Effects of Lit and Dark Market Fragmentation on Liquidity[♣]

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April 2015

JEL classification: G14, G15, G18

Keywords: Fragmentation, Liquidity, Multilateral Trading Facility (MTF), OTC trading, Internalization, Dark trading, Algorithmic trading

[♣] I address special thanks to IFS (Intelligent Financial Systems) and their managing directors, Sabine and Darren Toulson, for generously providing the data used in this study. I am particularly grateful to Mark Holloway, Oliver Speakman, and Sugandha Sharma of IFS for their technical work on the data. I also wish to thank Laurent Fournier, Laurent Grillet-Aubert, Ryan Davies, Hans Degryse, Simone Giansante, Terry Hendershott, Archana Jain, Albert Menkveld, Maureen O'Hara, Fabrice Pansard, Roberto Pascual, Giovanni Petrella, Ian Tonks, Jos van Bommel, Vincent van Kervel, Thanos Verousis, Gunther Wuyts, Ania Zalewska, as well as participants at the 2011 FMA conference, the 2013 FMA European conference, the 2013 3L Workshop in Brussels, the AMF 2014 Scientific Board seminar, the finance seminar of the Catholic University of Milan, and the finance seminar of the University of Bath, for helpful comments. All opinions expressed in this article only reflect my own views.

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Abstract

Based on data from eight exchanges and a trade reporting facility for a large sample of LSE- and Euronext-listed equities, this article investigates how lit and dark market fragmentation affects liquidity. Neither dark trading, nor fragmentation between lit order books, is found to harm liquidity. Lit fragmentation improves spreads and depth across markets and locally on the primary exchange, or at worst does not affect them. Benefits are greater for large stocks and stocks with less electronic trading. Lit fragmentation however harms the depth of small stocks. Adverse effects on the depth of large stocks result from algorithmic trading and not from fragmentation.

1. Introduction

With the development of sophisticated trading technologies and the enforcement of pro-competition market regulations, fragmentation of trading volumes between competing trading venues has undeniably increased in all large western stock markets. More than fifteen trading venues are now active in the U.S., with more than 40% of volume in S&P 500 stocks and more than 50% of volume in Nasdaq-100 stocks traded off primary exchanges in March 2015 according to Fidessa[1]. In Europe, more than ten trading venues have now become fairly active in liquid European stocks.

A market is fragmented when trading takes place simultaneously at different locations. In theory, market fragmentation should only be transitory as orders should concentrate in the most liquid market (Pagano, 1989), the optimal market structure being the electronic order book (Glosten, 1994). This order flow consolidation would be desirable because the marginal cost of a trade decreases with the quantity of orders executed in the market and because there are network externalities associated with running a market. As a result, the consolidation of the order flow creates economies of scale on the provision of liquidity (Mendelson, 1987). In practice however, stock markets are fragmented and the trade flow in a security may fragment in two ways essentially: (1) several multilateral trading platforms working as lit order books compete for the order flow; (2) a portion of the order flow is internalized off-exchange by dealers or crossing engines, either under regulation or in the OTC market. Case (1) will be referred to as lit fragmentation while case (2) will be referred to as dark fragmentation.

There is concern among regulators, issuers, and asset managers, about how a high level of fragmentation may impact the quality of order execution and market liquidity. Whereas competition between trading venues is most often considered as beneficial to the quality of

[1] Fidessa is a private company which provides trading systems, market data, and connectivity solutions.

order execution services offered to investors (Huang, 2002; O'Hara and Ye, 2011), there is little empirical evidence about the impact of market fragmentation on the consolidated liquidity of competing platforms. O'Hara and Ye (2011) provide some evidence about the benefits of fragmentation in terms of spreads and execution speed but their approach restricts to a cross-sectional analysis and it does not distinguish cross-market consolidated liquidity from local liquidity in a given market. Recently, with a long-term time series of order book data, Degryse, De Jong, and van Kervel (2014) have found a positive impact of visible fragmentation on consolidated liquidity but a negative impact on the liquidity of the primary market and a detrimental effect of dark trading on liquidity. While their approach tells more about the relation between fragmentation and liquidity through time, their sample is relatively small and it only covers one country whose stock market is not among the largest in Europe, which raises the question of whether their results can be generalized.

The present article complements the literature by examining how the consolidated liquidity of competing trading systems, here called global liquidity, and the local liquidity of the primary exchange relate to lit and dark fragmentation, on a large sample of equities listed at the London Stock Exchange (LSE) and on Euronext. To my knowledge, it is the first paper to address the issue with both a long time series and a large sample. It provides novel insights by disentangling the effects of algorithmic trading (AT) and fragmentation and by assessing their relative economic impact on various dimensions of liquidity. Both are beneficial to liquidity but the effect of fragmentation is more significant. Contrary to Degryse et al. (2014), I do not find harmful effects on local liquidity after controlling for AT, and I do not find dark trading to be harmful for any dimension of liquidity. Further, I provide new evidence on differentiated impacts of fragmentation according to the initial level of automation and/or centralization of the order flow before competition from new platforms.

An original aspect of the study lies in that it is conducted with two distinct approaches: a first approach which takes the implementation of the Markets in Financial Instruments Directive (MiFID)[2] as a natural experiment and examines cross-sectional differential effects, and a second approach which investigates the time series of spreads, depth, and fragmentation measures in fragmented markets. The first approach consists of comparing liquidity before and after the trading in European stocks fragmented with the implementation of MiFID on 1 November 2007. In Europe, the enforcement of MiFID abolished the concentration rule[3] in the countries of the European Economic Area (EEA), and has created a competitive environment for trading systems and services, in which new trading systems made available by technological innovation may be widely exploited. As a result, MiFID has served as a catalyst for the dramatic rise in competition between marketplaces, and the number of trading venues at the disposal of investors has rapidly increased for European equities. In that, the implementation of MiFID is a unique event of shifting from consolidated markets to fragmented markets within a relatively short period of time, and this specific feature makes it an ideal ground for original research on fragmentation. The MiFID event presents another interesting feature: several minimum-tick-size changes took place in the period following the event and they can serve as an instrument in the analysis. What makes the analysis somehow delicate is the overlapping of the 2008 financial crisis with the immediate post-MiFID period. The observation periods and the methodology were thus carefully chosen so as to avoid the background effect of the 2008 subprime crisis and its related potential biases. In the second approach, I analyze the two-way temporal relation

[2] This European Union law provides a comprehensive and harmonized regulatory regime for investment services and activities across the 30 member states of the European Economic Area (EEA), i.e. the 27 member states of the European Union (EU) plus Norway, Iceland, and Liechtenstein.

[3] A provision in the 1993 Investment Services Directive (ISD) permitted (but did not mandate) individual member states to require orders from investors in that member state to be executed only on regulated markets. This provision was applied in France, Italy, and Spain.

between fragmentation and liquidity by a two-stage panel methodology over a later post-MiFID period.

Results show that (1) spreads and depth improve with, or at worst are not affected by, multiple-trading-platforms competition after controlling for endogeneity and AT; (2) FTSE 100 stocks that had less electronic trading before MiFID benefit more from multiple-venue trading; (3) lit fragmentation reduces depth for smaller stocks; (4) OTC and internalized trading, designated as dark trading hereafter, do not harm liquidity but may on the contrary improve some of its dimensions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and presents testable hypotheses. Section 3 provides details about the regulatory framework that motivated the study as well as on the organization of the marketplace. Section 4 describes the sample and the data. The fragmentation and liquidity measures used in the empirics are presented in Section 5. Section 6 provides comparative statistics about fragmentation and liquidity before and after MiFID came into force. In Section 7, a two-stage multivariate analysis is conducted to compare the liquidity of the pre-MiFID quasi-consolidated marketplace with that of post-MiFID fragmented markets. Section 8 exposes panel analyses of the relation between fragmentation and liquidity in the post-MiFID fragmented markets. Section 9 concludes.

2. Literature review and testable hypotheses

Lit fragmentation is generally considered as producing positive competition effects (Hamilton, 1979; [4] Stoll, 2003). First, lit fragmentation often arises between trading systems that use different mechanisms, charge different fees, or offer different market access to

[4] Hamilton (1979) studied the effects of off-board trading of NYSE-listed stocks on the regional exchanges and in the third market. He documented two opposite effects: on the one hand, the dispersion of trading may increase competition and thus improve liquidity (competition effect); on the other hand, it may “prevent full realization of any economies of centralized trading on the exchange” (fragmentation effect).

participants, which contributes to addressing the needs of diverse categories of investors in a more efficient way (Harris, 1993; Hendershott and Mendelson, 2000; Gresse, 2006). Second, bid-ask spreads have been observed to narrow in the incumbent market for diverse financial instruments when a new market starts operating (Battalio, 1997; Lee, 2002; Huang, 2002; Boehmer and Boehmer, 2003; Nguyen, Van Ness, and Van Ness, 2007; Mayhew, 2002; Fontnouvelle, Fishe, and Harris, 2003). Foucault and Menkveld (2008) also show that, due to the absence of price priority across markets, consolidated depth, i.e., the sum of all shares available at that price or better in two markets, is larger after the entry of a new order book.

Nevertheless, none of those papers analyzed the interaction between fragmentation and liquidity when lit fragmentation becomes substantial and durable as in today's world. A first attempt to address the issue was made by O'Hara and Ye (2011) who exploited Securities and Exchange Commission (SEC) Rule 605 monthly data for 262 US stocks over six months of 2008. Their cross-sectional analysis shows that high fragmented stocks have lower transaction costs and faster execution speed than low fragmented stocks. Degryse et al. (2014) evaluate the impact of fragmentation on the market depth of 52 Dutch stocks from 2006 to 2009. They find that fragmentation between lit order books improves the depth of the consolidated marketplace but reduces that of the primary exchange. However, to date, no work has been conducted with high-frequency data covering all trading venues for a large sample of equities primary listed on leading exchanges. My empirical work fills this gap by examining a large sample of European stocks listed on the LSE and on Euronext. In particular, the sample allows comparing the impact of fragmentation for stocks that had different trading patterns on their primary exchanges before fragmentation soared. Indeed the off-order-book trading was substantial on the LSE while it was insignificant on Euronext. Another nice feature of the sample is that it includes a relatively large number of Euronext middle capitalization stocks for a robust comparison of large and small stocks.

In terms of methodological approach, this paper complements the literature by providing both (a) a natural experiment analysis around the implementation of MiFID which allowed European stock markets to shift from quasi-consolidation to fragmentation in a short period of time, and (b) a time series analysis of the relation between fragmentation and liquidity in the post-MiFID world. With data from eight markets and a trade reporting facility, and by calculating measures of liquidity for global traders who are connected to several platforms as well as for local traders whose trading universe is restricted to the primary exchange, I test a series of hypotheses on the way liquidity relates to fragmentation. Some of those hypotheses are derived from the theory (Buti, Rindi, and Werner, 2011a; Chowdry and Nanda, 1991; Ye, 2012; Zhu, 2014), but most of them stem from empirical observations.

Hamilton (1979) documented the competition benefits and the fragmentation costs of trading on multiples exchanges. On the one hand, if liquidity benefits arise from competition between markets, global traders are expected to be the ones who most enjoy those competition benefits. This motivates hypotheses H1a and H1b.

Due to competition effects between markets,

H1a. *global liquidity, measured by cross-market bid-ask spreads and consolidated depth, is greater in the post-MiFID fragmented market than in the pre-MIFID consolidated market;*

H1b. *in a market fragmented between order books, global liquidity increases with the level of lit fragmentation.*

Further, the experience shows that markets for large stocks are usually more fragmented than markets for small stocks. It therefore makes sense to test whether competition gains are more sizeable for large equities:

H1c. *the competition gains of shifting from the pre-MIFID consolidated market to the post-MiFID fragmented market have a greater magnitude for large equities than for small ones.*

On the other hand, local traders may undergo adverse effects. They could suffer from the fragmentation effect documented by Hamilton (1979) according to which the dispersion of trading may "prevent full realization of any economies of centralized trading on the exchange". Another reason why liquidity may suffer from fragmentation is information asymmetry. Chowdry and Nanda (1991) show that adverse selection costs increase with the number of markets listing an asset. Easley, Kiefer, and O'Hara (1996) and Bessembinder and Kaufman (1997) also coin that when a new market opens for a stock, it may skim the least informed and consequently most profitable orders, and then harm the liquidity of the primary market. Indeed, if some liquidity providers leave their market to offer liquidity in another market with more profitable trading opportunities, local traders may incur larger spreads in a thinner market. This motivates H2a and H2b.

Due to adverse fragmentation effects in the sense of Hamilton (1979),

H2a. *local liquidity measured by spreads and depth on primary exchanges is lower in the post-MiFID fragmented market than in the pre-MIFID consolidated market*;

H2b. *in a market fragmented between order books, local liquidity on the primary exchange decreases with the level of lit fragmentation.*

Differences in the magnitude of the effect potentially exist between large and small equities, as the latter usually suffer from greater information asymmetry. This leads me to complement H2a with hypothesis H2c:

H2c. *the adverse fragmentation effects of shifting from the pre-MIFID consolidated market to the post-MiFID fragmented market have a greater magnitude for small equities than for large ones.*

In practice, dealers or intermediaries who internalize trades are the most able to cream-skim profitable orders, so that the portion of dark trading that corresponds to dealers' off-exchange executions may be more detrimental to liquidity than lit fragmentation. Consistent with this view, Bennett and Wei (2006) provide empirical evidence that stocks switching from a fragmented market of dealers, as the old Nasdaq structure, to a more consolidated structure such as the electronic order book of NYSE, experience an improvement in spreads. Using European data, Gajewski and Gresse (2007) show that off-book trading in a hybrid market tends to increase trading costs in comparison with trading in a centralized order book. Dark pools running crossing engines are also likely to skim off the uninformed order flow. Zhu (2014) develops a model in which crossing networks (CNs) are proved to be more attractive to the uninformed. The empirical evidence of Jiang, McInish, and Upson (2012) is consistent with the conjecture that the off-exchange order flow is less informed than the on-exchange order flow. Under this hypothesis, dark trading should increase price informativeness but at the expense of greater adverse selection costs, which might harm liquidity:

H3a. *because dark trading cream-skims most profitable orders, global and local liquidity decreases with the level of dark fragmentation.*

This view is challenged by a couple of papers. Buti et al. (2011a) demonstrate that spreads increase with CN trading only if the primary order book is thin, otherwise spreads narrow. Converse to Zhu (2014), Ye (2012) demonstrates that a proportion of informed traders migrate to CNs, which lessens their price impact on-exchange and thereby reduces spreads. With private data from a UK CN, Gresse (2006) shows that the CN offers additional risk sharing capacities which contributes to improving liquidity in the primary market. Buti, Rindi, and Werner (2011b) also find that dark pool activity improves liquidity with US dark pool data. Further, Gajewski and Gresse (2007) show that internalization outside the book benefits large trades by providing them with immediacy. This allows me to posit the opposite of H3a:

H3b. *Due to positive risk sharing effects, global and local liquidity increases with the level of dark fragmentation.*

3. Regulatory framework, stock universe, and market organization

Since 1 November 2007, MiFID has recognized three types of order execution venues in Europe: Regulated Markets (RMs), Multilateral Trading Facilities (MTFs), and Systematic Internalizers (SIs). Any trade executed in a RM, on a MTF, or with a SI falls under regulation while trades executed outside those venues are OTC.

RMs and MTFs are multilateral trading systems with similar functionalities. Both RMs and MTFs are allowed to organize primary listings. However, they differ in that RMs are legally authorized to list regulated financial instruments while financial products listed on MTFs would be considered as unregulated instruments. In practice, most MTFs do not offer primary listing services, and MTFs may be viewed as the equivalent of ECNs in the U.S.

SIs are investment firms which, "on an organized, frequent and systematic basis," execute client orders outside a regulated market or a MTF, either on their principal accounts or against other clients' orders. Legally, a SI does not have to be designated by a regulated market, and an institution can be a SI for securities listed on different stock exchanges. Creating the legal status of SIs institutionalizes internalization. In counterpart, MiFID treats SIs as mini-exchanges and imposes pre-trade and post-trade transparency requirements on them.[5] In addition, under the post-trade transparency rules introduced by MiFID, all transactions in regulated financial instruments must be reported, even if they are carried out over the counter (OTC). Such disclosures do not have to be made with the regulated primary

[5] The same pre- and post-trade transparency requirements apply to all venues except dark pools, that is MTFs which trading mechanisms do not generate price discovery and are exempt from pre-trade transparency rules.

market exclusively; they may be made by using proprietary resources or the services of a MiFID-compliant trade reporting facility (TRF).

Main RMs are run by three exchange groups – Deutsche Boerse, LSE-Borsa Italiana and Euronext. They are challenged by a handful of pan-European MTFs that emerged in 2007 and 2008: BATS Europe, the subsidiary of US exchange BATS, opened on 31 October 2008; Chi-X, owned by broker Instinet at the time of the study and then taken over by BATS Europe in 2011, began trading a bunch of Dutch and German stocks on 30 March 2007 and then progressively extended its universe of stocks in 2007 and 2008; Turquoise, was launched on 22 September 2008 by a consortium of investment banks and then acquired by the LSE in late 2009; and Nasdaq OMX Europe, which belonged to the Nasdaq OMX group, was launched on 1 October 2008 and then closed on 21 May 2010. Further, PLUS-Markets, a relatively young UK exchange often called PLUS, operates as a RM for small caps and as an MTF for European securities.

hThe legislation on transaction reporting introduced by MiFID also led to the creation of several TRFs that offer MiFID-compliant services. The largest of these TRFs by market share, at the time of the study, was the BOAT platform of Markit, a financial information provider.[6]

MiFID changed the European trading industry in three key ways:[7]

(1) it abolished the concentration rule which existed on most continental exchanges, such as the European branches of Euronext, and forced any regulated trade to be executed on the primary exchange;

(2) it offered a regulatory framework for internalization;

[6] Markit decided to close BOAT in late 2013. The largest trade reporting service in Europe is now offered by BATS Chi-X.

[7] For details and comparison with RegNMS, the US counterpart of MiFID, refer to Davies (2008) and Petrella (2009).

(3) it extended post-trade transparency duties to OTC trades in regulated stocks and allowed entities other than primary exchanges to report trades, which resulted in a fragmentation of the trade reporting activity.

Those regulatory changes combined with the rise of AT allowed European stock markets to shift from quasi-consolidated markets to fragmented markets within a relatively short period of time. This changing environment offers a perfect field of investigation on how rapidly market competition can rise after regulatory changes and how liquidity is affected in relation. I use this event to test the impact of market fragmentation on the liquidity of three stock indices: the FTSE 100, the CAC 40, and the SBF 80. The FTSE 100 is comprised of the largest capitalization stocks of the LSE. The CAC 40 is the flagship index of Euronext Paris and comprises the largest stocks of Euronext Paris as well as some large-capitalization stocks primarily listed on Euronext Amsterdam and Euronext Brussels. The SBF 80 index comprises 80 middle capitalization stocks listed on Euronext Paris and elected for being the most traded just after the CAC 40 components.[8] Studying FTSE 100 and CAC 40 securities will allow me to compare stocks for which there was a concentration rule before MiFID (CAC 40) with stocks that had no concentration rule prior to MiFID (FTSE 100). Comparing the SBF 80 and the CAC 40 stocks will allow me to examine whether market fragmentation affects medium-capitalization stocks differently.

3.1. Market design of primary exchanges

The LSE and Euronext both run electronic order books on which buy and sell orders are continuously matched from the open to the close according to the price/time priority rules. Trading sessions commence and finish with call auctions. On both the LSE and Euronext, off-order-book trading is permitted but with different rules and practices. At the LSE, an important dealership activity has always existed simultaneous to order book trading since its

[8] For that reason, they are sometimes designated in the press as the "Next 80".

introduction in 1997 (cf. Gajewski and Gresse, 2007). Broker-dealers execute a significant part of the order flow outside the book and the majority of retail orders are routed to dealers specialized in retail trading, the so-called Retail Service Providers. Off-order-book trading is less developed on Euronext, where the order book market model has prevailed for a long time, and where concentration rules existed before the implementation of MiFID. Only two categories of trades are executed outside the central order book: block and VWAP trades.

3.2. Other trading venues

The most active MTFs at the time of the study were Chi-X, BATS Europe, Turquoise, and Nasdaq OMX Europe. They run order-driven matching engines in which anonymous orders are matched continuously in time-price priority. No call auctions are organized either at the open or at the close. Their business model is based on a make/take fee structure that remunerates liquidity-providing orders and charges aggressive orders. In addition, PLUS, a London-based quote-driven electronic platform, offers an execution venue for securities listed elsewhere in London and in continental Europe, in addition of those primarily listed on PLUS.[9]

4. Sample selection and data

My empirical work consists of two parts: a pre/post-MiFID comparison and a post-MiFID time series analysis. Both parts are based on trade and quote data generously provided by Intelligent Financial Systems (IFS) for FTSE 100, CAC 40, and SBF 80 stocks.

4.1. Sample selection

In the pre-post MiFID comparison, the pre-MiFID period of October 2007 is compared with three post-MiFID one-month periods: January, June and September 2009. Those three

[9] The list of stocks traded on PLUS covers more than 850 liquid securities including FTSE 100 stocks and other European blue chip stocks. On the PLUS platform, competing market makers display two-way quotes in a minimum size known as the Exchange Market Size, during the Mandatory Quote Period (MQP), i.e. from 8:00 to 16:30 UK time.

months were deliberately chosen in 2009 so as to sidestep the effects of the 2008 subprime crisis. In theory, choosing a post-event period immediately after the implementation of MiFID would be the best methodological choice. In practice, the immediate post-MiFID period overlaps the subprime crisis period characterized by extreme illiquidity, independent of regulation or market architecture changes. Using that period in the analysis would undoubtedly bias the results by the dominant impact of the crisis on liquidity, an impact that seems relatively impossible to isolate or control for.

Pre-MiFID period October 2007, which comprises 23 trading days, comes just after the start-up of Chi-X but precedes the launch of other MTFs, namely BATS Europe, Nasdaq OMX Europe, and Turquoise, so that it is characterized by a negligible level of fragmentation. The three post-MiFID monthly periods, each comprising 21 trading days, come after the launch of all MTFs considered in the study. They were determined in order to correspond to different levels of fragmentation. Fragmentation progressively increased from January to September 2009. Regarding fundamental volatility, here measured by the standard deviation of daily index returns (see Column 3 of Table 3), it was extreme in January, owing to the financial crisis. It had somewhat decreased by June 2009 but still exceeded the baseline level of October 2007. October 2007 and September 2009, while characterized by very different levels of fragmentation, were almost comparable in terms of volatility.

The post-MiFID time series analysis covers 63 trading days from 1 September to 30 November 2009. Stocks which were not continually part of their index from 2007 to 2009 were dropped from the sample. Financial stocks were excluded as very specific factors drove their liquidity and volatility during the observation periods. This selection procedure resulted in a pre/post-MiFID-comparison sample of 140 stocks of which 51 pertained to the FTSE 100, 32 to the CAC 40, and 57 to the SBF 80, and in a post-MiFID time-series-analysis sample of 152 stocks distributed between 64 FTSE-100 components, 32 CAC-40 components, and 56 SBF-80 components.

4.2. Daily data, high-frequency data, and data filtering

Daily closing prices, adjustment factors for corporate actions, and market values were collected from Datastream. Prices of UK stocks are expressed in pence sterling. Some metrics used in the study require expressing all prices and volumes in euro. For that purpose, the daily foreign exchange rates of the GBP against EUR were downloaded from the Oanda website (www.oanda.com).

The high-frequency data provided by IFS were generated from the original data flows of Euronext, the LSE, Deutsche Boerse, Chi-X, Turquoise, Nasdaq OMX Europe, BATS Europe, PLUS, and BOAT.[10] The database includes transaction and best-limit data time-stamped to the second. For each stock, the data contain the trade prices and best limit quotes of all trading venues. All timestamps in the database are in UK time and hours will be expressed in UK time throughout the article.

Best limit data provide, at each second of the trading session from 8:00 to 16:30, the best bid price, the best ask price, and quantities associated, for every trading venue where a quote is displayed. Bid and ask prices with times that could fall inside the opening auction periods or after the end of the continuous session of the primary exchange were eliminated. As a result of this rule, I deleted from the dataset bid and ask quotes with times before 08:01 and after 16:30.

Trade data cover the same markets as quote data plus BOAT-reported trades. For each trade, the data provide the execution time, the price, the size in number of shares, as well as best bid and ask prices and displayed quantities prevailing on every sampled RM or MTF at

[10] Data from dark pools such as POSIT, Liquidnet, or Chi-X Delta, are not covered, but the total market share of dark MTFs in trading volumes did not exceed a few percent at the time of the study, so that not holding their data should not bias the results.

the time of the trade. Euronext and LSE data encompass opening and closing auction transactions as well as all continuous trades except block and VWAP trades for Euronext. LSE data include an indicator that can be used to identify trades executed on the SETS order book, off-book trades executed by LSE members, and trades reported to the LSE European Trade Reporting Service but not executed on the LSE regulated market. The third category of trades (LSE-reported trades) are of the same type as trades reported by BOAT and should be considered as OTC or internalized trades.

For all trading venues, overnight transactions, that is transactions executed before 07:00 and after 17:00, have been eliminated from the dataset. LSE-reported trades have a 2-figure trade-type code. Any LSE trade for which this code indicates that the trade results from an option exercise, a stock swap, or the cancellation of a previous trade, is deleted.

I have then identified batch auction trades. For the LSE, SETS call auction trades are flagged with a special trade code. On Euronext, batch-auction trades have to be identified with trading times. At the open, trades whose execution time is the first trade time observed at or after the official start time of the open auction period are considered as open auction trades. At the close, trades executed at the first trade time immediately following or equal to the official start time of the close auction but no later than the end time of the close auction period are identified as close auction trades. Once auction trades have been determined, other trades are classified into three groups: continuous trades executed between the open and the close auctions, pre-open trades, and post-close trades. Only continuous trades are further considered for the computation of average effective spreads, average trade size, and fragmentation variables used in the econometric analysis.

5. Fragmentation and liquidity measures

The order flow in a given security distributes between trading volumes executed on MTFs and RMs, further referred to as the lit order flow, and trading volumes executed by SIs or in the OTC market, further referred to as either the internalized or the dark order flow. I present the metrics used to measure both sources of fragmentation and then describe the way traditional measures of liquidity are adapted to measure liquidity in a multi-market environment.

5.1. Measuring market fragmentation

Lit fragmentation is measured by using the reciprocal of a Herfindhal-Hirschman index based on RMs and MTFs market shares in the lit order flow. This fragmentation index[11] is calculated as one divided by the sum of the squared market shares of all RMs and MTFs covered by the database. The formula of this index writes as follows:

$$LitFrag = 1 \Big/ \sum_k \left(\frac{V_k}{\sum_j V_j} \right)^2 \tag{1}$$

where V_k and V_j denotes the volumes traded on markets k and j respectively, $\sum_j V_j$ represents the total volume traded in all markets under consideration, that is three RMs (Euronext, the LSE, and Deusche Boërse) and five MTFs (Chi-X, BATS Europe, Turquoise, Nasdaq OMX Europe, and PLUS), and $\frac{V_k}{\sum_j V_j}$ is the market share of market k among those markets. Over the four monthly periods used for the pre/post-MiFID comparison, levels of market

[11] Market services provider Fidessa uses this index to publish statistics on market fragmentation.

fragmentation by stock index, reported in Table 2, were calculated as cross-sample capitalization-weighted means of individual stocks' fragmentation indices.[12]

In the post-MiFID observation periods, the weight of dark fragmentation was estimated by using BOAT trade report data and LSE trade-reporting-service data.[13] The traded quantities reported by those reporting services were aggregated and reported to total trading volumes to calculate the share of dark trading, denoted *Dark*. Measure *Dark* covers various types of dark trading such as trades executed by SIs, OTC trades,[14] but also unregulated dark pool trades as most broker-dealer-owned dark pools reported their trades to Markit-BOAT at the time of the study.

5.2. Liquidity measures

Liquidity is measured for two categories of traders: local traders who connect to the primary exchange only, and cross-market traders who are connected to all trading venues or use smart order routers (SORs) that enable them to distribute their orders across several marketplaces. Three metrics of liquidity are considered: quoted spreads, effective spreads, and depth displayed at best quotes. These metrics are determined locally in each primary market in the perspective of local traders and across markets by optimizing the prices of all competing markets.

5.2.1. Global and local quoted spreads

In the data provided by IFS, the quoted spreads of each market are observable at every second. The spread observed on the primary market will be referred to as the local spread and

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[12] For the general volume and fragmentation statistics of Table 2, $\sum_j V_j$ includes the opening and closing auction volumes on the primary exchange. In the rest of the analysis, auction trading volumes are excluded from the calculation of *LitFrag*.

[13] BOAT and the LSE reporting services do not account for all dark volumes. However, BOAT was the market leader in post-trade reporting at the time of the study so that the estimate may be considered to be in the right order of magnitude.

[14] SI trades and OTC trades are similar on two aspects: negotiation is bilateral in both cases and none of those trades get cleared.

denoted *LQS*. Each second, the highest bid price and the lowest ask price across all competing markets are determined. The difference between these two prices divided by their mid value is the quoted spread resulting from matching quotes on all markets. It will be referred to as the global or consolidated quoted spread and denoted *GQS* in the remainder of the study, as contrasted with the local quoted spread. In the pre/post-MiFID comparison, global and local quoted spreads are averaged for each stock and each month. Monthly average quoted spreads are then computed for each stock index by weighting the averages of the individual stocks by market capitalization.[15] In the post-MiFID time-series analysis, local and global quoted spreads are averaged per stock and per day.

5.2.2. Global and local effective spreads

The effective spread of a given transaction is twice the difference between the transaction price and the mid quote prevailing at the time of the transaction, measured as a percentage of this median price. The mid quote used as the baseline is a cross-market consolidated mid quote, i.e., the mid-point of the best bid and ask prices, all markets combined. Effective spreads are averaged in the same way as quoted spreads, except that they are weighted by transaction size. The transaction universe used to calculate these averages is reduced to trades executed on-book in the continuous session. OTC, internalized, and off-book transactions are excluded. Local effective spreads, denoted *LES*, are obtained by averaging the effective spreads of the transactions executed on a given primary exchange, while global effective spreads (*GES*) are obtained by averaging the spreads of the trades from all markets.

5.2.3. Global and local depth at best limits

Best-limit depth is the sum of the quantities associated with the best bid and ask prices. It can be understood as the quantity of shares that can be instantaneously traded with no impact on quoted prices. To ensure that depth is comparable between stocks regardless of price level,

[15] Market capitalization for weighting purposes is the average of the stock's market capitalization on 1 October 2007 and its market capitalization on 30 September 2009.

it is expressed in terms of capital, specifically in thousands of euros, by multiplying quantities by the mid-price. Local depth (*LD*) is computed in the traditional way by considering the bid and offer quantities of the primary exchange. Global depth (also denominated consolidated depth and denoted *GD*) is determined by aggregating the quantities demanded at the best bid limit on all markets quoting the best bid price and the quantities offered at the best ask limit on all markets quoting the best ask price. Average depths are then calculated using the same procedure as for average quoted spreads.

6. Shifting from monopolistic-market trading to multi-market trading and contemporaneous changes in liquidity

Part A of Table 1 reports the market shares of the primary market, other regulated markets, MTFs, and dark trading, in September 2009, for FTSE 100, CAC 40, and SBF 80 stocks. Part B presents the same statistics for continuous trading only, excluding opening and closing auctions on the primary market. The primary market is found to have a majority share of order-flow execution in all the samples. When calculating a fragmentation index for the total order flow including dark trading, [16] the fragmentation levels of FTSE 100 stocks (index of 2.7) and CAC 40 stocks (index of 2.65) are comparable. In contrast, the SBF 80 middle capitalization stocks are much less fragmented (index of 1.89). Euronext was still capturing over 70% of all volumes for those stocks in September 2009, while its market share had decreased to 55% for CAC 40 stocks.

Table 1 about here

As to the competitive position of MTFs, three players stand out: Chi-X, Turquoise, and BATS Europe. Chi-X is the clear frontrunner with over 10% of volumes in the three samples. BATS Europe and Turquoise are on a par in terms of market share (3-4% for the CAC 40, 4-

[16] This fragmentation index is computed considering that all dark trades are executed in an additional trading venue. The market share of dark trading in the total traded volume is thus added at the denominator of the index.

5% for the FTSE 100). BATS Europe leads Turquoise in UK stocks, but Turquoise has the edge in French stocks.

There is virtually no direct order flow competition between the regulated markets. Euronext loses a few trades to the LSE and Deutsche Boerse, but no more than 1-2% of volume, and Euronext and Deutsche Boerse have no market share in LSE stocks.

Dark trades account for around 20% of total volumes – including auction, pre-open, and post-close trades – on the CAC 40 and FTSE 100. The share is slightly lower than 20% for UK large-cap stocks and significantly higher (approximately 24%) for French large-cap stocks.

6.1. Shifting from monopolistic-market trading to multi-market trading

Table 2 lists the monthly market shares of all markets and provides a fragmentation index in the last column. It reveals that fragmentation was substantial in June and September 2009 (around 1.9 for the CAC 40 and the FTSE 100 and between 1.4 and 1.5 for the SBF 80 securities) while it was still at an intermediate level in January 2009. The primary market's share in the lit volumes of the two large-cap samples fell from over 95% in October 2007 to around 70% in the final period. For French mid-cap equities, the primary market's share remained above 80% in September 2009. The share of volumes executed on MTFs stabilized at over 25% for CAC 40 constituents and reached about 30% for FTSE 100 constituents, but did not exceed 18% for the SBF 80 stocks.

Table 2 about here

In Table 2, the LSE market share is separated into volumes executed on the SETS order book and volumes executed by LSE members outside the book. This breakdown shows that the structure of the large-cap order flow on the LSE changed radically between 2007 and 2009, reflecting competition from MTFs and increased automation of securities trading. In October 2007, over 40% of trading volumes were executed by LSE members off the order book, whereas by September 2009, no more than 13.6% of the LSE 69% market share were traded off-book. According to these figures, the SETS system has not really lost market share, but the off-book order flow has diminished as the competition from other trading venues has gained ground.

6.2. Changes in liquidity: Univariate tests

Despite a sharp decline in trading volumes between October 2007 and September 2009 (–59% for FTSE 100 stocks, –28% for CAC 40 stocks and –32% for SBF 80 stocks, cf. Table 2), global spreads as well as the local spreads of primary markets, reported in Table 3, narrowed between October 2007 and September 2009 for the three samples. The biggest decline was on the FTSE 100, for which the average global quoted spread fell from 9.21 to 5.43 bps and the average local quoted spread fell from 9.21 to 7.07 bps. Spreads narrowed far less dramatically for the SBF 80 medium capitalization stocks. Effective spreads contracted by less than quoted spreads but nonetheless narrowed significantly, except in the case of SBF 80 medium capitalization stocks. The decline in spreads is especially noteworthy given that the average volatility of individual stocks was higher in September 2009 than in October 2007 despite returning to levels on a par with those of the pre-MiFID period.

Table 3 about here

Spreads declined steadily over the three months observed in 2009, despite high volatility in January and June 2009. Spreads did widen for Euronext stocks in January 2009, but this was weak compared with the surge in the volatility of the CAC 40 index and individual stocks over the period.

Depth did not display such a favorable change over the same period. Between October 2007 and September 2009, as shown in Table 3, average consolidated depth was divided by 3.7 for FTSE 100 stocks, by 2.2 for CAC 40 stocks, and by 1.7 for the SBF 80 stocks. Local depth showed a similar change between the two periods. Although substantial, the reduction in depth is far smaller than the decline in average transaction size. Whereas depth was divided by 3.7 on average for FTSE 100 stocks, average transaction size was divided by 5. Average size was divided by 2.6 for CAC 40 stocks and by 2 for SBF 80 stocks.

6.3. Changes in liquidity: A multivariate simple test

As a complement to univariate tests, I run fixed-effects panel regressions of monthly average measures of spreads and depth. Given that post-MiFID periods do not immediately follow the pre-MiFID period, this simple multivariate test is essential to check that changes in liquidity factors, such as volume, volatility, and price level, are not driving the univariate test's findings. Those factors are controlled for in the following model:

$$\begin{aligned} Liq_{im} = {} & \alpha_i + \alpha_1 \sigma_{im} + \alpha_2 \ln V_{im} + \alpha_3 1/P_{im} \\ & + \alpha_{01/09} B_{Jan09} + \alpha_{06/09} B_{Jun09} + \alpha_{09/09} B_{Sep09} + \varepsilon_{im}, \end{aligned} \tag{2}$$

where Liq_{im} is alternatively the average global quoted spread (GQS_{im}), the average global effective spread (GES_{im}), the average global depth (GD_{im}), the average local quoted spread (LQS_{im}), the average local effective spread (LES_{im}), and the average local depth (LD_{im}), for stock *i* over month *m*; σ_{im} measures volatility by the standard deviation of logarithmic daily closing returns for stock *i* over month *m*; $\ln V_{im}$ is the logarithm of the total trading volume in euros for stock *i* over month *m*; $1/P_{im}$ is the reciprocal of the average primary market's closing price of stock *i* during month *m*. B_{Jan09}, B_{Jun09}, and B_{Sep09} are binary variables equal to one in January 2009, June 2009, and September 2009 respectively, and set to zero otherwise. α_1, α_2, and α_3 are the coefficients of the control variables. $\alpha_{01/09}$, $\alpha_{01/09}$, and $\alpha_{01/09}$ denote the respective coefficients of B_{Jan09}, B_{Jun09}, and B_{Sep09}. The panel regressions are run with a fixed effect per stock (α_i) and with data covering the four month of October 2007, January 2009, June 2009, and September 2009. Dummies B_{Jan09}, B_{Jun09}, and B_{Sep09} play the role of fixed effects per month.

The estimates of the regressions of consolidated liquidity measures for the pooled sample and by stock index are reported in Panel A of Table 4. They indicate that global spreads decreased in the post-MiFID period with an increasing statistical and economic significance from January 2009 to September 2009. This spread improvement is most significant for FTSE 100 components. In contrast, SBF 80 mid-cap stocks do not exhibit significant spread reduction except for their global quoted spreads in September 2009. Global depth decreased significantly but this decrease did not follow the same pattern across time as the decrease in spreads: (1) the statistical significance of the decrease in depth was already as high in January 2009 as in later periods; (2) the economic significance of this depth reduction declined from January to September 2009. Another difference with spreads lies in that the decrease in depth is highly significant for the three stock indices and not only for large-capitalization indices.

Those observations, in particular the non-synchronization of changes in spreads with changes in depth, lead me to hypothesize that those changes are not driven by the same factors. Spread reductions seem to relate to the level of market competition as this market competition was weaker for the SBF 80 stocks in all periods and continually increased from January to September 2009 for all indices. At the opposite, most of the fall in depth happened before January 2009 for all indices and its statistical significance is not weaker for French medium-capitalization stocks, suggesting that the reduction in depth most probably has other determinants than the reduction in spreads, those determinants remaining to be determined at this stage.

Overall, those findings are supportive of hypothesis H1a and the weaker findings for SBF 80 stocks corroborate H1c.

Table 4 about here

Panel B of Table 4 reports the results for the regressions of local liquidity. These regressions produce the same findings with the difference that the coefficients of the monthly dummies have a slightly lower significance. This leads to reject H2a.

7. Comparing the pre-MiFID monopolistic-market liquidity with the post-MiFID multi-market liquidity: A two-stage panel regression analysis

In order to check to what extent the decrease in spreads and depth observed between October 2007 and September 2009 is actually assignable to market fragmentation, I test the relation between the level of fragmentation and liquidity measures with a two-stage regression model that accounts for the co-determination of fragmentation and liquidity. As widely discussed by O'Hara and Ye (2011), "An immediate challenge to testing for fragmentation effects on market quality are endogeneity issues". When testing the impact of market fragmentation on liquidity, endogeneity may arise at several levels: (1) at the firm level, if for example, the trading in large stocks is more fragmented, finding greater liquidity for more fragmented stocks could simply be the outcome of large stocks being more liquid; (2) at the order level, the choice of routing an order to a given venue or of splitting it between platforms is endogenous to the relative level of liquidity at each trading venue; (3) at the market level, liquidity and fragmentation may be co-determined, with not only fragmentation impacting liquidity but also liquidity determining fragmentation. For instance, insufficient liquidity in the primary market may induce traders to go to other markets. Conversely, if newly-established trading systems behave as satellite markets and therefore need a critical mass of orders to attract order flow, higher liquidity may be required to increase fragmentation. In brief, if the level of fragmentation is partly endogenous to liquidity, the residual terms of regressions of liquidity measures onto fragmentation measures may correlate with the independent-considered fragmentation variable. In order to remedy this potential bias, I implement a two-stage regression model in which the fragmentation index is first regressed on instrumental variables and the predicted values of fragmentation obtained from this first-stage regression serve as the regressor in the second-stage regression. Those regressions are conducted on monthly averages per stock over the four months of October 2007, January 2009, June 2009, and September 2009, with the intention of grasping the macro-trend in liquidity from the pre-MiFID period to the last post-MiFID period, with a deeper look into the cross-sections.

7.2. First-stage regressions

In the first stage, the fragmentation index of the lit order flow for stock *i* in month *m*,[17] denoted $LitFrag_{im}$, is modeled as follows:

$$LitFrag_{im} = a_0 + a_1 \ln MV_i + a_2 \ln V_{im} + a_3 \ln TS_{im} + a_4 Tick_{im} + a_5 MN_{im} + a_6 MC_{im} + \eta_{im}^{frag}, \quad (3)$$

where $\ln MV_i$ is the logarithm of stock *i*'s market value measured as the median between the start-of-month euro market capitalization in October 2007 and the end-of-month euro market capitalization in September 2009; $\ln V_{im}$ denotes the logarithmic monthly traded volume; $\ln TS_{im}$ denotes the logarithmic average trade size;[18] MN_{im} is the average number of trading platforms on which traders could find quotes for stock *i* during month *m*; and MC_{im} measures the intensity of the competition between those platforms as the average number of markets quoting either the best bid price or the best ask price divided by the average number of markets quoting stock *i*; $Tick_{im}$ is the average tick size relative to price on the primary exchange; and η_{im}^{frag} is the error term. Several minimum-tick-size changes were implemented

[17] This fragmentation index is the reciprocal of a Herfindhal index based on RMs' and MTFs' market shares as defined in Sub-section 5.1.

[18] In Regression (3), $\ln V_{im}$ and $\ln TS_{im}$ are the residuals of preliminary OLS regressions of respectively the average daily volume in logarithm and the average euro trade size in logarithm on $\ln MV_i$. This procedure was designed to eliminate colinearity. $\ln V_{im}$ and $\ln TS_{im}$ should be understood as the components of the logarithmic traded volume and the logarithmic trade size which are not correlated with market value.

by Euronext and the LSE in 2008 and 2009. As a result, $Tick_{im}$ varies across cross-sections and monthly periods. The complete history of those tick changes is provided in the Appendix. The prediction from first-stage regression (3), denoted $Lit\hat{F}rag_{im}$, then serves as a regressor for liquidity measures in the second stage.

In this first stage, I also model a proxy for AT. AT has been proved to impact liquidity (Hendershott, Jones, and Menkveld, 2011). Therefore, AT and fragmentation may have combined or competing effects on liquidity. I control for this by including an AT measure in the second-stage regressions of liquidity measures. To this aim, I proxy the level of AT by the negative of the turnover – euro volume in percentage of market value – of stock *i* in month *m* divided by the total number of quote changes per minute on both the primary exchange and Chi-X. This proxy, denoted AT_{im}, is built in the spirit of the "$algo\_trad_{it}$" measure of Hendershott et al. (2011), defined as the negative of dollar volume per electronic message, measured in hundreds of dollars. In the absence of data on electronic messages, I use the frequency of quote changes[19] in lieu of the number of messages at the denominator of the variable. To avoid a dominant effect of volume in the variance of the proxy, I scale volume by market value at the numerator.

To address any potential endogeneity, AT_{im} is modeled with the same instrumental variables as fragmentation, as follows:

$$AT_{im} = b_0 + b_1 \ln MV_i + b_2 \ln V_{im} + b_3 \ln TS_{im} + b_4 Tick_{im} + b_5 MN_{im} + b_6 MC_{im} + \eta_{im}^{hft}. \tag{4}$$

The value of AT_{im} predicted from regression (4), denoted $A\hat{T}_{im}$, is then used as a control variable in second-stage regressions.

[19] A quote change is considered to occur any time a price or a quantity is modified at one of the best quotes either on the primary exchange or on Chi-X.

7.3. Choice of instrumental variables

Any instrumental variable for AT or high-frequency trading is also a good instrument for lit fragmentation because this type of fragmentation is highly determined by AT, as suggested by Menkveld (2013). Indeed, algorithmic or high-frequency traders are the most eager for the low latency offered by alternative trading systems and the most likely to slice and dice orders across markets or to supply liquidity at several venues.

First, the effective entry in business of new electronic order books, measured by MN_{im}, and their ability to be competitive in quotes relative to incumbent markets, measured by MC_{im}, are natural instruments for both AT and lit fragmentation. New electronic order books use technologies tailored for AT, and by attracting AT, they contribute to fragment the order flow. I consider them as exogenous factors because they are greatly driven by capital investments, marketing efforts, and corporate strategies implemented by the trading industry in the background of markets.

Second, market size ($\ln MV_i$) and trading volume ($\ln V_{im}$) are inevitable instruments for AT. Indeed, the portion of AT corresponding to high-frequency market making is expected to be more profitable and thus more developed for heavily traded stocks. Consistently, Brogaard, Hendershott, and Riordan (2014) observe that high-frequency traders are more concentrated in large stocks. Market size and trading volume are also commonly used as regressors for fragmentation (cf. Madhavan, 2012; O'Hara and Ye, 2011) as the order flow of larger and more traded stocks usually fragment more.

Third, trade size ($\ln TS_{im}$) is a direct indicator of the presence of high-frequency traders because they trade in small lots by nature. For that reason, it serves as an instrument for both AT and lit fragmentation. Order size has also often been considered as a determinant of routing strategies, leading several researchers (Madhavan and Cheng, 1997; Bessembinder, 2003; O'Hara and Ye, 2011) to use trade size as a first-stage regression instrument in order to address the order-level endogeneity issue.

The last instrument considered is the average relative tick size ($Tick_{im}$). According to Yao and Ye (2014), tick size is a key factor in AT and multi-platform market-making strategies. O'Hara, Saar, and Zhong (2014) observe that high-frequency trading firms that operate as market makers on the NYSE take on a more prominent role in liquidity provision for stocks with larger relative tick sizes. Peng, Jarnecic, and Liu (2015) find that tick-constrained stocks tend to trade more on Chi-X to avoid queuing, proving that tick size impacts fragmentation. This is confirmed by O'Hara et al. (2015) who find that, with a larger relative tick size, some volume shifts from the primary market to other trading venues. This first-stage instrument is of particular interest as several tick size changes occurred inside my observation period (see the Appendix).

7.4. Second-stage regressions

The second-stage regressions of liquidity measures are designed as follows for the pooled sample:

$$Liq_{im} = \beta_m + \beta_c.Controls_{im} + \beta_{AT}\hat{AT}_{im} + \beta_{frag}Lit\hat{F}rag_{im} + \varphi^1_{im}. \tag{5}$$

β_m is a fixed effect per month. $Controls_{im}$ is a vector of control variables comprising: σ_{im}, the close price return volatility of stock *i* in month *m*; market size $\ln MV_i$; traded volume $\ln V_{im}$ as defined in equation (3); and $1/P_{im}$, the reciprocal of the average closing price. β_c is a 4-dimension coefficient vector. Variable $\widehat{AT}_{im}$ controls for the level of AT. $Lit\hat{F}rag_{im}$, which measures lit fragmentation, is the main variable of interest. φ^1_{im} is a residual term.

For the analysis by index sub-samples, a variable interacting market size and fragmentation is introduced as a complementary test for H1c and H2c:

$$Liq_{im} = \beta + \beta_c.Controls_{im} + \beta_{hft}\hat{AT}_{im} + \beta_{frag}Lit\hat{F}rag_{im} + \beta_{size}Size_i \times Lit\hat{F}rag_{im} + \varphi^2_{im}. \quad (6)$$

$Size_i$ denotes the market size quartile of stock *i* inside its index. It takes four discrete values from one to four, one corresponding to the quartile of the largest capitalizations and four corresponding to the quartile of the smallest.

Finding significantly negative (positive) values of β_{frag} in the regressions of global spreads (depth) would be in support of H1a. Finding significantly positive (negative) values of β_{frag} in the regressions of local spreads (depth) would be in support of H2a. Finding significantly negative (positive) values of β_{frag} combined with significantly positive (negative) values of β_{size} in the regressions of global spreads (depth) would be in support of H1c, while obtaining a significantly positive (negative) value of β_{frag} with a significantly positive (negative) value of β_{size} in the regressions of local spreads (depth) would be in support of H2c.

7.5. Results

First-stage regressions are estimated for each index separately. Second-stage regressions are estimated for global and local liquidity measures. Regression (5) is run over the total pooled sample and each index sub-sample whereas regression (6) is run on a by-index basis only. Results are reported in Table 5.

Table 5 about here

Consistent with Hendershott et al. (2011), all regressions show that spreads and depth decrease with AT. After controlling for AT, all liquidity measures either improve with lit fragmentation or are not significantly affected. The results for the pooled sample indicate that, global and local spreads significantly tighten with lit fragmentation, coefficient β_{frag} being significantly negative at the 1% level for all spread measures. The economic significance of the beneficial impact of fragmentation on spreads is however much greater than that of AT. For instance increasing the AT variable by one standard-deviation engenders a decrease in global quoted spreads of –0.74 basis points while, in comparison, increasing lit fragmentation by one standard-deviation reduces global quoted spreads by –4.63 basis points. Depth is significantly affected by lit fragmentation neither at the global and nor at the local level.

This either beneficial or not significant effect of lit fragmentation on liquidity holds in the by-index analysis, with the exception of a harmful effect on the depth of Euronext small stocks (SBF 80 index). The stocks that most benefit from fragmentation are those of the FTSE 100, for which all measures of liquidity significantly improve with fragmentation at the 1% statistical threshold. For CAC 40 stocks, spreads are not significantly impacted but their global depth increases with fragmentation. Those findings provide evidence in support of H1a and in contradiction with H2a, so that H2c becomes irrelevant. β_{size} is significantly negative (positive) in FTSE 100 spread (depth) regressions, which indicates that liquidity benefits from lit fragmentation are more pronounced for the smallest components of the FTSE 100 index. For CAC 40 stocks, β_{size} does not significantly differ from zero in spread regressions; and it is either insignificant or significantly positive at the 10% level in depth regressions. Those findings lead to reject H1c, according to which the competition gains of shifting from consolidated to fragmented markets should be greater for the largest components of the FTSE 100 and the CAC 40 indices.

H1c is however partly supported when contrasting the findings for SBF 80 stocks with those for the CAC 40. The global quoted spreads, the global effective spreads, and the local effective spreads of SBF 80 stocks negatively correlate to fragmentation, but converse to CAC 40 stocks, their global and local depth is adversely affected: all in all, the small stocks of Euronext benefit less from the shift to fragmented markets than the large ones. Further, the adverse effect of fragmentation on the depth of SBF 80 stocks is more pronounced for the largest components ($\beta_{size} \underset{5\%}{>} 0$ for global depth and $\beta_{size} \underset{10\%}{>} 0$ for local depth). In total for SBF 80 medium-capitalization stocks: H1a, and thereby H1c, are rejected; H2a is rejected with regard to spreads but it is supported by the findings on depth; the significantly positive value of β_{size} in the depth regressions leads to reject H2c. Last, comparing the findings for the FTSE 100 and CAC 40 large stocks with those for the SBF 80 medium stocks show that lit fragmentation is more beneficial to large stocks, which pleads in favor of H1c.

I then set out to investigate why the statistical significance and the economic magnitude of liquidity benefits are much greater for FTSE 100 constituents than for CAC 40 constituents. A possible explanation is that before MiFID, electronic trading was less developed at the LSE than on Euronext. According to the statistics provided in Table 2, nearly 44% of the LSE traded volume in FTSE 100 stocks was executed by dealers outside the book in October 2007. This share dramatically shrank with the expansion of alternative trading platforms to be less than 14% in September 2009. This might explain why FTSE 100 securities benefited more from lit market competition. To test this hypothesis I extended regression (6), for the FTSE 100 sub-sample, with term $\beta_{obs} OffBook_i^{preMiFID} \times Lit\hat{F}rag_{im}$, where $OffBook_i^{preMiFID}$ is the share of off-book trading in the LSE traded volume of stock *i* in October 2007 and β_{obs} is the associated coefficient. Estimates are provided in Table 5. β_{obs} is found to be significantly negative at the 1% statistical threshold in spread regressions and it turns out to be insignificant for depth. This supports the view that stocks with more off-book trading, that is less electronic trading before the fragmentation event, had their spreads more substantially improved by market competition.

8. A time series analysis of the relation between lit and dark fragmentation and liquidity in fragmented markets

While Sections 6 and 7 compare market liquidity in two different trading environment and regulatory regimes, this section focuses on how liquidity relates to fragmentation in a multi-market trading structure in which fragmentation has already reached a substantial level. To test this relation, I conduct panel analyses on the basis of daily fragmentation and liquidity measures over 63 trading days spreading from 1 September 2009 to 30 November 2009. The sample consists of 152 stocks distributing between 64 FTSE-100 constituents, 32 CAC-40 constituents, and 56 SBF-80 constituents, selected according to the sampling procedure described in Section 4. For that sample and that period the data allow measuring the level of dark trading with BOAT and LSE trade report data available in the post-MiFID period only. The analysis of this section thus examine both the effect of lit fragmentation (variable *LitFrag*) and the effect of dark fragmentation (variable *Dark*).

8.1. Regression design

To address endogeneity issues, I again implement a two-stage methodology which consists of modeling the lit and dark fragmentation daily measures as a function of instrumental variables in a first stage and using their predictions as regressors of daily liquidity measures in the second stage.

First-stage regressions are designed as follows:

$$LitFrag_{it} = c_0 + c_1 \ln MV_i + c_2 \ln V_{it} + c_3 \ln TS_{it} + c_4 MC_{it} + c_5 Tick_{it} + c_6 LitFrag_{it-1} + u_{it}^{frag}; \quad (7)$$

$$Dark_{it} = d_0 + d_1 \ln MV_i + d_2 \ln V_{it} + d_3 \ln TS_{it} + d_4 \ln DiffTS_{it} + d_5 MC_{it} + d_6 Tick_{it} + d_7 Dark_{it-1} + u_{it}^{dark}. \quad (8)$$

$LitFrag_{it}$ and $Dark_{it}$ are respectively the reciprocal of the Herfindhal fragmentation index and the share of dark volumes, as defined in Sub-section 5.1,[20] for stock i on day t. V_{it} denotes volume as previously defined. MV_i equals the market capitalization of stock i on the first day of the observation period. MC_{it} is the level of competition between markets, measured by the average number of markets quoting the best bid and ask prices divided by the average number of markets with quotes. This variable is computed in the same way as in Subsection 7.2 but on a daily basis. TS_{it} is the daily average euro size of lit trades, i.e., trades executed during the continuous session on lit venues. $DiffTS_{it}$ is the difference in size between lit trades and dark trades. $Tick_{it}$ is the tick size relative to price on the primary exchange. On 1 September 2009, both Euronext and the LSE were applying a dynamic tick size schedule for the stocks of the sample (cf. the appendix). Therefore, $Tick_{it}$ varies across cross-sections and dates not only because it is relative to price but also because the price may switch from one price class to the other in the tick size schedule. Further, a new dynamic tick size regime was implemented by the LSE on 21 September 2009 for the 12 stocks listed in the appendix. u_{it}^{frag} and u_{it}^{dark} are residual terms. Regressions (7) and (8) are OLS-estimated by stock index and include one lag of the dependent variable.

The reasons for using market value, volume, trade size, relative tick size, and multi-market competition level as first-stage instrumental variables are the same as those exposed in Subsection 7.3. Instrument MN, that is the average number of markets quoting prices for a stock, is abandoned here because its variance is insufficient to provide explanatory power on a daily frequency after September 2009. The modelling of $Dark_{it}$ in Equation (8) includes an additional instrument, $DiffTS_{it}$, which measures the average trade size difference between lit and dark markets. A central motivation for trading in dark venues is to find immediacy on large trades, i.e., depth that lit venues are unable to provide. The larger dark trades relative to

[20] For this analysis, the $Litfrag_{it}$ and $Dark_{it}$ fragmentation metrics are based on continuous trading only.

lit trades, the greater the ability of dark markets to provide large traders with immediacy in comparison with lit venues, and the greater the incentive for large traders to deal outside lit order books.

At the second stage, daily liquidity measures are regressed onto lit fragmentation and dark trading as predicted from the first stage and respectively denoted $Lit\hat{Frag}_{it}$ and $\hat{D}ark_{it}$:

$$Liq_{it} = \gamma_i + \gamma_t + \gamma_c.Controls_{it} + \gamma_{AT}\hat{AT}_{it} + \gamma_{frag}\hat{L}itFrag_{it} + \gamma_{dark}\hat{D}ark_{it} + v_{it}\,. \tag{9}$$

Dependent variable Liq_{it} is alternatively the global or local average quoted spread, average effective spread, and average best-limit depth of stock *i* on day *t*. $Controls_{it}$ is a control variable vector composed of daily volatility measured by the mid-quote range of stock *i* on day *t*, volume calculated as the daily euro trading volume in logarithm, and price level represented by the reciprocal of the primary market's closing price of stock *i* on day *t*. AT_{it} is calculated in the same way as in Sub-section 7.2 but on a daily basis. As the AT_{it} variable may be subject to an endogeneity bias as fragmentation measures, it is also modeled in a first-stage regression. Instruments used are the same as those used for $LitFrag_{it}$, that is market size ($\ln MV_i$), volume ($\ln V_{it}$), trade size ($\ln TS_{it}$), relative tick size ($Tick_{it}$), and the level of competition between trading venues (MC_{it}), plus the value of AT observed the day before (AT_{it-1}). The value predicted from this first-stage procedure, denoted $\hat{AT}_{it}$, is the regressor used in (9). γ_i and γ_t denotes cross-sections and time series fixed effects respectively. v_{it} is a residual term. Standard errors are clustered by stocks.

The main coefficients of interest in Regression (9) are those of variables $\hat{L}itFrag_{it}$ and $\hat{D}ark_{it}$. Finding significantly negative (positive) values of γ_{frag} in the regressions of global spreads (depth) would be in support of H1b. Finding significantly positive (negative) values of γ_{frag} in the regressions of local spreads (depth) would be in support of H2b. Finding positive (negative) values of γ_{dark} for spreads (depth) would support H3a while finding negative (positive) values of γ_{dark} for spreads (depth) would support H3b.

8.2. Results

Second-stage panel estimates for the pooled sample and for subsamples by index are displayed in Table 6. AT is found to be associated with lower spreads but also lower depth, consistent with Hendershott et al. (2011), with the exception that the improvement in spreads is not significant for SBF 80 stocks.

Lit fragmentation is not found to deteriorate liquidity except in the case of the smallest stocks, i.e., SBF 80 stocks, for which global and local depth is negatively correlated with *LitFrag* (Panel D of Table 6). On the contrary, for the pooled sample (Panel A of Table 6), spreads decrease with lit fragmentation, at the 1% significance level for quoted spreads and at the 10% level for effective spreads. Global depth is not significantly affected. Local depth is negatively impacted but this adverse effect is related to SBF 80 stocks only. Positive effects of lit fragmentation remain significant by sub-samples for the FTSE 100 and the CAC40. Effective spreads and depth of FTSE 100 stocks (Panel B of Table 6) improves with lit fragmentation both globally across venues and locally on the primary exchange, while their quoted spreads are not significantly affected. For CAC 40 stocks (Panel C of Table 6), lit fragmentation is beneficial to quoted spreads and global depth while it does not significantly impact effective spreads and local depth. As already mentioned, those positive effects do not benefit small stocks: the spreads of SBF 80 stocks (Panel D of Table 6) are not significantly affected by lit fragmentation and their depth decreases with both AT and lit fragmentation.

Table 6 about here

Dark fragmentation does not harm liquidity for any sample considered. It contributes to improving the liquidity of large stocks either by improving global and local depth as for FTSE 100 components, or by tightening global and local effective spreads as for CAC 40 stocks. Other measures of liquidity are not affected. Results on dark trading fail to be significant for SBF 80 components.

In conclusion, according to this time series analysis, hypothesis H1b, which states that lit fragmentation has positive competition effects on global liquidity, is validated for large stocks but rejected for small ones. Hypothesis H2b, according to which lit fragmentation harms local liquidity on the primary exchange, is rejected for large stocks. For small stocks, H2b is also rejected when considering global and local spreads but it cannot be rejected with respect to global and local depth. Regarding dark fragmentation, I reject hypothesis H3a, according to which dark trading would harm liquidity, and I fail to reject H3b which hypothesizes that dark trading enhances liquidity by creating positive risk sharing effects.

9. Conclusion

The coming into force of MiFID in November 2007 has caused increased competition, higher complexity, and dramatic change in trading in Europe. This study draws on high-frequency data from the most active markets for FTSE 100 constituents, CAC 40 constituents, and medium capitalization stocks of the SBF 80 index, before and after MiFID. It shows that the trading in European large equities had become substantially fragmented two years after the enforcement of MiFID. Primary exchanges, however, were still dominant players in terms of volume and price competitiveness. Three MTFs had built significant market shares: Chi-X in all categories of equities, BATS Europe more specifically in large UK securities, and Turquoise more specifically in Euronext large equities. Over the two years following MiFID, spreads decreased while depth and trade size declined dramatically, the decline in trade size being greater than that in depth. The pre/post-MiFID multivariate comparison shows that spreads narrowed gradually as the fragmentation of lit order flow increased. The spread reduction was less significant for mid-cap stocks than for large-cap stocks. Among large stocks, the decrease in spreads was more significant for LSE-listed stocks which were subject to fiercer competition from Chi-X. In contrast with spreads, the depth reduction identified with univariate tests did not increase in significance with fragmentation, meaning that it was likely driven by some other factor. This factor turns out to be AT in the rest of the analysis.

A multivariate two-stage approach involving AT and fragmentation measures shows that the post-MiFID reduction in spreads results more from lit fragmentation that from AT and that the post-MiFID reduction in depth results from AT. Liquidity benefits from lit fragmentation are greater for large-capitalization stocks and for stocks that had less electronic trading before MiFID. One caveat to put on about the pre/post-MiFID comparison is that it may be altered by the liquidity decline in the aftermath of the 2008 subprime crisis even though the post-MiFID periods were carefully selected. If so, the main conclusions would nevertheless be unchanged as the bias would be an underestimation of market competition benefits.

The post-MiFID time-series analysis confirms that lit market fragmentation should be viewed as value-creating competition that benefits global liquidity. In most cases, it positively impacts the local liquidity of the primary market as well. The spreads of large stocks decrease with both AT and lit fragmentation. The best-quote depth of large stocks increases with lit fragmentation, adverse effects on depth being the outcome of AT. This positive effect of fragmentation on depth is more significant for global depth across markets than for local depth on the primary exchange. Whether this inflated consolidated depth is real or artificially created by orders replicated across trading venues remains to be determined in future research.

There however are some limitations to those benefits. After an equilibrium level of market fragmentation is reached, marginal gains in liquidity become relatively low in terms of economic magnitude, even if their statistical significance is high. More importantly, lit fragmentation harms the market depth of small stocks without contributing to improving their spreads.

Finally, I find that dark fragmentation positively impacts liquidity, or at worst does not affect it. This result however leaves room for further research on dark trading and its impact on liquidity. In particular, the causal links between dark trading and the various dimensions of liquidity should be examined, and the various forms of dark trading should be distinguished.

Appendix. History of minimum-tick-size changes

A. Tick size changes on Euronext

On 19 February 2007, Euronext started decimal trading with a fixed tick size of 0.01 for all stocks. In 2008, Euronext began the implementation of multi-decimal trading with the application of a fixed tick size of €0.005 for a limited number of stocks. This implementation took place on 28 January 2008 for some Belgian and Portuguese stocks, and on 7 April 2008 for a bunch of Dutch and French stocks. The stocks of my sample impacted by this change are listed in Table A1.

Table A.1

Stock name	ISIN code	Implementation date
ALCATEL-LUCENT	FR0000130007	
STMICROELECTRONICS	NL0000226223	
FRANCE TELECOM	FR0000133308	7 April 2008
VIVENDI	FR0000127771	
TOTAL	FR0000120271	

Source: Info-Flash Euronext 28 December 2007.

On 26 May 2008, Euronext changed the tick size of two highly liquid but lower priced stocks from €0.005 to €0.001. Those stocks are STMICROELECTRONICS in Paris and AEGON in Amsterdam (Source: Info-Flash Euronext 23 May 2008), of which the first one is my sample.

As of 1 September 2008, a fixed tick size of three decimal places was implemented for a restricted list of stocks including the components of the CAC 40 index but not those of the SBF 80. The value of this new tick size was determined depending on the average trade price over the last two months, with a value of €0.005 where the average price exceeded €10 and a value of €0.001 otherwise. This new fixed tick size of €0.005 applied to all CAC 40 securities in our sample except ALCATEL-LUCENT for which the tick size was moved to €0.001. Then, from 15 December 2008, those price-depending tick sizes were implemented on a dynamic basis for all CAC 40 and SBF 80 stocks.

Last, on 16 July 2009, Euronext applied the European harmonized tick size regime for a list of blue-chip stocks including CAC 40 and SBF 80 securities. The dynamic tick size table implemented for those stocks follows Table A.2

Table A.2

Price from	To	Tick size
€0	€9.999	€0.001
€10.000	€49.995	€0.005
€50.000	€99.99	€0.01
€10.000	∞	€0.05

Source: Info-Flash Euronext 2 July 2009.

B. Tick size changes on the LSE

Before 4 December 2007, the dynamic tick size regime presented in Table B.1 was in use for FTSE 100 securities (market segment "SET1" at the LSE).

Table B.1

From	To	Tick size
Price in GBX		
0	499.75	0.25
500.0	999.5	0.5
1,000	∞	1
Price in GBP / USD / EUR		
0	4.9975	0.0025
5.000	9.995	0.005
10.00	∞	0.01

On 4 December 2007, a new dynamic tick size schedule was introduced. Table B.2 displays the regime then implemented for market segment "SET1" to which my sample stocks belongs.

On 19 May 2008, five FTSE 100 index securities moved from the dynamic price format code schedule to specific static tick sizes as shown in Table B.3.

On 22 June 2009, 12 other FTSE 100 stocks moved from the dynamic price format code schedule to specific static tick sizes and two FTSE 100 stocks had their static tick sizes revised in compliance with Table B.4.

Table B.2

From	To	Tick size
Price in GBX		
0	9.99	0.01
10	199.9	0.1
200	499.75	0.25
500	999.5	0.5
1,000	∞	1
Price in GBP / USD / EUR		
0	0.0999	0.0001
0.1	4.9975	0.0025
5	9.995	0.005
10	∞	0.01

Source: LSE Service Announcement 106-07- 27 November 2007.

Table B.3

Stock name	ISIN code	Static tick size	Trading currency
BP	GB0007980591	0.25	
GLAXOSMITHKLINE	GB0009252882	0.5	
HSBC HLDGS	GB0005405286	0.25	GBX
TESCO	GB0008847096	0.1	
VODAFONE GROUP	GB00B16GWD56	0.05	

Source: LSE Service Announcement 36-08- 6 May 2008.

Table B.4

Stock name	ISIN code	Static tick size	Trading currency
ANGLO AMERICAN	GB00B1XZS820	0.5	
ASTRAZENECA	GB0009895292	0.5	
BARCLAYS	GB0031348658	0.05	
BHP BILLITON	GB0000566504	0.5	
BP	GB0007980591	0.05	
BT GROUP	GB0030913577	0.05	
FRIENDS PROVIDENT[21]	GB00B3T69350	0.01	GBX
HSBC HLDGS	GB0005405286	0.05	
LEGAL & GENERAL	GB0005603997	0.01	
LLOYDS GRP.	GB0008706128	0.01	
OLD MUTUAL	GB00B77J0862	0.01	
RIO TINTO	GB0007188757	0.5	
ROYAL BANK SCOT	GB00B7T77214	0.005	
XSTRATA	JE00B4T3BW64	0.1	

Source: LSE Service Announcement 001/170609- 17 June 2009.

In July 2009, the LSE announced that it would apply the FESE tick size harmonization to FTSE 100 and FTSE 250 securities. As a consequence, from 3 August 2009, a new dynamic price format schedule complying with "FESE Table 2" (cf. Table B.5) was introduced for FTSE 100 securities. Further, a number of FTSE 100 stocks were placed on static tick sizes contained within "FESE Table 1" while others which were on a static price format codes

[21] The ISIN code of Friends Provident was GB0030559776 before 15 June 2009.

were moved to the new dynamic price format schedule. Details of those changes are provided in Table B.6. Stocks remaining on a static tick size with no change are listed in Table B.7.

Table B.5

Price (in GBX/GBP/USD/EUR) from	To	Tick size
0	0.4999	0.0001
0.5	0.9995	0.0005
1	4.999	0.001
5	9.995	0.005
10	49.99	0.01
50	99.95	0.05
100	499.9	0.1
500	999.5	0.5
1,000	4,999	1
5,000	9,995	5
10,000	∞	10

Source: LSE Service Announcement 001/170709- 17 July 2009.

Table B.6

Stock name	ISIN code	New tick size	Trading currency
FRIENDS PROVIDENT	GB00B3T69350	Dynamic	GBX
LEGAL & GENERAL	GB0005603997	Dynamic	
OLD MUTUAL	GB00B77J0862	Dynamic	
ROYAL BANK SCOT	GB00B7T77214	Dynamic	
XSTRATA	JE00B4T3BW64	Dynamic	
TESCO	GB0008847096	Dynamic	
HSBC HLDGS	GB0005405286	0.1 (Static)	
ROYAL DUTCH SHELL ‘A’	GB00B03MLX29	0.5 (Static)	

Source: LSE Service Announcement 001/170709- 17 July 2009
& LSE Service Announcement 001/200709- 20 July 2009

Table B.7

Stock name	ISIN code	Static tick size	Trading currency
ANGLO AMERICAN	GB00B1XZS820	0.5	GBX
ASTRAZENECA	GB0009895292	0.5	
BARCLAYS	GB0031348658	0.05	
BHP BILLITON	GB0000566504	0.5	
BP	GB0007980591	0.05	
BT GROUP	GB0030913577	0.05	
GLAXOSMITHKLINE	GB0009252882	0.5	
LLOYDS GRP.	GB0008706128	0.01	
RIO TINTO	GB0007188757	0.5	
VODAFONE GROUP	GB00B16GWD56	0.05	

Source: LSE Service Announcement 001/170709- 17 July 2009

In August 2009, the LSE introduced a second dynamic tick size regime (cf. Table B.8) with effect from 21 September 2009 to enhance price granularity for most liquid FTSE 100 stocks. The stocks submitted to this regime moved to a new market segment, “SET0”, created for the purpose. At the time of its introduction, the SET0 tick size regime was applied to the 12 FTSE 100 securities listed in Table B.9.

Table B.8

Price (in GBX/GBP/USD/EUR) from	To	Tick size
0	0.9999	0.0001
1	4.9995	0.0005
5	9.999	0.001
10	49.995	0.005
50	99.99	0.01
100	499.95	0.05
500	999.9	0.1
1,000	4,999.5	0.5
5,000	9,999	1
10,000		5

Source: LSE Service Announcement 001/180809 - 18 August 2009.

Table B.9

Stock name	ISIN code	Implementation date
ANGLO AMERICAN	GB00B1XZS820	
ASTRAZENECA	GB0009895292	
BARCLAYS	GB0031348658	
BHP BILLITON	GB0000566504	
BP	GB0007980591	
BT GROUP	GB0030913577	21 September 2009
GLAXOSMITHKLINE	GB0009252882	
HSBC HLDGS	GB0005405286	
LLOYDS GRP.	GB0008706128	
ROYAL DUTCH SHELL ‘A’	GB00B03MLX29	
RIO TINTO	GB0007188757	
VODAFONE GROUP	GB00B16GWD56	

Source: LSE Service Announcement 001/180809 - 18 August 2009.

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Table 1. Relative market shares and trading volumes in September 2009

	Trading volumes, EUR 000	Euronext	LSE	Deutsche Boerse	Chi-X	BATS Europe	Turquoise	Nasdaq OMX Europe	PLUS	Dark trades
Part A. ***Auctions and continuous trading***										
FTSE 100	97,610,438	0.00%	55.65%	0.00%	13.93%	5.05%	4.43%	0.96%	0.68%	19.30%
CAC 40	99,760,432	55.08%	0.55%	0.94%	11.63%	2.96%	3.96%	0.91%	0.00%	23.97%
SBF 80	13,959,377	70.53%	0.34%	0.20%	10.18%	1.11%	2.75%	0.40%	0.00%	14.48%
Part B. ***Continuous trading only***										
FTSE 100	84,694,596	0.00%	53.35%	0.00%	16.05%	5.82%	5.10%	1.10%	0.78%	17.79%
CAC 40	83,918,213	51.51%	0.57%	1.03%	13.82%	3.52%	4.71%	1.08%	0.00%	23.75%
SBF 80	12,131,266	70.18%	0.37%	0.22%	11.71%	1.28%	3.17%	0.46%	0.01%	12.59%

Note: This table shows the relative market shares of trading venues in September 2009 for each sample of stocks. The second column shows total trading volumes in thousands of euros. All trading volumes, regulated and OTC, are included in the statistics. OTC trades and trades executed by SIs included in the statistics are those reported by BOAT and the LSE trade reporting service. They are aggregated in the "dark trades" column. Part A of the table reports market shares when primary market auction transactions are included. Part B reduces the sample to transactions executed in continuous trading.

Table 2. Distribution of trading volumes between RMs and MTFs - October 2007 to September 2009

	Trading volumes EUR 000	Euronext	LSE			Deutsche Boerse	Chi-X	BATS Europe	Turquoise	Nasdaq OMX Eur.	PLUS	Fragmentation index
			Total	Order book	Off order-book							
FTSE 100												
Oct. 2007	191,653,000	0.00%	99.99%	56.46%	43.53%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%	1.00
Jan. 2009	76,368,643	0.00%	75.94%	67.44%	8.50%	0.00%	14.72%	1.72%	5.82%	0.29%	1.52%	1.66
June 2009	90,706,502	0.00%	71.59%	59.92%	11.67%	0.00%	17.14%	4.36%	4.58%	0.71%	1.62%	1.83
Sep. 2009	78,769,760	0.00%	68.96%	55.39%	13.57%	0.00%	17.26%	6.26%	5.49%	1.19%	0.84%	1.95
CAC 40												
Oct. 2007	105,322,607	96.45%	2.92%	---	---	0.63%	0.00%	0.00%	0.00%	0.00%	0.00%	1.07
Jan. 2009	66,111,453	76.41%	1.63%	---	---	0.61%	13.07%	1.28%	6.93%	0.08%	0.01%	1.65
June 2009	67,564,708	70.35%	1.18%	---	---	1.30%	16.42%	6.18%	3.74%	0.84%	0.00%	1.90
Sep. 2009	75,847,834	72.44%	0.72%	---	---	1.24%	15.29%	3.89%	5.21%	1.19%	0.01%	1.81
SBF 80												
Oct. 2007	17,582,701	99.99%	0.00%	---	---	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	1.00
Jan. 2009	8,569,064	92.87%	1.15%	---	---	0.01%	5.11%	0.31%	0.51%	0.03%	0.01%	1.16
June 2009	9,625,224	80.61%	0.95%	---	---	0.02%	13.87%	2.11%	2.26%	0.19%	0.00%	1.49
Sep. 2009	11,937,753	82.47%	0.40%	---	---	0.23%	11.90%	1.30%	3.22%	0.47%	0.01%	1.44

Note: This table shows the relative market shares of trading venues for each sample of stocks in each of the observation periods. The statistics are based on a transaction universe reduced to RMs and MTFs. Transactions executed during opening and closing auctions in the primary market are included. Dark trades are excluded. The second column shows total trading volumes in thousands of euros. The last column gives a fragmentation index calculated by taking the inverse of the sum of the squares of market shares.

Table 3. Comparison of quoted spreads, effective spreads, depth at the best limits, and trade sizes from October 2007 to September 2009

		Volatility		Quoted spreads		Effective spreads		Depth		
Sample	**Period**	**Index volatility**	**Average stock return volatility**	**Global**	**Primary market**	**Global**	**Primary market**	**Global**	**Primary market**	**Average trade size**
FTSE 100	**Oct. 2007**	0.91%	1.66%	0.0921%	0.0921%	0.0744%	0.0744%	531.017	531.017	91.227
	Jan. 2009	1.90%	9.99%	0.0898%	0.1129%**	0.0721%	0.0716%	118.782***	113.545***	18.037***
	Jun. 2009	1.16%	6.03%	0.0638%***	0.0864%	0.0669%*	0.0756%	137.711***	159.549***	19.924***
	Sep. 2009	0.77%	3.81%	0.0543%***	0.0707%***	0.0591%***	0.0680%	142.950***	134.107***	18.444***
CAC 40	**Oct. 2007**	0.70%	1.37%	0.0604%	0.0617%	0.0493%	0.05%	132.637	137.146	44.557
	Jan. 2009	2.42%	9.74%	0.0644%	0.0943%***	0.0614%***	0.0612%**	43.280***	41.015***	16.151***
	Jun. 2009	1.43%	4.41%	0.0502%**	0.0735%**	0.0506%	0.05%	44.582***	43.194***	14.83***
	Sep. 2009	0.90%	3.58%	0.0446%***	0.0595%	0.0414%**	0.0408%**	59.401***	54.846***	17.208***
SBF 80	**Oct. 2007**	0.62%	1.63%	0.1452%	0.1454%	0.1130%	0.1130%	35.028	35.222	16.077
	Jan. 2009	1.85%	12.12%	0.2502%***	0.2644%***	0.2010%***	0.2010%***	16.937***	16.919***	7.858***
	Jun. 2009	1.37%	4.99%	0.1615%	0.1945%***	0.1408%*	0.1394%*	17.955***	18.216***	6.988***
	Sep. 2009	0.88%	4.85%	0.1198%**	0.1399%	0.1129%	0.1117%	21.113***	21.594***	7.842***

Note: This table reports averages of volatility measures, spread measures, depth, and trade size, by month and by sample. Volatility is measured in two ways: the first column shows the volatility of daily returns on the index during the month; the second column is the capitalization-weighted average volatility of daily returns for the stocks in the sample. Average quoted spreads, average effective spreads, and average depths are measured globally across markets and locally in the primary market. Effective spread statistics are based on a reduced universe comprising transactions exchanged in on-book continuous trading. Depth and trade size are expressed in thousands of euros. Depth only includes disclosed quantities at the best quotes. ***,**,* means that the difference between the average in consideration and that of October 2007 is statistically different from zero at the 1%, 5%, or 10% level respectively.

Table 4. One-stage panel regressions of monthly liquidity measures

	Pooled sample	FTSE 100	CAC 40	SBF 80	Pooled sample	FTSE 100	CAC 40	SBF 80	Pooled sample	FTSE 100	CAC 40	SBF 80
Panel A – Global liquidity	**Global quoted spread (*GQS_{im}*)**				**Global effective spread (*GES_{im}*)**				**Global best-limit depth (*GD_{im}*)**			
Jan. 2009 dummy ($B_{01/09}$)	-0.00002	-0.00063***	-0.00008**	0.00052**	0.00009	-0.00041***	0.00001	0.00051***	-0.69604***	-0.79258***	-0.85670***	-0.41534***
	(-0.24)	(-7.38)	(-2.06)	(2.46)	(1.11)	(-6.24)	(0.26)	(2.75)	(-14.35)	(-8.05)	(-9.58)	(-6.68)
Jun. 2009 dummy ($B_{06/09}$)	-0.00050***	-0.00095***	-0.00023***	-0.00022	-0.00013*	-0.00049***	-0.00008**	0.00013	-0.61521***	-0.60153***	-0.84921***	-0.42931***
	(-5.83)	(-12.62)	(-7.87)	(-1.38)	(-1.78)	(8.45)	(-2.42)	(0.91)	(-14.60)	(-6.90)	(-11.89)	(-9.25)
Sep. 2009 dummy ($B_{09/09}$)	-0.00067***	-0.00105***	-0.00023***	-0.00048***	-0.00025***	-0.00053***	-0.00012***	-0.00005	-0.50359***	-0.54449***	-0.61695***	-0.31897***
	(-8.58)	(14.15)	(-9.20)	(-3.56)	(-3.80)	(-9.33)	(-4.28)	(-0.42)	(-13.22)	(-6.33)	(-9.94)	(-7.95)
Adjusted R^2	0.8353	0.8772	0.8890	0.8503	0.8362	0.8291	0.8580	0.8466	0.9306	0.8911	0.9017	0.8573
Panel B – Local liquidity	**Local quoted spread (*LQS_{im}*)**				**Local effective spread (*LES_{im}*)**				**Local best-limit depth (*LD_{im}*)**			
Jan. 2009 dummy ($B_{01/09}$)	0.00015	-0.00040***	0.00019***	0.00058***	0.00008	-0.00041***	0.00002	0.00051***	-0.73178***	-0.78983***	-0.92423	-0.40662***
	(1.59)	(-4.75)	(5.05)	(2.74)	(0.99)	(-6.19)	(0.52)	(2.75)	(-16.10)	(-9.54)	(-12.16)	(-6.38)
Jun. 2009 dummy ($B_{06/09}$)	-0.00023***	-0.00071***	-0.00001	0.00010	-0.00011	-0.00041***	-0.00007**	0.00012	-0.61427***	-0.53461***	-0.89054	-0.43049
	(-2.76)	(-9.51)	(-0.33)	(0.62)	(-1.48)	(-6.95)	(-2.61)	(0.88)	(-15.56)	(-7.30)	(-14.67)	(-9.05)***
Sep. 2009 dummy ($B_{09/09}$)	-0.00047***	-0.00083***	-0.00010***	-0.00029***	-0.00023***	-0.00044***	-0.00014***	-0.00005	-0.48063***	-0.44075***	-0.67329	-0.29059***
	(-6.30)	(-11.24)	(-3.92)	(-2.11)	(-3.44)	(-7.54)	(-6.22)	(-0.43)	(-13.47)	(-6.10)	(-12.75)	(-7.07)
Adjusted R^2	0.8449	0.8860	0.9329	0.8489	0.8333	0.8056	0.8977	0.8442	0.9381	0.9155	0.9284	0.8541
Number of cross sections	140	51	32	57	140	51	32	57	140	51	32	57
Time Series Length	4	4	4	4	4	4	4	4	4	4	4	4

Note: This table reports the estimates of panel regressions of global (Panel A) and local (Panel B) liquidity measures run with a fixed effect per stock and monthly dummies standing for January, June, and September 2009. The observation period includes those three post-MiFID months plus the pre-MiFID month of October 2007. Variables used in the regressions are monthly observations per stock for 140 non-financial equities (51 FTSE-100 components, 32 CAC-40 components, and 57 SBF-80- components). The set of control variables includes volatility measured by the standard deviation of closing returns, volume measured by the logarithm of the total euro trading volume; and price level measured by the reciprocal of the average primary market's closing price. ***,**,* indicates statistical significance at the 1%, 5%, or 10% level respectively. *t*-statistics are provided in brackets.

Table 5. Two-stage regressions of monthly liquidity measures: Second-stage estimates

	Pooled sample	**FTSE 100**	**CAC 40**	**SBF 80**	**Pooled sample**	**FTSE 100**	**CAC 40**	**SBF 80**	**Pooled sample**	**FTSE 100**	**CAC 40**	**SBF 80**
Panel A Global liquidity	**Global quoted spread (GQS_{im})**				**Global effective spread (GES_{im})**				**Global best-limit depth (GD_{im})**			
$\hat{AT}_{im}$	-0.5406*	-4.2329***	-0.5924***	0.0183	-0.5406***	-3.3722***	-0.6595***	0.02015	-3.5E+02***	-1.5E+04***	-1.8E+03***	-5.5E+02***
	(0.0540)	(0.0044)	(<.0001)	(0.9340)	(<.0001)	(0.0017)	(<.0001)	(0.9104)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$Lit\hat{F}rag_{im}$	-0.0011***	-0.0005**	-0.0001	-0.0012**	-0.0012***	-0.0004***	-0.0000	-0.0011***	0.0686	1.0506***	0.4271**	-0.3419***
	(<.0001)	(0.0360)	(0.2522)	(0.0442)	(<.0001)	(0.0076)	(0.6442)	(0.0020)	(0.4648)	(<.0001)	(0.0168)	(0.0064)
$Size_i \times Lit\hat{F}rag_{im}$		-0.0001***	0.0000	0.0001		-0.0001**	0.0000	0.0001		-0.0221	0.0149	0.0528**
		(0.0095)	(0.1786)	(0.7043)		(0.0112)	(0.1780)	(0.6439)		(0.3949)	(0.5017)	(0.0450)
Adjusted R²	67.64%	67.48%	83.34%	67.42%	67.72%	59.68%	76.62%	71.31%	76.99%	86.45%	89.68%	85.36%
$\hat{AT}_{im}$		-4.5391***				-3.5576***				-1.5E+04***		
		(0.0015)				(0.0007)				(<.0001)		
$Lit\hat{F}rag_{im}$		0.0000				-0.0001				1.0702***		
		(0.8672)				(0.4911)				(<.0001)		
$Size_i \times Lit\hat{F}rag_{im}$		-0.0001***				-0.0001***				-0.0228		
		(0.0014)				(0.0026)				(0.3857)		
$OffBook_i^{preMiFID} \times Lit\hat{F}rag_{im}$		-0.0009***				-0.0005***				-0.0347		
		(<.0001)				(0.0005)				(0.8363)		
Adjusted R²		70.17%				61.97%				86.38%		
Panel B Local liquidity	**Local quoted spread (LQS_{im})**				**Local effective spread (LES_{im})**				**Local best-limit depth (LD_{im})**			
$\hat{AT}_{im}$	-0.2274*	-3.1259**	-0.6671***	0.0315	-0.5500***	-3.1377***	-0.6735***	0.0316	-3.3E+02***	-1.2E+04***	-1.8E+03***	-5.4E+02***
	(0.0968)	(0.0388)	(<.0001)	(0.8886)	(<.0001)	(0.0033)	(<.0001)	(0.8613)	(0.0001)	(<.0001)	(<.0001)	(<.0001)
$Lit\hat{F}rag_{im}$	-0.0010***	-0.0007***	-0.0001	-0.0010	-0.0011***	-0.0005***	-0.0001	-0.0016***	-0.0041	0.3993***	0.1950	-0.3809***
	(<.0001)	(0.0014)	(0.3707)	(0.1029)	(<.0001)	(0.0026)	(0.5355)	(0.0017)	(0.9648)	(0.0071)	(0.2012)	(0.0033)
$Size_i \times Lit\hat{F}rag_{im}$		-0.0001**	0.00003**	0.0001		-0.0001***	0.0000	0.0001		0.0259	0.0336*	0.0532*
		(0.0469)	(0.0485)	(0.6198)		(0.0078)	(0.2168)	(0.6379)		(0.2508)	(0.0798)	(0.0504)
Adjusted R²	67.92%	67.76%	86.24%	66.05%	66.61%	56.94%	83.20%	71.02%	77.55%	88.77%	92.28%	84.76%

Table 5. cont'd

Panel B Local liquidity	Pooled sample	FTSE 100	CAC 40	SBF 80	Pooled sample	FTSE 100	CAC 40	SBF 80	Pooled sample	FTSE 100	CAC 40	SBF 80
	Local quoted spread (GQS_{im})				**Local effective spread (GES_{im})**				**Local best-limit depth (GD_{im})**			
$A\hat{T}_{im}$		-3.4633** (0.0163)				-3.3106*** (0.0015)				-1.2E+04*** (<.0001)		
$Lit\hat{F}rag_{im}$		-0.0002 (0.4775)				-0.0002 (0.2693)				0.4418*** (0.0094)		
$Size_i \times Lit\hat{F}rag_{im}$		-0.0001*** (0.0085)				-0.0001*** (0.0019)				0.0245 (0.2825)		
$OffBook_i^{preMiFID} \times Lit\hat{F}rag_{im}$		-0.0010*** (<.0001)				-0.0005*** (0.0011)				-0.0753 (0.6062)		
Adjusted R²		70.88%				59.06%				88.73%		
Number of cross sections	140	51	32	57	140	51	32	57	140	51	32	57
Time series length	4	4	4	4	4	4	4	4	4	4	4	4

Note: This table displays the estimates of second-stage regressions of global (Panel A) and local (Panel B) liquidity measures on lit and dark fragmentation. Variables used in the regressions are monthly observations per stock for 140 non-financial equities (51 FTSE-100 components, 32 CAC-40 components, and 57 SBF-80 components) over the pre-MiFID month of October 2007 and the three post-MiFID months of January, June, and September 2009. $Lit\hat{F}rag_{im}$ and $A\hat{T}_{im}$ are respectively the monthly fragmentation index and the monthly level of AT per stock as predicted from first-stage regressions. $Size_i$ is the market value quartile of stock *i* inside its index. $OffBook_i^{preMiFID}$ is the off-book trading share in the LSE traded volume for stock *i* October 2007. Unreported control variables are volatility, market value, volume, and price level. ***,**,* indicates statistical significance at the 1%, 5%, or 10% level respectively. *t*-statistics are provided in brackets.

Table 6. Panel regressions of daily liquidity measures by stock index: Second-stage estimates

	Global quoted spread (GQS_{it})	Global effective spread (GES_{it})	Global best-limit depth (GD_{it})	Local quoted spread (LQS_{it})	Local effective spread (LES_{it})	Local best-limit depth (LD_{it})
Panel A – Pooled sample						
$\hat{AT}_{it}$	-0.220599**	-5.167175***	-5.406651	-0.413102**	-5.300039***	-2.21E+02**
	(0.0177)	(<.0001)	(0.9631)	(0.0457)	(<.0001)	(0.0100)
$Lit\hat{F}rag_{it}$	-0.000185***	-0.000432*	0.010099	-0.000342***	-0.000431*	-0.103131***
	(<.0001)	(0.0514)	(0.8139)	(<.0001)	(0.0619)	(0.0039)
$\hat{D}ark_{it}$	0.000007	-0.000990***	0.293901***	-0.000065	-0.001056***	0.230155***
	(0.8961)	(0.0010)	(<.0001)	(0.5095)	(0.0007)	(<.0001)
R^2	95.58%	46.01%	99.64%	83.58%	44.48%	99.69%
Panel B – FTSE 100 stocks						
$\hat{AT}_{it}$	-3.314631**	-1.859603	-1.20E+04***	-5.043288*	-1.998138*	-9.38E+03***
	(0.0285)	(0.1147)	(0.0004)	(0.0778)	(0.0850)	(0.0002)
$Lit\hat{F}rag_{it}$	-0.000044	-0.000130***	0.400886***	-0.000052	-0.000098**	0.249639***
	(0.3840)	(0.0050)	(0.0004)	(0.6856)	(0.0500)	(0.0036)
$\hat{D}ark_{it}$	0.000070	0.000021	0.339149***	0.000070	0.000011	0.223450***
	(0.1685)	(0.7326)	(0.0004)	(0.7500)	(0.8866)	(0.0062)
R^2	96.91%	93.29%	99.71%	78.51%	91.93%	99.79%
Panel C – CAC 40 stocks						
$\hat{AT}_{it}$	-0.375878***	-14.6777***	-3.92E+02	-0.428933***	-15.0140***	-1.46E+02
	(<.0001)	(0.0093)	(0.1047)	(0.0003)	(0.0084)	(0.5192)
$Lit\hat{F}rag_{it}$	-0.000143***	0.000076	0.210154***	-0.000139***	0.000092	0.106352
	(0.0006)	(0.9525)	(0.0028)	(0.0027)	(0.9424)	(0.1081)
$\hat{D}ark_{it}$	-0.000001	-0.001441*	-0.013569	0.000003	-0.001506*	0.034520
	(0.9812)	(0.0690)	(0.8396)	(0.9120)	(0.0595)	(0.5517)
R^2	99.05%	52.90%	99.84%	99.17%	50.88%	99.86%

Table 6. cont'd

	Global quoted spread (GQS_{it})	Global effective spread (GES_{it})	Global best-limit depth (GD_{it})	Local quoted spread (LQS_{it})	Local effective spread (LES_{it})	Local best-limit depth (LD_{it})
Panel D – SBF 80 stocks						
$A\hat{T}_{it}$	-0.035962 (0.8410)	-1.164846 (0.6490)	-5.10E+02*** (0.0012)	0.095720 (0.6535)	-1.136209 (0.6691)	-4.60E+02*** (0.0016)
$Lit\hat{F}rag_{it}$	-0.000101 (0.2735)	0.000497 (0.4796)	-0.202234*** (0.0036)	-0.000083 (0.4091)	0.000585 (0.4346)	-0.371105*** (<.0001)
$\hat{D}ark_{it}$	-0.000022 (0.8414)	-0.000515 (0.3180)	0.083597 (0.2136)	-0.000038 (0.7336)	-0.000559 (0.3060)	0.081523 (0.2866)
R^2	95.52%	49.32%	99.53%	95.88%	47.53%	99.46%

Note: This table reports the estimates of second-stage two-fixed-effects panel regressions of daily liquidity measures on fragmentation measures for four samples of stocks – 64 FTSE-100 stocks (Panel B), 32 CAC-40 stocks (Panel C), 56 SBF-80 stocks (Panel D), and the pooled sample made of those 152 stocks (Panel A) – over 63 trading days from 1 September to 30 November 2009. The dependent variable is alternatively the average global quoted spread, the average global effective spread, the average global depth, the average local quoted spread, the average local effective spread, and the average local depth. The independent fragmentation measures are the lit fragmentation index ($Lit\hat{F}rag_{it}$) and the dark trading share ($\hat{D}ark_{it}$) as predicted in first-stage regressions. All regressions are controlled for price range, volume, and price level. They also control for AT as predicted in a first-stage regression ($A\hat{T}_{it}$). Standard errors are clustered by stock. ***,**,* indicates statistical significance at the 1%, 5%, or 10% level respectively. *p*-values are provided in brackets.