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THE IMPACT OF DARK AND VISIBLE FRAGMENTATION ON MARKET QUALITY

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The impact of dark and visible fragmentation on market quality

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Abstract

Two important characteristics of current European equity markets are rooted in changes in financial regulation (the Markets in Financial Instruments Directive). The regulation (i) allows new trading venues to emerge, generating a fragmented market place and (ii) allows for a substantial fraction of trading to take place in the dark, outside publicly displayed order books. This paper evaluates the impact on liquidity of fragmentation in visible order books and dark trading for a sample of 52 Dutch stocks. We consider global liquidity by consolidating the entire limit order books of all visible European trading venues, and local liquidity by considering the traditional market only. We find that fragmentation in visible order books improves global liquidity, but dark trading has a detrimental effect. In addition, local liquidity is lowered by fragmentation in visible order books.

JEL Codes: G10; G14; G15;

Keywords: Market microstructure, Market fragmentation, Liquidity, MiFID

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1 Introduction

Following the developments in the US, European equity markets have seen a proliferation of new trading venues. While traditional stock exchanges had a near monopoly on trading until the end of 2007, recent changes in financial regulation, in particular the Markets in Financial Instruments Directive (MiFID), allow new trading venues to compete for order flow. Consequently, trading has become dispersed over many trading venues, creating a fragmented market place. In addition to increased fragmentation of trading in visible order books (for short fragmentation), another important feature of current equity markets is that a substantial fraction of total traded volume is executed dark, e.g. Over The Counter (OTC), at Broker-Dealer Crossing Networks or in dark pools.[1] Both the impact of fragmentation and the role of dark trading in equity markets have since long interested researchers, regulators, investors and trading institutions. In this paper, we add to the literature by estimating the effects of both fragmentation and dark trading on liquidity. In addition, we improve upon previous research by employing a dataset that covers the relevant universe of trading platforms, provides stronger identification of fragmentation and allows for improved liquidity metrics.

In Europe, market fragmentation and the substantial share of dark trading are consequences of the implementation of MiFID in November 2007. MiFID's main goal is to improve market quality through two channels; by imposing rules on the degree of transparency for different types of trading venues and by allowing for competition between trading venues. First, in order to create a fair level playing field, most trading venues have to comply with similar transparency requirements. In particular, trading venues are requested to report continuously on the quotes they offer (pre-trade transparency) and on executed transactions (post-trade transparency). However, exceptions to pre-trade transparency rules are granted to certain types of transactions and trading venues, which makes these dark. Previous research suggests that enhanced pre-trade transparency rules allow for faster and cheaper access to information, hence improving efficiency (e.g. Biais, Bisière, and Spatt (2010), Boehmer, Saar, and Yu (2005)). Second, different types of trading venues are allowed to compete for order flow with the traditional market. Competition is expected to reduce the monopoly power of the traditional market, to lower transaction costs (Biais, Martimort, and Rochet, 2000) and to foster technological innovation (Stoll, 2003). How-

[1] Gomber and Pierron (2010) report a dark trading fraction of 40%, but these numbers are debatable because of data issues, such as double reporting and missing or double corrections.

ever, theory also suggests that fragmentation might reduce liquidity. When order flow becomes fragmented, the probability of finding a counterparty diminishes. Consequently, execution probabilities are lowered, which might cause some investors to leave the market or informed investors to leverage their informational advantage (e.g. Chowdhry and Nanda (1991)). Moreover, a single, consolidated market may enjoy economies of scale resulting in lower processing costs.

In this paper, we investigate the effect of fragmentation on market liquidity for a sample of European stocks and specifically distinguish between visible and dark trading. Foucault and Menkveld (2008) study competition between the LSE and Euronext for Dutch stocks in 2004, and find that fragmentation over these two traditional stock markets improves liquidity. O'Hara and Ye (2011) find that fragmentation resulting from both visible and dark trading venues lowers transaction costs and increases execution speeds for NYSE and Nasdaq stocks.

We address the impact of fragmentation on market liquidity by creating for every firm daily proxies of fragmentation, dark activity and liquidity, employing information from all relevant trading venues. Specifically, we study 52 Dutch stocks in a period before the start that fragmentation has set in, January 2006, until the end of 2009. These stocks are relatively large with an average size twice as high the NYSE and Nasdaq stocks analyzed in O'Hara and Ye (2011). We measure the degree of fragmentation by the Herfindahl-Hirschman Index (HHI, the sum of the squared market shares) based on executed trades on all visible trading venues. The market share of traded volume on dark venues and OTC represents dark activity.[2] Then, for each stock we construct a consolidated limit order book (i.e., the limit order books of all visible trading venues combined) to get a complete picture of the global liquidity available in the market. Based on the consolidated order book we analyze liquidity at the best price levels, but also deeper in the order book. This is important, as the depth of the order book reflects the quantity immediately available for trading and accordingly the price of immediacy. Next to global liquidity, available to an investor using Smart Order Routing Technology (SORT), we also address the impact of fragmentation on local liquidity, available to investors that tap the traditional market only.

Our panel dataset helps to identify an exogenous relation between liquidity and fragmentation by means of firm*quarter fixed effects and instrumental variables regressions.

[2] We treat executions of hidden and 'iceberg' orders as visible, since these trades take place on predominantly visible trading venues.

The firm*quarter dummies only allow for variation in fragmentation and liquidity within a firm-quarter, making the analysis robust to various industry specific shocks and time-varying firm specific shocks. As instruments of fragmentation we use (i) the number of limit orders to market orders on the new competing venues, and (ii) the average order size on the new competing venues, similar to O'Hara and Ye (2011). Dark trading is instrumented by the average dark order size.

Our main finding is that the effect of fragmentation on global liquidity has an inverted U-shape, while the effect of dark trading is strongly negative. That is, employing our most conservative estimates, the optimal degree of fragmentation improves global liquidity with approximately 32% compared with a completely concentrated market, while an increase in dark trading of one standard deviation lowers global liquidity by 9%. This result is a refinement to the more general conclusion of O'Hara and Ye (2011) that fragmentation does not harm market quality. In line with our results, Weaver (2011) shows that off exchange reported trades, which mostly represent dark trades in his sample, negatively affect market quality for US stocks. Contradictory to our results, Buti, Rindi, and Werner (2010a) find that dark pool activity is positively related to liquidity. Their data contains voluntarily reported trading volumes by 11 out of 32 active dark pools, while our dark measure also contains internalised trades and trades on crossing networks. Taken together, these findings confirm the relevance of distinguising between different types of trading systems when evaluating market quality.

In addition, the gains of fragmentation mainly hold for liquidity close to the midpoint, i.e. at relatively good price levels, but to a much lesser extent for liquidity deeper in the order book, which improves by only 12%. This result suggests that new entrants primarily improve liquidity close to the midpoint, but do not provide much liquidity deeper in the order book. Visible liquidity is lowered by dark activity, which might be explained by a "cream-skimming" effect between those markets. Since informed investor typically trade at the same side of the order book, they face low execution probabilities in crossing networks and dark pools. Consequently, dark markets attract predominantly uninformed traders, leaving the informed trades to visible markets (Hendershott and Mendelson, 2000, Zhu, 2011).

While global liquidity benefits from fragmentation, the traditional stock exchange is worse off as local liquidity close to the midpoint reduces by approximately 10%. This contrasts the empirical results of Weston (2002) and Foucault and Menkveld (2008), who find that fragmentation induced by new competitors improves liquidity of the traditional stock market (ECNs on Nasdaq and the LSE on Euronext, respectively). As a final result, competition between trading venues is fiercer for large stocks then for small stocks, as large stocks are more fragmented and benefit twice as much from fragmentation. In addition, only small stocks experience the negative effect of fragmentation on local liquidity.

In sum, these results suggest that local traders who only trade at the traditional stock market, i.e. do not use Smart Order Routing Technology, can be worse off in a fragmented market, especially for relatively small orders. This conclusion adds to the policy debate on the benefits and drawbacks of stock market fragmentation, where fragmentation appears to have a beneficial effect on total market quality, but is not equally enjoyed by all stock market participants.

The remainder of this paper is structured as follows. Section 2 describes the European financial market after the introduction of MiFID and Section 3 discusses related literature. The dataset and liquidity measures are described in sections 4 and 5. Section 6 explains the methodology and basic results, while section 7 reports a series of robustness checks. Finally, section 8 reports the conclusions.

2 Background on European financial markets after MiFID

This section gives a brief discussion on the contents of the Markets in Financial Instruments Directive (MiFID), effective November 1, 2007. By implementing a single legislation for the European Economic Area, MiFID aims to create a level playing field for trading venues and investors, which would ultimately improve market quality. The regulation entails three major changes to achieve this goal.

First, competition between trading venues is introduced by abolishing the "concentration rule"[3] and allowing three types of trading systems to compete for order flow. These are regulated markets (RMs), Multilateral Trading Facilities (MTFs) and Systematic Internalisers (SIs). RMs are the traditional exchanges, matching buyers and sellers through an

[3] The "concentration rule", adopted by some EU members, obliges transactions to be executed at the primary market as opposed to internal settlement. This creates a single and fair market on which all investors post their trades, according to a time and price priority. The repeal of the rule however allows markets to become fragmented and increases competition between trading venues (Ferrarini and Recine, 2006).

order book or through dealers. A firm chooses on which RM to list, and once listed, MTFs may decide to organize trading in that firm as well. MTFs, who closely resemble ECNs in the US, are similar to RMs in matching third party investors, but have different regulatory requirements and 'rules of the game'. For example, MTFs and RMs can decide upon the type of orders that can be placed, and the structure of fees, i.e. fixed fees, variable fees as well as make or take fees.[4] In order to survive, MTFs need to obtain a sufficient level of liquidity from order flow of their owners and outside investors. The largest MTFs with visible liquidity are Chi-X, Bats Europe, Nasdaq OMX and Turquoise. Lastly, SIs are organized by investment banks where customers trade against the inventory of the SI or with other clients, resembling market dealers.

MiFIDs second keystone refers to transparency which guarantees the flow of information in the market. As the number of trading venues increases, information about available prices and quantities in the order books becomes dispersed. Consequently, for investors to decide on the optimal venue and to evaluate order execution, a sufficient degree of pre-trade and post-trade transparency is necessary. Pre-trade transparency rules require trading venues to make (part of) their order books public and to continuously update this information. However, a number of waivers exist regarding pre-trade transparency. In particular, there is the "large-in-scale orders waiver", the "reference price waiver", the "negotiated-trade waiver", and the "order management facility waiver".[5] These waivers are used by MTFs such as dark pools and broker-dealer crossing networks who only have to report executed trades. Whether transparency has improved is a topic of current debate, which is complicated by increasingly fragmented markets, technological innovations and shortcomings in the quality of post-trade information.[6]

The third and final pillar of MiFID is the introduction of the best-execution rule, which obliges investment firms to execute orders against the best available conditions with respect to price, liquidity, transaction costs and likelihood and speed of execution (Aubry and McKee, 2007). However, such a broad definition of best-execution policy allows investment firms to decide themselves where to route their orders to. For example, an investment firm may stipulate an execution policy of trading on one market only. In absence of a clear benchmark, it becomes difficult for investors to evaluate the quality of executed trades and the overall performance of an investment firm (Gomber and Gsell, 2006). This is the main

[4]Make and take fees are costs charged to investors supplying and removing liquidity, respectively. Make fees can be negative, such that providers of liquidity receive a rebate for offering liquidity.

[5]See also Directive 2004/39/EC, article 29.

[6]CESR proposes changes to MiFID, July 29, 2010, ref. 10-926.

difference between MiFID and its US counterpart, Reg NMS, which solely focusses on the price dimension.[7] For an extensive summary of the implementation process of MiFID we refer the interested reader to Ferrarini and Recine (2006).

3 Literature on fragmentation and market quality

There is a trade-off between order flow fragmentation and competition. A single market benefits from lower costs, compared with a fragmented market. These consist of the fixed costs to set up a new trading venue; fixed costs for clearing and settlement; costs of monitoring several trading venues simultaneously; and advanced technological infrastructure to aggregate dispersed information in the market and connect to several trading venues. Also, a single market that is already liquid will attract even more liquidity due to positive network externalities (e.g. Pagano (1989a), Pagano (1989b) and Admati, Amihud, and Pfleiderer (1991)). Each additional trader reduces the stock's execution risk for other potential traders, attracting more traders. This positive feedback should cause all trades to be executed at a single market, obtaining the highest degree of liquidity.

However, while network externalities are still relevant, nowadays they may be realized even when several trading venues coexist. This happens to the extent that the technological infrastructure seamlessly links the individual trading venues, creating effectively one market. From a broker's point of view, the market is then virtually not fragmented, which alleviates the drawbacks of fragmentation (Stoll, 2006).[8] In addition, fragmentation might also enhance market quality, as increased competition among liquidity suppliers forces them to improve their prices, narrowing the bid-ask spreads (e.g. Biais, Martimort, and Rochet (2000) and Battalio (1997)). Confirming a competition effect, Conrad, Johnson, and Wahal (2003) find that Alternative Trading Systems in general have lower execution costs compared with brokers on traditional exchanges. Furthermore, Biais, Bisière, and Spatt (2010) investigate the competition induced by ECN activity on Nasdaq stocks. They find that ECNs with smaller tick sizes tend to undercut the Nasdaq quotes and reduce overall quoted spreads.

Differences between trading venues may arise to cater to the needs of heterogeneous

[7] In the U.S., the price of every trade is reported to the consolidated tape, such that the performance of a broker can clearly be evaluated.

[8] Confirming a high level of market integration, Storkenmaier and Wagener (2011) find that at least two venues offer the EBBO in 85% of the time for FTSE100 stocks in April/May 2010.

clientele, as investors differ in their preferences for trading speed, order sizes, anonymity and likelihood of execution (Harris (1993) and Petrella (2009)). In the US, Boehmer (2005) stresses the trade-off between speed of execution and execution costs on Nasdaq and NYSE, where Nasdaq is more expensive but also faster. In order to attract more investors, new trading venues may apply aggressive pricing schedules, such as make and take fees (Foucault, Kadan, and Kandel, 2009). The fact that some investors prefer a particular trading venue can also lead to varying degrees of informed trading at each exchange. For instance, the NYSE has been found to attract more informed order flow than the regional dealers (Easley, Kiefer, and O'Hara, 1996) and Nasdaq market makers (Bessembinder and Kaufman (1997) and Affleck-Graves, Hedge, and Miller (1994)). Furthermore, Barclay, Hendershott, and McCormick (2003) find that ECNs attract more informed order flow than Nasdaq market makers, as ECN trades have a larger price impact.

Stoll (2003) argues that competition fosters innovation and efficiency, but priority rules may not be maintained. Specifically, time priority is often violated in fragmented markets, and sometimes also price priority.[9] Foucault and Menkveld (2008) study the competition between an order book run by the LSE (EuroSETS) and Euronext Amsterdam for AEX firms in 2004, and find a trade-through rate of 73%. They call for a prohibition of trade-throughs as it discourages liquidity provision. More recently, this has been studied by Ende, Gomber, and Lutat (2009), who combine the order books of ten trading venues for Eurostoxx 50 stocks in December 2007 and January 2008. They find that 6.7% of all transactions are full trade-throughs and an additional 6.5% are partial trade-throughs. Possible explanations are high costs of monitoring multiple markets, or high variable and fixed trading fees and clearing and settlement costs.

Next to competition between trading venues with visible liquidity, this paper is related to competition effects in dark markets, i.e. venues without publicly displayed order books. A few papers theoretically investigate the impact of dark trading on traditional markets. Hendershott and Mendelson (2000) model a crossing network that competes with a dealer market, and find ambiguous effects on the dealer's spread. On the one hand, a crossing network may attract new liquidity traders and therefore lead to lower dealer spreads. On the other hand, when the dealer market is used as a market of last resort, the dealer's spread may increase. Also modeling the interaction between a crossing network and dealer

[9]Time priority is violated when two limit orders with the same price are placed on two venues and the order placed last is executed first. Price priority is violated, i.e. a trade-through, when an order gets executed against a price worse than the best quoted price in the market. A partial trade-through means that only part of the order could have been executed against a better price.

market, Degryse, Van Achter, and Wuyts (2009) find that the order flow dynamics and welfare implications depend on the degree of transparency but they do not endogenize the spread. Buti, Rindi, and Werner (2010b) model the competition between a dark pool and visible limit order book, and show that the initial level of liquidity determines the effect of the dark pool on quoted spreads. That is, for liquid stocks both limit and market orders migrate to the dark pool, leaving the spread very tight, while for illiquid stocks the competition induced by the dark pool makes limit orders relatively unattractive, causing the spread to increase. In contrast, Zhu (2011) argues that informed traders have relatively low execution probabilities in the dark pool since they typically trade on the same side of the order book. Therefore, informed trading diverts to the traditional market, which adversely affects liquidity in that market. Empirically, Gresse (2006) finds a positive effect on liquidity for UK stocks as crossing network volume is negatively related to dealer market spreads.

Finally, this paper is related to the literature on algorithmic trading,[10] i.e. the use of computer programs to manage and execute trades in electronic limit order books. Algorithmic trading has strongly increased over time, and has drastically affected the trading environment (Hendershott and Riordan, 2009). In particular, it affects the level of market fragmentation analyzed in our sample, as computer programs and Smart Order Routing Technology (SORT) allow investors to find the best liquidity in the market by comparing the order books of individual venues.[11] Moreover, algorithmic trading is related to liquidity as it reduces implicit transaction costs by splitting up large orders into many smaller ones (Hendershott, Jones, and Menkveld, 2011). Programs are also used to identify deviations from the efficient stock price, by quickly trading on new information or price changes of other securities. Furthermore, programs may provide liquidity when quoted spreads are large, e.g. when it is profitable to do so (Hendershott and Riordan, 2009). Hasbrouck and Saar (2009) describe "fleeting orders", a relatively new phenomenon in Europe and the US, where limit orders are placed and canceled within two seconds if they are not executed. The authors argue that fleeting orders are part of an active search for liquidity and a consequence of improved technology, more hidden liquidity and fragmented markets.

[10] Algorithmic trading is also know as High Frequency Trading.

[11] See e.g. Gomber and Gsell (2006) for a discussion on SORT and algorithmic trading in Europe.

4 Market description, dataset and descriptive statistics

4.1 Market description

Our dataset contains 52 Dutch stocks forming the constituents of the AEX Large and Mid cap indices. Over time, all these stocks are traded on several trading platforms, which is representative for the large European stocks analyzed by Gomber and Pierron (2010). In terms of size, the average market cap of our sample is approximately twice as large as the 2754 NYSE and Nasdaq firms analyzed in O'Hara and Ye (2011). In broad terms, we can summarize the most important trading venues for these stocks into three groups, which we describe shortly.

First, there are regulated markets (RMs), such as NYSE Euronext, LSE and Deutsche Boerse. These markets have an opening and closing auction, and in between there is continuous and anonymous trading through the limit order book. Since Euronext merged with NYSE in April 2007, the order books in Amsterdam, Paris, Brussels and Lisbon act as a fully integrated and single market. In our sample, the LSE and Deutsche Boerse are not very important as they attract less than 1% of total order flow.

Second, there are the new MTFs with visible liquidity, such as Chi-X, Bats Europe, Nasdaq OMX and Turquoise. Chi-X started trading AEX firms in April 2007; Turquoise in August 2008 and Nasdaq OMX and Bats Europe in October 2008. Whether these MTFs will survive depends on the current level of liquidity, but also on the quality of the trading technology (e.g. the speed of execution), the number of securities traded, make and take fees and clearing and settlement costs. A new trading venue in Europe typically starts with a test phase in which only a few liquid firms are traded, but will allow trading in all stocks of a certain index simultaneously when it goes live.

The third group contains MTFs with completely hidden liquidity (e.g. dark pools), SIs and the Over The Counter market. Dark pools are waived from the pre-trade transparency rules set out by the MiFID due to the nature of their business model. Most dark pools employ a limit order book with similar rules as those at Euronext for example. Other MTFs act as crossing networks, where trades are executed against the midpoint on the primary market, and do not contribute to price discovery. Gomber and Pierron (2010) report that the activity on dark pools, crossing networks and OTC has been fairly constant for European equities in 2008 - 2009, where they execute approximately 40% of total traded volume. We refer the interested reader to Davies (2008) for more details of some of the individual trading venues.

4.2 Dataset

Our dataset covers the AEX Large and Midcap constituents from 2006 to 2009, which currently have 25 and 23 stocks respectively. An advantage of using both indices is that we are able to follow stocks that switch between the large and mid cap index. We remove stocks that are in the sample for less than six months or do not have observations in 2008 and 2009. Due to some leavers and joiners, our final sample has 52 stocks.

The data for the 52 AEX Large and Midcap constituents stem from the Thomson Reuters Tick History Data base. This data source covers the seven most relevant European trading venues for the sample stocks, which have executed more than 99% of the visible order flow: Euronext, Chi-X, Deutsche Boerse, Turquoise, Bats Europe, Nasdaq OMX and SIX Swiss exchange (formerly known as Virt-X).[12] We employ data from all these venues but collect them only during the trading hours of the continuous auction of Euronext Amsterdam, i.e. between 09.00 to 17.30, Amsterdam time. Therefore, data of the opening and closing auctions at these venues are not included.[13]

Each stock-venue combination is reported in a separate file and represents a single order book. Every order book contains the ten best quotes at both sides of the market, i.e. the ten highest bid and lowest ask prices and their associated quantities, summing to 40 variables per observation.[14] A new "state" of a stock-venue limit order book is created when a limit order arrives, gets canceled or when a trade takes place. A trade is immediately reported and we observe its associated price and quantity, as well as an update of the order book. Price and time priority rules apply within each stock-venue order book, but not between venues. Furthermore, visible orders have time priority over hidden orders. Hidden

[12] The order books of the LSE are discarded as those stocks are denoted in pennies instead of Euros; which in essence are different assets. The remaining trading venues with visible liquidity attract extremely little order flow for the firms in our sample (e.g., NYSE, Milan stock exchange, PLUS group and some smaller MTFs).

[13] Unscheduled intra-day auctions are not identified in our dataset. These auctions, triggered by transactions that would cause extreme price movements, act as a safety measure and typically last for a few minutes. Given that we will work with daily averages of quote-by-quote liquidity measures, these auctions should not affect our results.

[14] Part of the sample only has the best five price levels: Euronext before January 2008. Only liquidity deep in the order book is affected. In section 7.4 we execute the analysis separately for 2008 and 2009; the results are unaffected.

orders are not directly observed in the dataset but are detected upon execution. Therefore, we have the same information set as traders have, i.e. the visible part of the order book on a continuous basis.

Our dataset also provides information on "dark trades", i.e. trades at dark pools, SIs and Over The Counter (including trades executed over telephone). These dark trades are part of the Thomson Reuters dataset and reported by Markit Boat, a MiFID-compliant trade reporting company. There are known issues with these dark data (e.g. double reporting), but it should be a good proxy for true dark activity. While we have information regarding price, quantity and time of execution, we do not observe the identity of the underlying trading venue. In addition, we also add the OTC and SI trades reported separately in the MiFID post trade files from Euronext, Xetra, Chi-X and Stockholm.

4.3 Descriptive statistics

Figure 1 shows the evolution of the daily traded volume, aggregated over all AEX Large and Mid cap constituents. The graph shows a steady increase in total trading activity, which peaks around the beginning of 2008. Moreover, the dominance of Euronext over its challengers is strong, but slowly decreasing over time. This pattern is representative for all regulated markets trading European blue chip stocks, as analyzed by Gomber and Pierron (2010). Finally, while Chi-X started trading AEX firms in April 2007, all MTFs together started to attract significant order flow only as of August 2008 (4.5%). The slow start up shows that these venues need time to generate trading activity.

In Table 7 in the Appendix, the characteristics of the different stocks and some descriptive statistics are presented. There is considerable variation in firm size (market capitalization), price and trading volume. In the sample, 38 stocks have a market capitalization exceeding one billion Euro, while the 14 remaining stocks have values above 100 million Euro. The table also reports realized volatilities, computed by first dividing the trading day into 34 fifteen-minute periods and then calculating stock returns of each period, based on the spread midpoint at the beginning and end of that period. The standard deviation of these stock returns are daily estimates of realized volatility.[15] The table also shows the average market share of Euronext and dark trades, which covers all trades reported by Markit Boat and OTC from the regulated markets. The market shares are percentages of executed

[15] The use of realized volatility is well established, see e.g. Andersen, Bollerslev, Diebold, and Ebens (2001).

trades as of November 2007 onwards, the period for which Markit Boat data have become available in the dataset.[16] According to our data, in 2009 37% of the total traded volume is dark; which can be split up into 38% for AEX large cap firms and 20% for mid cap firms.

5 Liquidity and fragmentation

5.1 The consolidated order book

The goal of this paper is to analyze the impact of equity market fragmentation on liquidity. We follow the approach of Gresse (2010) and distinguish between global traders and local traders. Global traders employ Smart Order Routing Technology (SORT) to access all trading venues simultaneously, while for local traders SORT is too expensive because of fixed trading charges and costs of adopting this trading technology. This distinction is empirically justified as SORT is not used by all investors (e.g. Foucault and Menkveld (2008) and Ende, Gomber, and Lutat (2009)). In our setting, Euronext Amsterdam is the local market and the consolidated order book represents the global market.

To construct the consolidated order book, we follow the methodology of Chlistalla and Lutat (2011) and Foucault and Menkveld (2008), based on snapshots of the limit order book. A snapshot contains the ten best bid and ask prices and associated quantities, for each stock-venue combination. Every minute we take snapshots of all venues and "sum" the liquidity to obtain a stock's consolidated order book. Therefore, each stock has 510 daily observations (8.5 hours times 60 minutes), containing the order books of the individual trading venues and the consolidated one.

5.2 Depth(X) liquidity measure

Our rich dataset allows to construct a liquidity measure that incorporates the limit orders beyond the best price levels; which we will refer to as the $Depth(X)$. The measure aggregates the Euro value of the number of shares offered within a fixed interval around the midpoint. Specifically, the midpoint is the average of the best bid and ask price of the consolidated order book and the interval is an amount $X = \{10, 20, ..., 50\}$ basis points

[16] The lack of Markit Boat data in 2006 and 2007 does not affect our results, as we execute the analysis separately for 2008 and 2009 only in section 7.4.

relative to the midpoint.[17] The measure is expressed in Euros and calculated every minute. Equation 1 shows the calculation for the bid and ask side separately, which are summed to obtain $Depth(X)$. This measure is constructed for the global and local order book (i.e., Euronext Amsterdam) separately. Define price level $j = \{1, 2, ..., J\}$ on the pricing grid and the midpoint of the consolidated order book as M, then

$$\begin{aligned} Depth\ Ask(X) &= \sum_{j=1}^{J} P_j^{Ask} * Q_j^{Ask} \mid \left(P_j^{Ask} < M * (1 + X)\right), && \text{(1a)} \\ Depth\ Bid(X) &= \sum_{j=1}^{J} P_j^{Bid} * Q_j^{Bid} \mid \left(P_j^{Bid} > M * (1 - X)\right), && \text{(1b)} \\ Depth\ (X) &= Depth\ Bid(X) + Depth\ Ask(X). && \text{(1c)} \end{aligned}$$

Figure 2 gives a graphical representation of the depth measure, where liquidity between the horizontal dashed lines is aggregated to obtain $Depth(20)$ and $Depth(40)$. The measure $Depth(X)$ is calculated every minute and then averaged over the trading day. This gives a proxy for a stock's liquidity on a certain day, where $Depth(10)$ represents liquidity close to the midpoint and $Depth(50)$ also includes liquidity deeper in the order book. Comparing different price levels X reveals the shape of the order book. For example, if the depth measure increases rapidly in X, the order book is deep while if it increases only slowly, the order book is relatively thin.

The $Depth(X)$ measure is very similar to the Exchange Liquidity Measure, $XLM(V)$, which also analyzes liquidity deeper in the order book (used by e.g., Gomber, Schweickert, and Theissen (2004)). More specifically, $XLM(V)$ fixes the quantity V of a potential trade, i.e. V equals €100.000, and analyzes the impact on price; while $Depth(X)$ fixes the price, i.e. X equals ten basis points around the midpoint, and analyzes the available quantity. Although both measures estimate the depth and slope of the order book, our approach solves two rather technical issues. First, the impact on price cannot be calculated when a stock's order book has insufficient liquidity to trade €100.000, such that the $XLM(V)$ becomes missing. In contrast, if no additional shares are offered within the range of X and $X + \varepsilon$ basis points from the midpoint, then $Depth(X)$ has a zero increment and $Depth(X) = Depth(X + \varepsilon)$. Second, $XLM(V)$ may become negative when the consolidated spread is negative, i.e. when the best ask price of a venue is lower than the best bid

[17] Foucault and Menkveld (2008) aggregate liquidity from one up to four ticks away from the best quotes. This approach is not appropriate in our setting, as tick sizes have changed over the course of our sample period. Furthermore, the tick size as a percentage of the share price is not constant.

price of another venue.[18] While negative transaction costs cannot be interpreted meaningfully, the midpoint and $Depth(X)$ are perfectly identified and reflect the available liquidity in a meaningful fashion.

An advantage of $Depth(X)$ measure over the traditional quoted depth and spread is that it is not sensitive to small, price improving orders. Such orders are placed by algorithmic traders, whose activity has increased substantially over time. In addition, the quoted depth and spread are sensitive to changes in tick sizes.[19] The impact of these phenomena on the quoted spread and depth also hinges on the degree of fragmentation and may therefore vary over time, which makes comparisons between periods troublesome.

The upper panel of Figure 3 shows a very linear shape of the order book, by plotting the median of the depth measure against the number of basis points around the midpoint. In the regression analysis we will work with the *logarithm* of the depth measures, where the 10, 50 and 90$^{\text{th}}$ percentiles are shown in the lower panel of Figure 3. There appear to be large differences between firms, as for example, the 90$^{\text{th}}$ percentile of $Depth(10)$ is €915.000, while the 10$^{\text{th}}$ percentile of $Depth(50)$ is €72.000. This is in line with high levels of skewness and kurtosis (not reported).

Table 1 contains the medians of the $Depth(X)$ measure for the global and local order book on a yearly basis, along with other liquidity measures discussed in the next section. As expected, the global and local depth measures vary substantially over time. However, some shocks affect liquidity close to the midpoint more than liquidity deep in the order book. That is, the ratio of $Depth(50)$ to $Depth(10)$ is not constant over time.

5.3 Other liquidity measures

This section compares our $Depth(X)$ liquidity measure to the more traditional liquidity measures. These are the price impact, effective and realized spread, based on executed transactions, and the quoted spread and quoted depth, based on quotes in the local and global order books. The quoted depth sums the Euro amount of shares offered at the best bid and ask price, whereas the quoted spread looks at the associated prices. The appendix (section 9) contains a formal description of the measures.

[18] Technically, a negative consolidated spread is an arbitrage opportunity, which might not be exploited because of explicit trading costs for example.

[19] The effect of the tick size on quoted depth and spread have been subject of analysis in several papers, e.g. Goldstein and Kavajecz (2000), Huang and Stoll (2001).

The medians of the liquidity measures are reported in the upper panel of Table 1, based on daily observations and calculated yearly, for the global and local order book. The table shows several interesting results.

Depth close to the midpoint has reduced strongly over time, while liquidity deeper in the order book only marginally. That is, the median of $Depth(10)$ has decreased by 35% from 2006 to 2009, while $Depth(50)$ by only 14%. In addition, the yearly standard deviations of the depth measures have decreased by approximately 50% over the years (not reported). While in 2006 and 2007 the local and global $Depth(X)$ are highly similar, in 2009 local $Depth(X)$ represents only about 50% of global depth.

Strikingly, between 2006 and 2009 the median quoted spread has improved by 9%, while the quoted depth has worsened by 68%. This result coincides with the decrease of 35% in the $Depth(10)$ measure, and shows a shortcoming of the quoted depth and spread. That is, based on the quoted depth and spread alone, one cannot state whether an investor is better off in 2006 or 2009, as this depends on the traded quantity. For a small investor mainly the quoted spread matters, while for a larger one the depth dimension becomes more important. To interpret these numbers, one can argue that a trader who places an order smaller than the median quoted depth in 2009, €30.000, is very likely to be better off with on average 10% (an argument similarly to that made in Hendershott, Jones, and Menkveld (2011)).

Turning to the liquidity measures based on executed trades, we observe that the median realized spread has reduced from 2.5 basis points in 2006 to 0 basis points in 2009. In this period, the price impact went up with 2.9 basis points while the effective spread reduced with 0.9 basis points. Because we show medians, the price impact and realized spread do not exactly add up to the effective spread.

Despite the reduction in $Depth(X)$, the local price impact, realized and effective spreads are almost identical to those of the global order book. This finding might be in line with "market tipping", where the local market switches between periods of relatively high liquidity, in which it attracts all trading, and periods of low liquidity, in which trading takes place at competing trading venues. As the price impact, effective and realized spread are based on trades, relatively liquid periods receive a larger weight in the calculation.

5.4 Equity market fragmentation

To proxy for the level of fragmentation in each stock, we construct a daily Herfindahl-Hirschman Index (HHI) based on the number of shares traded on each visible trading venue, similar to Bennett and Wei (2006) and Weston (2002). Formally, $HHI_{it} = \sum_{v=1}^{N} MS_{v,it}^2$, or the squared market share of venue v, summed over all N venues for firm i on day t. We then use $Frag = 1 - HHI$, such that a single dominant market has zero fragmentation whereas $Frag$ goes to one in case of complete fragmentation. In addition, $Dark$ is our proxy for dark trading, calculated as the percentage of volume executed at dark pools, crossing networks, SIs and Over The Counter. We use the percentage of dark volume, as we do not know the actual degree of dark fragmentation among dark venues. However, separating visible competition and dark trading is important, as they may affect liquidity in a different fashion. Our measure of fragmentation is more accurate than that of O'Hara and Ye (2011), where the origin of trades are classified as either Nasdaq, NYSE or external. The main benefits of competition in their paper arise from the external venues, but the actual level of fragmentation, and whether they are dark or lit, is unclear.

Table 2 shows the yearly mean, quartiles and standard deviation of $Frag$ and $Dark$, based on the sample firms. In 2009, the sample average $Frag$ is 0.28, which is in line with other European stocks analysed by Gomber and Pierron (2010). The US is more fragmented, as Nasdaq and NYSE combined have approximately 65% of market share in 2008 (O'Hara and Ye, 2011). As expected, fragmentation increases over time, as in 2006 and 2007 only few sample firms where traded on Virt-X and Deutsche Boerse. $Dark$ is fairly constant over time (see also Gomber and Pierron (2010)) with on average 25% in 2009, but has a very high daily standard deviation of 17%.[20]

Figure 4 shows the 10, 50 and 90$^{\text{th}}$ percentile of $Frag$ over time, calculated on a monthly basis and covering all firms. The sharp increase in fragmentation refers to the period where Chi-X and Turquoise started to attract substantial order flow, September 2008. In the next section, we estimate the effect of fragmentation on various liquidity measures in a regression framework.

[20] The dark share is calculated daily, and then averaged over all days and firms. When weighted by trading volume, 37% of all trading is dark in 2009, meaning that dark trades especially take place on high volume days.

6 The impact of fragmentation and dark trading on global and local liquidity

This section first explains the methodology, and then presents the regression results of the base model, for the global and local order book.

6.1 Methodology

We employ multivariate panel regression analysis to study the impact of fragmentation and dark trading on liquidity. We have a panel data set with 52 firms and 1022 days, from 2006 to 2009, which contains the liquidity and fragmentation measures discussed in section 5.

The panel approach allows for more flexibility compared to other papers investigating the impact of fragmentation on liquidity. For example, in contrast to the cross sectional regressions employed by O'Hara and Ye (2011), we can add firm fixed effects to absorb unobservable firm characteristics, and also measure the time series variation in liquidity and fragmentation. By using a fragmentation measure based on the Herfindahl-Hirschman Index we improve on papers such as Foucault and Menkveld (2008), Chlistalla and Lutat (2011) and Hengelbrock and Theissen (2010), who study the introduction of a new trading venue (EuroSETS, Chi-X and Turquoise respectively). That is, these articles use a dummy variable that equals one after the introduction of the new venue, to estimate the effect of fragmentation on liquidity. Given the research question we are after, our approach has three advantages compared with the aforementioned papers. First, instead of a single trading venue we can analyze the effect of fragmentation on liquidity over many trading venues simultaneously. Second, we allow for cross sectional variation in fragmentation as some firms are more heavily traded on new venues than others. And third, we allow for variation in the time series and analyze a long time window. This procedure takes into account that new trading venues might need time to grow, and allows the market as a whole to adjust to a new trading equilibrium.

In the regressions we include volatility, price, firm size and volume as control variables, which is common in this literature. Descriptives of these control variables are presented in Table 1.[21] In addition, we include a proxy for algorithmic activity, as this has been found to

[21] Weston (2000), Fink, Fink, and Weston (2006) and O'Hara and Ye (2011), among others, use similar controls.

improve liquidity (e.g. Hendershott and Riordan (2009)). We construct a measure similar to Hendershott, Jones, and Menkveld (2011). On average, algorithmic traders place and cancel many limit orders, so the daily number of electronic messages proxies for their activity, i.e. placement and cancelations of limit orders and market orders. This variable is divided by trading volume, as increasing volumes lead to more electronic messages even in the absence of algorithmic trading. Accordingly, $Algo_{it}$ is defined as the number of electronic messages divided by trading volume for firm i on day t.

The dependent variable in these regressions is one of the liquidity measures, and the independent variables are the level of fragmentation and dark trading, and several control variables. As the effect of fragmentation on liquidity might not be linear, we add a quadratic term. We employ $Frag_{it} = 1 - HHI_{it}$ and $Frag_{it}^2$ to measure fragmentation, where $Frag_{it} = 0$ if trading in a firm is completely concentrated. In our base specification, firm fixed effects and quarter dummies are included.[22] The regression equation thus becomes

$$\begin{aligned} Liq\ Measure_{it} \ = \ & \alpha_i + \delta_{q(t)} + \beta_1 Frag_{it} + \beta_2 Frag_{it}^2 + \beta_3 Dark_{it} + \\ & \beta_4 Ln(Volatility)_{it} + \beta_5 Ln(Price)_{it} + \beta_6 Ln(Size)_{it} + \\ & \beta_7 Ln(Volume)_{it} + \beta_8 Algo_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where α_i are firm dummies and $\delta_{q(t)}$ are time dummies that take the value 1 if day t is in quarter q, and are zero otherwise. For the inference we use heteroskedasticity and autocorrelation robust standard errors (Newey-West for panel datasets), based on five lags.

6.2 Results: global liquidity

The regression results for the liquidity measures employing the global (consolidated) order book are reported in Table 3. The results of models (1) to (5) show that the linear term $Frag$ has a positive coefficient and the quadratic term $Frag^2$ a negative one. The results are easier to interpret from Figure 5, which displays the implied results of the effect of fragmentation on liquidity for the five models. Liquidity first strongly increases with fragmentation and then decreases. The figure clearly reveals an optimal level of fragmentation, where maximum liquidity is obtained at $Frag = 0.35$. This level of fragmentation is fairly close to the actual level observed in 2009, where $Frag$ is around 0.30. The pattern is highly similar for all depth levels, although liquidity levels close to the midpoint benefit somewhat

[22]The results are almost identical when using day or month dummies instead of quarter dummies.

more from fragmentation. The economic magnitudes of the variables are large, where the maximum effect on $ln(Depth(10))$ is 0.50, meaning that observations here have 65% more liquidity than observations in a completely concentrated market. For $Depth(50)$, liquidity improves with 50% at the maximum compared with $Frag = 0$. Table 2 reports that the standard deviation of fragmentation is 0.15 in the entire sample, so that variation in fragmentation has a large impact on liquidity throughout the entire order book.

We now investigate the impact of fragmentation on the other liquidity indicators, as reported in models (6) to (10) in Table 3. At the optimal degree of fragmentation, $Frag = 0.35$, the price impact and the effective spread reduce by 6.4 and 6.8 basis points compared with a completely concentrated market. This is large, considering that the median effective spread in 2009 is 13.3 basis points. The economic impact of the optimal degree of fragmentation on the effective spread in our analysis is larger than estimated in O'Hara and Ye (2011), where the benefit is approximately three basis points for NYSE and Nasdaq firms.[23] This difference can partly be explained by our inclusion of a separate dark trading variable, which has a positive effect on the effective spread and price impact. The effect of fragmentation on the realized spread is much smaller however, with a reduction of only 0.5 basis points at the optimal level.

The quoted spread in model (9) is minimized at $Frag = 0.37$ and is eight basis points lower compared with a completely concentrated market. In stark contrast, the results in model (10) show that quoted depth (at the best bid and ask quote) reduce by 27% at $Frag = 0.37$. The results on the quoted depth point in the opposite direction of those of all other liquidity measures. Moreover, considering the low correlation between the quoted depth and $Depth(X)$ in Table 1, it appears that the quoted depth is not a suitable liquidity measure in the period we study. Possibly, this is a consequence of algorithmic traders who place many small and price improving orders.

We now turn to the effects of dark trading on liquidity. In Table 3, the coefficients on $Dark$ are strongly negative, with a coefficient of -0.91 for $Depth(10)$. As a result, a one standard deviation (0.18) increase in the fraction of dark trading reduces $Depth(10)$ by 16%. In addition, the coefficient on the price impact of 4.1 suggests that dark trading leads to more adverse selection and informed trading on the visible markets. Both findings are predicted by the theoretical work of Hendershott and Mendelson (2000) and Zhu (2011),

[23] O'Hara and Ye (2011) find a linear coefficient on "market share outside the primary markets" of 9 basis points, while the average level is 0.35, resulting in a benefit of approximately 3 basis points.

where dark markets are more attractive to uninformed traders, leaving the informed traders to the visible markets. The intuition is that informed traders typically trade at the same side of the order book, and therefore face relatively low execution probabilities in the dark pool or crossing network. As a result, the dark market "cream-skims" uninformed order flow, worsening liquidity and adverse selection costs in the visible market. In addition, our results are consistent with Weaver (2011), who shows that off exchange reported trades, which mostly qualify as dark trades, negatively affect market quality for US stocks. Our results are in contrast to Buti, Rindi, and Werner (2010a), who find that dark pool activity is positively related to liquidity. A likely explanation is that our *Dark* measure not only contains dark pool trades, but also trades from crossing networks and internalised trades. That is, the impact on liquidity depends on the type of exchange. In addition, Weaver (2011) cleverly points out that even within the set dark pools the impact on market quality may vary, depending on whether the purpose of the dark pool is to facilitate block trades or to internalize order flow. Since the data used by Buti, Rindi, and Werner (2010a) contain voluntarily reported trading volumes of 11 out of 32 active dark pools, their sample might not represent all types of dark pools.

However, there might be an endogeneity issue, as low levels of visible liquidity may induce an investor to trade in the dark as they are substitutes. Alternatively, both markets can be considered complements, since a liquid OTC market forces limit order suppliers in the visible market to improve prices as well, and vice versa (e.g., Duffie, Garleanu, and Pedersen (2005)). We tackle such reverse causality issues with an instrumental variables regression in section 7.2, but our main results are robust.

Turning to the control variables of the regressions, we find that the economic magnitude of *Algo* is fairly small and negative. For example, a one standard deviation increase ($s = 0.36$), lowers the $Depth(X)$ measures with 4%. However, as *Algo* might be indirectly related to fragmentation, we want to be careful in interpreting this result. The remaining control variables in the regressions have the expected signs. Larger firms tend to be more liquid, while the effect of price is marginally positive and economically small. As expected, increased trading volumes are related to better liquidity, but the causality might go either way. Finally, volatility has a negative impact on liquidity; especially for liquidity close to the midpoint. Not surprisingly, the price impact strongly increases in volatility, which proxies for the amount of information in the market.

6.3 Results: Local liquidity

We now turn to the impact of fragmentation available at the regulated market, which we call local liquidity. The estimates are reported in Table 4 and displayed in the lower panel of Figure 5. $Depth(10)$ first slightly improves with fragmentation, where the maximum lies at +10% at $Frag = 0.17$, but afterwards quickly reduces to −10% at $Frag = 0.4$. This reduction is in line with the theory of Foucault and Menkveld (2008), where the execution probability of the incumbent market diminishes as competing venues take away order flow. This side effect of competition makes the incumbent less attractive to liquidity providers, resulting in lower depth. The coefficients on $Dark$ are highly similar to those reported for the global order book.

Consequently, small investors, who mainly care for $Depth(10)$ and are limited to trading on Euronext only, are worse off. This result is in contrast to the empirical results of Weston (2002) for instance, who finds that the liquidity on Nasdaq improves when ECNs enter the market and compete for order flow. The difference is probably due to the market structure in the US, where Nasdaq market makers lost their oligopolistic rents after the entry of ECNs.

We now turn to the regressions of the remaining liquidity measures in Table 4, columns (6) to (10). In contrast to $Depth(10)$, these are not adversely affected by fragmentation. It might be the case that Euronext is very liquid on some parts of the day, while relatively illiquid during other parts. As the effective spread is based on trades, more liquid periods with many trades receive a larger weight in the calculation. In addition, order splitting behavior and smaller average order sizes may also generate lower average effective spreads.

Finally, the quoted spread on Euronext improves with fragmentation, while the quoted depth reduces with 30% at $Frag = 0.35$. Given the reduction in $Depth(10)$, the gains of improved prices are more than offset by the lower quantities offered.

7 Robustness checks

In this section we perform a series of robustness checks on the basic results. First, we control for potential endogeneity issues by introducing firm times quarter effects. These control for the simultaneous interactions between market structure, the degree of fragmentation, liquidity and competition in the market. In addition, this approach controls for a specific reverse causality issue, where fragmentation tends to be higher for high volume and more liquid stocks (Cantillon and Yin, 2010). To tackle remaining endogeneity problems of the fragmentation and dark trading variables we use an instrumental variables estimator. The instruments are (i) the number of MTF limit orders to market orders, (ii) the logarithm of the average MTF order size and (iii) the logarithm of dark order size; and their respective squares. We conclude by analyzing large and small firms separately, along with some additional robustness checks.

7.1 Regression analysis: firm*time effects

In this section we perform the regressions of formula (2), but add firm*quarter dummies. Instead of a single dummy for a period of four years, we add 16 dummies per firm. This is similar to Chaboud, Chiquoine, Hjalmarsson, and Vega (2009), who analyze the effect of algorithmic trading on volatility for currencies, and add separate quarter dummies for each currency pair. This procedure is aimed to solve the following issues.

First, the firm*quarter dummies make the analysis more robust to the impact of the financial crisis and industry specific shocks. For example, if the financial crisis specifically affects certain firms or industries (e.g., the financial sector), and affects both liquidity and fragmentation, then the previous analysis might suffer from an omitted variables problem, leading to a bias in the coefficients on fragmentation. The firm*quarter dummies capture industry shocks and time-varying firm specific shocks.

Second, the firm*quarter dummies can control for potential self selection problems. For example, Cantillon and Yin (2010) raise the issue that competition might be higher for high volume and more liquid stocks; an effect that will be absorbed by the firm*quarter dummies as long as most variation in volume is at the quarterly level.

Third, the firm*quarter dummies can, at least partially, control for dynamic interactions between market structure, competition in the market, the degree of fragmentation and liquidity. Specifically, such interactions are dynamic as, for example, a change in the current market structure will affect the level of competition in the future, which, in turn, will affect the market structure and liquidity in the future. Our approach controls for the long-term interactions of such forces by only allowing for variation in liquidity and fragmentation within a firm-quarter. Accordingly, the dummy variables absorb the variation between quarters, which is likely to be more prone to endogeneity issues.

The results for global liquidity reveal a similar pattern as those presented in the base regressions, as shown in panel A of Table 5 and displayed in the upper part of Figure 6. For the sake of brevity, the table only reports the coefficients of $Frag$, $Frag^2$ and $Dark$ for the depth measures, as these are the main focus of the paper. Results of the control variables and other liquidity measures are in line with those reported in Tables 3 and 4, and available upon request.

In the first regression, we observe that $Depth(10)$ monotonically increases with fragmentation, as the maximum of the curve lies beyond the highest observed value of fragmentation. There appears to be no harmful effect of fragmentation on liquidity close to the midpoint. This is not the case for the other depth levels, as the maximum lies around $Frag = 0.40$, implying a trade-off in the benefits and drawbacks of fragmentation.

Two additional findings emerge from the figure. First, at $Frag = 0.40$, the effect of fragmentation on $Depth(10)$ improves to 0.28 and $Depth(50)$ to 0.10, compared with 0.50 and 0.40 in the base case regressions in Table 3. The effect of fragmentation on liquidity is smaller but still highly significant. This is easily explained as the firm*quarter dummies absorb long-term trends in fragmentation, while only the day-to-day fluctuations remain. From the regression results, it appears that removing the long-term variation dampens the estimated daily effects. Second, liquidity deeper in the order book benefits less from fragmentation than liquidity close to the midpoint does. This finding was also confirmed in Figure 5, but becomes more pronounced. The fact that $Depth(10)$ still improves strongly with fragmentation suggests that competition of new trading venues mainly takes place at liquidity close to the midpoint. The coefficients on $Dark$ show a similar pattern as those reported in Table 3, but are about 15% lower in magnitude. That is, the detrimental effect of dark activity on visible liquidity remains.

The impact of fragmentation on local liquidity, including firm*quarter effects, is shown in panel B of Table 5 and the lower part of Figure 6. The figure shows that the results for the local order book have become more negative, as all depth measures reduce by 8% at $Frag = 0.40$. In the base specification, this reduction of liquidity was only observed for $Depth(10)$.

7.2 An instrumental variables approach

In the instrumental variables regressions we aim to solve for more general reverse causality issues of fragmentation and dark trading. For example, $Frag$ might be high because a stock is very liquid on a particular day; or $Dark$ might be high when an investor substitutes the visible market for dark trading because the visible market is illiquid. In such cases $Frag$ and $Dark$ depend on liquidity, causing us to make incorrect interpretations of the regression coefficients.

We employ an instrumental variables specification to alleviate these problems. We instrument $Frag$, $Frag^2$ and $Dark$ with (i) the number of MTF electronic messages to transactions,[24] (ii) the logarithm of the average MTF order size and (iii) the logarithm of the average $Dark$ order size, on day t for stock i. In addition, we add the squares of the instruments to capture non linear effects and to check the validity of the instruments with overidentifying restrictions tests. We also add firm*quarter dummies, and use the two stage GMM estimator which is efficient in the presence of heteroskedasticity (Stock and Yogo, 2002).

The first instrument, the ratio of MTF messages to transactions, is negatively related to fragmentation. After the startup of a new venue, typically the number of transactions is very low, while the available liquidity can already be substantial. As the venues liquidity reaches critical mass, the number of transactions will increase sharply, lowering the ratio and boosting fragmentation. At first glance the instrument might not seem exogenous because typically both the number of electronic messages and transactions are associated to better liquidity. However, using the ratio neutralizes the combined effect, as the exogeneity of the instrument is confirmed by the Hansen J test for overidentifying restrictions. The second instrument, the logarithm of the MTFs order size, positively relates to fragmentation as larger MTF orders typically lead to more MTF volume and market share.[25] We argue that the instrument is exogenous, as it is not obvious how the MTF order size would relate to liquidity except via fragmentation, after controlling for total traded volume and the other regressors. The third instrument, the logarithm of dark order size, positively affects dark activity. In a similar fashion to the previous instrument, larger dark orders lead to more dark volume and market share.

[24] MTF electronic messages are to the number of placed and canceled limit orders, aggregated over the MTFs Bats Europe, Chi-X, Nasdaq OMX and Turquoise.

[25] O'Hara and Ye (2011) also use the logarithm of average order size as an excluded instrument in their Heckman correction model.

Unreported first stage estimations reveal that all instruments are statistically and economically significant. Especially the ratio of MTF messages to transactions and the logarithm of the average MTF order size are particularly useful instruments for $Frag$, with standardized coefficients of -0.15 and 0.23, respectively. The logarithm of the average $Dark$ order size is a very strong instrument for $Dark$, with a standardized coefficient of 0.4. The six instruments can strongly predict fragmentation and dark activity as the Kleibergen-Paap and Angrist-Pischke Wald tests for weak and under identification are strongly rejected in all regressions, reported in the bottom part of Table 5. Unreported tests also reject the redundancy of all individual instruments.

The second stage IV regression results are reported in panel C and D of Table 5 and displayed in Figure 7. First, we observe that the magnitudes of the coefficients on fragmentation have strongly increased and are highly significant. At $Frag = 0.4$, global $Depth(10)$ and $Depth(50)$ improve with 55% and 23% compared with a completely concentrated market. The standard errors have strongly increased, as the IV procedure reduces the accuracy with which the coefficients are estimated. Importantly, Figure 7 shows that the optimal level of fragmentation is similar to previous specifications, and we confirm again that $Depth(10)$ benefits most from fragmentation. The coefficients on $Dark$ have slightly increased compared with those reported in panel A and B and are still highly significant. Assuming exogenous instruments, the initial estimates did not suffer from endogeneity issues.

Turning to the IV results for local liquidity, panel D and the lower panel in Figure 7, we observe the following. First, due to increased standard errors, only the coefficients of $Depth(10)$ and $Depth(50)$ are significantly different from zero. The standard errors have increased because the instruments need to generate variation in $Frag$ and $Frag^2$, which are very collinear. Accordingly, the plots do not reveal a clear trend and we cannot confirm previous results. In contrast, the coefficients on $Dark$ are again highly significant and negative, similar to previous findings.

Finally, we test the requirement that the set of instruments needs to be uncorrelated with the error term ε_{it} (exogeneity of the instruments). The exogeneity of the instruments is validated in eight out of ten regressions, as the Hansen J test does not reject the overidentifying restrictions. Only for global $Depth(40)$ and $Depth(50)$ the overidentifying restrictions are rejected, questioning the exogeneity of the instruments. A GMM distance test reveals that the logarithm of the MTF order size causes this rejection. In unreported regressions, using subsets of the instruments or treating $Dark$ as exogenous does not affect the main results. However, we prefer the current setup, as it allows us to perform overidentifying restrictions tests.

7.3 Small versus large stocks

The benefits and drawbacks of competition on liquidity might hinge on certain stock characteristics, such as firm size. We pursue the point in question by executing the base specification regressions for large stocks, with an average market cap exceeding ten billion Euro, and small stocks, with an average market cap below 100 million Euro. The results for the global and local order books of 15 large and 14 small sample stocks are reported in Table 6, panel A to D. The coefficients for the global order book are plotted in Figure 8, and show two interesting results. First, the benefits of competition are higher for large stocks than for small stocks. For large firms, the $Depth(10)$ is 64% higher at $Frag = 0.35$, while for small firms the maximum, at $Frag = 0.18$, has 30% more liquidity compared with a completely concentrated market. Second, the figure shows that the benefit of competition for large stocks is monotonically positive, meaning there are no harmful effects of fragmentation. By contrast, the liquidity of small stocks is negatively affected for levels of fragmentation exceeding 0.36. This suggests that the benefits of fragmentation strongly depend on firm size. The harmful effect of $Dark$ activity on liquidity is similar for small and large stocks.

Turning to the regressions in panel C and D of Table 6, we find that the local liquidity of large stocks also increases with fragmentation, while that of small stocks strongly decreases. That is, at $Frag = 0.35$, $Depth(10)$ of large stocks improves by 12%, while that of small stocks reduces with 38%. Again, this confirms that the drawbacks of a fragmented market place mainly hold for relatively small stocks. The fact that large stocks benefit more from fragmentation is in line with their actual levels of fragmentation, which is 0.41 in 2009, while for small stocks only 0.21.

7.4 Additional robustness checks

To investigate the sensitivity of our results, we perform a number of robustness checks. First, we execute the regressions with firm*quarter dummies, but only use observations from 2008 and 2009. The results do not change (not reported), likely because fragmentation especially took place in 2008 and 2009. This provides an additional robustness to potential time effects (e.g. the financial crisis), as the coefficients on fragmentation are estimated within a smaller time window. In addition, this covers for the fact that our dataset contains the ten best price levels on Euronext Amsterdam as of January 2008, while before only the best five price levels (as mentioned in footnote 14). Finally, this solves the potential issue that the data by Markit Boat on dark trades is available only as of November 2007.

Second, we execute the regressions in first differences, i.e. use the daily changes instead of the daily levels. By analyzing the day-to-day changes, we remove the long-term trends in the data. The results are very similar to those using firm*quarter dummies (not reported).

Third, instead of using $Frag$ to measure fragmentation, we use the market share of the traditional market (Euronext Amsterdam), and the qualitative results do not change. Finally, we have plotted higher order polynomials of $Frag$, and the inverted U-shapes remain, indicating that the finding on an optimal level of fragmentation is robust.

8 Conclusion

Changes in financial regulation (the Markets in Financial Instruments Directive) implemented in November 2007 allow for the proliferation of new trading platforms in European equity markets. Currently, many stocks are traded on a variety of trading venues and the market has become fragmented. In addition, the regulation allows for a large fraction of trading to take place on dark venues, such as broker-dealer crossing networks, dark pools and Over The Counter.

We find that fragmentation on visible exchanges improves liquidity, while dark trading harms liquidity. As such, we provide a refinement to the current view that market fragmentation improves liquidity. In general, our results imply that the type of trading venue determines the overall effect of competition between stock exchanges. We analyze a set of large Dutch stocks, which are representative for the European arena in terms of degree of fragmentation and dark activity. Next to separating visible from dark fragmentation, we explicitly differentiate between global and local liquidity, where global liquidity takes all relevant trading venues into account while local liquidity only the traditional stock market.

The main result is that the effect of fragmentation on global liquidity shows an inverted U-shape, while the effect of dark trading is strongly negative. Maximum liquidity is obtained when the degree of fragmentation is slightly above the average level in 2009. Then, global liquidity improves by approximately 35% compared with the case of a fully concentrated market, while an increase in dark trading of one standard deviation lowers liquidity by 9%. The negative coefficient on dark trading could be explained by a "cream-skimming" effect, where the dark markets mostly attract uninformed order flow which in turn increases adverse selection costs on the visible markets. Interestingly, while global liquidity generally improves in fragmentation, local liquidity does not. That is, the competing trading platforms take away liquidity, such that an investor who only has access to the traditional market is worse off. The reduction in liquidity close to the midpoint, i.e. at relatively good prices, can be more than 10% compared to the case of no fragmentation. As additional results, we find that competition between trading venues is fiercer for larger stocks, as these are more fragmented and have a higher marginal benefit of fragmentation. Also, large stocks do not face the drawbacks of fragmentation like small stocks do. This suggests that the benefits and drawbacks of fragmentation depend on certain stock characteristics, size in particular.

Our results add to the policy discussion on competition in financial markets, and suggest that the effect of on market quality strongly depends on the type of trading venues. While overall market quality has improved, investors without access to all visible and dark markets are worse off. We argue that the improvement of liquidity is due to competition between trading venues and suppliers and demanders of liquidity.

The current analysis does not incorporate iceberg orders and the liquidity at dark pools. This could lead to inaccuracies of the results, and as such, we want to be careful in interpreting the effect of dark trading on global liquidity. That said, the negative effect of dark activity supports the notion that traders without access to these venues are worse off. A second issue is that the consolidated order book does not take trading charges and other fees such as clearing and settlement into account, which might make it too expensive to trade simultaneously on several markets or to split up orders across venues. A potential avenue for future research is to incorporate these explicit transaction costs in the analysis, which would represent the true cost of trading to an investor.

9 Appendix: liquidity measures

The liquidity measures other than $Depth(X)$ are explained in this section. We calculate the price impact and the effective and realized spreads based on trades and weighted over all trades per day. In contrast, $Depth(X)$, quoted spread and quoted depth are liquidity measures based on quotes offered in the limit order book and time weighted over the trading day. The effective spread measures direct execution costs while the realized spread takes the order's price impact into account. The realized spread is often considered to be the compensation for the liquidity supplier. Denote MQ_o as the quoted midpoint before an order takes place and MQ_{o+5} the quoted midpoint, but five minutes later and $D = [1, -1]$ for a buy and a sell order respectively, then

$$Effective\, half\, spread = \frac{Price - MQ_o}{MQ_o} * D * 10.000, \tag{3}$$

$$Realized\, half\, spread = \frac{Price - MQ_{o+5}}{MQ_o} * D * 10.000, \tag{4}$$

$$Price\ impact = \frac{MQ_{o+5} - MQ_o}{MQ_o} * D * 10.000. \tag{5}$$

The price impact, realized and effective spread are first calculated per trade, based on the midpoint of that trading venue. Then, all calculations are averaged over the trading day, weighted by traded volume. Next, we average over trading venues, again weighted by trading venue. This approach gives the average spread in the whole market. Limited computer power is the reason we use the midpoint of the trading venue where the trade took place instead of the consolidated midpoint. That is, creating a consolidated midpoint quote-by-qoute, as is required for the effective and realized spreads, is computationally much more burdensome than creating a consolidated order book using one-minute snapshots.[26] The price impact and realized spread are calculated between 09.00 - 16.25, while the effective spread on 9.00 - 16.30. Therefore, $Effective\ spread \approx Realized\ spread + Price\ impact$. The global quoted spread is based on the best price in the consolidated order book (based on the one-minute snapshot data, see Section 5.1) and expressed in basis points, while the local quoted spread is based on the order book of Euronext. In a similar fashion,

[26]Our dataset also has a consolidated tape constructed by Thomson Reuters, containing best prices, quantities and all visible trades in the market. However, extensive checking shows that the time stamp of these trades may differ up to three seconds from the time stamp of the same trades in the original file.

the quoted depth aggregates the number of shares times their prices, expressed in Euros, or

$$Quoted\ spread = \frac{P^{ASK} - P^{BID}}{Midpoint} * 10.000, \tag{6}$$

$$Quoted\ depth = P^{ASK} * Q^{ASK} + P^{BID} * P^{BID}. \tag{7}$$

Note that the quoted depth on Euronext can be larger than that of the consolidated order book, for example when Chi-X offers a better price but with a lower quantity. The quoted spread of the consolidated order book is always equal or better than that of Euronext. Finally, the quoted depth is identical to $Depth(10)$ when the quoted spread equals 20 basis points.

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Table (1) Descriptive statistics: time series.
The table shows the medians of the liquidity measures on a yearly basis for the global and local order book (Panel A), and additional descriptive statistics of the sample stocks (Panel B). The medians are based on 52 firms and 250 trading days per year (11.250 observations). $Depth(X)$ is expressed in €1000s and represents the offered liquidity within X basis points around the midpoint. The realized spread, price impact and effective and quoted spread are measured in basis points. The price impact and realized spread are based on a 5 minute time window. The quoted depth is the amount of shares, in €1000s, offered at the best bid and ask price of the global and local order book. The descriptives show the natural logarithm of firm size, traded volume, realized return volatility and algorithmic trading. Return volatility is defined as the daily standard deviation of 15 minute returns on the midpoint. Typically, this standard deviation is lower than one, so the natural logarithm becomes negative. $Algo$ represents the number of electronic messages in the market divided by total traded volume (per €10.000). An electronic message occurs when a limit order in the order book is executed, changed or canceled.

Panel A: Liquidity measures								
	Global				**Local**			
	2006	2007	2008	2009	2006	2007	2008	2009
Depth(10)	102	134	50	66	101	127	39	36
Depth(20)	263	299	125	187	261	279	94	93
Depth(30)	367	404	183	291	359	366	141	155
Depth(40)	441	463	228	367	422	406	178	206
Depth(50)	488	505	258	420	463	426	205	244
Realized	2.5	1.1	-0.1	0.0	2.4	1.1	-0.2	0.1
Price Impact	10.4	9.4	14.3	13.3	10.4	9.5	14.2	13.5
Effective	14.1	11.2	15.1	13.2	13.8	11.1	14.5	13.1
Quoted Spread	13.3	10.9	14.5	12.0	13.5	11.5	16.8	14.7
Quoted Depth	101	82	41	32	102	85	40	30

Panel B: Descriptive statistics				
	2006	2007	2008	2009
Ln Size	14.7	15.0	14.7	14.4
Ln Volume	16.7	17.1	17.0	16.5
Algo	1.9	2.6	6.6	28.4
Ln SD	-6.2	-6.1	-5.5	-5.6

Table (2) Descriptive statistics of fragmentation and dark trading.
The yearly standard deviation, mean and quartiles of fragmentation and dark trading are reported. Fragmentation is defined as $1 - HHI$, where HHI is based on the market shares of *visible* trading venues. Dark share is the percentage of traded volume executed at dark pools, SIs and Over The Counter, available only as of November 2007. The statistics are based on daily observations per firm. That is, every observation is equally weighted as opposed to weighing according to traded volume, in which case the mean dark share is approximately 37%.

Year	Stdev	Mean	25^{th}	50^{th}	75^{th}
Fragmentation					
2006	0.081	0.027	0.000	0.000	0.010
2007	0.066	0.026	0.000	0.000	0.017
2008	0.119	0.097	0.000	0.044	0.168
2009	0.153	0.275	0.143	0.291	0.403
Total	0.150	0.106	0.000	0.015	0.182
Dark share					
2008	0.173	0.255	0.134	0.225	0.331
2009	0.169	0.250	0.131	0.221	0.327

Table (3) The effect of fragmentation on global liquidity.

The dependent variable in models (1) - (5) is the logarithm of the Depth(X) measure based on the consolidated order book. The Depth(X) is expressed in Euros and represents the offered liquidity within (X) basis points around the midpoint. The effective spread, realized spread, price impact and quoted spread, (6) - (9), are measured in basis points. Ln quoted depth is the logarithm of the quoted depth in Euros (10). Frag is the degree of market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and SIs. Algo represents the number of electronic messages divided by traded volume in the market (per €100); the other variables are explained in the descriptive statistics and Table 7. The regressions are based on 1022 trading days for 52 stocks, and have firm fixed effects and quarter dummies. T-stats are shown below the coefficients, calculated using Newey-West (HAC) standard errors (based on 5 day lags). ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Ln Depth(50)	(6) Effective Spread	(7) Realized Spread	(8) Price Impact	(9) Quoted Spread	(10) Ln Quoted Depth
Frag	2.844***	2.080***	2.188***	2.334***	2.420***	-31.32***	1.047	-32.40***	-41.94***	-0.888***
	(15.9)	(21.0)	(26.4)	(28.5)	(29.7)	(-16.0)	(0.5)	(-17.2)	(-24.8)	(-11.6)
$Frag^2$	-4.069***	-2.875***	-3.081***	-3.381***	-3.616***	33.94***	-6.615**	40.61***	55.72***	0.305**
	(-13.4)	(-15.7)	(-19.2)	(-21.1)	(-22.7)	(9.8)	(-2.0)	(12.8)	(19.0)	(2.0)
Dark	-0.914***	-0.685***	-0.587***	-0.540***	-0.503***	2.960***	-1.147	4.101***	4.476***	-0.544***
	(-20.2)	(-23.7)	(-24.0)	(-22.9)	(-21.8)	(3.7)	(-1.4)	(7.8)	(9.8)	(-26.8)
Ln Size	1.008***	0.623***	0.491***	0.427***	0.387***	-6.996***	-3.220***	-3.779***	-4.906***	0.279***
	(24.2)	(24.8)	(24.6)	(22.5)	(20.9)	(-15.8)	(-7.6)	(-8.6)	(-9.4)	(17.7)
Ln Price	-0.012	0.062***	0.069***	0.069***	0.067***	-0.137	-0.207	0.0728	1.759***	-0.056***
	(-0.5)	(3.8)	(4.7)	(4.8)	(4.5)	(-0.4)	(-0.7)	(0.3)	(4.3)	(-4.2)
Ln Vol	0.576***	0.429***	0.385***	0.353***	0.327***	-2.304***	0.380**	-2.682***	-3.724***	0.233***
	(40.9)	(45.7)	(47.0)	(47.4)	(46.9)	(-11.3)	(2.0)	(-17.0)	(-29.4)	(43.2)
Ln SD	-0.619***	-0.537***	-0.466***	-0.420***	-0.384***	7.312***	-4.963***	12.28***	5.733***	-0.223***
	(-40.0)	(-52.2)	(-54.0)	(-52.5)	(-50.7)	(31.9)	(-23.6)	(53.0)	(33.5)	(-33.7)
Algo	-0.116***	-0.106***	-0.094***	-0.097***	-0.097***	4.565***	0.034	4.527***	4.514***	-0.007
	(-5.4)	(-7.1)	(-7.6)	(-8.4)	(-8.8)	(14.6)	(0.1)	(13.7)	(15.5)	(-0.8)
Obs	46879	46879	46879	46879	46879	46879	46879	46879	46879	46879
R^2	0.461	0.663	0.681	0.659	0.641	0.236	0.042	0.331	0.352	0.673

Table (4) The effect of fragmentation on local liquidity.

The dependent variable in models (1) - (5) is the logarithm of the Depth(X) measure based on the order book of Euronext Amsterdam. The Depth(X) is expressed in Euros and represents the offered liquidity within (X) basis points around the midpoint. The effective spread, realized spread, price impact and quoted spread, (6) - (9), are measured in basis points. Ln quoted depth is the logarithm of the quoted depth in Euros (10). Frag is the degree of market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and SIs. Algo represents the number of electronic messages divided by traded volume in the market (per €100); the other variables are explained in the descriptive statistics and Table 7. The regressions are based on 1022 trading days for 52 stocks, and have firm fixed effects and quarter dummies. T-stats are shown below the coefficients, calculated using robust Newey-West (HAC) standard errors (based on 5 day lags). ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Ln Depth(50)	(6) Effective Spread	(7) Realized Spread	(8) Price Impact	(9) Quoted Spread	(10) Ln Quoted Depth
Frag	1.025***	0.006	0.162*	0.411***	0.589***	-31.07***	0.679	-31.79***	-35.21***	-0.416***
	(5.7)	(0.1)	(1.8)	(4.5)	(6.4)	(-14.7)	(0.3)	(-17.7)	(-18.3)	(-5.8)
Frag^2	-2.942***	-0.427**	-0.294	-0.624***	-0.960***	36.40***	-6.349*	42.82***	48.65***	-1.248***
	(-9.6)	(-2.2)	(-1.6)	(-3.3)	(-5.0)	(9.9)	(-1.7)	(14.2)	(17.0)	(-9.1)
Dark	-0.947***	-0.722***	-0.647***	-0.621***	-0.596***	2.348***	-1.784**	4.127***	4.043***	-0.541***
	(-20.8)	(-23.5)	(-23.3)	(-22.3)	(-21.6)	(2.9)	(-2.1)	(8.0)	(8.3)	(-27.5)
Ln Size	0.958***	0.542***	0.407***	0.344***	0.307***	-7.414***	-3.364***	-4.054***	-4.471**	0.224***
	(22.5)	(20.6)	(18.9)	(16.1)	(14.5)	(-16.5)	(-7.7)	(-9.3)	(-2.6)	(14.0)
Ln Price	-0.052**	0.044**	0.060***	0.060***	0.053***	0.069	-0.163	0.236	1.894***	-0.049***
	(-2.1)	(2.6)	(3.7)	(3.6)	(3.2)	(0.2)	(-0.5)	(0.8)	(4.7)	(-3.5)
Ln Vol	0.578***	0.426***	0.382***	0.351***	0.326***	-2.081***	0.598***	-2.676***	-4.066***	0.244***
	(40.1)	(43.1)	(43.1)	(42.6)	(41.7)	(-9.4)	(2.9)	(-17.4)	(-6.6)	(45.4)
Ln SD	-0.609***	-0.534***	-0.469***	-0.425***	-0.391***	7.312***	-5.057***	12.37***	8.337***	-0.223***
	(-38.4)	(-48.0)	(-47.7)	(-45.3)	(-43.2)	(30.8)	(-22.9)	(53.6)	(6.5)	(-34.4)
Algo	-0.128***	-0.187***	-0.206***	-0.216***	-0.214***	3.869***	0.108	3.756***	6.01***	0.056***
	(-5.9)	(-13.0)	(-16.2)	(-17.4)	(-17.5)	(12.4)	(0.4)	(11.9)	(18.4)	(6.7)
Obs	46879	46879	46879	46879	46879	46879	46879	46879	46858	46858
R^2	0.498	0.677	0.671	0.636	0.607	0.208	0.039	0.335	0.121	0.717

Table (5) The effect of fragmentation on liquidity: firm*quarter fixed effects and IV.

Panel A and B show the regression results for global and local depth respectively, where firm*quarter dummies are added. Panel C and D show the IV results, where Frag, Frag^2 and Dark are instrumented by (i) the number of MTF limit orders to market orders, (ii) the logarithm of the average MTF order size, (iii) the logarithm of the average Dark order size; and their respective squares, resulting in six instruments. The IV regressions also include firm*quarter dummies. The Hansen J statistic tests the overidentifying restrictions, under the null hypothesis that the instruments are valid (exogenous). The p-value of this statistic is reported below. The dependent variable is the logarithm of the Depth(X) measure based on the global and local order book. The Depth(X) is expressed in Euros and represents the offered liquidity within (X) basis points around the midpoint. Frag is the degree of market fragmentation, defined as 1 - HHI. Dark is the percentage of order flow executed OTC, on dark pools and SIs. The control variables (not reported) are Ln size, Ln price, Ln volume, Ln volatility and algo, as explained in Table 7. The regressions are based on 1022 trading days for 52 stocks. T-stats are shown below the coefficients, calculated using Newey-West (HAC) standard errors (based on 5 day lags). ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Ln Depth(50)	(6) Ln Depth(10)	(7) Ln Depth(20)	(8) Ln Depth(30)	(9) Ln Depth(40)	(10) Ln Depth(50)
	Panel A: Global, Firm*Quarter dummies					Panel B: Local, Firm*Quarter dummies				
Frag	0.984***	0.756***	0.700***	0.659***	0.593***	0.259*	-0.0250	-0.0542	-0.0538	-0.0617
	(6.4)	(9.7)	(10.6)	(10.7)	(10.2)	(1.8)	(-0.4)	(-0.9)	(-0.9)	(-1.1)
Frag^2	-0.749***	-0.697***	-0.872***	-0.927***	-0.877***	-1.049***	-0.419***	-0.413***	-0.428***	-0.409***
	(-2.8)	(-4.7)	(-7.0)	(-7.9)	(-7.8)	(-4.1)	(-3.1)	(-3.4)	(-3.7)	(-3.6)
Dark	-0.750***	-0.532***	-0.480***	-0.443***	-0.417***	-0.723***	-0.535***	-0.491***	-0.458***	-0.430***
	(-20.2)	(-21.4)	(-26.5)	(-27.1)	(-26.8)	(-19.6)	(-21.5)	(-26.3)	(-26.7)	(-26.2)
	Panel C: Global, IV					Panel D: Local, IV				
Frag	8.146***	5.300***	3.933***	3.287***	2.773***	2.877**	0.653	-0.125	-0.255	-0.492
	(6.1)	(8.4)	(9.0)	(8.3)	(7.6)	(2.2)	(1.1)	(-0.3)	(-0.7)	(-1.4)
Frag^2	-17.63***	-11.27***	-8.164***	-6.844***	-5.668***	-7.307**	-1.659	0.545	0.850	1.491
	(-5.1)	(-6.7)	(-7.2)	(-6.7)	(-6.1)	(-2.1)	(-1.0)	(0.5)	(0.8)	(1.6)
Dark	-0.836***	-0.600***	-0.531***	-0.496***	-0.463***	-0.798***	-0.600***	-0.538***	-0.502***	-0.470***
	(-12.5)	(-14.2)	(-15.2)	(-15.4)	(-15.1)	(-12.6)	(-14.7)	(-15.0)	(-14.8)	(-14.2)
Hansen J	2.451	4.094	8.173	17.16	25.66	7.506	7.218	3.019	0.907	2.217
Hansen p	0.484	0.252	0.0426	0.000656	1.13e-05	0.0574	0.0653	0.389	0.824	0.529
	First stage results: Kleibergen-Paap weak ID F stat: 108. Angrist-Pischke weak ID F stat: 48 (Frag), 36 (Frag^2), 855 (Dark).									

Table (6) The effect of fragmentation on liquidity: large and small firms.

The base specification regressions are executed separately for the 15 smallest stocks (average market cap < 100 million) and the 14 largest stocks (average market cap > 10 billion); for the global and local order books. The dependent variable is the logarithm of the Depth(X) measure. The Depth(X) is expressed in Euros and represents the offered liquidity within (X) basis points around the midpoint. Frag is the degree of market fragmentation, defined as $1 - HHI$. For the sake of brevity, the coefficients on the control variables are not reported, as they are very similar to those of Tables 3 and 4. The control variables are Ln size, Ln price, Ln volume, Ln volatility and algo, as explained in Table 7. The regressions contain firm fixed effects and quarter dummies. T-stats are shown below the coefficients and calculated using Newey-West (HAC) standard errors (based on 5 day lags). ***, ** and * denote significance at the 1, 5 and 10 percent levels, respectively.

	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Ln Depth(50)	(6) Ln Depth(10)	(7) Ln Depth(20)	(8) Ln Depth(30)	(9) Ln Depth(40)	(10) Ln Depth(50)
	Panel A: Global, large firms					Panel B: Local, large firms				
Frag	1.458***	1.150***	1.072***	1.052***	1.058***	0.640***	0.478***	0.355**	0.352**	0.393**
	(10.1)	(9.1)	(8.1)	(7.4)	(7.1)	(5.1)	(3.9)	(2.6)	(2.3)	(2.4)
$Frag^2$	-0.555*	-0.463*	-0.334	-0.374	-0.438	-0.869***	-0.484*	0.0768	0.194	0.141
	(-2.0)	(-1.8)	(-1.2)	(-1.3)	(-1.4)	(-3.5)	(-1.9)	(0.3)	(0.6)	(0.4)
Dark	-0.833***	-0.598***	-0.497***	-0.461***	-0.443***	-0.813***	-0.671***	-0.579***	-0.540***	-0.520***
	(-23.0)	(-17.3)	(-13.8)	(-12.0)	(-11.3)	(-21.3)	(-16.6)	(-13.1)	(-11.4)	(-10.7)
	Panel C: Global, small firms					Panel B: Local, small firms				
Frag	2.992***	2.086***	1.805***	1.649***	1.443***	1.330**	0.380	0.173	0.139	0.0487
	-4.9	-6.8	-7.4	-7.5	-6.9	(2.1)	(1.2)	(0.6)	(0.5)	(0.2)
$Frag^2$	-8.300***	-5.373***	-4.706***	-4.290***	-3.825***	-6.230***	-3.045***	-2.406***	-2.144***	-1.844***
	(-6.9)	(-8.4)	(-8.9)	(-9.1)	(-8.7)	(-5.0)	(-4.5)	(-4.0)	(-3.7)	(-3.2)
Dark	-1.180***	-0.714***	-0.687***	-0.639***	-0.613***	-1.205***	-0.765***	-0.757***	-0.729***	-0.711***
	(-8.3)	(-9.6)	(-12.4)	(-13.1)	(-13.4)	(-8.3)	(-9.2)	(-10.9)	(-11.2)	(-11.3)

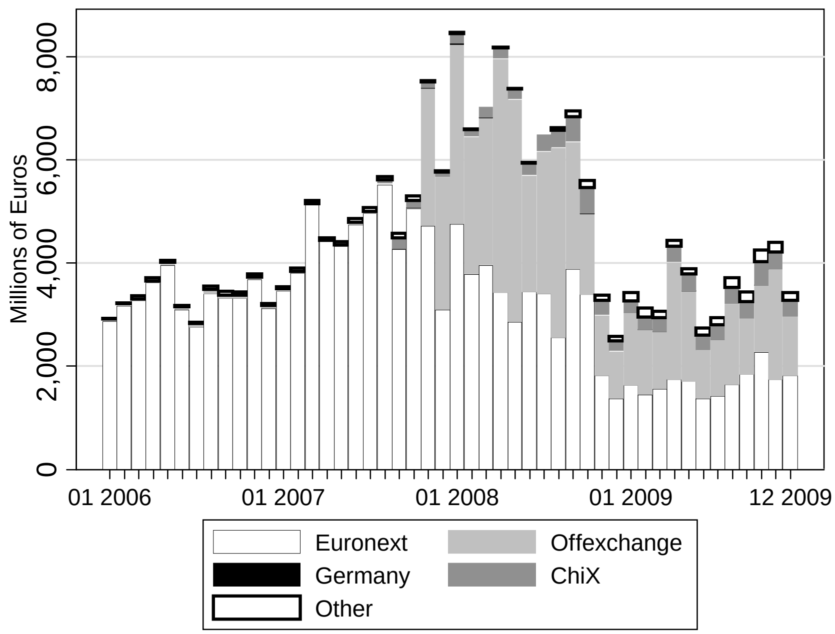

Figure (1) **Traded Volume in millions of Euros.**
The figure displays monthly averages of the daily traded volume in millions, aggregated over the 52 AEX Large and Mid cap constituents. Euronext consists of Amsterdam, Brussels, Paris and Lisbon. Germany combines all the German cities while Other represents Bats Europe, Nasdaq OMX Europe, Virt-x and Turquoise combined. Finally, Off exchange represents the orderflow executed Over The Counter, at Systematic Internalisers, crossing networks and dark pools; however, these numbers are not available prior to November 2007.

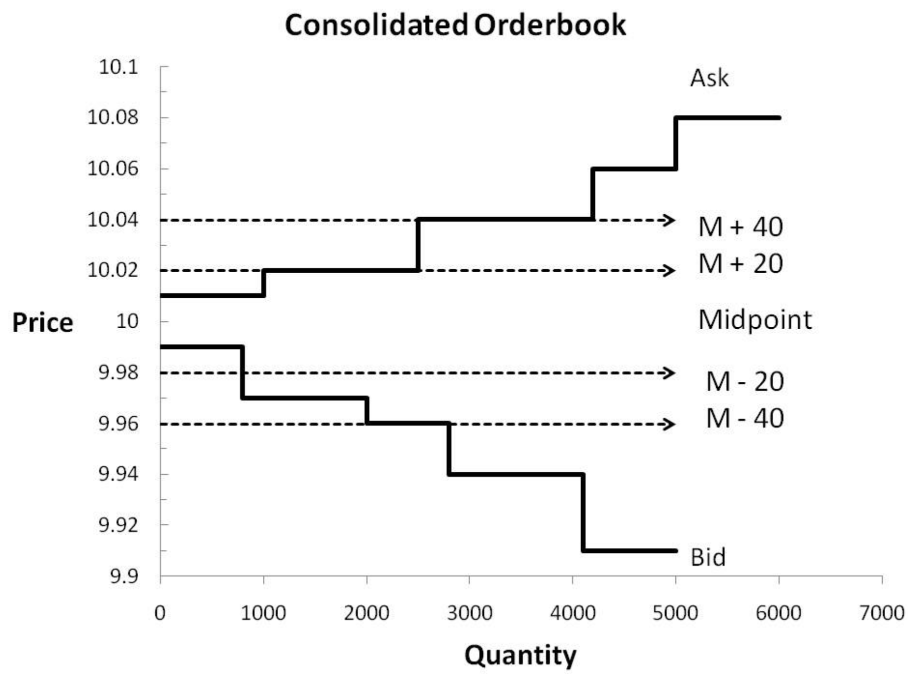

Figure (2) Snapshot of a hypothetical limit order book.
Depth(20) aggregates liquidity offered within the interval of (M - 20bps, M + 20bps), which are 2500 shares on the ask side and 800 on the bid side. Depth(40) contains 4100 and 2800 shares on the ask and bid side respectively. The number of shares offered are converted to a Euro amount.

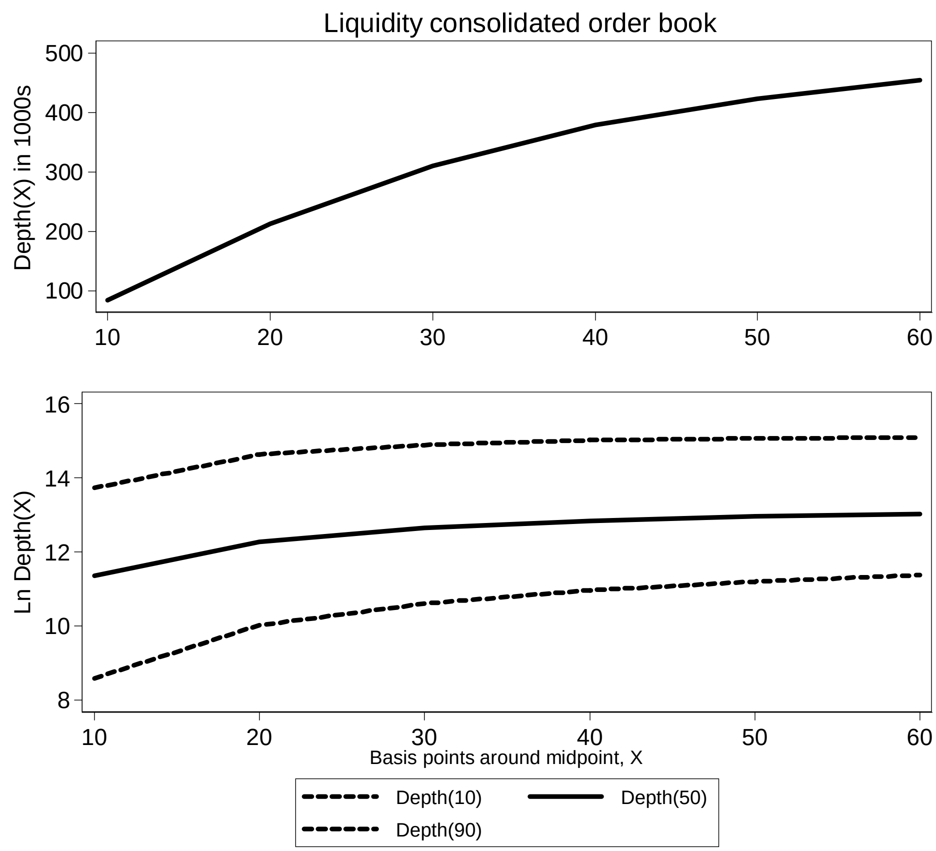

Figure (3) Depth in the consolidated order book.

The upper panel shows the median of the Depth(X) measure, expressed in €1000s. The measure aggregates the Euro value of the shares offered within a fixed amount of basis points X around the midpoint, shown on the horizontal axes. The consolidated order book represents liquidity to a global investor, where the order books of Euronext Amsterdam, Deutsche Boerse, Chi-X, Virt-X, Turquoise, Nasdaq OMX Europe and Bats Europe are aggregated. The median is based on the 52 AEX large and mid cap constituents between 2006 - 2009. The lower panel displays the 10, 50 and 90^{th} percentiles of the logarithm of Depth(X).

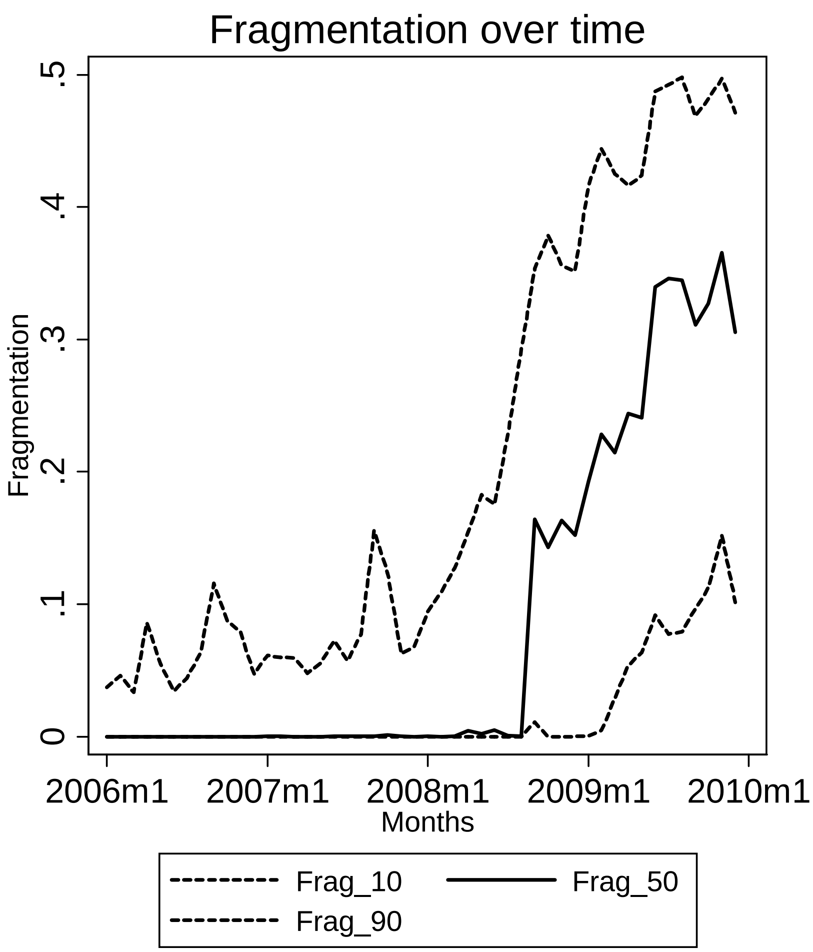

Figure (4) Fragmentation of AEX large and Mid cap firms.
The monthly 10, 50 and 90^{th} percentiles of Frag are shown, for the 52 AEX large and mid cap stocks between 2006 - 2009. Frag equals 1 - HHI, based on the number of shares traded at the following trading venues: Euronext (Amsterdam, Brussels, Paris and Lisbon together), Deutsche Boerse, Chi-X, Virt-X, Turquoise, Nasdaq OMX Europe and Bats Europe. Trades executed OTC, on crossing networks, SIs or dark pools are not taken into account, as we analyze the degree of market fragmentation of visible liquidity.

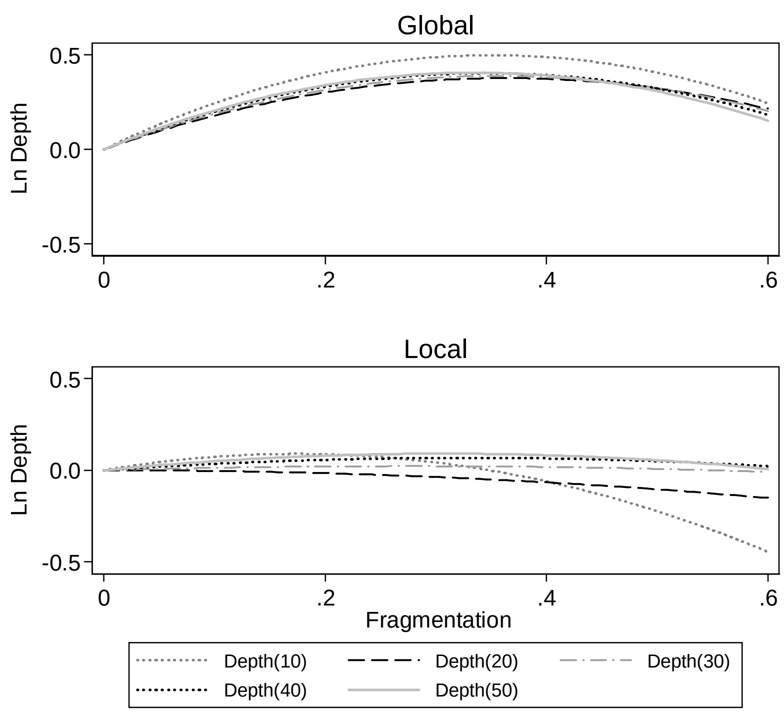

Figure (5) The effect of fragmentation on global and local liquidity.
The regression coefficients of fragmentation on liquidity are plotted, for the global order book (upper panel, model (1) - (5) of Table 3) and local order book (lower panel, model (1) - (5) of Table 4). The vertical axis displays the logarithm of the depth(X), while the horizontal axis shows the level of visible fragmentation, defined as (1 - HHI).

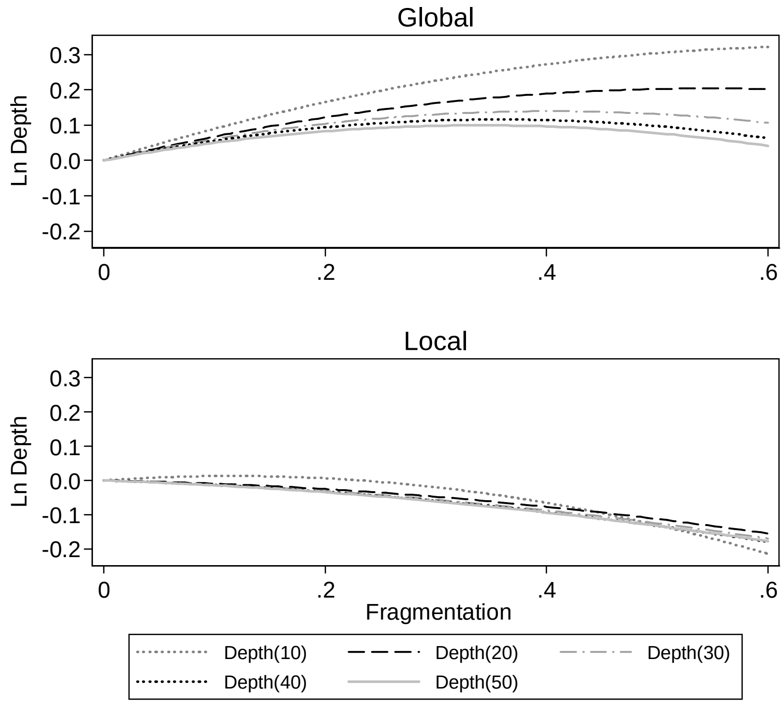

Figure (6) Fragmentation and liquidity: firm*quarter dummies.
The regression coefficients of fragmentation on liquidity of Table 5 are plotted, where the regressions have firm*quarter dummies. The upper panel shows the global order book and the lower panel the local order book. The vertical axis displays the logarithm of the depth(X), while the horizontal axis shows the level of visible fragmentation, defined as (1 - HHI).

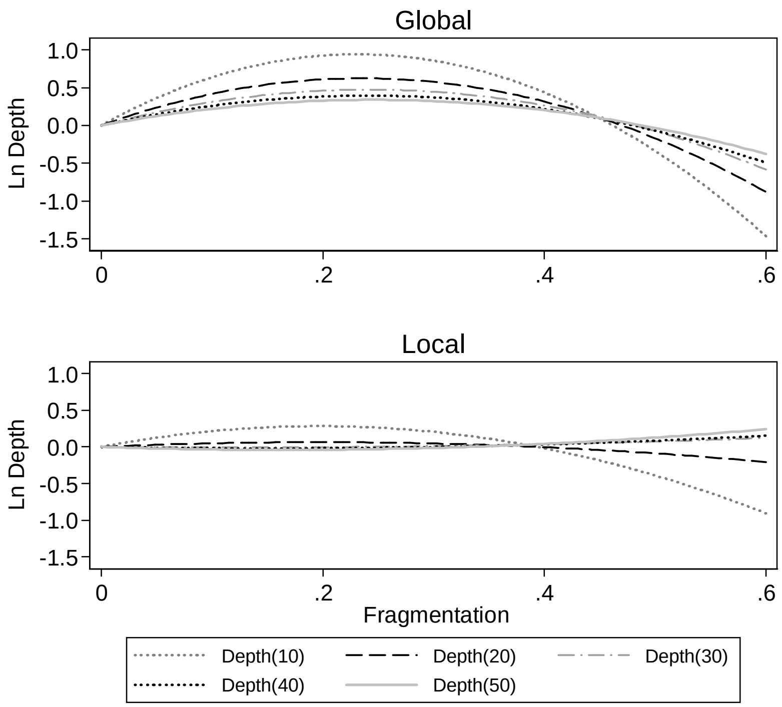

Figure (7) Fragmentation and liquidity: IV regressions.
The IV regression coefficients of fragmentation on liquidity of Table 5 are plotted. The instruments are (i) the number of MTF electronic messages to transactions, (ii) the logarithm of the average MTF order size and (iii) the logarithm of the average Dark order size; and their respective squares. The regressions include firm*quarter dummies. The vertical axis displays the logarithm of the depth(X), while the horizontal axis shows the level of visible fragmentation, defined as (1 - HHI).

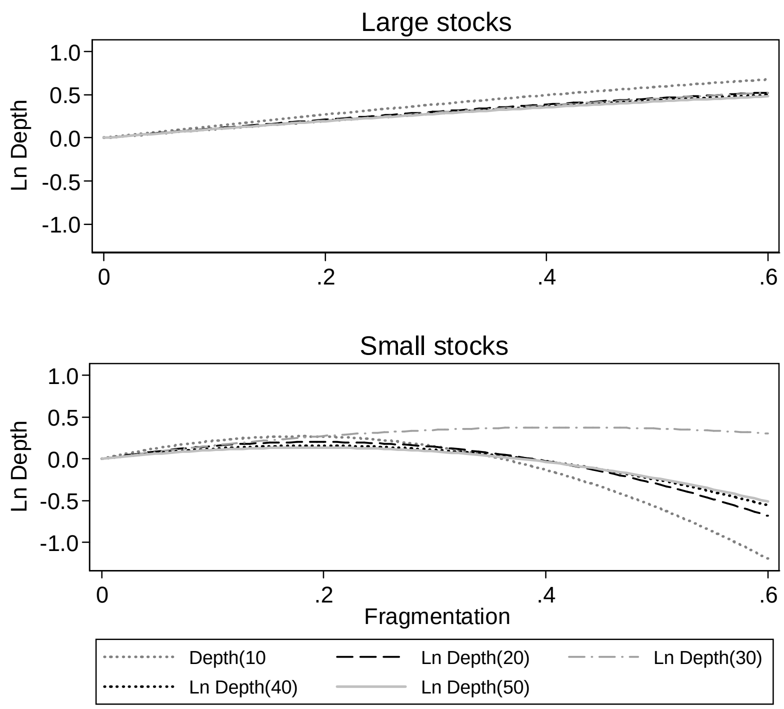

Figure (8) Fragmentation and global liquidity: small versus large stocks.
The regression coefficients of fragmentation on liquidity are plotted, for large and small stocks (regressions (1) - (5) in panel A and B, Table 6). The 14 large stocks have an average market cap exceeding ten billion Euro, while the 15 small caps Large stocks consist of the 14 stocks with an average market cap exceeding ten billion Euro, while the 15 small stocks have a market cap smaller than 100 million Euro. The regressions include firm*quarter dummies. The vertical axis displays the logarithm of the depth(X), while the horizontal axis shows the level of visible fragmentation, defined as (1 - HHI).

Table (7) Appendix Tables

Descriptive statistics of sample firms: cross section

The dataset covers daily observations for 52 AEX large and mid cap constituents, from 2006 to 2009. All variables in the table are averages. Firm size and traded volume are expressed in millions of Euros. Return volatility reflects the daily standard deviation of 15 minute returns on the midpoint and is multiplied by 100. Euronext represents the market share of executed trades on Euronext Amsterdam. Off exchange is the market share of Over The Counter trades, Systematic Internalisers and dark pools; this number is available as of November 2007.

Firm	Size	Price	Volume	Return Vol	Off Exchange	Euronext
Aalberts	1.3	29.01	7.4	0.39	7.95	89.98
Adv. Metal. Group	0.6	21.22	8.6	0.78	17.94	78.89
Aegon	16.6	10.25	161.0	0.46	15.21	76.92
Ahold	11.4	8.52	120.0	0.28	18.61	74.93
Air France	5.6	19.94	63.9	0.40	15.06	78.04
Akzo nobel	12.3	44.93	147.0	0.30	19.59	73.42
Arcadis	0.9	31.39	3.3	0.41	10.78	87.51
Arcellor Mittal	3.3	35.68	388.0	0.50	24.17	70.14
Asm Int.	0.8	14.47	7.0	0.44	10.23	86.31
ASML	8.1	17.78	144.0	0.39	16.75	75.52
Bamn Group	1.7	18.83	14.8	0.41	11.81	83.46
Binckbank	0.6	10.60	4.2	0.36	10.53	88.51
Boskalis	2.2	39.49	13.5	0.42	12.73	83.65
Corio	3.5	51.12	26.9	0.36	14.99	79.03
Crucell	1.0	15.49	9.2	0.36	8.49	89.80
CSMN	1.5	20.92	8.0	0.29	11.99	86.03
Draka Hold.	0.5	13.01	3.6	0.55	16.18	77.54
DSM	6.1	32.02	73.0	0.29	16.89	76.86
Eurocomm. Prop	1.2	32.47	5.8	0.37	11.14	86.99
Fortis	34.5	22.83	437.0	0.38	13.37	83.51
Fugro	2.8	38.99	25.0	0.34	10.30	84.83
Hagemeyer	2.0	3.76	43.4	0.31	0.00	99.28
Heijmans	0.6	25.07	3.8	0.40	8.30	90.56
Heineken	16.7	34.06	100.0	0.28	18.86	74.15
Imtech	1.2	15.04	9.2	0.40	18.02	77.45
ING	50.0	22.75	904.0	0.44	14.23	81.24
Nutreco	1.5	42.41	15.1	0.28	12.35	85.27
Oce	0.9	9.94	8.5	0.40	10.54	86.81
Ordina	0.4	10.95	2.8	0.41	7.30	89.97
Philips	28.4	25.00	301.0	0.32	21.05	71.25
R. Dutch Shell	88.5	24.22	529.0	0.27	21.57	69.54
R. KPN	20.4	10.93	220.0	0.26	23.25	69.79
R. ten cate	0.5	26.68	2.3	0.40	10.11	87.63
R. Wessanen	0.6	8.48	4.3	0.32	9.10	87.49
Randstad	4.5	35.17	38.3	0.39	14.21	79.11
Reed Elsevier	8.1	11.31	74.1	0.27	20.51	71.97
SBM Offshore	2.8	26.38	35.6	0.36	13.18	80.12
Smit Int.	10.7	48.09	4.6	0.38	15.30	80.02
Sns Reaal	2.9	11.65	11.5	0.42	12.94	85.50
Tele Atlas	1.8	20.06	37.0	0.33	8.24	68.20
Tnt	10.7	24.95	99.3	0.33	19.65	73.59
Tomtom	3.0	25.32	47.7	0.54	10.44	83.14
Unibail Rodamco	11.9	143.64	172.0	0.36	34.67	57.59
Unilever	32.2	23.62	327.0	0.26	17.58	73.85
Usg People	0.6	9.27	8.5	0.71	19.01	68.01
Vastned	1.0	55.99	5.0	0.32	10.50	87.41
Vdr Moolen	0.2	4.74	2.2	0.35	2.12	97.45
Vedior	2.9	16.70	67.7	0.27	2.99	96.48
Vopak Int.	2.3	36.52	8.9	0.30	12.24	84.75
Wavin	0.7	7.94	5.8	0.49	11.83	86.88
Wereldhave	1.6	78.77	16.0	0.28	13.56	81.87
Wolters Kluwers	5.5	18.10	42.1	0.30	13.15	78.09