Market Fragmentation: A Cushion Against Exchange Outages?

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Working paper No. 95

CNMV
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Abstract

When disruptions are costly, engineers use redundancies to enhance resiliency. In financial markets, where many exchanges compete for order flow in the same security, such redundancies may emerge as a positive side effect. We test this conjecture in a large sample of primary exchange outages in European equity markets. Although trading remains technically possible on other venues, the overall market in treated stocks turns illiquid during outages. The effective spread increases by 110% and turnover drops by 96%. We find that the degree of ex-ante fragmentation does *not* mitigate the illiquidity during outages. Overall, our findings imply a missed opportunity for European financial regulation.

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1 Introduction

When an airplane pilot falls ill, the co-pilot takes over the levers. When a car breaks down on the highway, multiple lanes mitigate traffic jams. Redundancies make systems resilient to shocks and prevent disruptions. In this paper, we investigate whether financial securities that are traded on multiple exchanges follow the same logic.

Exchange outages, technical malfunctions that disrupt trading, are a concern for market participants and financial policy makers. These events create uncertainty in the trading process, restrict price discovery, and undermine trust in financial markets. To address them, standardisation of communication protocols and transparent rules for the treatment of outages have been proposed (Optiver, 2020; European Securities and Markets Authority, ESMA, 2023; International Organization of Securities Commissions, IOSCO, 2023; Federation of European Securities Exchanges, FESE, 2023). At a more fundamental level, we point out that the fact that most securities trade at multiple venues may work as a cushion against the adverse effects of exchange outages.

O'Hara and Ye (2011, p. 459) describe a well-functioning fragmented market as a "single virtual market with multiple points of entry". With that image in mind, an exchange outage is akin to shutting one of those entry points. To the extent that orders continue to flow through the other doors, market fragmentation could make the trading system more resilient. According to the literature on system engineering, the redundancy attribute of resilient systems depends on substitutability (Francis and Bekera, 2014). In our context, that means that the resilience to outages gained by market fragmentation depends on the frictions traders face to migrating between trading venues.

We discuss three categories of frictions to market substitutability during outages: lack of network externalities, technical constraints, and behavioural issues. First, liquidity exhibits positive network externalities, as a larger number of market participants increases the likelihood of finding a trading counterparty. When the most active market is closed, market participants may lack an alternative focal market with deep enough liquidity. Consequently, execution costs may soar. Second, market participants may not migrate to alternative markets due to technical frictions. Trading on another venue requires pre-existing technical connections at the time an outage occurs. Participants without such connections may then be unable to trade. Moreover, trading algorithms may shut down if outages result in missing or unreliable inputs. Third, behavioural frictions may arise due to uncertainty aversion. For example, outages may cause price uncertainty, in particular when they prevent the price discovery of the opening call auction. Furthermore, during market malfunctions, traders may not know in real time whether their orders will eventually be cancelled.

To our knowledge, this paper is the first to analyse the link between market fragmentation and market resiliency around exchange outages in a comprehensive sample. We examine liquidity before, during, and after exchange outages, and explain cross-event and cross-stock differences through the lenses of market fragmentation and market substitutability.

Approach. We examine all exchange outages in European equity markets between 2018 and 2024. The 12 outages in our sample differ in scope, affecting between 49 and 195 stocks; in duration, ranging from one hour to more than five hours; and across exchanges, including Deutsche Börse, Euronext, the London Stock Exchange, Nasdaq Nordic, and SIX Swiss Exchange. While some outages occur before or during the opening session, others arise during the continuous trading session. Importantly, all outages in our sample disrupt continuous trading and occur at the primary listing exchange. This broad sample enables us to investigate the economic mechanisms underlying the heterogeneous outcomes across outages.

As outages are unanticipated and exogenous events, they are suitable for analysis as natural experiments. We conduct an event study of market-wide liquidity in treated stocks, benchmarked to trading before outages, as well as to stocks listed at other primary exchanges that remain open. The control stocks are matched to have similar size and degree of market fragmentation prior to the event. The matched sample includes 2,506 stocks.

We analyse intraday quote and trade data from the primary exchange as well as the four largest multilateral trading facilities (MTFs; exchanges that are not the listing exchange in these stocks). By measuring market liquidity in aggregate across the primary exchange and the MTFs, we can observe how liquidity develops before, during, and after each outage. From the quote data, we measure the quoted bid-ask spread and the expected price impact. From the trade data, we obtain the effective bid-ask spread and the effective price impact.

To gauge the effect of fragmentation on market quality, we compare the outcome for the top-tercile of treated stocks in terms of their degree of fragmentation, relative to other stocks. The degree of ex-ante fragmentation is measured on the basis of the volume market share of each exchange in the pre-event period. We run triple-difference event study regressions that compare stocks with high fragmentation to all other treatment stocks, relative to their respective control stocks, before, during, and after the outage.

Findings. Our comprehensive sample provides novel stylised facts about primary market outages in Europe. When an outage occurs, trading stops at the exchange in question, but remains technically possible at the MTFs. Nevertheless, liquidity at the MTFs almost freezes. On average, the quoted bid-ask spread increases by a factor of 10.4 (that is, it increases by 1,040%), relative to the control group. In economic terms, it widens from 13 basis points (bp) to 146 bp. The expected price impact increases tenfold, from 9 bp to 108 bp. These statistics show that trading during outages is prohibitively expensive. Accordingly, turnover drops by 96%, from €12 billion on average during normal times across all treated stocks, to €0.5 billion during outages. Those who nevertheless trade during outages pay effective bid-ask spreads that are more than twice as high (24 bp) as during normal times (11 bp). Moreover, turnover lost during an outage is not fully recovered when the primary market reopens. Daily turnover drops by around 18% on outage days compared to non-outage days.

The liquidity deterioration that we document for Europe is an order of magnitude stronger than what is found in the United States. Clark-Joseph et al. (2017) investigate the effects of a technical malfunction on the NYSE in July 2015, reporting a normalised effective spread increase of only 17%. They also show that an outage at Direct Edge, a US exchange without its own listings, in July 2015, did not significantly influence liquidity. For Australia, Baldauf and Mollner (2021) find that the bid-ask spread even shrinks by 28% when moving from a duopoly to a monopoly situation for an outage at Chi-X in June 2014. Our results for Europe are consistent with Comerton-Forde and Zhong (2021), who study an outage at Euronext in 2020 and report that the quoted bid-ask spreads widen by 260%.

Our main finding is that a higher degree of fragmentation does *not* provide the cushion during outages that may be expected given the redundancy of order entry points. If anything, the liquidity of more fragmented stocks deteriorates more than the liquidity of less fragmented stocks during the outage. Contrary to the predicted boost in resiliency, we find that the quoted bid-ask spread widens by an additional 12.5 bp for the most highly fragmented tercile of stocks.

Discussion. The absence of an association between fragmentation and resiliency through redundancy may reflect constraints on market substitutability. We examine this hypothesis using several approaches. First, we assess frictions arising from network externalities by focusing on stocks with a large alternative trading venue. Specifically, we sort stocks according to the market share of their second-largest trading venue. Stocks in the top-tercile of this distribution conduct at least 22% of their trading activity on one MTF. Analysing outage effects for these stocks, we find no evidence that the presence of a large alternative venue mitigates the impact of outages. Liquidity during outages is no higher for these stocks than for others.

Next, we explore whether technical frictions due to poor market connectivity disrupt liquidity migration during outages. Kaminski et al. (2025) show that 21% of marketable orders in European equity markets execute at prices at worse than the best available price, implying a lack of connectivity across venues. We proxy cross-market connectivity across stocks by studying close to simultaneous trades in the same stocks at different venues. Following Degryse et al. (2025), a higher intensity of such trades indicates a greater prevalence of smart order routers (SORs). In contrast to what would be expected if connectivity reduced technical frictions to substitutability, we find that a higher SOR intensity almost monotonically increases adverse outage effects. Although counterintuitive at first glance, a report by the Australian Securities and Investment Commission (ASIC, 2021, p. 21) states that during primary market outages "[...] brokers were unable to provide continuation of service due to electronic trading system dependencies on the affected market and limited arrangements to submit orders to the alternative market". Our findings are consistent with the fact that these algorithms fail during primary market outages and that brokers are then unable to systematically route client orders to alternative venues.

Finally, we investigate behavioural frictions. Do traders disconnect from trading due to price uncertainty? To study this, we identify the outages that lead to failure in producing an opening price. Such failures imply that overnight information is not incorporated in the price, leading to high price uncertainty. We find that such uncertainty almost doubles the adverse effects of outages on liquidity. This suggests that markets react strongly to the absence of an opening price and the price uncertainty associated with it. We also study Large-In-Scale trades, which is a category of trades that face no regulatory friction to continue independently of the status on the primary market. Consistent with price uncertainty, we find that this segment of the market becomes completely inactive during primary market outages.

We conclude that the European equity market is highly dependent on its primary markets, leading to fragility during outages.

What happens to liquidity after the outage has been resolved? We find that liquidity remains impaired for up to two hours after the primary market has reopened after an outage. Similarly to our finding for liquidity effects *during* an outage, we do not find signs of faster recovery for stocks with higher fragmentation *after* an outage.

Contribution. This paper adds to the literature on the determinants of market resiliency. Whereas most previous research on market microstructure interprets resiliency as the speed of recovery *after* a shock (as defined by Kyle, 1985), our focus is mainly the market's ability to continue normal operation *during* the shock. In the terminology of the system engineering literature, we focus on resiliency through *redundancy*, whereas the speed of recovery analyses imply a view of resiliency through the lens of *rapidity* (Francis and Bekera, 2014). Examples of market microstructure contributions to the rapidity category include the work on resiliency measurement by Kempf et al. (2015) and responses to extreme price movements by Brogaard et al. (2018).

This paper also contributes to an extensive literature that analyses the effects of market fragmentation on market quality. Previous evidence focuses on the impact on market liquidity (e.g., O'Hara and Ye, 2011; Degryse et al., 2015; Foucault and Menkveld, 2008), and market efficiency (Aitken et al., 2017; Chen and Duffie, 2021). Our investigation on how fragmentation influences resiliency through redundancy is new to the literature. The only preceding evidence we are aware of is a cross-sectional analysis during the Euronext 2020 outage, presented by Comerton-Forde and Zhong (2021). They show that stocks with concentrated MTF trading have lower adverse outage effects. Their analysis, however, is limited to one event. Our analysis establishes validity of the differential effects of fragmentation on

12 outages with varying outage characteristics. Félez-Viñas (2019) also studies the market resiliency effects of fragmentation, focusing on the market's ability to recover from mini-flash crashes, but that is resiliency in terms of rapidity rather than redundancy.

Finally, our study contributes to the literature on market outages. Previous empirical work in this vein includes Baldauf and Mollner (2021), Clark-Joseph et al. (2017), Comerton-Forde and Zhong (2021), Kerssenfischer and Helmus (2024), Yu (2023), and Woods (2021). A related field of study is the analysis of market crashes, such as the May 2010 flash crash (Kirilenko et al., 2017; Menkveld and Yueshen, 2017). In addition to analysing a comprehensive sample of outages, our focus on how the degree of fragmentation influences the liquidity effects of outages is new to this literature.

The remainder of the paper is structured as follows. Section 2 presents the empirical framework. Section 3 documents the main results, while Section 4 discusses frictions to market substitutability. Section 5 examines the recovery period. Section 6 concludes.

2 Empirical Framework

2.1 Event Sample

Our analysis studies outages on primary markets on European exchanges between 2018 and 2024.[1] Outages are technical glitches that disrupt essential trading services, such as placing orders or disseminating quotes. These are unanticipated and exogenous events that are arguably not linked to any trading behaviour (ESMA, 2023). We use them as natural experiments to improve our understanding of the role of market fragmentation in exchange competition and market resiliency.

To identify our events, we perform a search on Google, the exchanges' websites, newspaper articles, and Refinitiv's Eikon newsfeed. We focus on primary market outages in Europe between 2018 and 2024. The starting date is chosen to coincide with the second Markets in Financial Instruments Directive (MiFID II). The timing of each event is confirmed in the data by checking when trading stops and reopens. In addition, we analyse any irregular trading from 2018 to 2024 to confirm our event sample.

Event Sample TABLE 1

Exchange	Date	Reason	Session	Duration	Markets affected
Deutsche Börse	16/03/2018	Software issue	Opening	01:42	Germany
Nasdaq Nordics	18/04/2018	Fire	Opening	05:10	Iceland, Sweden, Denmark, Finland
London Stock Exchange	07/06/2018	N/A	Opening	01:00	United Kingdom
Deutsche Börse	15/10/2018	N/A	Opening	02:33	Germany
Euronext	29/10/2018	Software issue	Opening	03:19	Belgium, Netherlands, Portugal, France
London Stock Exchange	16/08/2019	Software issue	Opening	01:20	United Kingdom
Nasdaq Nordics	01/11/2019	Software issue	Continuous	04:50	Iceland, Sweden, Denmark, Finland
Deutsche Börse	14/04/2020	Software issue	Continuous	03:58	Germany, Austria
Deutsche Börse	01/07/2020	Software issue	Opening	02:42	Germany, Austria
Euronext	19/10/2020	Software issue	Continuous, Closing	02:27	Belgium, Netherlands, Portugal, France, Ireland

1 We do not find outages on the MTFs during this period. For example, an analysis on irregular trading in 15 minutes interval during this period does not reveal any outages.

Event Sample (*continuation*) TABLE 1

Exchange	Date	Reason	Session	Duration	Markets affected
SIX Swiss	13/06/2023	Software issue	Continuous	02:15	Switzerland
SIX Swiss	31/07/2024	Software issue	Continuous	03:33	Switzerland

This table shows the sample of primary market outages used in our analysis over the period 2018–2024. *Exchange* indicates the affected primary market, *Date* is the day of the event, and *Reason* the underlying driver of the outage. *Session* indicates which part of the trading session has been impaired by the primary market outage: *Opening* refers to the primary market failing to perform the opening auction at its regular time, *Continuous* refers to outages that affect the continuous trading session only, and *Closing* refers to the failure of performing the closing auction. The outage *duration* is expressed in hours. *Markets affected* indicates the main affected jurisdictions.

Two outages on the Frankfurt Stock Exchange and three on the London Stock Exchange are excluded because they affect only stocks that are either highly illiquid or insufficiently fragmented. A closing auction outage at Nasdaq Nordics on 16 November 2022 is also excluded, because it does not influence the continuous trading, which does not allow us to test the redundancy mechanism.

Table 1 summarises properties of the 12 primary market outages. The outages are predominantly caused by software issues consistent with IOSCO (2023). Our sample consists of five continuous trading session outages and seven opening session outages at five different listing exchanges. As opening delays also influence continuous trading, all our events affect continuous trading. Outages in the opening and closing auctions are expected to be more disruptive, since the trading session by alternative venues lacks an initial opening or closing price (IOSCO, 2023).

The longest outage in our sample lasts more than five hours, while the shortest outage is less than one hour. The median outage time is about 179 minutes, which highlights that these events last a substantial fraction of the continuous trading session. For the events at Euronext in 2018, SIX Swiss in 2023, and Nasdaq Nordics in 2019, the market reopened after the outage but had to stop trading again due to a reoccurrence of the same outage. As the trading session in these instances lasted on average less than 10 minutes, we treat repeated events on the same day as one event.

Overall, the cross-sectional variation in geography, type, timing, and duration between our sample outages is useful for the identification of their effects on market quality.

2.2 Sample and Data

We access tick-by-tick data on trades and quotes from the Tick History database, and market capitalisation information from the Eikon database. Both data sets are maintained by the London Stock Exchange Group. We follow Comerton-Forde and Zhong (2021) in establishing our sample of stocks.

Stocks. Our sample consists of the constituents of the STOXX Europe Total Market Index. This index covers approximately 95% of the free-float market capitalisation in 17 European countries (Austria, Belgium, Poland, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom). The sampling excludes small stocks that tend to have low liquidity and opaque trading mechanisms. The constituent information is accessed one month before the respective outage. We exclude stocks that are delisted during the event window of four weeks before and after the outage.

We exclude stocks with no daily trading volume on at least one MTF,[2] that means stocks that exclusively traded on the primary market on any day during the event window. Further, we exclude stocks with less than ten quotes per day, and closing prices below €1 to avoid contamination of our results by relatively illiquid stocks. For transaction-level and quote-level observations, we convert non- euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close.

Altogether, the sample outages affect 1,253 stocks that fit our inclusion criteria. We refer to these stocks as the treatment stocks. The outage that affects most stocks occurred on Euronext in 2020 (195 treated stocks), followed by the outages at the London Stock Exchange in 2019 (158) and in 2018 (148). The smallest outage occurred on Nasdaq Nordics in 2019, with 49 treated stocks. Table A1 in the appendix shows the geographic distribution of treated and control stocks in our sample.

Quotes. We follow Hagströmer and Landsberg (2024) to clean and aggregate the intraday data. We access quote-level data of Level II quality, which includes price and depths information for the ten best prices on each side of the limit order book.[3] We consolidate the data across the LOB markets of the primary exchange and the most active LOB markets operated by MTFs.[4] We refer to the consolidated liquidity as the global order book which mimics a consolidated tape. The global order book updates whenever one of the LOB markets posts new best prices or sizes. The highest bid price and the lowest ask price and their respective aggregate depths form the global best bid and offer. We exclude observations in the first minute after opening and in the last minute before closing.[5] In markets that operate intraday auctions, observations during such auctions are set as missing. Crossed and locked global spreads are also set as missing.

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2 Before Brexit, we consider the most active MTFs for the global liquidity: Aquis, Turquoise, Cboe BXE, and Cboe CXE. After Brexit, Cboe BXE has not opened a EU-pendant and is therefore excluded from consideration for the global liquidity of EU-stocks.

3 For stocks listed at Nasdaq Nordic, we have access to the top of book prices only. We exclude these stocks in analyses that require Level II information.

4 Rather than the native Tick History timestamps, we use the exchange time provided by the respective exchange. This is to account for potential latency in creating the consolidated liquidity. For the outage at Euronext in 2018, Chi-X and BATS timestamps are out of sync after daylight savings (29/10–31/10) in the sample. The timestamps miss the daylight savings adjustment and we add it to their timestamp. For the event at SIX Swiss in 2024, we notice that the exchange time on 31/07 is out of sync with no clear pattern. Consequently, we use the native Tick History timestamps.

5 We obtain trading hour information for each exchange in each year from the FESE. The information is cross-checked with an online search to correct potential misrepresentation.

Trades. We access transaction-level data from the LOB markets. We remove trades with negative or missing prices or sizes, and observations that lack trade condition classification. Trades in the same stock-day that have the exact same timestamp, trade condition and exchange are aggregated (volumes are summed and prices are volume-weighted). Each trade is matched to the global midpoint prevailing one microsecond before the trade. We remove trades that occur during auctions, trades before the first quote of the day, trades indicated as deferred or technical, and trades matched to locked or crossed markets. We infer the trade direction based on Lee and Ready (1991).

2.3 Matched Sample

We match each treatment stock to a stock from another country with a similar degree of fragmentation and market capitalisation. Controls are never exposed to the same outage and are required to meet the same criteria as the treatment stocks, outlined above.

Before matching, we sort all stocks into terciles based on their average degree of fragmentation (defined below) in the four weeks preceding the outage. Each treatment stock is matched to the stock that is the closest in terms of market capitalisation among those stocks that are in the same fragmentation tercile. The matching is done without replacement. For stocks that are subject to several outages, the matching is rerun for each outage.

2.4 Market Quality and Exchange Competition Measures

Our analysis focuses on market quality to assess the effect of the primary market outage and the differential effect of fragmentation on market quality.

The relative quoted bid-ask spread measures the costs of a hypothetical roundtrip trade of one share. It is defined as

$$QtdSpr_j = \frac{P_j^A - P_j^B}{M_j}, \tag{1}$$

where P^A_j, P^B_j, and M_j refer to the global best ask, global best bid and the global midpoint of a quote observation *j*, respectively.

The expected price impact represents the average price impact of a hypothetical roundtrip trade amounting to €10,000. In other words, it is the difference in transaction cost between a €10,000 roundtrip trade and a €1 roundtrip trade. It is defined as

$$ExpPrcImp_j = log(P_j^{A\,Y}) - log(P_j^A) + log(P_j^B) - log(P_j^{B\,Y}), \tag{2}$$

where P_j^{AY} and P_j^{BY} are the highest ask price and lowest bid price at which a €10,000 trade would be expected to execute given the order book observation *j*.

The effective spread captures the transaction cost relative to the midpoint price paid in actual trades. It is defined as

$$EffSpr_k = 2\, d_k \frac{P_k - M_k}{M_k}, \tag{3}$$

where d_k, P_k, and M_k refer to the trade direction, the transaction price, and the prevailing global midpoint of transaction *k*. The trade direction indicator *d* takes the value +1 if the trade is buyer-initiated and -1 if the trade is seller-initiated. The measure is multiplied by 2 to make the effective spread comparable to the quoted spread.

The effective price impact measures the midpoint change after an actual trade. It is defined as

$$EffPrcImp_k = 2d\, \frac{M_{+10\,s,k} - M_k}{M_k}, \tag{4}$$

where $M_{+10s,k}$ refers to the global midpoint prevailing 10 seconds after trade *k*. We consider the horizon of 10 seconds long enough for the market to reverse short-term transitory price impact (Lo and Hall, 2015; Pelizzon et al., 2020).

Each of the market quality measures outlined above is aggregated at a one-minute granularity for each stock. The quote-based measures *QtdSpr* and *ExpPrcImp* are averaged using quote duration weights. The trade-based measures *EffSpr* and *EffPrcImp* are averaged using volume-weights. Both weighting schemes aim to promote quotes and trades that are more dominant in the market by being active for longer or having higher volumes.

Since our main interest is on the differential effect of fragmentation on market quality, we focus on following Degryse et al. (2015) to measure of exchange competition. The degree of lit *Fragmentation* quantifies the dispersion of consumed liquidity across pre-trade transparent market venues. It is defined as

$$Fragmentation_i = 1 - \sum_{v=1}^{V} MarketShares_{i,v}^{2}, \tag{5}$$

where the market shares are a ratio of lit venue volumes to the total lit volumes, and the index *i* denotes stocks. We compute the average *Fragmentation* over the four weeks preceding each outage as our measure of interest.

2.5 Descriptive Statistics

Table 2 presents the descriptive statistics of daily market quality measures and exchange competition measures for our 1,253 treatment stocks and control stocks, respectively, pooled across 12 primary market outages four weeks before the outage. It compares means and medians of the treatment group to the control group.

Descriptive Statistics TABLE 2

	Treat		Control		Difference	
	Mean	**Median**	**Mean**	**Median**	**Mean**	**Median**
Market Capitalisation (MEUR)	14,300.54	5,699.61	13,716.25	5,523.27	584.29	176.34
Market Quality Measures						
Quoted Spread (bp)	12.81	8.12	12.19	8.18	0.62*	-0.06
Effective Spread (bp)	11.19	6.87	11.63	7.16	-0.44*	-0.29*
Expected Price Impact (bp)	9.38	5.61	9.69	5.41	-0.31	0.2*
Effective Price Impact (bp)	10.38	6.91	9.60	6.55	0.78*	0.36*
Exchange Competition						
Fragmentation	0.54	0.55	0.54	0.56	0.00	-0.01*

* denotes significance at the 5% level.

This table illustrates the descriptive statistics of market quality measures for 1,246 treated and control stocks, respectively, pooled across 12 primary market outages. All statistics are averaged over the 20 trading days before the primary market outage. The variables are defined as follows: the *Quoted Spread* is the duration-weighted quoted spread relative to the midpoint; the *Effective Spread* is twice the volume-weighted difference between transaction price and midpoint prevailing at the time of trade, signed by the trade direction; the *Expected Price Impact* is the duration-weighted average of the change in best ask prices and the change in best bid prices following a hypothetical roundtrip trade worth €10,000; the *Effective Price Impact* is twice the volume-weighted difference between midpoint 10 seconds after the time of trade and the midpoint prevailing at the time of trade; *Fragmentation* is 1 minus the daily average squared market shares across venues. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. We apply the unpaired student's *t* test to test the difference in the means, and the unpaired Mann-Whitney *U* test to test for differences in the median.

The average market capitalisation of around €14.3 billion for the treatment group and €13.7 billion for the control group shows that our sample contains large caps on average, but our sample also includes a significant proportion of mid-cap stocks as well with a median market capitalisation of around €5.7 (5.5) billion. The median relative quoted spread is around 8 bp for the treatment and control group, which are reasonable levels for large-cap and mid-cap stocks. The effective spread is narrower than the relative quoted spread, around 6.9 (7.2) bp, suggesting that either market participants trade when liquidity is high to reduce their transaction costs, or that the limit order book has hidden liquidity against which trades are executed.

The expected price impact shows that a €10,000 hypothetical trade is as sociated with a median price move of 5.6 bp for the treatment group, and 5.4 bp for the control group. To put €10,000 into perspective, it is approximately 0.03% of the daily average turnover for the treatment group and control group. The median effective price impact shows that the adverse selection imposed on liquidity providers is about 6.9 bp for the treatment group, and 6.5 bp for the control group. Fragmentation shows that the average degree of order flow dispersion is 0.54 for the treatment group and control group. It indicates that a significant proportion of trades are executed at the MTFs.

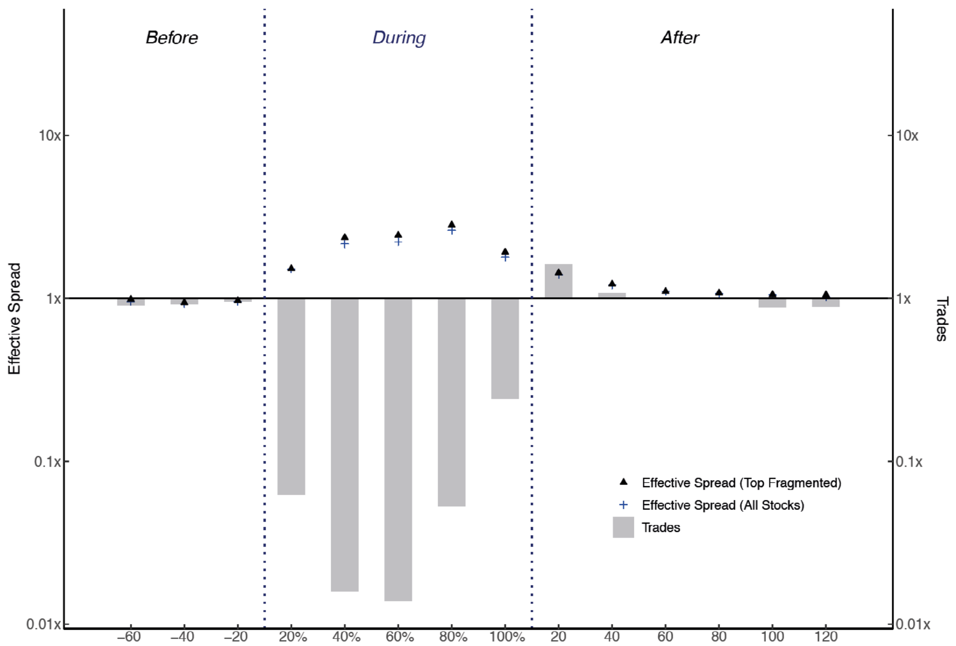
Despite our matching procedure, statistically significant differences in market quality prevail. However, the differences are arguably small in economic terms and should be no cause of concern for our subsequent analysis.

3 Results

3.1 Outage Effects and Fragmentation

The development of liquidity and trading activity around exchange outages is illustrated in Figure 1. The effective spread before, during, and after the outages is shown for all stocks (blue crosses), and high fragmentation stocks (black triangles). The effective spread shown is the difference between the cross-sectional mean of the treated and control group in each interval. We add a 1 as a base to the plot to visually highlight periods. Below 1 are periods where the effective spread of the treated group is larger and above one where the effective spread of the control group is larger. The number of trades for all treated stocks is the fraction of the total number of trades to its 20-day pre-outage average. It is plotted as a bar chart. The *Before* period contains 60 minutes of continuous trading session before the outage, and the *After* period contains 120 minutes after the reopening auction from the outage. Importantly, the *Before* (*After*) can period cross into the previous (following) trading session for outages with insufficient pre (post) outage trading time and takes the last (first) minutes to fill the respective intervals. We argue that the difference between control and treated stocks accounts for the level difference associated with intraday seasonality and its trading periods. The period labelled *During* is normalised into quintiles because outages differ in duration.

Effective Spread and Trading Activity around Exchange Outages FIGURE 1



This figure shows the *Effective spread* and the trading activity for the treatment stocks before, during, and after primary market outages. The *Effective spread* is defined as in Table 2 and is the difference between the cross-sectional mean of the treated and control group. *Trades* is the number of trades for treated stocks in the respective interval as a fraction of the total number of trades to its 20-day pre-outage average. The effective spread is winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. The presented statistics are averages across treatment stocks of 12 outages. Further, we take the natural logarithm to reduce the sensitivity of the averages to outliers. *All stocks* indicates the unconditional average of the effective spread across the treated stocks within the interval; *Top fragmented* stocks refers to the average of the effective spread of the top tercile of fragmented stocks in the pooled fragmentation distribution. *Before* contains 60 minutes of continuous trading session before the outage; *After* is 120 minutes after the reopening auction from the outage; *During* is normalised into quintiles since the outage time varies across the respective outage. The *Before* and *After* periods are split into 10-minute intervals. The *Before* (*After*) period crosses into the previous (following) trading session for outages with insufficient pre-outage time and takes the last (first) minutes to fill the intervals.

The figure shows that 60 minutes before the outage, the effective spread and the total number of trades are both around 1. This level represents their expected value. It suggests a stable parallel trend before the outage, since the treatment and control group are closely aligned. Before the outage, there is no visible difference between the unconditional and the top tercile of fragmented stocks.

During the outage period, the effective spread for both groups rises sharply. The average effective spread during the outage period indicates a widening of the spread by a factor of 1.1 compared to the control group. Consistent with prohibitively high trading costs, the total number of trades drops substantially. In line with that, the total lit turnover, which is the sum of lit turnover for treated stocks, drops by 96%. This suggests that only 4% of the normally expected volume is executed. To put it into perspective, only €0.5 billion is traded during the outage time, whereas about €12.3 billion is expected to trade during normal times. This rise in illiquidity shows that primary market outages substantially disrupt trading.

There is no strong sign of fragmentation working as a cushion against outages. The differential effect of fragmentation is not clearly distinguishable from the unconditional effective spread. Although modern equity structures are often proclaimed to provide many entrances to the same market, the observed illiquidity and the lack of a clear cushioning effect of fragmentation highlight the importance of the primary market.

After the reopening auction indicated by the vertical dashed line, the total number of trades shows higher levels during the initial 40 minutes with a return back to their expected levels thereafter. Despite the catch-up effect after the resumption of trading, the turnover lost during an outage has not been recovered in the remainder of the continuous trading session. The average daily turnover across all treated stocks in our sample is €25.4 billion on a regular day, but only €20.7 billion has been traded on an outage day. The effective spread demonstrates a levelling off with no visible difference across degrees of fragmentation. The levelling off illustrates the absorption of the shock and suggests that markets need about two hours to revert back to the expected liquidity levels. Given the substantial impact of the primary market outage, the transitory effect of primary market outages could be associated with the prevailing uncertainty.

Empirical Analysis. Following the visualisation above, we now turn to estimate the effects of outages econometrically. In the following model, we exploit the variation in fragmentation across stocks to understand its effect on market quality during and after outages. We estimate a triple-difference regression to analyse the effects and interact the highest degree of fragmentation, *D*, with $During_t \times Treat_i$:

$$MarketQuality_{i,t} = \beta_{DD} During_t \times Treat_i \times D_{Frag,i} + \beta_D During_t \times Treat_i + \rho X + \delta_i + \lambda_t + \gamma_o + E_{i,t} \tag{6}$$

where the index *i* refers to stocks, and *t* refers to the minute of the trading day, D_{Frag} is a dummy indicating the top tercile of fragmented stocks (*Fragmentation*). *During* is a dummy variable that takes on 1 during the outage period and 0 otherwise. The periods are mutually exclusive and the *Before* dummy is omitted. *Treat* is a dummy that equals 1 for stocks experiencing an outage and 0 for the control stocks. We control for unobserved characteristics with stock-, period- and outage-fixed effects that are captured by δ_i, λ_t, and γ_o, respectively. *X* captures the non-interacted coefficients prevailing because stocks can belong to the treatment group for one event and to the control group for another event.

We estimate Equation (6) using the natural logarithm of the market quality measures of Section 2.4 because of the large effects during outages. For *EffPrcImp*, we do not take the natural logarithm because the adverse selection component can be positive or negative depending on the information incorporated in the trade. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise.

The coefficient of interest is β_{DD}, which estimates the additional difference in market quality for treated stocks in the top-tercile of fragmentation with respect to *During* the outage. As such, it captures how the change in liquidity differs for highly fragmented treated stocks compared to less-fragmented treated stocks, their own before outage levels, and their matched control stocks during outages.

Table 3 presents the regression results of the baseline model without the interaction of the highest degree of fragmentation, and the triple-difference regression based on Equation (6).

During primary market outages, liquidity deteriorates significantly. The quoted spread (*QtdSpr*) and the expected price impact (*ExpPrcImp*) increase by 10.4x (obtained as $\exp^{2.43} - 1$) and 10.5x ($\exp^{2.44} - 1$) compared to their before outage levels for the treatment group.[6] For example, the average quoted spread increases from 12.8 bp to 132.7 bp, whereas the expected price impact increases by 98.3 bp to 107.6 bp. The results highlight that the global limit order book becomes substantially shallow. A €10,000 hypothetical trade changes mechanically the price by 1.1% on the average treated stock in our sample by walking the book.

6 The regression uses log-linear relationship with dummy variables. Following, the coefficient of dummy variables are interpreted as 100*(exp(β) – 1) based on Van Garderen and Shah (2002).

The effective spread (*EffSpr*) widens by a factor of 1.1 ($\exp^{0.76} - 1$) during the outage, which corresponds to an increase of 12.7 bp in economic magnitudes. The effective price impact (*EffPrcImp*) shows a deterioration of 1.8 bps compared to the control group. Since we do not take the natural logarithm of *EffPrcImp*, the measure represents basis points. The coefficients confirm the intuition of Figure 1 that liquidity is adversely affected by primary market outages. Despite the significant price discovery of MTFs (Aramian and Comerton-Forde, 2024b) and substantial market shares (Aramian and Comerton-Forde, 2024a), liquidity deteriorates and market participants observe prices at worse levels.[7]

Outage Effect on Market Quality Interacted with Fragmentation TABLE 3

	QtdSpr		EffSpr		ExpPrcImp		EffPrcImp	
	(Baseline)	**(Frag)**	**(Baseline)**	**(Frag)**	**(Baseline)**	**(Frag)**	**(Baseline)**	**(Frag)**
Treat	0.10***	0.12***	-0.05**	-0.01	0.07*	0.07	-0.24	-0.27
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.04)	(0.21)	(0.34)
During x Treat	2.43***	2.34***	0.76***	0.73***	2.44***	2.30***	1.77***	1.11**
	(0.06)	(0.07)	(0.03)	(0.04)	(0.07)	(0.08)	(0.39)	(0.52)
D_{Frag}		-0.03		0.04		0.00		-0.29
		(0.05)		(0.04)		(0.05)		(0.38)
During x D_{Frag}		-0.06**		-0.06**		-0.07**		-0.13
		(0.03)		(0.03)		(0.04)		(0.28)
D_{Frag} *x Treat*		-0.07		-0.12***		-0.01		-0.05
		(0.07)		(0.05)		(0.07)		(0.56)
During x D_{Frag} *x Treat*		0.24**		0.10*		0.35**		1.91***
		(0.12)		(0.06)		(0.14)		(0.73)
Observations	3,728	3,728	3,728	3,728	2,440	2,440	3,708	3,708
Adj. R^2	0.709	0.709	0.728	0.728	0.771	0.772	0.314	0.316
Stock	X	X	X	X	X	X	X	X
Period	X	X	X	X	X	X	X	X
Outage	X	X	X	X	X	X	X	X

This table shows the triple difference regressions of market quality 60 minutes before the outage and during the outage. The *Before* and *During* are dummy variables that indicate the respective outage period. The periods are mutually exclusive. The difference-in- differences coefficient, denoted as the interaction of *Treat x During*, is interacted with a dummy, D_{Frag}, that indicates the top-tercile stocks in the distribution of fragmentation, *Fragmentation*, across treated stocks with respect to the outages. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. We constrain observations to treatment-control pairs where the treatment trades during the outage period. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise. All variables are winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

7 We observe that liquidity for control stocks during the outage improves. The improvement might be associated with market participants shifting their trading attention to stocks that are not currently subject to an outage.

Turning to the results of the triple-difference regressions, the quoted spread for the highest degree of fragmentation (*Frag*) widens by an additional factor of 0.3 ($\exp^{0.24} - 1$) in the treatment group. As such, the quoted spread widens by an additional 12.5 bp for the stocks in the highest degree of fragmentation. The effect is not unique to the quoted spread but across our market quality measures. Interestingly, the effective price impact indicates that during outages market participants impose 1.9 bps of adverse selection on liquidity providers, suggesting trades are informative during that period. These results suggest that the top level of fragmentation is associated with a further deterioration of liquidity, also confirming the structure in Figure 1.

To conclude, our findings show that fragmentation does not provide the expected cushioning effect during outages. We find that instead of mitigating adverse outage effects, market quality further deteriorates for highly fragmented stocks. It suggests that those stocks are more adversely exposed to coordination problems. These results raise the question about the substitutability of the alternative venues.

4 Frictions to Market Substitutability

In this section, we examine the frictions to market substitutability to explain the documented adverse outage effects. Our main result shows that fragmentation does not provide resiliency through redundancy. The lack of a cushioning effect is potentially associated with network externality, behavioural, or technical frictions that disrupt trading activities during outages.

4.1 Frictions from Network Externalities

Following the main analysis, we now study frictions due to network externalities. Because exchanges compete to attract market participants, the amount of order flow executed at any particular exchange and its contribution to the price discovery is important. Liquidity exhibits positive network externalities. Market participants increase their probability of filling an order with the participation rate of others. A friction might arise during outages if substitute venues have insufficient volume shares ex-ante and trading is highly dispersed. The lack of a clear focal market might hinder liquidity migration. Small liquidity pools increase transaction costs by insufficiently solving the coordination problem of market participants (Menkveld and Yueshen, 2017).

Primary exchanges alone capture 40% to 62% of the total lit volume (Aramian and Comerton-Forde, 2024a) and contribute 50% to the price discovery (Aramian and Comerton-Forde, 2024b). MTFs capture the remainder, which is, however, split across multiple venues. Our fragmentation measure may have masked the need for a dominant alternative venue, since two stocks with different composition of trading can have similar fragmentation values. As such, one can argue that the outage effects are less severe when an alternative venue captures more market activity ex-ante because this venue is potentially more substitutable in terms of local liquidity pools and price discovery. A dominant MTF might cushion against adverse outage effects by allowing market participants to have an alternative focal point to coordinate their trading intentions.

Table 4 presents the results for our analysis regarding the presence of a "dominant" MTF. We calculate the 20-day average volume shares per alternative venue in the pre-event period and identify the highest market shares across these exchanges. We create a dummy variable, D_{MS}, that takes on 1 if the stock has a dominant alternative venue that is in the highest tercile of the highest volume shares distribution across treated stocks with respect to the outages. Based on the approach, the associated cutoff for the highest market shares of a dominant MTF is 22%, meaning that we identify treated stocks where an MTF captures at least 22% of trading volume on average in the 20 days leading up to the outage.

Outage Effects and Dominant MTFs

TABLE 4

	MTF Volume Shares			
	QtdSpr	EffSpr	ExpPrcImp	EffPrcImp
Treat	0.10**	-0.04	0.05	-0.19
	(0.04)	(0.03)	(0.04)	(0.29)
During x Treat	2.33***	0.73***	2.35***	1.26***
	(0.07)	(0.04)	(0.08)	(0.47)
D_{MS}	-0.14***	-0.12***	-0.10*	-0.62*
	(0.05)	(0.04)	(0.06)	(0.33)
During x D_{MS}	0.02	0.00	0.01	-0.26
	(0.03)	(0.03)	(0.04)	(0.26)
D_{MS} *x Treat*	-0.01	-0.05	0.01	-0.24
	(0.07)	(0.04)	(0.07)	(0.42)
During x D_{MS} *x Treat*	0.30**	0.09	0.25*	1.48*
	(0.12)	(0.06)	(0.14)	(0.82)
Observations	3,728	3,728	2,440	3,708
Adj. R^2	0.709	0.728	0.771	0.314
Stock	X	X	X	X
Period	X	X	X	X
Outage	X	X	X	X

This table shows the triple difference regressions of market quality 60 minutes before the outage and during the outage. The *Before* and *During* are dummy variables that indicate the respective outage period. The periods are mutually exclusive. The difference-in-differences coefficient, denoted as the interaction of *Treat x During*, is interacted with a dummy, D_{MS}, that indicates the top- tercile stocks in the distribution of MTF market shares with respect to the outages. We calculate the average 20-day market shares per MTF before the outage day and identify the MTF with the highest volume. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. We constrain observations to treatment-control pairs where the treatment trades during the outage period. For transaction-level and quote-level observations, we convert non- euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise. All variables are winsorised at the 2.5% and 97.5% for treated and control stock in each outage with respect to the period and market capitalisation buckets. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

Our coefficient of interest is the triple interaction, which captures the differential effect of a dominant MTF on our market quality measures during and after outages. The results show that high market shares in one MTF do not cushion against adverse outage effects. Similar to fragmentation, high market shares amplify adverse outage effects for the quoted spread, expected price impact, and effective price impact. For instance, the quoted spread further deteriorates during the outage by a factor of 0.35 ($exp^{0.3} - 1$), suggesting that high market shares of an MTF do not cushion against adverse outage effects.

Appendix C of Table A2 presents results on a different set of proxies for a single dominant MTF. We find that neither market shares measured by trading activity nor the highest degree of MTF concentration provides cushioning effect. As such, it suggests that a sufficient market share by a dominant MTF does not offset adverse effects of primary market outages and the market of these stocks becomes also highly illiquid. The lack of cushioning effects of high market shares is also associated with other frictions to market substitutability that hinder liquidity migration, such as technical or behavioural frictions which we turn to now.

4.2 Friction from Technical Dependencies

Following the analysis on network externalities, we now turn to technical dependencies from market connections. Whereas exchanges in the United States are responsible for routing orders to exchanges with the best price (as per the Order Protection Rule, Rule 611 of the Regulation National Market System, RegNMS), brokers in Europe need to establish exchange connections themselves. In the European Union, brokers are required to maintain best execution based on "price, costs, speed, likelihood of execution and settlement, size, nature or any other consideration relevant to the execution of the order" (ESMA, 2014a) but are not required to connect to all venues (ESMA, 2014b). Consequently, if brokers and participants have not created connections to trade at other exchanges, liquidity cannot migrate during outages. This increases the impact of a single entry failure.

We test market connectivity and primary market dependency using smart order routing (SOR) trades. Brokers that have multiple venue connections use SOR technology that monitors the primary market and MTFs to optimally execute trades across multiple venues. Thus, we can identify market connectivity by SOR trades since these brokers are connected to multiple venues and might still submit client orders when the primary exchange has an outage. As such, they could create liquidity pools that cushion against adverse outage effects. However, SOR trades are based on algorithms that are designed to stop trading if they detect missing input from one of their input layers. If these algorithms fail to function during outages, it shows a strong primary market dependency.

We create a smart order routing proxy in the spirit of Degryse et al. (2025). SOR_i is a proxy for the intensity of smart order routing. It captures trades that are possibly executed by the same traders hitting simultaneously different venues to measure connectivity. We identify all trades that originated on the primary venue and occur within 10 milliseconds on any MTF in the same trade direction.

$$SOR(i; buy) = N \times min\,[volume_{buy}(i; Market_1), ..., volume_{buy}(i; Market_N)] \tag{7}$$

where *Market* represents trading venues that we identify to have the same trade within 10 milliseconds. We restrict the volume per such SOR trade to be the minimum volume across venues that are identified, and multiply it by the number of such venues. Similarly, we calculate *SOR*(*i, sell*). We then sum buy and sell volumes of the day and scale it by the total lit volume of the day. Finally, we create a 20-day average relative SOR volumes before the outage day and stratify the sample into quintiles to run difference-in-differences regressions.

Table 5 presents the results and the coefficient of the interaction, *During x Treat*, are of interest. Although we would have expected a cushioning effect for the *Highest* quintile of relative SOR volumes, it shows the highest adverse outage effect. These coefficients show that stocks with higher pre-outage SOR intensity experience larger deterioration in spreads and price impacts during outages. In particular, the results show that stocks with higher pre-outage SOR intensity impose 4.7 bps in adverse selection on liquidity provider, suggesting that in those stocks market participants still incorporate information. Consequently, the SOR volumes do not capture a potential cushioning effect of broker connection.[8]

Outage Effects and Smart-Order Routing TABLE 5

	QtdSpr					EffSpr				
	Lowest	**2nd**	**3rd**	**4th**	**Highest**	**Lowest**	**2nd**	**3rd**	**4th**	**Highest**
During x Treat	1.40***	1.93***	2.27***	2.91***	3.67***	0.49***	0.87***	0.87***	0.78***	0.86***
	(0.07)	(0.11)	(0.12)	(0.13)	(0.12)	(0.06)	(0.06)	(0.07)	(0.07)	(0.05)
Treat	0.25***	0.15	0.01	0.09	-0.42***	-0.02	0.04	-0.16	0.03	-0.22***
	(0.07)	(0.10)	(0.11)	(0.09)	(0.08)	(0.16)	(0.08)	(0.13)	(0.06)	(0.07)
Observations	834	708	642	682	852	834	708	642	682	852
Adj. R^2	0.785	0.666	0.655	0.746	0.827	0.800	0.794	0.678	0.705	0.737
Stock	X	X	X	X	X	X	X	X	X	X
Period	X	X	X	X	X	X	X	X	X	X
Outage	X	X	X	X	X	X	X	X	X	X

	ExpPI					EffPI				
	Lowest	**2nd**	**3rd**	**4th**	**Highest**	**Lowest**	**2nd**	**3rd**	**4th**	**Highest**
During x Treat	1.78***	2.06***	2.15***	2.65***	3.31***	-1.01	1.91**	0.35	3.02***	4.70***
	(0.16)	(0.12)	(0.12)	(0.14)	(0.16)	(0.72)	(0.90)	(0.82)	(0.75)	(1.07)
Treat	0.01	0.41***	0.26	0.03	-0.27***	2.29***	-0.71	-1.43	-0.52	-1.66
	(0.30)	(0.12)	(0.18)	(0.10)	(0.09)	(0.67)	(0.76)	(1.19)	(0.63)	(1.11)
Observations	284	491	495	524	615	829	708	633	681	843
Adj. R^2	0.845	0.799	0.776	0.759	0.803	0.619	0.392	0.233	0.255	0.055
Stock	X	X	X	X	X	X	X	X	X	X
Period	X	X	X	X	X	X	X	X	X	X
Outage	X	X	X	X	X	X	X	X	X	X

This table presents the difference-in-differences results of market quality 60 minutes before the outage and during the outage. The *Before* and *During* are dummy variables that indicate the respective outage period. The periods are mutually exclusive. The difference-in-differences coefficient is denoted as the interaction of *Treat x During*. For the sorting variable, we create a smart-order routing proxy in the spirit of Degryse et al. (2025). We identify all trades originated on the primary venue and which occur within 10 milliseconds on any MTF in the same direction. We restrict the volume per SOR trade to be the minimum volume across venues that are identified, multiplied by the number of such venues. Then we sum buy

8 These results are robust and hold for 5 millisecond windows or the average number of venues used for SOR trades.

and sell SOR volumes of the day and scale it by the total lit volume of the day. Finally, we create 20-day average relative SOR volumes before the outage period and stratify the sample into quintiles based on these volumes. *Lowest* refers to the lowest quintile of relative SOR volumes; *2nd* refers to the 2nd lowest quintile of relative SOR volumes; *3rd* refers to the 3rd lowest quintile of relative SOR volumes; *4th* refers to the 4th lowest (2nd highest) quintile of relative SOR volumes; *Highest* refers to the highest quintile of relative SOR volumes. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. We constrain observations to treatment-control pairs where the treatment trades during the outage period. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. All variables are winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

Interestingly, on the other hand, the results seem to capture an aspect described in regulatory reports (ASIC, 2021). The Australian Securities and Investment Commission (ASIC) identified in a report about an outage in Australia that brokers were unable to systematically route client orders to alternative venues due to technical reasons. SOR trades are based on algorithms, and robust algorithms are designed to stop trading if they detect missing input from one of their input layers. These algorithms shut down during outages, and simply disabling them to bridge an outage requires overnight reconfiguration. As such, the results are in line with a technical friction that makes brokers unable to systematically submit client orders.[9]

4.3 Friction from Participant Behaviour

Following the analysis on technical frictions, we now turn to behavioural frictions stemming from price uncertainty and market participant withdrawal. Research shows that under unfavourable market conditions, endogenous liquidity providers synchronously withdraw their liquidity provision (Anand and Venkataraman, 2016; Brogaard et al., 2018; Kerssenfischer and Helmus, 2024) and a negative feedback loop could also prevail where market participants withdraw from trading in expectation of worse liquidity (Optiver, 2020). To understand whether market participants withdraw from trading during outages, we identify trading mechanisms that are not regulatory-dependent on the primary market. In European regulation, the primary market is the most relevant market for its listings (EU Commission, 2014; EU Commission, 2016). Trades on dark pools (which are only post-trade transparent) are pegged to the most relevant market under the Reference Price Waiver. During primary market outages, these venues mechanically shut down due to the lack of a reference price. Large-In-Scale (LIS) trades are also exempt from pre-trade transparency under MiFID II. However, these trades are arguably not dependent on the primary market being open because they do not necessarily peg their execution price. Consequently, a breakdown of LIS trades would imply that these market participants withdraw from trading. LIS trades are defined as trades that exceed ESMA thresholds tied to average daily trading volumes.

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9 We find in unreported results that treated stocks with relative more SOR benefit from faster recovery after outages, which is also in line with these algorithms as they are functional again and identify optimally trading opportunities.

Table 6 presents a simple cross-sectional regression on LIS volumes for the treated stocks in our event window. We classify LIS trades by identifying trades that are exempted from pre-trade transparency and are not traded at the mid price of the primary. We confirm that the trades in our sample are, indeed, large.

Before the outage period, the average LIS volume within one trading minute is €262,986. However, LIS volumes turn zero during the second to fourth quintile of the outage. This result implies that these market participants withdraw from trading.[10] A potential underlying driver of the withdrawal is the elevated price uncertainty and risk of incomplete information in the price (IOSCO, 2023; ESMA, 2023; ASIC, 2021). As such, we follow the analysis by turning to events with the highest level of price uncertainty. We use opening outages as a proxy for substantial price uncertainty. If the opening session fails due to the exchange outage and no opening price is provided, overnight information has not been incorporated and market participants face severe price uncertainty. As such, opening outages are characterised by the highest degree of price uncertainty. We create a dummy variable, D_{Open}, that captures outages originated during the opening session, 0 otherwise.

Participant Withdrawal – Large-In-Scale Volumes TABLE 6

	Large-In-Scale Volumes
Intercept	262,986.63***
	(62,399.82)
Outage 0–20%	-259,994.87***
	(62,082.71)
Outage 21–40%	-262,986.63***
	(62,399.82)
Outage 41–60%	-262,986.63***
	(62,399.82)
Outage 61–80%	-262,986.63***
	(62,399.82)
Outage 81–100%	-256,616.40***
	(61,871.58)
Observations	6,825
Adj R^2	0.050

Large-In-Scale (LIS) trades are exempt from pre-trade transparency under MiFID II. The European Securities Markets Authority (ESMA) specifies thresholds based on the average daily trading volumes to classify trades that can trade under the LIS waiver. We classify trades in our sample that are LIS by identifying trades that are exempted from pre-trade transparency and trade under no reference-price waiver. Importantly, those trades are also not deferred trades and participants have to publish those trades within one minute after the trade. We run a cross-sectional regression of the treated stocks on LIS volumes. *Intercept* captures the period before the outage; *Outage 0–20%* refers to the first quintile of the outage and is a dummy that is 1 if the period is in the first quintile of the outage, whereas *Outage 81–100%* is a dummy that is 1 if the period is in the last quintile of the outage. The periods are mutually exclusive. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

10 We observe a catch-up effect in the first period after the outage has been resolved. This further suggests that market participants postponed their trading until after the primary market functions again.

Table 7 presents regression results similar to Table 3. We find that price uncertainty related to opening outages substantially amplifies adverse outage effects. The effect on market quality for the quoted spread, expected price impact, and expected price impact substantially deteriorate compared to continuous outages, whereas the effective spread is slightly better off during opening outages. For instance, the quoted spread widens further by a factor of 4 ($exp^{1.6} - 1$) during opening outages compared to continuous outages. The additional deterioration corresponds to an increase in the quoted spread by 542 bp. We observe similar patterns for the expected price impact and effective price impact. These results highlight that liquidity on alternative venues substantially deteriorates in the face of price uncertainty. The effective spread widens to 39.8 bp during opening outages compared to 24.4 bp during continuous outages. Interestingly, the triple interaction, $During \times D_{Open} \times Treat$ is significant and negative, suggesting that opening outages do not impose an additional deterioration on the effective spread compared to continuous outages. The additional deterioration seems to be associated with substantial spill-over effects for the control group during opening outages. It highlights that this price uncertainty also affects liquidity in control stocks, which is line with the theoretical model by Cespa and Foucault (2014). Illiquidity spills over in assets that are correlated due to a cross-asset learning channel and a deterioration in liquidity increases the noise in this channel.

Outage Effect and Price Uncertainty TABLE 7

	QtdSpr	EffSpr	ExpPrcImp	EffPrcImp
Treat	0.14***	-0.06	0.05	-0.07
	(0.04)	(0.04)	(0.05)	(0.39)
D_{Open} *x Treat*	-0.14**	0.02	-0.04	-0.47
	(0.06)	(0.05)	(0.06)	(0.45)
During x D_{Open}	0.67***	0.60***	0.76***	3.99***
	(0.02)	(0.02)	(0.02)	(0.27)
During x Treat	1.50***	0.84***	1.92***	-0.47
	(0.05)	(0.04)	(0.05)	(0.50)
During x D_{Open} *x Treat*	1.60***	-0.13***	1.13***	3.89***
	(0.08)	(0.05)	(0.10)	(0.72)
Observations	3,728	3,728	2,440	3,708
Adj. R^2	0.821	0.759	0.855	0.377
Stock	X	X	X	X
Period	X	X	X	X
Outage	X	X	X	X

This table shows the triple difference regressions of market quality 60 minutes before the outage and during the outage. The *Before* and *During* are dummy variables that indicate the respective outage period. The periods are mutually exclusive. The difference-in-differences coefficient, denoted as the interaction of *Treat x During*, is interacted with a dummy, D_{Open}, that indicates outages that originated during the opening session. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. We constrain observations to treatment-control pairs where the treatment trades during the outage period. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise. All variables are winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

Overall, these findings show that even if execution algorithms seem to fail during outages as indicated in the previous section, market participants also withdraw endogenously from trading. The withdrawal arguably impairs liquidity and amplifies the coordination problem, since liquidity benefits from high participation rates. Finally, the highest degree of price uncertainty is associated with substantially larger adverse outage effects. It highlights that liquidity providers widen their quotes and reduce their supply in times when the risk of incomplete information is high.

5 Outage Recovery

Following the analysis on frictions to market substitutability during outages, we now examine the recovery path *after* the outage has been resolved.

We estimate a triple-difference regression to analyse the effects throughout the recovery period and interact the highest degree of fragmentation, *D*, with $After_t \times Treat_i$ where we split the *After* period into intervals of 20 minutes each. As such, each *After* interval indicates 20 minutes of trading where 1 indicates the first 20 minutes and 6 the 101th to 120th minute.[11]

The coefficients of interest are the triple interaction term that estimates the additional difference in market quality for treated stocks in the top-tercile of fragmentation with respect to *After* outage intervals.

Table 8 presents the recovery structure of market quality measures after the outage. The baseline effects (i.e., *After*Treat* coefficients) of the market quality measures confirm the levelling off in the treatment group observed in Figure 1. Although exchanges reopen with an auction after the outage, the adverse outage effects are not fully absorbed upon resumption of continuous trading. In the first 20 minutes of the continuous trading session, the quoted spread and the effective spread are around 0.64x ($exp^{0.5} - 1$) and 0.52x ($exp^{0.42} - 1$) higher compared to the control group and their before-outage levels. The global limit order book is shallower than during normal times. A hypothetical €10,000 trade changes the price by 16 bp compared to the expected 9.4 bp during normal times. Market quality remains at worse levels, which clearly tapers off in the course of the continuous trading session after the outage has been resolved. After two hours, most market quality is still slightly impaired with 0.05x but in unreported results we confirm that the transitory effects of outages dissipate quickly after that. Interestingly, the effective price impact has absorbed the shock around one hour of continuous trading after reopening, suggesting that liquidity providers are not exposed to differentially stronger adverse selection then.

The effect of fragmentation during the recovery period is less systematic. These coefficients are not associated with a faster recovery from outages but rather show some degree of slower recovery in some intervals. However, we caution against too strong inferences because we would have expected stronger effects in the first intervals and more consistently across market quality measures.

11 We omit coefficients to keep the table manageable.

Recovery Effect on Market Quality Interacted with Fragmentation

TABLE 8

	QtdSpr		EffSpr		ExpPrcImp		EffPrcImp	
	(Baseline)	(Frag)	(Baseline)	(Frag)	(Baseline)	(Frag)	(Baseline)	(Frag)
After 1 x Treat	0.50***	0.48***	0.42***	0.39***	0.53***	0.51***	1.73***	1.34***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.28)	(0.40)
After 2 x Treat	0.20***	0.17***	0.24***	0.22***	0.20***	0.18***	1.36***	1.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.27)	(0.38)
After 3 x Treat	0.11***	0.09***	0.14***	0.12***	0.13***	0.11***	0.44*	-0.14
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.26)	(0.36)
After 4 x Treat	0.08***	0.05***	0.10***	0.09***	0.11***	0.08***	0.56**	0.19
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.27)	(0.38)
After 5 x Treat	0.06***	0.03	0.08***	0.06***	0.07***	0.04	0.27	-0.15
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.27)	(0.37)
After 6 x Treat	0.04***	0.01	0.05***	0.02	0.05**	0.02	0.22	-0.17
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.24)	(0.34)
After 1 x Treat x D_{Frag}		0.06		0.08**		0.02		0.93*
		(0.04)		(0.04)		(0.06)		(0.51)
After 2 x Treat x D_{Frag}		0.09***		0.04		0.02		0.42
		(0.03)		(0.03)		(0.05)		(0.51)
After 3 x Treat x D_{Frag}		0.06		0.04		0.03		1.52***
		(0.03)		(0.03)		(0.04)		(0.47)
After 4 x Treat x D_{Frag}		0.06*		0.02		0.05		0.90*
		(0.03)		(0.04)		(0.04)		(0.49)
After 5 x Treat x D_{Frag}		0.08**		0.04		0.05		1.03**
		(0.03)		(0.03)		(0.04)		(0.48)
After 6 x Treat x D_{Frag}		0.09***		0.07**		0.06		1.04**
		(0.03)		(0.03)		(0.04)		(0.47)
Observations	16,587	16,587	16,587	16,587	11,976	11,976	16,526	16,526
Adj. R^2	0.841	0.841	0.834	0.834	0.862	0.862	0.477	0.477
Stock	X	X	X	X	X	X	X	X
Interval	X	X	X	X	X	X	X	X
Outage	X	X	X	X	X	X	X	X

This table shows the triple difference regressions of market quality 60 minutes before the outage and 120 minutes after the outage. The *Before* and *After* are dummy variables that indicate the respective outage period. We change the *After* dummy to a discrete variable; *After 1* to *After 6* indicate the first 20 minutes (*After 1*) to the 120 minutes (*After 6*) after the reopening from the outage. The intervals are mutually exclusive. We omit the *Before* dummy due to multicollinearity and coefficients from this table to keep it manageable. The difference-in-differences coefficients, denoted as the interaction of *Treat x Period*, is interacted with a dummy, D_{Frag}, that indicates the top-tercile stocks in the distribution of fragmentation, *Fragmentation*, across treated stocks with respect to the outages. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. We constrain observations to treatment-control pairs where the treatment reports trades during the before and after period. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. Further, we aggregate the minute-by-minute data to before and during the outage period averages to reduce influences from noise. All variables are winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. Standard errors reported in parentheses are clustered by stocks. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.

6 Conclusion

We study 12 primary market outages in Europe between 2018 and 2024 on a large sample of stocks. Outages are unanticipated and exogenous shocks that allow us to improve our understanding of how fragmentation influences market resiliency.

Our results document stylised facts about primary market outages. During a primary market outage, both the quoted spread and the expected price impact increase tenfold corresponding to an increase by 132 bp for the average quoted spread and increases by 98 bp for the average expected price impact. The effective spread widens by a factor of 1.1, highlighting an increase of 12.7 bp.

Since fragmentation allows for a market with many different entrances, it has the potential to cushion adverse effects from outages. We find, however, that during outages market quality deteriorates with the highest degree of fragmentation. Highly fragmented stocks in the treatment group are associated with an additional deterioration of the quoted spread by 12.5 bp for the treated stocks. These results hold for the effective spread, the expected price impact and the effective price impact. The lack of cushioning effects suggest that fragmentation does not enhance resiliency through redundancy and that frictions to market substitutability prevail. By analysing frictions due to network externalities, technical dependency, and participant behaviour, we find that the European stock market seems to be primary market dependent. First, despite having an alternative venue with substantial ex-ante trading activity, liquidity still deteriorates during outages and market participants do not migrate to these venues that ex-ante can arguably reduce coordination problems. Next, we find that stocks with high intensity of connected algorithmic broker trades experience stronger adverse outage effects. Despite the higher market connectivity of these stocks, liquidity does not migrate. Although counterintuitive at first glance, the results are in line with regulatory reports on frictions due to technical dependency of these algorithms on primary markets being open to route and execute trades. Finally, we show that participant behaviour is associated with adverse outage effects. Markets that are arguably not dependent on the primary market still break down, since market participants withdraw from trading. Consistent with the withdrawal, we find that high price uncertainty substantially increases adverse outage effects.

Overall, our results underline the central role of primary markets in the European market structure. The current design of exchange competition appears to be dependent on primary markets to function well. We find that liquidity does not migrate to alternative venues due to frictions to market substitutability and encourage regulators to promote policies that increase market substitutability between primary markets and other lit venues.

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Appendix A Venue Distribution

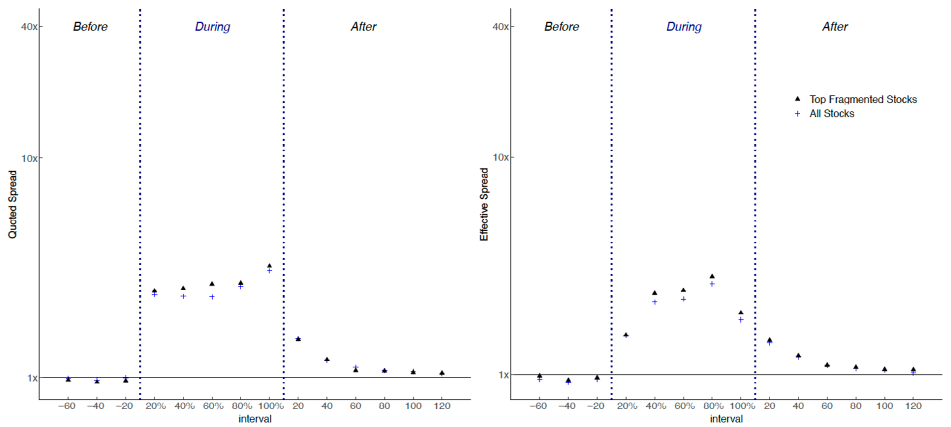
Primary Venue Distribution of Sample Stocks TABLE A1

	Treat	Control
Euronext Amsterdam	53	35
BME Spain	0	84
Euronext Brussels	65	48
London Stock Exchange	306	392
Nasdaq Helsinki	45	59
Deutsche Börse	309	131
Euronext Paris	192	137
Euronext Lisbon	14	6
Borsa Italiana	0	113
Nasdaq Copenhagen	47	53
Euronext Ireland	7	11
Nasdaq Stockholm	43	99
Nasdaq Oslo	0	45
Six Swiss Exchange	172	40
P	1,253	1,253

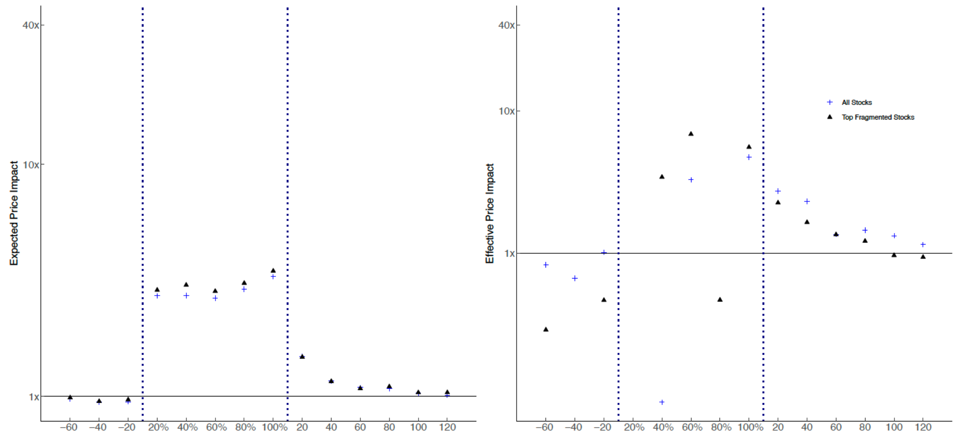
This table shows the sample distribution of treated (outage affected) stocks and control (non-outage affected) stocks. The sample is pooled across 12 primary market outages in Europe between 2018 and 2024 where outages entered the sample if they affected trading of all its listings.

Appendix B Additional Outage Plots

Market Quality During Outage Period and Fragmentation FIGURE A1



(a) Quoted Spread and Effective Spread



(b) Expected Price Impact and Effective Price Impact

We present the quoted spread; effective spread; expected price impact (the average price change that consumes €10,000 depth); and effective price impact. All variables are winsorised at the 2.5% and 97.5% for treated and control stocks in each outage with respect to the period and market capitalisation buckets. The variables represent the cross-sectional mean within the respective interval for the treated group. This figure shows the effect for the treated stocks during the primary market outages. We pool 12 outages. *All stocks* indicates the unconditional average across the treated stocks within the interval; *Top fragmented stocks* refers to the top tercile of fragmented stocks in the pooled fragmentation distribution. *Before* contains 60 minutes of continuous trading session before the outage; *After* is 120 minutes after the reopening auction from the outage; *During* is normalised into quintiles. The intervals are sampled in 10 minutes, respectively.

Appendix C Other Measures of Market Presence

Outage Effect across Proxies for Dominant MTFs TABLE A2

	MTF Trade Shares				MTF Concentration			
	QtdSpr	**EffSpr**	**ExpPrcImp**	**EffPrcImp**	**QtdSpr**	**EffSpr**	**ExpPrcImp**	**EffPrcImp**
Treat	0.16***	0.00	0.13***	0.01	0.13***	-0.05*	0.09**	-0.01
	(0.04)	(0.03)	(0.05)	(0.27)	(0.04)	(0.03)	(0.04)	(0.27)
During x Treat	2.35***	0.75***	2.38***	1.61***	2.35***	0.75***	2.37***	1.41***
	(0.07)	(0.04)	(0.08)	(0.47)	(0.07)	(0.04)	(0.08)	(0.51)
D	0.03	0.00	0.07	-0.40	-0.02	-0.10***	-0.01	0.06
	(0.05)	(0.03)	(0.06)	(0.35)	(0.05)	(0.03)	(0.06)	(0.34)
During x D	0.07**	0.05*	0.04	0.23	0.05*	0.03	0.08**	-0.46
	(0.03)	(0.03)	(0.04)	(0.28)	(0.03)	(0.03)	(0.04)	(0.29)
D x Treat	-0.17**	-0.14***	-0.18**	-0.66	-0.09	-0.01	-0.07	-0.64
	(0.07)	(0.04)	(0.08)	(0.42)	(0.07)	(0.04)	(0.07)	(0.46)
During x D x Treat	0.23*	0.05	0.16	0.44	0.22*	0.05	0.21	1.05
	(0.13)	(0.06)	(0.14)	(0.84)	(0.12)	(0.06)	(0.14)	(0.76)
Observations	3,728	3,728	2,440	3,708	3,728	3,728	2,440	3,708
Adj. R^2	0.709	0.728	0.771	0.314	0.709	0.728	0.771	0.314
Stock	X	X	X	X	X	X	X	X
Period	X	X	X	X	X	X	X	X
Outage	X	X	X	X	X	X	X	X

This table shows the triple difference regressions of market quality 60 minutes before the outage and during the outage. The *Before* and *During* are dummy variables that indicate the respective outage period. The periods are mutually exclusive. The regressions differ in their respective dummy, that aims to capture the dominant venues. *MTF Trade Shares* is a dummy that is 1 if a stock has an alternative venue where the numbers of trades are in the highest tercile of distribution across treated stocks. The measure is similar to *MTF Volume Shares* of Table 4, but instead of volume focuses on the activity based on numbers of trades. *MTF Concentration* is a dummy that is 1 for stocks that are in the highest tercile of distribution on MTF concentration across treated stocks. MTF concentration is measured by the Herfindahl-Hausmann index across the alternative venues. The difference-in-difference coefficients, denoted as the interaction of *Treat x Period*, is interacted with a dummy, *D*, that indicates the top-tercile stocks in the distribution of the respective proxy across treated stocks. We control for unobserved characteristics with stock, time of the day, and outage fixed effects. *QtdSpr* is the relative quoted spread; *EffSpr* is the relative effective spread; *ExpPrcImp* is the average price change that consumes €10,000 depth; *EffPrcImp* is the 10-second relative price impact. We take the natural logarithm of the market quality measures except for the *EffPrcImp,* which can be negative. For transaction-level and quote-level observations, we convert non-euro volumes and sizes by the average foreign exchange rate of the day based on high, low and close. All variables are normalised by their 20 trading days averages before the outage within the same time of the day to account for intraday seasonality. The normalised variables are winsorised at the 0.5% and 99.5% for each stock and interval. Standard errors reported in parentheses are clustered by stock and time of the day. *, **, and *** denote significance at the 10%, 5%, and 1% level respectively.