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

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# Drivers and Effects of Stock Market Fragmentation - Insights on SME Stocks[⋆]

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**Abstract**

We analyze how market fragmentation affects market quality of SME and other less actively traded stocks. Compared to large stocks, they are less likely to be traded on multiple venues and show, if at all, low levels of fragmentation. Concerning the impact of fragmentation on market quality, we find evidence for a hockey stick effect: Fragmentation has no effect for infrequently traded stocks, a negative effect on liquidity of slightly more active stocks, and increasing benefits for liquidity of large and actively traded stocks. Consequently, being traded on multiple venues is not necessarily harmful for SME stock market quality.

*Keywords:* Market Microstructure, Market Fragmentation, Securities Market Regulation, Market Quality, SME Trading
*JEL:* G10, G14

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## 1. Introduction

In the last two decades, regulatory reforms and new trading technology proliferated market fragmentation in securities trading. Market fragmentation in this context means that a stock is being traded on multiple venues and not only on its listing exchange. Regulatory authorities passed new legislation eliminating national monopolies of incumbent exchanges by enabling competitors to operate alternative trading venues to compete for investors' order flow.[1] The goal of the new rules was to ensure organized execution of investors' transactions, to encourage innovation, and to reduce trading costs due to increased competition (Gomber et al., 2017). Academic literature mostly analyzes the impact of market fragmentation on liquid and actively traded stocks. However, recent regulatory and industry discussions[2] regarding potential negative effects of market fragmentation on trading and market quality of small and medium enterprise (SME) stocks increased the interest regarding research analyzing the impact of fragmentation on SME and other less actively traded stocks. Therefore, this analysis is in the focus of our paper.

Early theoretical literature shows that fragmentation is harmful if market participants have incomplete information about all available orders and if transactors are unable to communicate across different liquidity pools quickly and cheaply (Mendelson, 1987; Garbade and Silber, 1979; Pagano, 1989). However, several empirical studies provide evidence that there is no negative effect of market fragmentation on market quality and even find that fragmentation benefits liquidity by leading to lower spreads and higher order book depth (Hengelbrock and Theissen, 2009; Gresse, 2017; O'Hara and Ye, 2011). This can be explained by fully electronic trading platforms, smart order routing technologies as well as algorithmic/ high frequency traders that create a virtually integrated marketplace in the absence of a single central limit order book (Riordan et al., 2011). These technologies eliminate the frictions which were the major concerns of the early theoretical literature. Yet, these empirical studies focus on larger, highly liquid stocks and disregard smaller stocks such as stocks of SME firms, which are traded less frequently and where the activity of high frequency traders, who connect different liquidity pools via

[1]For example, competition between trading venues was facilitated by Reg ATS in 1999 and Reg NMS in 2007 for US markets and by MiFID I in 2007 for European markets.

[2]See, e.g., Federation of European Securities Exchanges (2019).

multi-venue market making and arbitrage trading (Menkveld, 2013, 2016), is considerably lower.

Several market observers state that market fragmentation and the fragmentation of liquidity created unintended consequences for SME and other less liquid stocks by splitting up the already low trading activity and order flow across multiple venues. They argue that regulations fostering the fragmentation of stock markets did not improve the conditions for going and being public but increased the costs for SMEs. Hence, SME issuers "should have the right to choose where to be traded to avoid fragmentation of already low liquidity" (Federation of European Securities Exchanges, 2019). Yet, this discussion is not substantiated by academic evidence as there is no systematic empirical analysis on the trading conditions for SMEs since the introduction of alternative trading venues and on the impact of market fragmentation regarding the liquidity of SME stocks.

To close this research gap, we investigate which factors drive market fragmentation and how fragmentation affects stock market quality especially of SME stocks that are less liquid and are traded less frequently compared to blue chip stocks. Therefore, we empirically analyze whether these stocks experience adverse effects of market fragmentation as shown by theoretical research (e.g., Mendelson, 1987; Pagano, 1989).

In the first part of our analysis, we make use of the initial lit market fragmentation event, i.e., when stocks are traded on an alternative venue for the first time. Our results show that the fragmentation of a stock is driven by stock-specific characteristics. We find that stocks with higher market capitalization and trading activity are more likely to be traded on multiple venues and that alternative venues selectively choose to offer these stocks for trading on their venues. Based on matched stock-pairs following Davies and Kim (2009) to control for stock-specific characteristics, we find that market fragmentation in the first quarters after the initial fragmentation event does not affect liquidity. Most analyzed stocks, 94.42% of which are SME stocks with a market capitalization of less than one billion euro, only marginally fragment whereas the vast majority of trading still happens on the main venue. When analyzing the sub-sample of stocks that do substantially fragment after the initial fragmentation event, we find that higher fragmentation is related to higher liquidity in form of smaller spreads, which is in line with previous literature on blue chip stocks (e.g., O'Hara and Ye, 2011; Hengelbrock and Theissen, 2009).

In order to obtain a more granular picture of the impact of lit market fragmentation on market quality of SME and other less actively traded stocks, we conduct a second analysis based on intraday order book data of stocks traded on LSE, Euronext Paris, or Xetra and the corresponding largest alternative venues Aquis, Cboe Europe BXE, Cboe Europe CXE, and Turquoise. Specifically, we consolidate the order book information of these venues for the period from June 5, 2017 until September 30, 2020 and analyze the impact of fragmentation on liquidity in terms of relative spreads, depth on different order book levels, and order imbalance again based on pairs matching. Furthermore, we separate the sample based on six liquidity classes according to the European tick size regime. Our regression results confirm previous findings on the positive impact of fragmentation on different liquidity measures for the higher liquidity classes, i.e., blue chip stocks and other actively traded stocks. Moreover, we find that this positive effect vanishes in the lower liquidity classes, i.e., for SME stocks and other less actively traded stocks, which have not yet been investigated in this respect. The no-effect of fragmentation on these stocks results from the marginal level of fragmentation that these stocks experience. In case these stocks show at least some trading activity on multiple venues, fragmentation can even have a negative effect on liquidity in terms of relative spreads.

This paper contributes two important and new findings to research on the impact of lit market fragmentation on stock market quality and to the discussions regarding potential negative effects of fragmentation on SME and other less actively traded stocks: (i) Market fragmentation is determined by stock specific-characteristics such as market capitalization and trading activity. When SME and other less actively traded stocks are traded on alternative venues for the first time, they fragment only marginally. Furthermore, larger and more actively traded stocks are more likely to be traded on multiple venues and show higher levels of market fragmentation. (ii) The impact of market fragmentation on stock market quality follows a hockey stick curve. Fragmentation has no effect on stocks that trade very infrequently as these stocks only marginally fragment, has a negative effect on liquidity of slightly more active stocks that show at least some market fragmentation, and has increasing benefits on liquidity of actively traded stocks. Moreover, our results suggest that there is a liquidity-related threshold that determines when relevant levels of fragmentation emerge and when fragmentation becomes beneficial for stock market quality.

The remainder of the paper proceeds as follows: In Section 2, we provide a brief summary of related literature. In Section 3, we explain the current state of market fragmentation in European securities trading. Section 4 analyzes drivers and effects of stock-specific initial fragmentation events. In Section 5, we investigate the effect of market fragmentation on several dimensions of market quality. Finally, Section 6 concludes.

## 2. Literature Review

In this paper, we analyze the drivers and effects of stock market fragmentation, specifically for SME stocks. Hence, our research contributes to the literature stream of stock market fragmentation and its effect on market quality. While the general question of whether stock trading should rather be consolidated on a single market or fragmented across multiple trading venues is not new, recent debates have revived the issue with a special focus on less liquid SME stocks. So far, results in the literature are mixed and mainly focus on larger and more actively traded stocks.

The fundamental motivation for market fragmentation is to avoid monopolistic positions of trading venues and excessive rents that result in high trading costs and associated welfare losses due to concentration (Economides, 1996). Yet, several *theoretical papers* argue against market fragmentation and elaborate on the positive effects of concentrating order flow on a single trading venue to increase liquidity and gains from trade (Mendelson, 1987; Pagano, 1989). Moreover, models show that adverse selection costs and volatility rise with the number of markets on which a stock is traded (Chowdhry and Nanda, 1991; Madhavan, 1995). In contrast, Stoll (2001) reveals that it is important how the order routing process is implemented to overcome frictions resulting from market fragmentation and to realize the positive effects of fragmentation. Analyzing the impact of fragmentation on liquidity, Parlour and Seppi (2003) build a micro-structure model of liquidity based competition and show that fragmentation can reduce the cost of liquidity thereby increasing overall welfare. These results are confirmed by Degryse et al. (2009) based on a dynamic market model that uses the example of a dealer market and a crossing network. Furthermore, Malamud and Rostek (2017) show that fragmented markets are welfare improving if market participants have heterogeneous preferences. Baldauf and Mollner (2021) also find that trading costs can decline when competition among venues increases. However, they show that arbitrage opportunities can outweigh the positive fragmentation effects so that the overall effect of fragmentation is context-specific.

A variety of *empirical studies* that analyze the impact of fragmentation on stock market quality find *positive effects* of market fragmentation on liquidity. Foucault and Menkveld (2008) show that, due to the absence of price priority across markets, consolidated depth is larger after the entry of a new order book. Also, Hengelbrock and Theissen (2009) find evidence for a positive impact on liquidity due to the market entry of the MTF Turquoise starting to trade stocks from 14 European countries. Riordan et al. (2011) analyze the contribution of the LSE, as the main market, and of the alternative venues Chi-X, Turquoise and BATS to price discovery in the UK equities market. They find that the most liquid trading venues dominate price discovery. In an extensive study, O'Hara and Ye (2011) examine the impact of market fragmentation on market quality in the US market system and find evidence that more fragmented stocks have lower transaction costs and are executed faster. Similarly, Aitken et al. (2017) show that market quality is positively affected by fragmentation and that greater fragmentation fosters these benefits. They find that spreads of stocks that are least constrained by the minimum tick size reduce with fragmentation, whereas depth increases for those stocks which are most constrained.

Although several positive effects are associated with fragmentation, some *empirical studies* also find *negative effects* of fragmentation on stock market quality. Hendershott and Jones (2005) investigate price discovery as well as trading activity of ETFs after electronic communication networks stopped the display of ETF order books. According to their findings, this change in market structure resulted in higher fragmentation followed by worse liquidity and price efficiency. Similarly, Bennett and Wei (2006) examine the migration of stocks from the more fragmented NASDAQ to the less fragmented NYSE market. When stocks switched from NASDAQ to NYSE, prices became more efficient and execution costs declined. Chung and Chuwonganant (2012) analyze the introduction of Regulation NMS and show a reduction in depth, a decrease in the speed of execution, and an increase in effective and quoted spreads resulting in a negative effect of fragmentation on market quality. Beside studies that determine positive or negative associations between fragmentation and market quality parameters, some studies find an inverted-U relationship, in which a moderate degree of fragmentation is liquidity maximizing (Boneva et al., 2016; Degryse et al., 2015).

However, the majority of existing empirical studies focuses on rather large and very liquid stocks when analyzing the effect of fragmentation on market quality. Even more important, it is necessary to differentiate stocks not only by the level of fragmentation but also by size and liquidity since the market dynamics of stocks are different dependent on their characteristics. Furthermore, market participants state that the current regulatory set-up has not improved the conditions for thinly-traded securities such as SME stocks. In particular, the competitive and highly fragmented trading environment fostered by several regulatory actions is seen as disadvantageous for SME markets and less liquid stocks since already low order volume is split among multiple markets.[3] This negative effect for smaller stocks is supported by the studies of Gresse (2017), and Degryse et al. (2015) who find that market depth for medium sized stocks declines with sufficient fragmentation. In addition, Haslag and Ringgenberg (2016) find evidence for NYSE and NASDAQ listed stocks that although fragmentation decreases spreads for larger stocks, smaller stocks experience a reduction in market quality.

Yet, current research on the effects of fragmentation on market quality, especially in case of smaller and less liquid stocks, comes short in two important dimensions: First, there is no study that accounts for the drivers of stock market fragmentation when analyzing its effect on market quality of less liquid stocks and the development of these stocks over time. Second, while existing studies point out that the effects of market fragmentation seem to differ for larger and smaller stocks, there is no analysis regarding a potential liquidity or size threshold where relevant levels of fragmentation emerge and when they become beneficial. Therefore, this study addresses these research gaps based on comprehensive and granular analyses of the impact of lit market fragmentation by examining (i) the drivers and (ii) the effects of stock-specific initial fragmentation events and by analyzing (iii) the effects of market fragmentation on a wide range of market quality parameters for stocks of different size and liquidity classes. Moreover, (iv) we provide evidence for thresholds where stocks substantially fragment and when fragmentation positively affects market quality.

[3] See, e.g., statements of the Federation of European Securities Exchanges (2019) and NASDAQ, available at https://www.nasdaq.com/docs/2020/02/05/2020%20UTP%20Termination%20Application.pdf.

## 3. Market Fragmentation in European Securities Trading

In the following, we descriptively illustrate and analyze several characteristics of stock market fragmentation in Europe. For this purpose, we collect a data set based on a list of all stocks that have been traded on one of the largest European trading venues London Stock Exchange (LSE), Euronext Paris, and Xetra from Refinitiv Datastream. For each quarter in the period of Q1/2009 to Q4/2019, we retrieve market shares and volumes traded for the main market and all alternative venues on which each stock is traded from Fidessa resulting in a data set of 1300 stocks.[4] We enrich the data set with prices, volatility, market capitalization, and main market relative spreads from Refinitiv Datastream.[5] To measure market fragmentation, we collect data on trade executions by venue on a per stock basis (O'Hara and Ye, 2011). For the final data set, we determine the fragmentation for each stock $i$ at time $t$ using the inverse of the Herfindal-Hirschman index (inv. HHI), which is widely used in the market microstructure literature (e.g., Gresse, 2017; Clapham et al., 2021) representing the inverse of the sum of squares of the market shares $s$ of each individual trading venue $j$:

$$inv.\ HHI_{i,t} = 1/(\textstyle\sum_j s^2_{j_{i,t}}) \quad (1)$$

Since the introduction of MiFID I in 2007, European securities trading is fragmented among several trading venues. Different market operators compete for investors' order flow by offering various market models and fee structures. In the last decade, most of European equity trading volume was traded over the counter (OTC, about 35-40% of overall trading volume) and on so-called lit trading venues using public open limit order books (about 50% of overall trading volume). Trading activity on lit trading venues is primarily contributing to price discovery, since OTC trades are negotiated bilaterally without any public pre-trade transparency. Hence, market quality of lit trading venues is important to guarantee meaningful price discovery and efficient financial markets. Regarding lit venues, in addition to the incumbent main markets, four major players have established themselves in Europe's largest

[4] Data retrieved from Fidessa: `https://fragmentation.fidessa.com/`. More details regarding the sample selection and the data sets can be found in Tables A.1 and A.2 in the appendix (see Fidessa data set).

[5] We convert all data of UK stocks in euro using the respective daily exchange rate. For the analysis based on Fidessa data, we use main market spreads as a proxy for liquidity.

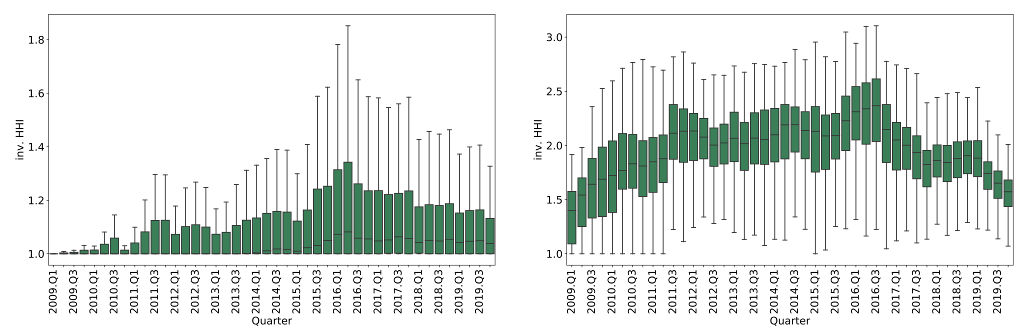
economies UK, France, and Germany: CXE and BXE (both operated by Cboe Europe), Turquoise, and Aquis.

Table 1: Trading venues and market shares

This table presents the largest trading venues for trading UK, French, and German stocks as well as their respective market share of overall lit trading volume between 2009 and 2019.

| | UK stocks (main venue: LSE) | French stocks (main venue: Euronext Paris) | German stocks (main venue: Xetra) |
|---|---|---|---|
| Main venue | 62.50% | 67.14% | 67.41% |
| Cboe CXE | 20.13% | 18.42% | 19.12% |
| Cboe BXE | 5.97% | 4.01% | 4.45% |
| Turquoise | 9.00% | 7.86% | 6.65% |
| Aquis | 0.99% | 0.84% | 0.91% |
| Sum | 98.59% | 98.27% | 98.54% |

Table 1 shows their respective market share in lit trading volume for shares traded between 2009 and 2019. Together with the main markets (LSE, Euronext Paris, and Xetra), these trading venues account for more than 98% of overall lit trading volume in each of the respective groups of stocks. For our different analyses regarding market fragmentation and market quality, we therefore concentrate on these venues, covering the major part of overall open limit order book trading activity in European stock trading.




(a) SME stocks (b) Non-SME stocks

This figure shows the distributions of fragmentation levels for SME stocks (with a market capitalization lower than one billion euro) and non-SME stocks between 2009 and 2019.

Figure 1: Fragmentation of lit trading volume for SME and non-SME stocks

Figure 1 depicts the development of market fragmentation and trading volume in European lit trading for each quarter in the period of 2009 to 2019.

The figure divides stocks by market capitalization in SME[6] (Figure 1 (a)) and non-SME stocks (Figure 1 (b)).

The graphs show that market fragmentation increased until mid 2016 with a regain in market share of the main markets and lower fragmentation since then. However, while the median inv. HHI of non-SME stocks shows a relevant fragmentation level between 1.5 and 2.5 (Figure 1 (b)), median inv. HHI values for SME stocks are mostly below 1.1, with only few SME stocks showing higher fragmentation levels (Figure 1 (a)). Hence, the graphs indicate that the market capitalization of stocks seems to be a relevant factor for explaining when and to what extent stock trading fragments over multiple venues.

Table 2: Fragmentation levels of SME versus non-SME stocks based on a split of the two groups into large, medium, and small stocks

This table shows the average fragmentation levels and trading volume of SME and non-SME stocks divided in thirds (large, medium, small) by market capitalization (mcap). Here, and in the following, "euro-volume" refers to stocks' trading volume in euro. Market capitalization is reported in million euro and euro-volume in hundred thousand euro. Values are based on stock-quarterly observations.

Panel A: inv. HHI

| | SME stocks | | | | Non-SME stocks | | | |
|---|---|---|---|---|---|---|---|---|
| | Observations | inv. HHI | euro-volume | mcap | Observations | inv. HHI | euro-volume | mcap |
| Large (L) | 8904 | 1.28 | 47.85 | 544.70 | 5925 | 2.04 | 2146.19 | 27100.11 |
| Medium (M) | 8244 | 1.07 | 9.20 | 170.60 | 5430 | 1.95 | 575.81 | 3892.20 |
| Small (S) | 8240 | 1.01 | 1.05 | 37.52 | 5431 | 1.68 | 189.86 | 1334.87 |

Panel B: differences in inv. HHI

| | SME stocks | | Non-SME stocks | |
|---|---|---|---|---|
| | Difference (inv. HHI) | p-Value | Difference (inv. HHI) | p-Value |
| L - M | 0.21 | 0.00 | 0.08 | 0.00 |
| L - S | 0.26 | 0.00 | 0.35 | 0.00 |
| M - S | 0.05 | 0.00 | 0.27 | 0.00 |
| S (Non-SME) - L (SME) | | | 0.41 | 0.00 |

Table 2 shows the average fragmentation level of SME and non-SME stocks divided in thirds by size (market capitalization). For both, SME and non-SME stocks, the table shows that larger stocks with higher market capitalization are significantly more fragmented than smaller stocks. Moreover, medium and small SME stocks are on average only marginally fragmented, which indicates that trading in these mostly illiquid and less frequently traded stocks (see the low euro-volume) concentrates on a single venue.

[6] We define SME stocks as stocks with a market capitalization lower than one billion euro in line with current regulatory discussions in the EU, see, e.g., https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=PI_COM%3AAres%282020%293914669.

Dividing the stocks in groups by trading activity further supports these indications. Table 3 shows the average fragmentation levels of SME and non-SME stocks divided in six different liquidity classes according to the liquidity bands of the European tick size regime[7]. The results show that besides a stock's market capitalization, also trading activity has a significant influence on the level of fragmentation. The majority of SME stocks is in the lower liquidity classes (less than 10 and less than 80 transactions per day) and exhibits low levels of fragmentation, which again supports that trading in small stocks is concentrated on one venue rather than fragmented across multiple venues.

Table 3: Fragmentation for SME and non-SME stocks split into liquidity classes

This table shows the average fragmentation levels of SME and non-SME stocks divided in different liquidity classes according to the European tick size regime. Each class is based on the number of daily transactions. The classes are 10: [0, 10), 80: [10, 80), 600: [80, 600), 2000: [600, 2000), 9000: [2000, 9000), and inf: $\geq$ 9000 transactions. Market capitalization (mcap) is reported in million euro and euro-volume in hundred thousand euro. Values are based on stock-quarterly observations.

Panel A: inv. HHI

| | SME stocks | | | | Non-SME stocks | | | |
|---|---|---|---|---|---|---|---|---|
| | Observations | inv. HHI | euro-volume | mcap | 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 |

Panel B: differences in inv. HHI

| | SME stocks | | Non-SME stocks | |
|---|---|---|---|---|
| | Difference (inv. HHI) | p-Value | Difference (inv. HHI) | p-Value |
| inf - 9000 | - | - | 0.03 | 0.00 |
| 9000 - 2000 | 0.20 | 0.00 | 0.35 | 0.00 |
| 2000 - 600 | 0.37 | 0.00 | 0.40 | 0.00 |
| 600 - 80 | 0.17 | 0.00 | 0.28 | 0.00 |
| 80 - 10 | 0.03 | 0.00 | 0.02 | 0.21 |

To summarize, these descriptive statistics show that the fragmentation of European equities trading has increased over time after the introduction of MiFID I until mid 2016 with a regain of market shares by the incumbent exchanges since then. They also indicate that fragmentation is driven by trading activity and market capitalization of a stock and show that the majority of SME stocks does not exhibit a relevant level of fragmentation. Instead, trading SME stocks is mostly concentrated on a single venue. These

[7]See annex to the regulatory technical standard RTS 11, available at https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017R0588.

results are important for analyzing the impact of fragmentation on market quality: First, because market capitalization and trading activity have a large influence on market quality measures, we need to overcome endogeneity issues. Second, because trading characteristics are significantly different between more and less actively traded stocks, we need to differentiate between these stocks to obtain meaningful results regarding the effect of market fragmentation.

## 4. Drivers and Effects of Stock-Specific Initial Fragmentation Events

We want to generate insights into the effect of fragmentation on market quality in securities trading. For this purpose, we analyze the initial fragmentation event of stocks to understand when and why stocks do fragment and then investigate how this fragmentation event affects market quality of the respective stocks. We use the same data set of 1300 stocks in the period of Q1/2009 to Q4/2019 as in Section 3. Based on this data set, we identify the initial fragmentation event for each individual stock, i.e., we identify per stock the respective quarter in our observation period where trading in that stock first took place on more than one trading venue.[8] Of the 1300 stocks, 578 stocks were already fragmented at the beginning of our observation period, 570 stocks have an initial fragmentation event during our observation period, and 152 stock do not fragment at all.

### *4.1. Drivers of Stock-Specific Initial Fragmentation Events*

To analyze drivers of stock trading fragmentation, we first descriptively compare stocks that fragment with stocks that do not fragment during our observation period. Table 4 provides the results of this analysis on a stock-quarter basis. The statistics for stocks with an initial fragmentation event in our sample are based on the quarterly observations before the event to ensure comparability with stocks that do not fragment. As shown by the distribution of market capitalization, our sample of stocks with no (152 stocks) or an (570 stocks) initial fragmentation event almost entirely consists of SME stocks with a market capitalization of less than one billion euro (specifically, 88.86% of the 722 stocks are below this threshold).

[8] The initial fragmentation event is not necessarily equal to a stock's first listing date on an alternative trading venue but refers to the quarter where the first trade on an alternative lit trading venue was executed, i.e., the date when fragmentation actually emerged.

Table 4: Descriptive statistics of stocks with and without fragmentation event

This table reports the descriptive statistics for stocks with an initial fragmentation event (yes) and stocks that do not fragment at all (no) in our observation period. Values for stocks with an initial fragmentation event are based on the quarterly observations before the event. Market capitalization (mcap) is reported in million euro and euro-volume in hundred thousand euro. Zero trading days is the share of trading days in a quarter without any trades being executed.

| **Panel A** | **Summary statistics** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | frag. event | count | mean | std | min | 25% | 50% | 75% | max |
| price | no | 2565 | 427.79 | 1176.10 | 0.08 | 3.76 | 16.74 | 147.40 | 8344.44 |
| | yes | 7345 | 110.83 | 392.14 | 0.10 | 4.61 | 16.03 | 69.85 | 11241.52 |
| volatility | no | 2565 | 21.03 | 68.11 | 0.00 | 0.19 | 0.73 | 7.20 | 1179.05 |
| | yes | 7342 | 5.85 | 25.59 | 0.00 | 0.26 | 0.80 | 3.84 | 1161.75 |
| mcap | no | 2565 | 251.31 | 593.85 | 0.39 | 14.79 | 47.78 | 200.20 | 5820.63 |
| | yes | 7345 | 257.13 | 853.06 | 0.00 | 36.81 | 84.88 | 203.16 | 11102.06 |
| relative spread | no | 2565 | 1759.77 | 2811.75 | 6.70 | 392.16 | 757.58 | 1877.02 | 19996.55 |
| | yes | 7301 | 788.46 | 1302.58 | 4.22 | 332.23 | 491.80 | 774.70 | 19999.23 |
| zero trading days | no | 2632 | 0.47 | 0.29 | 0.00 | 0.22 | 0.47 | 0.72 | 1.00 |
| | yes | 7549 | 0.24 | 0.21 | 0.00 | 0.09 | 0.17 | 0.32 | 1.00 |
| euro-volume | no | 2560 | 333.30 | 1841.35 | 0.00 | 0.02 | 0.08 | 0.99 | 33472.46 |
| | yes | 7258 | 72.91 | 667.88 | 0.00 | 0.14 | 0.49 | 3.78 | 48444.00 |
| **Panel B** | **Liquidity classes** | | | | | | | | |
| | frag. event | count | 10 | 80 | 600 | 2000 | 9000 | inf | |
| Share | no | 2632 | 0.78 | 0.13 | 0.06 | 0.03 | 0.01 | - | |
| | yes | 7549 | 0.40 | 0.52 | 0.08 | 0.00 | - | - | |

Panel A of Table 4 shows that, although there are no large differences in median price and volatility, market capitalization and volume traded are much higher for stocks with an initial fragmentation event. Furthermore, stocks that fragment have considerably lower spreads and have less zero trading days (i.e., days without any trades being executed) than stocks that do not fragment. Panel B additionally shows how stocks with an initial fragmentation event and stocks that do not fragment are distributed across the different liquidity classes. On average, stocks that fragment are already traded more frequently before the fragmentation event than stocks that do not fragment.[9] Hence, as discussed in Section 3, operators of alternative trading venues seem to selectively choose which stocks to offer for trading on their venues dependent on their size and trading activity.

To test whether there actually is a selection regarding the choice of a venue, we follow O'Hara and Ye (2011) and conduct the first stage of the Heckman correction model (Heckman, 1979). For this purpose, we estimate the following probit model:

$$Z_i = \alpha + \gamma \boldsymbol{W}_i + u_i \tag{2}$$

where $Z_i$ is a binary variable being 1 if the respective stock of observation $i$ is fragmented and 0 otherwise. $\boldsymbol{W}_i$ is a vector of variables explaining market fragmentation. For the choice of variables to include in $\boldsymbol{W}_i$, we follow the literature (O'Hara and Ye, 2011; Bessembinder, 2003) and include the logarithm of market capitalization as well as the logarithm of euro-volume. We furthermore include dummy variables for the membership in each of the different liquidity classes as described in Section 3 and estimate the probit model based on all 1300 stocks in our data set.

We then use the estimate $\hat{\gamma}$ to determine the inverse Mills ratio $\hat{\lambda}_i = \varphi(Z_i\hat{\gamma})/\Phi(Z_i\hat{\gamma})$, where $\varphi$ is the standard normal probability density function and $\Phi$ is the standard normal cumulative distribution function. The t-statistic of $\hat{\lambda}_i$ can then be used to determine whether there is a selection. A selection is present, if $\hat{\lambda}_i$ is significant.

[9] Since highly liquid stocks and particularly blue chip stocks were already listed on alternative trading venues in the first months after MiFID I went live in November 2007 and since our observation period starts in 2009, no or only very few stocks show up in the largest three liquidity classes.

In order to not only account for the likelihood but also the level of fragmentation (inv. HHI), we furthermore estimate the following standard OLS regression model:

$$inv.\ HHI_i = \alpha + \beta \boldsymbol{X}_i + \varepsilon_i \tag{3}$$

where $\boldsymbol{X}_i$ is a vector of the same independent variables as used in the probit model. However, due to the high correlation, we either include the logarithm of euro-volume or dummy variables for the membership in each of the different liquidity classes to account for trading activity.

Table 5: Results of the probit and OLS regression models explaining the selection and level of market fragmentation

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| Model | probit | | OLS | | OLS | |
| Dependent Variable | Z | | inv. HHI | | inv. HHI | |
| Variables | Estimate | p-Value | Estimate | p-Value | Estimate | p-Value |
| Constant | -4.68 | 0.00 | -0.43 | 0.00 | 0.91 | 0.00 |
| log(mcap) | 0.17 | 0.00 | 0.06 | 0.00 | 0.02 | 0.00 |
| log(euro-volume) | 0.23 | 0.00 | 0.09 | 0.00 | | |
| liquidity class 80 | 0.53 | 0.00 | | | 0.01 | 0.03 |
| liquidity class 600 | 1.18 | 0.00 | | | 0.17 | 0.00 |
| liquidity class 2000 | 1.30 | 0.00 | | | 0.58 | 0.00 |
| liquidity class 9000 | 1.54 | 0.00 | | | 0.93 | 0.00 |
| liquidity class inf | 3.65 | 0.88 | | | 0.94 | 0.00 |
| inv. Mills ratio | 358.12 | 0.00 | | | | |
| Observations | 40884 | | 40884 | | 40884 | |
| Adj. $R^2$ | - | | 0.65 | | 0.78 | |

Table 5 provides the estimates of the probit model regarding the likelihood whether a stock fragments and the estimates of the OLS model explaining the level of market fragmentation. The results show that the size and trading activity of a stock significantly influence both the likelihood of initial fragmentation as well as the level of market fragmentation. Larger stocks and stocks with higher trading volume are more likely to be traded in fragmented markets. Moreover, the lower the liquidity class of a stock, the less likely trading in this stock fragments across multiple markets. Furthermore, the inverse Mills ratio based on the probit model is highly significant, which shows that there is a selection regarding stocks that fragment. Therefore, the results of the Heckman correction model provide evidence that operators of alternative trading venues selectively choose which stocks to offer for trading on their venues and that size and trading activity are relevant factors for their decision. In addition, the OLS model shows that larger and more actively traded stocks are not only more likely to be traded on multiple venues but also exhibit higher levels of market fragmentation. Both market capitalization and trading volume significantly increase the level of market fragmentation. At the same time, stocks in higher liquidity classes show monotonically increasing levels of market fragmentation compared to stocks in the lowest liquidity class[10]. In particular, the least liquid stocks in the lowest two classes are substantially less fragmented than stocks in the other liquidity classes. For robustness, we repeat the analysis concerning the level of market fragmentation based on a panel regression to capture stock-specific effects and variations over time such as changes in transaction fees. The results are highly comparable and provided in Table A.3 in the appendix. Moreover, we also run the fragmentation level analysis conditional on stocks that are actually fragmented leading to almost identical results so we do not tabulate them here.

### *4.2. Effects of Stock-Specific Initial Fragmentation Events*

After the analysis of the drivers of stock market fragmentation, we investigate whether the initial stock trading fragmentation has an impact on the respective stocks' market quality. For this purpose, we focus on the 570 stocks in our data set that have an initial fragmentation event within our observation period. These are are almost entirely SME stocks (94.18%).

Figure 2 shows the distribution and development of stock characteristics for 16 quarters before and after the initial fragmentation event.[11] These descriptive results show that stocks on average become larger, more actively traded, and more liquid within the four years after being traded on multiple venues for the first time. Yet, and most important, this trend already existed in the four years before the initial fragmentation event and no particular jump

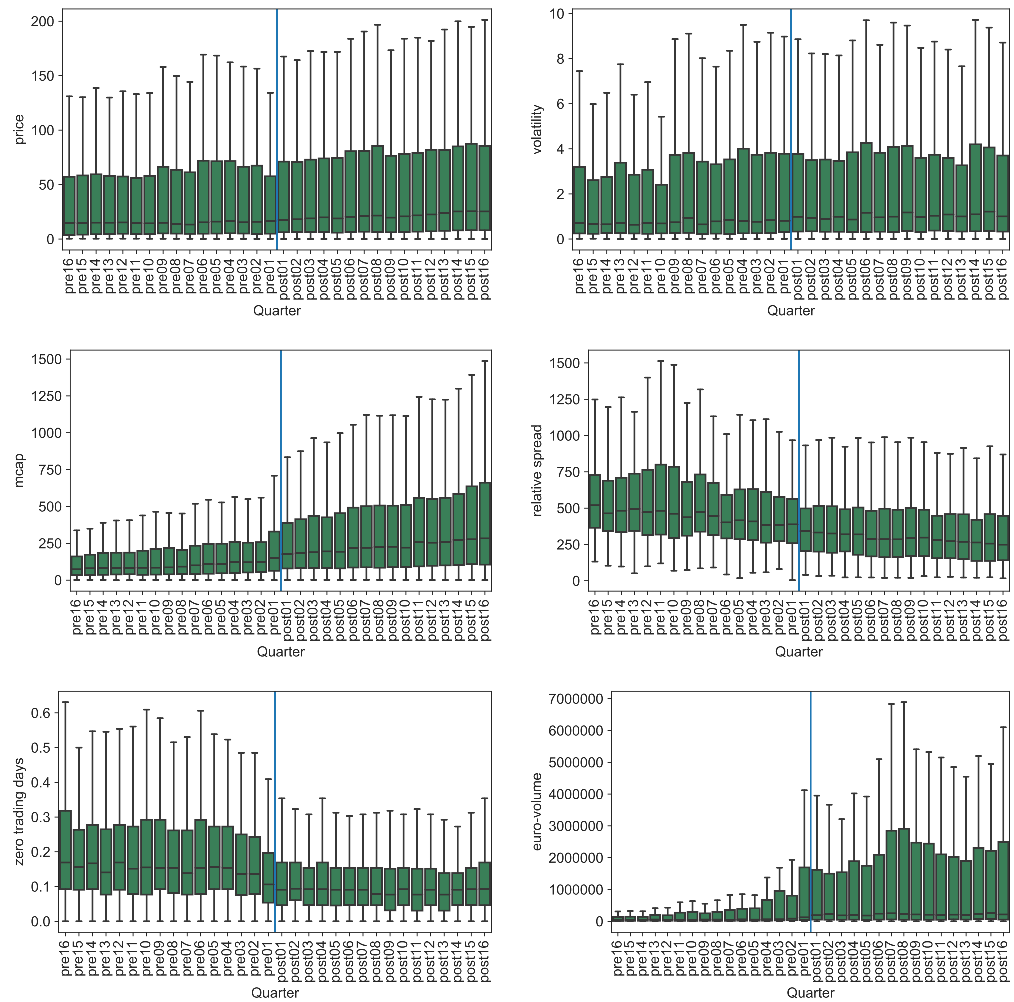
[10] The coefficient for the lowest liquidity class is dropped from the regression since it can be linearly combined with the other liquidity classes. Hence, the coefficients for the other liquidity classes need to be interpreted relative to the lowest liquidity class.

[11] We cover 16 quarters, i.e., four years of observations to include a sufficient time period before and after the initial fragmentation events.

after the event is visible. Therefore, these descriptive results rather support the findings of our previous analyses that stocks fragment and are selected by alternative venues once they achieve a relevant size and trading activity. Due to the observed trends regarding market capitalization, trading volume, and liquidity, these descriptive results provide no indication that fragmentation influences market quality of (SME) stocks.

Digging deeper into how an initial fragmentation event influences size and trading activity of a stock, Figure 3 plots the share of stocks with an initial fragmentation event (570 stocks) according to the SME market capitalization threshold and different liquidity classes over time around the fragmentation event, i.e., 16 quarters before and after the event. The left hand side of the figure provides the percentage of stocks with a market capitalization below one billion euro (*share of SME stocks*) for each quarter. While the vast majority of stocks that are traded on multiple venues for the first time are SME stocks until about three quarters before the event, the share already drops in the first quarter directly before the event and gradually declines after the fragmentation event. This provides evidence that due to increasing attractiveness of specific stocks, their market capitalization and liquidity increase so that they are being selected to be traded on multiple venues. Being traded on multiple markets again amplifies the development of increasing market capitalization and trading activity so that more and more of these stocks become larger than the SME threshold of one billion euro. This is supported by the share of the stocks belonging to the different liquidity classes shown on the right hand side of Figure 3. In line with the developments concerning size, the number of stocks in the higher liquidity classes rises while the number in the lower classes declines even before but also after the initial fragmentation event. Specifically, the percentage of stocks in the third liquidity class (between 80 and 600 transactions per day) shows a large increase before the initial fragmentation event. After the event, liquidity continues to rise as the share of stocks in the higher liquidity classes with more than 600 transactions per day increases (liquidity classes 2000 and 9000).

In order to analyze the actual effects of initial fragmentation on stock market quality, we perform a regression analysis for our subsample of 570 stocks with an initial fragmentation event. In the subsample, we require stocks to have at least one pre- and 16 post-event quarterly observations to be included in the analysis in order to ensure a robust and sound analysis. This results in a total of 420 stocks, of which 94.42% are SMEs. Because our




This figure shows the distribution and development of stock characteristics for 16 quarters before and after the initial fragmentation event. The blue line separates the pre- and post-event quarters.

Figure 2: Distribution and development of stock characteristics before and after the initial fragmentation event

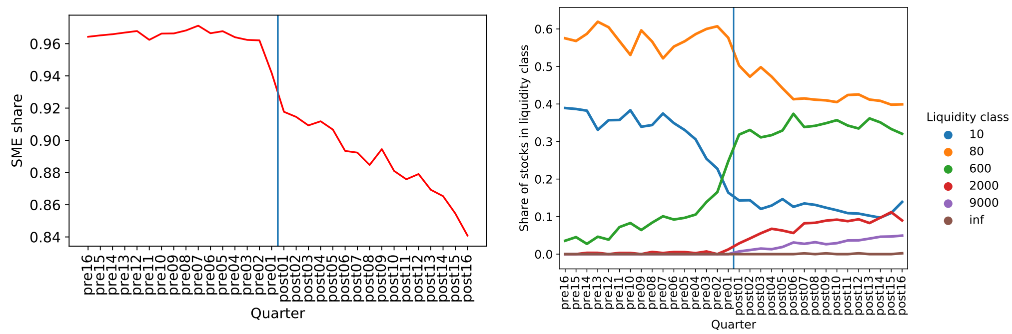



Figure 3: Share of SME stocks and share of stocks within the different liquidity classes before and after the initial fragmentation event

analyses so far have shown that stock characteristics such as size and trading activity influence a stocks' market fragmentation and at the same time a stocks' market quality as shown in previous research, we apply pair-wise matching to control for endogeneity. We follow Davies and Kim (2009) and match stocks to their nearest neighbor based on their market capitalization, closing price, closing spread, and euro-volume in the pre-event quarter. To obtain meaningful matches that also control for differences over time, we only match stocks that have their initial fragmentation event in the same quarter[12]. We then determine the differences between matched stocks for each variable in our regression model and control for outliers by removing those observations with the largest 5% of absolute difference for the dependent variable of our regression setup, i.e., relative spread. We estimate the following regression model based on the post-event period[13]:

$$\Delta Y_{i,t} = \beta_1(\Delta inv.\ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}. \tag{4}$$

$\Delta Y_{i,t}$ captures the difference between the respective stock and its match in relative spreads, where $i$ denotes the stock and $t$ the respective quarter.

[12] To ensure a relevant pool of comparable stocks, we require at least 15 potential matches (i.e., initial fragmentation events) in a quarter for a stock to be included in the analysis resulting in a final data set of 291 pairwise stock matches.

[13] Because the exact day of the initial fragmentation event within a quarter differs between stocks, we do not consider the quarter that includes the initial fragmentation event in our regression model but include the 16 subsequent quarters.

$\Delta inv.\ HHI_{i,t}$ is the difference of fragmentation levels and $\boldsymbol{X}_{i,t}$ is a vector of control variables including the differences for log trading volume, volatility, the inverse of stock price, and log market capitalization, which are widely adopted in the market microstructure literature (e.g., Huang and Stoll, 1996; Stoll, 2000; Venkataraman, 2001; Hendershott et al., 2011; Gresse, 2017; Clapham et al., 2021). We derive the results of the panel regression using fixed effects estimators to eliminate time-constant and unobserved effects as proposed by Wooldridge (2002). We furthermore include stock ($\nu_i$) and date ($\nu_t$) fixed effects and apply double clustered standard error estimation for the clusters stock and quarter.

Table 6: Results of the panel regression model for the effect of fragmentation on market quality after the initial fragmentation event

| 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 | |

Table 6 shows the results of the panel regression. The results show that the difference in the level of fragmentation does not significantly influence liquidity in terms of relative spreads after the initial fragmentation event. Although the respective coefficient is negative indicating that stocks that fragment less have larger spreads while stocks that fragment more have smaller spreads, the effect of fragmentation on liquidity is not significant. In contrast, relative spreads on the respective stock's main market are primarily determined by market capitalization and trading volume of the stock. However, stocks that are traded on multiple venues for the first time do not fragment a lot after the initial fragmentation event (median fragmentation of 1.05 in our sample), which is also visible in Figure 4 showing the development of the fragmentation level for the first 16 quarters after the initial fragmentation event.

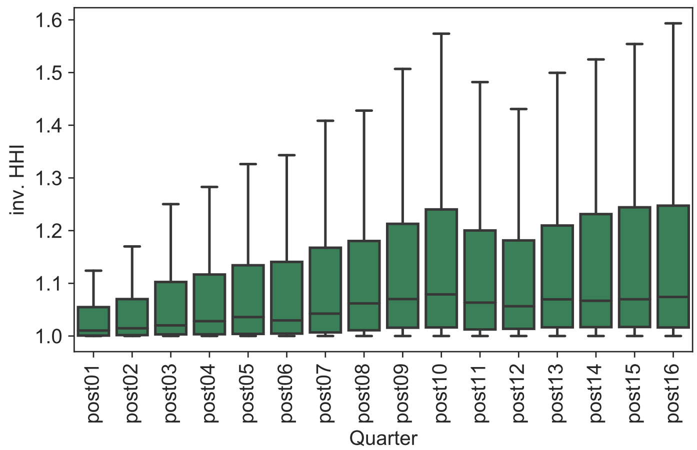



Figure 4: Distribution of fragmentation per quarter in the post fragmentation period for stocks with a fragmentation event

Yet, there are stocks in the sample that show substantial levels of market fragmentation. Therefore, we build another subsample containing only the most fragmented stocks in the post period and perform the same regression as above to identify whether higher levels of initial fragmentation have an effect on liquidity. Specifically, we filter the 25% most fragmented stocks in the data set (105 stocks with average fragmentation level in the post period $\geq$ 1.16 and share of SME stocks in the pre-event quarter of 85.07%) and match the stocks within this subset of stocks as described above resulting in a data set of 40 stock matches. Since the stocks that fragment more are quite similar regarding their trading characteristics, the pairs-matching within this subsample leads to almost as good matches as the matching within the whole sample.

Figure 5 shows the shares of SME stocks and liquidity classes over time within the subsample. The graph supports the results of the Heckman selection model showing that trading of stocks which exhibit a higher market capitalization and which are traded more actively are more likely to fragment. Similar to Figure 3 but even more pronounced, stocks in the more fragmented subset shift from the two lowest liquidity classes to the third liquidity class with trading activity between 80 and 600 transactions per day (liquidity class 600) before the fragmentation event. This indicates that relevant levels of fragmentation particularly realize for stocks in liquidity classes 600 and

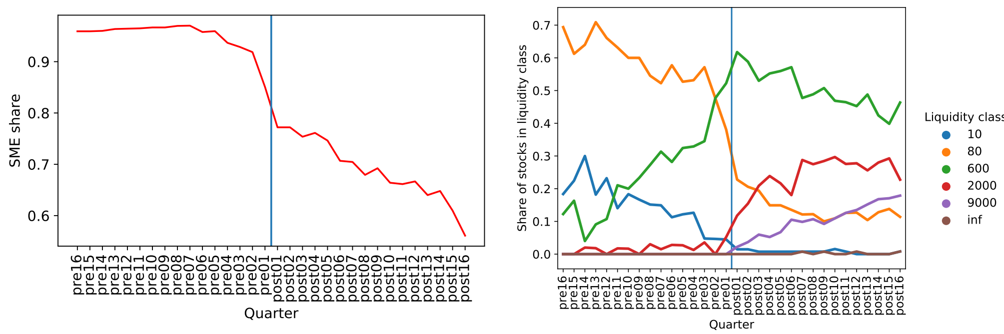



Figure 5: Share of SME stocks and stocks within the different liquidity classes before and after the initial fragmentation event (Subsample of stocks with a relevant fragmentation level after the initial fragmentation event)

higher. Furthermore, in comparison with Figure 3, a clearly larger share of stocks shifts to the higher liquidity classes of 600 and more transaction per day (liquidity classes 2000 and 9000) after the initial fragmentation event, further supporting that trading activity is a major driver of the level of stock market fragmentation. Table 7 provides the results of the subsample analysis. Different to the whole sample, the results of the panel regression based on the more fragmented subset show that higher levels of market fragmentation positively influence the liquidity of a stock. This means that higher levels of market fragmentation after being traded on multiple venues for the first time lead to smaller relative spreads on the main venue where the stock was solely traded before. In addition, these findings indicate the existence of a liquidity-related threshold (liquidity class 600), which determines when fragmentation becomes beneficial for stocks' market quality.

In summary, our results show that market fragmentation depends on stock characteristics and is primarily influenced by a stock's market capitalization and trading activity. This relation holds for both the likelihood of a stock being traded on multiple venues, i.e., the initial fragmentation event, and the level of market fragmentation. For our sample of less liquid and mostly SME stocks, we find that fragmentation after the initial event does not have an effect on market quality measured by the relative spread on the respective stock's main venue. However, this predominantly results from the fact that the average SME stock only marginally fragments after being traded on multiple venues for the first time. Instead, trading remains almost entirely on the incumbent venue. When focusing on those (few) stocks that show rele-

Table 7: Results of the panel regression model for the effect of fragmentation on market quality after the initial fragmentation event (Subsample of stocks with a relevant fragmentation level after the initial fragmentation event)

| 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 | |

vant levels of market fragmentation, we find that higher fragmentation leads to lower relative spreads consistent with previous literature on blue chips and other more actively traded stocks (Gresse, 2017; O'Hara and Ye, 2011). This indicates, that there is a liquidity-related threshold after which relevant levels of fragmentation emerge and when fragmentation becomes beneficial for stock market quality.

## 5. Fragmentation and Market Quality

In order to obtain a more granular picture of the impact of the level of fragmentation on market quality, we conduct a second analysis based on intraday order book data. Within this analysis, we investigate the impact of market fragmentation on different dimensions of liquidity and market quality. Different from the analyses conducted in the previous section, we now include all relevant trading venues that are available to market participants as liquidity pools by calculating all measures based on the consolidated order book of all venues. This analysis allows us to provide a comprehensive picture of the impact of fragmentation both in terms of affected dimensions and by differentiating between stocks from different liquidity classes.

*5.1. Data and Descriptive Statistics*

For this purpose, we derive data from the BMLL Data Lab[14]. In particular, based on the 1300 stocks as described in Section 3 we consolidate order book and trade information during continuous trading[15] based on one minute order book snapshots from all entire order books of the main venues Euronext Paris, LSE, and Xetra as well as the alternative venues Aquis, CXE, BXE, and Turquoise. Similar procedures for the consolidation of order book information to analyze different effects on overall market quality have been used before in academic literature (e.g., Clapham et al., 2021; Gresse, 2017; Degryse et al., 2015; Foucault and Menkveld, 2008). For stocks mainly traded on Euronext Paris and LSE, we cover the time period from June 5, 2017 until September 30, 2020 and for stocks mainly traded on Xetra we include the time period from February 1, 2019 until September 30, 2020.[16]

Based on the consolidated order book and trade information, we compute different market quality and trading volume measures. In specific, we derive the inv. HHI, the sum of overall trading volume in euro (euro-volume), and price volatility for each trading day in the respective time period. Furthermore, based on the one minute snapshots, we derive the price, the relative spread, euro-volume (depth) available at the best bid and offer (depth(L1)), euro-volume available at both sides of the first ten limits of the order book (depth(L10))[17], the order book imbalance regarding order book level one (depth(L1)-imbalance) and depth(L10) (depth(L10)-imbalance)[18], and the midpoint dispersion between all available trading venues[19]. We then aggre-

[14] https://bmlltech.com/

[15] We exclude call auction periods since opening, mid-day, and closing auctions only take place on the main venue.

[16] We cover a shorter time period for stocks that mainly trade on Xetra because of later data availability on the BMLL platform.

[17] The depth measures are based on the depth(Xbps) measure of Degryse et al. (2015) measuring the order volume available X bps around the midpoint. Because choosing X is challenging when comparing more and less liquid stocks with significant differences regarding their spreads, we adjust the measure to account for the first (L1) and the first ten (L10) order book levels.

[18] We compute order book imbalance for levels Y (L1 or L10) as follows:
$imbalance(Y) = \frac{|depth(Y)_{bid} - depth(Y)_{ask}|}{depth(Y)}$.

[19] We compute the midpoint dispersion as the mean absolute distance between the midpoints of all available trading venues. We normalize the mean distance by the midpoint of the main venue.

gate these measures by the median for each trading day and enrich the data set with market capitalization data from Refinitiv Datastream. Our final data set contains 868 stocks.[20]

Table 8 shows the descriptive statistics divided in the six different liquidity classes. The lower liquidity classes 10 to 600 ((1)-(3)) almost entirely consist of SME stocks. In contrast, only one third of the stocks in class 2000 (4) are SME stocks and only very few SME stocks are in the most liquid classes 9000 (5) and inf (6). The mean and median values show that stocks in the low liquidity classes 10 and 80 are hardly or not at all fragmented. In contrast, from liquidity class 600 onwards, we observe relevant and rising levels of market fragmentation, which again indicates a potential liquidity threshold for market fragmentation to realize. Furthermore, the level of fragmentation rises monotonically with the liquidity classes (together with market capitalization and in reverse to the share of SME stocks) again supporting our results of the previous section that stock-specific characteristics (size and trading activity) influence the level of market fragmentation. Regarding market quality, we find the same monotonicity, i.e., stocks in higher liquidity classes have lower relative spreads, more depth, lower order book imbalance, higher trading volume, and are less volatile. Also, stocks in higher liquidity classes show a smaller midpoint dispersion indicating that higher trading activity leads to a better connectedness of markets due to algorithmic and high frequency traders using smart order routing technology and arbitrage strategies that support a virtually integrated marketplace (Riordan et al., 2011). We provide more detailed descriptive statistics including the distribution of values within each liquidity class in Tables A.4 (for classes (1)-(3)) and A.5 (for classes (4)-(6)) in the appendix.

These descriptive results again support that stock-specific characteristics, market capitalization and trading activity, drive both the level of fragmentation and market quality dimensions such as liquidity and volatility. We control for this endogeneity by separating the stocks into the the six different liquidity classes of the European tick size regime also for the subsequent analysis. Furthermore, we follow O'Hara and Ye (2011) and conduct two different analyses to identify the effect of market fragmentation on market quality. First, we perform a matched-pairs analysis to control for stock-specific

[20]More details regarding the sample selection and the data sets can be found in Tables A.1 and A.2 in the appendix (see BMLL data set).

Table 8: Descriptive statistics (means and medians) for different market quality measures of the analyzed stocks separated by liquidity class

This table shows the mean and median values for the different market quality measures in our data set divided in different liquidity classes according to the European tick size regime. Market capitalization (mcap) is reported in million euro, euro-volume, depth(L1), and depth(L10) in hundred thousand euro, relative spread and midpoint dispersion in bps.

| | | (1)<br>10 | (2)<br>80 | (3)<br>600 | (4)<br>2000 | (5)<br>9000 | (6)<br>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 |

factors that can influence market quality measures, and second, we perform a panel regression analysis including different control variables accounting for variation in stock-specific characteristics.

*5.2. Matched-Pairs Analysis*

For the matched-pairs analysis, we use the time period from February 1, 2019 until September 30, 2020 where data is available for all markets to allow matches between all stocks. This results in a subsample of 840 stocks in the respective time period. As in the previous section, we follow Davies and Kim (2009) and match stocks to their nearest neighbors within each of the six liquidity classes based on average values of market capitalization, price, relative spread, and euro-volume in the whole observation period. We then determine the differences between matched stocks for each variable in our data set and estimate the following regression model:

$$\Delta Y_{i,t} = \beta_1(\Delta inv.\ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}. \tag{5}$$

$\Delta Y_{i,t}$ captures the difference between each dependent market quality measure, i.e., relative Spread, depth(L1), depth(L1)-imbalance, depth(L10), depth(L10)-imbalance, and midpoint dispersion of the respective stock and its match, where $i$ denotes the stock and $t$ the respective day. $\Delta inv.\ HHI_{i,t}$ is the difference of fragmentation levels and $\boldsymbol{X}_{i,t}$ is a vector of control variables (the same variables as in the previous section) including differences for log trading volume, volatility, the inverse of stock price, and log market capitalization. For each setup, we control for outliers by removing those observations with the largest 5% of absolute difference for the respective dependent variable. We derive the results of the panel regression using fixed effects estimators, include stock ($\nu_i$) and date ($\nu_t$) fixed effects, and apply double clustered standard error estimation for the clusters stock and day.

Table 9 provides the results of the matched-pairs analysis. Similar to previous studies and section 4, the results confirm that market fragmentation increases liquidity of larger and other more actively traded stocks by reducing their relative spread. However, while the effect of fragmentation on relative spreads of stocks in higher liquidity classes is positive (starting from liquidity class 600 (3)), stocks of lower liquidity classes are not benefiting (liquidity class 10 (1)) and can even be harmed by increasing fragmentation (liquidity class 80 (2)). The higher midpoint dispersion of the second lowest liquidity

Table 9: Regression results of the matched-pairs regression

This table shows the regression results of the matched-pairs regression for each of the different liquidity classes. Specifically, it reports the coefficient of the $\Delta inv.\ HHI$ variable, i.e., $\beta_1$ of Equation 5 and its respective p-value for each of the dependent variables $\Delta Y$.

| $\Delta Y$ | (1)<br>10 | (2)<br>80 | (3)<br>600 | (4)<br>2000 | (5)<br>9000 | (6)<br>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 |

class may provide a potential explanation to this finding as different liquidity pools seem less connected (e.g., due to less high-frequency trading activity), which might provide frictions and thus, in line with theoretical models, decreases liquidity. Moreover, trading interest and order flow of these stocks seem to be too low to be split up among multiple liquidity pools. These findings foster the existence of a liquidity-related threshold (liquidity class 600 (3)) determining when fragmentation is beneficial for stocks' market quality. Considering the impact of fragmentation on all liquidity classes, the fragmentation effect can be described as a hockey stick curve, showing (1) no effect for the lowest liquidity class due to non-existent fragmentation, (2) negative effects for stocks with low liquidity, and (3) increasing positive effects for stocks with increasing liquidity (liquidity class 600 and higher).

Besides the impact on relative spreads, our results show that increasing fragmentation is also positively affecting consolidated depth at the top level (L1) from liquidity class 600 onwards, while lower liquidity classes are negatively affected. These effects are highly significant across all liquidity classes except for the marginally fragmented liquidity class 10 (1). Regarding deeper levels of the order book (L10), depth increases significantly except for most actively traded stocks of liquidity classes 9000 (5) and inf (6). Additionally, order book imbalance improves with rising level of market fragmentation for medium liquid stocks while this effect is mostly insignificant or even negative for the two lowest and highest liquidity classes.

The results of the matched-pairs analysis show that fragmentation has positive effects on stocks with sufficient trading activity. These findings, however, cannot be extended to all stocks as effects of fragmentation seem to be dependent on stock-specific characteristics such as trading activity or stock size. Moreover, our results show that fragmentation can be even harmful for SME stocks that show only some trading activity (liquidity class 80 (2)).

*5.3. Panel Regression Analysis*

For the panel regression analysis without matches, we use the full data set of 868 stocks (covering longer observation periods for the main venues Euronext Paris and LSE) and estimate the following regression model:

$$Y_{i,t} = \beta_1(inv.\ HHI_{i,t}) + \delta' \boldsymbol{X}_{i,t} + \nu_i + \nu_t + \varepsilon_{i,t}. \tag{6}$$

$Y_{i,t}$ captures each dependent market quality measure, i.e., relative Spread, depth(L1), depth(L1)-imbalance, depth(L10), depth(L10)-imbalance, and midpoint dispersion, where $i$ denotes the stock and $t$ the respective day. $inv.\ HHI_{i,t}$ is the stock's respective fragmentation level and $\boldsymbol{X}_{i,t}$ is a vector of control variables including log trading volume, volatility, the inverse of stock price, and log market cap. For each setup, we remove outliers below the 2.5% and above the 97.5% percentiles for the respective dependent variable. We derive the results of the panel regression using stock ($\nu_i$) and date ($\nu_t$) fixed effects and apply double clustered standard error estimation for the clusters stock and day.

Table 10 provides the results of the panel regression analysis. Comparing the results of the panel regression analysis to those of the matched-pairs analysis in section 5.2 shows almost identical outcomes and hence, provides strong robustness of our findings based on the different methodologies and observation periods of the analyses. Again, we find positive effects of fragmentation on liquidity (in particular depth) for more liquid stocks. Furthermore, less actively traded stocks of liquidity class 80 (2) are negatively affected by increasing fragmentation (higher spreads and lower depth) and show an increasing midpoint dispersion, which could again be a potential reason for the observed results. Also, the liquidity threshold where fragmentation positively affects market quality is again represented by liquidity class 600 (3)

Table 10: Regression results of the panel regression

This table shows the regression results of the panel regression for each of the different liquidity classes. Specifically, it reports the coefficient of the *inv. HHI* variable, i.e., $\beta_1$ of Equation 6 and its respective p-value for each of the dependent variables $Y$.

| $Y$ | (1) 10 | (2) 80 | (3) 600 | (4) 2000 | (5) 9000 | (6) 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 |

and the results provide support for a hockey stick effect of market fragmentation. Depth imbalance improves with rising level of market fragmentation significantly for stocks included in the medium liquidity classes 600 (3) and 2000 (4), while the results are insignificant for more liquid stocks.

For robustness, we repeat both the matched-pairs and the panel regression analysis excluding the year 2020 to ensure that the market turbulences due to COVID-19 especially in spring 2020 do not bias our results. Our results remain robust with the limited observation period. Due to their similarity, the results of this analysis are not tabulated here but available from the authors upon request.

In summary, our results show that the effect of fragmentation on market quality depends on the size and trading activity of a stock and, thus, varies between different liquidity classes. In line with previous research, fragmentation has a positive effect on market quality of highly liquid and actively traded stocks. For these stocks, market fragmentation not only affects liquidity in terms of relative spreads but also depth on different order book levels and order imbalance. In particular, order imbalance is a relevant liquidity dimension for the resiliency of markets and market makers providing liquidity (Chordia et al., 2002). Yet, our results also show that fragmentation has no or even a negative effect on market quality of less actively traded stocks of SMEs and other smaller companies. The descriptive statistics show that the average SME stock does not or does only marginally fragment so that potential negative effects from market fragmentation do not realize for most of these stocks. The impact of fragmentation on market quality follows a hockey stick curve with no impact for stocks with lowest liquidity, negative impact for less liquid stocks and positive effects for stocks with higher liquidity, whereby these positive effects rely on a liquidity-related threshold. As indicated by the analysis of the stocks' midpoint dispersion between markets, a potential reason for the different effects of market fragmentation on less and highly active stocks is the connectedness of the different liquidity pools. Smart order routing technology and high-frequency trading lead to a virtual consolidation of markets for large and actively traded stocks thereby avoiding the negative effects of the spatial split of liquidity across different venues. As these technologies are less present in SME and other less actively traded stocks, frictions from a split of liquidity pools persist.

## 6. Conclusion

What are the drivers and effects of stock market fragmentation? Our analyses provide two major results: First, market fragmentation is not exogeneous but is rather driven by stock-specific characteristics, particularly market capitalization and trading activity. This holds for both the likelihood of a stock being traded on multiple venues and the level of market fragmentation. Second, the impact of market fragmentation on market quality is not identical for every stock but also depends on the size and trading activity of a stock. Our results suggest that there are liquidity-related thresholds after which relevant levels of fragmentation emerge and when fragmentation becomes beneficial for stock market quality. As our analysis shows, these two findings have important implications for SME and other less actively traded stocks.

Previous research has shown that market fragmentation positively affects market quality of large and blue chip stocks despite the spatial fragmentation of liquidity pools (e.g., Gresse, 2017). Due to advanced trading technology such as smart order routing and high-frequency trading, different markets for trading a specific stock are virtually connected, which allows the benefits of increased competition between multiple markets to persist (O'Hara and Ye, 2011). Our results not only confirm this finding, but we show that fragmentation improves liquidity of large stocks along a multitude of dimensions, i.e., spread, depth, and order book imbalance. Yet, our results also show that increasing fragmentation is not beneficial for all stocks but depends on the size and trading activity of a stock. In particular, market quality of SMEs and other less actively traded stocks initially does not improve with higher levels of fragmentation. In contrast, up to a certain liquidity threshold, relative spreads of less liquid stocks even increase (and market depth decreases) with higher levels of market fragmentation. For these stocks, trading interest and order flow are too low to be split up among multiple liquidity pools. As indicated by the higher midpoint dispersion, the virtual integration of different markets for trading less actively traded stocks is not accomplished so that frictions from splitting up liquidity pools persist.

The results of our analysis also show that the main reason for the mostly insignificant effect of market fragmentation on the quality of less liquid stocks is that these stocks do not show a substantial level of market fragmentation. We find that a high number of SME stocks only marginally fragment after being traded on multiple venues for the first time. Instead, trading of SME and other less actively traded stocks is mostly concentrated on a single venue, which is regularly the incumbent venue with the stock's primary listing.

Our analysis is limited to drivers and effects of lit market fragmentation and does not include fragmentation concerning other trading categories such as OTC trading, dark trading, and systematic internalisers. Moreover, our analysis of initial fragmentation events is only based on quarterly data and not on intraday data. However, based on two data sets with different granularity, we comprehensively analyze lit market fragmentation, which is most relevant for price discovery and efficient financial markets.

Our results are relevant for regulators and practitioners, in particular for market operators and issuers of SME stocks. These groups can revert to our findings within the current debate on the European Capital Markets Union, an initiative of the European Commission to increase the attractiveness of going and being public for SMEs and to increase the relevance of European securities markets as a source of capital for smaller firms (European Commission, 2015, 2020a), and within the currently ongoing review of MiFID II (European Commission, 2020b). In these debates, market observers have argued that issuers of SME stocks should be given the right to choose where to be traded to prevent a fragmentation of their already less liquid stocks (Federation of European Securities Exchanges, 2019). Our results show that a more nuanced and case-specific debate regarding the impact of fragmentation on SME and other less actively traded stocks is needed, which is supported by the observed liquidity thresholds and the hockey stick effect of market fragmentation.

As our results show, the impact of fragmentation depends on the trading activity of a stock and becomes beneficial for more liquid and actively traded stocks. Therefore, regulators should focus on creating an environment that increases the attractiveness and trading activity of SME stocks and, thereby, enable stocks that achieve some initial liquidity to reach a tipping point where fragmentation will likely improve market quality. Also, issuers could increase their efforts to gain investors' interest in their stocks, e.g., with increased investor relations initiatives. If relevant liquidity levels and trading activities in SME stocks are achieved, market fragmentation can even promote the aims of the Capital Markets Union and of MiFID by reducing implicit transaction costs for investors and cost of capital for issuers.

Since increased market fragmentation in today's securities markets does not seem to be the driving force of decreasing attractiveness of securities markets for SMEs, future research could investigate other factors that potentially influence the attractiveness of public listings, especially for smaller companies, since active and attractive securities markets build the backbone of modern economies.

## Appendix

Table A.1: Sample selection for the Fidessa and BMLL data sets

This table presents the sample selection for the Fidessa and BMLL data sets. Both data sets are based on a list of all active and delisted stocks that are and have been listed on one of the main regulated markets LSE, Euronext Paris, or Xetra in the period of Q1/2009 to Q4/2019 according to Refinitiv Datastream. For each main market, we filter stocks for the respective home market UK, France, or Germany. Selected stocks for the BMLL data set are based on the stocks in the Fidessa data set. The time period for the BMLL data set is June 5, 2017 until September 30, 2020 for stocks mainly traded on LSE and Euronext Paris and February 1, 2019 until September 30, 2020 for stocks mainly traded on Xetra.

| | **UK stocks** | **French stocks** | **German stocks** | **Sum of stocks** |
|---|---|---|---|---|
| All stocks (Q1/2009 - Q4/2019) | 1745 | 994 | 789 | 3528 |
| **Fidessa data set** | | | | |
| Stocks with available main market lit volume on Fidessa (Q1/2009 - Q4/2019) | 507 | 426 | 367 | 1300 |
| **BMLL data set** | | | | |
| Available stocks on BMLL with level three order book information | 336 | 342 | 190 | 868 |

Table A.2: Distribution of market capitalization and share of SME stocks for the Fidessa and BMLL data sets

This table presents the distribution of market capitalization and share of SME stocks for UK, French, and German stocks in both data sets (Panel A: Fidessa data set, Panel B: BMLL data set). Values are based on stock-quarterly observations for the Fidessa data set and stock-daily observations for the BMLL data set. Market capitalization (mcap) is reported in million euro.

| **Panel A** | **Fidessa data set** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| mcap | count | mean | std | min | 25% | 50% | 75% | max | SME share |
| UK stocks | 14451 | 4681.42 | 12945.74 | 0.60 | 303.53 | 875.75 | 2817.20 | 153265.00 | 54.02% |
| French stocks | 14825 | 4167.53 | 13015.81 | 0.39 | 65.25 | 264.25 | 1886.75 | 209349.50 | 70.39% |
| German stocks | 11798 | 4441.74 | 12556.13 | 1.19 | 82.78 | 357.78 | 2139.69 | 148354.20 | 65.74% |
| **Panel B** | **BMLL data set** | | | | | | | | |
| mcap | count | mean | std | min | 25% | 50% | 75% | max | SME share |
| UK stocks | 273781 | 5877.33 | 14905.32 | 5.65 | 490.85 | 1358.08 | 4196.35 | 159163.60 | 41.86% |
| French stocks | 252535 | 6283.10 | 18022.16 | 1.90 | 101.96 | 473.76 | 3168.29 | 221909.60 | 63.20% |
| German stocks | 77479 | 7898.68 | 17263.43 | 0.45 | 444.20 | 1716.81 | 6931.84 | 174865.30 | 40.98% |

Table A.3: Results of the panel regression models explaining the level of market fragmentation. We run the following model: $inv.\ HHI_{i,t} = \beta \boldsymbol{X}_{i,t} + \nu_t + \varepsilon_{i,t}$, where $\boldsymbol{X}_{i,t}$ is a vector of independent variables accounting for market capitalization ($log(mcap)$) and trading activity ($log(euro-volume)$ or dummies for the liquidity classes). We derive the results using time fixed effects on a year-quarter level and apply double clustered standard error estimation for the clusters stock and year-quarter.

| | (1) | | (2) | |
|---|---|---|---|---|
| Dependent Variable | inv. HHI | | inv. HHI | |
| Variables | Estimate | p-Value | Estimate | p-Value |
| log(mcap) | 0.06 | 0.00 | 0.03 | 0.00 |
| log(euro-volume) | 0.09 | 0.00 | | |
| liquidity class 80 | | | 0.002 | 0.68 |
| liquidity class 600 | | | 0.16 | 0.00 |
| liquidity class 2000 | | | 0.57 | 0.00 |
| liquidity class 9000 | | | 0.92 | 0.00 |
| liquidity class inf | | | 0.91 | 0.00 |
| Observations | 40884 | | 40884 | |
| Adj. $R^2$ | 0.68 | | 0.80 | |

Table A.4: Descriptive statistics for different market quality measures of the analyzed stocks separated by liquidity class (liquidity classes 10, 80, and 600)

This table shows the descriptive statistics for the different market quality measures in our data set divided in different liquidity classes (liquidity classes 10, 80, and 600) according to the European tick size regime. Market capitalization (mcap) is reported in million euro, euro-volume, depth(L1), and depth(L10) in hundred thousand euro, relative spread and midpoint dispersion in bps. Spreads can be negative due to the consolidation of different order books.

| **Panel A** | **Liquidity class 10 (51 stocks)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 25855 | 1.02 | 0.12 | 1.00 | 1.00 | 1.00 | 1.00 | 3.61 |
| price | 23480 | 42.59 | 62.99 | 0.0034 | 3.13 | 12.20 | 68.00 | 366.00 |
| volatility | 18232 | 0.33 | 0.85 | 0.00 | 0.01 | 0.04 | 0.24 | 13.11 |
| mcap | 29531 | 216.08 | 451.91 | 0.45 | 39.67 | 86.28 | 177.40 | 3600.06 |
| relative spread | 30843 | 390.89 | 556.05 | -1111.11 | 121.21 | 236.09 | 444.44 | 19928.70 |
| euro-volume | 31180 | 0.16 | 1.57 | 0.00 | 1.6E-5 | 0.02 | 0.10 | 122.72 |
| depth(L1) | 31180 | 0.54 | 8.92 | 0.00 | 0.03 | 0.07 | 0.14 | 451.87 |
| depth(L1)-imbalance | 31167 | 0.45 | 0.29 | 0.00 | 0.20 | 0.42 | 0.68 | 1.00 |
| depth(L10) | 31180 | 1.95 | 14.69 | 5.4E-5 | 0.40 | 0.72 | 1.38 | 576.57 |
| depth(L10)-imbalance | 31180 | 0.32 | 0.24 | 0.00 | 0.12 | 0.27 | 0.48 | 1.00 |
| midpoint dispersion | 25507 | 212.43 | 11077.50 | 0.00 | 0.00 | 0.00 | 0.00 | 766349.61 |
| **Panel B** | **Liquidity class 80 (164 stocks)** | | | | | | | |
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 114629 | 1.06 | 0.17 | 1.00 | 1.00 | 1.00 | 1.03 | 4.00 |
| price | 114153 | 39.55 | 108.95 | 0.02 | 2.41 | 8.14 | 34.08 | 1415.00 |
| volatility | 111730 | 0.25 | 0.82 | 0.00 | 0.02 | 0.05 | 0.19 | 31.50 |
| mcap | 115504 | 352.58 | 702.50 | 1.69 | 69.73 | 165.36 | 349.13 | 7178.72 |
| relative spread | 116397 | 150.65 | 155.50 | -2248.88 | 63.09 | 106.10 | 186.05 | 3471.07 |
| euro-volume | 116728 | 0.64 | 2.72 | 0.00 | 0.08 | 0.25 | 0.65 | 384.49 |
| depth(L1) | 116728 | 0.79 | 25.86 | 0.00 | 0.04 | 0.07 | 0.13 | 2409.15 |
| depth(L1)-imbalance | 116728 | 0.49 | 0.23 | 0.00 | 0.32 | 0.48 | 0.66 | 1.00 |
| depth(L10) | 116728 | 2.28 | 29.25 | 0.01 | 0.62 | 1.03 | 1.77 | 2431.77 |
| depth(L10)-imbalance | 116728 | 0.23 | 0.18 | 0.00 | 0.09 | 0.19 | 0.33 | 1.00 |
| midpoint dispersion | 108932 | 59.72 | 793.65 | 0.00 | 0.00 | 0.00 | 16.72 | 98034.19 |
| **Panel C** | **Liquidity class 600 (198 stocks)** | | | | | | | |
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 139009 | 1.21 | 0.25 | 1.00 | 1.03 | 1.13 | 1.30 | 4.89 |
| price | 138942 | 21.99 | 57.93 | 0.01 | 2.11 | 6.70 | 24.05 | 1048.00 |
| volatility | 138680 | 0.15 | 0.47 | 0.00 | 0.02 | 0.05 | 0.14 | 45.83 |
| mcap | 138495 | 575.24 | 680.62 | 2.36 | 187.81 | 414.13 | 696.32 | 12729.99 |
| relative spread | 139042 | 66.42 | 68.50 | -3030.30 | 32.05 | 47.21 | 76.63 | 1583.79 |
| euro-volume | 139241 | 4.97 | 12.97 | 0.00 | 0.99 | 2.46 | 5.55 | 1831.56 |
| depth(L1) | 139241 | 0.27 | 12.82 | 0.00 | 0.05 | 0.09 | 0.15 | 1857.87 |
| depth(L1)-imbalance | 139241 | 0.44 | 0.15 | 0.00 | 0.34 | 0.42 | 0.52 | 1.00 |
| depth(L10) | 139241 | 3.10 | 35.50 | 0.04 | 1.12 | 1.85 | 2.89 | 3325.35 |
| depth(L10)-imbalance | 139241 | 0.18 | 0.13 | 0.00 | 0.09 | 0.15 | 0.24 | 1.00 |
| midpoint dispersion | 132412 | 62.42 | 317.83 | 0.00 | 14.57 | 35.24 | 56.26 | 26526.40 |

Table A.5: Descriptive statistics for different market quality measures of the analyzed stocks separated by liquidity class (liquidity classes 2000, 9000, and inf)

This table shows the descriptive statistics for the different market quality measures in our data set divided in different liquidity classes (liquidity classes 2000, 9000, and inf) according to the European tick size regime. Market capitalization (mcap) is reported in million euro, euro-volume, depth(L1), and depth(L10) in hundred thousand euro, relative spread and midpoint dispersion in bps. Spreads can be negative due to the consolidation of different order books.

| **Panel A** | **Liquidity class 2000 (137 stocks)** | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 98819 | 1.61 | 0.33 | 1.00 | 1.36 | 1.56 | 1.80 | 3.56 |
| price | 98819 | 31.86 | 121.21 | 0.01 | 2.60 | 6.78 | 20.92 | 1711.00 |
| volatility | 98817 | 0.18 | 0.70 | 0.00 | 0.01 | 0.04 | 0.12 | 23.96 |
| mcap | 97137 | 2038.18 | 6080.06 | 9.09 | 764.90 | 1149.57 | 1664.45 | 88846.00 |
| relative spread | 98821 | 22.74 | 184.03 | -16395.49 | 13.55 | 17.86 | 26.60 | 1660.22 |
| euro-volume | 98823 | 30.66 | 38.49 | 0.00 | 11.30 | 20.57 | 36.36 | 2036.35 |
| depth(L1) | 98823 | 0.25 | 0.93 | 0.01 | 0.11 | 0.17 | 0.27 | 78.44 |
| depth(L1)-imbalance | 98823 | 0.37 | 0.08 | 0.05 | 0.31 | 0.36 | 0.41 | 1.00 |
| depth(L10) | 98823 | 4.04 | 4.56 | 0.29 | 1.84 | 2.99 | 5.02 | 318.36 |
| depth(L10)-imbalance | 98823 | 0.12 | 0.07 | 0.01 | 0.07 | 0.10 | 0.14 | 0.90 |
| midpoint dispersion | 97567 | 19.14 | 92.30 | 0.00 | 6.65 | 10.07 | 16.53 | 15922.18 |
| **Panel B** | **Liquidity class 9000 (219 stocks)** | | | | | | | |
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 156359 | 1.79 | 0.35 | 1.00 | 1.55 | 1.75 | 1.99 | 4.12 |
| price | 156359 | 33.45 | 55.49 | 0.08 | 5.25 | 15.04 | 39.71 | 782.20 |
| volatility | 156359 | 0.18 | 0.34 | 0.001 | 0.02 | 0.07 | 0.20 | 14.16 |
| mcap | 155518 | 5995.12 | 6794.59 | 61.10 | 2436.14 | 4205.99 | 7022.86 | 82998.31 |
| relative spread | 156358 | 9.72 | 9.43 | -1300.49 | 5.78 | 7.87 | 11.27 | 298.51 |
| euro-volume | 156361 | 192.87 | 199.61 | 0.00 | 77.21 | 140.70 | 247.01 | 14939.36 |
| depth(L1) | 156361 | 0.51 | 0.50 | 0.003 | 0.23 | 0.37 | 0.62 | 52.30 |
| depth(L1)-imbalance | 156361 | 0.34 | 0.06 | 0.14 | 0.30 | 0.34 | 0.38 | 1.00 |
| depth(L10) | 156361 | 8.93 | 7.22 | 0.32 | 3.90 | 6.95 | 11.81 | 149.68 |
| depth(L10)-imbalance | 156361 | 0.09 | 0.04 | 0.02 | 0.07 | 0.09 | 0.11 | 0.89 |
| midpoint dispersion | 156298 | 5.74 | 18.30 | 0.00 | 2.56 | 3.83 | 6.10 | 3008.45 |
| **Panel C** | **Liquidity class inf (99 stocks)** | | | | | | | |
| | count | mean | std | min | 25% | 50% | 75% | max |
| inv. HHI | 67610 | 1.78 | 0.30 | 1.00 | 1.57 | 1.75 | 1.96 | 3.85 |
| price | 67610 | 52.65 | 71.74 | 0.26 | 12.22 | 27.21 | 68.24 | 611.00 |
| volatility | 67610 | 0.26 | 0.46 | 0.0005 | 0.05 | 0.12 | 0.29 | 15.51 |
| mcap | 67610 | 37726.40 | 33751.65 | 72.92 | 13661.51 | 25764.00 | 50524.77 | 221909.60 |
| relative spread | 67610 | 3.97 | 4.71 | -252.47 | 2.42 | 3.55 | 4.72 | 113.34 |
| euro-volume | 67610 | 1248.88 | 1083.53 | 3.40 | 555.93 | 963.89 | 1599.88 | 61616.64 |
| depth(L1) | 67610 | 1.22 | 1.07 | 0.01 | 0.52 | 0.87 | 1.54 | 17.68 |
| depth(L1)-imbalance | 67610 | 0.36 | 0.06 | 0.15 | 0.33 | 0.36 | 0.40 | 1.00 |
| depth(L10) | 67610 | 24.78 | 17.73 | 0.50 | 11.66 | 20.57 | 33.35 | 272.60 |
| depth(L10)-imbalance | 67610 | 0.09 | 0.03 | 0.03 | 0.07 | 0.08 | 0.10 | 0.86 |
| midpoint dispersion | 66768 | 2.23 | 5.54 | 0.00 | 1.00 | 1.64 | 2.30 | 541.16 |

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

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