Drivers and Effects of Stock Market Fragmentation – Insights on SME Stocks

Jens Lausen, Benjamin Clapham, Peter Gomber, Micha Bender

Symposium on Market Fragmentation in Europe

Stockholm – May 4, 2022

Agenda

1. Motivation
2. Drivers of Stock Market Fragmentation
3. Fragmentation and Market Quality
4. Conclusion & Policy Implications

Agenda

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Motivation and Research Background I

- **Increased fragmentation** of European securities markets after MiFID I
  → Competition for investors' order flow among incumbent exchanges and alternative trading venues

- Effects on stock market quality:

Theory	vs.	Empirical Evidence

• Market fragmentation **avoids monopolistic positions** of trading venues that result in **high trading costs** (Economides, 1996)
 	
• Fragmentation is **harmful**
  • if market participants have **incomplete information** about all available orders
  • if traders are **unable to communicate** across different liquidity pools quickly and cheaply (Mendelson, 1987; Garbade and Silber, 1979; Pagano, 1989)
		• **No negative effect** of fragmentation on market quality
		
		• Fragmentation even **benefits liquidity provision** (e.g., O'Hara and Ye, 2011; Gresse, 2017)
		
		• **Technological developments** (e.g., HFT, SOR) **eliminate frictions** leading to a virtually integrated marketplace (Gresse, 2017; O'Hara and Ye, 2011; Riordan et al., 2011)

Motivation and Research Background II

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Shortcomings of the existing literature:

- Most empirical studies **focus on large caps and highly liquid stocks** and do not consider smaller stocks, especially SME stocks
- Smaller stocks are **traded less frequently** and the **activity of HFTs**, who connect different liquidity pools via multi-venue market making and arbitrage trading, is **considerably lower** (e.g., Menkveld, 2013, 2016)
- Market observers claim **negative effects of fragmentation for small stocks** and that **SME issuers** "should have the right to choose where to be traded to **avoid fragmentation of already low liquidity**" (FESE, 2019)

→ It is not clear whether the **positive effects** of market fragmentation are also **valid for SME stocks and other less liquid stocks** and whether **regulatory action** is needed

Research Objectives

We analyze the impact of market fragmentation on SME stocks in two important dimensions:

1. To understand **when** and **why stocks fragment**, we investigate:
   - the **drivers** of stock-specific initial fragmentation events
   - how these fragmentation events **affect market quality** of the respective stocks [skipped today]

2. To obtain a granular picture of the **impact of fragmentation on market quality**, we analyze:
   - a **wide range of market quality parameters** for stocks of **different size** and **liquidity classes**

Agenda

1. Motivation
2. Drivers of Stock Market Fragmentation
3. Fragmentation and Market Quality
4. Conclusion & Policy Implications

Data Set

- **Quarterly observations** of **1300 stocks** that have been traded on one of the largest European trading venues (LSE, Euronext Paris, and Xetra) in the period of **Q1/2009 to Q4/2019**

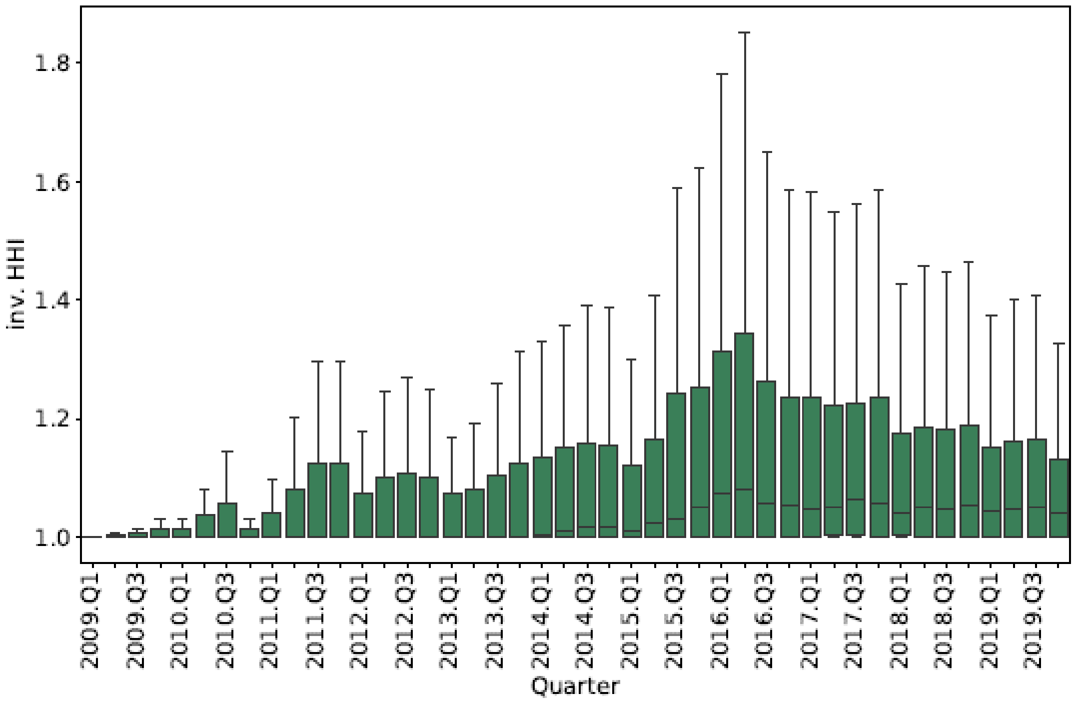
- We retrieve **market shares** and **volumes traded** for the **main market and relevant alternative venues** (Aquis, Cboe CXE, Cboe BXE, and Turquoise) from **Fidessa** on a **per stock basis**

- We enrich the data set with **prices**, **volatility**, **market cap**, and **main market relative spreads** from **Refinitiv Datastream**

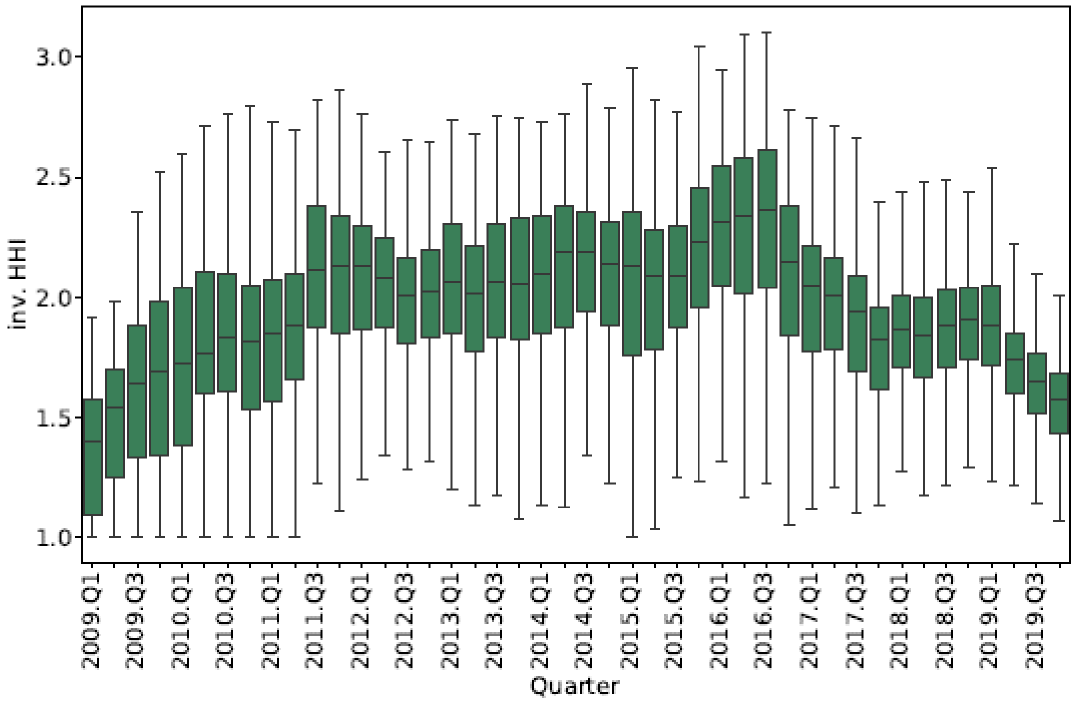
- We measure **fragmentation** using the **inverse of the Herfindahl index**: $inv.HHi_{i,t} = \frac{1}{\sum_j s_{j_{i,t}}^2}$

- We define **SME stocks** as stocks that have a **market cap lower than one billion euro** and differentiate **between different liquidity classes** based on the number of trades according to the European tick size regime
  - **10**: [0, 10), **80**: [10, 80), **600**: [80, 600), **2000**: [600,2000), **9000**: [2000, 9000), **inf**: $\geq$ 9000

Fragmentation Levels of SME and non-SME stocks



(a) SME stocks



(b) Non-SME stocks

Stock Characteristics and Market Fragmentation

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Market Cap

Mcap Terciles	SME stocks Observations	inv. HHI	Euro-Volume	Mcap	Non-SME stocks Observations	inv. HHI	Euro-Volume	Mcap
Largest	8904	1.28	47.85	544.70	5925	2.04	2146.19	27100.11
Medium	8244	1.07	9.20	170.60	5430	1.95	575.81	3892.20
Smallest	8240	1.01	1.05	37.52	5431	1.68	189.86	1334.87

Trading Activity

Liquidity Classes	SME stocks Observations	inv. HHI	Euro-Volume	Mcap	Non-SME stocks Observations	inv. HHI	Euro-Volume	Mcap
10	6538	1.01	1.41	105.87	240	1.02	26.26	3116.94
80	9942	1.04	5.50	179.57	449	1.04	11.65	3425.02
600	6827	1.20	26.03	377.15	1362	1.31	70.14	1530.06
2000	1717	1.58	96.88	599.08	3319	1.71	127.28	2198.97
9000	363	1.77	231.52	821.48	7290	2.06	597.61	5585.38
inf	-	-	-	-	4126	2.09	2803.02	31640.31

→ Descriptively, the level of **fragmentation strongly differs for SME and non-SME stocks**

→ Also, fragmentation significantly **varies for different levels of market cap and trading activity**

Methodology

Heckman Correction Model:

- Test whether there is a selection regarding stocks that fragment
- We follow O'Hara and Ye (2011) and conduct the first stage of the Heckman correction model (Heckman, 1979) by estimating the following probit model:

$$Z_i = W_i \gamma + u_i$$

- Z_i is a binary variable (1 if stock *i* is fragmented, 0 otherwise)
- W_i is a vector of variables explaining market fragmentation, i.e., log(mcap) and log(euro-volume) and dummy variables for the membership in the different liquidity classes
- The estimate γ is used to determine the inverse Mills Ratio: $\hat{\lambda}_i = \varphi(Z_i \hat{\gamma}) / \Phi(Z_i \hat{\gamma})$
- If the t-statistic indicates that $\widehat{\lambda_i}$ is significant, a selection is present

OLS Regression Model:

- To not only account for the likelihood, but also the level of fragmentation

$$inv.HHI_i = \beta_1 \log(mcap_i) + \beta_2 \log(eurovolume_i) + \epsilon_i$$

Drivers of Stock-Specific Initial Fragmentation Events

	(1)			(2)	
	probit			**OLS**	
Dependent Variable	Z		Dependent Variable	inv. HHI	
Variables	Estimate	p-Value	Variables	Estimate	p-Value
log(mcap)	0.17	0.00	log(mcap)	0.09	0.00
log(euro-volume)	0.23	0.00	log(euro-volume)	0.05	0.00
liquidity class 10	-4.67	0.00			
liquidity class 80	-4.15	0.00			
liquidity class 600	-3.49	0.00			
liquidity class 2000	-3.38	0.00			
liquidity class 9000	-3.14	0.00			
liquidity class inf	-1.03	0.97			
inv. Mills ratio	358.12	0.00	Adj. R^2	0.96	
Observations	40884		Observations	40884	

→ Market cap and trading activity significantly **influence both likelihood and level of fragmentation**

Agenda

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Data Set

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

- Intraday order book and trade data of **868 stocks** traded on the **major European trading venues** Euronext Paris, LSE, and Xetra as well as the **alternative trading venues** Aquis, Cboe CXE, Cboe BXE, and Turquoise from **BMLL**
- Market quality measures are based on **consolidated order book information** of all available venues using **one minute order book snapshots**
- Observation period: June 2017 (Feb. 2019 for Xetra) to Sep. 2020
- We aggregate all measures by taking the median for each trading day and enrich the data set with **market cap data from Refinitiv Datastream**
- As before, we determine the **liquidity class** of a stock based on the **average number of trades per day** according to the European tick size regime:
    - **10**: [0, 10), **80**: [10, 80), **600**: [80, 600), **2000**: [600,2000), **9000**: [2000, 9000), **inf**: $\geq$ 9000

Descriptive Statistics

		Liquidity classes					
		10	80	600	2000	9000	inf
# stocks		51	164	198	137	219	99
average share of SME stocks		94.53%	94.07%	83.88%	34.35%	2.59%	0.11%
inv. HHI	mean						
	median						
price	mean						
	median						
volatility	mean						
	median						
mcap	mean						
	median						
relative spread	mean						
	median						
euro-volume	mean						
	median						
depth(L1)	mean						
	median						
depth(L1)-imbalance	mean						
	median						
depth(L10)	mean						
	median						
depth(L10)-imbalance	mean						
	median						
midpoint dispersion	mean						
	median						

Descriptive Statistics

		Liquidity classes 10	80	600	2000	9000	inf
# stocks		51	164	198	137	219	99
average share of SME stocks		94.53%	94.07%	83.88%	34.35%	2.59%	0.11%
inv. HHI	mean	1.02	1.06	1.21	1.61	1.79	1.78
	median	1.00	1.00	1.13	1.56	1.75	1.75
price	mean						
	median						
volatility	mean						
	median						
mcap	mean						
	median						
relative spread	mean						
	median						
euro-volume	mean						
	median						
depth(L1)	mean						
	median						
depth(L1)-imbalance	mean						
	median						
depth(L10)	mean						
	median						
depth(L10)-imbalance	mean						
	median						
midpoint dispersion	mean						
	median						

Descriptive Statistics

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

		Liquidity classes					
		10	80	600	2000	9000	inf
# stocks		51	164	198	137	219	99
average share of SME stocks		94.53%	94.07%	83.88%	34.35%	2.59%	0.11%
inv. HHI	mean	1.02	1.06	1.21	1.61	1.79	1.78
	median	1.00	1.00	1.13	1.56	1.75	1.75
price	mean	42.59	39.55	21.99	31.86	33.45	52.65
	median	12.20	8.14	6.70	6.78	15.04	27.21
volatility	mean	0.33	0.25	0.15	0.18	0.18	0.26
	median	0.04	0.05	0.05	0.04	0.07	0.12
mcap	mean	216.08	352.58	575.24	2038.18	5995.12	37726.40
	median	86.28	165.36	414.13	1149.57	4205.99	25764.00
relative spread	mean	390.89	150.65	66.42	22.74	9.72	3.97
	median	236.09	106.10	47.21	17.86	7.87	3.55
euro-volume	mean	0.16	0.64	4.97	30.66	192.87	1248.88
	median	0.02	0.25	2.46	20.57	140.70	963.89
depth(L1)	mean	0.54	0.79	0.27	0.25	0.51	1.22
	median	0.07	0.07	0.09	0.17	0.37	0.87
depth(L1)-imbalance	mean	0.45	0.49	0.44	0.37	0.34	0.36
	median	0.42	0.48	0.42	0.36	0.34	0.36
depth(L10)	mean	1.95	2.28	3.10	4.04	8.93	24.78
	median	0.72	1.03	1.85	2.99	6.95	20.57
depth(L10)-imbalance	mean	0.32	0.23	0.18	0.12	0.09	0.09
	median	0.27	0.19	0.15	0.10	0.09	0.08
midpoint dispersion	mean	212.43	59.72	62.42	19.14	5.74	2.23
	median	0.00	0.00	35.24	10.07	3.83	1.64

Methodology

Matched-Pairs Analysis:

- Following Davies and Kim (2009), we **match stocks within each liquidity class** to their nearest neighbor based on market cap, price, relative spread, and euro-volume in the pre-event quarter
- We then obtain the differences for each variable in our data set and estimate the following regression model:

$$\Delta Y_{i,t} = \beta_1(\Delta inv.\ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$$

- ΔY captures the difference between the respective stock and its match in relative spreads, $\Delta inv. HHI$ is the difference of fragmentation levels and $\boldsymbol{X}$ is a vector of control variables including differences for log trading volume, volatility, inverse of stock price and log market cap
- We derive the results using fixed effects estimators, include stock and quarter fixed effects and apply double clustered SE estimation for the clusters stock and day

Results of the Matched-Pairs Analysis

ΔY	Liquidity classes 10	80	600	2000	9000	inf
relative spread	0.08	**10.71**	**-3.09**	**-1.593**	**-0.2543**	**-0.14**
	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
depth(L1)	-0.0016	**-0.0053**	**0.0199**	**0.0327**	**0.0335**	**0.1756**
	(0.88)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
depth(L1)-imbalance	-0.0265	0.0046	**-0.0057**	**-0.0046**	-0.0001	0.0043
	(0.34)	(0.56)	(0.09)	(0.04)	(0.95)	(0.14)
depth(L10)	**0.1633**	**0.0859**	**0.1343**	**0.2892**	-0.1261	0.6876
	(0.05)	(0.01)	(0.01)	(0.00)	(0.36)	(0.39)
depth(L10)-imbalance	**0.0433**	-0.0024	**-0.0060**	**-0.0077**	0.0002	**0.0046**
	(0.06)	(0.70)	(0.07)	(0.00)	(0.86)	(0.00)
midpoint dispersion	0.0001	**0.0026**	**0.0004**	**0.0001**	**-0.0001**	**-0.000014**
	(0.11)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Observations	16894	65488	83252	56409	86337	40279

Note: p-values in parenthesis, bold coefficients indicate significance at the 10%-level.

- Fragmentation has a **positive effect on market quality** of **highly liquid** and **actively traded stocks** in terms of relative spreads, depth, and order imbalance
- Fragmentation has **no effect** (liquidity class 10) or even a **negative effect** (liquidity class 80) **on market quality of less actively traded stocks**

Results of the Matched-Pairs Analysis (continued)

	Liquidity classes					
ΔY	10	80	600	2000	9000	inf
relative spread	0.08	**10.71**	**-3.09**	**-1.593**	**-0.2543**	**-0.14**
	(0.99)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)
depth(L1)	-0.0016	**-0.0053**	**0.0199**	**0.0327**	**0.0335**	**0.1756**
	(0.88)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
depth(L1)-imbalance	-0.0265	0.0046	**-0.0057**	**-0.0046**	-0.0001	0.0043
	(0.34)	(0.56)	(0.09)	(0.04)	(0.95)	(0.14)
depth(L10)	**0.1633**	**0.0859**	**0.1343**	**0.2892**	-0.1261	0.6876
	(0.05)	(0.01)	(0.01)	(0.00)	(0.36)	(0.39)
depth(L10)-imbalance	**0.0433**	-0.0024	**-0.0060**	**-0.0077**	0.0002	**0.0046**
	(0.06)	(0.70)	(0.07)	(0.00)	(0.86)	(0.00)
midpoint dispersion	0.0001	**0.0026**	**0.0004**	**0.0001**	**-0.0001**	**-0.000014**
	(0.11)	(0.00)	(0.01)	(0.02)	(0.00)	(0.00)
Observations	16894	65488	83252	56409	86337	40279

Note: p-values in parenthesis, bold coefficients indicate significance at the 10%-level.

- The impact of fragmentation on market quality follows a **hockey stick curve**:
  - no impact for stocks with lowest liquidity
  - negative impact for less liquid stocks and
  - positive effects for stocks with higher liquidity
- There is a **liquidity related threshold** (liquidity class 600) that determines when fragmentation becomes beneficial for stock market quality

Agenda

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

1. Motivation
2. Drivers of Stock Market Fragmentation
3. Fragmentation and Market Quality
4. Conclusion & Policy Implications

Conclusion

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

This study provides two major results:

1. **Market fragmentation** is **not exogenous**, but rather driven by stock-specific characteristics, particularly **market cap** and **trading activity**

2. **The impact of fragmentation** on market quality also **depends on market cap and trading activity of a stock**:

   → The impact of fragmentation on market quality shows a **hockey stick effect**

   → There are **liquidity-related thresholds** where relevant levels of fragmentation emerge and where fragmentation becomes beneficial for market quality

→ Implications?

Policy Implications I

- In general, **fragmentation is beneficial for stock markets** (as also shown in other studies)

  → Fragmentation leads to an **increase in liquidity** in terms of spread and quoted volumes

  → Consequently, competition between venues not only decreases transaction fees and fosters innovation but also **decreases implicit transaction costs**

- Nevertheless, industry participants are worried about negative consequences of market fragmentation for SME and other less liquid stocks and lobby for regulatory action:

  "To address [the negative impact of fragmentation], an **SME issuer** […] should have the right to **choose where to be traded to avoid fragmentation** of already low liquidity, i.e. to limit the trading of its stock outside its primary market" (FESE, 2019)

→ **Is such a regulation necessary/meaningful?**

Policy Implications II

- Our results show that there is **no one-size-fits-all solution** as not all SMEs are impacted equally:
  - A lot of SME and other infrequently traded stocks experience **no negative effect** of market fragmentation because they **only marginally fragment**
  - Yet, if they do fragment, the **effect initially is negative** but becomes **positive with increasing trading activity**
  - The effect of fragmentation on SME stocks is case-specific and **dependent on their activity level**

→ A **regulation allowing SME issuers to prevent** their stock from **trading on alternative venues** does **not necessarily increase market efficiency** and the conditions of SMEs for going and being public

→ Rather, regulators and market operators should create an **ecosystem which enables stocks to quickly attract liquidity** to reach the tipping point where fragmentation improves market quality (e.g., with the help of liquidity provider programs)

Thank you for your attention!

References

- Davies and Kim (2009). Using matched samples to test for differences in trade execution costs. Journal of Financial Markets 12, 173-202.
- Economides (1996). The economics of networks. International Journal of Industrial Organization 14, 673-699.
- Federation of European Securities Exchanges (2019). FESE Blueprint: Capital Markets Union by 2024 - A Vision for Europe.
- Garbade and Silber (1979). Dominant and Satellite Markets: A Study of Dually-Traded Securities. In: Review of Economics and Statistics 61.3, pp. 455–460.
- Gresse (2017). Effects of Lit and Dark Market Fragmentation on Liquidity. In: Journal of Financial Markets 35, pp. 1–20.
- Heckman (1979). Sample selection bias as a specification error. Econometrica 47, 153-161.
- Mendelson (1987). Consolidation, Fragmentation, and Market Performance. In: Journal of Financial and Quantitative Analysis 22.2, pp. 189–207.
- Menkveld (2013). High Frequency Trading and the New Market Makers. In: Journal of Financial Markets 16.4, pp. 712–740.
- Menkveld (2016). The economics of high-frequency trading: Taking stock. In: Annual Review of Financial Economics 8, 1-24.
- O'Hara and Ye (2011). Is Market Fragmentation Harming Market Quality? In: Journal of Financial Economics 100.3, pp. 459–474.
- Pagano (1989). Trading Volume and Asset Liquidity. In: Quarterly Journal of Economics 104.2, pp. 255–274.
- Riordan et al. (2011). Do Multilateral Trading Facilities Contribute to Market Quality? In: Working Paper.

BACKUP I

Effects of Stock-Specific Initial Fragmentation Events

Methodology I

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

- We identify the **initial fragmentation event** of a stock as the **quarter** where trading in that stock first took place on **more than one trading venue:**
  - 578 stocks were already fragmented in Q1/2009
  - 570 stocks have an initial fragmentation event
  - 152 stocks do not fragment at all
- Based on the 570 stocks, we identify those stocks that have at least one pre- and 16 post-event quarterly observations → 420 stocks (94.42% SMEs)
- To identify the effect of market fragmentation on market quality, we perform a **matched-pairs analysis**

Methodology II

Matched-Pairs Analysis:

- Following Davies and Kim (2009), we **match stocks** to their nearest neighbor based on market cap, price, relative spread, and euro-volume in the pre-event quarter
- We only match stocks with at least 15 potential matches → 291 final stock matches
- We then obtain the differences for each variable in our data set and estimate the following regression model:

$$\Delta Y_{i,t} = \beta_1(\Delta inv.\ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$$

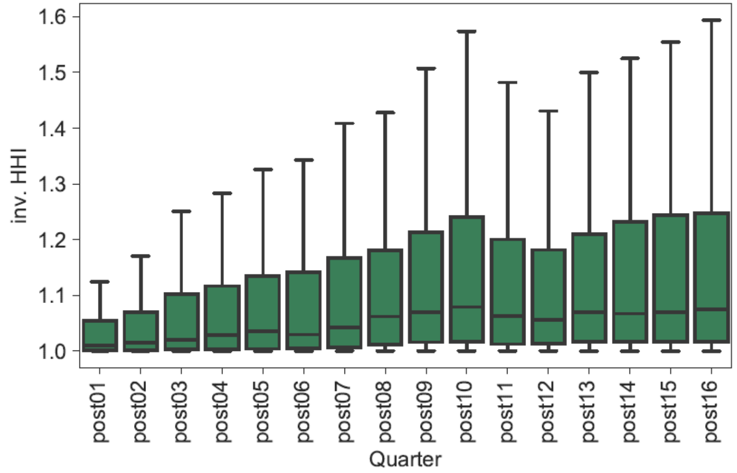
- ΔY captures the difference between the respective stock and its match in relative spreads, $\Delta inv.HHI$ is the difference of fragmentation levels and $\boldsymbol{X}$ is a vector of control variables including differences for log trading volume, volatility, inverse of stock price and log market cap
- We derive the results using fixed effects estimators, include stock and quarter fixed effects and apply double clustered SE estimation for the clusters stock and quarter

Effects of Stock-Specific Initial Fragmentation Events

Main results of the regression analyses:

- Fragmentation after the **initial fragmentation event** has **no effect on market quality** in terms of main market spreads
- However, the **average SME stock only marginally fragments** after being traded on multiple venues for the first time

Dependent Variable	relative spread	
Variables	Estimate	p-Value
inv. HHI	-14.74	0.62
log(mcap)	-57.67	0.00
log(euro-volume)	-41.38	0.00
inverse price	-0.05	0.65
volatility	0.06	0.72
Adj. R^2	0.26	
Observations	4421	



Effects of Stock-Specific Initial Fragmentation Events

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Main results of the regression analyses:

- Fragmentation after the **initial fragmentation event** has **no effect on market quality** in terms of main market spreads
- However, the **average SME stock only marginally fragments** after being traded on multiple venues for the first time
- We further filter the 25% most fragmented stocks in the data set (105 stocks with average inv. HHi > 1.15 and 85.07% SMEs)
- These stocks show **lower spreads due to fragmentation** consistent with previous literature

Dependent Variable	relative spread	
Variables	Estimate	p-Value
inv. HHI	-14.74	0.62
log(mcap)	-57.67	0.00
log(euro-volume)	-41.38	0.00
inverse price	-0.05	0.65
volatility	0.06	0.72
Adj. R^2	0.26	
Observations	4421	

Dependent Variable	relative spread	
Variables	Estimate	p-Value
inv. HHI	-62.19	0.09
log(mcap)	-78.76	0.01
log(euro-volume)	-15.05	0.32
inverse price	-22.11	0.37
volatility	0.09	0.54
Adj. R^2	0.26	
Observations	606	

BACKUP II

Panel Regression Results

Methodology II

Standard Panel Regression Analysis (full observation period):

$$Y_{i,t} = \beta_1(inv.\ \ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}$$

- Y captures each dependent market quality measure, $inv. HHI$ is the stock's respective fragmentation level and **X** is a vector of control variables including log trading volume, volatility, inverse of stock price and log market cap
- We derive the results using fixed effects estimators, include stock and date fixed effects and apply double clustered SE estimation for the clusters stock and day

Results of the Panel Regression Analysis

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

Y	Liquidity classes 10	80	600	2000	9000	inf
relative spread	-4.94	**13.76**	-1.81	-0.39	**-0.44**	-0.08
	(0.89)	(0.00)	(0.15)	(0.44)	(0.00)	(0.43)
depth(L1)	**-0.0224**	**-0.0204**	**0.0256**	**0.0459**	**0.0309**	**0.1388**
	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)
depth(L1)-imbalance	0.017	0.0072	**-0.0146**	**-0.0103**	-0.00004	-0.0028
	(0.47)	(0.19)	(0.00)	(0.00)	(0.98)	(0.31)
depth(L10)	-0.0608	-0.0170	**0.1531**	**0.4259**	-0.1820	0.1679
	(0.25)	(0.64)	(0.01)	(0.00)	(0.37)	(0.85)
depth(L10)-imbalance	**0.0268**	0.0020	**-0.0143**	**-0.0075**	**-0.0015**	0.0007
	(0.00)	(0.65)	(0.00)	(0.00)	(0.08)	(0.59)
midpoint dispersion	1.35	**17.39**	-1.92	**-3.20**	**-0.91**	**-0.19**
	(0.81)	(0.00)	(0.16)	(0.00)	(0.00)	(0.01)
Observations	31180	116728	139241	98823	156361	67610

Note: p-values in parenthesis, bold coefficients indicate significance at the 10%-level.

- The impact of fragmentation on market quality follows a **hockey stick curve**:
  - no impact for stocks with lowest liquidity
  - negative impact for less liquid stocks and
  - positive effects for stocks with higher liquidity
- There is a **liquidity related threshold** (liquidity class 600) that determines when fragmentation becomes beneficial for stock market quality