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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 choose to send orders 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 https://www.dropbox.com/s/xqk74pnm9f9a86z/Webappendix.pdf

1 Introduction

Equity trading all over the world has seen a proliferation of new trading venues. The traditional stock exchanges are challenged by a variety of trading systems of which some are designed as publicly displayed limit order books (e.g., electronic communication networks (ECNs) in the US and multilateral trading facilities (MTFs) in Europe) whereas others operate in the dark (e.g., dark pools, internalized trades, and over-the-counter trading (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 2010, the SEC conducted a broad review of current equity markets, and it was particularly interested in the effect of dark trading on execution quality.[1] 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 has a market share of approximately 30% in the US and 40% in European blue chips.[2] We further address whether the effects of fragmentation are beneficial to all investors or are enjoyed by certain investors only. In particular, we study the effect of fragmentation on liquidity for traders that access all markets, and for traders who face restrictions inducing them to trade on a subset of markets only.

The impact on equity markets of fragmentation in visible order books and of dark

[1] See the SEC concept release on equity market structure, February 2010, File No. S7-02-10.

[2] 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.

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. However, their fragmentation metric consists of off-exchange trades, which stem from both publicly displayed limit order books and dark venues. Therefore, they do not distinguish between the differential impact on liquidity of fragmentation stemming from visible and dark trading venues. Buti, Rindi, and Werner (2011a) employ detailed data on dark-pool activity and find that these are positively related to liquidity on visible markets in the cross-section, but economically insignificant in the time series. Our data set has several advantages relative to the data used in the previous literature. We have data on dark trading encompassing all forms of dark trading and have order book information from all transparent trading venues. The main contribution of our paper therefore is that we disentangle the liquidity effects of fragmentation in visible order books ("visible fragmentation") and dark trading. This distinction is important as competition from publicly displayed order books and dark trading have substantially different impacts.

We further address the regulatory issues of best execution and access to markets. To this end, we distinguish between liquidity aggregated over all visible trading venues (*Global* liquidity), liquidity when choosing the best visible market only (*Best-Market* liquidity), and liquidity of the traditional market only (*Local* liquidity). *Global* 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 (i.e., due to trading or post-trading fees) but chooses the most liquid market at the time. These trader types are particularly relevant to European markets, where the broker chooses the best execution benchmark. This benchmark is broad, including price, transaction costs, and speed and likelihood of execution. Therefore, unlike the US, a European broker may choose to violate price priority (a "trade-through"), if compensated by the other dimensions of best execution. We furthermore improve on previous research by employing a data set that covers the relevant universe of trading platforms, and which 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 listed firm, daily proxies of visible fragmentation, dark trading, and liquidity. Specifically, we use high-frequency data from all relevant trading venues from November 2007, when fragmentation set in, to the end of 2009 when markets were quite fragmented. Similar to Foucault and Menkveld (2008), we select all Dutch large- and mid-cap stocks, which are relatively large with an average market capitalization approximately twice that of the NYSE and Nasdaq stocks analysed in O'Hara and Ye (2011). We deal with Dutch stocks as these were among the first to be fragmented (e.g., Chi-X first rolled out for Dutch large cap stocks and German stocks, and only later added other large European indices). We measure the degree of visible fragmentation using the Herfindahl-Hirschman index (*HHI*, the sum of the squared market shares) based on the daily 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 global depth available in the market. Based on the consolidated order book we analyse depth 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 empirical strategy aims to identify the causal 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. This makes the analysis robust to various market-wide changes (e.g., changes in trading fees), time-varying firm-specific shocks and self-selection issues as discussed in Cantillon and Yin (2011). Following Buti, Rindi, and Werner (2011a), we instrument visible fragmentation and dark trading by the average level of visible fragmentation and dark trading of all stocks in the same size group (calculated by excluding the current stock) which removes firm-specific reverse causality concerns. We also exploit the heterogeneous impact of different types of dark trading (large block traders versus others) and study cross-sectional heterogeneity (large versus mid cap stocks) in the impact of fragmentation and dark trading providing further support to the causal mechanisms linking fragmentation or dark trading to liquidity. We nevertheless remain cautious and recognize the limits of our identification approach and avoid making strong causal statements.

While our data provide order book information on the lit venues only, we also consider the *consolidated* liquidity of the visible and dark markets jointly. We do so by estimating the liquidity available in dark markets based on the effective spread of dark trades. To address the selection issue that dark liquidity is only observed at time of a dark trade, we estimate a Heckman selection model. In the first stage equation we predict whether a trade is dark or visible, and in the second stage equation we predict the dark effective spread which is only observed in case of a dark trade. Based on the models' predicted dark effective spread, we construct a dark liquidity measure and a consolidated liquidity measure that incorporates both dark and visible liquidity.

Our main finding is that the effect of visible fragmentation on global depth is generally positive, while the effect of dark trading is negative. An increase in dark trading of one standard deviation lowers the global depth by 7%, which is consistent with most of the theoretical research but has not been documented empirically. The effect of visible fragmentation has an inverted U-shape, i.e., the marginal effect decreases as fragmentation increases. The optimal degree of visible fragmentation improves consolidated liquidity by approximately 49% 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 25%. This result suggests that newly entering trading venues with visible order books primarily improve liquidity close to the midpoint, and that traders employing smart order routing technologies benefit from visible fragmentation. All the results hold when we measure liquidity by depth in the order book, or by the quoted and trade based spreads. The various spread measures improve by approximately two to three basis points when comparing a concentrated market to the optimal level of fragmentation, which is sizeable given sample medians of about 13 basis points.

We also find a strongly negative impact of dark trading on the liquidity consolidated over visible and dark markets (based on the Heckman model). This finding indicates that dark trading does not merely shift liquidity from the visible to the dark market, but in fact harms overall liquidity. The main results on visible fragmentation equally hold for consolidated liquidity. Further, the Heckman model shows that investors are more likely to trade in the dark when the visible market is illiquid, which indicates a substitution effect. At the same time, the dark liquidity is positively correlated with the visible liquidity, which indicates that the liquidity of these markets are complementary. Also, there is a significant self-selection effect that dark liquidity is only observed at time of a dark trade, which further motivates our Heckman model.

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 5-10%. Thus, investors without access to all markets are worse off in a fragmented market, especially for relatively small orders. However, *Best-Market* liquidity also benefits from visible fragmentation: when trading volume becomes more dispersed across markets the liquidity of the most liquid venue does not reduce.

Our findings on liquidity are consistent with several theoretical studies. The positive effect of visible fragmentation is consistent with enhanced competition between liquidity suppliers, as the compensation for liquidity suppliers, (the realized spread) reduces with fragmentation. Fragmentation may increase the number of liquidity providers leading to more competition (e.g., Battalio (1997) and Biais, Martimort, and Rochet (2000)); enables liquidity providers to bypass time priority (Foucault and Menkveld, 2008); and allows liquidity providers to compete on a finer pricing grid (e.g., Biais, Bisière, and Spatt (2010)); or triggers a drop in trading fees for liquidity providers that may be passed on to liquidity demanders (e.g., Colliard and Foucault (2012)). 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 (see e.g., Zhu (2014)). 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.[3] Our cross-sectional results on large versus mid cap stocks are in line with the predictions of Buti, Rindi, and Werner (2011b), who model competition between a dark pool and a visible limit order book. They show that for large and liquid stocks predominantly market orders move to the dark pool which improves the visible spread, whereas for illiquid stocks mostly limit orders move to the dark pool which worsens the visible spread.

Our findings on liquidity are related to those of several recent empirical studies. 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 (2014) 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 (2011a) find that dark-pool activity is

[3] Degryse, Van Achter, and Wuyts (2009) also model competition between a dealer market and a dark pool. Their model focuses on how imbalances in the order book of the dark pool impact on the choice to go to a dealer market or dark pool.

positively related to liquidity in the cross-section, but economically insignificant in the time series. They only focus on dark pool trading, whereas our measure also includes internalized and over-the-counter trades. 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.[4]

The remainder of this paper is structured as follows. The dataset and liquidity measures are described in Sections 2 and 3. Section 4 explains the methodology and main results, and an analysis to measure consolidated liquidity across dark and visible markets. Finally, Section 5 provides concluding remarks.

2 Market description, dataset and descriptive statistics

2.1 Market description

Our dataset contains Dutch stocks forming the constituents of the so-called Amsterdam Exchange (AEX) Large and Mid cap indices. Over time, all these stocks are traded on several trading platforms. 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).[5]

First, there are regulated markets (RMs), such as NYSE Euronext, LSE and Xetra. These markets have an opening and closing auction, and in between there is continuous

[4]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.

[5]Available at https://www.dropbox.com/s/xqk74pnm9f9a86z/Webappendix.pdf

and anonymous trading through the limit order book. For our sample stocks, the LSE and Xetra are not very important as they execute less than 1% of total order flow.

Second, Multilateral Trading Facilities (MTFs, the European equivalent of ECNs) with publicly displayed limit order books have been introduced, 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 MTFs differ in terms of the speed of execution, the number of securities traded and trading fee structure. RMs and MTFs allow for the use of hidden or iceberg orders. These orders are not directly observed in the dataset but are detected upon execution. We treat executions against them as visible, since these trades take place on predominantly visible trading venues.

The third group contains the dark markets: dark pools which are not pre-trade transparent, internalized trades and over-the-counter (OTC) trades. 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, or cross at the midpoint of the primary market. Consistent with our findings, Gomber and Pierron (2010) report that the activity on dark markets has been fairly constant for European equities in 2008 - 2009, which execute approximately 40% of total traded volume.

2.2 Dataset

The sample period of the AEX Large and Mid cap constituents starts on Nov 1, 2007, the day MiFID was implemented and the required data become available, and lasts through December 2009. We select Dutch stocks, as these were among the first to become fragmented in Europe.[6] Furthermore, their degree of fragmentation and dark trading is representative for large European stocks (Gomber and Pierron, 2010).[7] We remove stocks that are in the sample for less than six months. Due to some changes in the index composition, our final sample has 51 stocks.

The data for trading on lit markets and dark markets stem from the Thomson Reuters Tick History Data base. The data for lit markets cover the seven most relevant European trading venues for the sample stocks, which have executed more than 99% of visible order flow: Euronext, Chi-X, Xetra, Turquoise, Bats Europe, Nasdaq OMX and SIX Swiss exchange (formerly 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 the limit order book is created when a limit order arrives, gets modified, cancelled 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

[6] At the launch of Chi-X it initially started trading only AEX25 and DAX30 stocks (Chi-X press release April 16, 2007, "Chi-X Successfully Begins Full Equity Trading, Clearing and Settlement")

[7] Trading in smaller stocks is typically less fragmented. Our analysis is therefore mainly valid for similar sized larger capitalization stocks.

[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 Euro's, and are in essence different assets.

[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 only affects liquidity very deep in the order book; and removing this period from the sample does not affect the results.

orders have time priority over hidden orders.

Our dataset also provides information on "dark trades", i.e. trades at dark pools, internalized trades and OTC trades. These dark trades are also taken from the Thomson Reuters Tick History Data base. They are reported in a separate file and are constructed by Markit Boat, a MiFID-compliant trade reporting company.[11] The file contains a list of trades with price, size and timestamp of the execution (to the millisecond). The file contains trades from all dark markets, but does not report the identity of the executing venue and does not contain any information on the order book. We complete the dark trades data by adding the trades reported in the separate files by Euronext, Xetra and Chi-X. We cannot know how each trade took place as this is not part of the reporting requirements. The trading technology company Fidessa[12] however shows that the largest part of the trades are internalized and OTC.

2.3 Descriptive statistics

Figure 1 shows the monthly averages of the daily trading volume in millions, equal weighted across days and stocks. There is a decline in total trading activity around the start of the financial crisis. The dominance of Euronext over its competitors is strong, but slowly reducing over time. 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 the top panel of Table 1 we present descriptive statistics of the sample stocks. There is considerable variation in market capitalization (size) and trading volume (volume) and price. The table also reports realized volatility (SD), computed daily as the standard

[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] http://fragmentation.fidessa.com/fragulator/

deviation of the 34 intra-day fifteen minute stock returns,[13] and the proxy for algorithmic trading (algo) from Hendershott, Jones, and Menkveld (2011) which is further discussed in the methodology section. The last row of that panel shows the average market share of Euronext.

3 Measures of liquidity and fragmentation

In this section we explain our liquidity measures and definition of market fragmentation.

3.1 Liquidity available to different types of traders

We consider three measures of liquidity, which we motivate below. First, we measure the liquidity available to traders with Smart Order Routing Technology (SORT), i.e. those who can trade on all venues simultaneously and can access the *Global* liquidity. Second, we consider *Best-Market* liquidity to those traders who may access all venues but may trade on only one venue at each point in time. Third, we measure *Local* liquidity, which is the liquidity available to traders who only have access to the traditional exchange.

The motivation stems from the European definition of best-execution, which incorporates price, speed, transaction costs, anonymity, and the likelihood of execution. A broker may choose to violate price priority (a "trade-through"), if this is more economical in terms of the other dimensions of best execution. Such a broker has access to *Best-Market* or *Local* liquidity.

Our classification is empirically justified by van Kervel (2012). 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,

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

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 traders are able to choose the most liquid venue at each point in time (i.e., have access to *Best-Market* liquidity). Reasons why traders are unable to send market orders simultaneously to several venues are because they are too slow (e.g., human traders), or because they economize on the costs of the technological infrastructure required for smart order routing. Foucault and Menkveld (2008) and Ende, Gomber, and Lutat (2009) show that not all investors use SORT.

We consider *Local* liquidity as some investors have access to only the traditional exchange. Gomber, Pujol, and Wranik (2012) analyse 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.

To construct the global order book, we construct 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 global order book. Therefore, each stock has 510 observations per day (8.5 hours times 60 minutes), containing the order books of the individual trading venues and the global one. Also, at each observation we can select the most liquid venue which represents the liquidity available to non-SORT traders.

3.2 Depth(X) liquidity measure

The dataset allows to construct a liquidity measure that incorporates the limit orders beyond the best price levels; which we will refer to as $Depth(X)$. The measure aggregates the monetary value of the shares offered within a fixed interval around the midpoint. In detail, the midpoint is the average of the best bid and ask price of the global order book and the interval is an amount $X = \{10, 20, 30\}$ basis points relative to the midpoint. The measure is expressed in Euro's 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, 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 global order book as M, then

$$Depth\ Ask(X) = \sum_{j=1}^{J} P_j^{Ask} Q_j^{Ask} \mathbf{1}\{P_j^{Ask} < M(1+X)\}, \tag{1a}$$

$$Depth\ Bid(X) = \sum_{j=1}^{J} P_j^{Bid} Q_j^{Bid} \mathbf{1}\{P_j^{Bid} > M(1-X)\}, \tag{1b}$$

$$Depth(X) = Depth\ Bid(X) + Depth\ Ask(X). \tag{1c}$$

The measure is averaged over the trading day, where $Depth(10)$ represents liquidity close to the midpoint and $Depth(30)$ also includes liquidity deeper in the order book.

An advantage of $Depth(X)$ over the traditional quoted depth and spread is the 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. [14]

Figure 2 shows the slope of the global 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 log-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 $Depth(10)$ over the whole sample are €5.000 and €915.000. This is in line with high levels of skewness and kurtosis (not reported).

[14] 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 $Best\text{-}Market\ Depth(X)$,[15] 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 *Global*, *Best-Market* and $Local\ Depth(X)$.

Table 2 contains the medians and standard deviations of the $Depth(X)$ measure for the global, 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 2007, before the market became very fragmented, the *Global*, *Best-Market* and $Local\ Depth(X)$ largely coincide, but in 2009, $Local\ Depth(X)$ represents only 60% of $Global\ Depth(X)$. Depth close to the midpoint reduced strongly over time, but liquidity deeper in the order book to a much lesser extent. In addition, the yearly standard deviations of the depth measures have halved over the years, which implies that liquidity became more evenly distributed across stocks and days.

3.3 Other liquidity measures

This section describes the more traditional liquidity measures. These are the time weighted quoted spreads based on the local, best-market and global limit order book, and the trade weighted effective spread, price impact and realized spread.

[15] The best market can be different on the ask and bid side.

Denote the best quoted ask and bid price by P^{ASK} and P^{BID}, then

$$Quoted\ spread = \frac{P^{ASK} - P^{BID}}{M} \times 10.000. \tag{3}$$

The *Local* and *Global* quoted spreads are based on the bid and ask prices of the local and global limit order books respectively. The *Best-Market* quoted spread picks the lowest quoted spread of all venues at each point in time. The three daily spread measures are based on the averages over one-minute snapshots.

The effective spread, price impact and realized spread are calculated per trade (visible or dark), and then averaged over the trading day weighted by trade volume. Denote M_τ as the global quoted midpoint before trade τ takes place, $M_{\tau+5}$ the quoted midpoint five minutes later, and $D = [1, -1]$ for a buy and a sell order respectively, then

$$\begin{aligned}
Effective\ half\ spread &= \frac{Price - M_\tau}{M_\tau} D \times 10.000, &(4)\\
Realized\ half\ spread &= \frac{Price - M_{\tau+5}}{M_\tau} D \times 10.000, &(5)\\
Price\ Impact &= \frac{M_{\tau+5} - M_\tau}{M_\tau} D \times 10.000. &(6)
\end{aligned}$$

The medians and standard deviations of the liquidity measures are reported in Table 2, based on daily observations and calculated yearly. The table shows several interesting results. Between 2007 and 2009 the *Global* quoted spread improved slightly (a reduction of 3%), while the *Global Depth*(10) decreased by 31% over the same time period. This implies that the prices of limit orders have improved, but the quantities have worsened. Further, due to increasing competition between exchanges the difference between the *Local* and *Global* quoted spread increases from 0.9 basis points in 2007 to 2.6 in 2009.

3.4 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 exclude dark markets in the calculation of HHI_{it}, as we want to analyse it separately. 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, internalization 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 detailed than that of O'Hara and Ye (2011), who classify the origin of trades as either Nasdaq, NYSE or external.

The bottom panels of Table 1 shows the yearly mean, quartiles and standard deviation of $VisFrag$ and $Dark$. As expected, fragmentation increases over time due to the increasing competition between venues. $Dark$ is fairly constant over monthly and annual frequencies (25% in 2009), but has a high daily standard deviation of 17%.[16]

Figure 3 shows the 10, 50 and 90$^{\text{th}}$ percentile of $VisFrag$ and $Dark$ 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.

[16] The dark share is calculated daily, and averaged (equally weighted) 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.

4 The impact of visible fragmentation and dark trading on liquidity

This section analyses the effect of fragmentation and dark trading on various liquidity measures. It first presents the methodology and the main regression results, followed by an analysis that consolidates dark and visible liquidity.

4.1 Methodology

We are interested in the impact of fragmentation and dark trading on various liquidity indicators. We have a panel dataset containing daily liquidity and fragmentation measures, as discussed in Section 3. We estimate the following equation

$$Liq_{it} = \alpha_i \times \delta_{q(t)} + \beta_1 VisFrag_{it} + \beta_2 VisFrag^2_{it} + \beta_3 Dark_{it} + \beta_4 AvgLiq_{-i,t} + \gamma' W_{it} + \varepsilon_{it}, \tag{7}$$

where Liq_{it} is our liquidity indicator for stock i on day t i.e., *Global Depth*(X), *Best-Market Depth*(X), *Local Depth*(X) effective spread, price impact, realized spread, and various quoted spreads. We employ $VisFrag_{it} = 1 - HHI_{it}$ to measure fragmentation, where $VisFrag_{it} = 0$ if trading in a firm is completely concentrated. The theory predicts a trade-off in the benefits and drawbacks of fragmentation, and therefore we model a non-linear effect by adding a quadratic term $VisFrag^2$ in the model.[17] $Dark_{it}$ is defined as the fraction of trading volume executed in the dark (OTC, internalization, and dark pools). Following Buti, Rindi, and Werner (2011a), the regression includes the average degree of liquidity of stocks in the same size group, $AvgLiq_{-i,t}$, defined as the average of the

[17]The results of the linear specification are reported in Table A.2 of the Web appendix.

dependent variable of the stocks in the same size group excluding stock i itself.[18]

The vector W_{it} is a set of control variables that is commonly employed in this literature, and contains volatility, price, firm size and trading volume.[19] In addition, we include a proxy for algorithmic trading activity as this has been found to improve liquidity (e.g. Brogaard, Hendershott, and Riordan (2014)). 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. Descriptive statistics of these control variables are presented in Table 1.

To control for potential effects of firm specific, time-varying unobserved variables that simultaneously determine liquidity and fragmentation, we include firm-quarter fixed effects. There are nine quarterly dummies per firm, $\alpha_i \times \delta_{q(t)}$, where α_i are firm dummies and $\delta_{q(t)}$ are quarter dummies, which take the value of one if day t is in quarter q and zero otherwise. This approach is similar to Chaboud, Chiquoine, Hjalmarsson, and Vega (2009), who analyse the effect of algorithmic trading on volatility for currencies, and add separate quarter dummies for each currency pair. The firm-quarter fixed effects allow to control for self-selection problems. Cantillon and Yin (2011), for example, 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. Furthermore, it controls for the impact of changes in trading fees over time across venues. Foucault and Menkveld (2008) showed that these are important drivers of liquidity. The implication of including the firm-quarter fixed effects is that we exploit the impact of variation in liquidity, fragmentation and dark trading within a firm-quarter.

Although the firm-quarter fixed effects are likely to mitigate endogeneity issues, they may not entirely solve these. There might be reverse causality when the level of liquidity

[18]Stock i is excluded from the average to make sure that there is no mechanical relation between the average and the dependent variable.

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

affects the decision of investors to trade across several venues (both visible and dark). To alleviate such endogeneity problems we follow the instrumental variables approach suggested by Hasbrouck and Saar (2011). This IV approach is also applied by Buti, Rindi, and Werner (2011a), who analyse the impact of dark pool trading on liquidity. They instrument dark pool trading of stock i on day t with the average degree of dark pool trading of all other stocks in the same industry and size group on day t. In our case we have three potentially endogenous variables, $VisFrag_{it}$, $VisFrag_{it}^2$ and $Dark_{it}$, which we instrument with the average of each variable on the same day over all stocks in the same size group (we consider four size groups). Denote the instruments $AvgVisFrag_{-i,t}$, $AvgVisFrag^2_{-i,t}$ and $AvgDark_{-i,t}$, where the subscript $-i$ indicates that the current stock is excluded from calculating the average. We expect these instruments to be positively correlated with the endogenous variables: an increase in $AvgVisFrag_{-i,t}$ or $AvgDark_{-i,t}$ predicts a higher level of fragmentation or dark trading for the current stock. This positive correlation could stem from the behaviour of institutional investors, who might trade on alternative markets (both visible and dark) for several stocks on the same day. We argue that the instruments address the reverse causality issue between liquidity and fragmentation (and dark trading), as it is unlikely that a change in the liquidity of stock i causes a larger level of fragmentation (or dark trading) in other stocks in the same size group. A potential issue is that some state variable causes commonality in liquidity and fragmentation (and dark trading) across stocks. However, the regression controls for the average degree of liquidity of the stocks in the same size group ($AvgLiq_{-i,t}$). Thus, the instruments create variation in fragmentation (and dark trading) stemming from the commonality of fragmentation (and dark trading) across stocks that is orthogonal to the commonality in liquidity across stocks. We nevertheless remain cautious and acknowledge that there are limits to the identification strategy and that all results should be interpreted with care and not necessarily be interpreted as causal.

Our analysis differs from Buti, Rindi, and Werner (2011a) in three respects. First, they only focus on dark pool trading, whereas our measure $Dark$ represents 37% of aggregate trading volume as it includes trading at all dark pools, internalized trades and OTC. When investors choose to trade off-exchange, these different markets are likely to be substitutes. Our measure therefore is representative of dark trading in general. Second, we use firm-quarter dummies which makes the analysis more robust to various potential endogeneity and selection issues as argued above. Third, our empirical model does not only measure the effect of dark trading on liquidity, but also contains visible fragmentation and control variables such as volatility and trading volume, among others. These additional variables need to be controlled for as they are important predictors of liquidity and $Dark$.

To estimate the model in equation (7) we use a panel dataset with 51 firms and 546 days, from November 2007 to December 2009. We use the two stage GMM estimator which is efficient in the presence of heteroscedasticity (Stock and Yogo, 2002), and apply heteroscedasticity and autocorrelation robust standard errors (Newey-West for panel datasets) based on five lags.

4.2 Main Results

This section presents the second stage results of Equation (7) for the $Depth(X)$ and spread measures. The first stage results for the three endogenous variables are presented in the Web appendix.[20]

[20] The instruments strongly predict the endogenous variables in the first stage of the IV model. As expected, each instrument is strongest for the endogenous variable it is constructed for, which indicates a strong cross-sectional commonality in dark trading and visible fragmentation. The large t-statistics of the coefficients indicate that the instruments are strong (also, the Angrist-Pischke and Kleibergen-Paap weak identification hypotheses are highly rejected).

4.2.1 Depth(X), fragmentation and dark trading

The regression results for the *Global*, *Best-Market* and *Local Depth*(X) are reported in Table 3. The results in columns (1) to (3) show that *Global* depth 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 4, which displays the implied results of the effect of visible fragmentation on *Depth*(X). The upper panel shows an inverted U-shape for *Global* depth, which implies a trade-off in the benefits and drawbacks of visible fragmentation. The maximum of *Depth*(10) lies at $VisFrag = 0.48$, and is 0.40 higher compared to a completely concentrated market, i.e., the global market is 49% more liquid (exp(0.4) = 0.49). Results are similar for *Ln Depth*(20) and *Ln Depth*(30), which improve by 55% and 35% at the maximum. These magnitudes are economically sizeable and all statistically significant at the 1% level. The channel driving the impact of fragmentation mainly stems from an increase in the number of liquidity providers and enabling them to bypass time priority as in Foucault and Menkveld (2008). Competition on a finer price grid seems less relevant as tick sizes of the entrant markets are generally in line with the primary market. We furthermore expect that the impacts of drops in trading fees are picked up by our firm-quarter dummies.

The impact of fragmentation on *Best-Market* and *Local Depth*(X) is shown in Table 3 and the middle and lower panels of Figure 4. We discuss the main results by focusing on Figure 4. It shows that *Best-Market Depth*(10) and *Best-Market Depth*(20) improve by 15% at $VisFrag = 0.35$, but *Best-Market Depth*(30) by only 3%. These results indicate that the benefits of competition between liquidity suppliers mostly hold for liquidity close to the midpoint, but less so for liquidity deeper in the order book. Traders with access to the best market therefore enjoy greater liquidity for smaller orders, but not for very large orders. The coefficients on *Local* depth are statistically insignificant, but the point estimates are all negative. At $VisFrag = 0.4$, *Local Depth*(X) reduces by 2% to 10% for all levels of X. [21] Consequently, investors who are limited to trading on Euronext only are worse off when the level of fragmentation is high.

We now turn to the effects of dark trading, which reduces the $Depth(X)$ measures across the board. The coefficient for *Global Ln* $Depth(10)$ is -0.29, such that a one standard deviation (0.18) increase in the fraction of dark trading reduces $Depth(10)$ by 5.5%. The results for *Best-Market* and *Local* liquidity are similar. Interestingly, it seems that liquidity deeper in the order book is somewhat less affected by dark trading, as the coefficients on $Depth(30)$ are smaller than those of $Depth(10)$. This reduction in depth at the visible exchanges is consistent with the model of Buti, Rindi, and Werner (2011b), where limit orders migrate from the limit order book to the dark pool.

Turning to the control variables in Table 3, we find that algorithmic trading (*Algo*) generally worsens *Global* depth. That is, a one standard deviation (0.54) increase in *Algo* lowers $Depth(10)$ by 14%. 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. Large stocks and stocks with high prices tend to have higher liquidity. Also, more trading volume ($Ln\ Volume$) and less volatility ($Ln\ SD$) are associated with higher depth.

4.2.2 Spreads, fragmentation and dark trading

The impact of visible fragmentation on the spread measures is reported in Table 4. The results for fragmentation are only statistically significant for the *Global* quoted spread, price impact and realized spread.[22] At $VisFrag = 0.4$, the *Global* quoted spread decreases by approximately 2 basis points as compared to a completely concentrated market. These

[21] These results are economically the same as the OLS results (reported in the Web appendix), which are statistically significant.

[22] We also estimate a linear model IV model (by excluding $VisFrag^2$) and the OLS model, in which cases the coefficients are similar and statistically significant. The results are in Table A.2 and A.3 in the Web appendix.

coefficients are sizeable, given that the median *Global* quoted spread is 12.2 basis points in 2009 (see Table 2).

The impact of $VisFrag = 0.4$ on the effective spread is slightly negative (and statistically insignificant), but when we decompose the effective spread into the price impact and realized spread we observe that the former increases and the latter decreases by fragmentation. At $VisFrag = 0.4$, the price impact and realized spread change by 3.2 and -6.3 basis points respectively—all coefficients are statistically significant. Investors with Smart Order Routing technology (SORT) are likely to provide and consume liquidity across multiple venues, which drives market fragmentation. These SORT traders seem more informed (as reflected by the increased price impact), and appear to act as competitive liquidity providers (as reflected by the reduced realized spread—which is typically considered the reward of supplying liquidity).

The impact of $Dark$ on liquidity is also negative when using the spread measures. A one-standard deviation increase in dark trading increases the effective spread by one basis point, which is sizeable given that the sample median is 13 basis points. The coefficient on the price impact is more positive, and suggests that dark trading leads to more adverse selection and informed trading on the visible markets. In addition, the coefficient on the realized spread is negative, such that the profits to liquidity suppliers decrease for higher levels of dark trading. Both findings are consistent with the theoretical work of Hendershott and Mendelson (2000) and Zhu (2014), where dark markets are more attractive to uninformed traders, leaving the informed traders to the visible markets.

The coefficients on the control variables are similar to those of the $Depth(X)$ regressions, and are therefore not further discussed.

4.2.3 Cross-sectional heterogeneity

We now exploit heterogeneity in types of dark trades and stock market capitalization to further argue that the estimated links are in line with theory helping us to identify the causal link. We take two steps. First, we employ the strategy of Hatheway, Kwan, and Zheng (2013) to discriminate between large trades ($Dark^{Block}$) and other dark trades ($Dark^{Other}$). Large trades are much more likely to be OTC trades whereas smaller trades are more likely internalized or dark pool trades. Large dark trades are defined as those trades in the top 1% of trades by trade value for each stock and month. We again instrument $Dark^{Block}$ and $Dark^{Other}$ with the values from similar sized stocks. The results are reported in column (1) of Table 5 where for brevity we suppress the other variables included in the regression. The full regression results are in the Web appendix. We find that the negative coefficient on $Dark$ is mostly driven by the large trades. This is in contrast to Hatheway, Kwan, and Zheng (2013) who find that large dark trades reduce the effective spread. Our results therefore suggest that larger trades seem to cream-skim order flow. The coefficient on $Dark^{Other}$ is not significant (but we admit we start to ask a lot from the data and the instruments). The smaller trades that are more likely to be internalized do not seem to impact liquidity on the visible markets. This is in line with Battalio and Holden (2001), who show that internalization may allow to cream-skim but that competition among brokers competes these rents away such that trading costs remain unaffected. Degryse, Van Achter, and Wuyts (2012) show that more settlement internalization lowers post-trading fees and leads to higher observed spreads. Our empirical findings on smaller dark trades are not significant.

Second, to the original model we add an interaction term between $Dark$ and a large cap dummy which equals one when a firm is part of the Amsterdam 25 Large cap index and zero otherwise. The results for dark trading are reported in column (2) of Table 5, where again we only show the coefficients of interest. The negative impact of dark trading is most important for the smaller (less liquid) stocks and close to the midpoint. This is consistent with Buti, Rindi, and Werner (2011b) where it is shown that more limit orders move to the dark pool for illiquid stocks whereas more market orders move to the dark for liquid stocks. The results for fragmentation are plotted in Figure 4 and tabulated in Table A.11 in the Web appendix. Those results show the impact of fragmentation on *Global* depth for large caps is most pronounced close to the midpoint. Furthermore we notice that *Local* depth decreases deeper in the book for large caps. This is consistent with Foucault and Menkveld (2008) who find larger impacts on *Global* depth for more liquid stocks and predict negative impacts on depth for the *Local* market.

4.3 Consolidating liquidity of dark and visible markets

4.3.1 Methodology

An unanswered question is the impact of fragmentation and dark trading on the consolidated liquidity of visible and dark markets. The challenge is that we do not observe the dark liquidity to calculate $Depth(X)$. However, we can calculate the dark effective spread whenever a dark trade occurs by using the prevailing midpoint on the visible exchange. This measure has two drawbacks: first, dark trades are different from visible trades which makes a direct comparison difficult. In particular, dark block trades are very large, while dark pool trades are typically very small. Second, the dark effective spread is only observed at time of a dark trade. If dark trades occur more often when the dark market is liquid, then there is a selection effect that overestimates the true dark liquidity.

To address both issues, we propose to measure dark liquidity with the following two stage selection model proposed by Heckman (1979). The first stage indicates whether a trade is visible or dark, and is estimated with Probit. The second stage predicts the dark effective spread, which is only observed if a dark trade occurs. For trade τ of a stock in a given month, we estimate

$$\begin{aligned} Dark\_trade_\tau &= \alpha_1 + \gamma_1 V_\tau + \gamma_2 Z_\tau + \varepsilon_{1,\tau}, \\ Dark_\tau^{Ef} &= \alpha_2 + \beta V_\tau + \lambda IMR_\tau + \varepsilon_{2,\tau}, \end{aligned} \tag{8}$$

where the subscripts for the stock and month are omitted. Below we discuss the vectors V_τ and Z_τ, which represent the control variables and the excluded instruments.

The predicted value of the second stage regression is used as a proxy of dark effective liquidity, which is calculated for *all* trades (both dark and visible). This imputed dark spread is directly comparable to the visible spread, because it is a function of the trade characteristics as captured by V_τ. The Inverse Mill's Ratio IMR_τ of the Heckman model corrects for the self-selection issue that the dark spread is only observed at time of a dark trade. From this model we construct two liquidity measures that incorporate dark liquidity. First, from the predicted value of the second stage regression $\widehat{Dark_\tau^{Ef}}$ we take the daily average over all trades τ to obtain $\widehat{Dark^{Ef}}$. Second, we take the daily average over all trades τ of the minimum of the prevailing visible *Global* quoted half spread and $\widehat{Dark_\tau^{Ef}}$. This measure, $\widehat{Cons^{Ef}}$, is a proxy of the effective liquidity consolidated over both dark and visible markets.

The vector V_τ represents the control variables that affect the dark effective spread. We use the $Best$-$Market$ quoted spread and the logarithm of the $Best$-$Market$ quoted depth on the visible markets that prevail at the time of the trade; the logarithm of the the order size; the return volatility;[23] and dummy variables that indicate whether the trade is a block ($\mathrm{D}^{\mathrm{Block}}$, with a size larger than the 99^{th} percentile of the particular month), or very small ($\mathrm{D}^{\mathrm{Small}}$, with a size less than €1.000). The IMR is the Inverse Mill's Ratio, which is calculated from the first stage predicted value.

The vector Z represents the instruments which are excluded from the second equation

[23] We take the prices of the ten most recent trades, and sum the ten squared returns to measure volatility.

8. We take the time (in minutes) since the previous trade, and a dummy $Dark\_trade_{\tau-1}$ which indicates whether the previous trade was dark. The intuition is that a large time between two trades indicates an inactive visible market (given that more than 95% of the trades are visible). In these cases perhaps a dark trade is more likely. Similarly, a current dark trade implies dark trading interest, which increases the likelihood that the next trade is dark too.

This methodology has two drawbacks however. First, it assumes there is only a single dark market, whereas in reality there are many locations to trade dark. Second, the imputed liquidity measures $\widehat{Dark^{Ef}}$ and $\widehat{Cons^{Ef}}$ are fully identified from the variables in V and Z.[24]

4.3.2 Results

Table 6 shows the results of the Heckman model, which is estimated per stock for each month. At this frequency we have a sufficient number of dark trades, but also flexibility as the estimated coefficients are stock-month specific. The reported coefficients are equal weighted averages over all stocks and months. The table reports the marginal effects of the first stage Probit regression, evaluated at the sample means of all variables.

The signs of most coefficients are as expected. The excluded instruments in the first stage Probit both have positive signs and are statistically highly significant, meaning they are strong predictors of observing a dark trade. The coefficients are also positive for the dummy variables for $\mathrm{D^{Block}}$ and $\mathrm{D^{Small}}$.

Interestingly, an increase in the prevailing visible quoted spread of 10 basis points increases the likelihood of a dark trade by one percentage point, which is large given that 2.3% of the trades in our sample are dark. This finding indicates a substitution effect, where traders go to the dark market if the visible market is illiquid. This result contrasts

[24] We have tried various specifications, and selected a set of variables most commonly used in the literature.

Ray (2010) and Ready (2013), who find that an increase in the effective spread of exchanges *decreases* the market share of crossing networks. Our measure of dark trading encompasses all forms of dark trading, including internalization and OTC, which might explain the different results.

Column (2) of Table 6 reports the second stage Heckman results. As expected, larger trades have a higher dark effective spread. Also the dummies for block and small trades, which are functions of the trade size also in the model, indicate a larger dark effective spread (coefficients of 46.9 and 14.1 basis points respectively). Further, we observe that the liquidity on the visible market, as measured by the Best quoted spread and Best quoted depth, are positively correlated to the dark liquidity. This finding indicates a complementarity between dark and visible liquidity, consistent with the theory of (Buti, Rindi, and Werner, 2011b). The Inverse Mill's Ratio (IMR) is strongly negative and significant, which confirms that a dark trade is more likely to occur when the dark market is more liquid.

The dark markets add substantial liquidity as the median $\widehat{Cons^{Ef}}$ is 8 basis points in the sample (not reported), which is much lower than the median effective spread of 14 basis points.

The fragmentation regressions using as liquidity measure $\widehat{Dark^{Ef}}$ and $\widehat{Cons^{Ef}}$ are reported in columns (3) and (4). Visible fragmentation also improves dark liquidity, as $\widehat{Dark^{Ef}}$ reduces by 9 basis points at $VisFrag = 0.4$ when compared to a concentrated market. Similarly, $\widehat{Cons^{Ef}}$, which incorporates both visible and dark liquidity, improves by 4 basis points at $VisFrag = 0.4$. The coefficient of $Dark$ on $\widehat{Cons^{Ef}}$ is 1.60, which is slightly smaller than the coefficient on the effective spread of 5.65 in Table 4. This result confirms that dark trading is detrimental to the aggregate liquidity in the market, even when incorporating the liquidity available at dark venues. The coefficient of $Dark$ on the dark effective spread ($\widehat{Dark^{Ef}}$) is negative, as more dark trading indicates more dark liquidity. As robustness we estimate different versions of the fragmentation models using measures of dark liquidity as dependent variable. The results are similar, and reported in Table A.5 of the Web appendix.

5 Conclusion

Stocks are simultaneously traded on a variety of different trading systems, creating a fragmented 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. More generally, 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*, *Best-Market* and *Local* liquidity. *Global* liquidity takes all relevant trading venues into account while *Local* liquidity only the traditional stock market. Although *Global* 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.

Our main analysis focuses on the relationship between fragmentation, dark trading and the liquidity of all visible trading venues. However, using a Heckman procedure we also take a step at consolidating effective liquidity across visible venues and dark venues. For this consolidated liquidity all the main results on visible fragmentation and dark trading hold.

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Table (1) Descriptive statistics of the sample firms.

The data set covers daily observations for 51 AEX large and mid cap constituents, from 2007:11 to 2009:12. The table shows the mean, standard deviation (StDev) and quartiles of all variables. In the top panel, the variables firm size (size) and traded volume (volume) are expressed in millions of Euro's. Return volatility (SD) reflects the daily standard deviation of 15 minute intra-day returns on the midpoint, and is multiplied by 100. Euronext represents the market share of trading volume of Euronext Amsterdam. Algo is 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 cancelled. The bottom panels show the statistics for visible fragmentation and dark trading on a yearly basis. Visible fragmentation (VisFrag) is defined as 1-HHI, where HHI is the sum of squared market shares of *visible* trading venues. Dark is the market share of over-the-counter trades, internalization and dark pools. The statistics are equally weighted based on daily observations per firm.

	Mean	Stdev	25^{th}	50^{th}	75^{th}
Size	8.2	15.3	0.8	2.3	8.7
Price	23.29	23.06	9.74	16.34	28.34
Volume	103.0	255.0	5.0	19.5	92.2
SD	0.39	0.26	0.23	0.32	0.47
Algo	0.32	0.55	0.05	0.13	0.32
Euronext	0.67	0.18	0.55	0.68	0.81
VisFrag					
2007	0.04	0.06	0.00	0.00	0.05
2008	0.10	0.12	0.00	0.05	0.19
2009	0.28	0.15	0.14	0.30	0.41
Dark					
2007	0.26	0.17	0.14	0.23	0.34
2008	0.26	0.16	0.16	0.24	0.35
2009	0.25	0.17	0.14	0.23	0.34

Table (2) Descriptive statistics of the liquidity measures.
The table shows the median and standard deviation (StDev) of the liquidity measures on a yearly basis. The statistics are based on 51 firms in the period 2007:11 to 2009:12. *Depth*(X) is expressed in €1000s and represents the offered depth within X basis points around the midpoint. *Global Depth*(X) is the aggregated depth across all trading venues, *Best-Market* picks the most liquid venue at each point in time and *Local* refers to the traditional stock exchange (Euronext Amsterdam). The next blocks show the time weighted quoted spread (based on the global, best-market and local order book), and the trade weighted effective spread, realized spread and price impact. The realized spread and price impact are based on a 5 minute time window.

Panel A : Liquidity Measures		Median			StDev		
	Depth(X):	2007	2008	2009	2007	2008	2009
Global	10	86	50	59	1,491	649	433
	20	180	126	166	1,921	1,162	982
	30	252	184	262	2,036	1,306	1,248
Best-Market	10	83	44	39	1,388	443	198
	20	174	105	97	1,605	769	443
	30	245	156	158	1,649	823	584
Local	10	82	39	35	1,386	363	170
	20	173	94	92	1,605	713	433
	30	245	141	152	1,649	770	581
	Spreads:						
Quoted	*Global*	12.63	14.62	12.21	11.01	15.95	16.24
	Best-Market	13.34	15.75	13.62	10.84	17.12	17.05
	Local	13.51	16.71	14.78	10.67	16.76	16.88
Traded	Effective Spread	12.77	15.16	12.76	10.05	12.39	13.01
	Realized Spread	2.41	4.82	4.36	8.11	9.28	9.29
	Price Impact	10.42	9.52	8.17	10.51	12.56	11.78

Table (3) The effect of fragmentation on Depth(X): Second stage IV regressions.

The table shows the second stage results of the two-stage IV model (Equation (7)), for the *Global*, *Best-Market* and *Local* $Depth(X)$. The three endogenous variables VisFrag, VisFrag^2 and Dark are instrumented by the average level of these variables of stocks in the same size group on day t. The averages are calculated by excluding stock i. The $Depth(X)$ is expressed in Euro's and represents the offered depth within X basis points around the midpoint. Each model specification contains as independent variable Avgdepvar$_{-i}$, which represents the average dependent variable of all stocks in the same size group on day t excluding stock i. VisFrag is the degree of visible market fragmentation, defined as $1 - HHI$. Dark is the fraction of traded volume executed at dark pools, internalization and over-the-counter. The other variables are explained in the descriptive statistics and Table 1. The regressions are based on 546 trading days for 51 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Global			*Best-Market*			*Local*	
	Ln Depth(10)	Ln Depth(20)	Ln Depth(30)	Ln Depth(10)	Ln Depth(20)	Ln Depth(30)	Ln Depth(10)	Ln Depth(20)	Ln Depth(30)
VisFrag	1.669***	2.297***	1.858***	0.787	0.955***	0.445	-0.188	0.195	0.035
	(2.6)	(6.6)	(6.2)	(1.3)	(3.0)	(1.6)	(-0.3)	(0.6)	(0.1)
VisFrag^2	-1.740*	-2.961***	-2.836***	-1.117	-1.530***	-1.052**	-0.0215	-0.604	-0.504
	(-1.7)	(-4.9)	(-5.4)	(-1.1)	(-2.7)	(-2.1)	(-0.0)	(-1.1)	(-1.0)
Dark	-0.290**	-0.158	-0.147*	-0.255**	-0.146	-0.120	-0.204*	-0.112	-0.083
	(-2.4)	(-1.6)	(-2.0)	(-2.1)	(-1.5)	(-1.6)	(-1.7)	(-1.1)	(-1.1)
Avgdepvar$_{-i}$	0.448***	0.377***	0.408***	0.444***	0.372***	0.418***	0.460***	0.399***	0.451***
	(15.7)	(17.9)	(25.7)	(15.1)	(17.6)	(27.6)	(15.7)	(19.5)	(31.0)
Ln Size	0.704***	0.601***	0.478***	0.703***	0.630***	0.492***	0.714***	0.623***	0.482***
	(5.6)	(7.6)	(7.5)	(5.6)	(8.0)	(7.9)	(5.6)	(7.7)	(7.7)
Ln Price	0.235**	0.242***	0.169***	0.187*	0.177***	0.116**	0.177	0.176**	0.110*
	(2.1)	(3.6)	(2.9)	(1.7)	(2.6)	(2.0)	(1.6)	(2.6)	(1.9)
Ln Volume	0.237***	0.172***	0.155***	0.234***	0.174***	0.154***	0.231***	0.166***	0.145***
	(12.1)	(11.3)	(12.7)	(12.0)	(11.4)	(12.5)	(11.7)	(10.8)	(11.5)
Ln SD	-0.325***	-0.300***	-0.252***	-0.311***	-0.296***	-0.249***	-0.311***	-0.294***	-0.244***
	(-15.6)	(-19.6)	(-19.6)	(-15.0)	(-19.4)	(-19.1)	(-14.8)	(-19.0)	(-18.5)
Algo	-0.266***	-0.211***	-0.146***	-0.258***	-0.209***	-0.157***	-0.264***	-0.217***	-0.167***
	(-12.7)	(-13.8)	(-13.1)	(-12.7)	(-14.0)	(-14.0)	(-12.9)	(-14.6)	(-14.6)
Obs	25,300	25,300	25,300	25,300	25,300	25,300	25,300	25,300	25,300
R^2	0.237	0.298	0.352	0.225	0.293	0.350	0.230	0.298	0.356

Table (4) The effect of fragmentation on the spread measures: Second stage IV regressions.
The table shows the second stage results of the two-stage IV model (Equation (7)), for the spread liquidity measures. The three endogenous variables VisFrag, VisFrag^2 and Dark are instrumented by the average level of these variables of stocks in the same size group on day t. The averages are calculated by excluding stock i. The time weighted quoted spread measures are based on the depth of the *Global*, *Best-Market* or *Local* market. The effective spread, realized spread and price impact are based on the trades of all visible venues. All spreads are measured in basis points. Each model specification contains as independent variable Avgdepvar$_{-i}$, which represents the average dependent variable of all stocks in the same size group on day t excluding stock i. VisFrag is the degree of visible market fragmentation, defined as $1 - HHI$. Dark is the fraction of traded volume executed at dark pools, internalization and over-the-counter. The other variables are explained in the descriptive statistics and Table 1. The regressions are based on 546 trading days for 51 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)	(2)	(3)	(4)	(5)	(6)
	Time weighted quoted spreads			Trade weighted spreads		
	Global	*Best-Market*	*Local*	Effective Spread	Price Impact	Realized Spread
VisFrag	-11.12**	-1.431	-3.456	-7.973	18.47**	-25.95***
	(-2.0)	(-0.2)	(-0.6)	(-1.0)	(2.1)	(-3.1)
VisFrag^2	8.555	-8.556	-2.267	3.894	-26.53*	25.28*
	(0.9)	(-0.8)	(-0.2)	(0.3)	(-1.8)	(1.8)
Dark	1.358	3.756***	2.198*	5.645***	7.259***	-2.661
	(1.2)	(2.7)	(1.7)	(2.8)	(3.5)	(-1.4)
Avgdepvar$_{-i}$	0.590***	0.680***	0.648***	0.453***	0.291***	0.278***
	(28.6)	(26.6)	(30.3)	(16.3)	(13.8)	(11.1)
Ln Size	-3.399**	-1.970	-2.397	-1.929	-1.931	-0.970
	(-2.5)	(-1.3)	(-1.6)	(-1.5)	(-1.1)	(-0.7)
Ln Price	2.546*	2.506*	2.423	-2.402**	1.918	-4.474***
	(1.9)	(1.7)	(1.6)	(-2.1)	(1.1)	(-3.4)
Ln Volume	-1.457***	-1.821***	-1.560***	-1.166***	-2.831***	1.556***
	(-8.3)	(-7.9)	(-7.0)	(-3.7)	(-8.7)	(5.2)
Ln SD	3.864***	4.391***	4.552***	5.354***	10.47***	-4.684***
	(20.5)	(19.6)	(20.9)	(17.3)	(29.5)	(-15.7)
Algo	3.736***	3.920***	4.235***	3.224***	2.213***	1.175***
	(16.1)	(15.3)	(16.7)	(11.0)	(6.6)	(4.0)
Obs	25,300	25,300	25,300	25,300	25,300	25,300
R^2	0.287	0.312	0.325	0.141	0.167	0.043

Table (5) Cross-sectional heterogeneity: Second stage IV regressions.
The regressions of the IV model in Equation (7) are estimated, which we modify in regression (1) by decomposing Dark into the fraction of volume by block trades $\text{Dark}^{\text{Block}}$ (trades with size exceeding the 99^{th} level of the particular stock and month) and the remaining smaller dark trades $\text{Dark}^{\text{Other}}$; and in regression (2) by adding an interaction term between Dark and a Large cap dummy (which equals 1 when the stock belongs to the Amsterdam large cap index and zero otherwise). We estimate both regressions for all liquidity measures, but only report the coefficients and t-stats of the variables of interest. The last column tests whether the sum of the coefficients on Dark and Dark$times$LargeCap is statistically different from zero. The instruments for $\text{Dark}^{\text{Block}}$ and $\text{Dark}^{\text{Other}}$, and Dark and Dark×LargeCap are constructed similarly as those in Table 3. The control variables (not reported) are VisFrag, VisFrag^2, Ln Size, Ln Price, Ln Volume, Ln SD and Algo, as described in Table 3. The regressions are based on 546 trading days for 51 stocks, and have firm-quarter fixed effects. T-stats are 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)				(2)				
	$\text{Dark}^{\text{Block}}$		$\text{Dark}^{\text{Other}}$		Dark		Dark× LargeCap		T-test Sum
Global									
Ln Depth(10)	-0.424***	(-2.9)	0.513	(0.4)	-1.013**	(-2.2)	0.822*	(1.8)	*
Ln Depth(20)	-0.237**	(-2.3)	1.200	(1.1)	-0.123	(-0.3)	-0.029	(-0.1)	*
Ln Depth(30)	-0.215***	(-2.6)	1.000	(1.6)	-0.197	(-0.9)	0.090	(0.4)	
Best-Market									
Ln Depth(10)	-0.379***	(-2.6)	0.304	(0.2)	-0.962**	(-2.1)	0.799*	(1.7)	*
Ln Depth(20)	-0.237**	(-2.3)	1.109	(1.0)	-0.082	(-0.2)	-0.088	(-0.2)	**
Ln Depth(30)	-0.201**	(-2.4)	0.866	(1.4)	-0.147	(-0.7)	0.031	(0.1)	*
Local									
Ln Depth(10)	-0.332**	(-2.2)	0.646	(0.5)	-0.846*	(-1.8)	0.723	(1.6)	
Ln Depth(20)	-0.198*	(-1.9)	1.256	(1.1)	-0.021	(-0.1)	-0.110	(-0.3)	*
Ln Depth(30)	-0.162*	(-1.9)	0.992	(1.5)	-0.096	(-0.4)	0.020	(0.1)	
Time Weighted Quoted Spreads									
Global	0.450	(0.3)	6.052	(0.5)	-7.344	(-1.6)	11.00**	(2.3)	***
Best-Market	7.857***	(3.9)	-10.11	(-0.6)	9.927*	(1.7)	-3.921	(-0.6)	***
Local	-3.162	(-1.4)	17.34	(1.0)	-11.99*	(-1.8)	12.89*	(1.9)	***
Trade weighted Spreads									
Effective Spread	3.250**	(2.5)	-17.14	(-1.4)	-3.123	(-0.7)	6.781	(1.6)	***
Price Impact	5.161***	(3.6)	-17.23	(-1.3)	-1.809	(-0.4)	7.510	(1.6)	***
Realized Spread	3.689***	(2.7)	-19.73	(-1.5)	-3.972	(-0.9)	8.322*	(1.8)	

Table (6) Consolidating liquidity of dark and visible markets.
This table documents the determinants of the predicted effective spread in the dark markets and consolidated spread across dark and visible markets. The predicted dark effective spread is obtained by a Heckman model, which overcomes the selection bias that the dark effective spread is only observed when a dark trade occurs. Per stock-month, we estimate for trade τ (visible or dark)

$$Dark\_trade_\tau = \alpha_1 + \gamma_1 V_\tau + \gamma_2 Z_\tau + \varepsilon_{1,\tau}, \tag{1}$$
$$Dark_\tau^{Ef} = \alpha_2 + \beta V_\tau + \lambda IMR_\tau + \varepsilon_{2,\tau}, \tag{2}$$

where Dark_trade_τ is a dummy variable equal to one when the trade is dark and zero otherwise, and Dark_τ^{Ef} is the dark effective spread which is only observed when the trade is dark. The excluded instruments Z in the first stage Probit are the number of minutes since the previous trade (Δminutes) and a dummy equal to one when the previous trade is dark and zero otherwise ($\text{Dark\_trade}_{\tau-1}$). The vector V contains the logarithm of the order size (Ln Size); a dummy D^{Block} for trades with a size larger than the 99^{th} percentile of the particular stock and month; a dummy D^{Small} for trades with size less than €1.000; the prevailing global quoted spread and the logarithm of the global quoted depth on the visible markets (Ln Global Quoted Depth); and return volatility (SD). We estimate the model per stock-month (1,230 times), and save the first stage marginal effects (evaluated at the means of all variables) and the second stage OLS coefficients. Columns (1) and (2) report the averages of the first stage marginal effects and the second stage coefficients, and t-statistics based on the standard deviation of these averages. Columns (3) and (4) show the daily fragmentation regressions of Equation (7), but using as dependent variable a liquidity measure based on the predicted dark effective spread $\widehat{Dark_\tau^{Ef}}$. Specifically, (3) uses the daily average across trades τ of the minimum of the predicted dark spread and the *Global* quoted spread, denoted $\widehat{Cons_\tau^{Ef}}$, and (4) uses the daily average of $\widehat{Dark_\tau^{Ef}}$.

	(1)	(2)		(3)	(4)
	Heckman Probit and OLS			Fragmentation	
	$Dark\_trade_t$	$Dark_t^{Ef}$		$\widehat{Cons^{Ef}}$	$\widehat{Dark^{Ef}}$
$\text{Dark\_trade}_{\tau-1}$	0.046***		VisFrag	-8.794**	-16.03**
	(38.8)			(-2.1)	(-2.1)
Δminutes	0.007***		VisFrag^2	3.981	-0.197
	(22.5)			(0.6)	(-0.0)
D^{Block}	0.040***	8.223***	Dark	1.604*	-3.635*
	(13.0)	(10.0)		(1.7)	(-1.9)
D^{Small}	0.008***	0.995**	Avgdepvar_{-i}	0.528***	0.479***
	(5.4)	(2.3)		(21.0)	(16.2)
Ln trade size	0.013***	0.749	Ln Size	-2.157*	-9.421***
	(19.5)	(0.3)		(-1.9)	(-4.8)
Global Quoted Spread	0.001***	0.829***	Ln Price	0.570	3.728*
	(31.2)	(35.1)		(0.5)	(1.9)
Ln Global Quoted Depth	0.001***	-1.162***	Ln Volume	-0.546***	2.787***
	(5.0)	(-20.6)		(-3.4)	(8.6)
SD	-1.426***	308.868***	Ln SD	2.509***	0.251
	(-23.9)	(19.2)		(16.0)	(0.8)
Inv Mill's Ratio		-1.061***	Algo	1.761***	1.650***
		(-9.5)		(10.6)	(6.1)
Avg number obs	53,696	1,256	Obs	25,301	25,301
R^2		0.139	R^2	0.184	0.081

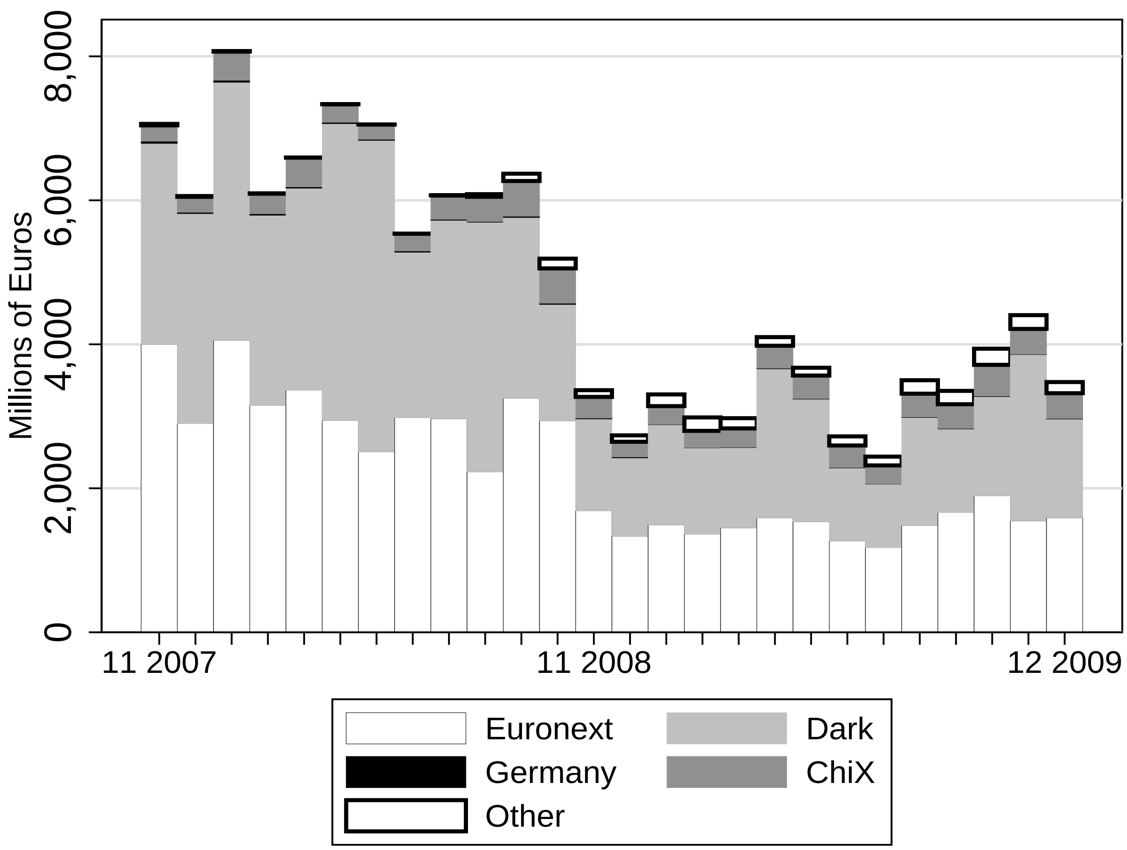

Figure (1) Traded Volume in millions of Euros.
The figure displays monthly averages of the daily trading volume in millions, equal weighted across days and stocks. Euronext consists of Amsterdam, Brussels, Paris and Lisbon. Germany represents all the local German exchanges (including Xetra), and Other represents Bats Europe, Nasdaq OMX Europe, Virt-x and Turquoise combined. Finally, Dark represents the order flow executed ovef, at crossing networks, dark pools and internalized.

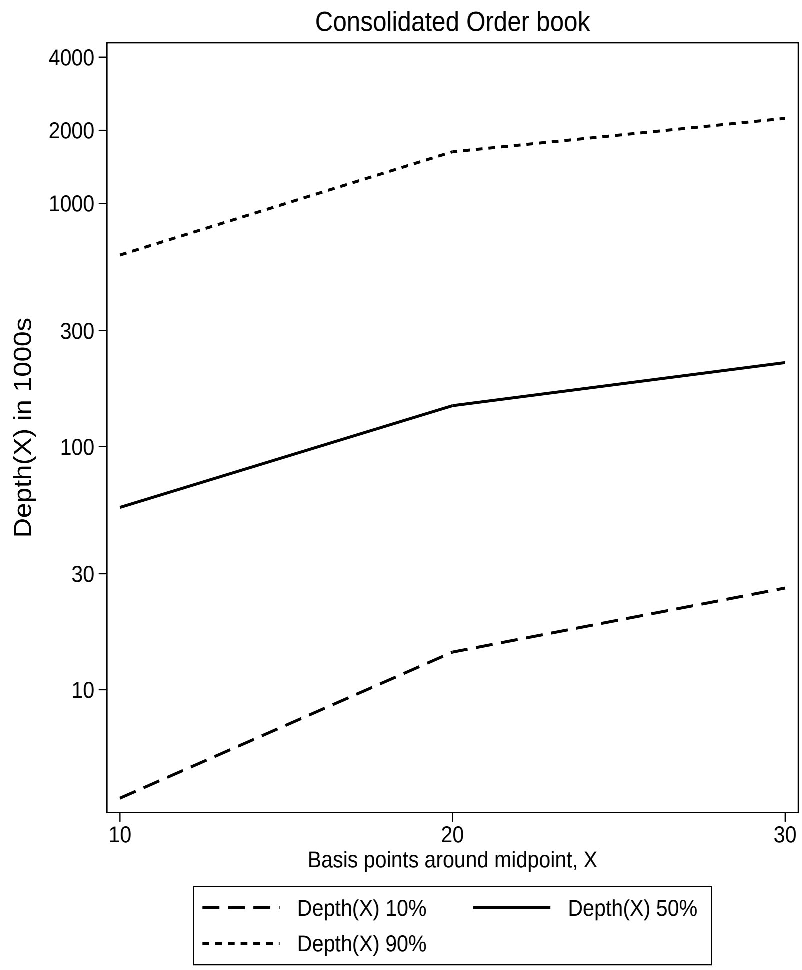

Figure (2) Depth in the consolidated order book.
The figure shows the 10, 50 and 90^{th} percentiles of the $Depth(X)$ measure, expressed on a logarithmic scale in €1000s. The measure aggregates the Euro value of shares offered within a fixed amount of basis points X around the midpoint, shown on the horizontal axes. The consolidated order book represents liquidity to a SORT investor, where the order books of Euronext Amsterdam, Xetra, Chi-X, Virt-X, Turquoise, Nasdaq OMX Europe and Bats Europe are aggregated.

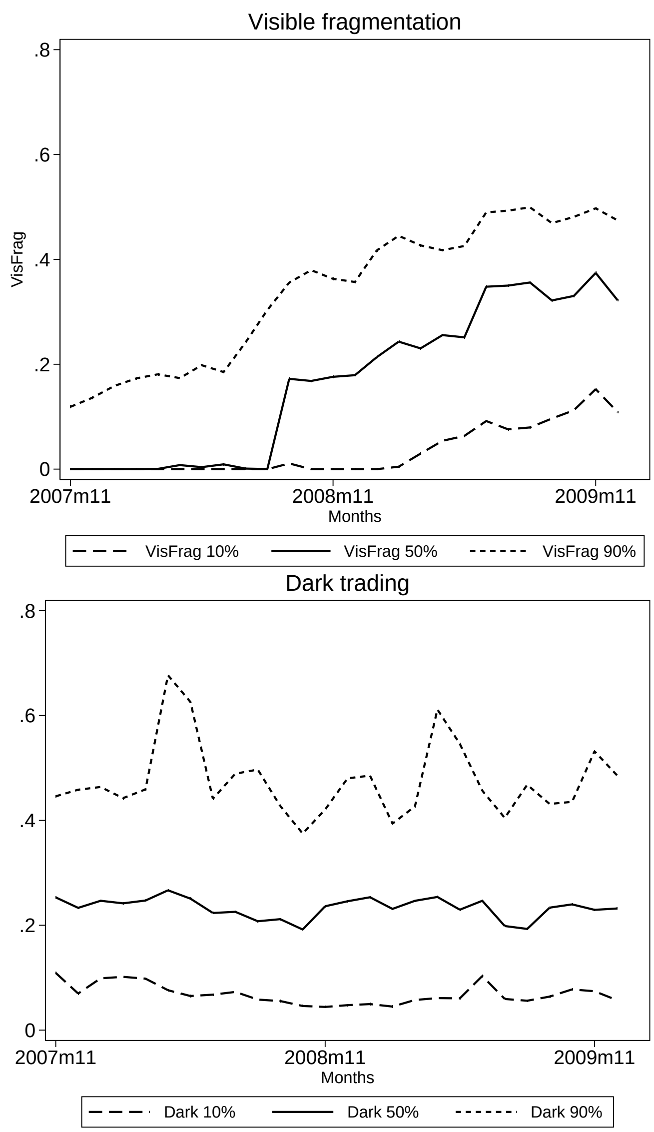

Figure (3) Visible fragmentation and Dark trading over time.
The monthly 10, 50 and 90^{th} percentiles of VisFrag and Dark are shown, for the 51 AEX large and mid cap stocks between 2007:11 - 2009:12. The statistics are calculated using daily observations, equally weighted across stocks. VisFrag equals $1-HHI$, based on the number of shares traded at the following trading venues: Euronext (Amsterdam, Brussels, Paris and Lisbon together), the German exchanges including Xetra, Chi-X, Virt-X, Turquoise, Nasdaq OMX Europe and Bats Europe. Dark trading represents the order flow at over-the-counter markets, dark pools and internalization.

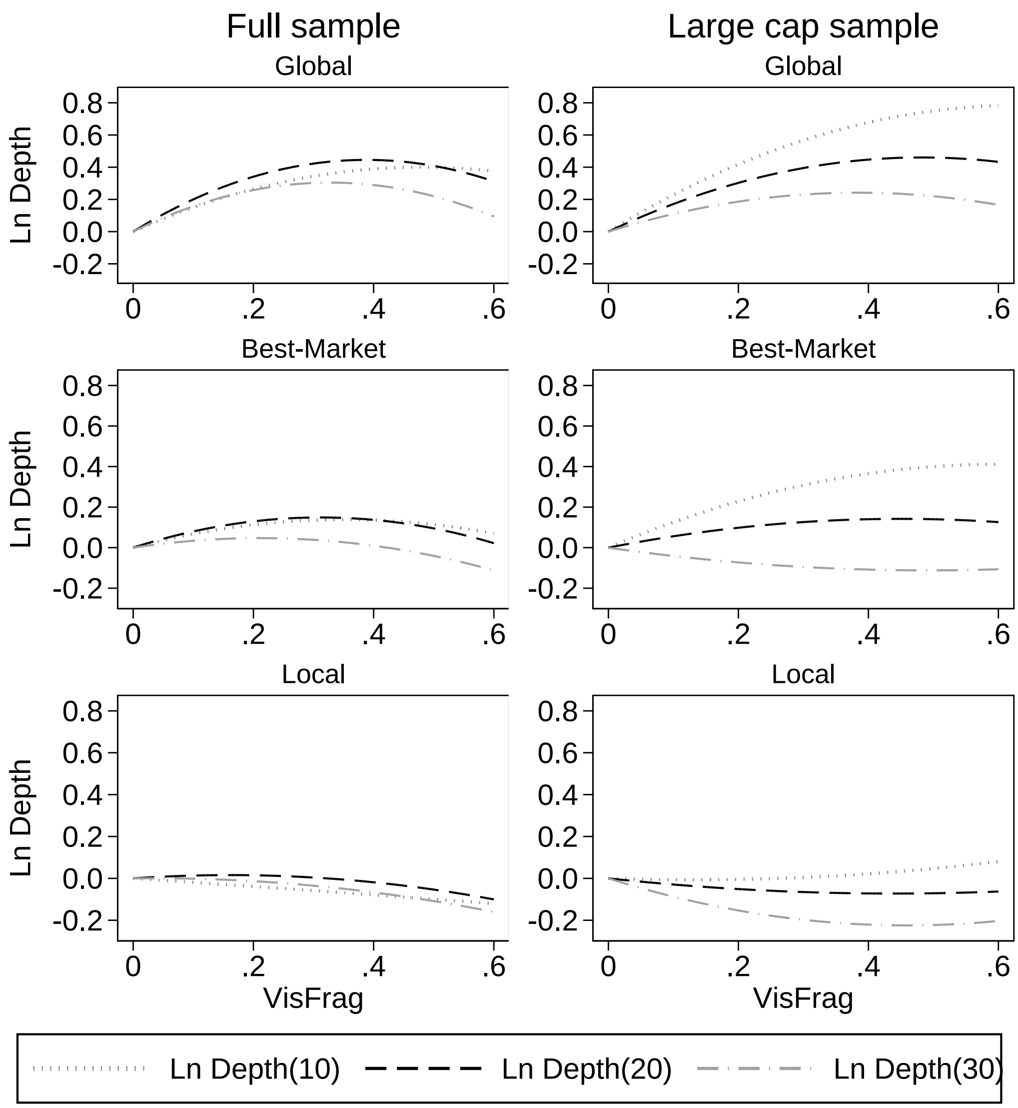

Figure (4) The effect of visible fragmentation on depth, for the full and Large-cap sample.
The panels show the implied effect of visible fragmentation on depth of the IV regressions of Table 3 for the full sample (left figures), and for the subsample containing the 25 constituents of the Amsterdam large cap index (the full results are reported in Table A.10 of the Web appendix). The results are shown for the logarithm of *Global Depth*(X), *Best-Market Depth*(X) and *Local Depth*(X), displayed on the vertical axis. The horizontal axis shows the level of visible fragmentation, defined as $(1 - HHI)$. The regressions include firm-quarter dummies. The instruments are $\text{AvgVisFrag}_{-i,t}$, $\text{AvgVisFrag}^2_{-i,t}$ and $\text{AvgDark}_{-i,t}$.