

Every cloud has a silver lining

Fast trading, microwave connectivity and trading costs

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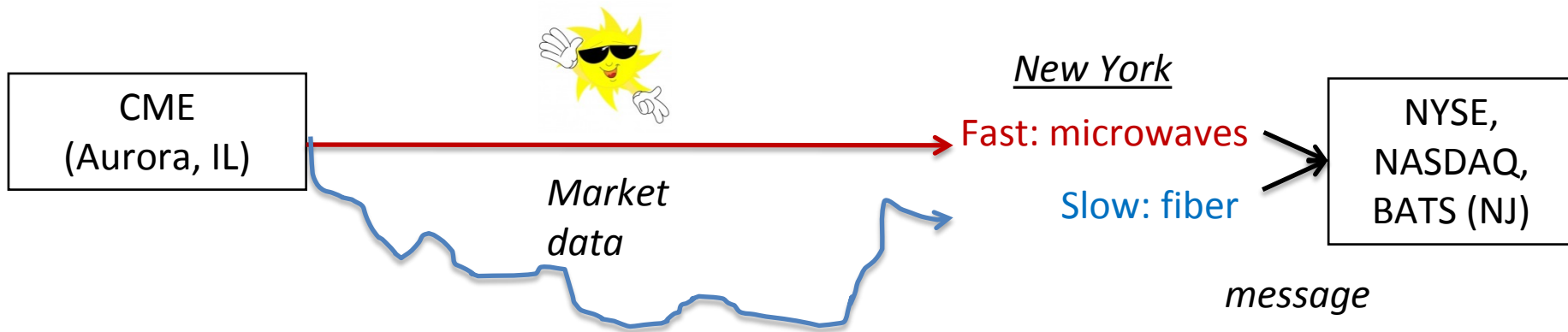
Basic idea

- 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



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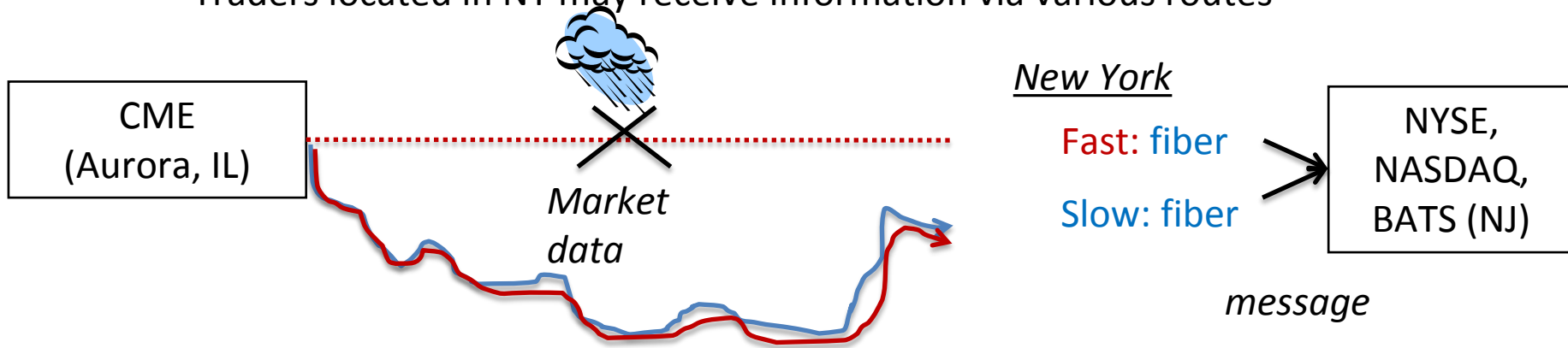
- The environment:
 - CME data on futures contain fundamental information that may be useful to adequately price ETF on NY equity markets
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- Traders who use MW links have a speed advantage that they may use to pick off stale limit orders and/or update their stales 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
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- 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 Roşu, 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 *equilibrium* models...

- Fast impose adverse selection

SLOW LIMIT ORDER

FAST → SLOW MARKETABLE LIMIT ORDER

Disruption => equilibrium outcome: PR IMP -, Eff. Spd -, Volume +

In the short run, *exit of fast informed traders* mechanically => PR IMP -, Volume -

- Fast monitor better

FAST → SLOW LIMIT ORDER

SLOW MARKETABLE LIMIT ORDER

Disruption => equilibrium outcome: Eff. Spd + (/ -), PR IMP +, Realized Spds -, Volume -

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

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): $(E(b_{t+h} | I_t) - a_t - \text{take fee})$
- => Not profitable to pay the spread (and a take fee?) if no information on a_{t+h} .
- Fast market makers gain (if buy) : $E\{ (a_{t+h} - b_t + \text{make fee}) \cdot 1_{a_{t+h} > b_t} | I_t \}$
- ⇒ Monitoring helps them avoiding being picked off (condition $a_{t+h} > b_t$) 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 lose 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?

Event study

$$\text{DEPVAR}_{it} = \alpha_i + \beta_1 \text{POST}_t + \beta_2 \text{YR13_14}_t + \beta_3 \text{POST}_t \times \text{YR13_14}_t + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

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)

$$\text{DEPVAR}_{it} = \alpha_i + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

2. Post-event Spring: Feb-Apr 2013 (POST = 1, YR13_14 = 0)

$$\text{DEPVAR}_{it} = \alpha_i + \beta_1 + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

3. Post-event Fall: Sept-Nov 2013 (POST = 0, YR13_14 = 1)

$$\text{DEPVAR}_{it} = \alpha_i + \beta_2 + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

4. Post-event Spring: Feb-Apr 2014 (POST = 1, YR13_14 = 1)

$$\text{DEPVAR}_{it} = \alpha_i + \beta_1 + \beta_2 + \beta_3 + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

The coeff. β_1 captures the impact of Quincy; but not very clear because Quincy was there in Sept-Nov 2013 as well

Event study

$$\text{DEPVAR}_{it} = \alpha_i + \beta_1 \text{POST}_t + \beta_2 \text{YR13_14}_t + \beta_3 \text{POST}_t \times \text{YR13_14}_t + \beta_4 \text{VIX}_t + \varepsilon_{it}$$

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. β_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?