Resiliency
A Dynamic View of Liquidity

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"Granted, the Board of Directors didn't think much of your proposal, but I think they'll be impressed by your resilience!"

What is Liquidity?

- Macro view:
  - Liquidity = money
- Micro view:
  - Liquidity = solvency at the firm level
  - **Liquidity = ease of trading securities**
- **Measuring Trading liquidity**
  - *Liquidity, like pornography, is easily recognized but not so easily defined*.

    O'Hara (1995), p. 215

Liquidity is Multi-dimensional

Market Liquidity

Garbade (1982), Kyle (1985), and Harris (2002) decompose liquidity into three dimensions.

First dimension: Spread

Spread is the ***cost*** dimension: how much does a trade cost?

- Extensively researched

Second dimension: Depth

Depth is the ***quantity*** dimension: how much can be traded at the current price?

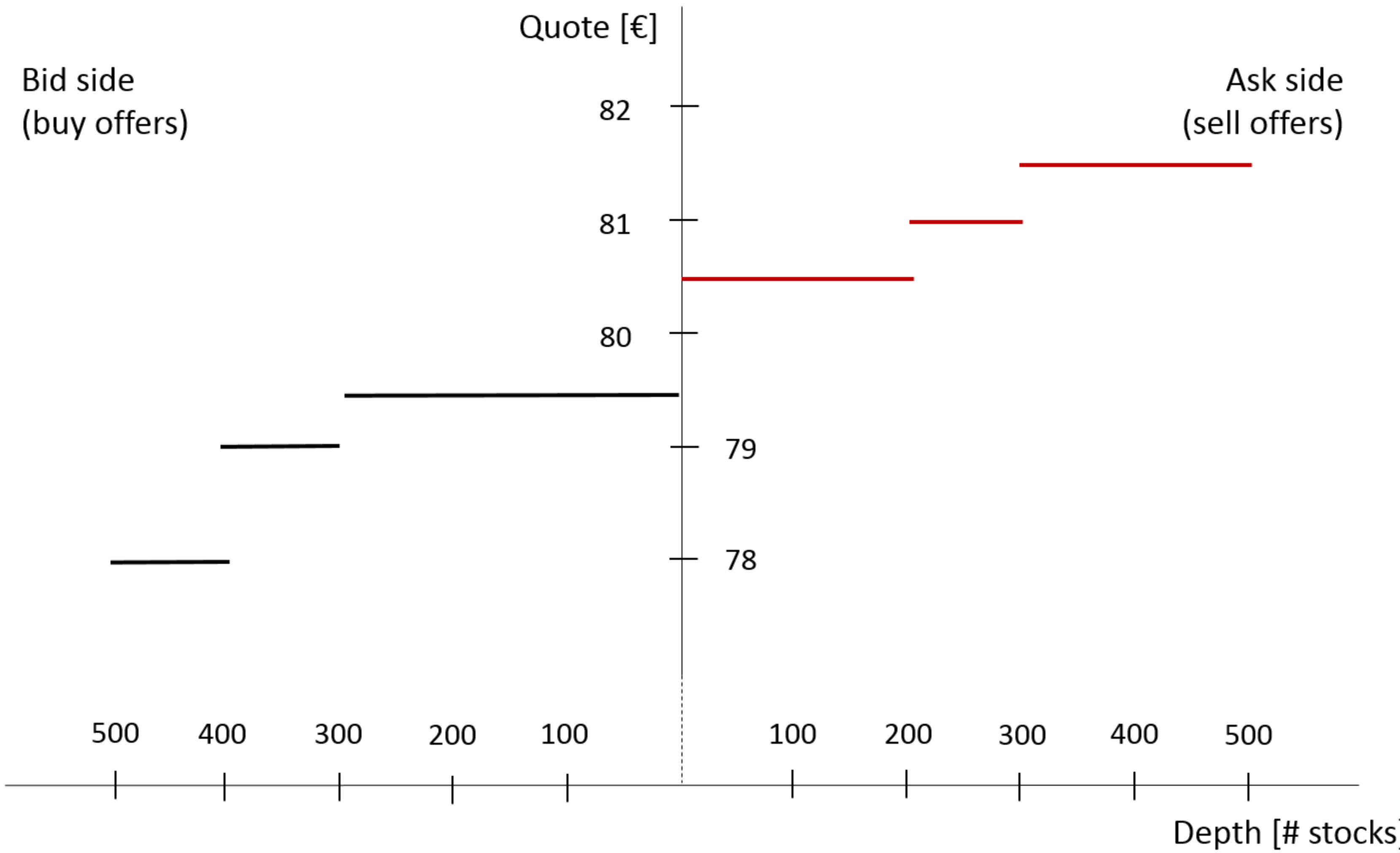
- Reasonably well researched.

Third dimension: Resiliency

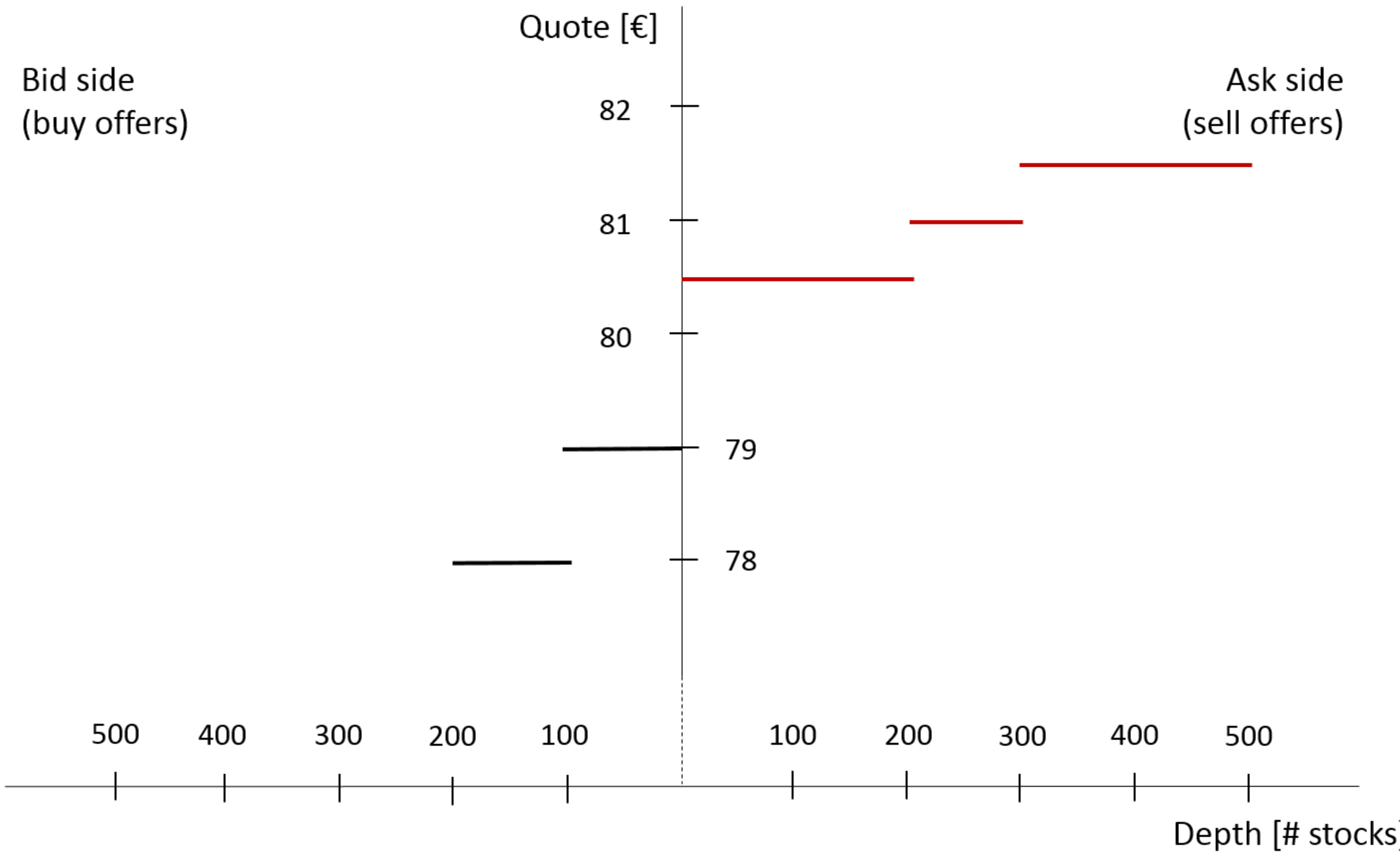
Resiliency is the ***time*** dimension: Characterizes the recovery of a market after a liquidity shock.

- Researched only to a very limited extent.
- We investigate resiliency in liquidity.

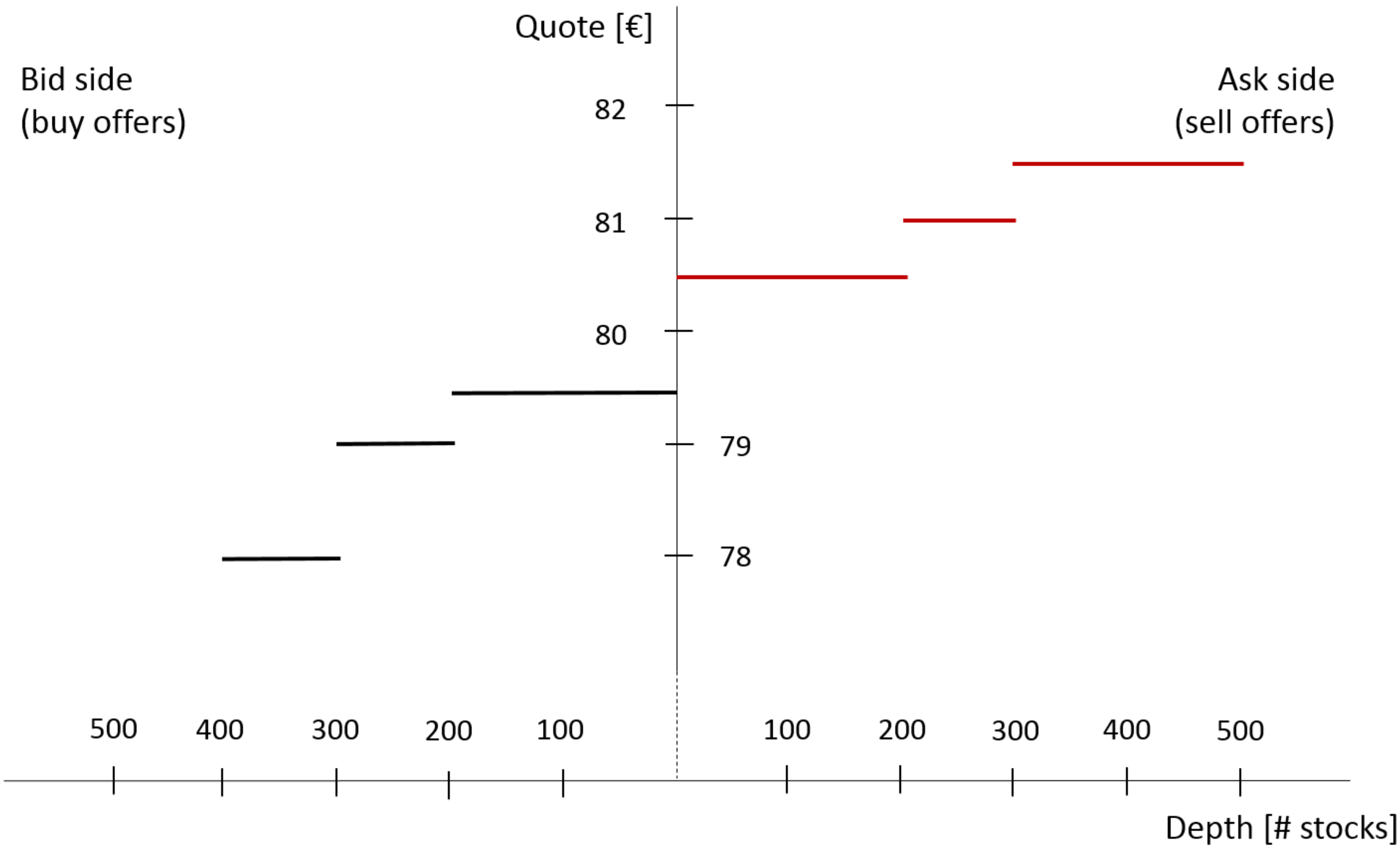
Resiliency in the limit order book I



Resiliency in the limit order book II



Resiliency in the limit order book III



What is Resiliency?

We define and empirically investigate measures of resiliency that represent the extent to which scarce liquidity gets replenished, or excess liquidity gets consumed, within a pre-specified time as a result of the competitive actions of value traders, dealers and other market participants.

Why is Resiliency Important?

- Exchanges around the world are increasingly organised as electronic order-driven markets.

- Electronic limit order markets are crucially dependent on the existence of adequate resiliency.

  - In dealer markets, market-makers can be contractually obliged to stand ready to buy and sell.

  - Limit order book markets depends *only* on limit orders for new liquidity. This raises the empirical issue of whether enough new liquidity is submitted to the book as liquidity gets consumed.

  - Resiliency is critical since it reflects the stability, or the fragility, associated with the ability of liquidity demanders to always reliably get immediate execution of their orders.

    - Particularly important in the algorithmic trading world.

Why is Resiliency Important?

- Arbitrageurs (large volume/small margin strategies) are essential for fair pricing and market integrity.
  - Resiliency determines volatility of trading costs and tradeable quantities.
  - High resiliency decreases risks and margins at which arbitrageurs trade.

- Institutional investors break up large trades into smaller blocks.
  - High resiliency speeds up execution of successive blocks.

Resiliency: Theoretical Models

- Foucault, Kadan and Kandel (2005): A model of a limit order book market with traders of different degrees of “impatience”. Equilibrium dynamics determined by proportion of patient traders and order arrival rate.
  - Conclude that *spread* resiliency increases as:
    - Proportion of patient traders increases.
    - Order arrival rate decreases.
    - Tick size increases.
    - And at the end of the trading day.
  - Model does ***not*** consider *depth resiliency.*
  - Model does **not** include any information-related considerations.

Resiliency: Extant Empirical Work

- Existing literature on ‘resiliency‘ focuses on extreme events.
  - Bhattacharya et al. (1998):
    - How large can shocks get before exchanges close down?
  - Coppejans et al. (2004), Degryse et al. (2005); Gomber et al. (2014):
    - How does liquidity react to very large trades?

- There is no general analysis of resiliency as the recovery after a liquidity shock.

This Paper....

- Framework for measuring resiliency.
- Descriptive analyses of resiliency: how resilient are electronic limit order books?
- Is resiliency a priced risk factor?
- What are the determinants of resiliency?
  - Test the Foucault, et al. (2005) hypotheses.
  - Test for the causal relevance of the competition across different trading venues, information-related risks, and algorithmic trading.

Data

- High frequency order-book snapshots of FTSE-100 stocks
  - Number of transactions, volumes and prices
  - Quoted depth and prices at best quotes and various levels
  - New orders (limit/market) and cancellations

- Why FTSE-100?
  - Electronic limit order book, 99.5% of all orders
  - Large cross-section (120 stocks)

- Observation interval July 2007 – September 2009
  - Long time series (514 trading days)
  - Calm and highly volatile market phases

Measuring Resiliency

Mean reversion model for the spread, or the depth of the order book at different ticks:

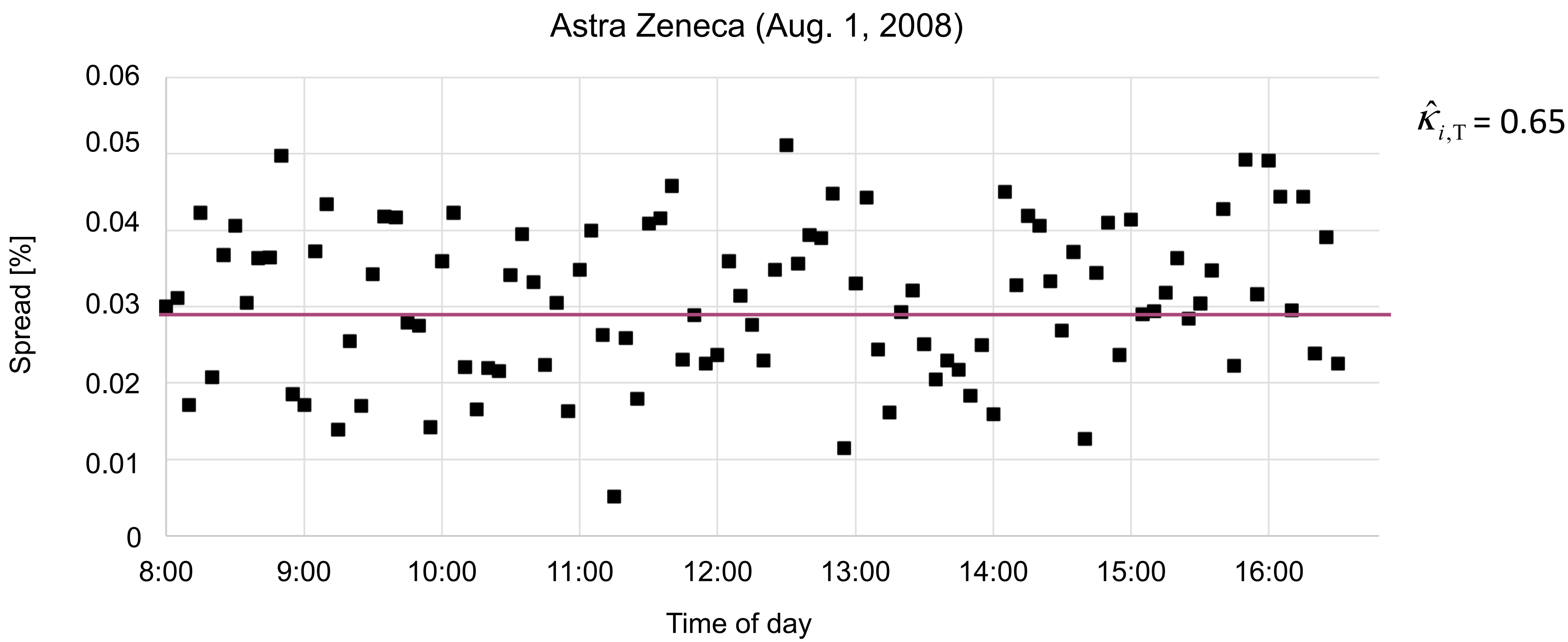
$$\Delta L_t = \kappa\left(\theta - L_{t-1}\right) + \varepsilon_t$$

κ, the mean reversion parameter, is resiliency

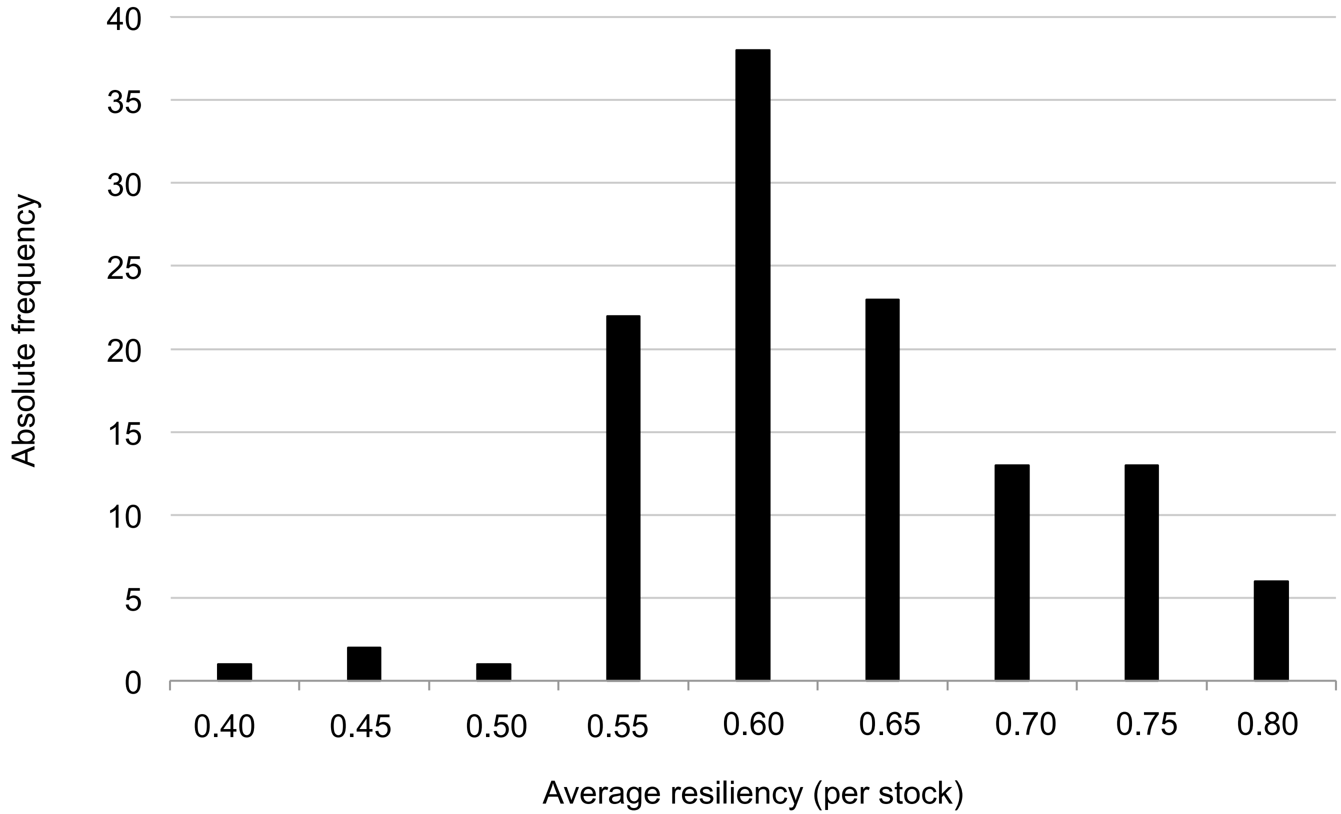
$$\Delta L_{i,t} = \alpha_i - \kappa_{i,t} L_{i,t-1} + \sum_{\tau=1}^{p} \gamma_\tau \Delta L_{i,t-\tau} + \varepsilon_{i,t}$$

How resilient is the limit order book?

- Estimation of model parameters for each stock *i* and trading day *T*
- $\hat{\kappa}_{i,\mathrm{T}}$ is a daily measure of the stock-specific resiliency



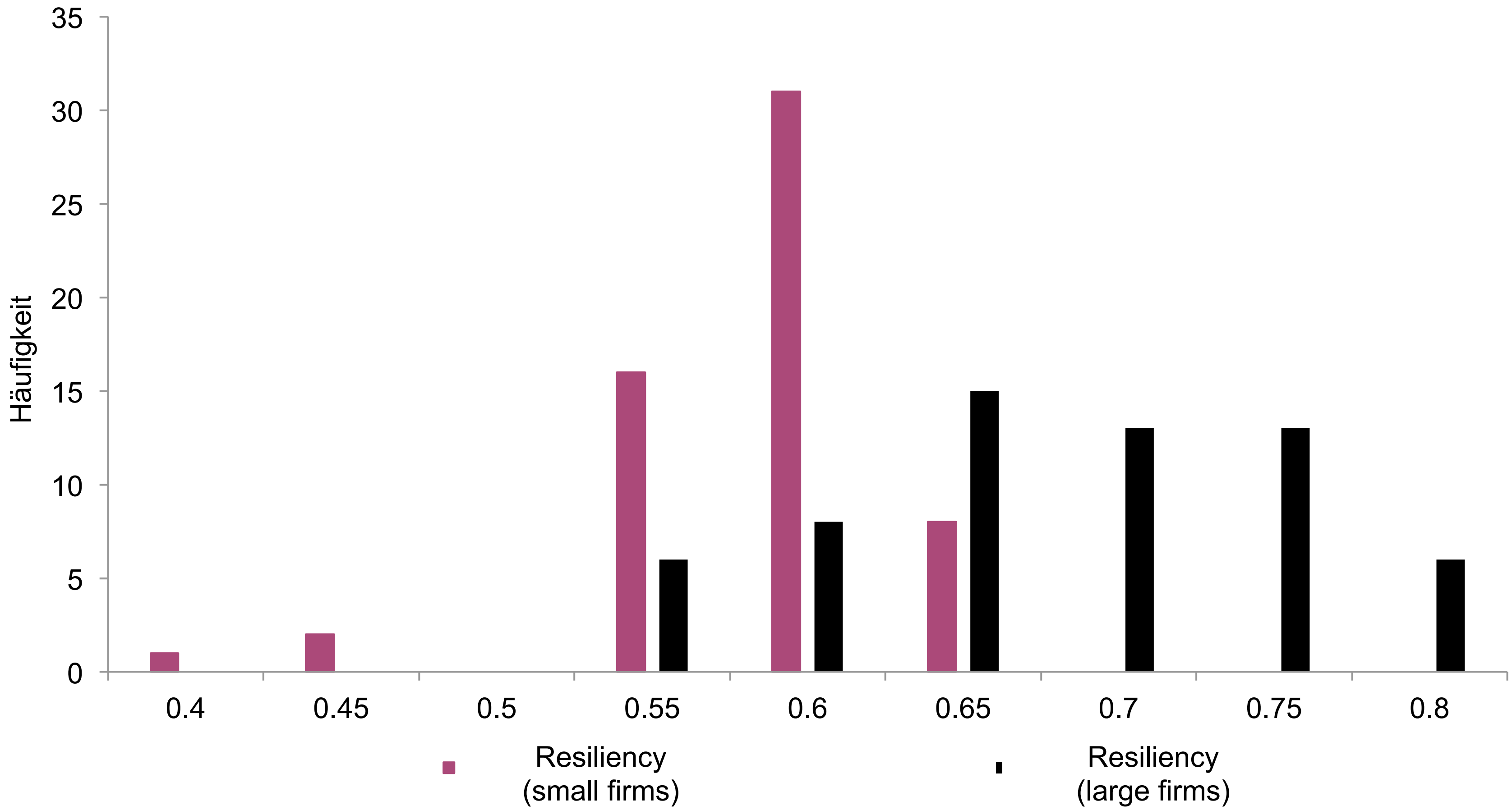
How resilient is the limit order book?



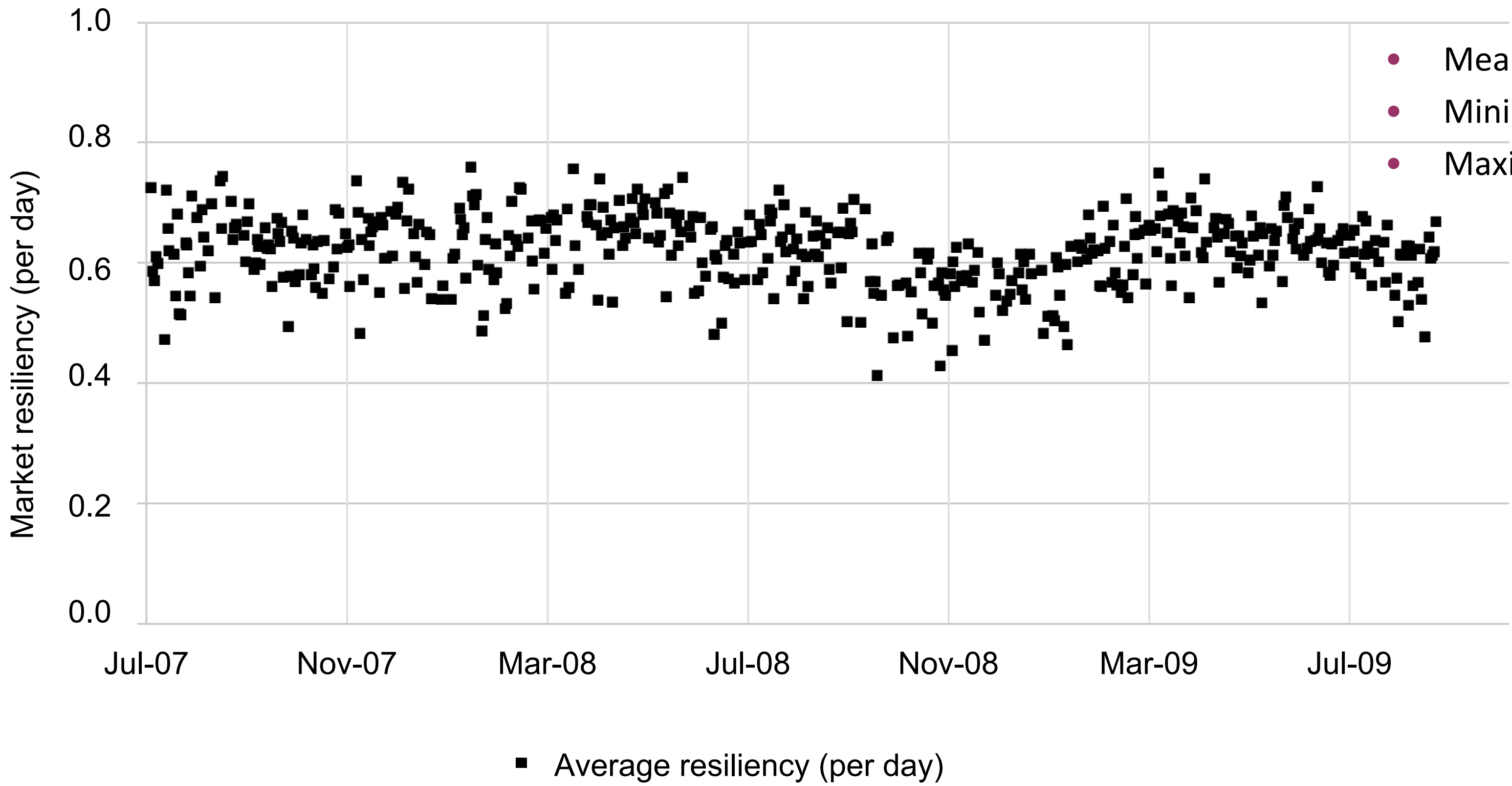
- Mean: 0.60
- Minimum: 0.39
- Maximum: 0.80

➢ Liquidity deviations have a half-life of 6 minutes

How resilient is the LOB?



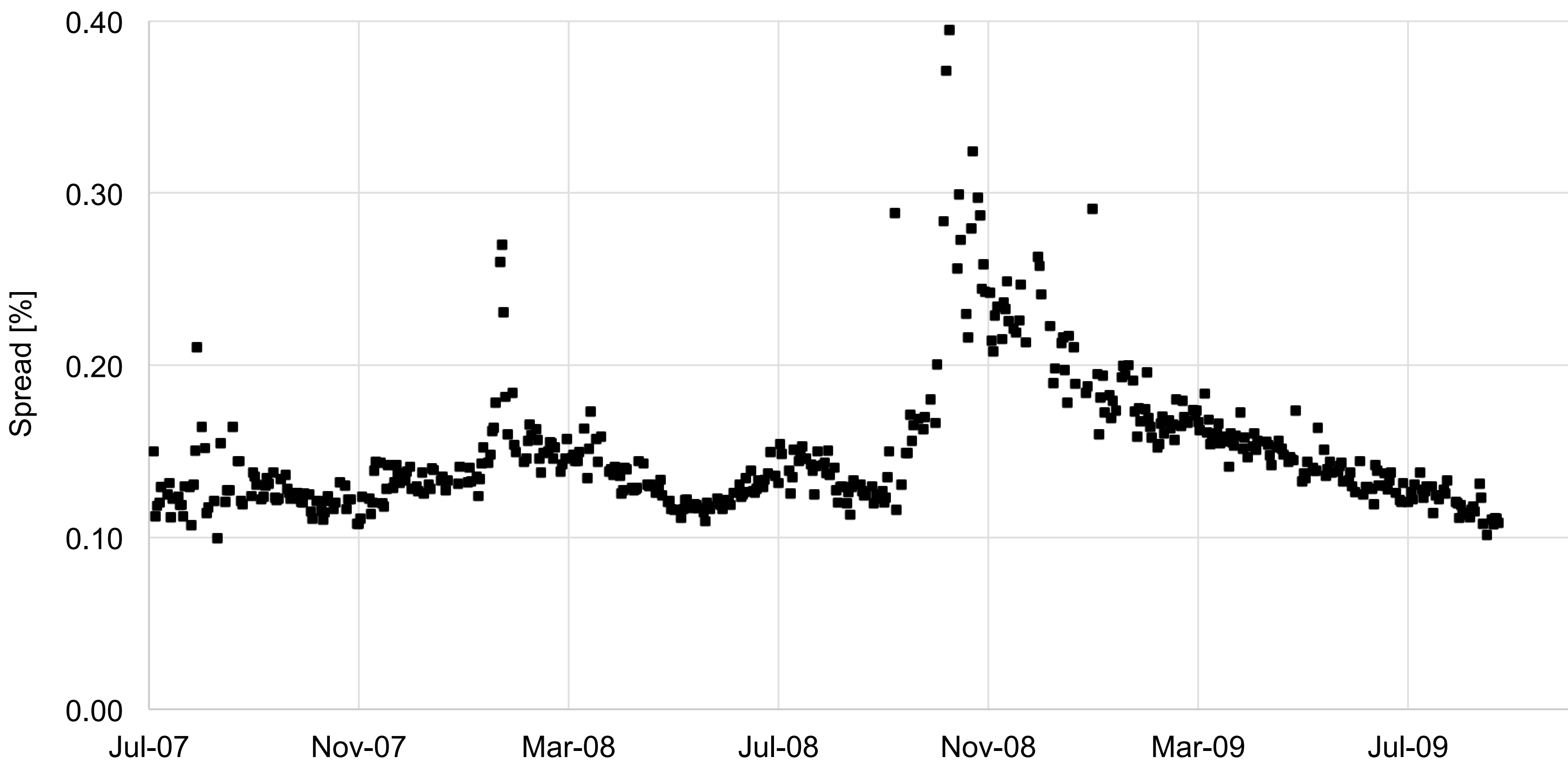
How resilient is the limit order book?



- Mean: 0.60
- Minimum: 0.41
- Maximum: 0.78

➢ Market resiliency is fairly stable over time

How stable is resiliency over time?



Is resiliency a priced risk factor?

Brennan/Subrahmanyam (1996) time-series approach

- Sort stocks into 6 portfolios based on three resiliency classifications and two size classifications.
- Compute equally-weighted monthly excess return
- Regress portfolio return on portfolio resiliency and control variables size, book-to-market, momentum (Gregory/Christidis 2013), market spread and depth

Is resiliency a priced risk factor?

Brennan/Subrahmanyam (1996) time-series approach

Panel A: Portfolios sorted on size and spread resiliency

	Daily return [%]		Monthly return [%]		Spread resiliency		Spread		Depth	
	Size large	Size small	Size large	Size small	Size large	Size small	Size large	Size small	Size large	Size small
Resiliency large	-0.1413	-0.0403	-1.1547	-0.3451	0.7259	0.5875	0.0970	0.1625	46,757.32	13,210.40
Resiliency medium	-0.0901	0.0120	-0.5607	0.2324	0.6483	0.5560	0.1185	0.1746	26,751.54	24,580.16
Resiliency small	-0.0723	0.0470	-0.3876	0.8437	0.5773	0.4931	0.1585	0.2752	20,537.63	9,040.62

Panel B: Portfolios sorted on size and depth resiliency

	Daily return [%]		Monthly return [%]		Spread resiliency		Spread		Depth	
	Size large	Size small	Size large	Size small	Size large	Size small	Size large	Size small	Size large	Size small
Resiliency large	-0.1926	-0.0487	-1.8994	-0.5389	0.6259	0.5680	0.1253	0.1706	40,311.74	26,486.11
Resiliency medium	-0.0909	-0.0317	-0.7750	-0.3154	0.5361	0.5221	0.1257	0.1816	27,559.84	18,658.16
Resiliency small	-0.0712	0.0221	-0.7145	1.4314	0.4936	0.4642	0.1215	0.2833	27,284.73	8,505.72

Is resiliency a priced risk factor?

Brennan/Subrahmanyam (1996) time-series approach

Panel A: Spread resiliency

	Constant	Resiliency	Spread	Depth	Market risk premium	SMB	HML	Adj. R^2
Daily returns	0.6912	-1.5020	-2.4684	-0.0019	6.9687	9.7866	4.7259	0.0144
	(2.4001)	(-2.2283)	(-4.5024)	(-0.6272)	(2.6072)	(2.5026)	(0.8974)	
Monthly returns	18.9761	-27.2376	-10.5153	0.0625	24.5419	91.1222	14.7559	0.1589
	(4.0008)	(-3.8168)	(-1.2903)	(1.1017)	(1.3432)	(3.3008)	(1.1028)	

Panel B: Depth resiliency

	Constant	Resiliency	Spread	Depth	Market risk premium	SMB	HML	Adj. R^2
Daily returns	1.0617	-1.1276	-2.3732	0.0051	6.0148	9.608	5.9167	0.0126
	(3.7882)	(-2.8197)	(-5.2244)	(1.8155)	(2.1622)	(2.3608)	(1.0814)	
Monthly returns	6.9443	-25.7215	-5.1173	-0.0323	25.6212	83.538	14.4085	0.1634
	(1.2166)	(-1.7056)	(-0.6936)	(-0.5745)	(1.3093)	(2.7882)	(1.0086)	

Commonality in Resiliency
Chordia, et al. (2000) approach

	$MR^{S/D}$	% Sign.	Adj. R^2
Spread resiliency	0.8106 (4.99)	95.83	6.63
Depth resiliency	0.7899 (4.51)	93.33	5.53

Strong evidence of commonality in resiliency

Is resiliency a priced risk factor?

Cross-sectional approach

- Estimate the exposure of a stock's resiliency to market resiliency.
- Also estimate the exposure of a stock's spread (depth) to the market spread (depth), and the exposure of a stock's return to the Fama-French factors.
- Run a cross-sectional regression of average stock returns on these factor exposures, including systematic resiliency.

	Constant	$\hat{\beta}_i^{S/D}$	$\hat{\beta}_i^{spread}$	$\hat{\beta}_i^{depth}$	$\hat{\beta}_i^{market}$	$\hat{\beta}_i^{SMB}$	$\hat{\beta}_i^{HML}$	Adj. R^2
Spread resiliency	-0.1057	0.0060	-0.0219	0.0146	0.2092	-0.1473	-0.4505	0.0156
	(-1.5431)	(1.9090)	(-1.0950)	(1.6268)	(2.3019)	(-0.4876)	(-1.1510)	
Depth resiliency	-0.1016	0.0013	-0.0218	0.0147	0.2001	-0.1527	-0.4429	0.0154
	(-1.3506)	(1.7100)	(-1.6880)	(1.5444)	(2.8830)	(-0.5154)	(-1.1180)	

Determinants of resiliency

- Hypotheses: proportion of patient traders, order arrival rate, and tick size affect resiliency (Foucault et al.)

$$\hat{\kappa}_{i,\mathrm{T}} = \beta_0 + \beta_1 \cdot PPT_{i,\mathrm{T}} + \beta_2 \cdot OAR_{i,\mathrm{T}} + \beta_3 \cdot TS_{i,\mathrm{T}} + \beta_4 \cdot CV_{i,\mathrm{T}} + \zeta_{i,\mathrm{T}}$$

	Constant	*PPT*	*OAR*	*TS*	*Size*	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2972	0.0796	-0.0491	0.0233	0.1251	0.8766	14.69
	(5.65)	(4.27)	(-6.90)	(2.97)	(13.34)	(29.83)	
Depth resiliency	0.3339	0.0802	-0.0537	0.0180	0.0383	0.9198	9.95
	(11.10)	(5.18)	(-11.45)	(1.92)	(3.94)	(37.68)	

- Clear support for the Foucault et al. (2005) model

Determinants of resiliency
Information Risk

- Hypothesis: Information risk makes supplying liquidity more risky, leading to lower resiliency

$$\hat{\kappa}_{i,\mathrm{T}} = \beta_0 + \beta_1 \cdot PPT_{i,\mathrm{T}} + \beta_2 \cdot OAR_{i,\mathrm{T}} + \beta_3 \cdot TS_{i,\mathrm{T}} + \beta_4 \cdot Info_{i,\mathrm{T}} + \beta_5 \cdot CV_{i,\mathrm{T}} + \zeta_{i,\mathrm{T}}$$

Determinants of resiliency
Information risk reduces resiliency

Panel A: Information proxied by volatility

	Constant	PPT	OAR	TS	Size	Vola	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2751	0.0763	-0.0472	0.0251	0.1247	-0.0118	0.8919	14.82
	(5.12)	(4.12)	(-6.48)	(3.11)	(13.31)	(-2.82)	(23.00)	
Depth resiliency	0.3389	0.0790	-0.0516	0.0200	0.0380	-0.0169	0.8880	10.28
	(11.06)	(5.14)	(-11.69)	(2.24)	(4.11)	(-2.97)	(30.19)	

Panel B: Information proxied by imbalance in executed orders

	Constant	PPT	OAR	TS	Size	OI	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.3924	0.0716	-0.0358	0.0259	0.1375	-0.0015	-0.0023	12.59
	(4.74)	(2.78)	(-3.11)	(2.66)	(11.51)	(-2.75)	(-1.96)	
Depth resiliency	0.4416	0.0869	-0.0420	0.0149	0.0284	-0.0313	-0.0086	7.07
	(8.64)	(3.16)	(-6.71)	(2.45)	(2.72)	(-4.47)	(-5.59)	

Determinants of resiliency
Algorithmic trading

- Hypothesis: Algorithmic traders (AT) act as liquidity suppliers, leading to higher resiliency when more AT are present

$$\hat{\kappa}_{i,\mathrm{T}} = \beta_0 + \beta_1 \cdot PPT_{i,\mathrm{T}} + \beta_2 \cdot OAR_{i,\mathrm{T}} + \beta_3 \cdot TS_{i,\mathrm{T}} + \beta_4 \cdot Vola_{i,\mathrm{T}} + \beta_5 \cdot OI_{i,\mathrm{T}}$$

$$+ \beta_6 \cdot AT_{i,\mathrm{T}} + \beta_7 \cdot CV_{i,\mathrm{T}} + \zeta_{i,\mathrm{T}}$$

Determinants of resiliency
Algorithmic trading

Panel C: Algorithmic trading, volatility, and size

	Constant	PPT	OAR	TS	Size	Vola	OI	Algo	VolaAlgo	SizeAlgo	$MR^{S/D}$	Adj. R^2
Spread resiliency	0.2527	0.0383	-0.0560	0.0221	0.0980	-0.0013	-0.0063	0.0158	-0.0024	0.0299	0.8926	15.13
	(4.95)	(2.35)	(-7.22)	(2.65)	(6.06)	(-1.82)	(-1.80)	(2.20)	(-1.95)	(2.72)	(29.07)	
Depth resiliency	0.3282	0.0198	-0.0713	0.0148	0.0876	-0.0031	-0.0068	0.0688	-0.0052	0.0218	0.7924	11.58
	(14.05)	(2.93)	(-13.31)	(0.70)	(5.21)	(-2.56)	(-3.29)	(10.83)	(-3.29)	(2.22)	(7.91)	

Algorithmic trading increases resiliency, but not in volatile periods, and particularly for large stocks.

Establishing causality

- Competition for order execution, information risks and algo trading may arguably depend on liquidity – e.g., resiliency.

- Our regressions thus far are tests of association, not tests of causality

- First pass: Granger causality test

- Second pass: Instrumental variables‘ tests

Establishing causality Granger Causality tests

Panel A:	Spread resiliency			
	$l_{2,1}$ (if significant, explanatory variable Granger-causes resiliency)	% Sign.	$l_{3,1}$ (if significant, resiliency Granger-causes explanatory variable)	% Sign.
PPT	0.0444	77%	0.0008	18%
OAR	-0.0249	98%	-0.0192	14%
Vola	-0.1757	92%	-0.0801	25%
OI	-0.0487	90%	0.0035	13%
Algo	0.0725	74%	-0.0012	13%

Panel B:	Depth resiliency			
	$l_{2,1}$ (if significant, explanatory variable Granger-causes resiliency)	% Sign.	$l_{3,1}$ (if significant, resiliency Granger-causes explanatory variable)	% Sign.
PPT	0.069	83%	0.0226	14%
OAR	-0.0297	81%	0.0056	6%
Vola	-0.4196	36%	0.0731	17%
OI	-0.1506	63%	-0.0027	3%
Algo	0.4737	75%	0.0043	5%

Establishing causality – Instrumental Variables Competition for order execution: PPT & OAR

- PPT (proportion of patient traders) and for OAR (order arrival rate) are both related to the competition for order execution at LSE.

- Chi-X started full coverage, of FTSE-100 stocks on July 13, 2007, Turquoise on September 8, and BATS on November 7, 2008.

- We therefore use a count variable indicating the number of venues with full coverage as an instrument for *PPT* and *OAR*.

Establishing causality – Instrumental Variables

Information risks: Volatility and Order Imbalances

- Recent empirical studies have shown that Google Search Intensity can help to predict investor demand for information (Da, Engelberg, and Gao, 2011) and stock volatility (Dimpfl and Jank, 2015).
- We therefore use the volume of the firm searched for a given week as an instrument for *Vola* and *OI*.

Establishing causality – Instrumental Variables Algo trading

- During our observation interval, we observe four decreases in latency: to 11 milliseconds on October 10, 2007, to 6 milliseconds on September 1, 2008, to 5 milliseconds on May 2, 2009, and to 3.7 milliseconds on July 20, 2009.
- We define a count variable indicating the number of latency changes and use this as an instrument for *Algo*.

Establishing causality – Instrumental Variables

Panel A: First-stage regression

	PPT	OAR	Vola	OI	Algo
Constant	-0.9747 (-25.7347)	4.3314 (25.4710)	0.1245 (8.6390)	0.0969 (11.3860)	2.5429 (8.5900)
Instrument	0.1265 (6.5145)	-0.3003 (3.4430)	0.0648 (2.5200)	0.0711 (4.0890)	0.8219 (7.0440)
Adj. R^2	0.0853	0.0243	0.0228	0.1169	0.0940

Panel B: Second-stage regression

	PPT	OAR	Vola	OI	Algo
Spread resiliency	0.1653 (4.3140)	-0.1971 (-8.5440)	0.6162 (2.7780)	0.8262 (8.7830)	0.0148 (6.1040)
Depth resiliency	0.3860 (10.3010)	-0.2875 (-5.0630)	0.2356 (2.6130)	0.1885 (2.1760)	0.0261 (10.6580)

All coefficient estimates have the hypothesized coefficient sign and remain statistically significant.
We therefore conclude that our results are not due to endogeneity or to an omitted variables issue.

Robustness

- Estimation of resiliency parameters
  - Time-of-day dummies
  - **Asymmetric model**
  - Resiliency deeper in the order book
- Additional controls
  - Short-selling ban for financial stocks
  - Stock prices / returns
- Specific time periods
  - **Financial crisis period**

Robustness I – Consumption vs. replenishment

- Up to now: symmetric model for mean reversion
- Liquidity replenishment could, however, differ from liquidity consumption

$$\Delta L_{i,t} = \kappa_{down,i}\left(\theta_i - L_{i,t-1}\right) + 1_{L_{i,t-1}<\theta_i}\,\kappa_{\mathrm{up},i}\left(\theta_i - L_{i,t-1}\right) + \varepsilon_{i,t}$$

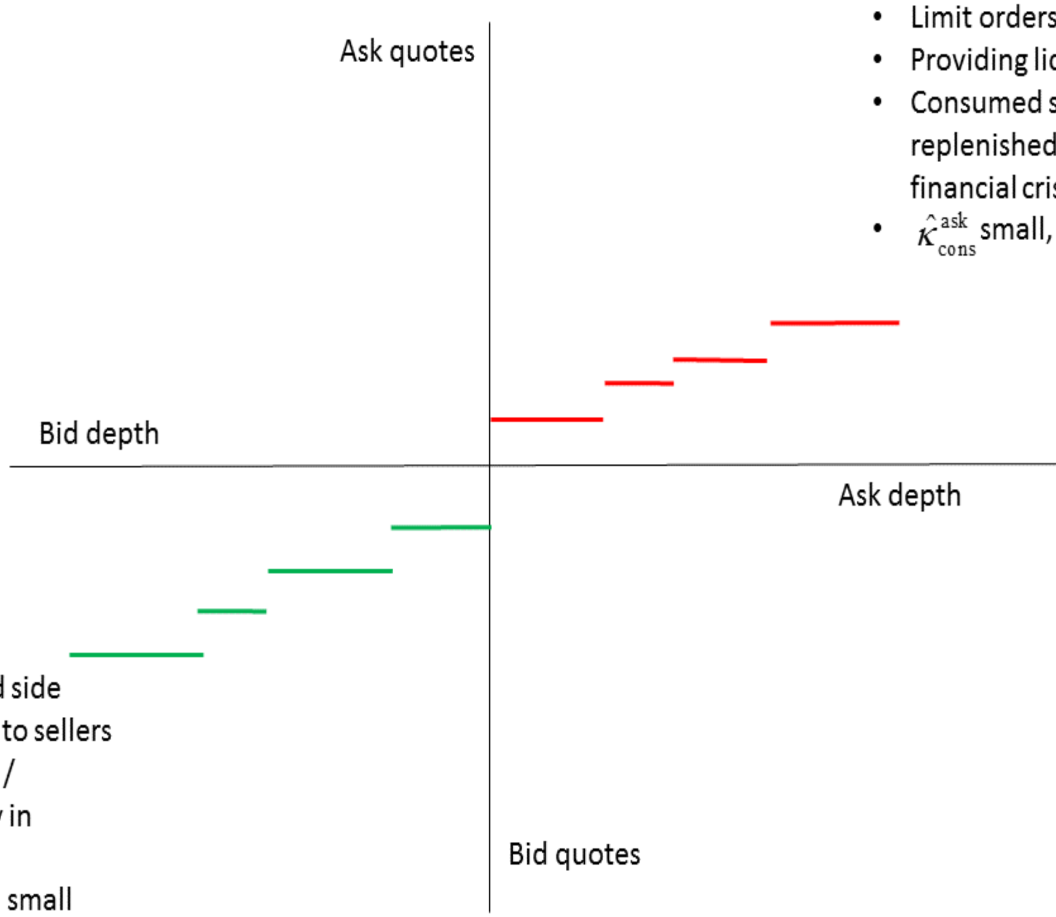
κ_{cons} κ_{replen}

	Mean	Median	Min	Max
κ_{cons}	0.6833	0.6671	0.0530	0.9583
κ_{replen}	0.6328	0.6274	0.2358	0.8634

- Consumption resiliency is larger, but differences are not significant
- Determinants remain unaffected

Robustness II – Financial crisis hypotheses

- Limit orders on ask side
- Providing liquidity to buyers
- Consumed slowly / replenished quickly in financial crisis
- $\hat{\kappa}^{ask}_{cons}$ small, $\hat{\kappa}^{ask}_{replen}$ large



- Limit orders on bid side
- Providing liquidity to sellers
- Consumed quickly / replenished slowly in financial crisis
- $\hat{\kappa}^{bid}_{cons}$ large, $\hat{\kappa}^{bid}_{replen}$ small

Robustness II – Financial crisis results

- Mean estimates

Bid depth resiliency: cons. large, repl. small				Ask depth resiliency: cons. small, repl. large			
Consumption		Replenishment		Consumption		Replenishment	
Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis
0.72	0.60	0.66	0.68	0.60	0.65	0.72	0.69

- Loadings on market resiliency (mean estimate)

Bid depth resiliency				Ask depth resiliency			
Consumption		Replenishment		Consumption		Replenishment	
Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis	Crisis	Non-crisis
0.69	0.77	0.92	0.04	0.76	0.73	0.91	0.07

Robustness III – Resiliency at higher levels

- Resiliency is measured at best quotes
- These are subject to frequent cancellations
- Estimate resiliency at tick 3 and tick 5

	Mean	Median	Min	Max
Tick 1	0.6033	0.5951	0.3874	0.7980
Tick 3	0.5231	0.5141	0.2943	0.6776
Tick 5	0.4613	0.4626	0.2671	0.5853

- Resiliency is higher at best quotes
- Determinants remain unaffected

Summary and Conclusions

- Electronic limit order books offer high and stable resiliency.
- (Lack of) resiliency is a priced risk factor.
- Resiliency is high when:
  - competition for execution is high,
  - information risks are small,
  - algorithmic trading is high, but not when volatility is high.
- Results are robust for both consumption and replenishment resiliency, across different time-periods, and when measured at different ticks.