
John Cartlidge, C. Szostek, M. De Luca and D. Cliff
Outline

• Lightening-fast background of…
  …automated trading agents in financial markets (HFTs)
  …impact of agents on financial markets (specifically crashes)
  …academic literature on experimental human vs. agents financial markets

• The Problem
  – Does agent speed affect the dynamics of human-agent financial markets?

• Methodology
  – Human-agent experiments in a virtual commodities market

• Results & Conclusions
  – Faster agents can produce less efficient markets
Financial-Market Trading Agents Continually Grab the Headlines…

December 14, 2011 11:11 am
High stakes over definition of high frequency trading

Monday, January 30, 2012 As of 9:57 PM
CFTC to Step Up Focus on High-Frequency Trading

But why is everybody [suddenly] so interested?
'twas ever thus...

Traders were human [and male] and bought and sold face-to-face on ‘open-outcry’ trading floors.
And then, on October 27th 1986, the markets were changed forever…
‘Big Bang’

Huge deregulation of Britain’s financial markets ushered in a move in London from open outcry to screen based electronic trading.
‘loadsamoney’

Charlie Sheen in ‘Wall Street’, 1987
Copyright: © 20th Century Fox

Anonymous computer-based trading platforms enabled greater transaction speed, better price discovery and increased liquidity
Death of the Trader?

[by 2015] “survey respondents, on average, plan to shrink their number of traders from forty to four across most product groups” [IBM 2006]

…with hindsight, this was probably an underestimate
Rise of the Robots

In Europe & USA major exchanges are reporting that 30%-75% of all transactions currently involve automated [robot] traders [Foresight 2011]
Wired for Speed

• Current trend for financial agents is to increase speed by hardwiring algorithms using FPGAs

• HFTs hold very short term positions, arbitraging across markets

• Profits generally go to the first firm to act

• Speed of light is a limiting factor. A 60ms round trip from New York to London can leave data looking ‘stale’
How has the introduction of trading agents affected the dynamics of financial markets?

To answer this, let’s take a quick stroll through the history of market crashes...
1929, Wall Street Crash

‘Black Thursday’ Oct 24\textsuperscript{th}, Dow Jones Industrial Average opens at 305.85

By Nov 13\textsuperscript{th}, Dow had fallen to 199

35% of market value lost in \textbf{3 weeks}

Oct 19th 1987, ‘Black Monday’

Electronic trading systems and computer-generated trading still in their infancy

Largest one day percentage decline in Dow Jones history (22%)

May 6th 2010, ‘Flash Crash’

Within **20 minutes**, Dow plummets 9% and then largely recovers the loss.
May 6\textsuperscript{th} 2010, ‘Flash Crash’

In 14 seconds more than 27,000 e-Mini S&P futures contracts were bought and sold.

But only 200 aggregate net purchases.

The ‘hot potato’ effect.
May 6th 2010, ‘Flash Crash’

Some stock, like Accenture, plummeted to 1 cent…
May 6th 2010, ‘Flash Crash’

…while others traded at $100,000

At this value, Sotheby’s would have a net worth greater than the entire Chinese economy!

NYSE cancelled all trades executed between 14:40-15:00 that were more than 60% away from last print at 14:40

This resulted in arbitrary winners … and losers
and then, one year later…
Lessons for exchanges in oil’s ‘flash crash’

By Javier Blas, Commodities Editor

5th May 2011

Brent Crude lost 13%
Copper slid 5%
Cotton fell 8%

Traders work in the oil options pit on the floor of the New York Mercantile Exchange
Observations…

• The move to computer-based trading and the introduction of automated trading agents has altered market dynamics
  – E.g., market ‘crashes’ now occur more rapidly and more regularly
• How to better understand the effects of agents on market dynamics?
  – This question is being asked by academia, industry and government alike…
Understanding Market Dynamics

• By observation of real-world market activity

• By controlled experimentation in laboratory settings with traders interacting in artificial markets
  • We can assess market ‘quality’ by measuring the equilibrium finding behaviour, allocative efficiency and profit dispersion
  • We introduce these concepts next…
Supply & Demand 101

Supply: as price increases more people are willing to sell

Demand: as price decreases more people are willing to buy

The market is in equilibrium when supply equals demand \((Q_0, P_0)\)
Equilibration Behaviour

The equilibrium-finding behaviour of a market (Smith’s $\alpha$)

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

(1)

r.m.s. difference between each transaction price, $p_i$, and $P_0$, expressed as a percentage of equilibrium price
Allocate Efficiency

Profit earned by traders as a proportion of maximum theoretical profit

\[ E = \frac{1}{n} \sum_{i=1}^{n} \frac{\pi_i}{\hat{\pi}_i} \]  \hspace{1cm} (2)

that is, the profit a trader could have made if all market participants would have traded units at the theoretical market equilibrium price, \( P_0 \)
Profit Dispersion

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

The deviation of actual profits of traders from the maximum theoretical profit of traders
Economics, Experiments & Agents

• **Human vs. Human Markets** (1960s onwards)
  – Experimental Economics: Vernon Smith established field early 1960s, received Nobel Prize in 2002

• **Agent vs. Agent Markets** (1990s onwards)
  – ACE: Agent-Based Computational Economics; AMEC: Agent-Mediated Economic Commerce; TAC/CAT: Trading Agent Competition / Market Design Competition; MBC: Market-based Control

• **Human vs. Agent Markets** (2000 onwards)
  – Very little work in this area…
Humans vs. Agents 1

• IBM’s Research Labs (2001)
  – First ever scientific study of the interactions between human and agent traders in experimental CDA markets
  – Showed ZIP and MGD consistently out-perform human traders
  – Outcome generated worldwide press coverage
Humans vs. Agents 2

  - Used own simple agents to explore the effect of knowledge of the presence of agents on the behaviour of humans
  - Found a significant “knowledge effect”: market dynamics were altered just by telling the humans that there were agents in the market
Humans vs. Agents 3

- De Luca & Cliff 2011
  - Replication of IBM’s setup
  - GDX outperformed ZIP on all metrics
  - AA outperformed GDX
  - Concluded that AA is best-performing published CDA trading strategy
Humans vs. Agents 4

- **Foresight 2011**
  - Explored AA and ZIP
  - No division of trading into discrete days
  - Market liquidity continuously replenished
  - Human traders *outperformed* AA and ZIP!
  - Concluded previously-reported dominance of ZIP & AA over humans an artifact of experiment design used in earlier studies
Humans vs. Agents 5

– Here, we test the effect of agent speed on dynamics of human vs. agent markets

– We use continuous ‘drip-feed’ replenishment
  • This follows the more ‘realistic’ Foresight setup, not the traditional ‘artificial’ setup used by Smith onwards

– We compare a fast and a slow version of AA
  • AA—“slow” (10s sleep time)
  • AA—“ultra”—fast (0.1s sleep time)

– We use OpEx trading platform (DeLuca)
OpEx Platform

Developed by Marco DeLuca, University of Bristol, 2010

OpEx platform for Human / Agent trading experiments
Opex Trader GUI

GUI for Human Traders on OpEx platform
Adaptive Aggressive (AA) Agents

Experimental Setup

- 6 humans (3 buyers & 3 sellers) and 6 agents (3 buyers & 3 sellers)
- 20 minutes of continuous trading (in 7 assignment cycles)
- Continual replenishment (assignments drip-fed into market every 10s)
- 4 experiments with AA-Slow and 3 experiments with AA-Ultra
  1. AA-Ultra: robots set to wake and calculate every 0.1s
  2. AA-Slow: robots set to wake every 10s and perform internal calculations every 2.5s
- Participants UoB postgrad. students in non-finance/analytical subjects
  - All paid £20 for participating (+£40 to winner, +£20 to runner-up)
Supply & Demand Schedules

Equilibrium Price = $200

Replenishment schedule

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer1</td>
<td>350</td>
<td>250</td>
<td>220</td>
<td>190</td>
<td>150</td>
<td>140</td>
</tr>
<tr>
<td>Buyer2</td>
<td>340</td>
<td>270</td>
<td>210</td>
<td>180</td>
<td>170</td>
<td>130</td>
</tr>
<tr>
<td>Buyer3</td>
<td>330</td>
<td>260</td>
<td>230</td>
<td>170</td>
<td>160</td>
<td>150</td>
</tr>
<tr>
<td>Seller1</td>
<td>50</td>
<td>150</td>
<td>180</td>
<td>210</td>
<td>250</td>
<td>260</td>
</tr>
<tr>
<td>Seller2</td>
<td>60</td>
<td>130</td>
<td>190</td>
<td>220</td>
<td>230</td>
<td>270</td>
</tr>
<tr>
<td>Seller3</td>
<td>70</td>
<td>140</td>
<td>170</td>
<td>230</td>
<td>240</td>
<td>250</td>
</tr>
</tbody>
</table>

3 minute cycle period
7 cycles per experiment
Results: Shout Dynamics

All shouts entered during one experimental run (UoB12)

Traders shout throughout experiment, with agents (blue) tending to enter limit prices closer to equilibrium than humans (red)
Results: Trade Dynamics

All trades during one experimental run (UoB12)

Trading occurs in cyclical bursts, clustering about equilibrium ($200)
Results: Equilibration

In every cycle, slow-agent markets give significantly* better equilibration results than faster agents

* Significant using Robust Rank Order non-parametric test
  (Cycles 2, 3, 4, 7: p<2.9%), (Cycle 6: p<5.7%), (Cycle 5, p<11.4%)
Results: Profit Dispersion

<table>
<thead>
<tr>
<th></th>
<th>Trials</th>
<th>Dispersion (Agents)</th>
<th>Dispersion (Humans)</th>
<th>Dispersion (Market)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA-Slow</td>
<td>4</td>
<td>100</td>
<td>164*</td>
<td>139*</td>
</tr>
<tr>
<td>AA-Ultra</td>
<td>3</td>
<td>105</td>
<td>236</td>
<td>185</td>
</tr>
</tbody>
</table>

- Profit dispersion of humans significantly* lower in slow-agent markets (p<11.4%)
- Profit dispersion of whole market significantly* lower in slow-agent markets (p<5.7%)

Evidence suggests that fast agents produce greater deviation in the profits of human competitors; an undesirable result

* Significant difference using Robust Rank Order non-parametric test
### Results: Efficiency

<table>
<thead>
<tr>
<th></th>
<th>Trials</th>
<th>Efficiency (Agents)</th>
<th>Efficiency (Humans)</th>
<th>Efficiency (Market)</th>
<th>Δ Profit (Agent-Human)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA-Slow</td>
<td>4</td>
<td>0.957</td>
<td>0.963*</td>
<td>0.960*</td>
<td>-0.003</td>
</tr>
<tr>
<td>AA-Ultra</td>
<td>3</td>
<td>0.966</td>
<td>0.906</td>
<td>0.936</td>
<td>0.032</td>
</tr>
</tbody>
</table>

- Humans have significantly* higher efficiency in slower agent markets ($p<2.9\%$)
- Markets with slower agents have significantly* higher efficiency ($p<2.9\%$)

Evidence suggests humans trade more efficiently when the agents’ sleep-cycle is comparable to the thinking-and-reaction times of humans.

* Significant difference using Robust Rank Order non-parametric test
Results: Summary

• Agent speed produces no significant difference in agents’ efficiency
• However, superhumanly fast agents made the market perform worse
  • Statistically significant on equilibration, profit dispersion and allocative efficiency
• Difference in market performance is attributable to human behaviour
  • We speculate ultra-fast agents either confuse humans, or their actions are ignored
Conclusion

• We explored the behaviour of financial markets containing humans and AA agents with ‘slow’ and ‘ultra’-fast reaction times
  – pertinent problem with relevance to financial markets and the agents community
  – we use a ‘realistic’ model with continuous replenishment, drip-feed liquidity
• Evidence suggests ultra-fast trading agents make humans, and the market as a whole, perform worse
• The first time controlled laboratory experiments have shown ‘HFTs’ can have a negative effect on human–agent financial markets
  – offers new insight into our understanding of the real world financial markets
  – but, much more work in this area is needed…
Questions?

Contact:
John Cartlidge
University of Bristol
john.cartlidge@bristol.ac.uk
http://www.cs.bris.ac.uk/~cszjpc