Order duplication and liquidity measurement in EU equity markets

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Executive summary

This report is the second part of ESMA's high-frequency trading (HFT) research. The starting point for both reports is the change in the trading landscape of equity markets over the last decade. The defining features of this change are increased competition between trading venues, fragmentation of trading of the same financial instruments across EU venues and the increased use of fast and automated trading technologies. In our first report we analysed the extent of HFT activity across the EU in such an environment using a novel identification method for HFT activity. We found that HFT activity represents between 24% and 43% of value traded and between 58% and 76% of orders in our sample.[1] In this report we focus on liquidity measurement where equity trading is fragmented.

In an environment characterised by competition between trading venues, traders do not always know on which venue they will be able to trade. They may "advertise" their intention to trade by posting similar orders on more than one trading venue at the same time ("duplicated orders"). This, however, leads to the risk of trading more shares than wanted. Therefore some traders may immediately cancel unmatched duplicated orders on other venues after one of their duplicated orders has been filled.

Using the HFT identification method developed in our first report, we find evidence for this trading pattern. 20% of the orders in our sample are duplicated orders and in 24% of trades the trader immediately cancels unmatched duplicated orders. We believe that duplication of orders and immediate cancellation of duplicates after a trade has become part of the strategy to ensure execution in fragmented markets, e.g. for market makers or where institutional investors are searching for liquidity. However, we show that taking duplicated orders into account when measuring liquidity leads to overestimation of available liquidity in fragmented markets.

The proportion of duplicated orders varies with the type of traders, the market capitalisation of the underlying stock and the fragmentation of trading in a stock. As expected, duplicated orders are more prevalent for HFTs (34% of orders) than for non-HFTs (12% of orders). They account for 22% of orders in large cap stocks compared to 12% of orders in small cap stocks. Also, fragmentation of trading is positively correlated with order duplication. We find 13% of duplicated orders for stocks with low trading fragmentation and 23% for high fragmentation.

Regarding the extent to which duplicated orders are immediately cancelled after trades (and thus subsequently are not available to the market), we carry out a number of analyses. First, we find that for 24% of all trades, the trader on the passive side of the trade immediately cancels order duplicates after the trade. This proportion is higher for HFTs (28%), large cap stocks (27%) and where trading is more fragmented (31%). Second, we look at the different reaction of two measures of liquidity: gross liquidity, the aggregated volume of displayed orders across multiple markets, and net liquidity, which deducts duplicated orders from the gross liquidity measure. We compare these two measures to establish whether order duplication should be taken into account when measuring liquidity in fragmented markets. A stronger fall of the gross liquidity measure after trades compared to the net liquidity measure is an additional indication that a proportion of duplicated orders is indeed immediately cancelled after trades and thus not available to the market. Our descriptive and econometric analyses confirm this hypothesis.

Both in our first HFT report and in this report we use unique data collected by ESMA, covering a sample of 100 stocks on 12 trading venues in nine EU countries for May 2013. Our data allow us to identify market participants' actions across different venues. Thus we are able to complement the literature, as most of the HFT studies published so far focus either on the US or on a single country within Europe and few are able to analyse the behaviour of market participants across trading venues.

Previous studies have found evidence supporting that fragmentation of trading increases liquidity in equity markets. Our analysis qualifies these results, as using data that allow us to identify market participants' actions across different venues, we find a substantial extent of order duplication in fragmented markets. It is important to state that unless they are successfully cancelled, duplicated orders are available to the market and all of them can be matched. However we find that a substantial proportion of order duplicates are immediately cancelled after a trade occurs and thus subsequently not available to the market. From an analytic perspective, our findings suggest that to avoid overestimation of available liquidity duplicated orders should be taken into account when measuring liquidity in fragmented markets, for example with our net liquidity measure.

[1] https://www.esma.europa.eu/sites/default/files/library/2015/11/esma20141_-_hft_activity_in_eu_equity_markets.pdf

Introduction

In recent years, financial markets have undergone a series of significant changes. Regulatory developments, technological innovation and growing competition have increased the opportunities to employ innovative infrastructures and trading practices.

On the regulatory side, the entry into force of the Market in Financial Instruments Directive (MiFID) in 2007 has re-shaped markets in the EU. Simultaneously, developments in new technologies have enabled the use of automated and very fast trading technologies.[2] The resulting trading landscape can be characterised by higher competition between trading venues, the fragmentation of trading in the same financial instruments across venues in the EU, as well as the increased use of fast and automated trading technologies.

It has been suggested that the order books of exchanges are today less informative than previously since liquidity is more transitory or “less certain”, as in fragmented markets it is not easy to anticipate where potential counterparties will trade next, or if they are active only on one venue or on multiple venues. Lescourret and Moinas (2015) analyse liquidity supply in fragmented financial markets and find that ex ante fragmentation may decrease total transaction costs (a measure of market liquidity): The possibility to compete in a single venue forces in some cases competitors to post aggressive quotes across all venues.

In this context, the disparity in terms of speed and technology between ordinary traders and high-frequency traders (HFTs) has become significant. Investment in fast trading technology helps financial institutions cope with market fragmentation (Biais et al, 2015). Thus, fragmentation may be more likely to attract HFTs, as they are able to implement cross-venue arbitrage strategies.

At the same time, recent events of short-term liquidity shortages and sudden spikes of volatility across market segments have triggered questions related to the impact of HFT on volatility, liquidity and, more generally, market quality.

When it comes to analysing the impact of HFT activity the operational definition of HFT becomes crucial. In general, total trading activity can be divided into algorithmic trading (AT) and non-algorithmic trading, depending on whether or not market participants use algorithms to make trading decisions without human intervention. Kirilenko and Lo (2013), for example, describe AT as “the use of mathematical models, computers, and telecommunications networks to automate the buying and selling of financial securities”.[3]

Following definitions proposed in the literature, HFT is a subset of AT and has the following features

- proprietary trading;
- very short holding periods;
- submission of a large number of orders that are cancelled shortly after submission;
- neutral positions at the end of a trading day; and
- use of colocation and proximity services to minimise latency.

From an analytical perspective, the absence of a unique definition makes it difficult to achieve a precise identification of HFT activity. The literature employs a number of approaches to identify HFT activity. None of these approaches is able to exactly capture HFT activities and they lead to widely differing levels of HFT activity. In 2014, ESMA published a report discussing the identification of HFT and providing estimates of HFT activity based on a cross-EU sample of stocks. The report, using unique data collected by ESMA covering a sample of 100 stocks from 9 EU countries and 12 trading venues for May 2013, shed further light on the extent of HFT in EU equity markets. The report provided a lower and an upper bound for HFT activity, employing two main methodologies:

a) direct approach: an institution based measure (each institution is either HFT or not) focusing on the primary business of firms (lower bound), and

[2] See e.g. Lo (2016) for an overview of technological change in finance.

[3] A legal definition of algorithmic trading is provided by MiFID II. Article 4(1)(39) of MiFID II states that algorithmic trading “means trading in financial instruments where a computer algorithm automatically determines individual parameters of orders such as whether to initiate the order, the timing, price or quantity of the order or how to manage the order after its submission, with limited or no human intervention, and does not include any system that is only used for the purpose of routing orders to one or more trading venues or for the processing of orders involving no determination of any trading parameters or for the confirmation of orders or the post-trade processing of executed transactions”. http://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32014L0065&from=EN

b) indirect approach: a stock-based measure (an institution may be HFT for one stock but not for another one) focusing on the lifetime of orders (upper bound).[4]

In the analysed sample, HFT activity accounts for 24% of value traded using the direct approach, and 43% using the lifetime of orders approach. For the number of trades the corresponding numbers for HFT activity are 30% and 49%, and for the number of orders 58% and 76%. Overall, these differences show that, depending on the identification approach chosen, the estimated level of HFT activity varies significantly though remaining relevant for EU equity markets (C.1).

C.1
HFT activity – Overall results for the HFT flag and lifetime of orders approaches

	HFT flag	Lifetime of orders	
	Total	Total	Thereof investment banks
Value traded	24	43	22
Number of trades	30	49	23
Number of orders	58	76	19

Note: Figures are weighted by value of trades (value traded), number of trades and number of orders, in %.
Source: ESMA.

The observation that HFT provides for a large part of activity in equity and other financial markets raised the question of the impact of HFT activity on these markets.

One first general question is related to the effect of HFT on market quality. Research generally found that HFTs improve traditional market quality measures: Hasbrouck and Saar (2013) find that HFT is related to decreasing spreads, increasing displayed depth in limit order book and lowering short-term volatility in US equity markets. Malinova et al (2014) using a different sample also conclude that HFT activity is associated with improved market quality (mainly measured by tighter bid-ask spreads) while Brogaard et al (2014 and 2016) underline the positive impact of HFT on price efficiency. Despite these findings, many investors are concerned that HFT liquidity provision is selective and limited to periods of low stress.[5] Chordia et al (2013) write: "There is growing unease on the part of some market observers that […] violent price moves are occurring more often in financial instruments in which HFTs are active."

More recent research qualifies some of the positive findings. While Boehmer et al (2015) find that AT on average increases market quality, but also increases volatility, they also find that AT reduces the market quality and leads to a stronger increase in volatility of small stocks. Bongaerts and Van Achter (2016) argue that the combination of speed technology and information processing technology can lead to the implementation of inefficient speed technology, endogenous entry barriers and rents. This can result in liquidity evaporating when it is most needed. Chakrabarty et al (2016) carry out analysis during a time of market stress. They analyse market quality on the Spanish Stock Exchange (SSE) from the beginning of 2010 to the end of 2013. Two events coincide: On the one hand, short selling restrictions were in place on the SSE from 11 August 2011 to 15 February 2012 (for financial sector stocks) and from 23 July 2012 to 31 January 2013 (for all stocks). On the other hand, the SSE introduced technological changes to attract HFTs. A smart trading platform was introduced in April 2012 (where no short selling restrictions were in place), HFT activity increased afterwards. Colocation was introduced in November 2012 (during the second short selling ban); here HFT activity did not increase afterwards. Following technological changes, liquidity and price efficiency deteriorated.

Another strand of the literature focuses on the best market design in presence of HFT. Budish et al (2015) argue that the high-frequency trading arms race is a symptom of flawed market design and that financial exchanges should use frequent batch auctions.[6] The batch auctions system processes orders received during a fixed time interval simultaneously, thus treating concurrently orders submitted by faster traders with those by slower

[4] A similar approach is used by Bellia et al. (2016) who find that traders generally exhibit different types of behaviour across stocks and over time. Therefore, they conclude that the usual characterisation of a trader acting as HFT, for all time and for all stocks, is likely to be invalid.

[5] Korajzcyk and Murphy (2015) find that HFTs do provide liquidity for institutional trades, but to a significantly smaller extent when trades are stressful, i.e. comparatively large. Bongaerts and Van Achter (2016) describe mechanisms where HFT activity can reduce or lead to the evaporation of liquidity.

[6] Bongaerts et al (2016) analyse in a theoretical model the likelihood of arms race behaviour in markets with liquidity provision by HFTs. Liquidity providers (makers) and liquidity consumers (takers) make costly investments in monitoring speed. They highlight two opposing economic channels that influence such effect in partially offsetting ways. Competition among makers and among takers may indeed trigger an arms race in the classic sense. However, complementarity between the two sides, the increased success rate of trading, may offset this effect if the gains from trade are large enough. Therefore, the likelihood of arms races depends on how gains from trade depend on transaction frequency.

traders and reducing the benefit of marginal superiority in speed.

Other researchers argue that HFTs are a heterogeneous group and they employ a variety of strategies, with different impact on financial markets. Menkveld (2013) focuses on just one HFT following a market making strategy and shows the relationship between market fragmentation and HFT in current financial markets. Indeed, he shows how the HFT entry into a large incumbent market NYSE-Euronext and the entrant market Chi-X at the same time not only fragmented trading, but it also coincided with a 50% drop in the bid-ask spread. Hagstromer and Norden (2013) distinguish between HFTs following market making strategies and others following opportunistic strategies and show that the latter are associated with increases in volatility, whereas the former are associated with decreases in volatility.

One of the concerns often mentioned with respect to HFTs is that they overload the exchanges with submissions and cancellations of limit orders,[7] even though this strategy can be essential in current fragmented market.

In this report we focus exclusively on the presence of duplicated orders across multiple venues and how this may affect the accurate measurement of genuine liquidity and thus the accurate understanding of liquidity dynamics.

We define duplicated orders as those posted on the same side of the order book, at the same price and by the same market agent but on different venues. Our hypothesis is that order duplication is partially explained by the search for counterparties in fragmented markets[8] and that, once the trading objective has been fulfilled in one venue, in many cases the liquidity will be immediately removed from the other venues. Such a strategy requires fast reaction, thus it is likely that mostly HFTs are able to act in this way. This fast disappearance of orders will have an impact on observed market liquidity. The SEC's Concept Release on Equity Market Structure (2010) recognised the importance of high frequency quoting in that it might represent "phantom liquidity (which) disappears when most needed by long-term investors". If this is the case, a liquidity measure that takes account of the existence and the extent of order duplication should be more accurate than a gross measure of liquidity that does not control for order duplication.[9] Conrad et al (2015) describe the disadvantage characterising most of the literature focusing on a single stock exchange: In a fragmented market it is entirely possible that HFT behaviour in one market may not reflect aggregate market behaviour.[10] Our unique dataset allows us to avoid this disadvantage.

The structure of the paper is as follows. First, we provide an overview of the existing literature on the impact of HFT activity and fragmentation on liquidity in financial markets. Second, we describe our unique dataset. Then, we introduce the duplicated orders metric which is based on the concepts of gross and net liquidity.

We also analyse the behaviour of the different traders performing the order duplication strategy after the execution of trades for which they provided liquidity. We then look at the extent and the relevance of order duplication in EU equity markets, in particular for HFTs. Finally, we analyse the relevance of order duplication for liquidity measurement in fragmented equity markets. We carry out descriptive and econometric analyses comparing the behaviour of the gross and net liquidity measures after trades occur in the market. This enables us to provide indications regarding the extent to which duplicated orders are not available to the market after trades and thus traditional liquidity measures based on gross liquidity may overestimate available liquidity in fragmented equity markets.

Literature review

There is a large body of literature scrutinizing the activity, behaviour and impact of HFT firms.[11] Based on various market quality metrics, there is mixed evidence on the question whether HFT activity has been beneficial to financial markets. Most notably, HFT is associated with tighter bid-ask spreads (Hendershott, et al, 2011; Malinova et al, 2013), and more efficient

[7] See Egginton et al (2014), Friedrich and Payne (2015) for more analysis on the impact of quote stuffing and high order-to trade-ratios on financial markets.

[8] See AFM (2016) for a discussion based on interviews with market participants (HFT and buy-side firms as well as trading venues).

[9] See AFM (2016).

[10] For instance, a high frequency trader may extract liquidity from Exchange X (which is known to be cheaper for extracting liquidity for a particular group of stocks) but may be providing liquidity in Exchange Y: research only observing trades on Exchange X would erroneously conclude that this high frequency trader is a liquidity extractor.

[11] For an extensive review of the literature on HFT see e.g. SEC (2014).

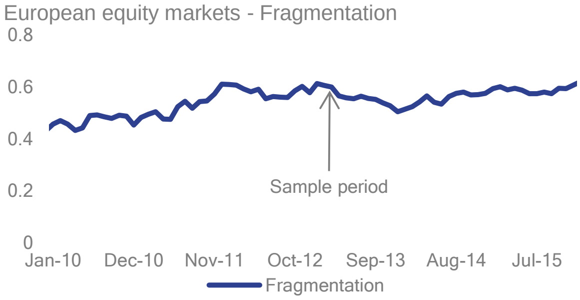
price formation (Brogaard et al, 2014). However, this may not hold under all market conditions. Breckenfelder (2013) finds that in situations where HFTs compete for trades liquidity decreases and short-term volatility rises. Boehmer et al (2015) find that AT on average increases market quality, but also increases volatility, they also find that AT reduces the market quality and leads to a stronger increase in volatility of small stocks. Results with regard to volatility are found to vary between market makers and aggressive HFTs, where the latter are associated with increases in volatility and vice versa for the former (Benos and Sagade, 2016; Hagströmer and Norden, 2013). Aquilina and Ysusi (2016), using orders and trades data on 120 UK stocks from the main UK lit venues, address the question whether HFTs can predict when orders are going to arrive at different trading venues and trade in advance of slower traders. They find no evidence that HFTs in the UK are able to systematically anticipate near-simultaneous orders sent by non-HFTs to different trading venues and thus making risk-free profits due to their latency advantages. When looking at longer time periods (seconds or tens of seconds), they find patterns consistent with HFTs anticipating the order flow of non-HFTs. For these longer time periods they however could not conclude whether this is because HFTs can in fact anticipate the order flow or whether they are faster to react to new information.

A limitation of most publications to date is that they rely on data covering a single trading venue either in the US, Canada or in a single country within Europe. Results based on data from a particular trading venue may not necessarily hold on other venues or when a cross-venue analysis is carried out.[12] Only few studies use cross-venue data. Exemptions are e.g. Boehmer et al (2016) who analyse trading activity of HFT firms across all Canadian trading venues and Baron et al (2016) who use regulatory transaction data to analyse HFT activity across venues for most stocks in the Swedish OMX30 index.

Our study complements the HFT literature by looking at equity trading across 9 EU countries and 12 trading venues. Further, we are able to identify the same trader's activity on multiple venues. This allows having a clearer picture of HFT behaviour in fragmented markets.

The trading landscape that investors face today has grown to be increasingly fragmented. Angel et al (2011) note that the market share of the NYSE in equity trading has decreased from 80 percent in 2003 to just 25.8 percent in 2009. As much of the literature analyses only a limited number of trading venues, the liquidity studied is only a subset of the actual liquidity available to investors. In Europe, the intensity of the fragmentation process has significantly increased since the adoption of MiFID. The share of trading on multilateral trading facilities (MTF) was close to zero at the beginning of 2008, while at the beginning of 2011 it was equal to 18% of total turnover (Fioravanti and Gentile, 2011). For our sample period in May 2013, the share of turnover of new venues had reached 28% of trading in electronic order books and 22% of total equity trading, according to data from the Federation of European Securities Exchange. The level of fragmentation of EU national indices has remained broadly stable since 2013 (C.2).

C.2
European equity markets - Fragmentation



Note: Median value of the trading fragmentation of selected national indices measured as (1-Herfindahl-Hirschman index), monthly average. Included indices are AEX, BEL20, CAC40, DAX, FTSE100, MIB, IBEX35, ISEQ20 and PSI20.
Sources: BATS, ESMA.

Only a small number of studies analyses the impact of HFT on liquidity in the context of fragmented markets. The majority of publications consider the effect of fragmentation on market quality, with some nuances about AT activity by use of a proxy.[13]

Biais et al (2015) find in a theoretical work that investment in fast trading technology helps financial institutions cope with market fragmentation. To the extent that this enhances their ability to reap mutual gains from trade, it improves social welfare. On the other hand, fast

12 See Conrad et al (2015) for a description of this issue.

13 The data underlying those publications considered here does not identify individual traders and does thus not allow for direct or indirect identification of HFT firms.

institutions observe value relevant information before slow ones, which creates adverse selection. Thus, investment in fast trading generates negative externalities, which are not internalised by financial institutions and therefore are detrimental to social welfare.

In Van Kervel (2015) market quality is found to be improved as a result of increased market fragmentation, but there is evidence that order duplication may bias traditional measures of liquidity. Holden and Jacobsen (2014) highlight how cancelled orders in current fast, competitive market contribute to increased difficulties and biases of liquidity measurement.

Degryse et al (2014) study the effect of dark trading and fragmentation on market quality. Using order book data for 51 Dutch stocks for several lit and dark markets[14], their findings indicate that lit fragmentation improves liquidity aggregated over all visible trading venues. However, liquidity is lowered in the traditional market. This suggests that the benefits of fragmentation are not enjoyed by investors who send orders only to the traditional market.

Aitken et al (2015) provide evidence using US data on listed Nasdaq securities. Employing a simultaneous equations model, they find that fragmentation of the lit market order flow, with the ensuing increase in competition, particularly from HFT and AT firms, has been largely beneficial for financial markets. Effective spreads and end-of-day manipulation both fell as a result of increased fragmentation. Similar to Degryse et al (2014), the effect of dark market fragmentation was found to be detrimental.

O'Hara and Ye (2011) focus on the impact of market fragmentation on market quality for US stocks, using data covering 150 Nasdaq stocks and 112 NYSE stocks. Their findings indicate that fragmentation is largely beneficial to market quality in various respects. More fragmented stocks have lower transaction costs in terms of effective spreads, and faster execution speeds. Small stocks are particular beneficiaries from this effect. While short-term volatility was found to increase with fragmentation, overall price efficiency is improved in that prices tend to be closer to a random walk.

Gresse (2014) employing a different sample contrasts the results of O'Hara and Ye (2011) with an empirical analysis of the effect of fragmentation on price inefficiency coefficients (PICs). Using a sample of French and UK stocks, the author does not find a clearly significant impact of fragmentation on price quality. The results for a subset of the PICs analysed show, however, that price quality of large UK stocks improved with fragmentation. Improvements for large French stocks appeared only on the traditional market. When measured across markets, the price quality appears to deteriorate for French large caps. The same holds for French mid-caps, irrespective of where the effect is measured.

More evidence on the effect of dark trading and fragmentation on liquidity is provided by Gresse (2015), who draws on high-frequency data for a sample of French and UK stocks. AT activity is considered in her study via a proxy based on message frequency. A comparison of quasi-consolidated pre-MiFID to fragmented post-MiFID markets shows that spreads narrowed gradually as fragmentation increased, particularly for large-cap stocks. This effect was attributable to both fragmentation and AT activity, as a time series analysis of the post-MiFID period in her sample reveals. Concurrently, best-quote depth is found to be reduced after the introduction of MiFID. However, this reduction in depth is attributable to AT rather than lit fragmentation, which was found to have a positive effect. In contrast to Degryse et al (2014), Gresse (2015) finds that the positive effects were not limited to global liquidity, but that the formerly monopolistic markets benefited as well in most cases[15].

Van Kervel (2015) analyses the close link between market fragmentation and order duplication. He first develops a theoretical model of competition between two centralized limit order books. In this context, he shows that HFTs, who can access both trading venues simultaneously, have an incentive to duplicate limit orders on both venues. A trade on one venue is then followed by a cancellation on the other venue. This implies that depth aggregated across venues overestimates true liquidity, since a trade on a given venue reduces aggregate

[14] A lit market is one where orders are displayed on order books and are therefore pre-trade transparent. On the contrary, orders in dark pools or dark orders are by definition not displayed, and therefore are not pre-trade transparent.

[15] The difference between the two results may also be related to different samples analysed: French and UK stocks for Gresse (2015) and Dutch stocks for Degryse et al (2014).

depth by more than its own size. Given the costs of simultaneous execution and adverse selection, order duplication strategies are feasible only to traders that can monitor several venues simultaneously and cancel limit orders swiftly. In that sense, only traders operating with high frequency technology can benefit from the duplication of orders effectively. The theoretical evidence is confirmed through an empirical analysis. Using order book data for 10 FTSE 100 stocks that are cross-listed on five venues, Van Kervel (2015) tests the effect of (lagged) trades occurring on any of the five venues on the order book depth of each venue. The results are in line with the theoretical predictions. For instance, a GBP1 buy trade on Chi-X is immediately followed by cancellations on the LSE of GBP0.21. The effect is long-lasting. After 10 seconds, the reduction in the LSE order book increases to GBP0.61, implying that more than half of the Chi-X trade size is cancelled on LSE. Moreover, the author shows via a proxy that AT increases the magnitude of cancellation. The results are similar across venues and go in all directions, suggesting that consolidated depth overestimates the true depth that is actually available in the market for non-AT traders.

We contribute to the literature on the impact of market fragmentation on market liquidity (Degryse et al. 2014 and Gresse, 2015) by including in the analysis the extent of duplicated orders across multiple venues.

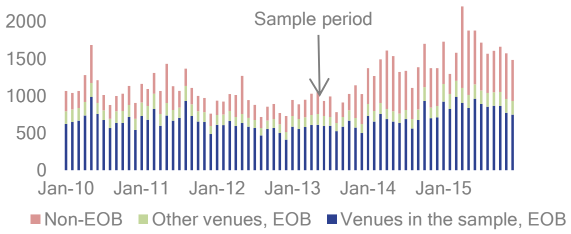
We innovate with respect to Van Kervel (2015) by analysing orders and trades for a sample of 100 stocks traded in nine EU countries and in 12 trading venues. Moreover, we developed a unique methodology for identifying HFTs. It is based on the different properties of our dataset that allow for a cross-venue identification of market participants. This is not feasible for almost all of the datasets described above as they contain either data for one particular or a limited number of venues or do not allow for identification of traders across venues.

Dataset description

The analysis is based on data collected by ESMA through National Competent Authorities for the month of May 2013, which have also been used for ESMA's first research report on HFT.[16] The dataset covers all messages and trades on twelve trading venues: NYSE Euronext Amsterdam (XAMS), Brussels (XBRU), Lisbon (XLIS) and Paris (XPAR), Deutsche Börse (XETR), Borsa Italiana (MTAA), London Stock Exchange (XLON), Irish Stock Exchange (XDUB), Spanish Stock Exchange (XMCE), BATS Europe (BATE), Chi-X Europe (CHIX)[17] and Turquoise (TRQX). For some venues the dataset also includes some additional information for market members, such as the use of colocation, identification of market making activity and flags for use of Direct Market Access[18]. The dataset includes around 10.5 million trades and 456 million messages. Message types include new, modified and cancelled orders.

During the sample period, the total turnover of the venues included in our sample – according to Federation of European Stock Exchanges data – represented 58% of the total trading activity in European equity markets (C.3).[19]

C.3
European equity markets - Turnover



Note: Monthly trading activity in European equity markets. EUR bn. EOB= Electronic order book. Venues in the sample, EOB is the sum of trading activity through EOB in venues represented in our sample. Other venues, EOB represent trading through EOB in venues absent from our sample. Non-EOB represent the trading not using EOB in any European venue.
Sources: FESE, ESMA.

A random sample of 100 stocks traded in Belgium (BE), Germany (DE), Spain (ES), France (FR), Ireland (IE), Italy (IT), the Netherlands (NL), Portugal (PT) and the United Kingdom (UK) has been chosen (C.4).

16 For more details on the database see ESMA (2014).

17 BATS Europe and Chi-X Europe merged in 2011 to form BATS Chi-X Europe. They continue to operate separate order books.

18 We cannot use this information in our empirical analysis since it is not available for a significant number of venues.

19 The 42% includes trading activity on other European venues as well as trading activity which is not carried out via electronic order books. Considering only activity carried out via electronic order books, the venues in our sample account for 81% of trading activity during May 2013.

C.4
Sample of stocks by country

Country	Number of stocks	Country	Number of stocks
BE	6	IT	11
DE	16	NL	13
ES	12	PT	5
FR	16	UK	16
IE	5	All sample	100

Note: Number of stocks in the sample.
Source: ESMA.

A stratified sampling approach has been used taking into consideration market capitalisation, value traded and fragmentation. The sample includes stocks with very different features. During the observation period (May 2013), average value traded ranged from less than EUR 0.1mn to EUR 611mn. In terms of market capitalization, values ranged from EUR 18mn to EUR 122bn during the observation period (average at EUR 8.7bn and median at EUR 2.9bn; C.5).

C.5
Sample stocks statistics – Value traded and market capitalisation

Country	Value traded (EUR mn)			Market Cap (EUR bn)		
	Avg	Max	Min	Avg	Max	Min
All sample	33.7	611.3	<0.1	8.7	122	<0.1
BE	45.7	357.1	0.3	24.3	122	0.8
DE	37.1	611.3	<0.1	8.2	73	<0.1
ES	42.8	526	2.6	9.6	41.8	0.7
FR	34.8	497.2	<0.1	7.5	58	0.1
IE	5.3	184.7	<0.1	3.6	8.1	<0.1
IT	33.1	300.7	<0.1	6.5	28.2	0.3
NL	37.3	350.5	0.3	7.7	51	0.4
PT	17.2	143.1	<0.1	5.3	11.4	2
UK	29.2	290.2	0.1	8.5	71.2	0.4

Note: Monthly average, minimum and maximum for May 2013.
Sources: Thomson Reuters Datastream, ESMA.

The degree of fragmentation[20] is also heterogeneous in our sample,[21] and varies significantly with market capitalisation.

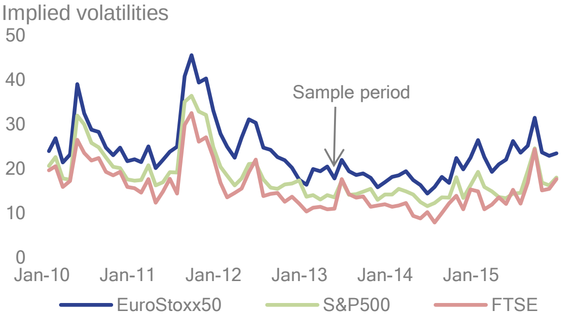
C.6
Sample stocks statistics – Trading fragmentation

Country	Fragmentation		
	Small Caps	Mid Caps	Large Caps
	Avg	Avg	Avg
All sample	0.75	0.63	0.55
BE	0.67	-	0.51
DE	0.81	0.58	0.55
ES	0.83	0.77	0.68
FR	0.73	0.6	0.47
IE	0.87	0.71	0.72
IT	0.91	0.72	0.68
NL	0.7	0.52	0.52
PT	-	0.81	0.48
UK	0.57	0.45	0.42

Note: Trading fragmentation is measured as (1 – Herfindahl-Hirschman Index). For the fragmentation index a value of 0 indicates no fragmentation (all trading is on one venue), whereas higher values indicate that trading is fragmented across several trading venues. One stock has been excluded due to missing information on market capitalisation.
Source: ESMA.

One of the questions raised regarding HFT activity is whether the impact of HFT is different during calm and volatile market conditions. As can be seen in C.7, market conditions during the sample period of May 2013 were calm with low price volatility in equity markets – measured using option implied volatilities.[22]

C.7
Implied volatilities



Note: Implied volatilities on EuroStoxx50 (VSTOXX), S&P500(VIX) and FTSE100, monthly averages, %.
Sources: Thomson Reuters Datastream, ESMA.

The identification of market participants is based on a stratified approach which allows us to analyse – on an anonymised basis – the behaviour of market participants across trading venues:

20 Please see Annex 1 for more details on the fragmentation metric.

21 In our dataset, a stock can be traded on a maximum of 4 venues.

22 As part of the analysis in this report, we split the sample of our stocks into terciles according to the price volatility of stocks during May 2013. It is worth noting that – even though we differentiate our results by volatility – our estimations of the effects of volatility on order duplication are computed for a calm period in equity markets and cannot be directly extrapolated to periods of very high stress, as the relationship between order duplication strategies and market uncertainty may not be linear.

- For each market participant a Unique ID has been created for each venue where he has membership;[23]
- If a participant has several accounts on the same venue, each account will have a separate Unique ID but the same Account ID;
- If a market participant is a member of several venues, all these accounts will have the same Group ID.

The Group ID allows us to identify the orders by a market participant across the trading venues contained in our sample. The assessment whether a market participant is considered to be a HFT or non-HFT is also based on the Group ID, thus allowing us to assess the extent of order duplication for HFT and non-HFT activity.

Identifying high-frequency trading – the key results of ESMA (2014)

ESMA's first research report on HFT focussed on the identification of HFT activity in EU trading venues. ESMA (2014) provides the foundation for the analysis in this report, as we follow a HFT identification approach developed in detail in ESMA (2014).

The literature on HFT uses different approaches to identify HFT, broadly falling into two categories: direct and indirect approaches. In ESMA (2014) we provided an extensive review on methodological advantages and disadvantages of different HFT identification approaches – both in a general context and in the context of our dataset. It is worth noting that a precise identification of HFT activity is difficult to achieve; any HFT identification method will to some extent identify non-HFT activity as HFT activity and vice versa. Since from an analytical perspective no single method is able to exactly capture the extent of HFT activity, we provided estimates based on a direct HFT identification approach, using a HFT flag, and an indirect identification approach, based on the lifetime of orders.

For the HFT flag approach a list of firms that engage in HFT has been established. A firm is classified as HFT where HFT is its primary business. The classification is based on the information available on the websites of firms, on business newspaper articles and on industry events. In certain cases the flagging of firms was also discussed with supervisors. 20 groups (out of a total of 394) were classified as HFTs in this way.[24]

Our identification rule for HFT activity according to the lifetime of orders approach is as follows: if the 10% quickest order modifications and cancellations of a given Group ID in any particular stock are faster than 100ms, then the trading activity of the firm in that particular stock is considered HFT activity. There is no rule which threshold would characterise HFT activity in a precise manner. We have therefore carried out robustness checks and have provided an overview of levels of HFT activity under a lifetime of orders approach for a range of time thresholds in ESMA (2014).

This classification is based on the ability of a market participant to very quickly modify or cancel orders and can be computed for individual stocks rather than at firm level. Firms may have HFT activity in some stocks, but not in others. The lifetime approach can identify trading activity in stocks where firms act as HFT. Bellia et al (2016) point out the advantages of such an approach rather than classifying the entire activity of a firm as HFT or non-HFT. In this report we use the lifetime of orders approach, as it allows for a cross-venue perspective in the trading activity of a specific stock, which is the perspective we are taking in our analysis.

In ESMA (2014) we presented a range of estimates for HFT activity based on a HFT flag approach and an order lifetime approach. The results based on the HFT flag provide a lower bound for HFT activity, as they do not capture HFT activity by investment banks. The results based on the lifetime of orders are likely to be an upper bound for HFT activity.

23 However, our data does not contain information about Direct Electronic Access (DEA). Where DEA is involved a unique ID may contain a number of market participants.

24 For the HFT flag approach each market participant is flagged as HFT, investment bank or other.

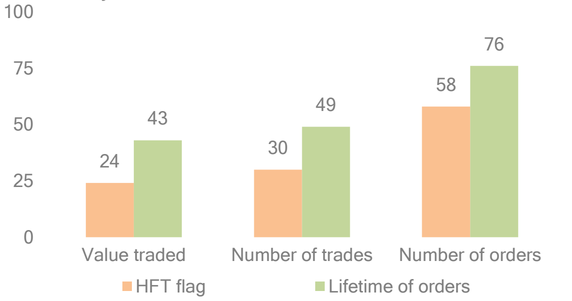
Overall, HFT firms account for 24% of value traded in our sample, based on the HFT flag approach. Based on the lifetime of orders approach, HFT activity accounts for 43% of value traded. This estimate is broadly in line with existing studies at the European and on country level.

For the number of trades, the corresponding numbers are between 30% for the HFT flag approach and 49% for the lifetime of orders approach; for the number of orders they are between 58% and 76%, respectively (C.8).

The difference is mainly explained by the activity of investment banks. They account for around 61% of total value traded, of which roughly one third (22% of total value traded) is identified as HFT activity in a lifetime of orders approach (C.1). In this report we will follow the lifetime of orders approach.

Across all venues, the share of HFTs by value traded was smaller than the share by number trades, which in turn was lower than the HFT share by number of orders. This indicates firstly that the trade size of HFT trades is smaller than the trade size of non-HFT trades. Moreover, it indicates that the order-to-trade ratio of HFTs is on average higher than the order-to-trade ratio of non-HFTs.

C.8
HFT activity – overall results



Note: HFT activity by value traded, number of trades and number of orders according to the HFT flag and lifetime of orders approach, in %..
Source: ESMA.

HFT activity varies significantly between trading venues. It is generally higher for the newly established trading venues BATS Europe, Chi-X Europe and Turquoise than for incumbent exchanges.

In terms of value traded, HFT activity ranges from 8% to 40% (average 24%) for the HFT flag approach and from 19% to 63% (average 43%) for the lifetime of orders approach. For number of trades, HFT activity ranged between 9% and 44% (average 30%) for the HFT flag approach and between 18% and 65% (average 49%) for the lifetime of orders approach. For number of orders the range for HFT activity is between 31% and 76% (average 58%) for the HFT flag approach and between 34% and 87% (average 76%) for the lifetime of orders approach (C.9).

C.9
Overview of HFT activity – HFT flag and lifetime of orders

Trading venue	Value traded		Number of trades		Number of orders	
	HFT flag	Lifetime of orders	HFT flag	Lifetime of orders	HFT flag	Lifetime of orders
All venues	24	43	30	49	58	76
BATE	40	60	44	63	76	85
CHIX	40	56	40	58	59	80
MTAA	25	20	26	18	51	34
TRQX	34	63	35	65	73	84
XAMS	24	48	28	54	53	77
XBRU	18	48	23	50	38	64
XDUB	8	19	9	28	43	87
XETR	21	35	24	35	33	63
XLIS	11	40	17	45	31	65
XLON	21	32	26	35	44	56
XMCE*	0	32	0	29	0	46
XPAR	21	45	30	51	50	70

Note: Figures are weighted by value of trades (value traded), number of trades and number of orders, in %. For trades on UK stocks, value traded has been converted to EUR using end-of-day exchange rates.
BATE=BATS, CHIX=Chi-X MTAA= Borsa Italiana, TRQX=Turquoise, XAMS=NYSE Euronext Amsterdam, XBRU=NYSE Euronext Brussels, XDUB=Irish Stock Exchange, XETR=Deutsche Boerse AG, XLIS=NYSE Euronext Lisbon, XLON=London Stock Exchange, XMCE=Mercado Continuo Español, XPAR=NYSE Euronext Paris.
*No HFT firms were direct members of XMCE during the observation period. Therefore no HFT activity is reported for XMCE under the HFT flag approach.
Source: ESMA.

Regarding the characteristics of market participants we find that HFT firms are members of more trading platforms than other types of market participants, which amongst other reasons may indicate that they are more likely to perform cross-venue arbitrage. On average, HFT groups have 9.1 different unique IDs, indicating that their trading is spread across multiple venues. Investment banks have 5.6 different IDs and other firms 2.2. Those features are in line with the assumption that HFTs are more likely to arbitrage across venues than other types of market participants. However, as shown in Table C.10, there is substantial variation within each group, especially for investment banks and other members.

C.10
Number of IDs by type

Type	Average	Median	Max	Min
HFT	9.1	10	13	1
Investment Banks	5.6	3	23	1
Other	2.2	1	13	1
All	3.1	1	23	1

Note: Number of IDs within HFT groups, Investment Bank groups or other groups across all trading venues in sample.
Source: ESMA.

The extent of order duplication in EU equity markets

In fragmented markets traders find it more difficult to anticipate where potential counterparties will trade. As a result, they may need to “advertise” their intention to trade on more than one trading venue. For instance, a trader may want to trade 100 shares of company X at a given price but does not know at which trading venue he will be able to do so. Therefore, he inserts the same order for 100 shares of company X on more than one trading venue even though his intention is to trade 100 shares, i.e. he duplicates orders.

Thus, we define duplicated orders as those posted on the same side of the order book, at the same price and by the same market agent but on different venues. Our hypothesis is that order duplication arises from the search for counterparties in fragmented markets to increase the probability of execution and that, once the trading objective has been fulfilled on one venue, a proportion of duplicated orders are immediately removed or updated on the other venues to avoid trading higher quantities than desired. Order duplication is not a risk free strategy; indeed, some orders could still be matched by other fast market participants.

If a substantial proportion of orders are affected by this type of behaviour, market-wide measures of liquidity which do not take account duplicated orders may overstate the actual liquidity available to investors.

Order duplication strategies may be employed by different types of market participants, e.g. HFTs and institutional investors. HFT strategies are heterogeneous and different types of institutions are increasingly engaged in HFT. For instance, speed is an important feature of market-making strategies. It enables market-makers to quickly react to quote updates, news releases or temporary changes in market liquidity and allows them to manage their inventory risk more efficiently. HFTs, acting as market makers, duplicate their limit orders on several venues to increase execution probabilities before repricing these orders after one of their orders trades on one venue. Asset managers have also progressively adopted AT and HFT strategies to cope with new market conditions that arose from the fragmentation of markets. They may now more frequently duplicate orders in an effort to “find” the liquidity that is now split between different trading venues.

All duplicated orders are part of the order book of the respective trading venues. Thus, all these orders are a priori available to the market. However, to avoid trading higher quantities than desired, duplicated orders are susceptible to be cancelled after a trade matching parts of the duplicated orders has occurred. For example, it is likely that in the previous example after a market participant trades 100 shares on one trading venue, the trader cancels the orders he had inserted at other venues. Cancelling duplicated orders is needed to avoid trading higher volumes than desired. Bearing in mind the speed of trading, immediate deletion of duplicated orders on other trading venues once the trading is executed on one trading venue requires ultra-fast reaction. Thus it is likely that mostly market participants employing HFT technology are able to implement this cross-venue strategy.

There are several reasons for employing such a strategy. We will implicitly make the distinction between two of them: either the trader is quickly repricing the cancelled orders at a “close” price (e.g. market makers would behave in this way), or he is repricing at a price “far” from the original one (or simply deleting order duplicates without re-inserting new orders). While the last situation will be considered as order duplication, the first one will not. This will be reflected in the way we will define our measures.

Where duplicated orders are immediately cancelled, this fast disappearance of orders will have an impact on available market liquidity. A liquidity measure that takes account of the existence and the extent of order duplication should therefore be more accurate than a gross measure of liquidity that does not control for order duplication.

Therefore, we introduce the concepts of gross and net liquidity. Gross liquidity is computed as the aggregated volume of displayed orders in multiple markets for each market participant. Net liquidity is calculated subtracting duplicated orders from gross liquidity. Net liquidity is a more genuine representation of the orders available in the market but it is not observable by market participants.

By aggregating across market participants we are able to obtain a market-wide measure of gross liquidity (which market participants can observe) and a market-wide measure of net liquidity (without duplicated orders and unobservable by market participants).

To compute the net liquidity measure, we need to define and compute duplicated orders for each snapshot of the order book. Order book snapshots are taken each 10 milliseconds in our sample period.[25] Basis for the calculation is the mid-price, i.e. the average of the best bid and ask prices across venues.

For all market participants, we calculate the aggregated volume of displayed orders across all venues within ± 0.5% of each mid-price.[26] We then aggregate across all market participants to obtain the gross liquidity measure for this order book snapshot. Then, we define net orders as the largest order of a market participant on a single venue within ± 0.5% of each mid-price. Again, we aggregate across all market participants to obtain our net liquidity measure. The net liquidity measure is based on the assumption that a trader pursuing a duplicated orders strategy will at most execute the biggest outstanding quantity for each stock within ± 0.5% of mid-price.

Finally, by construction, we define the duplicated orders variable as the difference between gross liquidity and net liquidity. Box 1 provides a simple example of the order duplication metrics.

Order duplication metrics Box 1

Gross and net liquidity measures are calculated as follows for Agent 1:

- gross liquidity is the aggregated volume of orders at a price of 10.00 across all venues: 500+300+200=1000
- net liquidity is the largest of these orders: 500
- duplicated orders: gross liquidity – net liquidity = 1,000 – 500 = 500

Similarly the gross liquidity for agent 2 is 300 shares; net liquidity is 150 shares, which implies duplicated orders of 150 shares.

On a market wide basis, we compute the order duplication metrics as the sum of gross and net liquidity measures of all market participants, here agents 1 and 2:

- gross liquidity: 1,000 + 300 = 1,300
- net liquidity: 500 + 150 = 650
- duplicated orders: gross liquidity – net liquidity = 1,300 – 650 = 650

	Price	Venue 1	Venue 2	Venue 3	Gross Liquidity	Net Liquidity
Agent 1	10.00	500	300	200	1000	500
Agent 2	10.00	100	150	50	300	150
Total		600	450	250	1300	650

These metrics are computed for all stocks in our sample at 10-millisecond intervals throughout our sample period. We also consider separately the two sides of the trading book (bid side and ask side).

For instance, for a given stock *i* a given day D and for the bid side of the order book, the gross liquidity, net liquidity and duplicated orders measures are computed the following way:

$$Gross_{i,D,BID} = \frac{1}{N}\sum_{t=1}^{N}\sum_{p\,\in\,\Omega_t}\sum_{v\,\in\,\Omega_p} Q_v$$

$$Net_{i,D,BID} = \frac{1}{N}\sum_{t=1}^{N}\sum_{p\,\in\,\Omega_t}\max_{v\,\in\,\Omega_p} Q_v$$

$$Duplicated_{S,D,BID} = Gross_{S,D,BID} - Net_{S,D,BID}$$

Where:

— N is the number of observations

— Ω_t is the vector of prices available within ± 0.5% of the mid-price at observation time t[27]

[25] As we are working with cross-venue order data, clock synchronisation is an issue. The longest time interval of timestamps provided by trading venues to us is 3ms. By using orderbook snapshots at 10ms intervals we reduce the clock synchronisation bias, i.e. that orders are incorrectly included in an orderbook snapshot due to clock synchronisation issues.

[26] The +/-0.5% spread is applied to all the stocks of the sample, without considering their specific liquidity and may be considered large for liquid stocks. We apply a common spread to all the stocks of the sample because it increases computing feasibility and we do not introduce a bias deriving from using a liquidity-based spread adjusted per stock to compute liquidity measures. Choosing a relatively large common spread avoids the issue of not capturing any orders in situations where the top of the order book would be outside the spread. On the other hand, a relatively large common spread will probably lead to the underestimation of order duplication – as duplication is more prevalent for narrower spreads.

[27] At observation time t, for a given trader and for each price we compute gross liquidity and net liquidity for all his orders at +/-0.5%.

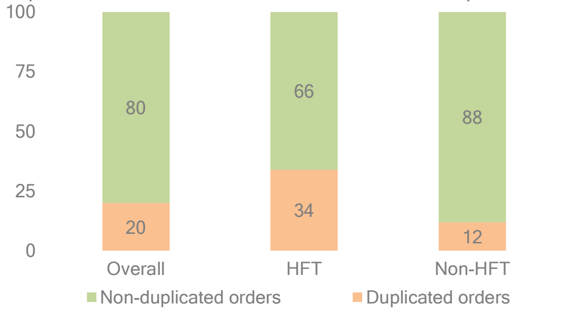
- Ω_p is the vector of trading venues for which there exists an order at price p at observation time t
- Q_v is the aggregated volume of displayed orders available on venue v, at price p and at observation time t

To obtain the overall results, we take the averages of the values calculated for each existing combination of stock and day.

We analyse our sample differentiating between HFTs and non-HFTs. As mentioned in the previous section, in this report we identify HFTs following the lifetime of orders approach. In our sample, HFT activity, measured with this approach, accounts for 43% of the value traded, 49% of the number of trades and 76% of the number of orders.[28]

In the overall sample, duplicated orders account for around 20% of all orders and are broadly homogeneous on both sides of the order book. [29] The extent of duplicated orders varies significantly between HFT firms and non-HFT firms; for HFTs duplicated orders account for around 34% of all their orders compared to 12% for non-HFTs (C.11).

C.11
Duplicated orders – HFT vs non-HFT across sample

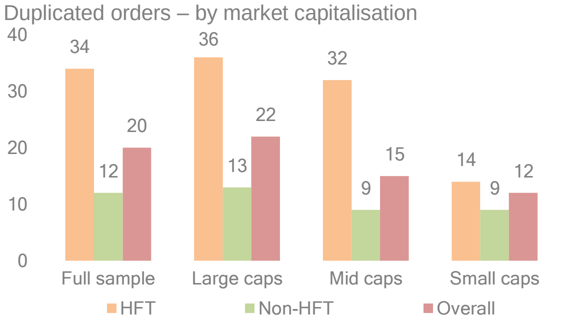


Note: Duplicated orders, in %, for HFTs, non-HFTs and overall.
Source: ESMA.

The extent of order duplication also depends on stock characteristics. We therefore look at order duplication by market capitalisation, price volatility and trading fragmentation of the shares in our sample. In all of these cases we also differentiate between the extent of order duplication for HFTs and non-HFTs.

When we take into account the different categories of market capitalisation (large caps, mid caps and small caps) duplicated orders seem to be more relevant for large caps (23% compared to 11% for small caps), consistent with the evidence showing that HFTs are more active in this market segment.[30] As expected, we do not find any significant difference between the buy side and the sell side of the book. Across different categories of market capitalisation, HFTs consistently display a higher percentage of duplicated orders than non-HFTs (C.12).

C.12
Duplicated orders – by market capitalisation



Note: Proportion of duplicated orders by market capitalisation, displayed for HFTs, non-HFTs and total. In %.
Sources: Thomson Reuters Datastream, ESMA.

The extent of order duplication is lower for the shares in our sample with higher price volatility during our sample period (16% for high-volatility stocks compared to 22% for low-volatility stocks). Using duplicated orders implies the risk of trading more shares than desired if order duplicates are matched on more than one trading venue. Observing less duplicated orders when uncertainty is higher is consistent with reducing this risk. Duplicated orders are consistently more relevant for HFTs than for non-HFTs when different levels of price volatility are taken into account. Moreover, we observe that the extent of order duplication for HFTs varies with volatility; there are only small changes in the extent of order duplication for non-HFTs with volatility levels (C.13).[31]

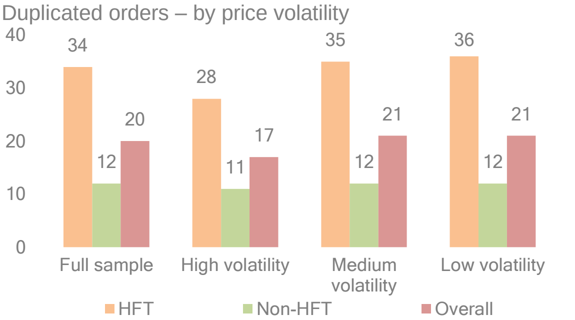
[28] See ESMA (2014) for more details on different HFT identification approaches.

[29] The amount of duplicated orders is calculated as the average of the stock daily averages of all 10ms intervals.

[30] See e.g. Brogaard et al (2013) and ESMA (2014).

[31] Overall levels of price volatility were low in our sample period of May 2013 (see C.7). Hence, our results regarding order duplication and volatility may be substantially different in periods with high market-wide volatility.

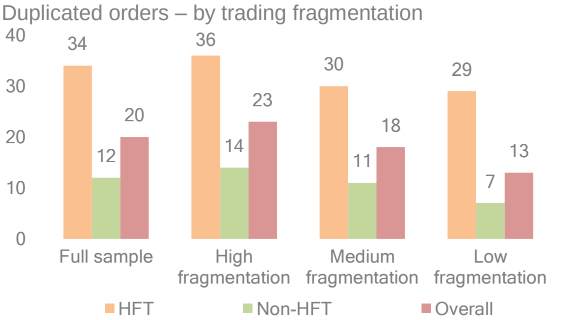
C.13
Duplicated orders – by price volatility



Note: Proportion of duplicated orders by price volatility for the sample stocks, displayed for HFTs, non-HFTs and total. In %.
Source: ESMA.

As expected (see e.g. Van Kervel, 2015) fragmentation is positively correlated with order duplication. In markets characterised by high fragmentation, duplicated orders range from 14% for non-HFTs to 36% for HFTs. When fragmentation is low the proportion of duplicated orders is 7% and 29% respectively (C.14).

C.14
Duplicated orders – by trading fragmentation



Note: Proportion of duplicated orders by trading fragmentation for the sample stocks, displayed for HFTs, non-HFTs and total. In %.
Source: ESMA

In the next sections we analyse in more detail how duplicated orders are used and whether our net liquidity measure better reflects available liquidity in fragmented markets compared to a gross liquidity measure.

— First we analyse the behaviour of trade participants, especially to which extent they use duplicated orders and cancel them after a trade.

— Second, we carry out descriptive and econometric analyses to look at the different reaction of two market-wide measures of liquidity after trades: gross liquidity, computed for each market participant as the aggregated volume of displayed orders in multiple markets, and net liquidity, computed subtracting duplicated orders from gross orders. A steeper decline of the gross liquidity measure after trades compared to the net liquidity measure is an indication that in some cases duplicated orders are indeed immediately cancelled after trades and thus are de facto not available to the market. Net liquidity would then provide a more accurate picture of available liquidity in fragmented markets.

The behaviour of trade participants

In this section we analyse the behaviour of traders who provided liquidity, i.e. have been on the passive side of a trade. We distinguish between four types of behaviour:[32]

a) Use of duplicated orders and immediate cancellation of non-matched order duplicates or update of order duplicates at more than ±0.5% of the trade price;
b) Use of duplicated orders and no cancellation of order duplicates;
c) Use of duplicated orders and update of order duplicates at less than ±0.5% of the trade price;
d) No use of duplicated orders.

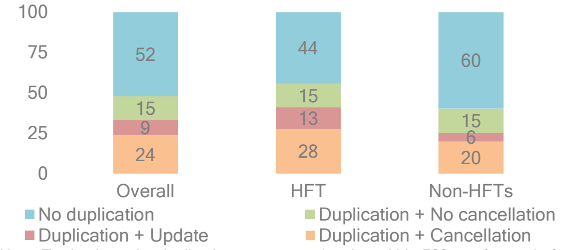
In case a) order duplicates are de facto not available to the market, as they are either quickly withdrawn or updated at a price which is far away from the last trade price and thus far from the top of the order book. Overall we find that in in 24% of trades the trader immediately cancels his unmatched duplicated orders or updates them at a price far from the trade price.

In cases b) and c) order duplicates are available to the market. For 15% of the trades traders use duplicated orders and do not cancel them after a trade (case b). For 9% of the trades traders use duplicated orders and update them at a price close to the trade price (case c). For 52% of the trades the trader makes no use of order duplication (case d; C.15).

As shown in C.15 to C.18 results vary depending on trader and stock characteristics.

[32] We analyse the first reaction of the trader within 500ms of the trade.

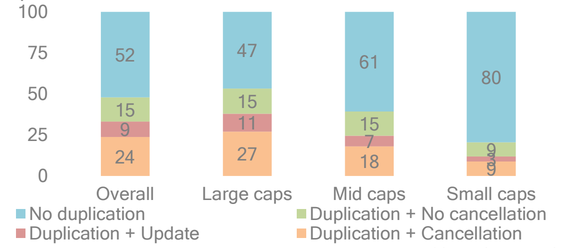
C.15
Behaviour of trader after trade event



Note: Trades by order duplication strategy and action within 500ms after trade for traders on the passive side of the trade. 1) No duplicated orders. 2) Duplicated orders and cancellation of order duplicates. 3) Duplicated orders and update of order duplicates 4) Duplicated orders and no action. For overall sample, HFTs and non-HFTs. In %.
Source: ESMA.

Order duplication is more common for large cap shares with traders using order duplication in 53% of trades, while it tends to be less frequent in case of mid cap and small cap stocks (39% and 20% respectively). The same pattern is observed for the traders immediately deleting their orders after the trade is executed; we observe this behaviour for 27% of trades in large cap stocks, 18% for mid cap and 9% for small cap stocks. Similarly, order duplication and immediate update of new orders close to the trade price is observed more frequently for large cap stocks (11%) than for mid cap and small cap stocks (7% and 3% respectively; C.16).

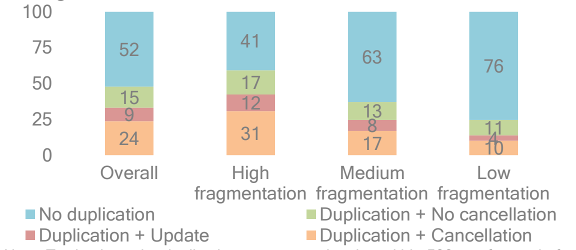
C.16
Behaviour of trader after trade event – by market capitalisation



Note: Trades by order duplication strategy and action within 500ms after trade for traders on the passive side of the trade. 1) No duplicated orders. 2) Duplicated orders and cancellation of order duplicates. 3) Duplicated orders and update of order duplicates 4) Duplicated orders and no action. For overall sample, large cap, mid cap and small cap stocks. In %.
Sources: Thomson Reuters Datastream, ESMA.

The analysis of order duplication strategies for different levels of market fragmentation confirms our previous results. We find that duplicated orders are present in 59% of trades when market fragmentation is high, but only in 24% of trades when market fragmentation is low. The difference is even larger when the order duplication and cancellation behaviour is considered; this strategy is performed by 31% of traders in stocks where trading is highly fragmented while in a low fragmentation environment it is limited to 10% of trades (C.17).

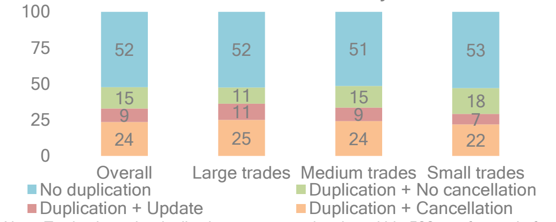
C.17
Behaviour of trader after trade event – by fragmentation of trading



Note: Trades by order duplication strategy and action within 500ms after trade for traders on the passive side of the trade. 1) No duplicated orders. 2) Duplicated orders and cancellation of order duplicates. 3) Duplicated orders and update of order duplicates 4) Duplicated orders and no action. For overall sample, stocks with high, medium and low trading fragmentation. In %.
Source: ESMA.

Finally, we do not observe different behaviour with respect to order duplication strategies and the size of the trade (C.18).

C.18
Behaviour of trader after trade event – by trade size



Note: Trades by order duplication strategy and action within 500ms after trade for traders on the passive side of the trade. 1) No duplicated orders. 2) Duplicated orders and cancellation of order duplicates. 3) Duplicated orders and update of order duplicates 4) Duplicated orders and no action. For overall sample, large, medium and small trades in sample. Large, medium, small trades represent the first, second and third tercile of trades in our sample by trade size. In %.
Source: ESMA.

Impact of trading on gross and net liquidity

Descriptive analysis

We have identified a significant proportion of duplicated orders in our sample. If those duplicated orders are immediately cancelled after a trade has taken place, this result points at a risk of systematic overestimation of liquidity in fragmented equity markets. In the previous chapter we established that for 24% of trades duplicated orders are involved on the passive side of the trade and immediately cancelled after the trade.

An alternative way to look at this question is to analyse the decrease in gross and net liquidity measures after a trade. We introduced the concepts of gross and net liquidity earlier to establish the extent of order duplication. If we consistently observe a stronger decrease for the gross liquidity measure compared to the net liquidity measure after a trade, this indicates that duplicated orders are indeed often cancelled directly after trades. Taking them into account when measuring liquidity in fragmented markets would thus overestimate available liquidity and the concept of net liquidity would be a more accurate measure of available liquidity in fragmented markets.

In this section we look at the impact of trades on gross and net liquidity measures. We run the empirical analysis on 95 stocks[33] from 9 countries for 23 trading days in May 2013. We consider all trades occurring on the trading venues included in our sample between 9:15 and 17:15. We exclude trading occurring in the first and last 15 minutes of the day to avoid auction periods. We look at the reaction of gross and net liquidity in specific non-overlapping windows, 100ms and 500ms after each trade.[34] The 100ms and 500ms samples do not intersect each other, the 500ms sample contains all the trades for which there has not been any trade in the following 500ms. Therefore, the 100ms sample contains all the trade for which there has been a trade between 100ms and 500ms after a trade event[35][36].

We analyse the change of gross and net liquidity divided by the size of the respective trade after each trade. We are interested in understanding how strongly the order book reacts on average to a given trade size.[37] A priori, we expect stronger reduction of both gross and net liquidity in the 100ms window. The 100ms is likely to capture the trades of more liquid stocks, where orders are updated more frequently, which in turn would lead to a stronger reduction of the gross and net liquidity measures.

For each stock, the cumulated impact of a trade occurring at t_0 on the buy-side of the order book for the gross liquidity at t $= T$ is computed as follows:

$$\sum_{t=t_0}^{T} \Delta Liquidity(buy)_{it} \,/\, Trade\_Size_{it_0}$$

Where $\Delta Liquidity(buy)_{it}$ is the difference between the gross liquidity available at time *t* and at time *t-1* on the buy side of the order book for stock *i*.[38]

To reduce the impact of outliers, we remove the top and bottom 1% of observations. We then compute a simple average to build the gross and net liquidity curves for the buy side of the order book. Calculations for sell-side gross liquidity and buy-side and sell-side net liquidity are carried out in a similar way.

Our results show that across different samples the reduction in gross liquidity is always higher than the reduction in net liquidity for both 100ms and 500ms windows. C.19 shows the decrease of the gross and net liquidity measures (divided by the trade size) in response to a trade for the 100ms window on the buy side of the order book. Gross and net liquidity are computed in discrete data points corresponding to the end of 10ms periods.[39] We have order book snapshots at 10ms intervals. This means that the trades take place at some point in the interval -10ms to 0ms. The biggest decrease of available liquidity occurs in the first 10ms after the trade; the size

33 Five stocks were excluded due to an insufficient number of trades and insufficient liquidity (1 for Ireland, 1 for Portugal, 1 for France, 1 for the United Kingdom and 1 for the Netherlands).

34 Windows are non-overlapping and contain only a single trade.

35 The 100ms sample generally includes trades for more liquid, mostly large cap stocks. Trade events for these stocks are absorbed more quickly in the order book. Choosing a longer time window will decrease the sample of available trades for liquid stocks, as these are traded very frequently and thus longer time windows will very often include more than one trade, implying that these trades have to be removed from our sample. The 500ms includes a larger proportion of mid and small cap stocks, which are less liquid. For less liquid stocks it takes longer for a trade event to be absorbed in the order book, hence the need for a longer time window. As robustness check we also tested a 1000ms window with similar results compared to the 500ms window.

36 It is more likely that subsequent trades take place within the 100ms or 500ms when the initial trade had a low impact on market liquidity and the bid-ask spread is still attractive to market participants. In that sense we are aware that our non-overlapping samples may be affected by a bias, as higher impact trades are more likely represented in our samples. However, the bias affects both the gross and net measures of liquidity in a similar way. As the variable we are interested in is the difference in reaction between the gross and net liquidity measures, we consider that our analysis still provides valuable insights.

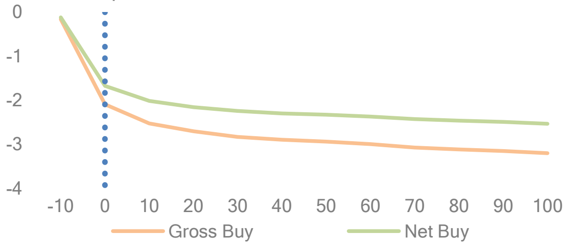
37 This measure is similar to the one used by Van Kervel (2015). Changes in liquidity closely related to trade events do not suffer scale sensitivity. We carried out robustness checks to ensure the gross and net liquidity measures are not differently affected by trade sizes.

38 Similarly, for each stock, the cumulated impact of a trade occurring at t=0 on the sell-side of the order book for the gross liquidity at t=T is computed as $\sum_{t=t_0}^{T} \Delta Liquidity(sell)_{it} \,/\, Trade\_Size_{it_0}$, where ΔLiquidity(sell)$_{it}$ is the difference between the gross liquidity available at time t and at time t-1 on the sell side of the order book for stock *i*.

39 As mentioned in the previous section the most detailed interval available for computing liquidity is 3ms, as for some of the reporting venues the timestamp was provided with such detail. We picked 10ms interval because it is easier to truncate timestamps to 10ms rather than to 3ms and we keep a reasonable precision.

of this reaction is depicted at 0ms on the x-axis of graphs C.19 and C.20. Part of this reaction is explained by the trade itself. However, as described in previous section in 24% of trades the trader immediately cancels his unmatched duplicated orders or updates them at a price far from the trade price, which explains the stronger fall in the net liquidity measure.

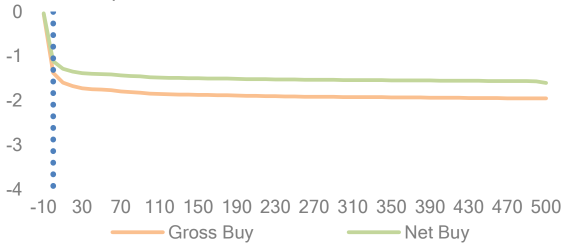
C.19
Reaction of gross and net liquidity in the 100ms window – overall sample



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

Similar results are obtained when a larger time window is considered. C.20 shows the reduction of gross and net liquidity for the 500ms window on the buy side of the order book. The liquidity decrease for the 100ms window is always more pronounced than for the 500ms window.

C.20
Reaction of gross and net liquidity in the 500 ms window – overall sample



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

The results remain robust when the sell side of the order book is considered or when different categories of market capitalisation, price volatility and market fragmentation are taken into account. In line with the empirical evidence on the level of duplicated orders seen in the descriptive statistics part, the strength of reaction to trade by large caps, stocks with low price volatility and high fragmentation is higher compared to small caps, stocks with high price volatility and low fragmentation. These results are presented in Annex 2[40].

Time series analysis

The time-series analysis is inspired by Van Kervel (2015): it tests the hypothesis that a trade on one venue is followed by changes in the order book liquidity for a stock on both the bid and ask sides of all venues.

The dependent variable is

$$\Delta Liquidity(s)_{it} = Liquidity(s)_{it} - Liquidity(s)_{it-1}$$

Where s indicates the trade side, $s \in \{buy, sell\}$.

Changes in Liquidity (buy) and Liquidity (sell) reflect changes in liquidity offered at prices in the interval $\{midprice_{t-1} \pm 0.5\%\}$. These changes arise from limit order book activity (placements, cancellations and executions of limit orders). The models regresses the change in Liquidity (buy) or Liquidity (sell) on the contemporaneous and lagged buy and sell trading volumes of all the trading venues in the database. The model contains lags up to 1000ms to allow for sufficient time for the market to incorporate the information content of trades.

The time-series approach enables us to refine our analysis of duplicated order strategies in two ways. In contrast with the previous descriptive analysis, in the time-series analysis there is no need to remove from the sample close-in-time trades, preventing the possibility of sampling bias. As in the previous approach, periods close to the opening and closing of the trading are excluded.

We estimate coefficients for five groups of lagged variables and assume that the coefficients are constant within each group. This is obtained by adding in the regression five average lagged trading volumes of the following intervals of milliseconds L_1=[0,10], L_2=[10,40], L_3=[40,100], L_4=[100,200], L_5=[200,1000].

40 The difference between the reactions of the gross and net liquidity is more interesting than the absolute values of the decrease in the measures: The 100ms window, by construction, is capturing trades in more liquid stocks. Therefore, the overall reaction is likely to be stronger than for a less liquid stock. When defining the windows, we checked for trades occurring in the following 100 or 500ms but not before. Some of the trades in our sample are at the end of a series of trades. In these cases the reaction observed after the trade, i.e. the decrease in the gross and net liquidity measures will be higher than the results for trades which are not at the end of a series of trade.

The following model is independently estimated for the buy- and sell-sides of the order book.

$$\Delta Liquidity(s)_t = \alpha + \alpha_{HFT} D_{HFT} + \sum_{l=0}^{5} \big((\beta_l + \delta D_{HFT,l,t} \big) \mu(s)_{l,t} + \alpha_l \mu(\check{s})_{l,t} + \lambda_1 \sigma(t) + \lambda_2 spread_{(t-1)} + \varepsilon_t$$

Where:

$\mu(s)_{l,t} = \sum_{i \in L_l} (tradesize_{t-i}) / length(L_l)$ is the average of all trade volumes in a given interval L at time t;

D_{HFT} is a dummy variable that equals 1 when a HFT is on the passive side of the trade, and zero otherwise;

$\check{s}$ is the opposite side of the order book, introduced as a control;

$\sigma(t)$ controls for volatility, computed as the variance of the mid price on a 5-minute rolling window;

$spread_{(t-1)}$ is the bid-ask spread of the previous observation period;

and ε_t is the error term.

We use two specifications in the empirical model:

— In the first specification (tables C.21 and C.22), the dummy variable representing HFTs providing the liquidity is not used. This allows us to check for the existence of a market-wide order duplication phenomenon.
— In the second specification (tables C.23 and C.24), we use the dummy variable D_{HFT} so we can check if the order duplication effect is larger when a HFT was involved in the provision of liquidity (passive side of the trade).

We estimate the model separately for each stock, trading day, side of the order book, gross and net liquidity measures, and the two model specifications described above. As 2,075 combinations of stocks and dates are available, the number of separated estimations is 16,600.[41]

Results are reported as the average of the cumulated coefficients in the individual estimations.[42]

We expect that the impact of trades on both gross and net liquidity should be negative and exceed the trade size, i.e. the amount of orders in the book should decrease after the occurrence of a trade (cumulated β coefficients<-1).

In addition, our hypothesis on order duplication is tested by comparing the effects on the gross liquidity measure to the ones on the net liquidity measure. In that sense, if similar sized trades have bigger effects on gross liquidity than on net liquidity, there is evidence that order duplication and immediate cancellation of duplicates after a trade are partially provoking the effect of overreaction of the observed liquidity supply to the trade flow and thus a gross liquidity measure is likely to overestimate the liquidity which is de facto available in the market.

Finally, we expect that HFTs acting as the passive side in the trades execute more order-duplication strategies across different venues. If that is the case, we expect increases in the absolute difference between the reactions of gross and net liquidity measures when we use the second model specification which includes a HFT dummy variable.

Tables C.21 to C.24 contain the results for the buy- and sell-sides of the order book and the different specifications of the model. Cumulated values of the coefficients of the model are represented by BI_t (buy side) and SI_t (sell side). The first column represents the computations with the gross liquidity measure, the second column with the net liquidity measure and the third the difference between both. Each column shows the results for one regression model and displays the contemporaneous coefficients and the cumulative effects after 10, 40, 100 200 and 1000 milliseconds. BI_t refers to the impact of a trade on the buy side of the book while SI_t represents the impact of trading on sell side. BI_t and SI_t coefficients apply to different time windows with t=0 corresponding to contemporaneous relations, t=1, t=2, t=3, t=4, t=5 respectively to the following time intervals: {0-10ms, 10ms-40ms, 40ms-100ms, 100ms-200ms, 200ms-1000ms}. For tables C.23 and C.24 $HFTBI_t$ (buy side) and $HFTSI_t$ (sell side) represent the values of the coefficients that incorporate the dummy variable that takes value 1 when a HFT was providing liquidity for the

41 For each estimation, we include 300mn observations corresponding to discrete points in time, separated by 10ms.

42 We assumed that the individual estimations are independent processes. We tested the significance of the reported coefficients. Errors are clustered by date and stock.

trade. The total overreaction of the liquidity measure to a trade involving an HFT is the sum of this coefficient with the BI_t (or SI_t) coefficient.

As mentioned above, the first column shows the impact on the change of gross liquidity on the buy side of the order book of a seller initiated trade. BI_0 represents the immediate effect of the purchase of a specific stock in one of the considered trading venues on the change of the gross liquidity of the buy side of the book. For example, in table C.21 trades hitting a buy order immediately reduce the gross liquidity of the buy side of the book by 1.31 times its size and the net liquidity of the buy side by 1.11 times its size. The cumulated effect of trades after 1000ms is displayed by BI5, being -1.64 times the size of the trade for the gross liquidity and -1.43 for the net liquidity.

For both the buy and sell side of the order book, tables C.21 and C.22 respectively, we find that the cumulated coefficients are smaller (i.e., larger in absolute value) than -1 for both gross and net liquidity measures providing evidence that overreaction to the trade flow affects both measures.

The coefficients for the change in gross liquidity are consistently smaller (i.e., larger in absolute value) than the coefficients for the change in net liquidity. This result confirms the overreaction of the gross liquidity measure compared to the net liquidity measure already outlined in our descriptive analysis. Furthermore, it provides strong indication that the presence of order duplication explains part of the overreaction to the trade flow that is observed by markets participants in the gross or market-wide liquidity measures.

C.21

Regression analysis results for the overall sample without HFT interaction term – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-8.81	-25.05	
BI0	-1.31 ***	-1.11 ***	-0.21 ***
BI1	-1.47 ***	-1.22 ***	-0.25 ***
BI2	-1.53 ***	-1.27 ***	-0.26 ***
BI3	-1.57 ***	-1.31 ***	-0.26 ***
BI4	-1.59 ***	-1.33 ***	-0.26 ***
BI5	-1.64 ***	-1.43 ***	-0.21 ***
SI0	0.29 ***	0.25 ***	0.04 ***
SI1	0.35 ***	0.29 ***	0.06 ***
SI2	0.36 ***	0.3 ***	0.06 ***
SI3	0.39 ***	0.32 ***	0.07 ***
SI4	0.4 ***	0.33 ***	0.07 ***
SI5	0.52 ***	0.4 ***	0.13 ***
Lagged spread	8172.29	22825.87	
Volatility	672.01 ***	547.56 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.22

Regression analysis results for the overall sample without HFT interaction term – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	40.51	12.81	
SI0	-1.32 ***	-1.11 ***	-0.21 ***
SI1	-1.48 ***	-1.23 ***	-0.25 ***
SI2	-1.53 ***	-1.27 ***	-0.26 ***
SI3	-1.57 ***	-1.31 ***	-0.26 ***
SI4	-1.59 ***	-1.33 ***	-0.26 ***
SI5	-1.64 ***	-1.43 ***	-0.21 ***
BI0	0.26 ***	0.22 ***	0.03 ***
BI1	0.31 ***	0.26 ***	0.05 ***
BI2	0.33 ***	0.27 ***	0.05 ***
BI3	0.36 ***	0.3 ***	0.06 ***
BI4	0.38 ***	0.31 ***	0.07 ***
BI5	0.5 ***	0.38 ***	0.12 ***
Lagged spread	-41213.03	-15149.08	
Volatility	1087.04 **	820.28 **	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

Tables C.23 and C.24 contain the results for the specification that takes into account if a HFT was providing the liquidity for the trade. Thus, coefficients BI_t (buy side) and SI_t (sell side) represent the reaction when no HFT was involved and $HFTBI_t$ or $HFTSI_t$ represent the difference in reaction to the previous value when a HFT was providing liquidity.

For this specification, our previous findings hold, as there is overreaction in both measures but it is larger for the gross liquidity measure. In addition, we can confirm our hypothesis that HFTs tend to use more order duplication strategies, as the difference in reaction between gross liquidity and net liquidity increases. This is reflected in the negative values for the difference column for the coefficients $HFTBI_t$ (buy side) and $HFTSI_t$ (sell side) in tables C.23 and C.24. However, although the difference between reactions of gross and net liquidity measures increases when HFTs provide the liquidity for the trade, the level of overreaction for both measures is decreased. This is shown by the positive values of the coefficients $HFTBI_t$ (buy side) and $HFTSI_t$ (sell side) in the gross liquidity and net liquidity columns of tables C.23 and C.24. Even though these results are still in line with our hypotheses, they warrant further investigation regarding the reasons behind them.

C.23
Regression analysis results for the overall sample with HFT interaction term – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
HFT Intercept	-88.08 ***	-71.79 ***	
Intercept	5.36	-25.12	
BI0	-1.41 ***	-1.23 ***	-0.18 ***
BI1	-1.58 ***	-1.35 ***	-0.23 ***
BI2	-1.64 ***	-1.4 ***	-0.24 ***
BI3	-1.69 ***	-1.44 ***	-0.24 ***
BI4	-1.72 ***	-1.48 ***	-0.24 ***
BI5	-1.74 ***	-1.57 ***	-0.18 ***
HFTBI0	0.11 ***	0.16 ***	-0.05 ***
HFTBI1	0.11 ***	0.15 ***	-0.04 ***
HFTBI2	0.11 ***	0.15 ***	-0.04 ***
HFTBI3	0.11 ***	0.16 ***	-0.05 ***
HFTBI4	0.11 ***	0.16 ***	-0.05 ***
HFTBI5	0.2 ***	0.28 ***	-0.08 **
SI0	0.29 ***	0.25 ***	0.04 ***
SI1	0.35 ***	0.29 ***	0.06 ***
SI2	0.37 ***	0.3 ***	0.06 ***
SI3	0.39 ***	0.33 ***	0.07 ***
SI4	0.4 ***	0.33 ***	0.07 ***
SI5	0.53 ***	0.41 ***	0.12 ***
Lagged spread	-4173.07	24376.39	
Volatility	728.61 ***	584.53 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.24
Regression analysis results for the overall sample with HFT interaction term – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
HFT Intercept	-95.14 ***	-77.11 ***	
Intercept	43.75	14.34	
SI0	-1.38 ***	-1.21 ***	-0.17 ***
SI1	-1.57 ***	-1.36 ***	-0.21 ***
SI2	-1.61 ***	-1.39 ***	-0.23 ***
SI3	-1.67 ***	-1.44 ***	-0.23 ***
SI4	-1.68 ***	-1.46 ***	-0.22 ***
SI5	-1.75 ***	-1.58 ***	-0.17 ***
HFTSI0	0.07 ***	0.12 ***	-0.05 ***
HFTSI1	0.1 ***	0.15 ***	-0.05 ***
HFTSI2	0.09 ***	0.14 ***	-0.05 ***
HFTSI3	0.11 ***	0.16 ***	-0.05 ***
HFTSI4	0.12 ***	0.18 ***	-0.06 ***
HFTSI5	0.28 ***	0.32 ***	-0.05 ***
BI0	0.26 ***	0.22 ***	0.03 ***
BI1	0.31 ***	0.26 ***	0.05 ***
BI2	0.33 ***	0.28 ***	0.05 ***
BI3	0.36 ***	0.3 ***	0.06 ***
BI4	0.39 ***	0.32 ***	0.07 ***
BI5	0.53 ***	0.4 ***	0.12 ***
Lagged spread	-42586.98	-15152.75	
Volatility	1168.13 **	876.39 **	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

Conclusion

This report describes the results of our analysis on order duplication and liquidity measurement in fragmented EU equity markets.

This report is the second part of ESMA's HFT research. The starting point for both reports is the change in the trading landscape of equity markets over the last decade. The defining features of this change are increased competition between trading venues, fragmentation of trading of the same financial instruments across EU venues and the increased use of fast and automated trading technologies. In our first report we analysed the extent of HFT activity across the EU in such an environment using a novel identification method for HFT activity. We found that HFT activity represents between 24% and 43% of value traded and between 58% and 76% of orders in our sample. In this report we focus on liquidity measurement where equity trading is fragmented.

In an environment characterised by competition between trading venues, traders do not always know on which venue they will be able to trade. They may "advertise" their intention to trade by posting similar orders on more than one trading venue at the same time ("duplicated orders").

This, however, leads to the risk of trading more shares than wanted. Therefore some traders may immediately cancel unmatched duplicated orders on other venues after one of their duplicated orders has been filled.

Using the HFT identification method developed in our first report, we find evidence for this trading pattern. 20% of the orders in our sample are duplicated orders and in 24% of trades the trader immediately cancels unmatched duplicated orders. We believe that duplication of orders and immediate cancellation of duplicates after a trade has become part of the strategy to ensure execution in fragmented markets, e.g. for market makers or where institutional investors are searching for liquidity. However, we show that taking duplicated orders into account when measuring liquidity leads to overestimation of available liquidity in fragmented markets.

The proportion of duplicated orders varies with the type of traders, the market capitalisation of the underlying stock and the fragmentation of trading in a stock. As expected, duplicated orders are more prevalent for HFTs (34% of orders) than for non-HFTs (12% of orders). They account for 22% of orders in large cap stocks compared to 12% of orders in small cap stocks. Also, fragmentation of trading is positively correlated with order duplication. We find 13% of duplicated orders for stocks with low trading fragmentation and 23% for stocks with high fragmentation.

Regarding the extent to which duplicated orders are immediately cancelled after trades (and thus subsequently are not available to the market), we carry out a number of analyses. First, we find that for 24% of all trades, the trader on the passive side of the trade immediately cancels order duplicates after the trade. This proportion is higher for HFTs (28%), large cap stocks (27%) and where trading is more fragmented (31%). Second, we look at the different reaction of two measures of liquidity: gross liquidity, the aggregated volume of displayed orders across multiple markets, and net liquidity, which deducts duplicated orders from the gross liquidity measure. We compare these two measures to establish whether order duplication should be taken into account when measuring liquidity in fragmented markets. A stronger fall of the gross liquidity measure after trades compared to the net liquidity measure is an additional indication that a proportion of duplicated orders is indeed immediately cancelled after trades and thus not available to the market. Our descriptive and econometric analyses confirm this hypothesis.

Both in our first HFT report and in this report we use unique data collected by ESMA, covering a sample of 100 stocks on 12 trading venues in nine EU countries for May 2013. Our data allow us to identify market participants' actions across different venues. Thus we are able to complement the literature, as most of the HFT studies published so far focus either on the US or on a single country within Europe and few are able to analyse the behaviour of market participants across trading venues.

Previous studies have found evidence supporting that fragmentation of trading increases liquidity in equity markets. Our analysis qualifies these results, as using data that allow us to identify market participants' actions across different venues, we find a substantial extent of order duplication in fragmented markets. It is important to state that unless they are successfully cancelled, duplicated orders are available to the market and all of them can be matched. However we find that a substantial proportion of order duplicates are immediately cancelled after a trade occurs and thus subsequently not available to the market. From an analytic perspective, our findings suggest that to avoid overestimation of available liquidity duplicated orders should be taken into account when measuring liquidity in fragmented markets, for example with our net liquidity measure.

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Annex 1: Sample characteristics

Annex 1 provides information about the different characteristics of stocks we use in our study to analyse order duplication: market capitalisation, price volatility and fragmentation. For each of these categories we split our sample into terciles (i.e. three equally sized groups) based on the level of market capitalisation, price volatility and fragmentation. We find that HFT contribution to liquidity, measured as the total quantity of orders submitted for each stock and price on all trading venues (gross liquidity measure), varies according to the different categories of stocks taken into account.

The market capitalisation of the stocks in our sample is heterogeneous, ranging between EUR 18mn and EUR 122bn. Median market capitalisation for our large caps tercile is EUR 10.38bn, while for the mid and small caps terciles it is respectively EUR 2.983bn and EUR 778mn (C.25).

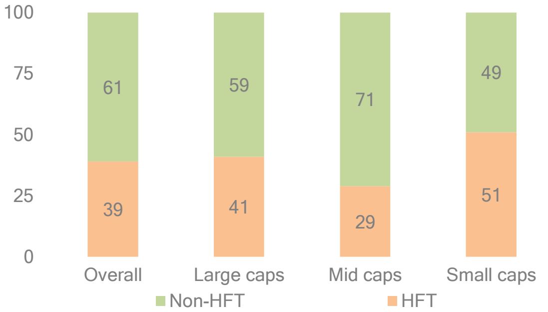
C.25
Sample characteristics – Market capitalisation

Group	Min.	Median	Mean	Max
Overall	18	2,983	8,685	122,000
Small caps	18	778	794	1,669
Mid caps	1,678	2,983	3,355	5,940
Large caps	5,943	10,380	21,910	122,000

Note: Market capitalisation, in EUR mn.
Sources: Thomson Reuters Datastream, ESMA.

HFT gross liquidity accounts for 39% of the total gross liquidity in the whole sample, while it ranges from 29% to 51% when different market capitalisations are taken into account (C.26).

C.26
HFT activity – By market capitalisation



Note: Proportion of HFT and non-HFT activity by market capitalisation, in %.
Sources: Thomson Reuters Datastream, ESMA.

During our sample period of May 2013, price volatility has been relatively low (see C.7 in the main body of the text). However, we observe some variation within our sample stocks. Median price volatility for our low volatility tercile is 0.012, while for the medium and high price volatility terciles it is respectively 0.019 and 0.031 (C.27).

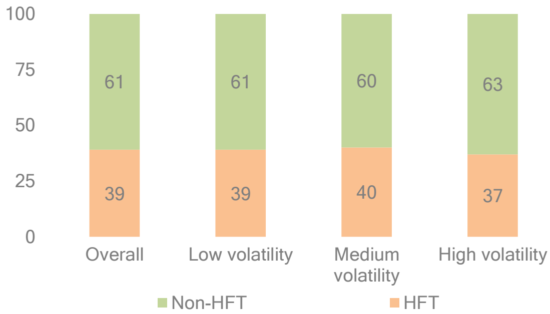
C.27
Sample characteristics – Price volatility

Group	Min.	Median	Mean	Max
Overall	0.004	0.019	0.022	0.517
Low volatility	0.004	0.012	0.012	0.015
Medium volatility	0.015	0.019	0.019	0.023
High volatility	0.023	0.031	0.036	0.517

Note: Price volatility calculated as (maximum mid price – minimum mid price) / median mid price.
Source: ESMA.

Less significant differences in HFT contribution to gross liquidity seem to emerge when we consider different levels of price volatility with HFT liquidity provided by HFTs ranging from 37% to 40% of the total liquidity (C.28).

C.28
HFT activity – By price volatility



Note: Proportion of HFT and non-HFT activity by price volatility, in %.
Source: ESMA.

The trading fragmentation of the stocks in our sample is heterogeneous, ranging between 0 and 0.687 and EUR 122bn. Median trading fragmentation for our high fragmentation tercile is 0.541, while for the medium and low fragmentation terciles it is respectively 0.374 and 0.169 (C.29).

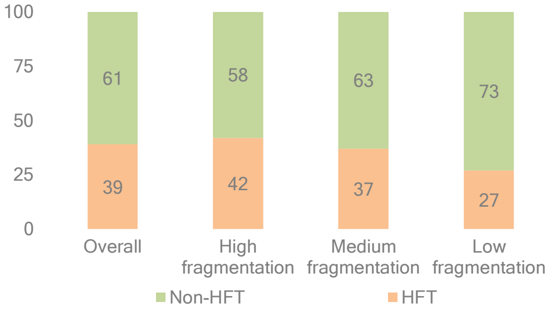
C.29
Sample characteristics – Trading fragmentation

Group	Min.	Median	Mean	Max
Overall	0.000	0.374	0.358	0.687
Low fragmentation	0.000	0.169	0.151	0.288
Medium fragmentation	0.288	0.374	0.375	0.466
High fragmentation	0.467	0.541	0.547	0.687

Note: Trading fragmentation, calculated as Frag = 1 – HHI where HHI is the Herfindahl-Hirschman index[43].
Source: ESMA.

HFTs tend to play a more relevant role in highly fragmented markets (42% of total gross liquidity) compared to less fragmented markets (27% of total gross liquidity; C.30).

C.30
HFT activity – By trading fragmentation



Note: Proportion of HFT and non-HFT activity by fragementation of trading, in %
Source: ESMA.

[43] The Herfindahl-Hirschman index is computed on the basis of the sum of squared market shares (value traded) per trading venue. A value of 1 indicates no fragmentation (all trading is on one venue), whereas lower values indicate that trading is fragmented across several trading venues. Consequently for the fragmentation index a value of 0 indicates no fragmentation (all trading is on one venue), whereas higher values indicate that trading is fragmented across several trading venues.

Annex 2: Impact of trading on gross and net liquidity- additional results

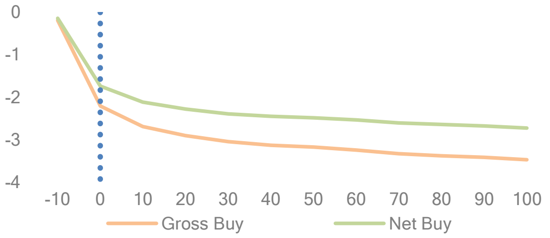
Descriptive analysis

In this section, we provide more results on the reaction of gross and net liquidity to trades across different stock characteristics: market capitalisation, price volatility and trading fragmentation.[44] The results are robust to different sample specifications: reactions to trades are always stronger for gross liquidity than for net liquidity; Similarly the reaction for the 100ms window is always more pronounced than for the 500ms window.

The impact of trades on gross and net liquidity: market capitalisation

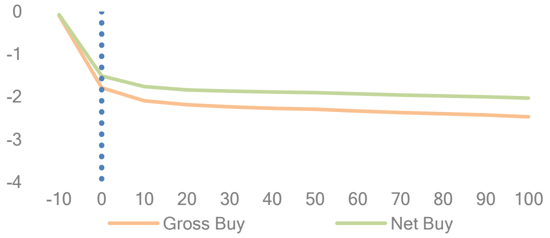
When different market capitalisations are taken into account (see Annex 1 for more details on the segmentation), we observe that the liquidity reaction after trades is stronger for large cap compared to small cap stocks and that the reduction in liquidity is more pronounced for the 100ms window than for the 500ms window (C.31-C.36).

C.31
Reaction of gross and net liquidity in the 100ms window – large caps



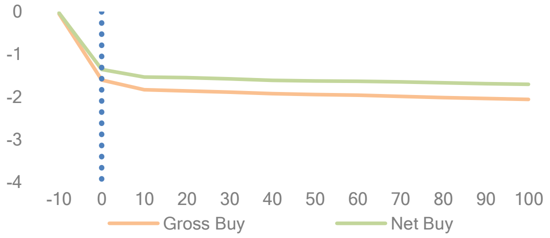
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

C.32
Reaction of gross and net liquidity in the 100ms window – mid caps



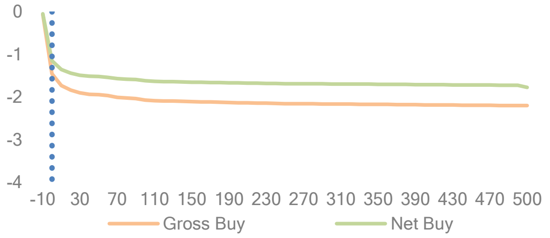
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

C.33
Reaction of gross and net liquidity in the 100ms window – small caps



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

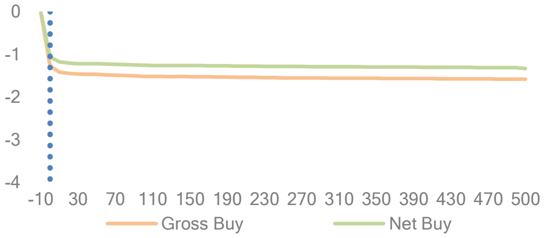
C.34
Reaction of gross and net liquidity in the 500ms window – large caps



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

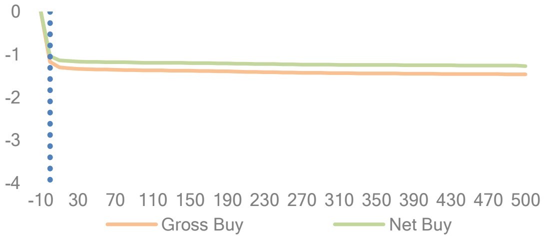
44 We present results for the buy side of the order book only. Results for the sell side are similar and are available on request.

C.35
Reaction of gross and net liquidity in the 500ms window – mid caps



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

C.36
Reaction of gross and net liquidity in the 500ms window – small caps

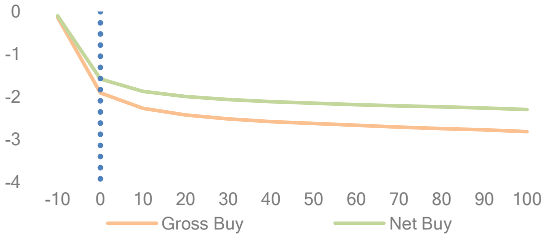


Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Sources: Thomson Reuters Datastream, ESMA.

The impact of trades on gross and net liquidity: price volatility

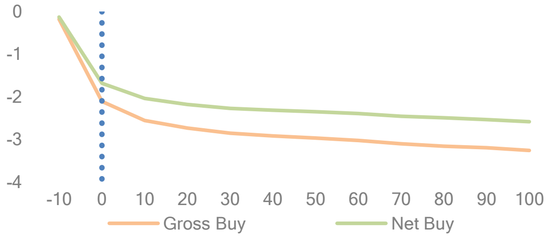
The reaction of liquidity to trade events is stronger for stocks with low price volatility compared to stocks with high price volatility (see Annex 1 for more details on the segmentation of our sample with respect to price volatility). This result confirms the descriptive statistics showing that duplicated orders tend to be more frequent in a low volatility environment (C.37-C.42).

C.37
Reaction of gross and net liquidity in the 100ms window – high price volatility



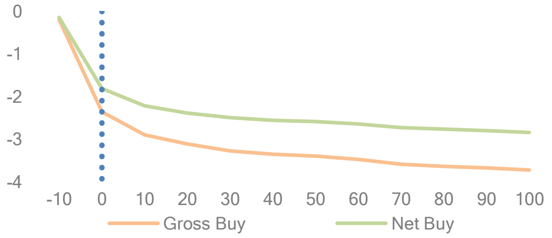
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.38
Reaction of gross and net liquidity in the 100ms window – medium price volatility



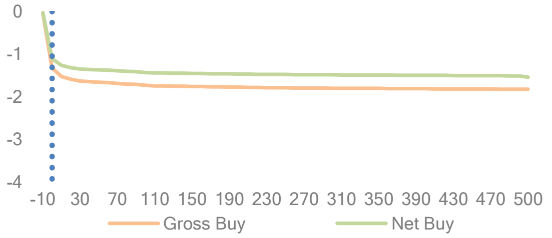
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.39
Reaction of gross and net liquidity in the 100ms window – low price volatility



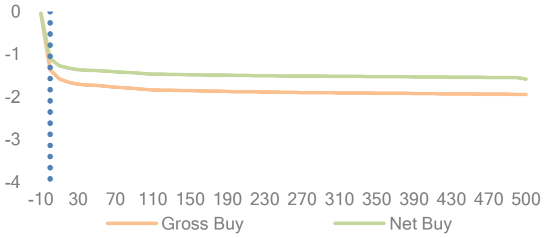
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.40
Reaction of gross and net liquidity in the 500ms window – high price volatility



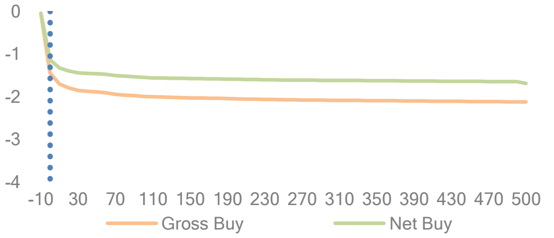
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.41
Reaction of gross and net liquidity in the 500ms window – medium price volatility



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.42
Reaction of gross and net liquidity in the 500ms window – low price volatility

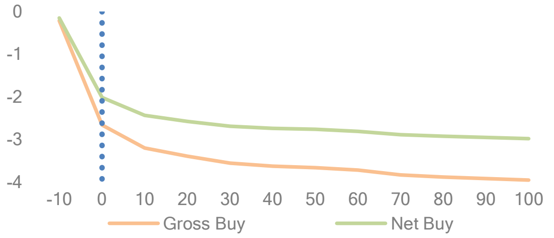


Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

The impact of trading on gross and net liquidity: fragmentation of trading

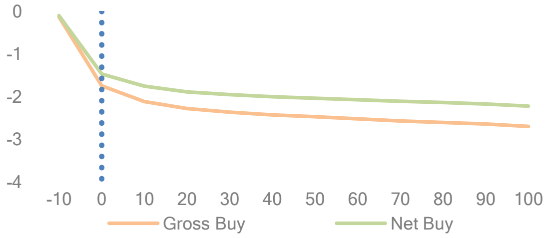
When fragmentation of trading is higher the reduction of gross and net liquidity to the trade events is stronger, in line with the descriptive statistics showing that we observe a larger amount of duplicated orders and a bigger contribution of HFTs to gross liquidity in stocks with a higher degree of trading fragmentation (C.43-C.48; See Annex 1 for more details on the segmentation of our sample with respect to fragmentation of trading).

C.43
Reaction of gross and net liquidity in the 100ms window – high fragmentation



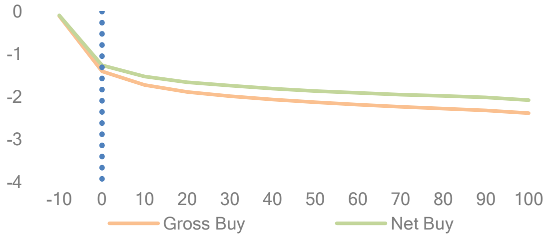
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.44
Reaction of gross and net liquidity in the 100ms window – medium fragmentation



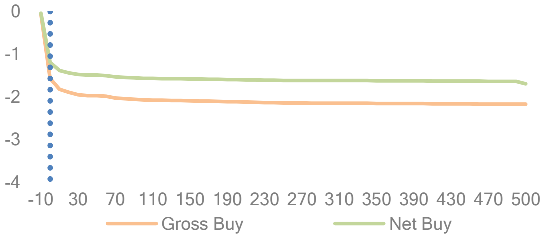
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.45
Reaction of gross and net liquidity in the 100ms window – low fragmentation



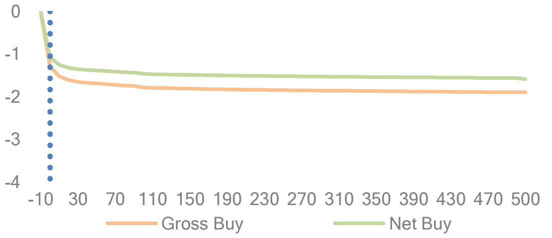
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.46
Reaction of gross and net liquidity in the 500ms window – high fragmentation



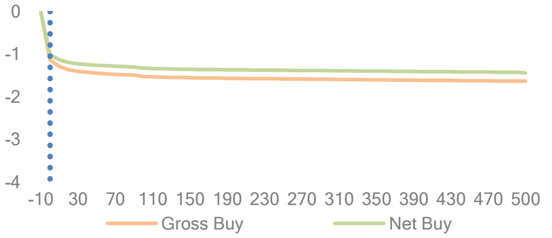
Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.47
Reaction of gross and net liquidity in the 500ms window – medium fragmentation



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

C.48
Reaction of gross and net liquidity in the 500ms window – low fragmentation



Note: Y-axis depicts the variation in time of available liquidity levels, Gross and Net measures, divided by the size of each trade. Given data constraints, available liquidity is only computed in equally-spaced and discrete points in time (each 10 ms). The X-axis represents time in ms; the trade takes place in the -10ms and the 0ms interval.
Source: ESMA.

Time series analysis

In this section we provide more details on our regression results. As in Annex 2, we show the results trades across different stock characteristics: market capitalisation (C.49-C.54), price volatility (C.55-C.60) and trading fragmentation (C.61-C.66). In all cases the results are displayed for the buy and sell side of the order book.

Regression results – Market capitalisation

C.49
Regression analysis results for large caps – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-1.24	-6.98 ***	
BI0	-1.41 ***	-1.14 ***	-0.27 ***
BI1	-1.58 ***	-1.27 ***	-0.3 ***
BI2	-1.66 ***	-1.34 ***	-0.32 ***
BI3	-1.72 ***	-1.4 ***	-0.32 ***
BI4	-1.75 ***	-1.43 ***	-0.32 ***
BI5	-1.77 ***	-1.48 ***	-0.29 ***
SI0	0.47 ***	0.37 ***	0.09 ***
SI1	0.58 ***	0.44 ***	0.14 ***
SI2	0.59 ***	0.45 ***	0.15 ***
SI3	0.63 ***	0.47 ***	0.16 ***
SI4	0.64 ***	0.47 ***	0.16 ***
SI5	0.73 ***	0.54 ***	0.19 ***
Lagged spread	1101.87 ***	1968.16 ***	
Volatility	893.71 ***	751.85 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for large caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

C.50
Regression analysis results for large caps – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	-1.69 *	-7.48 ***	
SI0	-1.42 ***	-1.14 ***	-0.28 ***
SI1	-1.6 ***	-1.29 ***	-0.31 ***
SI2	-1.69 ***	-1.36 ***	-0.33 ***
SI3	-1.76 ***	-1.42 ***	-0.33 ***
SI4	-1.78 ***	-1.45 ***	-0.33 ***
SI5	-1.83 ***	-1.52 ***	-0.31 ***
BI0	0.4 ***	0.31 ***	0.09 ***
BI1	0.5 ***	0.37 ***	0.14 ***
BI2	0.53 ***	0.37 ***	0.15 ***
BI3	0.57 ***	0.4 ***	0.17 ***
BI4	0.59 ***	0.41 ***	0.17 ***
BI5	0.67 ***	0.47 ***	0.2 ***
Lagged spread	1226.72 ***	2045.87 ***	
Volatility	1027.59 ***	836.22 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for large caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

C.51
Regression analysis results for mid caps – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-24.32	-67.84	
BI0	-1.33 ***	-1.13 ***	-0.2 ***
BI1	-1.49	-1.24 ***	-0.24 ***
BI2	-1.54	-1.29 ***	-0.25 ***
BI3	-1.59 ***	-1.33 ***	-0.26 ***
BI4	-1.6 ***	-1.34 ***	-0.26 ***
BI5	-1.71 ***	-1.49 ***	-0.23 ***
SI0	0.21 ***	0.18 ***	0.02 ***
SI1	0.23 ***	0.19 ***	0.04 ***
SI2	0.24 ***	0.2 ***	0.04 ***
SI3	0.27 ***	0.22 ***	0.04 ***
SI4	0.28 ***	0.23 ***	0.05 ***
SI5	0.4 ***	0.3 ***	0.1 ***
Lagged spread	23565.62	67174.56	
Volatility	1077.56 ***	843.74 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for mid caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

C.52
Regression analysis results for mid caps – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	125.84	47.59	
SI0	-1.33 ***	-1.13 ***	-0.2 ***
SI1	-1.48 ***	-1.25 ***	-0.23 ***
SI2	-1.52 ***	-1.28 ***	-0.24 ***
SI3	-1.55 ***	-1.31	-0.24 ***
SI4	-1.55 ***	-1.31 ***	-0.24 ***
SI5	-1.65 ***	-1.43 ***	-0.22 ***
BI0	0.19 ***	0.17 ***	0.02 ***
BI1	0.23 ***	0.19 ***	0.04 ***
BI2	0.24 ***	0.19 ***	0.05 ***
BI3	0.26 ***	0.21 ***	0.05 ***
BI4	0.28 ***	0.22 ***	0.06 ***
BI5	0.39 ***	0.29 ***	0.1 ***
Lagged spread	-126522.82	-48219.78	
Volatility	2204.87	1594.19	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for mid caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

C.53
Regression analysis results for small caps – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-1.13 ***	-0.95 ***	
BI0	-1.2 ***	-1.05 ***	-0.14 ***
BI1	-1.34 ***	-1.14 ***	-0.2 ***
BI2	-1.37 ***	-1.16 ***	-0.21 ***
BI3	-1.4 ***	-1.19 ***	-0.2 ***
BI4	-1.42 ***	-1.21 ***	-0.2 ***
BI5	-1.42 ***	-1.3 ***	-0.12 ***
SI0	0.19 ***	0.2 ***	-0.01 *
SI1	0.24 ***	0.24 ***	-0.01
SI2	0.26 ***	0.26 ***	0
SI3	0.28 ***	0.28 ***	0
SI4	0.29 ***	0.29 ***	0.01
SI5	0.44 ***	0.36 ***	0.08 ***
Lagged spread	111.05 ***	104.03 ***	
Volatility	39.85 ***	42.44 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for small caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

C.54
Regression analysis results for small caps – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	-1.21 ***	-1.01 ***	
SI0	-1.2	-1.06	-0.14 ***
SI1	-1.34 ***	-1.15 ***	-0.19 ***
SI2	-1.36 ***	-1.17 ***	-0.19 ***
SI3	-1.38 ***	-1.2 ***	-0.19 ***
SI4	-1.41 ***	-1.22 ***	-0.19 ***
SI5	-1.42 ***	-1.31 ***	-0.11 ***
BI0	0.18 ***	0.19 ***	-0.02 ***
BI1	0.19 ***	0.22 ***	-0.03 ***
BI2	0.23 ***	0.26 ***	-0.03 ***
BI3	0.25 ***	0.28 ***	-0.03 ***
BI4	0.28 ***	0.31 ***	-0.02 ***
BI5	0.44 ***	0.38 ***	0.06 ***
Lagged spread	105.71 ***	102.32 ***	
Volatility	33.74 ***	32.03 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for small caps. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Sources: Thomson Reuters Datastream, ESMA.

Regression results – Price volatility

C.55
Regression analysis results for high volatility stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	17.93	-61.32	
BI0	-1.25 ***	-1.09 ***	-0.16 ***
BI1	-1.4 ***	-1.19 ***	-0.21 ***
BI2	-1.44 ***	-1.22 ***	-0.22 ***
BI3	-1.48 ***	-1.26 ***	-0.22 ***
BI4	-1.51 ***	-1.29 ***	-0.22 ***
BI5	-1.53 ***	-1.36 ***	-0.17 ***
SI0	0.22 ***	0.2 ***	0.02 ***
SI1	0.28 ***	0.25 ***	0.03 ***
SI2	0.31 ***	0.27 ***	0.04 ***
SI3	0.34 ***	0.3 ***	0.04 ***
SI4	0.35 ***	0.31 ***	0.05 ***
SI5	0.47 ***	0.37 ***	0.09 ***
Lagged spread	-20347.65	58282.69	
Volatility	856.6 ***	720.68 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for high volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.56
Regression analysis results for high volatility stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	88.32	59.17	
SI0	-1.26 ***	-1.1 ***	-0.16 ***
SI1	-1.4	-1.2	-0.2 ***
SI2	-1.45 ***	-1.24	-0.21 ***
SI3	-1.49 ***	-1.28 ***	-0.21 ***
SI4	-1.5 ***	-1.29 ***	-0.21 ***
SI5	-1.55 ***	-1.38 ***	-0.17 ***
BI0	0.22 ***	0.2 ***	0.02 ***
BI1	0.25 ***	0.23 ***	0.02 ***
BI2	0.28 ***	0.25 ***	0.03 ***
BI3	0.31 ***	0.28 ***	0.03 ***
BI4	0.34 ***	0.3 ***	0.04 ***
BI5	0.46 ***	0.37 ***	0.09 ***
Lagged spread	-90650.01	-62241.88	
Volatility	614.1 ***	526.61 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for high volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.57
Regression analysis results for medium volatility stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	28.4	2.25	
BI0	-1.32 ***	-1.11 ***	-0.21 ***
BI1	-1.49 ***	-1.24	-0.26 ***
BI2	-1.54 ***	-1.27	-0.27 ***
BI3	-1.59 ***	-1.31 ***	-0.27 ***
BI4	-1.6 ***	-1.33 ***	-0.27 ***
BI5	-1.65 ***	-1.43 ***	-0.22 ***
SI0	0.3 ***	0.26 ***	0.04 ***
SI1	0.35 ***	0.29 ***	0.06 ***
SI2	0.37 ***	0.3 ***	0.06 ***
SI3	0.39 ***	0.32 ***	0.07 ***
SI4	0.39 ***	0.32 ***	0.07 ***
SI5	0.53 ***	0.4 ***	0.14 ***
Lagged spread	-28661.69	-4178.57	
Volatility	586.79 ***	477.79 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for medium volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.58
Regression analysis results for medium volatility stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	123.4	34.06	
SI0	-1.33 ***	-1.11 ***	-0.21 ***
SI1	-1.49 ***	-1.24 ***	-0.25 ***
SI2	-1.54 ***	-1.28 ***	-0.26 ***
SI3	-1.58 ***	-1.32	-0.26 ***
SI4	-1.6 ***	-1.34 ***	-0.26 ***
SI5	-1.64 ***	-1.42 ***	-0.21 ***
BI0	0.24 ***	0.21 ***	0.03 ***
BI1	0.29 ***	0.24 ***	0.05 ***
BI2	0.31 ***	0.26 ***	0.05 ***
BI3	0.34 ***	0.28 ***	0.06 ***
BI4	0.37 ***	0.3 ***	0.07 ***
BI5	0.49 ***	0.37 ***	0.12 ***
Lagged spread	-123634.27	-36042.14	
Volatility	551.68 ***	439.84 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for medium volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.59
Regression analysis results for low volatility stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-74.39	-16.62	
BI0	-1.37 ***	-1.13 ***	-0.24 ***
BI1	-1.54	-1.25 ***	-0.28 ***
BI2	-1.6 ***	-1.31 ***	-0.3 ***
BI3	-1.66 ***	-1.36 ***	-0.3 ***
BI4	-1.67 ***	-1.37 ***	-0.3 ***
BI5	-1.74 ***	-1.49 ***	-0.25 ***
SI0	0.35 ***	0.3 ***	0.05 ***
SI1	0.42 ***	0.33 ***	0.08 ***
SI2	0.42 ***	0.34 ***	0.08 ***
SI3	0.45 ***	0.36 ***	0.09 ***
SI4	0.46 ***	0.36 ***	0.1 ***
SI5	0.57 ***	0.43 ***	0.15 ***
Lagged spread	75257.86	14897.03	
Volatility	573.33 ***	444.48 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for low volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.60
Regression analysis results for low volatility stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	-93.68	-56.1	
SI0	-1.37 ***	-1.13 ***	-0.25 ***
SI1	-1.55 ***	-1.26 ***	-0.29 ***
SI2	-1.6	-1.3 ***	-0.3 ***
SI3	-1.64 ***	-1.34 ***	-0.3 ***
SI4	-1.66 ***	-1.36 ***	-0.3 ***
SI5	-1.73 ***	-1.48 ***	-0.25 ***
BI0	0.31 ***	0.26 ***	0.05 ***
BI1	0.39 ***	0.31 ***	0.08 ***
BI2	0.4 ***	0.31 ***	0.09 ***
BI3	0.43 ***	0.33 ***	0.1 ***
BI4	0.45 ***	0.34 ***	0.1 ***
BI5	0.56 ***	0.4 ***	0.15 ***
Lagged spread	94329.7	54228.21	
Volatility	2121.29	1512.26	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for low volatility stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

Regression results – Fragmentation

C.61
Regression analysis results for high fragmentation stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-0.6	-4.44 ***	
BI0	-1.54 ***	-1.17 ***	-0.37 ***
BI1	-1.74 ***	-1.33 ***	-0.41 ***
BI2	-1.81 ***	-1.38 ***	-0.43 ***
BI3	-1.88 ***	-1.44 ***	-0.44 ***
BI4	-1.9	-1.47 ***	-0.43 ***
BI5	-1.95 ***	-1.58 ***	-0.37 ***
SI0	0.4 ***	0.31 ***	0.09 ***
SI1	0.46 ***	0.33 ***	0.13 ***
SI2	0.45 ***	0.32 ***	0.13 ***
SI3	0.5 ***	0.36 ***	0.14 ***
SI4	0.53 ***	0.37 ***	0.15 ***
SI5	0.7 ***	0.47 ***	0.23 ***
Lagged spread	504.14 ***	866.98 ***	
Volatility	359.37 ***	250.56 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for high fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.62
Regression analysis results for high fragmentation stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	-0.6	-4.81 ***	
SI0	-1.55 ***	-1.18 ***	-0.37 ***
SI1	-1.76 ***	-1.34 ***	-0.42 ***
SI2	-1.81 ***	-1.38 ***	-0.42 ***
SI3	-1.87 ***	-1.44 ***	-0.43 ***
SI4	-1.9 ***	-1.47	-0.43 ***
SI5	-1.98 ***	-1.6 ***	-0.38 ***
BI0	0.38 ***	0.29 ***	0.09 ***
BI1	0.45 ***	0.33 ***	0.12 ***
BI2	0.43 ***	0.32 ***	0.12 ***
BI3	0.5 ***	0.36 ***	0.13 ***
BI4	0.53 ***	0.38 ***	0.15 ***
BI5	0.69 ***	0.47 ***	0.22 ***
Lagged spread	1510.11	1903.99 *	
Volatility	1898.06	1293.05	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for high fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.63
Regression analysis results for medium fragmentation stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-2.33 ***	-3.7 ***	
BI0	-1.31 ***	-1.14 ***	-0.16 ***
BI1	-1.47 ***	-1.27 ***	-0.21 ***
BI2	-1.54 ***	-1.32 ***	-0.22 ***
BI3	-1.59	-1.37	-0.22 ***
BI4	-1.61	-1.39	-0.22 ***
BI5	-1.69 ***	-1.53 ***	-0.16 ***
SI0	0.21 ***	0.2 ***	0
SI1	0.25 ***	0.23 ***	0.02 ***
SI2	0.27 ***	0.24 ***	0.02 ***
SI3	0.28 ***	0.26 ***	0.03 ***
SI4	0.28 ***	0.26 ***	0.03 ***
SI5	0.4 ***	0.31 ***	0.09 ***
Lagged spread	1365.51 ***	1729.41 ***	
Volatility	710.85 ***	611.1 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for medium fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.64
Regression analysis results for medium fragmentation stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	-0.86	-3.16 ***	
SI0	-1.31 ***	-1.14 ***	-0.17 ***
SI1	-1.48 ***	-1.26 ***	-0.22 ***
SI2	-1.55 ***	-1.32 ***	-0.23 ***
SI3	-1.59 ***	-1.36 ***	-0.23 ***
SI4	-1.61	-1.38 ***	-0.23 ***
SI5	-1.68 ***	-1.5 ***	-0.17 ***
BI0	0.2 ***	0.19 ***	0.01 **
BI1	0.24 ***	0.22 ***	0.02 ***
BI2	0.26 ***	0.23 ***	0.03 ***
BI3	0.29 ***	0.25 ***	0.04 ***
BI4	0.29 ***	0.26 ***	0.04 ***
BI5	0.42 ***	0.32 ***	0.09 ***
Lagged spread	-938.1	508.41	
Volatility	749.34 ***	658.9 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for medium fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.65
Regression analysis results for low fragmentation stocks – buy side

Coefficient	Gross Liquidity Buy	Net Liquidity Buy	Difference
Intercept	-24.94	-71.15	
BI0	-1.08	-1 ***	-0.08 ***
BI1	-1.18 ***	-1.06 ***	-0.12 ***
BI2	-1.21 ***	-1.08 ***	-0.12 ***
BI3	-1.23 ***	-1.11 ***	-0.12 ***
BI4	-1.24 ***	-1.11 ***	-0.12 ***
BI5	-1.24 ***	-1.14 ***	-0.1 ***
SI0	0.25 ***	0.24 ***	0.01 **
SI1	0.34 ***	0.31 ***	0.02 ***
SI2	0.38 ***	0.35 ***	0.03 ***
SI3	0.39 ***	0.36 ***	0.03 ***
SI4	0.4 ***	0.36 ***	0.03 ***
SI5	0.47 ***	0.41 ***	0.06 ***
Lagged spread	24099.17	70200.06	
Volatility	973.28 ***	804.43 ***	

Note: The table shows the cumulative effect over time of the aggregated buy turnover changes in the gross and net liquidity across stocks and across venues for low fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

C.66
Regression analysis results for low fragmentation stocks – sell side

Coefficient	Gross Liquidity Sell	Net Liquidity Sell	Difference
Intercept	131.11	49.71	
SI0	-1.08 ***	-1.01 ***	-0.07 ***
SI1	-1.17 ***	-1.08 ***	-0.1 ***
SI2	-1.2 ***	-1.1 ***	-0.1 ***
SI3	-1.21 ***	-1.11 ***	-0.1 ***
SI4	-1.22 ***	-1.12 ***	-0.1 ***
SI5	-1.23 ***	-1.15 ***	-0.07 ***
BI0	0.18 ***	0.18 ***	0
BI1	0.23 ***	0.22 ***	0.01 **
BI2	0.29 ***	0.28 ***	0.01 ***
BI3	0.29 ***	0.27 ***	0.01 ***
BI4	0.32 ***	0.3 ***	0.02 ***
BI5	0.38 ***	0.34 ***	0.04 ***
Lagged spread	-132536.52	-51140.78	
Volatility	566.25 ***	477.64 ***	

Note: The table shows the cumulative effect over time of the aggregated sell turnover changes in the gross and net liquidity across stocks and across venues for low fragmentation stocks. It also shows whether the difference between gross and net measures is significant or not. *** P-value<1%, ** P-value<5%, * P-value<10%.
Source: ESMA.

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