human traders. So, while G&S might reasonably be described as having been inspired by the IBM work; they had certainly not replicated it. G&S found that there was indeed a significant “knowledge effect”: market dynamics were altered just by telling the humans that there were software agents in the market.

2.4 De Luca & Cliff 2011

In their ICAART-2011 paper, De Luca and Cliff (2011a) introduced De Luca’s *Open Exchange* (OpEx) system, an experimental algorithmic trading platform designed to closely resemble the structure and behaviour of modern commercial financial market electronic trading systems, and to be generic enough to support experimental economics simulations of arbitrary complexity. OpEx involves a number of ‘netbook’ cheap portable PCs connected to a central ‘exchange server’. Human traders enter their orders in the Trading GUI (graphical user interface) running on their netbook; the GUI allows users to view the market order book, their “blotter” (personal history of orders and trades), and their current assignments of stock or money. Trader-agents, on the other hand, produce orders automatically, without the need of human intervention, on the basis of the market conditions that they observe: in principle the trader-agents can be given the same information as is presented to the human traders on the GUI, although many trading-agent strategies use only a subset of such information. For further details of the design, implementation, and use of OpEx, see De Luca and Cliff (2011a) and De Luca et al. (2011).

De Luca and Cliff (2011a) presented results that replicated and extended IBM’s paper. The replication involved running human-agent CDA experiments with the agents using Cliff’s ZIP strategy; the extension explored the response of GDX, an extended form of the MGD algorithm that IBM had used in 2001. GDX was invented by IBM researchers Tesauro and Bredin (2002), some time after IBM’s human-agent paper: from the order in which the papers appeared, and given that MGD and ZIP scored approximately the same in the 2001 paper, it seems reasonable to speculate that GDX was invented in an attempt to establish it as clearly the best-performing CDA strategy in the published literature. However, the paper introducing GDX (Tesauro & Bredin, 2002) only shows results from agent-vs-agent experiments: it had never been tested against human traders before De Luca & Cliff’s experiments.

De Luca and Cliff (2011a) monitored Smith’s α metric and also two other standard measures of market activity: the *allocative efficiency*, E , of traders is the total profit earned by a trader, π_i , divided by the maximum theoretical profit for that trader, $\hat{\pi}_i$: that is, the profit a trader could have made if all market participants would have traded units at the theoretical market equilibrium price, P_0 .

$$E = \frac{1}{n} \sum_{i=1}^n \frac{\pi_i}{\hat{\pi}_i} \quad (2)$$

And the *profit dispersion*, which we denote here as π_{disp} , is the deviation of actual profits of traders, π_i , from the maximum theoretical profit of traders, $\hat{\pi}_i$.

$$\pi_{disp} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\pi_i - \hat{\pi}_i)^2} \quad (3)$$

De Luca and Cliff (2011a) found that GDX did indeed outperform ZIP in human-vs.-agent experiments, on all these metrics.

In a subsequent paper, De Luca and Cliff (2011b) tested a more recent trading strategy called AA, one that again had previously only been evaluated in agent-vs-agent experiments. AA stands for *Adaptive Aggressive* and was the primary contribution of Vytelingum’s (2006) PhD Thesis (see also Vytelingum, Cliff, & Jennings, 2008). Vytelingum had demonstrated that AA dominates GDX in agent-vs-agent experiments, but he had not tested it in human-vs-agent contexts. De Luca & Cliff’s results from human-vs-AA experiments demonstrated that AA indeed outperformed GDX, and they concluded that AA is hence the best-performing published CDA trading strategy.

2.5 De Luca *et al.* 2011

In De Luca *et al.* (2011), a 24,000-word briefing paper written for, and published by, the UK Government Office for Science as part of their Foresight project on the future of computer trading in the financial markets,¹ we reported on a new set of experiments designed to explore the response of AA and ZIP strategies in a setting significantly closer to the reality of current financial markets. Ever since Smith's seminal 1962 paper, many experimental economic studies have copied his initial experiment design of dividing the experiment into a number of discrete periods or "days", each lasting a few minutes, with allocations of stock and money expiring at the end of each day, and with fresh allocations then being assigned to all participants at the start of each new "day".

The longevity of that experiment design can perhaps be explained by the desire for consistency that each successive set of authors had need for in comparing their results with earlier work. For example, De Luca and Cliff (2011a, 2011b) used this design because they wanted to be able to make direct comparisons between their results and Vytelingum's from his publications introducing AA, and IBM's from the 2001 paper. Presumably, in turn, Vytelingum had used this experiment design because it had been used by IBM; IBM used it because it had been used by Cliff's first publications describing the ZIP algorithm and also, independently, by Gjerstad & Dickhaut when they introduced the GD algorithm.

Despite its longevity, this design of experiment is clearly artificial. Smith referred to the discrete periods in his experiments as "days", presumably as a sign that he intended his experiments as studies of the equilibration dynamics of CDA markets measured over periods of days with the market closing at the end of each day and then reopening some hours later for the next day's trading. But many present-day financial markets are, for practical purposes, continuously running. For instance, if a trader wants to convert a quantity of US Dollars into a quantity of Euros, whatever time of day it is at that trader's location, somewhere in the world there will be a foreign exchange (FX) market operating that the trader can connect to, to do the deal. As the London FX market closes each evening, dealers in New York take over as the world's primary FX market; as New York closes, the focus of market activity switches to Tokyo, and as Tokyo closes, the next day's FX trading is starting in London.

In addition to being continuously running rather than broken into a sequence of discrete CDA auctions,

real-world CDA financial markets also have the obvious feature that traders can join the market or leave the market at any time. When they join the market, they bring stock or money with them, thereby adding to the liquidity of the market; and when they leave the market, their withdrawal reduces the liquidity in the market. This is in stark contrast to Smith's experiment design where liquidity is gradually consumed during each trading period (as traders transact and withdraw from the market for that day) and then at the start of each new trading period liquidity spikes back up to its initial maximum again.

We explored the response of AA and ZIP in CDA experiments where there was no division of trading into discrete days, and where the market liquidity was continuously replenished by trickle-feeding it in over the duration of the experiment rather than all arriving in one burst at the start of each trading period. For this we used the design explored in a human-market experimental economics study reported by Cliff and Preist (2001). Surprisingly, we found that when the experiment design was changed to a single period with continuous replenishment, both AA and ZIP were outperformed by the human traders, and so we concluded that the previously-reported dominance of ZIP and AA over humans in CDA markets (*i.e.*, Das *et al.*, 2001; De Luca & Cliff, 2011a, 2011b) appeared to be a consequence of the experiment design that was used in those earlier studies. In that paper we concentrated on exploring the responses on "fast" ($s = 1.0$) versions of the algorithms, as had been used in IBM's work, but we also ran two experiments with a "slow" ($s = 10.0$) version. Differences in the response of the fast and slow versions led us to speculate that perhaps the algorithms would outperform the human traders if they were given even faster response times.

And it is for that reason that we undertook our latest batch of experiments, the results from which are reported for the first time in the next section. Our intention was to generate additional data for "slow" versions of the algorithms, so that we had enough samples that we could draw statistically significant conclusions, and then to contrast those results with the first-ever studies of humans interacting with "ultra-fast" versions of the agent algorithms, with a sleep-time of only $s = 0.1$ seconds—a 'reaction time' that is manifestly faster than that at which a human could plausibly be relied on to operate successfully. In the following section we describe our methods and the results, and then discuss the surprising outcome of our experiments: giving the trading agents faster reaction times *worsened* the efficiency of our CDA markets.

¹<http://www.bis.gov.uk/foresight/our-work/projects/current-projects/computer-trading>

3 METHOD

We present here a new series of artificial trading experiments between humans and agents using DeLuca’s OpEx framework. We explore the performance of AA under two conditions: AA-ultra (“ultra-fast” trader-agents set to wake and calculate every 0.1s) and AA-slow (“slow” trader-agents set to wake every 10s and perform further internal calculations every 2.5s). All experiments were run at the University of Bristol between April and July 2011 using postgraduate students in non-financial but analytical subjects (i.e., students with skills suitable for a professional career in finance, but with no specific trading knowledge or experience). Moving away from the artificial constraint of regular simultaneous replenishments of currency and stock historically used in previous experiments, we instead choose to drip-feed order assignments into the market at regular intervals.

3.1 Experimental Setup

AA trading agents have short term and long term adaptive components (Vytelingum, 2006). In the short term, agents use learning parameters β_1 and λ to adapt their order aggressiveness. Over a longer time frame, agents use the moving average of the previous N market transactions and a learning parameter β_2 to estimate the market equilibrium price, \hat{p}_0 . For all experiments, we set parameter values $\beta_1 = 0.5$, $\lambda = 0.05$, $N = 30$, and $\beta_2 = 0.5$. The convergence rate of bids/asks to transaction price is set to $\eta = 3.0$.

For each experiment, 6 human participants were seated around a rectangular table with three buyers on one side and three sellers opposite. Participants were given a brief introduction to the trading GUI and the rules of the market. Typically, this lasted less than 10 minutes. The market was then reset to clear any residual orders from the system before the experiment was started. Each experiment lasted 20 minutes, during which the 6 human participants (3 buyers and 3 sellers) and 6 trader-agents (3 buyers and 3 sellers) competitively traded to maximise profit. Trader-agents were homogeneously configured to be either AA-slow or AA-ultra.

To encourage participation, humans were each given a cash payment, P , for taking part. Then, as a further incentive to encourage competition, the participants finishing first (the human with the highest efficiency score) and second were given an additional cash bonus payment of $2P$ and P , respectively.²

²In early trials, cash prizes were set to $P = £20$, hence, the winner received a total sum of £60, including participation fee. However, in later experiments, to reduce costs,

Table 1: Permit replenishment schedule (170s cycle). Limit prices of traders’ order assignments and the time-step they are sent (numbers in brackets are multiples of 10s).

	1	2	3	4	5	6
Buyer 1	350 (0)	250 (4)	220 (7)	190 (9)	150 (14)	140 (16)
Buyer 2	340 (1)	270 (3)	210 (8)	180 (10)	170 (12)	130 (17)
Buyer 3	330 (2)	260 (4)	230 (6)	170 (11)	160 (13)	150 (15)
Seller 1	50 (0)	150 (4)	180 (7)	210 (9)	250 (14)	260 (16)
Seller 2	60 (1)	130 (3)	190 (8)	220 (10)	230 (12)	270 (17)
Seller 3	70 (2)	140 (4)	170 (6)	230 (11)	240 (13)	250 (15)

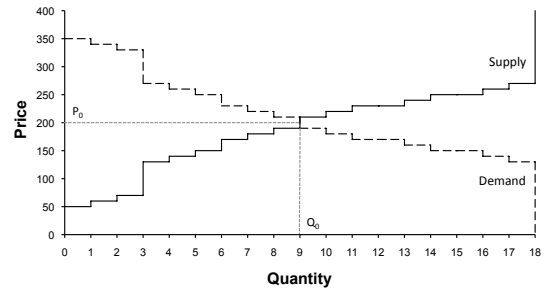


Figure 1: Supply and demand schedule generated by permit schedule shown in Table 1. Each replenishment cycle, equilibrium price $P_0 = 200$ and equilibrium quantity $Q_0 = 9$.

Each experiment started with an empty marketplace. Then, order assignments were periodically distributed to traders. Table 1 shows the permit schedule used to generate order assignments and describes one full replenishment cycle lasting 170s. The permit schedule describes the limit price of each trader’s assignment and the time-step that it is sent (numbers in brackets represent the time in 10s steps relative to the start of the replenishment cycle). Thus, we see that at the start of each cycle, human Buyer1 and trader-agent Buyer1 each receive a buy order assignment with limit price 350; and human Seller1 and trader-agent Seller1 each receive a sell order assignment with limit price 50. After 170s the replenishment cycle repeats, producing 7 full permit cycles during the 20 minutes experiment (no assignments were sent in the final 10s). Fig. 1 shows the demand and supply schedules generated by Table 1. We see that demand and supply is symmetric (and unbiased) about $P_0 = 200$. Each replenishment cycle, the sequence of limit prices for order assignments are arranged in an arithmetic progression. Thus, early in the cycle (time < 90s), assignments are easier to execute, having buy (sell) limit prices above (below) P_0 .

When a trader receives an assignment it is automatically queued until the trader decides to work it.

humans were required to compete in 3 consecutive experimental trials. For these experiments, the participation payment was doubled to $P = £40$, with the overall winner from the 3 trials receiving a total cash sum of £120 (£80 for second place).

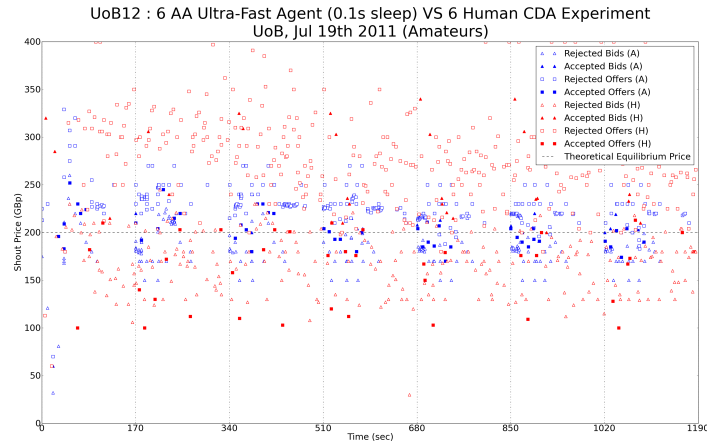


Figure 2: Time-series of all quotes posted onto the order book during run U12-ultra. The dashed horizontal line represents P_0 and vertical lines represent the start and end of each replenishment cycle.

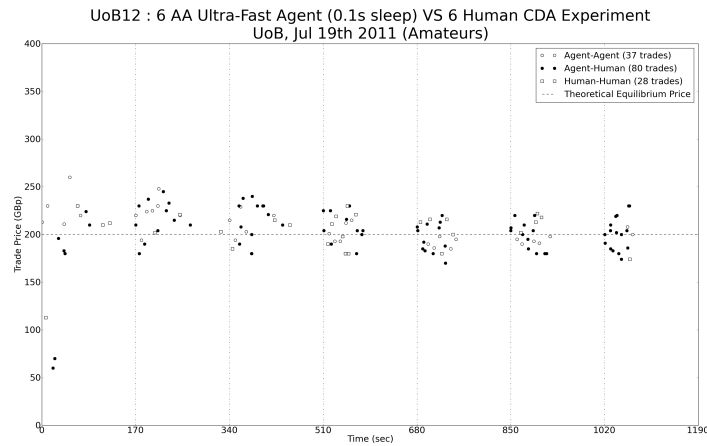


Figure 3: Time-series of all execution prices during un U12-ultra. The dashed horizontal line represents P_0 and vertical lines represent the start and end of each replenishment cycle.

Traders are able to work assignments in any order and at any time, thus enabling them to have multiple simultaneous orders on the exchange. To stop traders from making a loss, order submissions are capped at the limit price. Thus, the profit on each trade is calculated as the difference between execution price and limit price. To ease analysis, the maximum theoretical profit, $\hat{\pi}$, available to each trader was deliberately kept equal.

In total, a series of 7 experiments were run: 3 under condition AA-ultra, and 4 under AA-slow.

4 RESULTS

Fig. 2 shows the time-series of shouts (buy and sell orders submitted to the exchange) for experiment

UoB12-ultra, with human quotes in red and agents in blue. This rich data set is selected as a representative example of market activity. Filled and open-faced markers show accepted and rejected shouts respectively, with triangles representing bids and squares representing offers. Vertical lines denote the start and end of each permit replenishment cycle (170s) and the dashed horizontal line shows the theoretical market equilibrium price, $P_0 = 200$. Fig. 3 shows the time-series of execution prices for the same experiment. It is clear from this view that the majority of trading occurs in clusters at the start of each replenishment cycle. This correlates with our expectation, since assignments that are easiest to trade are distributed early in the cycle (refer to Table 1). Further, it can be seen that after an initial exploratory period, trade prices in each cycle are distributed in clusters around P_0 .

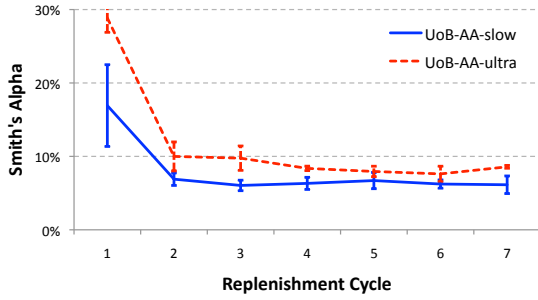


Figure 4: Smith's alpha \pm standard deviation.

Table 2: Allocative efficiency.

	Trials	Eff(A)	Eff(H)	Eff(Market)	Δ Profit(A-H)
AA-slow	4	0.957	0.963	0.960	-0.003
AA-ultra	3	0.966	0.906	0.936	0.032

This distribution of trade prices around the theoretical equilibrium price can be quantified using Smith's alpha measure (α , equation 1). In Fig. 4, mean $\alpha \pm$ s.d. is plotted for each replenishment cycle.

Fig. 4 shows that under both conditions, alpha drops quickly after the initial permit-replenishment cycle and then maintains a consistently low level for the rest of the experiment. The volatile activity of the market shortly after opening is a result of traders probing demand and supply at varying price levels. Overall, alpha values for AA-slow experiments are lower than for AA-ultra, suggesting that slow trader-agents improve market convergence.

Table 2 tabulates the allocative efficiency (equation 2) of traders. The mean efficiency of trader-agents, Eff(A), is similar under both conditions. However, the efficiency of humans, Eff(H), is 6% lower under condition AA-ultra. Thus, an increase in agents' speed leads to a reduction in overall market efficiency, Eff(Market). AA-ultra agents achieve approximately 3% more profit than humans (final column) while AA-slow agents achieve slightly less profit than humans. However, this does not imply that AA-ultra outperform AA-slow but rather that humans perform more poorly when competing against the faster trader-agents.

Table 3 displays the profit dispersion (equation 3) of traders: the deviation of profits about the maximum theoretical profit. We see that the profit dispersion of agents is similar under both conditions, however the profit dispersion of humans and hence the market as a whole is lower under condition AA-slow. This suggests that AA-ultra fast trader-agents produce greater deviation in the profits of human competitors; an undesirable result.

Table 3: Profit dispersion.

	Trials	Disp(A)	Disp(H)	Disp(Market)
AA-slow	4	100	164	139
AA-ultra	3	105	236	185

5 DISCUSSION

As with our analysis of results in De Luca et al. (2011), here we use the Robust Rank-Order (RRO) test (Feltovich, 2003) to explore the significance of the differences between the results from the AA-ultra experiments and those from AA-slow.

We first explored the scores for Smith's α metric (equation 1) over replenishment cycles 2 to 7 of our experiments (results from the initial Cycle 1 are not analysed as they do not represent the steady-state behaviour of the CDA markets). The outcome of this sequence of tests was that in each cycle, the α scores for AA-slow CDA markets were significantly better (i.e., lower) than those of the AA-ultra CDA markets. The RRO test gives exact values for p , the confidence level. In Cycles 2, 3, 4, and 7, the difference was significant at $p < 2.9\%$. In Cycle 6, the difference was significant at $p < 5.7\%$, and in Cycle 5, $p < 11.4\%$. This is an unequivocal result: in every cycle, the AA-slow markets give significantly better equilibration results than the AA-ultra do.

Results for profit dispersion (equation 3) showed no significant difference between profit dispersion of agents in AA-ultra and AA-slow markets. However, for the four AA-slow markets, profit dispersion for humans was significantly better (i.e., lower) than those of the AA-ultra markets: $p < 11.4\%$. Further, for AA-slow, profit dispersion for the market as a whole was significantly lower than for AA-ultra: $p < 5.7\%$.

Finally, we compared overall allocative efficiency (equation 2) scores for the seven experiments, and found that the efficiency scores for the four AA-slow markets were significantly better (i.e., higher) than those of the AA-ultra markets: $p < 2.9\%$. That is, when the agents had faster 'reaction' times, the markets were less efficient. In an attempt to understand why efficiency is better in the AA-slow markets, we compared the allocative efficiency scores of the AA-slow trader-agents to those of the AA-ultra trader agents across our seven experiments. The RRO test found no significant difference ($U = 0.0$). Thus, it seems that in fact altering the reaction-speed of the trader-agents has no detectable effect (in our seven experiments, at least) on the efficiency of the trader-agents themselves.

However, when we used the same test to explore the efficiency scores of the human traders in

the seven experiments, we found that the human efficiency scores were significantly better when they were trading against AA-slow agents ($p < 2.9\%$).

From this, it is clear that the extra efficiency in the AA-slow markets is due primarily to the fact that the human traders are able to trade more efficiently when the trader-agents' sleep-cycle is running on a timescale comparable to the thinking-and-reaction times of humans.

Exactly why this is so is unclear, but we speculate here that it is due to the fact that when the trader-agents are operating on slow timescales, their actions in the market can be taken into account by the human traders, and hence the human's actions in the markets is better-informed. When the trader-agents are operating on superhumanly fast timescales, either their presence in the markets is so fleetingly brief that they do not figure in the human's reasoning process, or possibly their 'flickering' in and out of the market's book positively confuses the humans. Either way, the evidence we have generated here in our seven experiments involving a total of 42 human subjects points to the conclusion that, if human traders are active in the markets, it is better for the overall market if any trader-agents active at the same time are running at human-intelligible timescales. However, as markets homogenise this effect is likely to reduce. If trader-agents formed a greater proportion of the market, executing, say, 90% of all trades, we would expect market efficiency to increase. Further experiments are needed to test this hypothesis.

Finally, it is important to note that the results we have presented here would have been unintelligibly different if we had used the "traditional" experiment design where trading is broken into discrete periods ("days") with full replenishment of maximum liquidity at the start of each "day" and a progressive reduction in liquidity occurring across each day as traders transact and drop out of the market, waiting for the next simultaneous replenishment. If we had used that traditional design, it is reasonable to expect that in all the AA-ultra experiments at the start of each day there would be a sudden flurry of activity where all the AA-ultra traders quote into the market and transact with each other where they are able to, all of that taking place in the first second or two after the start of the trading "day", and then for the rest of that day the humans interact with one another, and/or with any of the AA-ultras that didn't manage to trade in the opening frenzy. This is further, and we hope final, evidence that it is time for the field to move on from the design of experiment that Vernon Smith happened to choose for his experiments reported in his 1962 paper. The research we conduct in 2012 should aim to model the

real-world markets of 2012, and should avoid recycling an experiment design from half a century ago.

6 CONCLUSIONS

In this paper we have presented results from seven new experiments where human and software-agent traders competed against one another in continuous double auction market experiments, under controlled laboratory conditions. Building on previous work that we had published (De Luca & Cliff, 2011a, 2011b; De Luca et al., 2011), we set out to explore the extent to which the setting for the "sleep cycle" parameter, s , affected the dynamics of the market. We used Vytelingum's (2006) AA trader-agent strategy because that had previously been shown to be the best-performing agent strategy for the CDA (De Luca & Cliff, 2011b).

We explored a "slow" version of AA for which $s = 10.0$ seconds, and an "ultra" fast version for which $s = 0.1$ seconds. We ran three experiments involving humans-vs-AA-ultra, and four evaluating humans-vs-AA-slow. Each experiment had six human subjects and six trading agents.

We found no statistically significant difference between the allocative efficiency scores of the AA-ultra and AA-slow trader-agents. That is, varying the reaction speed of the AA agents did not appear to affect their efficiency.

When we compared aggregate market results from the AA-ultra and AA-slow data-sets, we found a statistically significant difference in the equilibration behaviour, profit dispersion, and also the allocative efficiency scores: all measures were better in the AA-slow experiments and worse in the AA-ultra experiments; that is, speeding up the agents made the markets perform worse.

This difference in performance of the two types of CDA market is attributable to the behaviour of the humans in the markets: when pitted against AA-slow agents, humans are more efficient and have lower profit dispersion than when competing with AA-ultra agents. We speculate that this is because the humans can accommodate the actions of the AA-slow agents when formulating their trading strategies, whereas the AA-ultra agents operate so fast that they either confuse the humans, or their actions are simply ignored.

The design of our experiments differs from the "traditional" design that has been used repeatedly for 50 years. In the traditional design, trading is broken into discrete trading periods with liquidity (stock and money) replenished to its maximum at the start of each such period. This is clearly an artificial structure,

unlike the reality of the real-world financial markets. In the design we used here, there is only one continuous trading period and liquidity is constantly replenished in a drip-feed manner. If we had used the traditional, unrealistic, experiment design, there are good reasons to believe that the superiority of slow-trader markets would simply not have been revealed. Confirmation of this, however, will require further comparative experiments using the traditional framework.

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