DISCUSSION PAPER SERIES

No. 8630

THE IMPACT OF DARK TRADING AND VISIBLE FRAGMENTATION ON MARKET QUALITY

Hans Degryse, Frank de Jong and Vincent van Kervel

FINANCIAL ECONOMICS

ISSN 0265-8003

THE IMPACT OF DARK TRADING AND VISIBLE FRAGMENTATION ON MARKET QUALITY

Hans Degryse, CentER, Tilburg University and CEPR
Frank de Jong, Tilburg University
Vincent van Kervel, CentER, Tilburg University

Discussion Paper No. 8630
November 2011

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 8630

November 2011

ABSTRACT

The impact of dark trading and visible fragmentation on market quality*

Two important characteristics of current equity markets are the large number of trading venues with publicly displayed order books and the substantial fraction of trading that takes place in the dark, outside such visible order books. This paper evaluates the impact of dark trading and fragmentation in visible order books on liquidity. We consider global liquidity by consolidating the limit order books of all visible trading venues, and local liquidity by considering the traditional market only. We find that fragmentation in visible order books improves global liquidity, whereas dark trading has a detrimental effect. In addition, local liquidity is lowered by fragmentation in visible order books, which suggests that the benefits of fragmentation are not enjoyed by market participants who resort only to the traditional market.

JEL Classification: G10, G14 and G15
Keywords: dark trading, fragmentation, liquidity and market microstructure

Hans Degryse
TILEC, CentER
Tilburg University
PO Box 90153
5000 LE Tilburg
THE NETHERLANDS

Email: h.degryse@uvt.nl

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=121947

Frank de Jong
CentER
Tilburg University
PO Box 90153
5000 LE Tilburg
THE NETHERLANDS

Email: f.dejong@uvt.nl

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=115389

Vincent van Kervel
TILEC, CentER
Tilburg University
PO Box 90153
5000 LE Tilburg
THE NETHERLANDS

Email: v.l.vankervel@uvt.nl

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=174426

* The authors thank Albert Menkveld, Mark Van Achter, Gunther Wuyts, seminar participants at the 2010 Netherlands Authority for the Financial Markets workshop on MiFID, the 2010 Erasmus liquidity conference (Rotterdam), the European Retail Investment Conference (ERIC) 2011, and seminar participants at the K.U. Leuven and Tilburg University for helpful comments and suggestions.

Submitted 15 October 2011

1 Introduction

Equity markets in the US, Europe and Canada have seen a proliferation of new trading venues. The traditional stock exchanges are challenged by a variety of trading systems, such as electronic communication networks (ECNs), broker-dealer crossing networks, dark pools and over-the-counter markets (OTC). Consequently, trading has become dispersed over many trading venues –visible and dark– creating a fragmented market place. These changes in market structure follow recent changes in financial regulation, in particular the Regulation National Market System (Reg NMS) in the US and the Market in Financial Instruments Directive (MiFID) in Europe.

An important question is how market quality is affected by the many and different types of competing venues. In this paper, we study the impact of market fragmentation on liquidity, which is an important aspect of market quality. We investigate the impact of different types of fragmentation by classifying trading venues according to pre-trade transparency into visible and dark venues, i.e., with and without publicly displayed limit order books. According to this definition, US stocks have a dark market share of approximately 30% and European blue chips of 40%.[1] Recently, the SEC is conducting a broad review of current equity markets, and is particularly interested in the effect of dark trading on execution quality.[2]

Both the impact of fragmentation in visible order books and dark trading on equity markets have since long interested researchers, regulators, investors and trading institutions.[3] In a recent study, O'Hara and Ye (2011) find that fragmentation lowers transaction costs and increases execution speed for NYSE and Nasdaq stocks. They do not distinguish, however, between the differential impact on liquidity of fragmentation stemming from visible and dark trading venues. The main contribution of our paper is that we disentangle the liquidity effects of both fragmentation in visible order books ("visible fragmentation" for short) and dark trading. In addition, we address regulatory issues of fair markets and retail investor protection. To this end, we distinguish between liquidity aggregated over all trading venues (global liquidity) and liquidity of the traditional market only (local liquidity). Global liquidity is available to investors using Smart Order Routing Technology and

[1] Speech of SEC chairman Mary Schapiro, "Strengthening Our Equity Market Structure", US SEC New York, Sept 7, 2010, and Gomber and Pierron (2010) for Europe.

[2] See the speech of Schapiro, and the SEC concept release on equity market structure, February 2010, File No. S7-02-10.

[3] See section 2 for a review of the academic literature.

local liquidity is accessible to investors who tap the traditional market only. We furthermore improve upon previous research by employing a new dataset that covers the relevant universe of trading platforms, provides stronger identification of fragmentation and allows for improved liquidity metrics.

Our main finding is that the effect of visible fragmentation on global liquidity is generally positive, while the effect of dark trading is negative. An increase in dark trading of one standard deviation lowers global liquidity by 9%. The effect of visible fragmentation has an inverted U-shape, i.e. the marginal effect is declining when fragmentation increases. Employing our most conservative estimates, the optimal degree of visible fragmentation improves global liquidity with approximately 32% compared with a completely concentrated market. In addition, we find that the gains of visible 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 newly entering trading venues with visable order books primarily improve liquidity close to the midpoint. Furthermore, compared to small stocks, trading in large stocks is more fragmented and its liquidity benefits twice as much from fragmentation. This suggests that competition between trading venues is fiercer for large stocks than for small stocks.

While global liquidity benefits from fragmentation, we find that the market quality at the traditional stock exchange is worse off as local liquidity close to the midpoint reduces by approximately 10%. As such, investors without access to Smart Order Routing Technology are worse off in a fragmented market, especially for relatively small orders.

We address the impact of fragmentation on market liquidity by creating, for every firm, daily proxies of visible fragmentation, dark activity and liquidity, employing information from all relevant trading venues. Specifically, we study a period before fragmentation set in, January 2006, until the end of 2009, when markets were already quite fragmented. Similar to Foucault and Menkveld (2008), we select all Dutch mid- and large-cap stocks, which are relatively large with an average market capitalization approximately twice that of the NYSE and Nasdaq stocks analyzed in O'Hara and Ye (2011). We measure the degree of visible fragmentation by the Herfindahl-Hirschman Index (HHI, the sum of the squared market shares) based on executed trades on all visible trading venues. Dark trading is captured by the market share of traded volume on dark venues and OTC. 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 global 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, we also analyze local liquidity, available at the traditional exchange only.

Our panel dataset helps to identify the exogenous relation between liquidity and fragmentation by means of firm-quarter fixed effects. The inclusion of firm-quarter dummies implies that the impact of fragmentation on liquidity stems from variation within a firm-quarter, making the analysis robust to various industry specific shocks and time-varying firm specific shocks. Furthermore, in order to address concerns about endogeneity of visible fragmentation and dark trading, we use instrumental variables. Similar to O'Hara and Ye (2011), we use as instruments for visible fragmentation the average order size of the visible competitors, and also the number of limit orders to market orders on the visible competitors. Dark trading is instrumented by the average dark order size.

Our findings on liquidity can be related to several recent studies. The positive effect of fragmentation on visible trading venues is consistent with competition between liquidity suppliers, since the compensation for liquidity suppliers, the realized spread, reduces with fragmentation. A similar argument is made in Foucault and Menkveld (2008), who study competition between the LSE and Euronext for Dutch stocks in 2004, and find that fragmentation over these two traditional stock markets improves liquidity. The negative impact of dark trading is consistent with a "cream-skimming" effect between dark and visible markets, since the informativeness of trades, the price impact, strongly increases with dark activity. The "cream-skimming" effect is predicted by Zhu (2011), who argues that informed investors face low execution probabilities in crossing networks and dark pools because they typically trade at the same side of the order book. Consequently, dark markets attract predominantly uninformed traders, leaving the informed trades to visible markets. The negative effect of dark trading can also be related to pre-trade transparency, as visible markets are more efficient because of faster and cheaper access to information, in line with e.g., Biais, Bisière, and Spatt (2010) and Boehmer, Saar, and Yu (2005).

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. In contrast to our results, Buti, Rindi, and Werner (2010a) find that dark pool activity is positively related to liquidity in the cross section. In their time series regressions however, which are mostly similar to ours, the effect of dark pool activity on liquidity is economically insignificant and statistically marginally significant. We contributi to Buti, Rindi, and Werner (2010a) by controlling for visible fragmentation.

In sum, our findings imply a deeper understanding of the more general conclusion of O'Hara and Ye (2011) that fragmentation does not harm market quality. We show that the composition of the fragmentation – visible versus dark – determines the total impact of fragmentation on market quality. Moreover, our conclusions especially relate to the issues raised by the SEC on the benefits and drawbacks of stock market fragmentation, and show that the benefits are not equally enjoyed by all stock market participants. This latter finding is particularly relevant to regulators who strive for fair markets and protection of retail investors.

The remainder of this paper is structured as follows. Section 2 discusses literature on competition between exchanges. The dataset and liquidity measures are described in sections 3 and 4. Section 5 explains the methodology and main results, while section 6 reports a series of robustness checks. Finally, section 7 concludes.

2 Literature on fragmentation and market quality

There is a trade-off between order flow fragmentation and competition. A single exchange benefits from lower costs, compared with a fragmented market structure. 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).[4] 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 clientele. For example, 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.[5] Foucault and Menkveld (2008) study the competition between an LSE order book (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. Possible explanations of trade-throughs are high costs

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

[5]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.

of monitoring multiple markets, or high variable and fixed trading fees and clearing and settlement costs. Gresse (2006) finds that trading activity on a crossing network improves quoted spreads in the dealer market, especially when the dealers also trade on the crossing network.

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 market, Degryse, Van Achter, and Wuyts (2009) show 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 reduces the execution probability of limit orders, 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.

Finally, our paper is related to the literature on algorithmic trading,[6] 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.[7] 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

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

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

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 the US and Europe, 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.

In summary, the literature suggests that fragmentation of trading may improve liquidity, and offers some empirical evidence for that. However, the empirical studies so far do not distinguish between fragmentation in visible and dark trading venues. This is precisely our contribution.

3 Market description, dataset and descriptive statistics

3.1 Market description

Our dataset contains 52 Dutch stocks forming the constituents of the so-called AEX Large and Mid cap indices. Over time, all these stocks are traded on several trading platforms, to a degree 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 that of the average NYSE and Nasdaq firms analyzed in O'Hara and Ye (2011). We can summarize the most important trading venues for these stocks into three groups as follows (Appendix A contains a more general description of current European financial markets).

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. For 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 ECNs (in European terminology Multi-lateral Trading Facilities, MTFs) with visible liquidity, such as Chi-X, Bats Europe, Nasdaq OMX and

Turquoise. Chi-X started trading AEX firms in April 2007, before the introduction of MiFID; 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. Nasdaq OMX closed down in May 2010, outside our sample period, as they did not meet their targeted market share.[8] 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 at once when it goes live.

The third group contains MTFs with completely hidden liquidity (e.g. dark pools), broker-dealer crossing networks (internalization) and Over-The-Counter markets. This set of exchanges is 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. Crossing networks typically execute trades against the midpoint of 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, and they execute approximately 40% of total traded volume.

3.2 Dataset

Our dataset covers the AEX Large and Midcap constituents from 2006 to 2009, which currently have 25 and 23 stocks respectively. 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 stocks 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 visible order flow: Euronext, Chi-X, Deutsche Boerse, Turquoise, Bats Europe, Nasdaq OMX and SIX Swiss exchange (formerly known as Virt-X).[9] We employ data from all these venues but collect them only during the trading

[8]See “Nasdaq OMX to close pan-European equity MTF”, www.thetradenews.com.

[9]The visible order books of Dutch stocks on the LSE are discarded, as those stocks have different symbols, are denoted in pennies instead of Euros, and are in essence different assets. The remaining trading venues with visible liquidity attract extremely little order flow for the firms in our sample (e.g., NYSE, Milan

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.[10]

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.[11] All observations are time stamped to the millisecond. A new "state" of a 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 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. We treat executions of hidden and 'iceberg' orders as visible, since these trades take place on predominantly visible trading venues.

Our dataset also provides information on "dark trades", i.e. trades at dark pools, broker-dealer crossing networks, internalized 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. [12] 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 internalized trades reported separately in the MiFID post trade files from Euronext, Xetra, Chi-X and the Stockholm exchange.

---

stock exchange, PLUS group and some smaller exchanges).

[10]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.

[11]Part of the sample only has the best five price levels: Euronext before January 2008. This affects only liquidity deep in the order book. As robustness, we execute the analysis separately for 2008 and 2009 in section 6.4; the results are unaffected.

[12]There has been some discussion on issues with these dark data (e.g. double reporting). See the Federation of European Securities Exchanges (FESE) response to the MiFID consultation paper, February 2011. The market shares as reported in our data are consistent with those reported by FESE.

3.3 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 competitors 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, the new competitors 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 A1 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 market capitalization 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.[13] The table also shows the average market share of Euronext and dark trades, calculated as of November 2007 onwards, the period for which Markit Boat data have become available in the dataset.[14] 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.

4 Liquidity and fragmentation

4.1 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 trad-

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

[14]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 6.4.

ing 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 of the different visible trading venues represents the global market.

To construct the consolidated order book, we follow the methodology of Foucault and Menkveld (2008) among others, 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.

4.2 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 relative to the midpoint.[15] 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

[15] 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.

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 is averaged over the trading 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 closely related to the Cost of Round-trip, $CRT(D)$ (e.g. Irvine, Benston, and Kandel (2000) and Barclay, Christie, Harris, Kandel, and Schultz (1999)), which also analyzes liquidity deeper in the order book.[16] More specifically, $CRT(D)$ fixes the quantity D of a potential trade, i.e. D equals €100.000, and analyzes the impact on price. In contrast, $Depth(X)$ 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 $CRT(D)$ does not exist. 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, $CRT(D)$ 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 price of another venue.[17] 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 $Depth(X)$ over the traditional quoted depth and spread is that it is

[16] The $CRT(D)$ is also known as the Exchange Liquidity Measure, $XLM(V)$, (e.g. Gomber, Schweickert, and Theissen (2004)).

[17] Technically, a negative consolidated spread (or crossed quotes) is an arbitrage opportunity, which might not be exploited because of explicit trading costs for example.

not sensitive to small, price improving orders. Such orders are often 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.[18]

Figure 3 plots the 10, 50 and 90$^{\text{th}}$ percentile of the depth measure against the number of basis points around the midpoint. The vertical axis is plotted on a logarithmic scale, as we work with the logarithm of the depth measures in the regression analysis. Overall, the shape of the order book appears very linear. Also, there are large differences between firms, as 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.

4.3 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. Appendix B contains a formal description of the measures.

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, but liquidity deeper in the order book to a lesser extent. 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

[18] 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).

$Depth(X)$ represents only about 50% of global depth.

Strikingly, between 2006 and 2009 the median quoted spread has improved by 9%, while the quoted depth (at the best quoted prices) has worsened by 68%. This is very likely due to the strong increase in very small orders. The $Depth(10)$ measure decreases by 35% over the same time period. This shows the shortcomings of the quoted depth and spread measures, because 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.

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.

4.4 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 e.g. Bennett and Wei (2006) and Weston (2002). Formally, $HHI_{it} = \sum_{\upsilon=1}^{N} MS_{\upsilon,it}^2$, or the squared market share of venue υ, summed over all N venues for firm i on day t. We then use $VisFrag = 1 - HHI$, short for visible fragmentation; such that a single dominant market has zero fragmentation whereas $VisFrag$ goes to one in case of complete visible fragmentation. In addition, $Dark$ is our proxy for dark trading, calculated as the percentage of volume executed at dark pools, crossing networks, internalizers and OTC. We use the percentage of dark volume since we do not have information on fragmentation within the different 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 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 $VisFrag$ and $Dark$, based on the sample firms. In 2009, the sample average $VisFrag$ 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, since in 2006 and 2007 only few sample firms where traded on Virt-X and Deutsche Boerse. $Dark$ is fairly constant over time with on average 25% in 2009, but has a very high daily standard deviation of 17%.[19]

Figure 4 shows the 10, 50 and 90$^{\text{th}}$ percentile of $VisFrag$ 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.

5 The impact of visible 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.

5.1 Methodology

We employ multivariate panel regression analysis to study the impact of visible fragmentation and dark trading on liquidity. We have a panel dataset with 52 firms and 1022 days, from 2006 to 2009, which contains the liquidity and fragmentation measures discussed in section 4.

[19] 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.

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 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 approach 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.[20] In addition, we include a proxy for algorithmic activity, as this has been found to 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 $VisFrag_{it} = 1 - HHI_{it}$ and $VisFrag_{it}^2$ to measure fragmentation, where $VisFrag_{it} = 0$ if trading in a firm is completely concentrated. We add firm fixed

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

effects to make sure the variation we pick up is due only to variability in fragmentation and dark trading relative to the firm's own average. We also add time effects to control for common, market wide fluctuations in all variables. We use quarterly time fixed effects, but the results are almost identical when using day or month dummies instead of quarter dummies. The regression equation thus becomes

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

where α_i are the firm fixed effects and $\delta_{q(t)}$ are 16 quarterly dummies that take the value of one if day t is in quarter q, and zero otherwise. For the inference we use heteroskedasticity and autocorrelation robust standard errors (Newey-West for panel datasets), based on five lags.

5.2 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 liquidity first strongly increases with visible fragmentation and then decreases, as the linear term $VisFrag$ has a positive coefficient and the quadratic term $VisFrag^2$ a negative one. The results are easier to interpret from Figure 5, which displays the implied results of the effect of visible fragmentation on liquidity for the five models. The figure clearly reveals an optimal level of visible fragmentation, where maximum liquidity is obtained at $VisFrag = 0.35$. This level of visible fragmentation is fairly close to the actual level observed in 2009, where $VisFrag$ is around 0.28. The pattern is highly similar for all depth levels, although liquidity levels close to the midpoint benefit somewhat more from visible 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 $VisFrag = 0$. Table 2 reports that the standard deviation of visible fragmentation is 0.15 in the entire sample, so that variation in visible fragmentation has a large impact on liquidity throughout the entire order book.

We now investigate the impact of visible fragmentation on the other liquidity indicators, as reported in models (6) to (10) in Table 3. At the optimal degree of visible fragmentation, $VisFrag = 0.35$, the price impact and effective spread reduce by 6.3 and 6.8 basis points compared with a completely concentrated market, respectively. This is large, considering that the median effective spread in 2009 is 13.3 basis points (Table 7). The economic impact of the optimal degree of visible fragmentation on the effective spread in our analysis is larger than estimated in O'Hara and Ye (2011) for total fragmentation, where the benefit is approximately three basis points for NYSE and Nasdaq firms.[21] 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 visible fragmentation on the realized spread is 0.5 at the optimal level, which is relevant given a median realized spread of virtually zero in 2009. The realized spread represents the reward of supplying liquidity, which seems to reduce by the competition between liquidity suppliers in a fragmented market. The quoted spread in model (9) improves with eight basis point at $VisFrag = 0.37$, while the median is twelve basis points. In stark contrast, the results in model (10) show that quoted depth (at the best bid and ask quotes) reduces 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 $Ln\ Depth(10)$. 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 consistent with the theoretical work of Hendershott and Mendelson (2000) and Zhu (2011), 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. Buti, Rindi, and Werner (2010b) also predict a reduction in depth of the visible exchanges because limit

[21] 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.

orders migrate from the limit order book to the dark pool. In addition, our results are consistent with Weaver (2011), who shows that off exchange reported trades, which mostly qualify as dark trades in his sample, negatively affect market quality for US stocks. Our results are in contrast to Buti, Rindi, and Werner (2010a), who find that dark pool activity improves the quoted spread in the cross section. In time series regressions however, similar to ours, the authors find statisticilly marginally significant and economically insignificant results. An additional explanation is that our $Dark$ measure not only contains dark pool trades, but also trades from crossing networks and internalized trades. Trading activity across such venues is likely to be correlated, implying an omitted variables bias. For example, dark pool activity is generally higher for larger firms, which also benefit from higher levels of visible fragmentation in our sample.

The decision to trade in the dark might be endogenous as low levels of visible liquidity may induce an investor to trade in the dark, implying that 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 6.2, 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.

5.3 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 visible fragmentation, where the maximum lies at +10% at $VisFrag = 0.17$, but afterwards quickly reduces to −10% at $VisFrag = 0.4$. 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 visible 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 visible fragmentation, while the quoted depth reduces with 30% at $VisFrag = 0.35$. Given the reduction in $Depth(10)$, the gains of improved prices are more than offset by the lower quantities offered.

6 Robustness checks

In this section we investigate the robustness of our main results. First, we control for potential endogeneity issues by introducing firm-quarter fixed 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 visible fragmentation and dark trading variables we use an instrumental variables estimator. The instruments are (i) the number of limit to market orders on the new competing venues, (ii) the logarithm of the average order size of the new competing venues 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.

6.1 Regression analysis: firm-time effects

In this section we add to (2) firm-quarter dummies. Instead of a single dummy for a period of four years, we add 16 quarterly dummies per firm. This approach 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. The 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 $VisFrag$, $VisFrag^2$ and

$Dark$ for the Depth(X) 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 visible fragmentation, as the maximum of the curve lies beyond the highest observed value of visible fragmentation. There appears to be no harmful effect of visible 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 $VisFrag = 0.40$, the effect of visible 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 visible fragmentation on liquidity is smaller but still highly significant. This is easily explained as the firm-quarter dummies absorb long-term trends in visible 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 visible fragmentation than liquidity close to the midpoint does. This finding was also observed in Figure 5, but becomes more pronounced. The fact that $Depth(10)$ still improves strongly with visible 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 liquidity remains.

The impact of visible 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 $VisFrag = 0.40$. In the base specification, this reduction of liquidity was only observed for $Depth(10)$.

6.2 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 $VisFrag$ 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 $VisFrag$, $VisFrag^2$ and $Dark$ with (i) the ratio of the number of limit orders to the number of market orders on the visible competitors (Bats Europe, Chi-X, Nasdaq OMX and Turquoise),[22] (ii) the logarithm of the visible competitors average order size and (iii) the logarithm of the average $Dark$ order size, on day t for stock i. These instruments are specifically aimed to tackle the aforementioned reverse causality issues. The first instrument, the ratio of limit to market orders on the visible competitors, 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 venue reaches critical mass, the number of transactions will increase sharply, lowering the ratio and boosting fragmentation. We argue that the instrument is exogenous, as it is not clear how higher levels of visible liquidity would reduce the ratio of limit to market orders on the visible competitors. The second instrument, the logarithm of the visible competitors order size, positively relates to fragmentation as larger orders typically increase competitors market share.[23] Since the regression controls for total traded volume, it is unclear how a shift of volume from the primary market to the new competitors improves liquidity, except via fragmentation. The third instrument, the logarithm of average dark order size, positively affects dark activity. In a similar fashion to the previous instrument, larger dark orders increase dark market share. The instrument seems exogenous, since we do not expect lower visible liquidity to increase the average dark order size.

Unreported first stage estimations reveal that all instruments are statistically and economically significant. As expected, especially the ratio of messages to transactions and the logarithm of average visible competitors order size are particularly useful instruments for $VisFrag$, 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

[22] The number of limit orders represent placed, modified and canceled limit orders.

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

also reject the redundancy of all individual instruments, meaning each instrument improves the estimators asymptotic efficiency.

We estimate the second stage IV regressions with firm-quarter dummies, and use the two stage GMM estimator which is efficient in the presence of heteroskedasticity (Stock and Yogo, 2002). The 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 visible fragmentation have strongly increased and are highly significant. At $VisFrag = 0.35$, global $Depth(10)$ and $Depth(50)$ improve with 100% and 32% 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 visible fragmentation is similar to previous specifications, and we confirm again that $Depth(10)$ benefits most from visible fragmentation. The coefficients on $Dark$ have slightly increased in magnitude compared with those reported in panel A and B of Table 5 and are highly significant. Assuming exogenous instruments, in economical terms the initial estimates did not suffer from endogeneity issues.

Turning to the IV results for local liquidity, panel D of Table 5 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 $VisFrag$ and $VisFrag^2$, which are very collinear. Accordingly, the plots do not reveal a clear pattern 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. The joint null hypothesis is that the instruments are valid, i.e., uncorrelated with the error term, and that the instruments are correctly excluded from the estimated equation. The Hansen J test statistics and p-values are reported in the bottom part of panel C and D of Table 5, and do not reject the overidentifying restrictions in eight out of ten regressions. Only for global $Depth(40)$ and $Depth(50)$ exogeneity of the instruments is questioned. A GMM distance test reveals that the logarithm of the visible competitors 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.

6.3 Small versus large stocks

The benefits and drawbacks of fragmentation 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 visible fragmentation are higher for large stocks than for small stocks. For large firms, the $Depth(10)$ is 64% higher at $VisFrag = 0.35$, while for small firms the maximum, at $VisFrag = 0.18$, has 30% more liquidity compared with a completely concentrated market. Second, the figure shows that the benefit of visible fragmentation 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 visible fragmentation exceeding 0.36. This suggests that the benefits of visible 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 visible 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 visible fragmentation is in line with their actual levels of fragmentation, which is 0.41 in 2009, while for small stocks only 0.21.

6.4 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 11). 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 $VisFrag$ to measure visible 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 $VisFrag$, and the inverted U-shapes remain, indicating that the finding on an optimal level of visible fragmentation is robust.

7 Conclusion

Nowadays, stocks are simultaneously traded on a variety of different trading systems, creating a fragmented equity market. We show that the effect of fragmentation on liquidity crucially depends on the type of trading venue – visible versus dark. Our results reveal a key role for pre-trade transparency, which we define as having a publicly displayed limit order book. Liquidity seems to reap the gains of competition for order flow in case of visible fragmentation, whereas dark trading appears to have detrimental effects.

The positive effect of visible fragmentation might be due to competition between liquidity suppliers, as evidenced by the reduction in the reward of supplying liquidity. The negative effect of 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. These findings relate to pre-trade transparency, which has been shown to reduce adverse selection costs (e.g., Boehmer, Saar, and Yu (2005)). As such, we provide a deeper understanding of the current view that market fragmentation improves liquidity. More general, our results imply that the type of trading venue determines the overall costs and benefits of competition between trading venues.

Next to separating visible from dark fragmentation, we explicitly differentiate between global and local liquidity. Global liquidity takes all relevant trading venues into account while local liquidity only the traditional stock market. Although global liquidity improves with visible fragmentation, local liquidity does not. That is, limit orders migrate from the local exchange to the competing trading platforms, such that an investor with only 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 visible fragmentation. In addition, we find that competition between trading venues is fiercer for larger stocks, as these are more fragmented and have a higher marginal benefit of visible fragmentation. Also, large stocks do not face the drawbacks of visible fragmentation like small stocks do. This suggests that the benefits and drawbacks of fragmentation also depend on certain stock characteristics, size in particular.

In sum, our results add to the policy discussion on competition in financial markets, which is amplified by recent financial regulation (Reg NMS in the US and MiFID in Europe, both implemented in 2007). In addition, our results can be seen in light of fair markets and investor protection. While overall market quality has improved, investors without access to all visible and dark markets, typically retail investors, are worse off.

8 Appendix A: Background on European financial market

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"[24] 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 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

[24] 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).

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.[25] 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".[26] 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.[27]

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. 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 difference between MiFID and its US counterpart, Reg NMS, which solely focusses on the price dimension.[28] For an

[25] 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.

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

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

[28] In the U.S., the price of every trade is reported to the consolidated tape, such that the performance of a

extensive summary of the implementation process of MiFID we refer the interested reader to Ferrarini and Recine (2006).

9 Appendix B: 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.[29] The price impact and realized spread are calculated between 09.00 - 16.25, while the effective spread on 9.00 - 16.30. Therefore, $Effective\ spread \approx Realized\ spread + Price$

broker can clearly be evaluated.

[29]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.

$impact$. The global quoted spread is based on the best price in the consolidated order book (based on the one-minute snapshot data, see Section 4.1) and expressed in basis points, while the local quoted spread is based on the order book of Euronext. In a similar fashion, 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.

References

ADMATI, A., Y. AMIHUD, AND P. PFLEIDERER (1991): "Sunshine trading and financial market equilibrium," *The Review of Financial Studies*, 438, 443–481.

AFFLECK-GRAVES, J., S. HEDGE, AND R. MILLER (1994): "Trading Mechanisms and the Components of the Bid-Ask Spread," *Journal of Finance*, 49(4), 1471–1488.

ANDERSEN, T., T. BOLLERSLEV, F. DIEBOLD, AND H. EBENS (2001): "The distribution of realized stockreturn volatility," *Journal of Financial Economics*, 61, 43–76.

BARCLAY, M., W. CHRISTIE, J. HARRIS, E. KANDEL, AND P. SCHULTZ (1999): "Effects of Market Reform on the Trading Costs and Depths of NASDAQ Stocks," *The Journal of Finance*, 54(1), 1–34.

BARCLAY, M., T. HENDERSHOTT, AND D. MCCORMICK (2003): "Competition among trading venues: Information and trading on electronic communications networks," *Journal of Finance*, 58, 2637 – 2666.

BATTALIO, R. (1997): "Third Market Broker-Dealers: Cost Competitors or Cream Skimmers?," *Journal of Finance*, 52(1), 341–352.

BENNETT, P., AND L. WEI (2006): "Market structure, fragmentation, and market quality," *Journal of Financial Markets*, 9(1), 49 – 78.

BESSEMBINDER, H., AND H. KAUFMAN (1997): "A Comparison of Trade Execution Costs for NYSE and NASDAQ-Listed Stocks," *The Journal of Financial and Quantitative Analysis*, 32, 287–310.

BIAIS, B., C. BISIÈRE, AND C. SPATT (2010): "Imperfect Competition in Financial Markets: An Empirical Study of Island and Nasdaq," *Management Science*, 56(12), 2237–2250.

BIAIS, B., D. MARTIMORT, AND J. ROCHET (2000): "Competing Mechanisms in a Common Value Environment," *Econometrica*, 68(4), 799–837.

BOEHMER, E. (2005): "Dimensions of execution quality: Recent evidence for US equity markets," *Journal of Financial Economics*, 78, 553–582.

BOEHMER, E., G. SAAR, AND L. YU (2005): "Lifting the Veil: An Analysis of Pre-Trade Transparency at the NYSE," *Journal of Finance*, 60, 783–815.

BUTI, S., B. RINDI, AND I. . WERNER (2010a): "Diving into Dark pools," *Working Paper Fisher College of Business, Ohio State University*.

BUTI, S., B. RINDI, AND I. WERNER (2010b): "Dynamic Dark Pool Trading Strategies in Limit Order Markets," *Working Paper Fisher College of Business, Ohio State University*.

CANTILLON, E., AND P. YIN (2010): "Competition between Exchanges: A Research Agenda," *International Journal of Industrial Organization, forthcoming*.

CHABOUD, A., B. CHIQUOINE, E. HJALMARSSON, AND C. VEGA (2009): "Rise of the machines: Algorithmic trading in the foreign exchange market," *Discussion paper Federal Reserve System*.

CHLISTALLA, M., AND M. LUTAT (2011): "The impact of new execution venues on European equity markets liquidity: The case of Chi-X," *Financial Markets and Portfolio Management, forthcoming*.

CONRAD, J., K. JOHNSON, AND S. WAHAL (2003): "Institutional Trading and Alternative Trading Systems," *Journal of Financial Economics*, 70, 99–134.

DEGRYSE, H., M. VAN ACHTER, AND G. WUYTS (2009): "Dynamic order submission strategies with competition between a dealer market and a crossing network," *Journal of Financial Economics*, 91, 319–338.

DUFFIE, D., N. GARLEANU, AND L. PEDERSEN (2005): "Over-The-Counter Markets," *Econometrica*, 73(6), 1815–1847.

EASLEY, D., N. KIEFER, AND M. O'HARA (1996): "Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow," *The Journal of Finance*, 51, 811–833.

ENDE, B., P. GOMBER, AND M. LUTAT (2009): "Smart order routing technology in the New European Equity Trading Landscape," *Software Services for E-Business and E-Society: 9th IFIP WG 6.1 Conference*.

FERRARINI, G. A., AND F. RECINE (2006): *Investor Protection In Europe: Corporate Law Making, the MiFID and Beyond*. Oxford University Press.

FINK, J., K. FINK, AND J. WESTON (2006): "Competition on the Nasdaq and the growth of electronic communication networks," *Journal of Banking & Finance*, 30, 2537–2559.

FOUCAULT, T., O. KADAN, AND E. KANDEL (2009): "Liquidity Cycles and Make/Take Fees in Electronic Markets," *EFA 2009 Bergen Meetings Paper*.

FOUCAULT, T., AND A. MENKVELD (2008): "Competition for order flow and smart order routing systems," *Journal of Finance*, 63(1), 119–158.

GOLDSTEIN, M., AND K. KAVAJECZ (2000): "Eights, sixteenths, and market depth: changes in the tick size and liquidity provision on the NYSE," *Journal of Financial Economics*, 56, 125–149.

GOMBER, P., AND M. GSELL (2006): "Catching Up with Technology - The Impact of Regulatory Changes on ECNs/MTFs and the Trading Venue Landscape in Europe," *Competition and Regulation in Network Industries,*, 1(4), 535–557.

GOMBER, P., AND A. PIERRON (2010): "MiFID: Spirit and Reality of a European Financial Markets Directive," *Report Published by Celent*.

GOMBER, P., U. SCHWEICKERT, AND E. THEISSEN (2004): "Zooming in on Liquidity," *Working Paper Series*.

GRESSE, C. (2006): "The Effect of Crossing-Network Trading on Dealer Market's Bid-Ask Spread," *European Financial Management*, 12(2), 143–160.

——— (2010): "Multi-Market Trading and Market Quality," *Working Paper Paris-Dauphine*.

HARRIS, L. (1993): "Consolidation, Fragmentation, Segmentation and Regulation.," *Financial Markets, Institutions & Instruments*, 5, 1–28.

HASBROUCK, J., AND G. SAAR (2009): "Technology and Liquidity Provision: The Blurring of Traditional Definitions," *Journal of Financial Markets*, 12, 143–172.

HENDERSHOTT, T., C. JONES, AND A. MENKVELD (2011): "Does Algorithmic Trading Improve Liquidity?," *Journal of Finance*, 66, 1–33.

HENDERSHOTT, T., AND H. MENDELSON (2000): "Crossing networks and dealer markets: competition and performance," *Journal of Finance*, 55(5), 2071Ű2115.

HENDERSHOTT, T., AND R. RIORDAN (2009): "Algorithmic Trading and Information," *Net Institute Working Paper 09-08*.

HENGELBROCK, J., AND E. THEISSEN (2010): "Fourteen at one blow: The market entry of Turquoise," *Working Paper University of Bonn, University of Mannheim*.

HUANG, R., AND H. STOLL (2001): "Tick Size, Bid-Ask Spreads and Market Structure," *Journal of Financial and Quantitative Analysis*, 36, 503–522.

IRVINE, P., G. BENSTON, AND E. KANDEL (2000): "Liquidity beyond the inside spread: measuring and Using Information in the Limit Order Book," *Working Paper, Emory University and Hebrew University*.

O'HARA, M., AND M. YE (2011): "Is Market Fragmentation Harming Market Quality?," *Journal of Financial Economics, forthcoming*.

PAGANO, M. (1989a): "Endogenous Market Thinness and Stock Price Volatility," *The Review of Economic Studies*, 56, 269–287.

——— (1989b): "Trading volume and asset liquidity," *Quarterly Journal of Economics*, 104, 25–74.

PETRELLA, G. (2009): “MiFID, Reg NMS and Competition Across Trading Venues in Europe and United States,” *Working Paper University of Milan*.

STOCK, J., AND M. YOGO (2002): “Testing for Weak Instruments in Linear IV Regression,” *NBER Working Paper No. T0284*.

STOLL, H. (2003): *Market Microstructure*. Handbook of the Economics of Finance.

——— (2006): “Electronic Trading in Stock Markets,” *Journal of Economic Perspectives*, 20(1), 153–174.

STORKENMAIER, A., AND M. WAGENER (2011): “European Market Integrity: Regulating Equity Trading in Fragmented Markets,” *Working paper Karlsruhe Institute of Technology*.

WEAVER, D. (2011): “Off-Exchange Reporting and Market Quality in a Fragmented Market Structure,” *Working Paper Rutgers Business School*.

WESTON, J. (2000): “Competition on the Nasdaq and the Impact of Recent Market Reforms,” *Journal of Finance*, 55(6), 2565–2598.

——— (2002): “Electronic Communication Networks and Liquidity on the Nasdaq,” *Journal of Financial Services Research*, 22, 125–139.

ZHU, H. (2011): “Do Dark Pools Harm Price Discovery?,” *Working Paper Stanford University*.

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 (Ln SD) 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 Spread	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 Spread	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 visible fragmentation and dark trading.
The yearly standard deviation, mean and quartiles of visible fragmentation and dark trading are reported. Visible fragmentation (VisFrag) is defined as $1 - HHI$, where HHI is based on the market shares of *visible* trading venues. Dark is the percentage of traded volume executed at dark pools, crossing networks and Over The Counter, available only as of November 2007. The statistics are based on daily observations per firm. As such, each observation is equally weighted; when weighing according to traded volume the average dark is approximately 37%.

Year	Stdev	Mean	25^{th}	50^{th}	75^{th}
VisFrag					
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					
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). VisFrag is the degree of visible market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and internalized. 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 2. 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
VisFrag	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)
VisFrag^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). VisFrag is the degree of visible market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and internalized. 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 2. 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
VisFrag	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)
VisFrag^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 VisFrag, VisFrag^2 and Dark are instrumented by (i) the number of electronic messages to transactions on the visible competitors, (ii) the logarithm of the visible competitors average 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 joint null hypothesis that the instruments are valid (exogenous) and correctly excluded from the main equation. 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. VisFrag is the degree of visible fragmentation, defined as 1 - HHI. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and internalized. The control variables (not reported) are Ln size, Ln price, Ln volume, Ln volatility and algo, as explained in Table 2. 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				
VisFrag	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)
VisFrag^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				
VisFrag	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)
VisFrag^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	0.001	0.000	0.057	0.065	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 (VisFrag^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. VisFrag is the degree of visible fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed OTC, on crossing networks, dark pools and internalized. 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 2. 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				
VisFrag	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)
VisFrag^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				
VisFrag	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)
VisFrag^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)

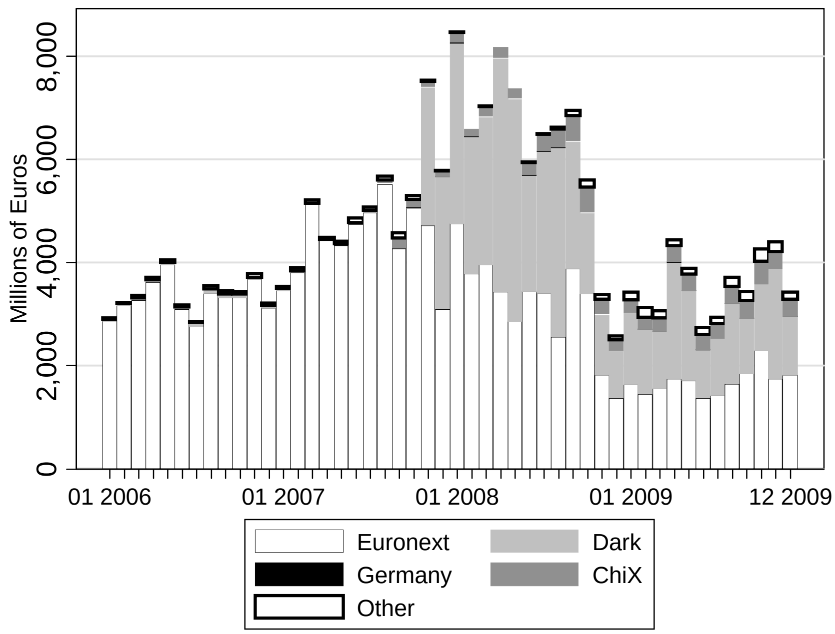

Figure (1) **Traded Volume in millions of Euros.**
The figure displays monthly averages of the daily traded volume in millions, aggregated over the 52 AEX Large and Mid cap constituents. Euronext consists of Amsterdam, Brussels, Paris and Lisbon. Germany combines all the German cities while Other represents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

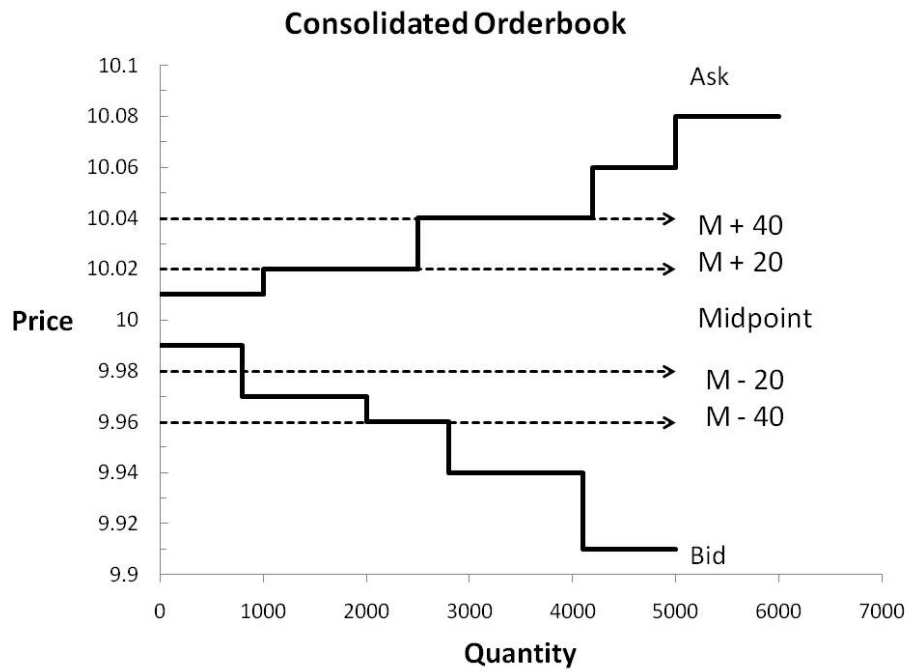

Figure (2) Snapshot of a hypothetical limit order book.
Depth(20) aggregates liquidity offered within the interval of (M - 20bps, M + 20bps), which are 2500 shares on the ask side and 800 on the bid side. Depth(40) contains 4100 and 2800 shares on the ask and bid side respectively. The number of shares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

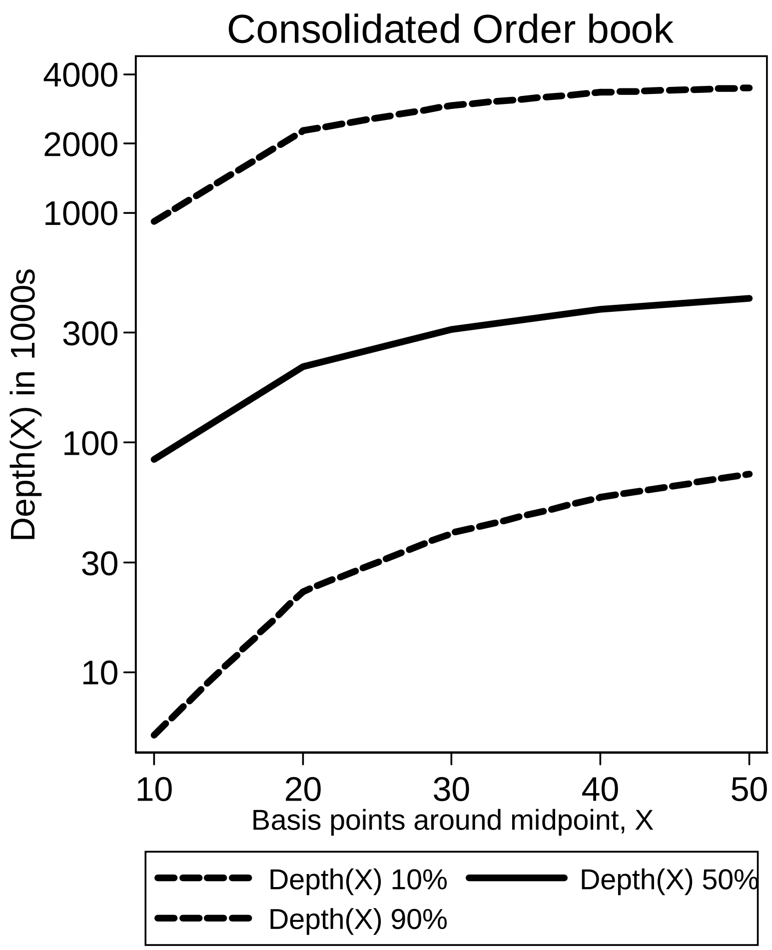

Figure (3) Depth in the consolidated order book.
The figure shows the 10, 50 and 90th percentiles of the Depth(X) measure, expressed on a logarithmic scale in €1000s. The measure aggregates the Euro value of shares offered within a fixed amount of basis points X around the midpoint, shown on the horizontal 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 percentiles are based on the 52 AEX large and mid cap constituents between 2006 - 2009.

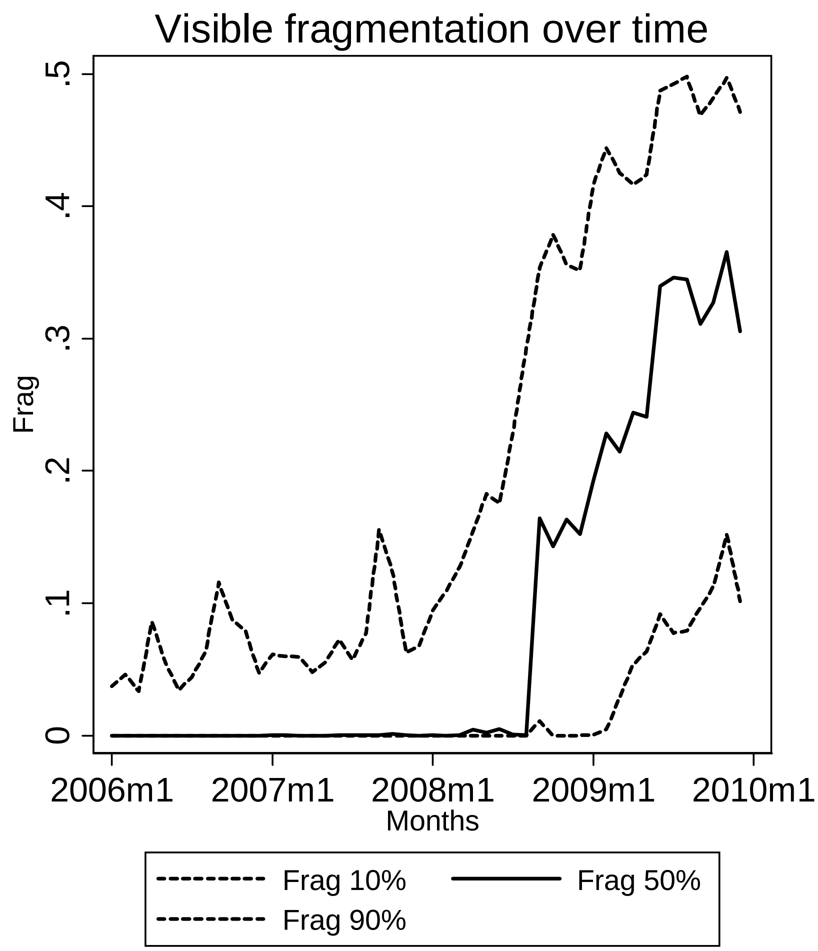

Figure (4) Visible fragmentation of AEX large and Mid cap firms.
The monthly 10, 50 and 90th percentiles of VisFrag are shown, for the 52 AEX large and mid cap stocks between 2006 - 2009. VisFrag equals 1 - HHI, based on the number of shares traded at the following trading venues: Euronext (Amsterdam,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

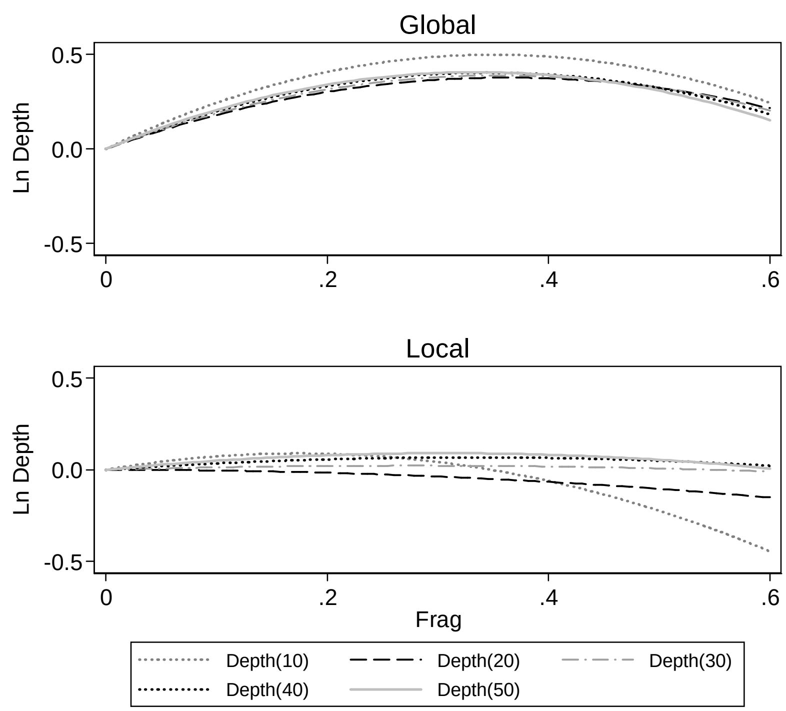

Figure (5) The effect of visible fragmentation on global and local liquidity.
The regression coefficients of visible fragmentation on liquidity are plotted, for the global order book (upper panel, model (1) - (5) of Table 3) and local order book (lower panel, model (1) - (5) of Table 4). The vertical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

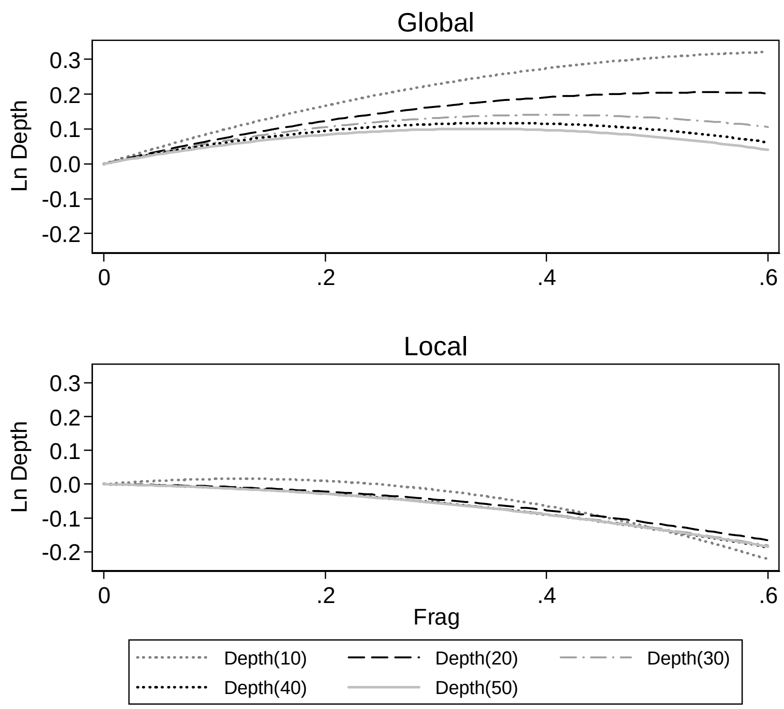

Figure (6) Visible fragmentation and liquidity: firm-quarter dummies.
The regression coefficients of visible fragmentation on liquidity of Table 5 are plotted, where the regressions have firm-quarter dummies. The upper panel shows the global order book and the lower panel the local order book. The vertical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

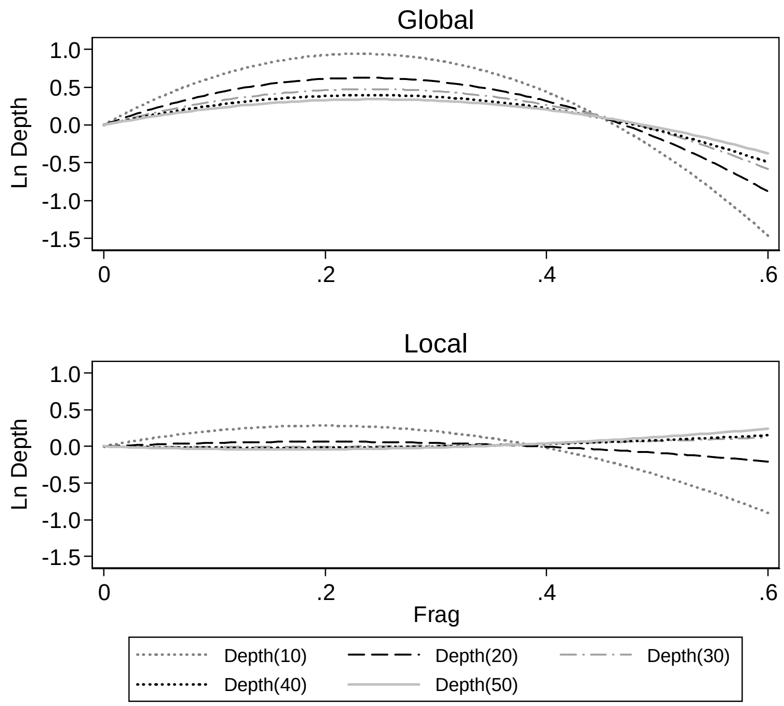

Figure (7) Visible fragmentation and liquidity: IV regressions.
The IV regression coefficients of visible fragmentation on liquidity of Table 5 are plotted. The instruments are (i) the number of electronic messages to transactions on the visible competitors, (ii) the logarithm of the visible competitors average order size, (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).

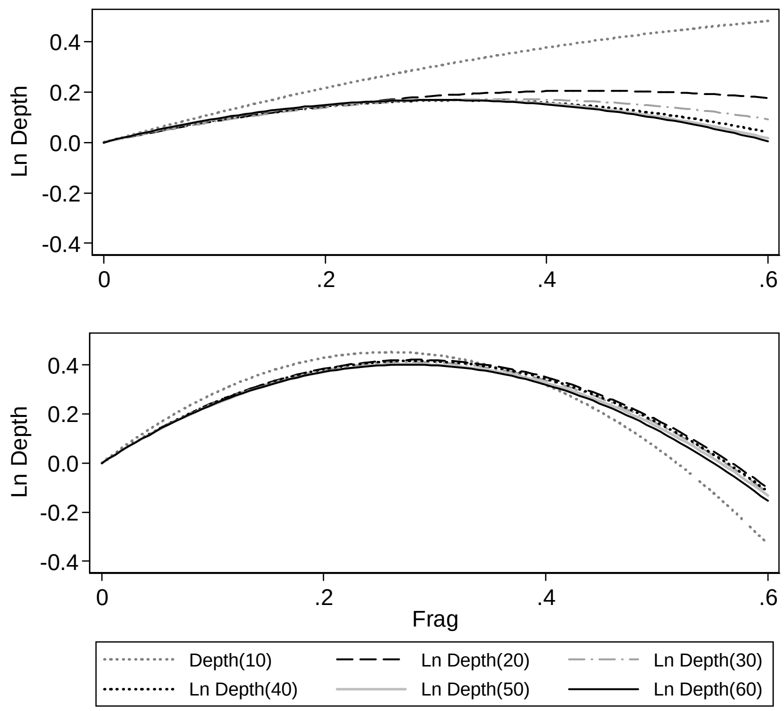

Figure (8) Visible fragmentation and global liquidity: small versus large stocks. The regression coefficients of visible fragmentation on liquidity are plotted, for large and small stocks (regressions (1) - (5) in panel A and B, Table 6). The 14 large stocks have an average market cap exceeding ten billion 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 Table A1

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. Dark 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	Dark	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