Potential Pilot Problems

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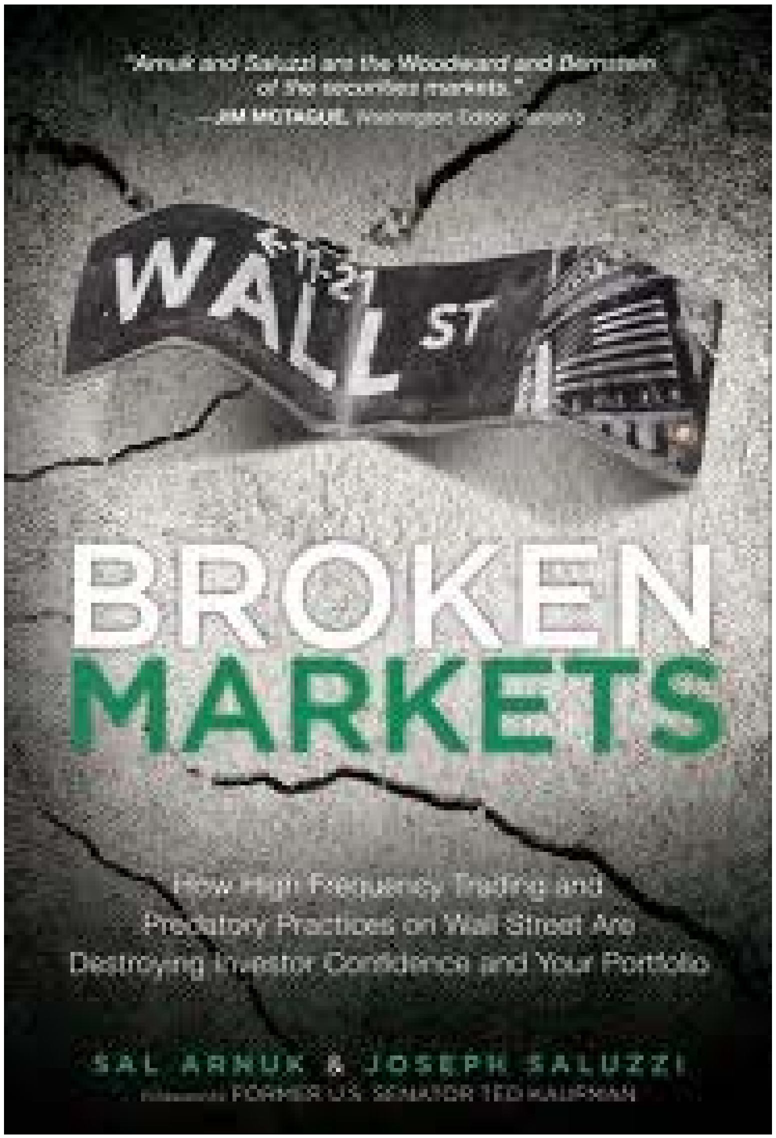
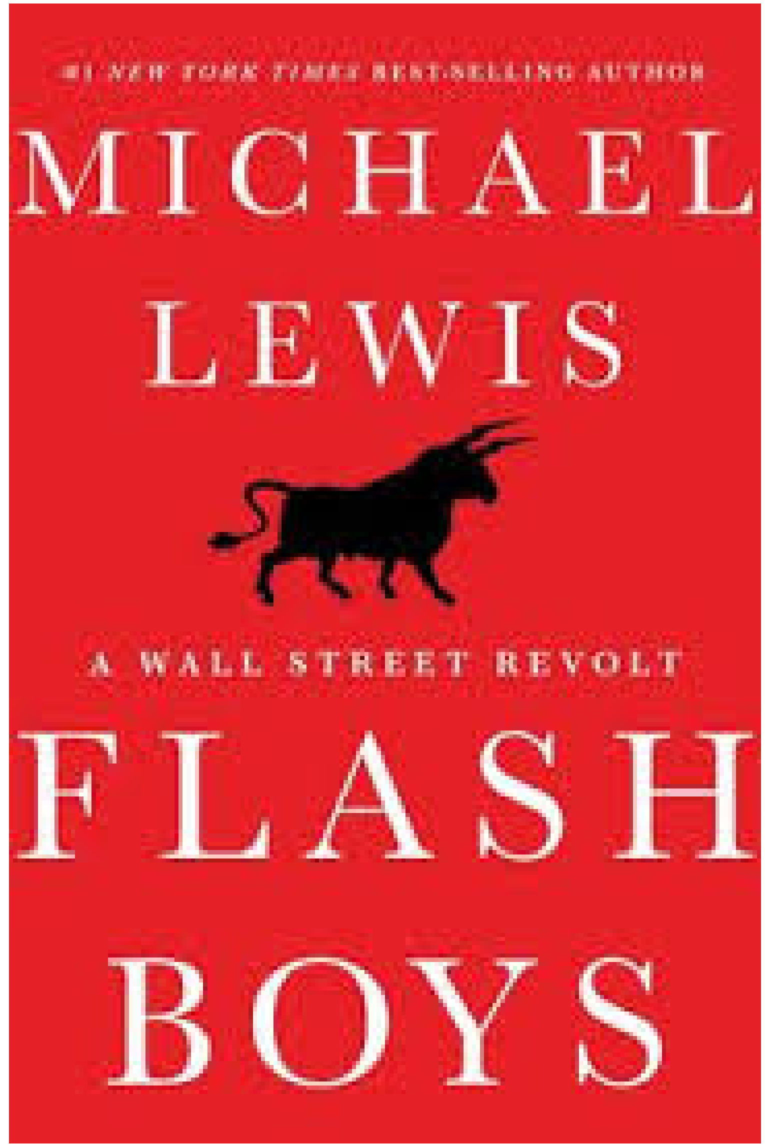
The popular view about equity markets





Trading certainly looks different today…

20th century

21st century

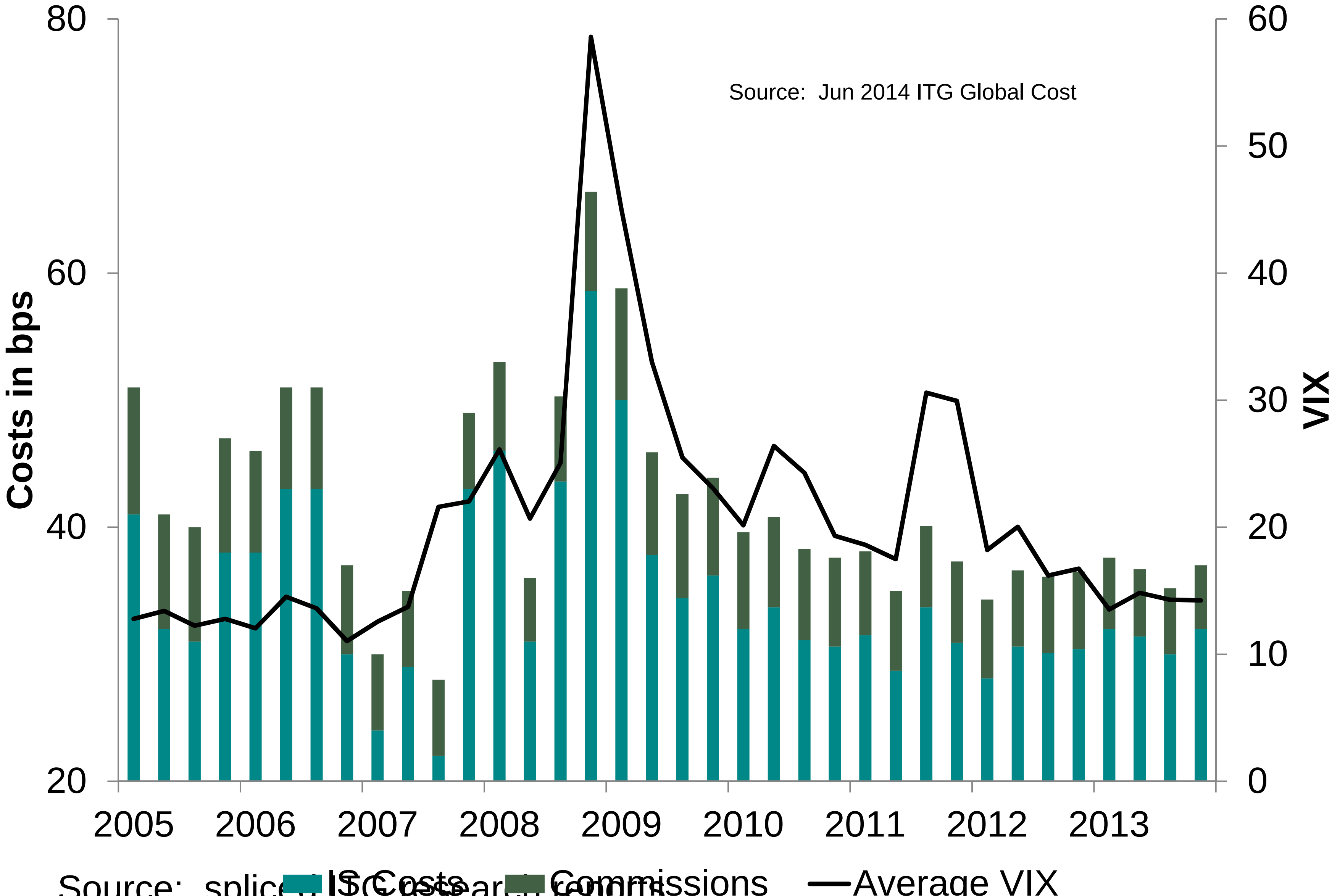
Automation has driven out costs.

Is it increasing liquidity and helping firms raise capital?

Two liquidity measures defined

- Effective bid-ask spreads
  - $ES_{it} = | P_{it} - M_{it} |$
  - Distance from prevailing midpoint M_{it} to trade price P_{it}
  - Actually a half-spread or one-way cost
  - Defined for a single (child) transaction
- Implementation shortfall
  - More relevant for a parent order (e.g., buy 1mm shares of IBM)
  - For buys, $IS_{it} = \bar{P} - M_{it}$
  - Distance (usually in bps) from decision-time price M_{it} to average trade price $\bar{P}$
  - Captures effect of driving prices up with sequences of buy orders

US large-cap trading costs have trended down



Source: spliced ITG research reports

…all during the rise of the machines

What caused the improvements?

- There is a straightforward Econ 101 story
  - More competition within and across exchanges
  - Scalable technology drives down costs
- But we can't be sure: correlation is not causality!
- Many other things have changed over the past 20 years
  - Various regulatory changes
  - Perhaps less private information now
- Can use market structure changes as instruments:
  - Example: Hendershott, Jones and Menkveld (2010 JF)
- But the gold standard for determining causal effects is **randomized controlled trials**

An example: 2007 repeal of short sale uptick rule

- Before 2005, NYSE short sales could only happen:
  - On an uptick (at a price higher than the last sale price)
  - Or on a zero-plus tick (at the same price as the previous transaction if the most recent price change was positive)

- Regulation SHO:
  - Adopted by the SEC in 2005.
  - Initiated a pilot program suspending the NYSE’s uptick rule and the Nasdaq’s analogous bid test.

- All Russell 3000 stocks ranked by market value; every third stock assigned to the pilot.

- Pilot continued into 2007.

- SEC decided to repeal all price tests
  - Announced June 13, 2007
  - Effective July 6, 2007

Empirical design

- Takes advantage of virtually random assignment

- Econometric approach: look before and after repeal

- Initial approach: treatment vs. control
  - Treatment group (non-pilot stocks) experiences the repeal
  - Control group (pilot stocks) free of the uptick rule throughout

- Implemented via a differences-in-differences regression:

  $$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 A_t + \beta_3 T_i A_t + \varepsilon_{it}$$

  where

  Y_{it} is the outcome variable for stock i at time t,

  $T_i = 1$ if stock i is in the treatment group, $T_i = 0$ otherwise

  $A_t = 1$ if date t is after treatment (after repeal), else $A_t = 0$

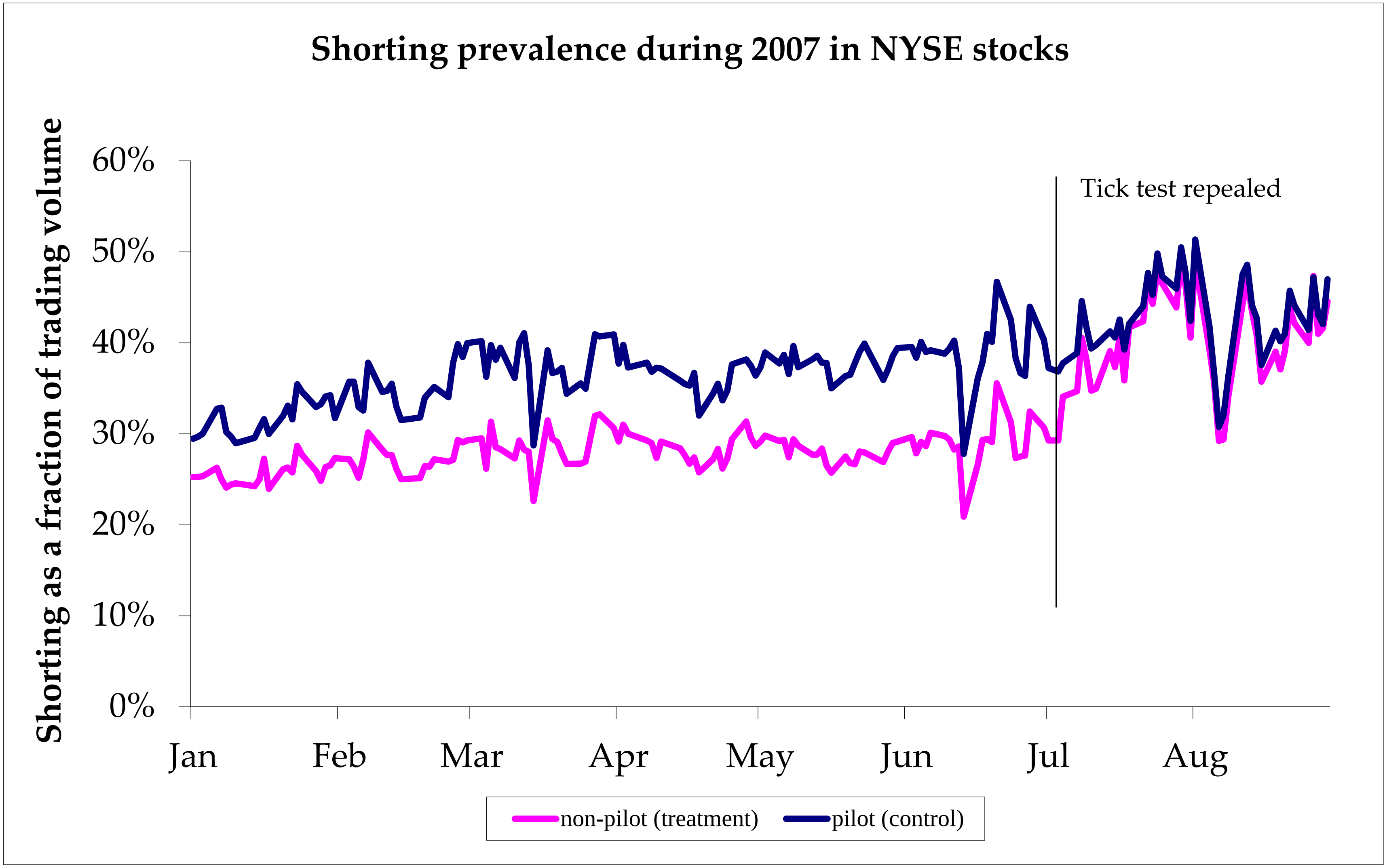
- The interaction term β_3 measures the average treatment effect.

Why the name?

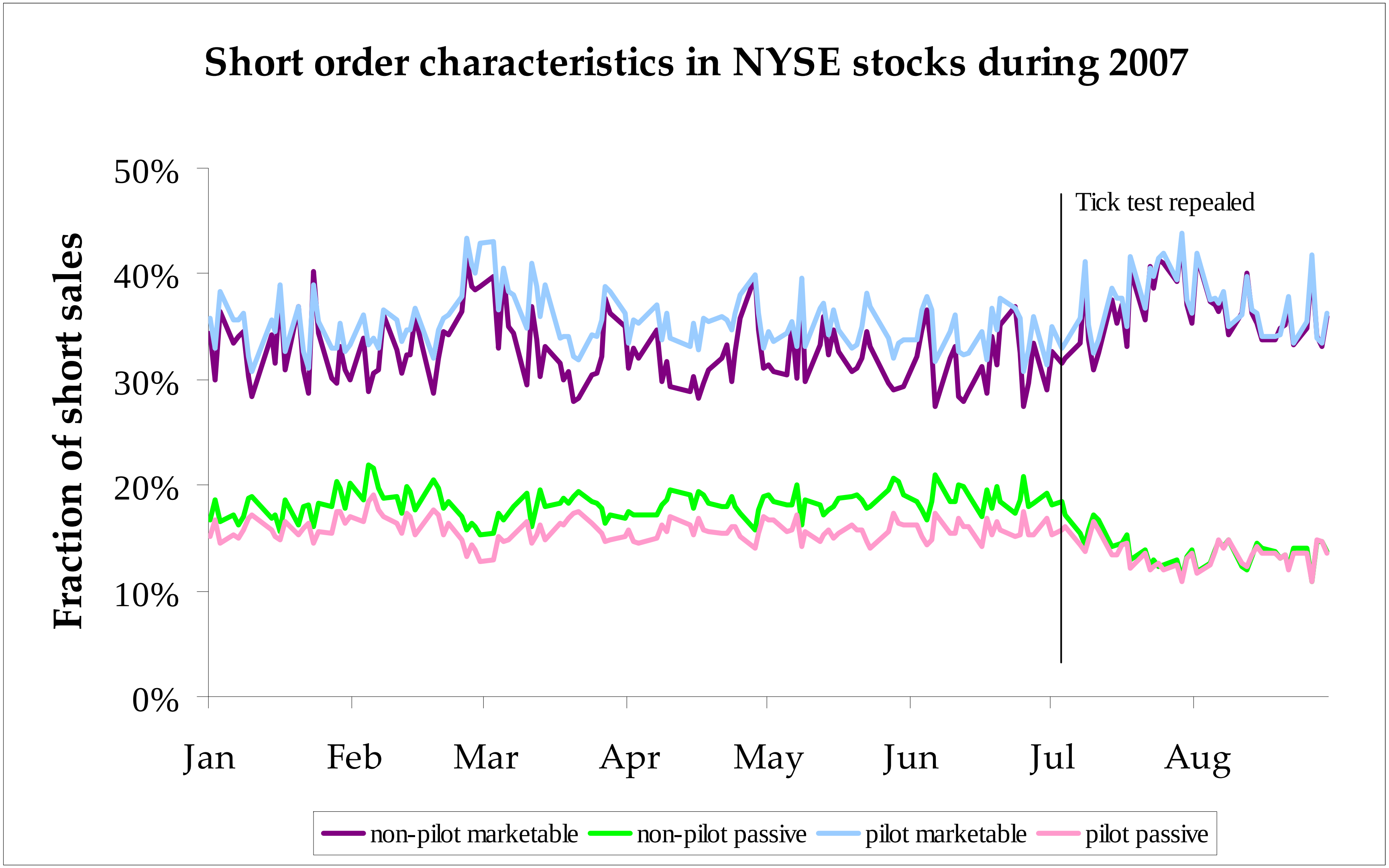
$$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 A_t + \beta_3 T_i A_t + \varepsilon_{it}$$

	Average Before Change	Average After Change	Difference
Treatment Group	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\Delta Y_{treatment} = \beta_2 + \beta_3$
Control Group	β_0	$\beta_0 + \beta_2$	$\Delta Y_{control} = \beta_2$
Difference			$\Delta\Delta Y = \beta_3$

More shorting since tick test repealed

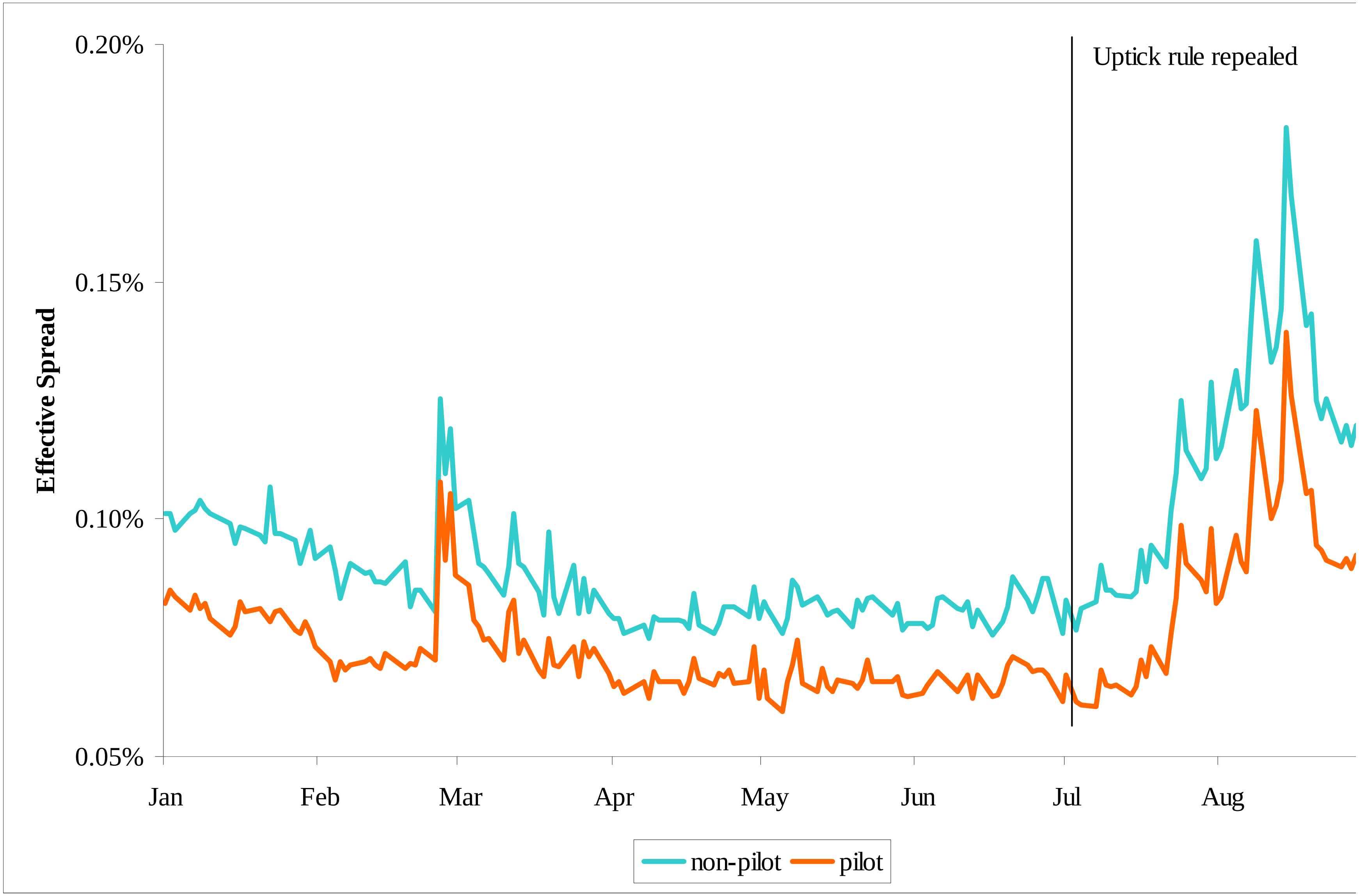


Short-sale orders become more aggressive



Passive short-sale orders are those placed at or above the prevailing ask price.

Repeal widens effective bid-ask spreads



The problem with this empirical design

- Doesn't work if there are treatment spillover effects.
- Spillovers mean control stocks are affected by the treatment too.
- Controls aren't actually controls.
- Not clear what the difference-in-difference approach measures.
- Seminal paper in econ: "Worms" (Miguel and Kremer, 2004)
  - Study randomized deworming treatments on Kenyan village children
  - But children in the control group also benefit via less transmission
  - So can't do simple treatment vs. control
- These spillovers are called *interference* in the statistics literature.

What's the problem with uptick repeal?

- Many short sale strategies are portfolio strategies

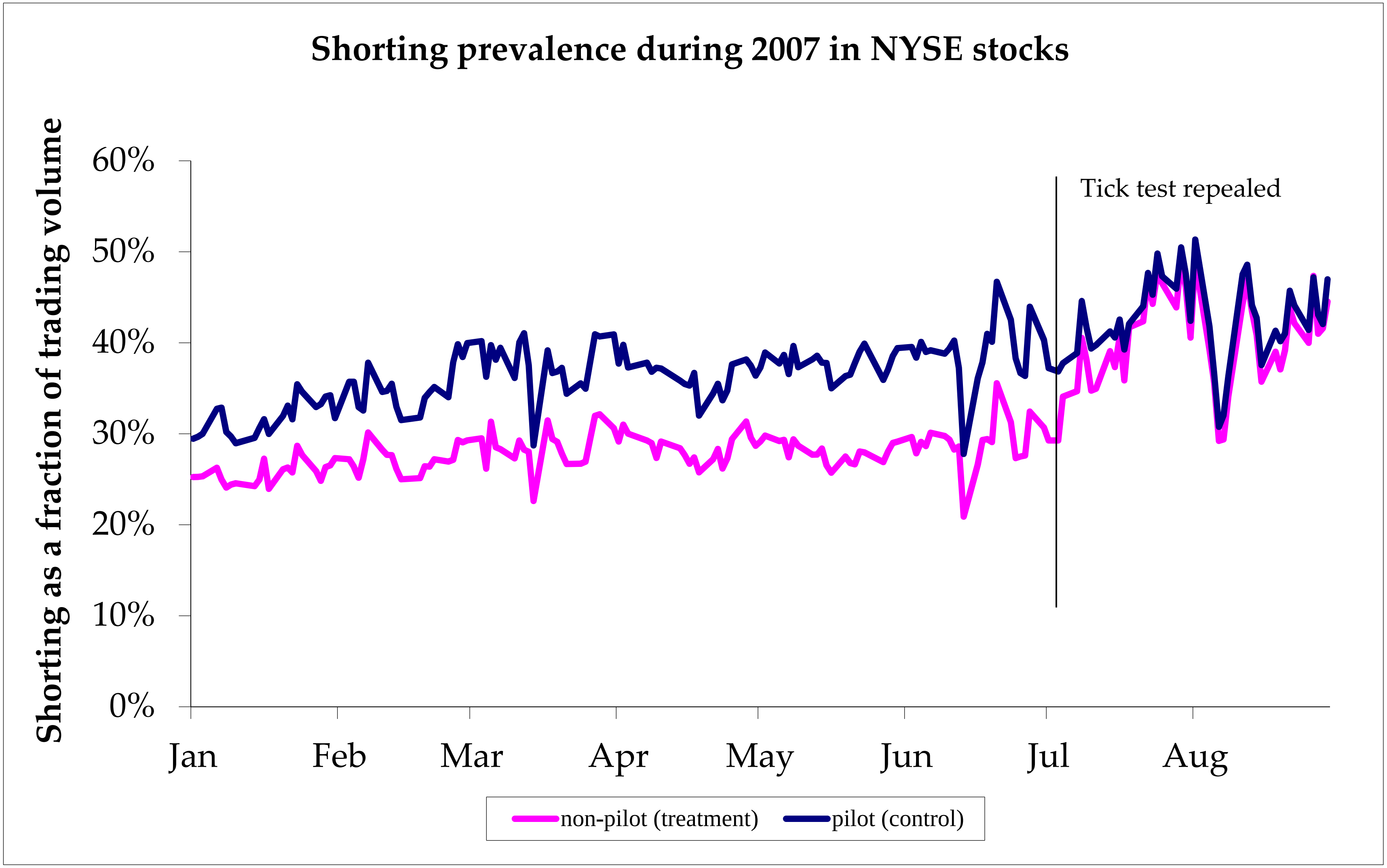
- Example: index arbitrage. If the index is cheap:
  - Buy futures or an index ETF
  - Simultaneously short all of the underlying stocks

- During the Reg SHO pilot, this strategy was hard to execute:
  - Only about 1/3 of S&P500 stocks exempt from the uptick rule
  - For all the rest, can't short without complying with the uptick rule
  - Introduced substantial risk into this strategy.

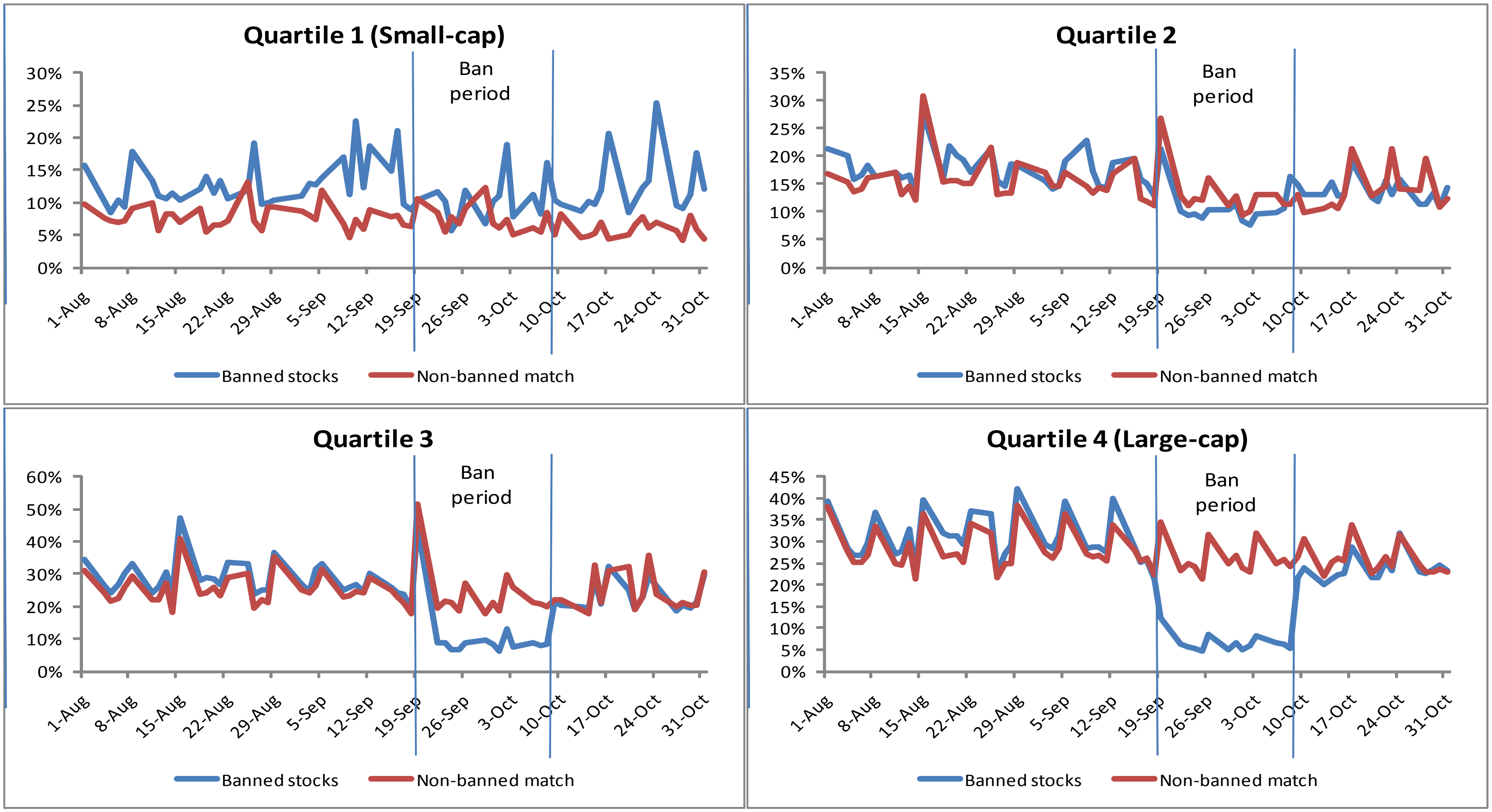
- After repeal, could short all stocks without this constraint
  - Would expect more shorting of lists of stocks
  - More shorting of pilot (control) stocks
  - Voila! Treatment spillover.

- Same is true for any list-based strategy (e.g., factors)

Revisiting the evidence



This is not always a problem: no evidence of spillovers during 2008 shorting ban



Cross-sectional mean of short sales as a percentage of trading volume (RELSS) for stocks on the original Sep 2008 SEC ban list with matched non-banned stocks.

Tackling spillovers methodologically

- Using notation from causal effects literature, $Y_i(z_i,\psi)$ is the potential outcome for firm i given:
  - its own treatment $z_i = \{0, 1\}$
  - ψ is the fraction of firms treated at random
  - We only observe one of these outcomes; the other is the unobserved counterfactual

- Overall treatment effect moving from treatment strategy ψ to strategy φ:

$$TE(\psi, \varphi) = \Sigma\ E[Y_i(1, \psi) - Y_i(0, \varphi)]$$

- This can be rewritten as:

$$TE(\psi, \varphi) = \Sigma\ E[\underbrace{Y_i(1, \psi) - Y_i(0,}_{\text{direct treatment effect}}\ \psi) + \underbrace{Y_i(0, \psi) - Y_i(0,}_{\text{indirect treatment effect}}\ \varphi)]$$

Tackling spillovers (cont'd.)

- A treatment strategy ψ is often compared to no treatment ($\varphi = 0$).
  - corresponds to the beginning of a regulatory pilot program.
- If the pilot is extended to all firms, treatment strategy changes from the original pilot fraction φ to $\psi = 1$.
- In biostatistics, other fractions make sense:
  - Vaccinating 75% vs. 50% of the population
- Statistical inference is easier if you have many different groups with only within-group spillovers.
  - Most stats papers discuss this case.
  - Example: "Worms" studies randomized trials in many villages.

But most regulatory pilots are one village

- Solution: identify off of differences-in-differences regression with controls:

  $$Y_{it} = \beta_0 + \beta_1 T_i + \beta_2 A_t + \beta_3 T_i A_t + \gamma X_{it} + \varepsilon_{it}$$

  where

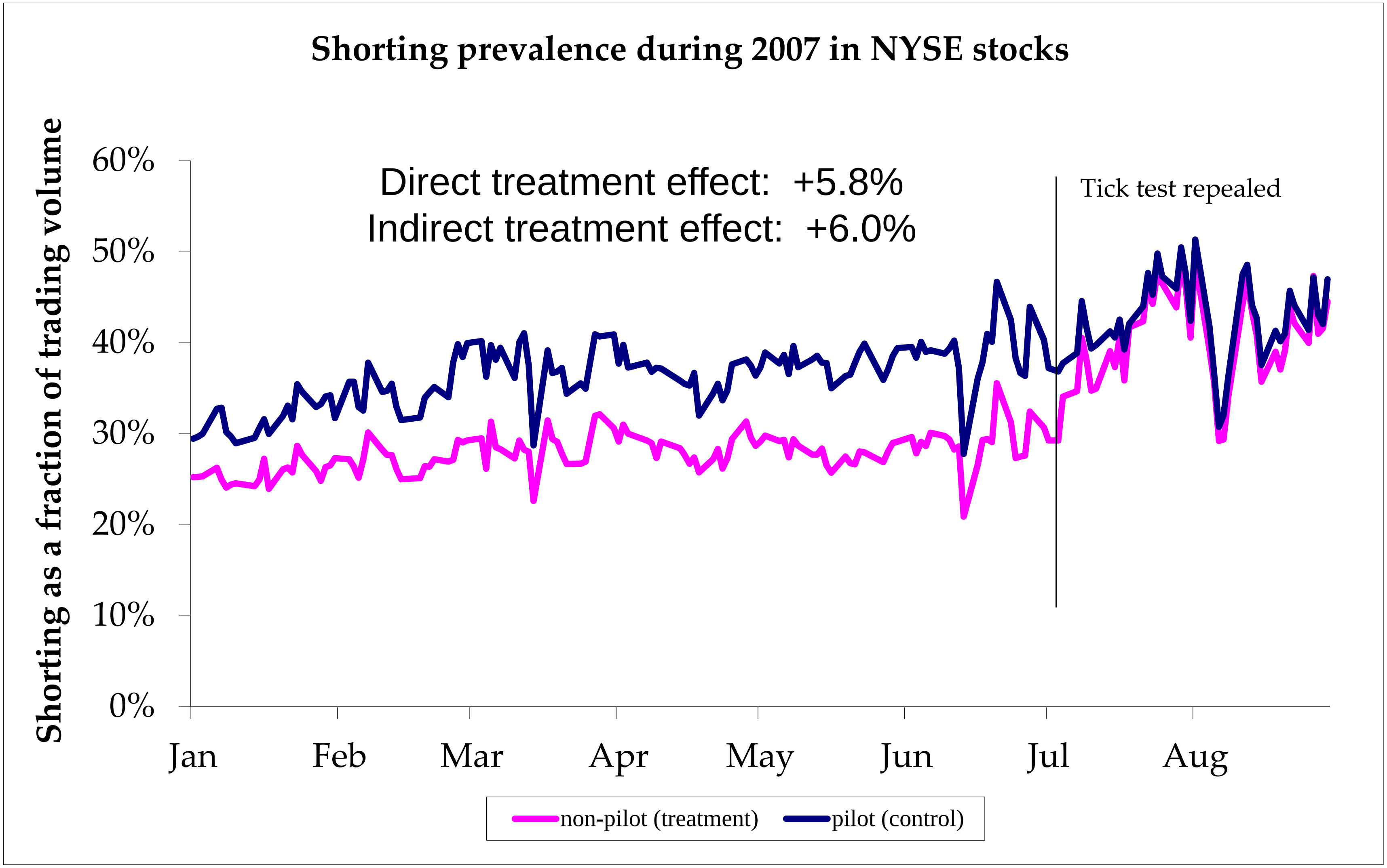
  Y_{it} is the outcome variable for stock i at time t,
  $T_i = 1$ if stock i is in the treatment group, $T_i = 0$ otherwise
  $A_t = 1$ if date t is after treatment (after repeal), else $A_t = 0$
  X_{it} is a vector of control variables

- The interaction term β_3 measures the direct treatment effect.

- β_2 measures the indirect treatment effect (the average change in control firm outcome from moving to new treatment strategy).

- Controls become quite important here.

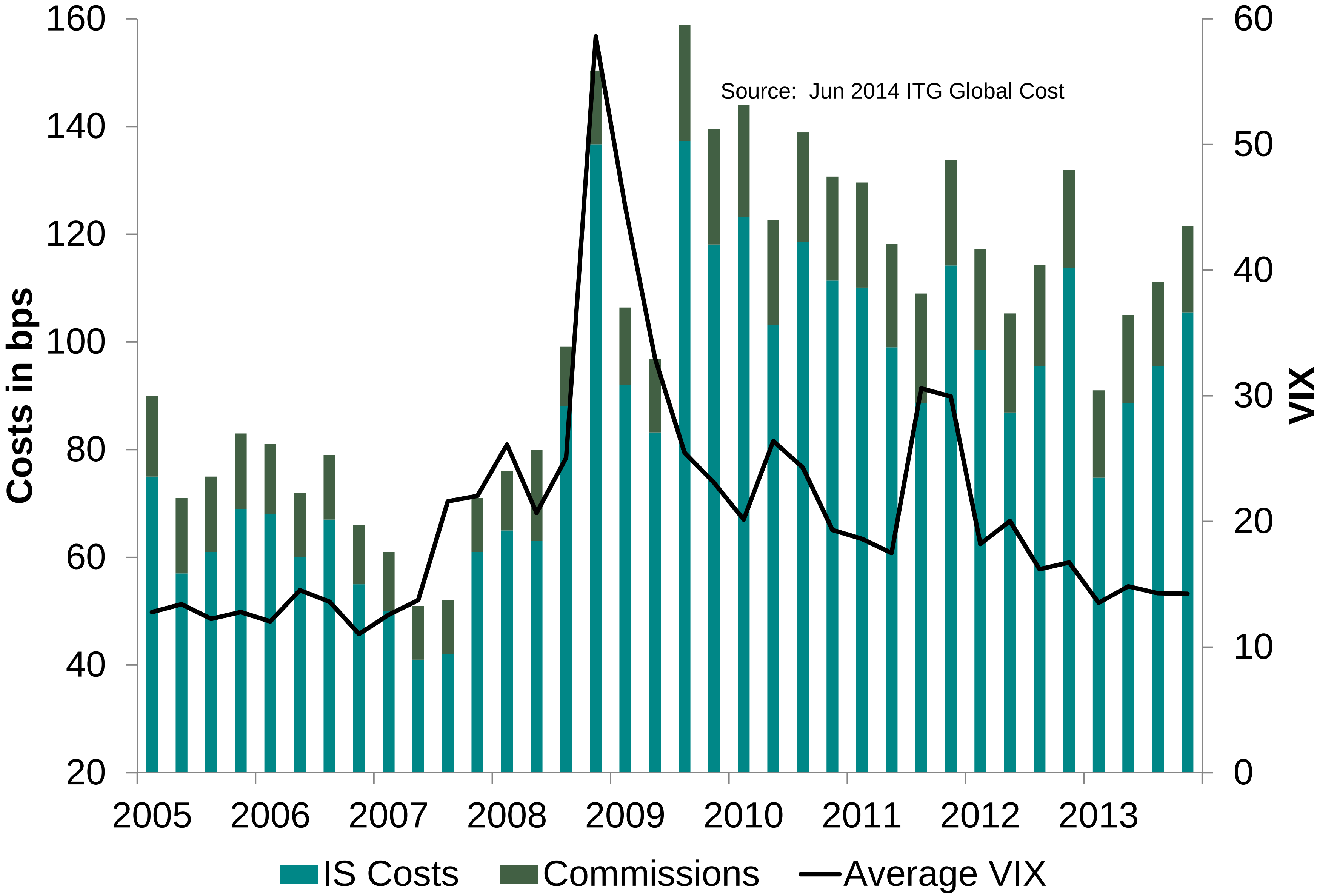
Indirect effect non-trivial for uptick repeal



What's HFT got to do with all this?

- Pilot designers need to think about potential spillovers.
- Currently in the U.S.: concern that current market structure is not ideal for small-cap firms.

But small-cap trading costs remain high



SEC plans a new pilot program for smaller-caps

- To be a pilot stock, must satisfy all of the following:
  - Market cap of $5 billion or less
  - Average daily volume (ADV) of 1 million shares or less
  - Share price of $2 or more.
- Pilot design: 1 control group and 3 test groups
  - Approximately 300 securities in each of the four buckets
- Test group 1:
  - Quoted in nickels ($0.05), no other restrictions
- Test group 2:
  - Quoted & traded in nickels OR at the mid-point of the NBBO.
  - Retail orders internalized only with price improvement of at least $0.005.
  - No price improvement required for trades off-exchange (e.g., dark pool).
- Test group 3 same as group 2 plus:
  - Trade-at requirement: off-exchange trades require significant price or size improvement.
  - Otherwise, must first execute against the full size of on-exchange, protected quotations at the NBBO before executing off-exchange.

Overall conclusions

- Equity market liquidity in large caps is clearly better than it was 10 years ago.
  - Competition and cost reduction are *probably* the cause
- Regulatory experiments have the potential to clearly identify causal effects.
  - Would be great if Europe could start to do them
  - Must think carefully about spillovers
  - Must design the experiment carefully to maximize info gained
- My predictions and pleas:
  - Due to the nature of information about small firms, small cap liquidity will always be lousy regardless of market structure
  - Tick size and trade-at will have close to zero effect
  - Trade-at should dramatically increase liquidity in large-cap stocks; let's try the pilot there!

For further reading

This talk incorporates elements from the following papers:

Ekkehart Boehmer, Charles M. Jones, and Xiaoyan Zhang (2013), "Shackling short sellers: the 2008 shorting ban," *Review of Financial Studies*, 26:1363-1400.

Ekkehart Boehmer, Charles M. Jones, and Xiaoyan Zhang (2014), "Unshackling short sellers: the repeal of the uptick rule," SSRN working paper.

Terrence Hendershott, Charles M. Jones, and Albert Menkveld (2010), "Does algorithmic trading improve liquidity?" Journal of Finance.

Terrence Hendershott, Charles M. Jones, and Albert Menkveld (2013), "Implementation shortfall and high-frequency price dynamics," Chapter 9 of *High Frequency Trading* (edited by Maureen O'Hara, Marcos López de Prado and David Easley), Risk Books.

Charles M. Jones (2013), "What do we know about high-frequency trading?" SSRN working paper.