The impact of dark trading and visible fragmentation on market quality

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Abstract

Two important characteristics of current equity markets are the large number of competing trading venues with publicly displayed order books and the substantial fraction of dark trading, which takes place outside such visible order books. This paper evaluates the impact on liquidity of dark trading and fragmentation in visible order books. Dark trading has a detrimental effect on liquidity. Visible fragmentation improves liquidity aggregated over all visible trading venues but lowers liquidity at the traditional market, meaning that the benefits of fragmentation are not enjoyed by investors who resort only to the traditional market.

JEL Codes: G10; G14; G15.

Keywords: Market microstructure, Fragmentation, Dark trading, Liquidity

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Web Appendix available at http://dl.dropbox.com/u/13468320/Webappendix.pdf

1 Introduction

Equity trading all over the world has seen a proliferation of new trading venues. The traditional stock exchanges are being challenged by a variety of trading systems of which some are designed as publicly displayed limit order books (e.g., electronic communication networks (ECNs)) whereas others operate in the dark (e.g., 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 marketplace. 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 unanswered question is how market quality is affected by the many different types of competing venues—visible and dark. 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 into visible and dark venues, i.e., with and without publicly displayed limit order books. According to this definition, dark trading venues have a market share of approximately 30% in the US and 40% in European blue chips.[1] Recently, the SEC has been conducting a broad review of current equity markets, and it is particularly interested in the effect of dark trading on execution quality.[2]

The impact on equity markets of fragmentation in visible order books and of dark trading have long interested researchers, regulators, investors, and trading institutions. In a recent study, O'Hara and Ye (2011) find that fragmentation lowers transaction costs and increases execution speed for NYSE and Nasdaq stocks. While clearly an improvement over

[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.

previous work, their data do not identify the location of trade executions by venue on a per-stock basis, and therefore lump together all trades that took place on off-exchange venues independent on whether they stem from publicly displayed limit order books or took place in the dark. Therefore, they do not distinguish 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 fragmentation in visible order books ("visible fragmentation") and dark trading. As we will argue below, this distinction is important as competition from publicly displayed order books and dark trading may have substantially different impacts. In addition, we address the regulatory issues of fair markets and retail investor protection. To this end, we distinguish between liquidity aggregated over all trading venues (consolidated liquidity), liquidity when choosing the best market only (best-market liquidity), and liquidity of the traditional market only (local liquidity). Consolidated liquidity is a relevant indicator for investors employing smart order routing technology (SORT). Local liquidity, in contrast, is of importance to traders whose best-execution policy is restricted to the traditional market only. Best-market liquidity is an in-between concept where the trader does not split up a trade across markets but chooses the most liquid market at the time. We furthermore improve on previous research by employing a new dataset that covers the relevant universe of trading platforms, contains information on a venue by venue basis allowing for a stronger identification of fragmentation as well as improved liquidity metrics.

We address the impact of fragmentation on market liquidity by creating, for every firm, daily proxies of visible fragmentation, dark activity, and liquidity. Specifically, we use high-frequency data from all relevant trading venues from January 2006 (before fragmentation set in) to the end of 2009, when markets were 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 using the Herfindahl-Hirschman index (*HHI*, the sum of the squared market shares) based on the trading volumes of all venues employing publicly displayed limit order books. Dark trading is defined as the market share of trading volume on dark venues, which reflects over-the-counter, dark pools, and internalization by broker dealers. 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 consolidated liquidity available in the market. Based on the consolidated order book we analyze liquidity at the best price levels and also deeper in the order book. The depth beyond the best price levels matters to investors because it reflects the quantity immediately available for trading and therefore the price of immediacy.

Our panel dataset helps to identify the exogenous relationship between liquidity and fragmentation. The inclusion of firm-quarter fixed effects implies that the impact of fragmentation on liquidity stems from variation within a firm-quarter, making the analysis robust to various market-wide shocks and time-varying firm-specific shocks. Furthermore, while employing firm-quarter fixed effects, to address remaining concerns about the 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 new entrants, and the number of limit orders to market orders on the visible new entrants. Dark trading is instrumented by the size of the average dark order.

Our main finding is that the effect of visible fragmentation on consolidated liquidity is generally positive, while the effect of dark trading is negative. An increase in dark trading of one standard deviation lowers the consolidated liquidity by 9%, which is consistent with most of the theoretical research but has not been documented empirically (see Section 2 for a literature review). The effect of visible fragmentation has an inverted U-shape, i.e., the marginal effect decreases as fragmentation increases. With our most conservative estimates, the optimal degree of visible fragmentation improves consolidated liquidity by approximately 30% compared with a completely concentrated market. In addition, we find that the gains of visible fragmentation are strongest for liquidity close to the midpoint, i.e., at relatively good price levels, and are weaker for liquidity deeper in the order book, which improves by only 12%. This result suggests that newly entering trading venues with visible order books primarily improve liquidity close to the midpoint.

While consolidated liquidity benefits from visible fragmentation, we find that the market quality at the traditional stock exchange is worse off: local liquidity close to the midpoint reduces by approximately 10%. Thus, investors without access to all markets are worse off in a fragmented market, especially for relatively small orders. However, best-market liquidity does not reduce by visible fragmentation, which is an important finding as it implies that the enhanced competition between the suppliers of liquidity increases consolidated liquidity, but does not negatively affect the liquidity on the single (most liquid) market. This finding does not support the theory that in a fragmented market liquidity becomes dispersed across the venues, such that each individual venue becomes less liquid (e.g., Foucault and Menkveld (2008), van Kervel (2012)).

Our findings on liquidity are related to those of several recent studies. The positive effect of visible fragmentation is consistent with competition between liquidity suppliers, since the compensation for liquidity suppliers, the realized spread, reduces with fragmentation (e.g., Biais, Bisière, and Spatt (2010)). A similar argument is made by Foucault and Menkveld (2008), who use 2004 data to show that liquidity improves with competition between two traditional stock exchanges (the LSE and Euronext). The negative impact of dark trading on liquidity is consistent with a "cream-skimming" effect, as the informativeness of trades, the price impact, increases strongly with dark activity (Zhu, 2011). Informed traders typically trade at the same side of the order book, such that they face low execution probabilities in dark pools and crossing networks. Consequently, dark markets attract relatively more uninformed traders, leaving the informed trades to visible markets. According to Hendershott and Mendelson (2000), the visible market might be used as a market of last resort which attracts mostly informed order flow.

In line with our results, Weaver (2011) shows that off-exchange reported trades, which mostly represent dark trades in his sample, negatively impact the market quality for US stocks. Similarly, Nimalendran and Ray (2012) find that quoted spreads and price impact measures on the quoting exchanges increase following transactions on one important dark pool. In contrast to our results, Buti, Rindi, and Werner (2010a) find that dark-pool activity is positively related to liquidity in the cross-section, but economically insignificant in the time series. Similarly, Ray (2010), Ye (2010) and Ready (2012) find that an increase in the effective spread of exchanges decreases the market share of dark pools. They study pure dark pools however, whereas our measure of dark trading encompasses all forms of dark trading such as dark pools, OTC and internalization. Furthermore, our identification of the impacts of different forms of fragmentation on market quality – and not only dark trading– is not in the cross-section but within the same stock-quarter, removing any stock-time specific unobserved heterogeneity.[3]

In summary, by splitting up fragmentation into visible fragmentation and dark trading, we sharpen the insights 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 relate to the issues raised by the SEC on the benefits and drawbacks of stock market fragmentation, showing 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 the protection of retail investors.

The remainder of this paper is structured as follows. Section 2 discusses the 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

[3] Another type of dark trading are (fully) hidden orders. Boulatov and George (2013) model how hidden and displayed liquidity interact in limit order markets. They show that liquidity may deteriorate when hidden orders are forbidden as informed traders reduce liquidity provision. Folley, Malinova, and Park (2012) study how the introduction of such trading impacts market quality on the Toronto Stock Exchange.

reports a series of robustness checks. Finally, Section 7 provides concluding remarks.

2 Literature on fragmentation and market quality

Some theoretical arguments highlight a trade-off between order flow fragmentation and competition. A single exchange has costs lower than those of a fragmented market structure. The latter costs are the fixed costs to set up a new trading venue; the fixed costs for clearing and settlement; the costs of monitoring several trading venues simultaneously; and the cost of advanced technological infrastructure to aggregate dispersed information in the market and to connect to several trading venues. Also, a single market that is already liquid will attract even more liquidity because of positive network externalities (e.g., Pagano (1989a), Pagano (1989b), and Admati 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, giving the highest degree of liquidity.

However, while network externalities are still relevant, nowadays they may be realized even when trading venues coexist. This happens to the extent that the technological infrastructure seamlessly links the individual trading venues, creating effectively one market. From an investor's point of view, the market is then not fragmented, which alleviates the drawbacks of fragmentation (Stoll, 2006).[4] In addition, fragmentation might also enhance market quality, because increased competition among liquidity suppliers forces them to improve their prices, narrowing the bid-ask spreads (e.g., Battalio (1997) and Biais, Martimort, and Rochet (2000)). 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) inves-

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

tigate 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 the overall quoted spreads.

Differences between trading venues may arise to cater to the different needs of 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. To attract more investors, new trading venues may apply aggressive pricing schedules, such as make and take fees (Foucault, Kadan, and Kandel (2009), Colliard and Foucault (2011)). 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 attracts more informed order flow than the regional dealers (Easley, Kiefer, and O'Hara, 1996) and Nasdaq market makers (Affleck-Graves, Hedge, and Miller (1994) and Bessembinder and Kaufman (1997)). Furthermore, Barclay, Hendershott, and McCormick (2003) find that ECNs attract more informed order flow than Nasdaq market makers, because 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 Dutch firms in 2004, and find a trade-through rate of 73%. They call for a prohibition of trade-throughs since these events discourage liquidity provision. Possible explanations of trade-throughs are the high costs of monitoring multiple markets or the high variable and fixed trading fees and clearing and settlement costs. Gresse (2006) finds that trading activity on a crossing

[5]Time priority is violated when two limit orders with the same price are placed on two venues and the later order 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. In a partial trade-through only part of the order could have been executed against a better price.

network improves the quoted spreads in the dealer market, especially when the dealers also trade on the crossing network.

In addition to competition between trading venues with visible liquidity, this paper is related to the literature on 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 they 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 the quoted spreads. That is, for liquid stocks both limit and market orders migrate to the dark pool, leaving the spread tight. For illiquid stocks the competition induced by the dark pool reduces the execution probability of limit orders, causing the spread to increase. Zhu (2011) and Ye (2012) model how exchanges and dark pools interact when there is informed trading. Zhu (2011) argues that dark pools "cream-skim" uninformed trades, leaving informed trades to the visible exchange. Informed traders face a relatively low execution probability on the dark pool because they typically trade on the same side of the order book. Price discovery on the exchange is therefore improved but liquidity deteriorates. Ye (2012) focuses on how the opportunity to trade in the dark impacts price discovery. He shows that informed traders faces two types of costs: price impact on the exchange and execution probability impact on the crossing network. The informed trader reduces his aggressiveness on the exchange to balance those costs and therefore price discovery is negatively impacted due to the presence of a crossing network.

Fundamental asset uncertainty increases the market share of the crossing network as the informed trader has more incentives to hide his trade.

Finally, our paper is related to the literature on algorithmic trading, 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 it has drastically affected the trading environment. In particular, it affects the level of market fragmentation analyzed in our sample, since computer programs and SORT allow investors to find the best liquidity in the market by comparing the order books of individual venues. Some algorithms are designed to split up trades over time to reduce implicit transaction costs (e.g., Huberman and Stanzl (2005)). Boehmer, Fong, and Wu (2012) find that an increase in algorithmic trading intensity improves liquidity, but also increases volatility. Programs are also used to identify deviations from the efficient stock price, by quickly trading on new information or price changes of other securities (Brogaard, Hendershott, and Riordan, 2012). Furthermore, programs may provide liquidity when the quoted spreads are large, e.g., when it is profitable to do so (Brogaard, Hendershott, and Riordan, 2012). 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. Hasbrouck and Saar (2011) find that liquidity is positively affected by low-latency trading, i.e., extremely fast proprietary trading desks.

In summary, the literature suggests that the impact of fragmented trading may crucially depend upon whether fragmentation stems from visible trading venues or dark markets. However, the empirical studies to date 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 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 large European stocks (Gomber and Pierron, 2010). We can summarize the most important trading venues for these stocks into three groups as follows (a more general description of current European financial markets can be found in the web Appendix).[6]

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 execute less than 1% of total order flow.

Second, new ECNs have been introduced (in European terminology Multilateral Trading Facilities) with publicly displayed limit order books, 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. The success of the MTFs depends on the trading volumes and 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

[6] Available at http://dl.dropbox.com/u/13468320/Webappendix.pdf

market share.[7] A new trading venue in Europe typically starts with a short 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 trading venues 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 at the midpoint of the primary market, and do not contribute to price discovery. Consistent with our findings, 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, as they execute approximately 40% of total traded volume.

3.2 Dataset

Our dataset contains 52 Dutch stocks forming the constituents of the so-called AEX Large and Mid cap indices. In terms of size, the average market cap of our sample is approximately twice that of the NYSE and Nasdaq sample analyzed in O'Hara and Ye (2011). Our dataset covers the AEX Large and Mid cap 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 changes in the composition in the indices, 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 (for-

[7] See "Nasdaq OMX to close pan-European equity MTF", www.thetradenews.com.

merly known as Virt-X).[8] We employ data from all these venues but collect them only during the trading hours of the continuous auction of Euronext Amsterdam, i.e. between 09.00 to 17.30, Amsterdam time. Therefore, data of the opening and closing auctions at these venues are not included.[9]

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.[10] 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 available to the market, 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 trades and over-the-counter trades (including trades executed over telephone). These dark trades are reported in a separate file and

[8]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 stock exchange, PLUS group and some smaller exchanges).

[9]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.

[10]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 6.2; the results are unaffected.

are constructed by Markit Boat, a MiFID-compliant trade reporting company.[11] The file contains the price, quantity and time of the execution (time stamped to the millisecond). The file contains trades from all trading venues, but does not report the identity of the executing venue and does not contain any quotes. We complete the dark trades data by adding the over-the-counter and internalized trades reported in separate files by Euronext, Xetra and Chi-X. The largest part of dark trading is internalization, but we do not know the exact decomposition. The fraction of trading volume in pure dark pools is very small in our sample period ($< 1\%$, according the 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 entrants together started to attract significant order flow only as of August 2008 (4.5%). The slow start up shows that the venues needed time to generate trading activity.

In Table 1 we present some descriptive statistics of the sample stocks. There is considerable variation in firm size (market capitalization), price and trading volume. The table also reports realized volatility, computed by first dividing the trading day into 34 fifteen-minute periods and then calculating stock returns of each period, based on the midpoint at the beginning and end of that period. The standard deviation of these stock returns are daily estimates of realized volatility.[12] The last columns of the table shows the average

[11]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.

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

market share of Euronext and the dark venues, calculated as of November 2007 onwards, the period for which Markit Boat data have become available in the dataset.[13]

4 Liquidity and fragmentation

4.1 Liquidity available to different types of traders

The goal of the paper is to analyze the impact of equity market fragmentation on liquidity. We distinguish between the liquidity available to traders with smart order routing technology (SORT), i.e. those who can access all trading venues simultaneously, and to non-SORT traders, i.e. those who may access all venues but may trade on only one venue at each point in time. van Kervel (2012) shows that high-frequency traders operating like market makers duplicate their limit order schedules across venues, but immediately cancel these duplicate limit orders after a trade on a competing venue. Therefore, traders who are unable to send market orders *simultaneously* to several venues in essence have access to the liquidity of only a single venue. However, these non-SORT traders are able to choose the most liquid venue at each point in time. Potential reasons why non-SORT traders are unable to send market orders simultaneously to several venues are because they are too slow (e.g., human traders),[14] or they actively search for hidden liquidity which causes delays, or because they economize on the costs of the technological infrastructure required for smart order routing. The distinction between SORT and non-SORT traders is empirically justified, as not all investors use SORT (e.g. Foucault and Menkveld (2008) and Ende, Gomber, and Lutat (2009)).

(2001).

[13]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 6.2.

[14]Indeed, when a trader leaves a delay of milliseconds when sending two market orders to two venues, the high frequency traders may observe the first market orders and quickly cancel their limit orders before the second market order arrives.

For the above reasons, we consider the *consolidated* liquidity available to SORT traders, and the liquidity of the most liquid venue at each point in time available to non-SORT traders (which we call *best-market* liquidity). In addition, we also consider the liquidity available to traders who only have access to the traditional exchange (which we call *local* liquidity). Gomber, Pujol, and Wranik (2012) analyze a sample of 75 best-execution policies of the 100 largest European financial institutions and brokers in 2008 and 2009, and find that 20 of them specifically state that they only access the traditional stock exchange. These brokers ignore the liquidity available at other venues to achieve best execution, which is permitted by the European regulator.[15]

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. Also, at each observation we can select the most liquid venue which represents the liquidity available to non-SORT traders (the definition of liquidity is given in the next section).

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 pecuniary value of the number of shares offered within a fixed interval around the midpoint. In the detail, the midpoint is the average of the best bid and ask price of the

[15]MiFID has a very broad definition of best execution (incorporating the price, speed, transaction costs, anonymity, and likelihood of execution), and therefore any type of order routing strategy qualifies for the best-execution requirement.

consolidated order book (the NBBO) and the interval is an amount $X = \{10, 20, ..., 40\}$ basis points relative to the midpoint.[16] 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 consolidated, local (i.e., Euronext Amsterdam) and best market order book (explained below). Denote price level $j = \{1, 2, ..., J\}$ on the pricing grid and the midpoint of the consolidated order book as M, then

$$\begin{aligned}
Depth\ Ask(X) &= \sum_{j=1}^{J} P_j^{Ask} Q_j^{Ask} \mathbf{1}\{P_j^{Ask} < M(1+X)\}, \\
Depth\ Bid(X) &= \sum_{j=1}^{J} P_j^{Bid} Q_j^{Bid} \mathbf{1}\{P_j^{Bid} > M(1-X)\}, \\
Depth(X) &= Depth\ Bid(X) + Depth\ Ask(X). \qquad (1a)
\end{aligned}$$

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 $Depth(40)$ 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.[17] More specifically, $CRT(D)$

[16] 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 in the cross-section and over time.

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

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. it measures the quantity available within X basis points around the midpoint. Although both measures estimate the depth and slope of the order book, our approach solves two 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 $Depth(X + \varepsilon) = Depth(X)$. 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.[18] While negative transaction costs cannot be interpreted meaningfully, the midpoint and $Depth(X)$ always represent liquidity in an economically meaningful manner.

An advantage of $Depth(X)$ over the traditional quoted depth and spread is it's insensitivity 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 the tick size.[19]

Figure 3 shows the slope of the consolidated order book plotting the 10, 50 and 90$^{\text{th}}$ percentile of the daily average 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. There is a large variation in $Depth(X)$ over time and across firms, as for example the 10^{th} and 90^{th} percentile of $Depth(10)$ are €5.000 and €915.000. This is in line with high levels of skewness and kurtosis (not reported).

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

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

We define the liquidity of the most liquid venue as $Best\text{-}Market\ Depth(X)$, which represents the liquidity available to non-SORT traders. Denote venue $v \in V = \{Euronext\ Amsterdam, Chi\text{-}X, Bats, Turquoise, Nasdaq\ OMX\}$, then at each snapshot we have

$$\begin{aligned} Best\ Depth\ Ask(X) &= \max_{v \in V}\{Depth\ Ask(X)_v\}, \\ Best\ Depth\ Bid(X) &= \max_{v \in V}\{Depth\ Bid(X)_v\}, \\ Best\text{-}Market\ Depth(X) &= Best\ Depth\ Bid(X) + Best\ Depth\ Ask(X). \end{aligned} \tag{2}$$

In the regression analysis we use as liquidity measures the daily averages per firm of *Best Market*, *Consolidated* and *Local Depth*(X).

Panel A of Table 2 contains the medians of the $Depth(X)$ measure for the Consolidated, Best-Market and Local order books on a yearly basis, along with other liquidity measures discussed in the next section. As expected, the depth measures vary substantially over time. In 2006 and 2007, before the market became very fragmented, the Consolidated, Best-Market and Local $Depth(X)$ largely coincide, but in 2009, Local Depth represents only about 60% of Consolidated Depth. Depth close to the midpoint reduced strongly over time, but liquidity deeper in the order book to a much lesser extent. That is, the median of Consolidated *Depth(10)* decreased by 44% from 2006 to 2009, while Consolidated *Depth(40)* decreased by only 26%. In addition, the yearly standard deviations of the depth measures have decreased by approximately 50% over the years (not reported).

4.3 Other liquidity measures

This section describes some more traditional liquidity measures. These are the price impact, effective spread and realized spread, based on executed transactions, and the quoted spread based on prices of the consolidated limit order book. The web appendix contains a formal definition of the measures.

The medians of the liquidity measures are reported in Table 2, based on daily observations and calculated yearly. The table shows several interesting results. Between 2006 and 2009 the median quoted spread has improved (i.e., reduced) by 9%, while the Consolidated *Depth(10)* decreased by 44% over the same time period. This implies that the prices of limit orders have improved, but the quantities within 10 basis points from the midpoint have worsened. Turning to the liquidity measures based on executed trades, we observe that the median realized spread has reduced from 2.2 basis points in 2006 to 0.2 basis points in 2009. The realized spread is considered the reward to liquidity suppliers, which has strongly reduced. In this period, the price impact increased by 3.1 basis points while the effective spread remained virtually unaffected. Note that because we show medians, the price impact and realized spread do not exactly add up to the effective spread.

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, $HHI_{it} = \sum_{v=1}^{N} MS_{v,it}^2$, or the squared market share of venue v, summed over all N venues for firm i on day t. We then use $VisFrag = 1 - HHI$, short for visible fragmentation, such that a single dominant market has zero fragmentation whereas $VisFrag$ goes to $1 - 1/N$ in case of complete visible fragmentation. In addition, *Dark* is our proxy for dark trading, calculated as the percentage of daily trading volume executed at dark pools, crossing networks, internalizers and over-the-counter. 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 theory predicts that they affect liquidity in a different fashion. Our measure of fragmentation is more accurate than that of O'Hara and Ye (2011), who classify the origin of trades as either Nasdaq, NYSE or external. The market share of "external venues" is employed as indicator of fragmentation. 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 3 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 analyzed 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 monthly and annual frequencies (26% in 2009), but has a very high daily standard deviation of 17%.[20]

Figure 4 shows the 10, 50 and 90$^{\text{th}}$ percentile of $VisFrag$ over time, calculated on a monthly basis and covering all firms. The sharp increase in fragmentation in September 2008 is explained by Chi-X and Turquoise starting to attract substantial order flow.

5 The impact of visible fragmentation and dark trading on liquidity

In this section, we estimate the effect of fragmentation on various liquidity measures. We first explain the methodology and then presents the regression results. Section 6 shows the instrumental variables regressions and other robustness checks.

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

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, containing the liquidity and fragmentation measures discussed in Section 4. The panel approach allows for more flexibility compared to other papers investigating the impact of fragmentation on liquidity. For example, compared to the cross sectional regressions employed by O'Hara and Ye (2011), we add firm fixed effects to absorb for 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 contribute to papers such as Foucault and Menkveld (2008), Chlistalla and Lutat (2011) and Hengelbrock and Theissen (2010), who study the introduction of a single new trading venue (EuroSETS, Chi-X and Turquoise respectively). That is, these papers 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. This is important as the starting up of a new trading venue is often associated with other changes that may determine liquidity (e.g., competition in trading fees or clearing and settlement fees). 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 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 trading volume as control variables, which is common in this literature.[21] Descriptives of these control variables are

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

presented in Table 2. In addition, we include a proxy for algorithmic activity, as this has been found to improve liquidity (e.g. Brogaard, Hendershott, and Riordan (2012)). We construct a measure similar to Hendershott, Jones, and Menkveld (2011), defined as the daily number of electronic messages (i.e., the placement and cancelations of limit orders and market orders) 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, dark trading and the 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 $VisFrag^2_{it}$ to measure fragmentation, where $VisFrag_{it} = 0$ if trading in a firm is completely concentrated. The regression equation thus becomes

$$\begin{aligned} Liq\,Measure_{it} = \alpha_i \times \delta_{q(t)} + \beta_1 VisFrag_{it} + \beta_2 VisFrag^2_{it} + \beta_3 Dark_{it} + \\ \beta_4 Ln(Size)_{it} + \beta_5 Ln(Price)_{it} + \beta_6 Ln(Volume)_{it} + \\ \beta_7 Ln(Volatility)_{it} + \beta_8 Algo_{it} + \varepsilon_{it}, \end{aligned} \tag{3}$$

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

We add firm-quarter dummies $\alpha_i \times \delta_{q(t)}$: rather than a single dummy for each firm, we add 16 quarterly dummies per firm.[22] 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 a number of issues.

First, the firm-quarter dummies allow to control for potential self-selection problems.

[22]The regression results with firm and quarter dummies can be found in the web appendix.

For example, Cantillon and Yin (2010) raises 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. Similarly, 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. These phenomena may be simultaneously determined and interact, such that a change in the market structure may cause the market to converge only slowly to a new equilibrium. 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.

Second, 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 analysis would suffer from an omitted variable problem, leading to a bias in the coefficients on fragmentation. The firm-quarter dummies capture industry shocks and time-varying firm specific shocks.

5.2 Results consolidated liquidity

The regression results for the $Consolidated\ Depth(X)$ and traditional liquidity measures are reported in Table 4. The results of models (1) to (4) 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 consolidated liquidity for the four models (upper panel). The figure reveals 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 *Depth*(40), where the maximum lies at $VisFrag = 0.40$, implying a trade-off in the benefits and drawbacks of fragmentation. At $VisFrag = 0.40$, visible fragmentation improves *Depth*(10) by 30% and *Depth*(40) by 12% compared to the case when $VisFrag = 0$. This level of visible fragmentation is fairly close to the average level in 2009, 0.28. The magnitudes are economically sizeable and all statistically significant at the 1% level.

We now investigate the impact of visible fragmentation on the other liquidity indicators, as reported in models (5) to (8) in Table 4. When $VisFrag = 0.40$, the effective spread reduces by 2.4 basis points compared with a completely concentrated market. This is sizeable, considering that the median effective spread in 2009 is 12.5 basis points (Table 2). The economic impact of visible fragmentation on the effective spread in our analysis is similar to the estimate of O'Hara and Ye (2011) for total fragmentation, where the benefit is approximately three basis points for NYSE and Nasdaq firms.[23] At $VisFrag = 0.40$, the price impact reduces by 0.6 basis points. However, the coefficients are individually insignificant. The coefficient of fragmentation does become significant when we estimate only a linear term (-1.54 with a t-stat of 2.4). The effect of visible fragmentation on the realized spread is 1.8 at $VisFrag = 0.40$, which is large given a median realized spread of 0.2 in 2009. The realized spread represents the reward to the suppliers of liquidity, which reduces because of enhanced competition between liquidity suppliers in a fragmented market. The quoted spread in model (9) improves by 2 basis point at $VisFrag = 0.4$, while the sample median is twelve basis points.

We now turn to the effects of dark trading on liquidity. In Table 4, the coefficients on *Dark* are strongly negative, with a coefficient of -0.74 for *Ln Depth*(10). As a result, a

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

one standard deviation (0.18) increase in the fraction of dark trading reduces $Depth(10)$ by 13%. The coefficient on the price impact of 5.48 suggests that dark trading leads to more adverse selection and informed trading on the visible markets. The coefficient on the realized spread is -3.41, i.e., the profits to liquidity suppliers decrease for higher levels of dark trading. These 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. The reduction in depth at the visible exchanges is also consistent with the model of Buti, Rindi, and Werner (2010b), since limit orders migrate from the limit order book to the dark pool. Empirically, 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 contrast Buti, Rindi, and Werner (2010a), who find that dark pool activity improves the quoted spread in the cross section. In time series regressions similar to ours, however, Buti, Rindi, and Werner (2010a) find economically insignificant results. In addition, the authors do not control for the degree of visible fragmentation, and for trades on crossing networks and OTC. Trading activity across such venues is likely to be correlated, implying an omitted-variable bias. For example, dark pool activity is generally higher for larger firms, which also benefit more from higher levels of visible fragmentation in our sample.

Turning to the control variables of the regressions, we find that algorithmic trading ($Algo$) worsens liquidity. That is, a one standard deviation (0.36) increase in $Algo$ lowers the $Depth(X)$ measures by 11%. 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. Volatility has a negative impact on liquidity; especially for liquidity close to the midpoint. Not surprisingly, the price impact strongly increases by volatility, which proxies for the amount of asymmetric information in the market.

5.3 Results best-market and local liquidity

The impact of fragmentation and dark trading on *Local* and *Best-Market Depth*(X) is shown in Table 5 and the middle and lower panels of Figure 5. The figure shows that *Best-MarketDepth*(10) improves by 10% at $VisFrag = 0.4$, but liquidity deeper in the order book, *Best-Market Depth*(40), reduces mildly. This suggests that the benefits of competition between liquidity suppliers mostly hold for liquidity close to the midpoint, i.e., at good price levels. Traders accessing the best market only therefore enjoy greater liquidity for smaller orders but not for larger orders.

Visible fragmentation reduces *Local Depth*(X) by 6% to 10% at $VisFrag = 0.4$, for all levels of X. Consequently, small investors who are limited to trading on Euronext only are worse off. 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. 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. Most likely, the difference is due to the market structure in the US, where Nasdaq market makers lost their oligopolistic rents after the entry of ECNs.

The coefficients on *Dark* are of similar magnitude as those reported for consolidated liquidity. That is, the detrimental effect of dark trading on *consolidated* liquidity also holds for *best-market* and *local* liquidity. Results of the control variables are in line with those reported in Table 4.

The decision to trade in the dark might be endogenous however, 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 address these reverse causality issues with an instrumental variables regression in the next section, but can already announce that our main results continue to hold.

6 Robustness checks

In this section we investigate the robustness of the main result. To tackle endogeneity problems of the visible fragmentation and dark trading variables we use an instrumental variables estimator. The section concludes with some additional robustness checks.

6.1 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, $VisFrag$ might be high because a stock is very liquid on a particular day; or $Dark$ might be high when investors substitute the visible markets for the dark market because the visible markets are 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 new entrants (Bats Europe, Chi-X, Nasdaq OMX and Turquoise),[24] (ii) the logarithm of the visible new entrants average order size and (iii) the logarithm of the average $Dark$ order size, for each stock and day. We also add the squares of these variables, summing to six instruments, because we have a linear and quadratic term for fragmentation. These instruments are specifically aimed to tackle the reverse causality issues. The first instrument, the ratio of limit to market orders on the visible new entrants, 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 higher levels of visible liquidity should not affect the ratio of limit to market orders on the visible new entrants. The second instrument, the logarithm of the visible new entrants order size, positively relates to fragmentation as larger orders typically increase the market share of the entrants.[25] Since the regression controls for total traded volume, a shift of volume from the primary market to the new entrants should not improve liquidity except via fragmentation. The third instrument, the logarithm of average dark order size, positively affects dark activity as larger dark orders increases dark market share. The instrument seems exogenous, as lower visible liquidity should not increase the average dark order size.

Unreported first stage estimations reveal that all instruments are statistically and economically significant. Especially the ratio of messages to transactions and the logarithm of average visible entrants 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 indicated by the

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

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

Kleibergen-Paap and Angrist-Pischke Wald tests, reported in the bottom part of Table 6. Unreported tests also reject the redundancy of all individual instruments, meaning each instrument improves the estimators' asymptotic efficiency.

The *IV* regressions include firm-quarter dummies and we use the two stage GMM estimator which is efficient in the presence of heteroscedasticity (Stock and Yogo, 2002). The regression results are reported in Table 6 and displayed in Figure 6. First, we observe that the magnitudes of the coefficients on visible fragmentation have increased and are highly significant. At $VisFrag = 0.40$, *Consolidated Depth*(*10*) and *Depth*(*40*) improve by 55% and 29% compared with a completely concentrated market. The standard errors have increased, as the *IV* procedure reduces the accuracy with which the coefficients are estimated. Figure 6 shows more clearly that an optimal level of visible fragmentation exists at around $VisFrag = 0.30$. Also, 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 Table 4, and are statistically significant in all regression specifications. Assuming exogenous instruments, in economical terms the initial estimates did not suffer from endogeneity issues. However, the *IV* results for the traditional liquidity measures are statistically insignificant, except for the quoted spread which reduces by 6 basis points at the minimum of the parabola at $VisFrag = 0.2$.

The results for *Best-Market Depth*(X) show that, as before, liquidity close to the midpoint improves by fragmentation whereas liquidity deeper in the order book does not.

Turning to the *IV* results for local liquidity, the bottom left panel in Table 6 and the lower panel in Figure 6, we observe the following. First, due to increased standard errors, only the coefficients of *Depth*(*10*) 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. The coefficients on *Dark* however are again highly significant and negative, similar to previous findings.

Finally, we test the requirement that the set of instruments are uncorrelated with the error term. The joint null hypothesis of the overidentifying restrictions test 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 below the regression results in of Table 6, and do not reject the overidentifying restrictions in eleven out of sixteen regressions. For the *Consolidated Depth(40)*, the realized spread, price impact and quoted spread the exogeneity of the instruments is questioned. A GMM distance test reveals that the logarithm of the visible new entrants 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 tests of overidentifying restrictions.

6.2 Additional robustness checks

To investigate the sensitivity of our results, we perform a number of robustness checks. First, we perform the main regression using only observations from 2008 and 2009. The results do not change (not reported), mainly because fragmentation especially took place in 2008 and 2009. This provides an additional robustness to potential time effects, 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 10). 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). Our results remain qualitatively unaffected.

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 source of fragmentation – 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 has a detrimental effect.

The positive effect of visible fragmentation stems from competition between liquidity suppliers, as evidenced by the reduction in the reward of supplying liquidity. The negative effect of dark trading is consistent with a "cream-skimming" effect, where the dark markets mostly attract uninformed order flow which in turn increases adverse selection costs on the visible markets. We relate this finding to pre-trade transparency, which has been shown to reduce adverse selection costs (e.g., Boehmer, Saar, and Yu (2005)). As such, we show that it is important to distinguish different types of fragmentation to deepen 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 consolidated, best-market and local liquidity. Consolidated liquidity takes all relevant trading venues into account while local liquidity only the traditional stock market. Although consolidated liquidity, and to a lesser extent best-market liquidity, improve 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 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). A caveat is that we cannot observe the liquidity in the dark markets, yet, the result remains that investors without access to dark markets are worse off. This result should be seen in the light of fair markets and investor protection.

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Table (1) **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. Dark is the market share (in %) of over-the-counter trades, Systematic Internalisers and dark pools; this number is available as of November 2007. Euronext represents the market share (in %) of executed trades on Euronext Amsterdam.

Firm	Size	Price	Volume	Return Vol	Dark	Euronext
Aalberts	1.3	29.03	7.4	0.33	7.94	90.00
Aegon	16.6	10.23	158.0	0.38	14.97	77.71
Ahold	11.4	8.52	117.0	0.23	17.57	76.25
Air France	5.6	19.95	63.5	0.33	14.71	78.37
Akzo nobel	12.3	44.93	143.0	0.25	18.81	74.20
Adv. Metal. Group	0.6	21.24	8.6	0.65	17.95	78.92
Arcadis	0.9	31.40	3.3	0.35	10.78	87.52
Asm Int.	0.8	14.47	7.0	0.37	10.21	86.35
ASML	8.1	17.78	143.0	0.32	16.25	75.97
Bamn Group	1.7	18.84	14.8	0.35	11.70	83.60
Binckbank	0.6	10.60	4.2	0.30	10.50	88.55
Boskalis	2.2	39.50	13.4	0.36	12.34	84.04
R. Wessanen	0.6	8.49	4.3	0.27	9.07	87.57
Corio	3.5	51.12	26.5	0.30	14.35	79.84
Crucell	1.0	15.49	9.2	0.31	8.49	89.84
CSMN	1.5	20.93	8.0	0.24	11.99	86.04
Draka Hold.	0.5	13.01	3.6	0.47	16.21	77.55
DSM	6.1	31.99	71.4	0.25	16.32	77.49
Reed Elsevier	8.1	11.31	70.1	0.22	19.21	73.17
Fortis	34.5	22.82	335.0	0.32	14.76	81.68
Fugro	2.8	38.99	25.9	0.29	12.58	82.87
Hagemeyer	2.0	3.76	43.4	0.25	0.00	99.39
Heijmans	0.6	25.08	3.8	0.34	8.32	90.61
Heineken	16.7	34.06	96.8	0.23	17.96	75.00
Imtech	1.2	15.03	12.0	0.34	27.68	65.13
ING	50.1	22.75	885.0	0.37	13.28	82.55
Eurocomm. Prop	44.0	35.69	371.0	0.42	23.32	71.02
R. KPN	20.4	10.92	211.0	0.22	22.50	70.57
R. ten cate	0.5	26.69	4.6	0.34	10.09	87.68
Nutreco	1.5	42.41	15.1	0.23	12.34	85.30
Oce	0.9	9.95	8.5	0.33	10.54	86.99
Ordina	0.4	10.96	2.8	0.34	7.29	90.00
Philips	28.4	25.00	294.0	0.27	20.64	72.07
Randstad	4.5	35.18	38.0	0.33	13.83	79.50
R. Dutch Shell	88.5	24.22	671.0	0.22	41.37	51.63
SBM Offshore	2.8	26.39	35.5	0.30	13.00	80.33
Arcellor Mittal	1.2	32.46	5.9	0.31	12.50	85.73
Smit Int.	10.7	48.06	5.0	0.32	20.24	75.35
Sns Reaal	2.9	11.66	11.5	0.35	12.94	85.51
Tele Atlas	1.8	20.06	33.3	0.27	8.22	91.77
Tnt	10.7	24.96	94.7	0.27	19.11	74.70
Tomtom	3.0	25.34	47.5	0.45	10.30	83.48
Unilever	32.2	23.62	359.0	0.22	21.94	70.89
Unibail Rodamco	11.9	143.61	168.0	0.29	33.99	58.17
Usg People	0.6	9.27	8.5	0.59	19.02	68.00
Vastned	1.0	55.99	5.0	0.28	10.46	87.45
Vdr Moolen	0.2	4.74	2.2	0.30	2.12	97.72
Vedior	2.9	16.70	34.9	0.22	4.24	94.80
Vopak Int.	2.3	36.51	8.9	0.25	12.24	84.78
Wavin	0.7	7.94	5.8	0.42	11.80	86.92
Wereldhave	1.6	78.78	15.9	0.24	13.29	82.15
Wolters Kluwers	5.5	18.10	43.1	0.25	14.98	76.73

Table (2) Descriptive statistics: time series.
The table shows the medians of the liquidity measures on a yearly basis (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. *Consolidated Depth*(X) represents aggregated liquidity across all trading venues, *Best-Market* picks the most liquid venue at each point in time and *Local* refers to Euronext Amsterdam, the traditional stock exchange. The fourth block of panel A shows the other liquidity measures: the quoted spread (Q^S), the effective spread (E^S), the price impact (PI) and the realized spread (R^S), all measured in basis points. The price impact and realized spread are based on a 5 minute time window. The descriptive statistics in panel B show the percentage of dark trading volume, the natural logarithm of firm size, daily trading volume, realized return volatility (*Ln SD*), and algorithmic trading (*Algo*). 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								
	Consolidated					*Best-Market*			
	2006	2007	2008	2009		2006	2007	2008	2009
Depth(10)	108	136	49	60		107	130	44	40
Depth(20)	281	311	124	168		273	285	103	98
Depth(30)	388	423	181	266		371	378	154	160
Depth(40)	461	482	226	341		438	418	190	210
	Local					*Other*			
Depth(10)	106	127	39	36	Q^S	13.0	10.9	14.6	12.2
Depth(20)	272	279	93	93	E^S	12.7	10.4	14.0	12.5
Depth(30)	371	368	139	155	PI	9.5	8.6	13.3	12.6
Depth(40)	437	407	176	206	R^S	2.2	1.2	0.2	0.2
	Panel B: Descriptive statistics								
	2006	2007	2008	2009					
Dark share	0.0	0.0	23.0	23.2					
Ln Size	14.8	15.1	14.8	14.4					
Ln Volume	16.8	17.0	17.0	16.5					
Ln SD	-6.4	-6.3	-5.7	-5.8					
Algo	1.8	2.5	6.3	28.0					

Table (3) 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 the sum of squared 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 equal weighted based on daily observations per firm (when weighted according to trading volume the average dark fraction is approximately 37%, as mentioned in the main text.

Year	Stdev	Mean	25$^{\text{th}}$	50$^{\text{th}}$	75$^{\text{th}}$
VisFrag					
2006	0.081	0.027	0.000	0.000	0.010
2007	0.066	0.026	0.000	0.000	0.017
2008	0.120	0.098	0.000	0.045	0.172
2009	0.153	0.278	0.147	0.296	0.405
Dark					
2008	0.172	0.259	0.138	0.230	0.338
2009	0.169	0.257	0.136	0.232	0.339

Table (4) The effect of fragmentation on consolidated liquidity.
The dependent variable in models (1) - (4) 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, (5) - (8), are measured in basis points. VisFrag is the degree of visible market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed over-the-counter, 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-quarter fixed effects. 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) Effective Spread	(6) Realized Spread	(7) Price Impact	(8) Quoted Spread
VisFrag	0.951***	0.674***	0.635***	0.615***	-5.463***	-3.940**	-0.440	-9.137
	(6.3)	(8.8)	(9.8)	(10.2)	(-3.4)	(-2.5)	(-0.3)	(-0.6)
VisFrag^2	-0.726***	-0.541***	-0.728***	-0.815***	-1.133	-1.246	-2.451	3.293
	(-2.8)	(-3.7)	(-5.9)	(-7.1)	(-0.4)	(-0.4)	(-0.8)	(0.2)
Dark	-0.737***	-0.523***	-0.472***	-0.435***	2.145***	-3.409***	5.479***	4.535***
	(-19.7)	(-20.9)	(-25.7)	(-26.1)	(4.6)	(-7.6)	(12.5)	(4.7)
Ln Size	0.777***	0.585***	0.437***	0.424***	-4.015***	-1.350*	-2.715***	-15.28***
	(9.9)	(11.0)	(10.6)	(10.7)	(-5.3)	(-1.8)	(-3.2)	(-3.8)
Ln Price	0.486***	0.450***	0.387***	0.377***	-2.385***	-3.679***	1.150*	-9.548***
	(9.2)	(13.7)	(12.1)	(11.8)	(-3.8)	(-6.1)	(1.6)	(-3.4)
Ln Vol	0.380***	0.279***	0.249***	0.231***	-1.091***	0.861***	-1.986***	-2.660***
	(36.4)	(42.0)	(48.2)	(48.6)	(-8.9)	(7.1)	(-17.3)	(-3.8)
Ln SD	-0.459***	-0.386***	-0.334***	-0.303***	5.779***	-4.037***	9.858***	6.356***
	(-38.0)	(-48.4)	(-54.8)	(-54.0)	(40.3)	(-28.7)	(62.0)	(6.6)
Algo	-0.321***	-0.238***	-0.173***	-0.143***	4.561***	0.624*	3.941***	3.100***
	(-14.2)	(-14.4)	(-13.8)	(-12.6)	(14.5)	(1.9)	(10.9)	(4.1)
Obs	46,833	46,833	46,833	46,833	46,833	46,833	46,833	46,833
R^2	0.144	0.271	0.303	0.299	0.105	0.031	0.170	0.005

Table (5) The effect of fragmentation on best-market and local liquidity.

The *Best-Market Depth*(X) is based on the order book of the most liquid venue at each point in time, and the *Local Depth*(X) on Euronext Amsterdam. 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 market fragmentation, defined as $1 - HHI$. Dark is the percentage of order flow executed over-the-counter, 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-quarter fixed effects. 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.

	Best-market				Local			
	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Ln Depth(10)	(6) Ln Depth(20)	(7) Ln Depth(30)	(8) Ln Depth(40)
VisFrag	0.523***	0.134*	0.0591	0.0270	0.210	-0.0738	-0.0941	-0.0922
	(3.6)	(1.9)	(1.0)	(0.5)	(1.4)	(-1.1)	(-1.5)	(-1.6)
VisFrag^2	-0.673***	-0.140	-0.195*	-0.249**	-0.914***	-0.308**	-0.319***	-0.341***
	(-2.7)	(-1.0)	(-1.7)	(-2.2)	(-3.6)	(-2.3)	(-2.7)	(-3.0)
Dark	-0.718***	-0.530***	-0.483***	-0.448***	-0.711***	-0.526***	-0.482***	-0.448***
	(-19.4)	(-21.4)	(-26.3)	(-26.7)	(-19.0)	(-20.9)	(-25.6)	(-25.9)
Ln Size	0.742***	0.581***	0.435***	0.407***	0.748***	0.587***	0.435***	0.407***
	(9.5)	(11.0)	(10.7)	(10.1)	(9.5)	(10.6)	(10.6)	(10.0)
Ln Price	0.452***	0.410***	0.357***	0.360***	0.450***	0.413***	0.356***	0.358***
	(8.6)	(12.1)	(10.9)	(10.6)	(8.6)	(12.1)	(10.9)	(10.5)
Ln Vol	0.378***	0.282***	0.253***	0.234***	0.380***	0.283***	0.255***	0.236***
	(36.4)	(42.6)	(48.8)	(48.9)	(36.2)	(41.8)	(48.0)	(48.2)
Ln SD	-0.445***	-0.382***	-0.336***	-0.306***	-0.454***	-0.390***	-0.344***	-0.314***
	(-37.1)	(-48.2)	(-54.9)	(-54.0)	(-37.4)	(-48.0)	(-55.0)	(-54.1)
Algo	-0.325***	-0.262***	-0.213***	-0.193***	-0.345***	-0.281***	-0.226***	-0.202***
	(-14.6)	(-16.0)	(-16.8)	(-16.6)	(-15.1)	(-17.1)	(-17.5)	(-17.0)
Obs	46,833	46,833	46,833	46,833	46,833	46,833	46,833	46,833
R^2	0.140	0.272	0.305	0.299	0.144	0.272	0.303	0.296

Table (6) The effect of fragmentation on liquidity: IV regressions.

The panels show the instrumental variables regression results for consolidated, best-market and local $Depth(X)$ and the traditional liquidity measures. VisFrag, VisFrag^2 and Dark are instrumented by (i) the number of electronic messages to transactions on the visible new entrants, (ii) the logarithm of the visible new entrants 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 consolidated, best-market 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 over-the-counter, on crossing networks, dark pools and internalized. The control variables (not reported) are Ln size, Ln price, Ln volume, Ln volatility and Algo, as described 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.

	Consolidated				Traditional liquidity indicators			
	(1) Ln Depth(10)	(2) Ln Depth(20)	(3) Ln Depth(30)	(4) Ln Depth(40)	(5) Effective Spread	(6) Realized Spread	(7) Price Impact	(8) Quoted Spread
VisFrag	7.330***	4.910***	3.483***	2.891***	-6.745	-13.43	19.00	-60.25***
	(5.9)	(8.0)	(8.4)	(7.7)	(-0.7)	(-1.1)	(1.5)	(-6.5)
VisFrag^2	-15.61***	-10.22***	-6.852***	-5.622***	12.17	28.74	-52.51	143.3***
	(-4.8)	(-6.2)	(-6.4)	(-5.8)	(0.5)	(0.9)	(-1.6)	(5.9)
Dark	-1.016***	-0.682***	-0.578***	-0.516***	4.007***	-1.210*	4.726***	7.046***
	(-20.9)	(-22.2)	(-23.7)	(-22.9)	(6.3)	(-1.9)	(7.7)	(14.8)
Hansen J	1.281	1.574	4.834	13.62	5.632	31.10	18.88	120.6
Hansen p	0.734	0.665	0.184	0.003	0.131	0.000	0.000	0.000
	Best-market				Local			
	(9) Ln Depth(10)	(10) Ln Depth(20)	(11) Ln Depth(30)	(12) Ln Depth(40)	(13) Ln Depth(10)	(14) Ln Depth(20)	(15) Ln Depth(30)	(16) Ln Depth(40)
VisFrag	4.947***	2.030***	0.613	0.138	2.280*	0.523	-0.312	-0.441
	(4.0)	(3.4)	(1.5)	(0.4)	(1.8)	(0.9)	(-0.8)	(-1.2)
VisFrag^2	-11.11***	-4.202***	-0.640	0.396	-5.832*	-1.370	1.037	1.372
	(-3.4)	(-2.6)	(-0.6)	(0.4)	(-1.8)	(-0.8)	(1.0)	(1.4)
Dark	-0.960***	-0.657***	-0.562***	-0.505***	-0.949***	-0.661***	-0.570***	-0.511***
	(-20.3)	(-22.2)	(-23.4)	(-22.3)	(-20.1)	(-21.6)	(-22.6)	(-21.4)
Hansen J	2.461	1.304	0.138	3.623	7.501	6.567	2.841	0.421
Hansen p	0.482	0.728	0.987	0.305	0.058	0.087	0.417	0.936
	Kleibergen-Paap weak ID F stat: 113.3. Angrist-Pischke weak ID F stat: 51.1 (Frag), 38.8 (VisFrag^2), 855 (Dark).							

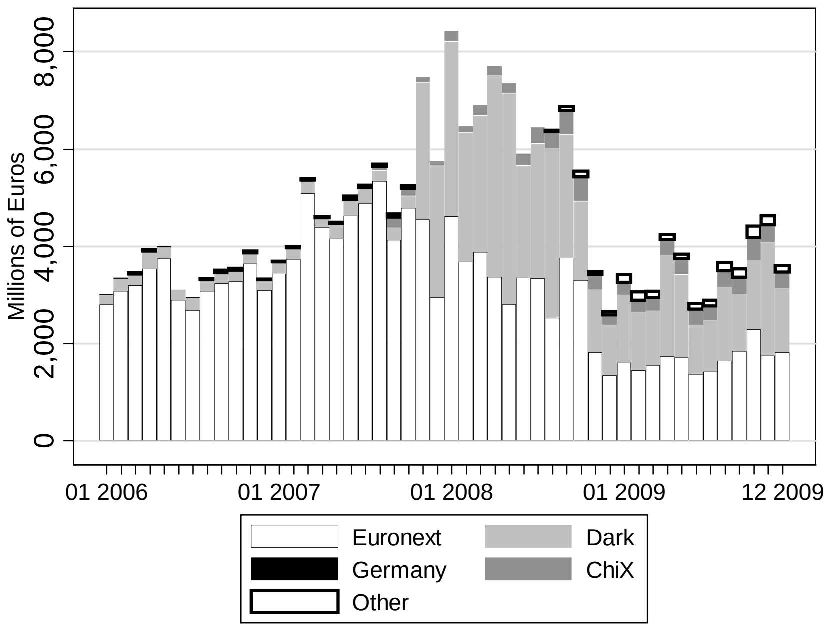

Figure (1) Traded Volume in millions of Euros.
The figure displays monthly averages of the daily traded volume in millions, aggregated over the 52 AEX Large and Mid cap constituents. Euronext consists of Amsterdam, Brussels, Paris and Lisbon. Germany combines all the German cities while Other represents 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.

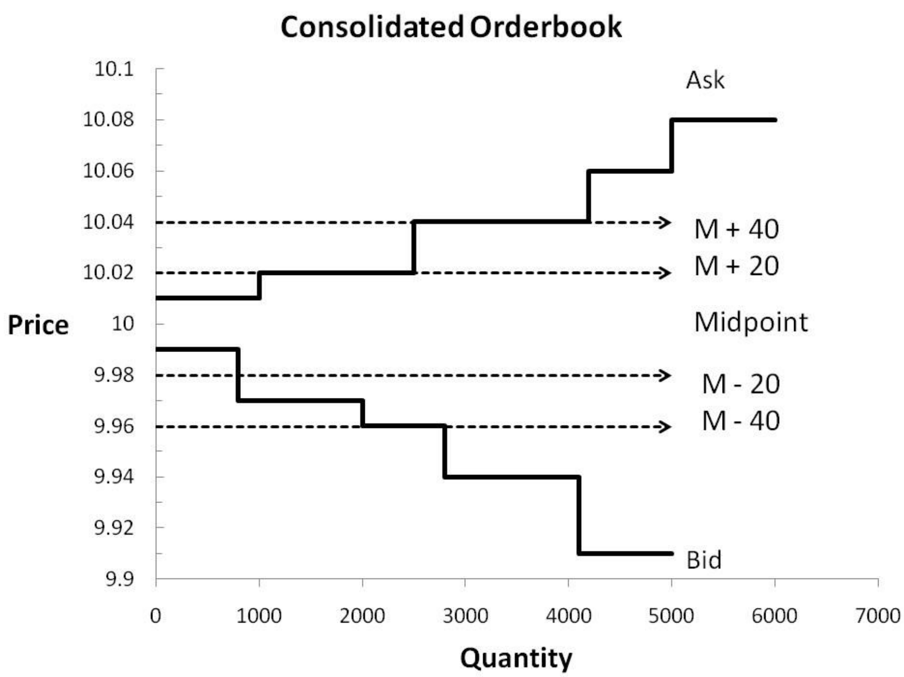

Figure (2) Snapshot of a hypothetical limit order book.
Depth(20) aggregates liquidity offered within the interval of (M - 20bps, M + 20bps), which are 2500 shares on the ask side and 800 on the bid side. Depth(40) contains 4100 and 2800 shares on the ask and bid side respectively. The number of shares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

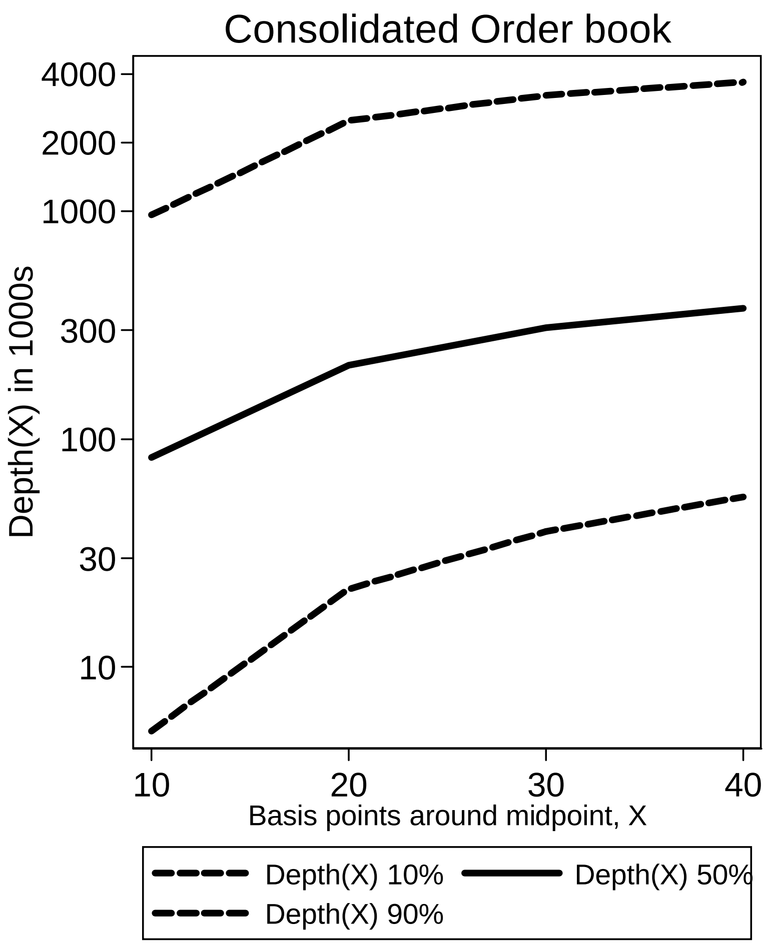

Figure (3) Depth in the consolidated order book.
The figure shows the 10, 50 and 90^{th} percentiles of the $Depth(X)$ measure, expressed on a logarithmic scale in €1000s. The measure aggregates the Euro value of shares offered within a fixed amount of basis points X around the midpoint, shown on the horizontal axes. The consolidated order book represents liquidity to a SORT 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.

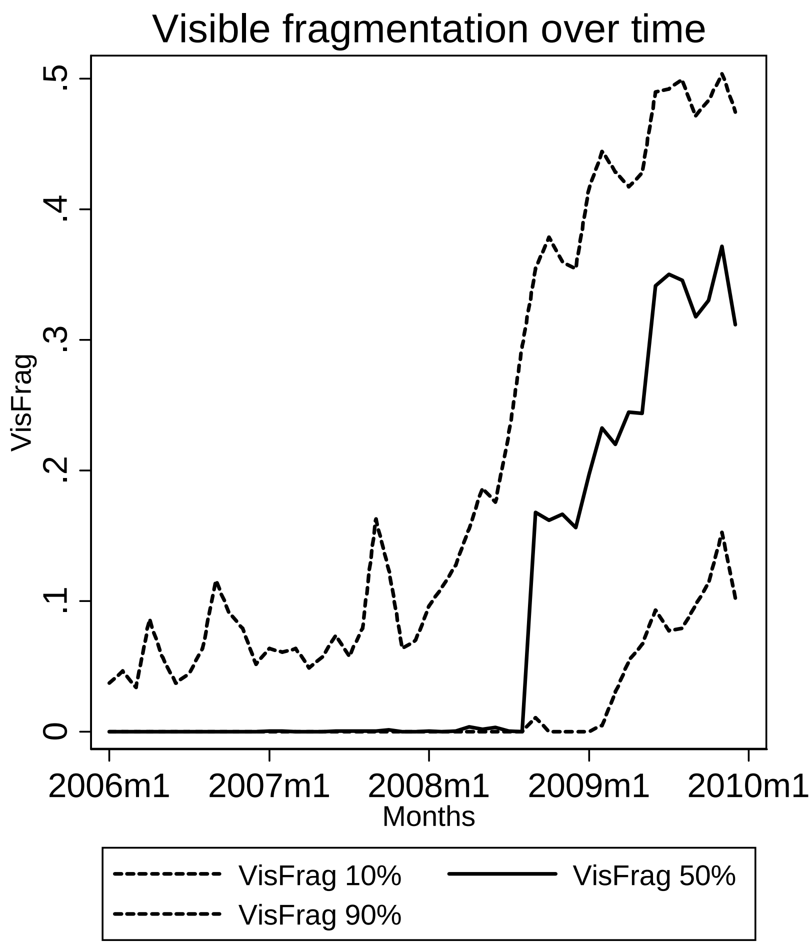

Figure (4) Visible fragmentation of AEX large and Mid cap firms.
The monthly 10, 50 and 90$^{\text{th}}$ percentiles of VisFrag are shown, for the 52 AEX large and mid cap stocks between 2006 - 2009. VisFrag equals $1 - HHI$, based on the number of shares traded at the following trading venues: Euronext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

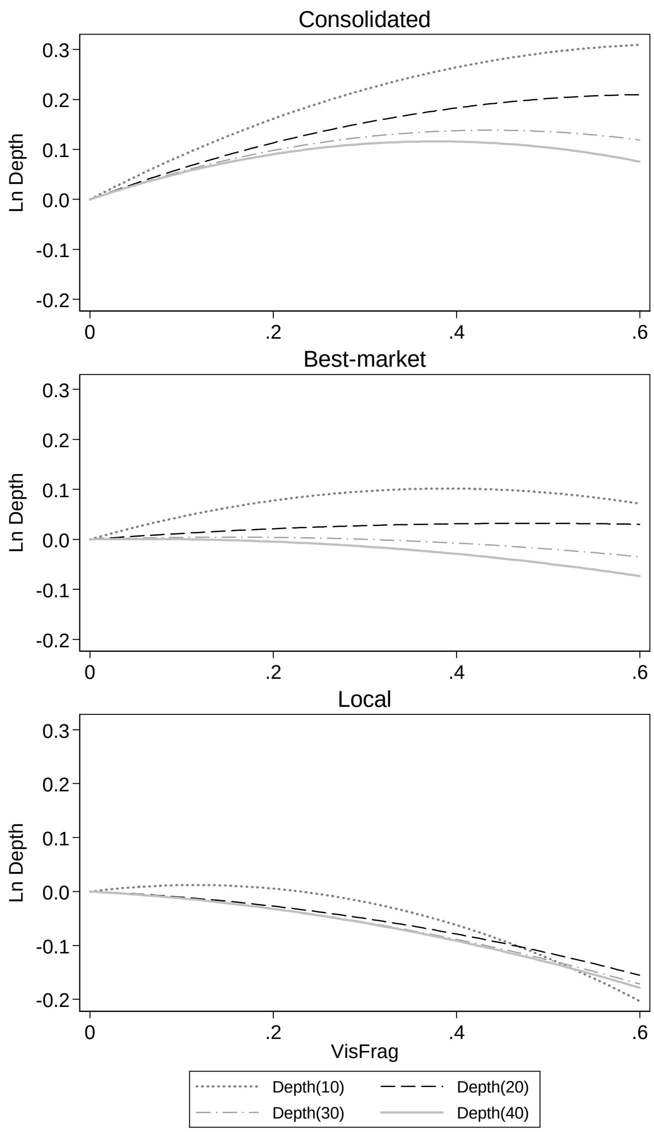

Figure (5) Visible fragmentation and liquidity: firm-quarter dummies. The regression coefficients of visible fragmentation on liquidity of Table 4 and 5 are plotted. The three panels shows the results for *Consolidated* $Depth(X)$, *Best-Market* $Depth(X)$ and *Local* $Depth(X)$. The vertical axis displays the logarithm of the $Depth(X)$, while the horizontal axis shows the level of visible fragmentation, defined as $(1 - HHI)$.

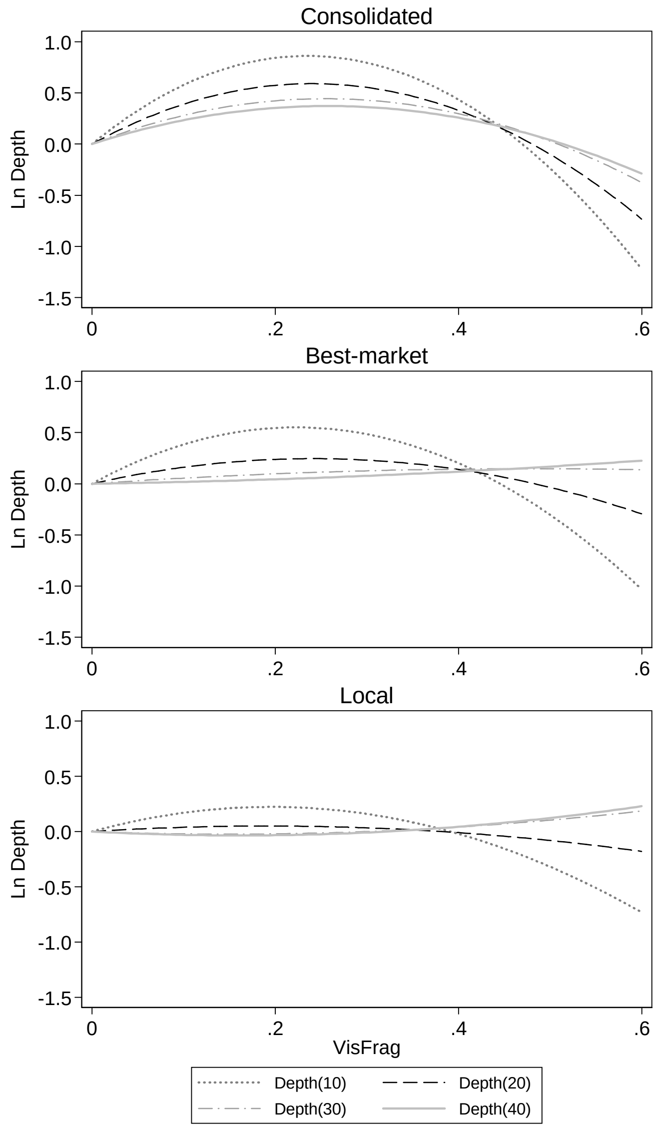

Figure (6) Visible fragmentation and liquidity: IV regressions.
The IV regression coefficients of visible fragmentation on liquidity of Table 6 are plotted. The three panels show the results for *Consolidated Depth*(X), *Best-Market Depth*(X) and *Local Depth*(X). The vertical axis displays the logarithm of the *Depth*(X), while the horizontal axis shows the level of visible fragmentation, defined as $(1 - HHI)$. The regressions include firm-quarter dummies. The instruments are (i) the number of electronic messages to transactions on the visible new entrants, (ii) the logarithm of the visible new entrants average order size, (iii) the logarithm of the average Dark order size; and their respective squares.