Every cloud has a silver lining
Fast trading, microwave connectivity and trading costs

Andriy Shkilko and Konstantin Sokolov

Discussion by:
Sophie Moinas
(Toulouse School of Economics)

Basic idea

• The environment:
  – CME data on futures contain fundamental information that may be useful to adequately price ETF on NY equity markets
  – Traders located in NY may receive information via various routes

CME (Aurora, IL) → New York microwaves fiber message

NYSE, NASDAQ, BATS (NJ)
Basic idea

• The environment:
  – CME data on futures contain fundamental information that may be useful to adequately price ETF on NY equity markets
  – Traders located in NY may receive information via various routes

Traders who use MW links **have a speed advantage** that they may use to pick off stale limit orders and/or update their stale quotes before being picked off
Basic idea

• The environment:
  – CME data on futures contain fundamental information that may be useful to adequately price ETF on NY equity markets
  – Traders located in NY may receive information via various routes

• During weather disruptions, traders who use MW links lose their speed advantage and must temporarily switch from microwave to fiber transmissions.
Summary

• Fun way to tackle the endogeneity issue of participation of HFT / market liquidity 😊
  – Using weather as an instrument makes sense because HFT use microwaves
  – Completely exogenous
  – Methodology: How do abnormal precipitations along the Chicago-New York corridor impact various measures of the liquidity of ETF?

\[ \text{DEPVAR}_{it} = \alpha_i + \beta_1 \text{PRECIP}_t + \beta_2 \text{VIX}_t + \varepsilon_{it} \]

• Take-away: removing speed advantages of some lowers trading costs (price impacts, effective spreads) ... and profits (realized spreads)

=> How does it help us better understanding whether HFT is “good” (=provide liquidity, absorb price pressure...) or “bad” (=impose adverse selection)?
Underlying assumptions

• Information transmission: **Futures market lead price discovery**
  – Robustness checks: 1. document a significant reaction of the ETFs to trades in futures but not vice-versa, and 2. precipitations do not impact liquidity in futures markets

• Explanatory variable: **Precipitations = Susceptibility of MWNs disruptions**
  – Robustness checks: Precip2 = 1 when Total Precip > mean + 1 std; Mprecip = 1 when Average Precip by station > mean + 0.5 or 1 std
  – *Still: PRECIP1 & PRECIP2 events on a 15-minute interval are observed during 71% and 59% of the trading days. Seems very frequent.*

• The explanatory variable does **not** capture a well-known “weather effect”
  – Robustness check: focus on precipitations in Ohio

• **Hidden assumption: are (all) traders aware that the speed differential changes during MWN disruptions?**
What do we expect?

- Fast impose adverse selection (Biais, Foucault and Moinas, 2015; Budish, Cramton and Shim, 2015; Foucault, Hombert and Roșu, 2016)

SLOW LIMIT ORDER/MM ➔ FAST ➔ SLOW MARKETABLE LIMIT ORDER

Disruption => adverse selection disappears

equilibrium outcome: PR IMP -, Eff. Spd -

Realized Spreads? (RS = ES − PI, competitive MM), Volume +?, Volat - ?

- Fast monitor better (Hoffmann, 2014; Jovanovic and Menkveld, 2015)

FAST ➔ SLOW LIMIT ORDER ➔ SLOW MARKETABLE LIMIT ORDER

Disruption=> fast market makers cannot properly monitor

equilibrium outcome: Eff. Spd + (actually may also -!), PR IMP +,

Realized Spreads -?, Volume -, Volat?
What should we expect “out of equilibrium”?

Most of the theoretical models quoted here are \textit{equilibrium} models...

- Fast impose adverse selection

  \begin{align*}
  \text{SLOW LIMIT ORDER} & \rightarrow \text{FAST} \rightarrow \text{SLOW MARKETABLE LIMIT ORDER} \\
  \text{Disruption} \Rightarrow \text{equilibrium outcome: PR IMP -, Eff. Spd -, Volume +}
  \end{align*}

  In the short run, \textit{exit of fast informed traders} mechanically \Rightarrow \text{PR IMP -, Volume -}

- Fast monitor better

  \begin{align*}
  \text{FAST} & \rightarrow \text{SLOW LIMIT ORDER} \quad \text{SLOW MARKETABLE LIMIT ORDER} \\
  \text{Disruption} \Rightarrow \text{equilibrium outcome: Eff. Spd + (/-), PR IMP +, Realized Spds -, Volume -}
  \end{align*}

  In the short run, \textit{if fast informed market makers exit/ lower aggressiveness: Eff. Spd +, PR IMP +}

  \textit{BUT DO THEY EXIT? DO THEY PRICE LESS AGGRESSIVELY?}
It depends on assumptions

1. Business models of liquidity takers / makers
   - Fast directional HFTs gain (if buy): \( E(b_{t+h} | I_t) - a_t - \text{take fee} \)
   \[ \Rightarrow \text{Not profitable to pay the spread (and a take fee?) if no information on } a_{t+h}. \]
   - Fast market makers gain (if buy) : \( E\{ (a_{t+h} - b_t + \text{make fee}) \cdot 1_{a_{t+h} > b_t} | I_t \} \)
   \[ \Rightarrow \text{Monitoring helps them avoiding being picked off (condition } a_{t+h} > b_t \text{) which increases the profits} \]
   But it may still be profitable to make the market (simply reduces inf. rents)

2. If intense competition (in particular among very liquid ETF), (fast) market makers may not be in a position to quote less aggressively

3. Information on MWN disruptions: would slow market makers know that they need not price the risk of being picked off when it’s raining a lot in Ohio? Wouldn’t fast market makers know that the MWN is down for everyone?
Conclusion

• Very nice idea, well executed

• I did not emphasize: additional event study (Quincy data) (I am not completely sure I agree with the interpretation of the coefficients), focus on situations in which tick size is binding

• (My) Take away: PR IMP -, Eff. Spd -, Realized Spds -, Volume -
  – Fast marketable limit order traders impose adverse selection
  – Fast limit order traders do not disappear when they loose their speed advantage (Keep a speed advantage when rebalancing portfolios in NY/NJ? Know that fast directional traders will not pick up their orders?)

• Need to clarify a bit more the “hidden assumptions” and the theoretical framework

Price discovery?
DEPVAR_{it} = \alpha_i + \beta_1 \text{POST}_t + \beta_2 \text{YR13\_14}_t + \beta_3 \text{POST}_t \times \text{YR13\_14}_t + \beta_4 \text{VIX}_t + \varepsilon_{it}

POST: 1 in Feb-Apr 2013 or Feb-Apr 2014;
YR13\_14: 1 for the period from Sept 2013 to April 2014
Objective: compare Pre-event Sept-Nov 2012 to Post-event Feb-Apr 2013

1. Pre-event Fall: Sept-Nov 2012 (POST = 0, YR13\_14 = 0)
DEPVAR_{it} = \alpha_i + \beta_4 \text{VIX}_t + \varepsilon_{it}

2. Post-event Spring: Feb-Apr 2013 (POST = 1, YR13\_14 = 0)
DEPVAR_{it} = \alpha_i + \beta_1 + \beta_4 \text{VIX}_t + \varepsilon_{it}

3. Post-event Fall: Sept-Nov 2013 (POST = 0, YR13\_14 = 1)
DEPVAR_{it} = \alpha_i + \beta_2 + \beta_4 \text{VIX}_t + \varepsilon_{it}

4. Post-event Spring: Feb-Apr 2014 (POST = 1, YR13\_14 = 1)
DEPVAR_{it} = \alpha_i + \beta_1 + \beta_2 + \beta_3 + \beta_4 \text{VIX}_t + \varepsilon_{it}

The coeff. \beta_1 captures the impact of Quincy; but not very clear because Quincy was there in Sept-Nov 2013 as well
Event study

\[ \text{DEPVAR}_{it} = \alpha_i + \beta_1 \text{POST}_t + \beta_2 \text{YR13}_14_t + \beta_3 \text{POST}_t \times \text{YR13}_14_t + \beta_4 \text{VIX}_t + \epsilon_{it} \]

Assume for instance that there is a seasonality -0.05 in Feb-Apr and that there is an impact of 0.1 on DEPVAR (\& all other coefficients are 0).

1. Pre-event Fall: Sept-Nov 2012 (POST = 0, YR13_14 = 0)
   \[ \text{DEPVAR Sept-Nov 2012} = \alpha \]

2. Post-event Spring: Feb-Apr 2013 (POST = 1, YR13_14 = 0)
   \[ \text{DEPVAR Feb-Apr 2013} = \alpha + \beta_1 \Rightarrow \beta_1 = -0.05 + 0.1 \]

3. Post-event Fall: Sept-Nov 2013 (POST = 0, YR13_14 = 1)
   \[ \text{DEPVAR Sept-Nov 2013} = \alpha + \beta_2 \Rightarrow \beta_2 = +0.1 \]

4. Post-event Spring: Feb-Apr 2014 (POST = 1, YR13_14 = 1)
   \[ \text{DEPVAR Feb-Apr 2014} = \alpha + \beta_1 + \beta_2 + \beta_3 \Rightarrow \beta_3 = (-0.05 + 0.1) - (-0.05+0.1) - 0.1 = -0.1 \]

Clean analysis but I am not sure about the interpretation of the coefficients. Doesn’t the coeff. \( \beta_1 \) captures seasonality and event? Difficult to see because not a standard diff in diffs... According to my computations the coefficient of interest should be: - \( \beta_3 \)
Minor questions/comments

• Traditional weather effect: as a robustness check, what happens when it rains in Ohio but not in New York?
• Can you provide a time line of latencies? For instance in 2015-2016 they are still evolving. Thus are speed so homogenous in the control sample of 2013-2014?
• Do rain and snow have a similar impact on the susceptibility of MWN disruptions?
• Alternative models: inventory models? Arbitrage (Foucault, Kozhan, Tham, 2015)?
• Price impacts are similar to those observed in equities; isn’t it due to a different trade size?
• Do you have Fixed Effects in the panel regressions? They show up in Eq. (1) -- a_i -- but then you write « All asset-specific variables are standardized, so the regression models control for asset fixed effects. » (which is incorrect)
• Define volatility in the text (only shows up in Table 2).
• Plot statistics of #NBBO updates, volume and trade size by precipitation.
• Add # observations in the regressions.
• Provide more details on Quincy data: market data and not news for instance.
• “Latent liquidity invoked by the network disruptions mainly improves the spreads”

What framework do you have in mind?