The Effect of Fragmentation in Trading on Market Quality in the UK Equity Market*

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Abstract

We investigate the effects of fragmentation in equity markets on the quality of trading outcomes in a panel of FTSE stocks over the period 2008-2011. This period coincided with a great deal of turbulence in the UK equity markets which had multiple causes that need to be controlled for. To achieve this, we use the common correlated effects estimator for large heterogeneous panels. We extend this estimator to quantile regression to analyze the whole conditional distribution of market quality. We find that both fragmentation in visible order books and dark trading that is offered outside the visible order book lower volatility. But dark trading increases the variability of volatility, while visible fragmentation has the opposite effect in particular at the upper quantiles of the conditional distribution. The transition from a monopolistic to a fragmented market is non-monotonic with respect to the degree of fragmentation.

JEL codes: C23, G28, L10
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1 Introduction

The implementation of the "Markets in Financial Instruments Directive (MiFID)" has had a profound impact on the organization of security exchanges in Europe. Most importantly, it abolished the concentration rule in European countries that required all trading to be conducted on primary exchanges and it created a competitive environment for equity trading; new types of trading venues that are known as Multilateral Trading Facilities (MTF) or Systematic Internalizers (SI) were created that fostered this competition. As a result, MiFID has served as a catalyst for the competition between equity marketplaces we observe today. The first round of MiFID was implemented across Europe on November 1st, 2007, although fragmentation of the UK equity market began sometime before that (since the UK did not have a formal concentration rule), and by 13th July, 2007, Chi-X was actively trading all of the FTSE 100 stocks. In October 2012, the volume of the FTSE 100 stocks traded via the London Stock Exchange (LSE) had declined to 53%.[1] Similar developments have taken place across Europe.

At the same time, there has been a trend towards industry consolidation: a number of mergers of exchanges allowed cost reductions through "synergies" and also aided standardization and pan European trading. For example, Chi-X was acquired by BATS in 2011. There are reasons to think that consolidation fosters market quality. A single, consolidated exchange market creates network externalities. Some have argued that security exchanges even qualify as natural monopolies. On the other hand, there are arguments for why competition between trading venues can improve market quality. Higher competition generally promotes technological innovation, improves efficiency and reduces the fees that have to paid by investors. Furthermore, traders that use Smart Order Routing Technologies (SORT) can still benefit from network externalities in a fragmented market place.

[1] `http://www.batstrading.co.uk/market_data/market_share/index/`, accessed on August 24, 2013

In view of the ambiguous theoretical predictions, whether the net effect of fragmentation on market quality is negative or positive is an empirical question. In this paper, we investigate the effect of visible fragmentation and dark trading on measures of market quality such as volatility, liquidity, and trading volume in the UK equity market. Our analysis distinguishes between the effect of fragmentation on average market quality on the one hand and on its variability on the other hand. The first question sheds light on the relationship between fragmentation and market quality during "normal" times. In contrast, the second question investigates whether there is any evidence that fragmentation of trading has led to an increase in the frequency of liquidity droughts or to more extraordinary price moves. This latter issue has been raised in several studies that have analyzed the Flash Crash and other recent market meltdowns. Of course, there is no market structure that can entirely eliminate variability in liquidity or trading volume. But regulators aim at constructing a robust market structure that contributes to an orderly and resilient functioning of equity markets in times of market turmoil. One reason for this objective is that investors particularly value the ability to trade in times of market stress and a stable market structure is thus important to maintain investor confidence (SEC, 2013).

We use a novel dataset that allows us to calculate weekly measures for overall fragmentation, visible fragmentation and dark trading that is offered outside the visible order book for each firm of the FTSE 100 and FTSE 250 indices. We combine this with data on indicators of market quality. To investigate the effect of fragmentation on market quality, we use a version of Pesaran's (2006) common correlated effects (CCE) estimator for heterogeneous panels. That model is suitable for our data because it can account for common but unobserved factors that affect both fragmentation and market quality. For example, these factors account for the activity of High Frequency Traders (HFT) whose activity has generated so much scrutiny (Foresight, 2012). The unobserved factors also control for the global financial crisis, changes in trading technology or new types of trading strategies. We extend Pesaran's (2006) estimator to quantile regression (the QCCE estimator) to analyze the whole conditional distribution of market quality. This estimator is also robust to large observations on the response.

We find that overall fragmentation, visible fragmentation and dark trading lower volatility at the LSE. But dark trading increases the variability of volatility, while fragmentation has the opposite effect, in particular at the upper quantiles of the conditional distribution. This result is robust across several alternative measures of variability in market quality. Trading volume both globally and locally at the LSE is higher if visible order books are less fragmented or if there is more dark trading. Compared to a monopoly, visible fragmentation lowers liquidity measured by quoted bid-ask spreads at the LSE. We also investigate the transition between monopoly and competition in terms of the level of fragmentation. We find this transition is non-monotonic for overall and visible fragmentation and takes the form of an inverted U shape. The level of optimal fragmentation varies across individual firms but it is positively related to market capitalization.

The remainder of this paper is organized as follows. Section 2 discusses the related literature. The data and measures for fragmentation and market quality are introduced in Section 3. Section 4 proposes an econometric framework suitable for answering the questions of interest and Section 5 reports the results. Section 6 concludes. The online appendix provides additional empirical results and a theoretical justification for our QCCE estimator.

2 Related Literature

Recently, regulators in both Europe and the US introduced new provisions to modernize and strengthen their financial markets. The "Regulation of National Markets (RegNMS)" in the US was implemented in 2005, two years earlier than its European counterpart MiFID.[2] One common theme of these regulations is to foster competition between equity trading venues. But RegNMS and MiFID differ in important aspects: under RegNMS, trades and quotes are recorded on an official consolidated tape and trade-throughs are prohibited, while in Europe, a (publicly guaranteed) consolidated tape does not yet exist, and trade-throughs are allowed.[3]

These regulatory changes and institutional differences between Europe and the US have motivated an ongoing debate among academics and practitioners on the effect of competition between trading venues on market quality. The remainder of this section summarizes some theoretical predictions and existing empirical evidence for both Europe and the US.[4]

Theoretical predictions On the one hand, there are theoretical reasons for why competition can harm market quality. Security exchanges may be natural monopolies because a single exchange has lower costs when compared to a fragmented market place. In addition, a single, consolidated exchange market creates network externalities. The larger the market, the more trading opportunities exist that attract even more traders by reducing the execution risk. Theoretical models that incorporate network externalities, such as Pagano (1989), predict that liquidity should concentrate at one trading venue. This prediction is at odds with the fragmentation of order flow we observe today. One possible explanation is that traders that use SORT can still benefit from network externalities in a fragmented market place. Such a situation is modelled by Foucault and Menkveld (2008) who study the competition between Euronext and the LSE in the Dutch equity market. Before the entry of LSE, the Dutch equity market had a centralized limit order book that was operated by Euronext. Their theory predicts that a larger share of SORT increases the liquidity supply of the entrant.

[2]The different pillars of MiFID are summarized in the online appendix.

[3]A trade-through occurs if a sell (buy) order is executed at a price that is higher (lower) than the best price quoted in the market.

[4]In the online appendix, we survey the methodology used in related research and relate them to our econometric framework.

On the other hand, there are reasons why competition between trading venues can improve market quality. Higher competition generally promotes technological innovation, improves efficiency and reduces the fees that have to be paid by investors.[5] Biais et. al. (2000) propose a model for imperfect competition in financial markets that is consistent with the observation that traders earn positive profits and that the number of traders is finite. Their model also assumes that traders have private information on the value of financial assets, giving rise to an asymmetric information issue. When compared to a monopolistic market, their model predicts that a competitive market is characterized by lower spreads and a higher trading volume. Buti et. al. (2010) study the competition between a trading venue with a transparent limit order book and a dark pool. Their model implies that after the entry of the dark pool, the trading volume in the limit order book decreases, while the overall volume increases.

Empirical evidence for Europe After the introduction of MiFID, equity trading in Europe became more fragmented as new trading venues gained significant market shares from primary exchanges. Gresse (2011) investigates if fragmentation of order flow has had a positive or negative effect on market quality in European equity markets. She examines this from two points of view. First, from the perspective of a sophisticated investor who has access to SORT and thus to the consolidated order book. Second, from the point of view of an investor who can only access liquidity on the primary exchange. Her sample covers stocks listed on the LSE and Euronext exchanges in Amsterdam, Paris and Brussels for 1 month in 2007 and 3 months in 2009. Gresse finds that increased competition between trading venues creates more liquidity both locally and globally, and that dark trading does not have a negative effect on liquidity.

[5]For example, the latency at BATS was about 8 to 10 times lower when compared to the LSE in 2010 (Wagener, 2011), and the LSE has responded by upgrading its system at a faster pace (cp. the online appendix). Chesini (2012) reports a reduction in explicit trading fees on exchanges around Europe due to the competition between them for order flow.

De Jong et. al. (2011) study the effect of fragmentation on market quality in a sample of 52 Dutch stocks for the period from 2006 to 2009. They distinguish between platforms with a visible order book and dark platforms that operate an invisible order book. Their primary finding is that fragmentation on trading venues with a visible order book improves global liquidity, but has a negative effect on local liquidity. But visible fragmentation ceases to improve global liquidity when it exceeds a turning point. Dark trading is found to have a negative effect on liquidity.

Studying UK data, Linton (2012) does not find a detrimental effect of fragmentation on volatility using daily data for the FTSE 100 and FTSE 250 indices for the period from 2008 to 2011. Hengelbrock and Theissen (2009) study the market entry of Turquoise in September 2008 in 14 European countries. Their findings suggest that quoted bid-ask spreads on regulated markets declined after the entry of Turquoise. Riordan et al. (2011) also analyze the contribution of the LSE, Chi-X, Turquoise and BATS to price discovery in the UK equity market. They find that the most liquid trading venues LSE and Chi-X dominate price discovery. Over time, the importance of Chi-X in price discovery has increased.

Overall, the evidence for Europe suggests that the positive effects of fragmentation on market quality outweighs its negative effects. A possible reason for the observed improvement in market quality despite the lack of trade-through protection and a consolidated tape are algorithmic traders and HFT (Riordan et al., 2011). By relying on SORT, these traders create a virtually integrated marketplace in the absence of a commonly owned central limit order book.

Empirical evidence for the US. In contrast to Europe, competition between trading venues is not a new phenomenon in the US where Electronic Communication Networks (ECN) started to compete for order flow already in the 1990s. Boehmer and Boehmer (2003) investigate if the entry of the NYSE into the trading of Exchange Traded Funds (ETFs) has harmed market quality. Prior to the entry of the

NYSE, the American Stock Exchange, the Nasdaq InterMarket, regional exchanges and ECNs already traded ETFs. Boehmer and Boehmer document that increased competition reduced quoted, realized and effective spreads and increased depth.

O'Hara and Ye (2011) analyze the effect of the proliferation of trading venues on market quality for a sample of stocks that are listed on NYSE and Nasdaq between January and June 2008. They find that stocks with more fragmented trading had lower spreads and faster execution times. In addition, fragmentation increases short-term volatility but is associated with greater market efficiency. Drawing on their findings for the US, O'Hara and Ye (2011) hypothesize that trade-through protection and a consolidated tape are important for the emergence of a single virtual market in Europe. This hypothesis is supported by the findings of Menkveld and Foucault (2008). However, Riordan et al. (2011) conclude that the existence of trade-throughs does not harm market quality.

To summarize, the evidence for the US points to an improvement in average market quality in a fragmented market place. Notwithstanding these results on average quality, Madhavan (2012) finds that both trade fragmentation and quote fragmentation prior to the Flash Crash associated with larger drawdowns during the Flash Crash. This finding suggests that fragmentation may be affecting the variability of market quality. Below, we further investigate this question.

3 Data and Measurement Issues

This section discusses how we measure fragmentation, dark trading and market quality. Our data on market quality and fragmentation covers the period from May 2008 to June 2011 and includes all individual FTSE 100 and 250 firms. At the time of writing, the FTSE350 index companies are valued at $3400 billion, which represents a substantial part of the UK (and European) equity market.

3.1 Fragmentation and Dark Trading

Weekly data on the volume of the individual firms traded on each equity venue was supplied to us by Fidessa.[6] For venue $j = 1, \ldots, J$, denote by w_j the market share (according to the number of shares traded) of that venue. We measure fragmentation by the dispersal of volume across multiple trading venues, or $1 - \sum w_j^2$, where $\sum w_j^2$ is the Herfindahl index.

In May 2008, equity trading in the UK was consolidated at the LSE as reflected by an average fragmentation level of 0.4 (Figure 1). By June 2011, the entry of new trading venues has changed the structure of the UK equity market fundamentally: fragmentation has increased by about half over the sample period. The rise of HFT is one explanation of the successful entry of alternative trading venues. These venues could attract a significant share of HFT order flow by offering competitive trading fees and sophisticated technologies. In particular, MTF's typically adopt the so-called maker-taker rebates that reward the provision of liquidity to the system, allow various new types of orders, and have small tick sizes. Additionally, their computer systems offer a lower latency when compared to regulated markets. This is probably not surprising since MTFs are often owned by a consortium of users, while the LSE is a publicly owned corporation.

The data allows us to distinguish between public exchanges with a visible order book ("lit"), regulated venues with an invisible order book ("regulated dark pools"), over the counter ("OTC") venues, and systematic internalizers ("SI"). [7] We use this information in our analysis to distinguish between fragmentation in visible order books (Figure 1) and different categories of dark trading such as OTC, regulated dark pools and SI (Figure 2). The share of volume traded at OTC, SI and regulated dark venues increased over the sample period, while the share of volume traded at lit venues has fallen considerably. For all categories, the observed changes are largest

[6] In the online appendix, we give a full list of the trading venues in our sample.

[7] Not all trading venues with an invisible order book are registered as dark pools: unregulated categories of dark pools are registered as OTC venues or brokers (Gresse, 2012).

in 2009. In the period after 2009, volumes have approximately stabilized with the exception of regulated dark venues where volume kept increasing. Quantitatively, the majority of trades are executed on lit and OTC venues while regulated dark and SI venues attract only about 1% of the order flow.

Following Gresse (2011) and De Jong et al. (2011), dark trading is measured as the share of volume trading on OTC venues, regulated dark pools or SI which is likely to be dominated by OTC trading volumes.

3.2 Market Quality

We measure market quality by volatility, liquidity, and trading volume of the FTSE 100 and 250 stocks. Since our measure of fragmentation is only available at a weekly frequency, all measures of market quality are constructed as weekly medians of the daily measures.[8]

With the exception of trading volume, our measures of market quality are calculated using data from the LSE. In that sense, our measures are local as compared to global measures that are constructed by consolidating measures from all markets. Global measures are relevant for investors that have access to SORT, while local measures are important for small investment firms that are only connected to the primary exchange (perhaps to save costs) or for retail investors that are restricted by the best execution policy of their investment firm.[9] For example, Gomber et al. (2012) provide evidence that 20 out of 75 execution policies in their sample state that they only execute orders at the primary exchange.

[8]While the available measures of market quality are positive, we wish to emphasize that market quality is a normative concept. Translating positive measures of market quality into welfare is difficult and subject to much controversy (Hart and Kreps, 1986, Stein, 1987).

[9]Under MiFID, investment firms are required to seek best execution for their clients, cp. the online appendix for details.

Volatility. Volatility is often described in negative terms, but its interpretation should depend on the perspective and on the type of volatility.[10] For example, Bartram et al. (2012) argue that volatility levels in the US are in many respects higher than in other countries but this reflects more innovation and competition rather than poor market quality.

One well known method to estimate volatility is due to Parkinson (1980). The Parkinson estimator is based on the realized range that can be computed from daily high and low price. It has recently been shown to be relatively robust to microstructure noise, see Alizadeh et al. (2002). The Rogers and Satchell (1991) estimator is an enhancement of the Parkinson estimator that makes additional use of the opening and closing prices. Rogers and Satchell (1991) show that their estimator is unbiased for the volatility parameter of a Brownian motion plus drift, whereas the Parkinson estimator is biased in that case. Formally, the Rogers and Satchell volatility estimator can be computed as

$$V_{it_j} = (\ln P^H_{it_j} - \ln P^C_{it_j})(\ln P^H_{it_j} - \ln P^O_{it_j}) + (\ln P^L_{it_j} - \ln P^C_{it_j})(\ln P^L_{it_j} - \ln P^O_{it_j}), \quad (1)$$

where V_{it_j} denotes volatility of stock i on day j within week t, and P^O, P^C, P^H,P^L are daily opening, closing, high and low prices that are obtained from Datastream. Total volatility increased dramatically during the financial crisis in the latter half of 2008 (Figure 3). Figure 4 shows total volatility for the FTSE 100 index jointly with entry dates of new venues and latency upgrades at the LSE. Casual inspection suggests that total volatility declined when Turquoise and BATS entered the market. However, this conclusion would be premature because many other events took place at the same time, most importantly, the global financial crisis.

We also decompose total volatility into temporary and permanent volatility. Permanent volatility relates to the underlying uncertainty about the future pay-

[10]There is a vast econometric literature on volatility measurement and modelling that is summarized by Anderson et al. (2010).

off stream for the asset in question. If new information about future payoffs arrives and that is suddenly impacted in prices, the price series would appear to be volatile, but this is the type of volatility that reflects the true valuation purpose of the stock market. On the other hand, volatility that is unrelated to fundamental information and that is caused by the interactions of traders over- and under-reacting to perceived events is thought of as temporary volatility. [11]To decompose total volatility into a temporary and permanent component, we assume that permanent volatility can be approximated by a smooth time trend. For each stock, temporary volatility is defined as the residuals from the nonparametric regression of total volatility on (rescaled) time (this is effectively a moving average over 1 quarter with declining weights). This approach has been used previously by e.g. Engle and Rangel (2008). The evolution of temporary volatility is shown in the upper right panel of Figure 3.

Liquidity. Liquidity is a fundamental property of a well-functioning market, and lack of liquidity is generally at the heart of many financial crises and disasters. In practice, researchers and practitioners rely on a variety of measures to capture liquidity. High frequency measures include quoted bid-ask spreads (tightness), the number of orders resting on the order book (depth) and the price impact of trades (resilience). These order book measures may not provide a complete picture since trades may not take place at quoted prices, and so empirical work considers additional measures that take account of both the order book and the transaction record. These include the so-called effective spreads and quoted spreads, which are now widely accepted and used measures of actual liquidity. Another difficulty is that liquidity suppliers often post limit orders on multiple venues but cancel the additional liquidity after the trade is executed on one venue (van Kervel, 2012).

[11]A good example is the "hash crash" of April 24, 2013 when the Dow Jones index dropped by nearly 2% very rapidly due apparently to announcements emanating from credible twitter accounts (that had been hacked into) that there had been an explosion at the White House. It subsequently recovered all the losses when it became clear that no such explosion had occurred. See http://blueandgreentomorrow.com/2013/04/24/twitter-hoax-wipes-200bn-off-dow-jones-for-five-minutes/, accessed on June 20, 2013

Therefore, global depth measures that aggregate quotes across different venues may overstate liquidity. On the other hand, the presence of "iceberg orders" and dark pools suggest that there is substantial hidden liquidity.

Since we do not have access to order book data, our main measure of liquidity is the percentage bid-ask spread.[12]. The quoted bid ask spread for stock i on day t_j is defined as

$$BA_{it_j} = \frac{P^A_{it_j} - P^B_{it_j}}{\frac{1}{2}(P^A_{it_j} + P^B_{it_j})}, \tag{2}$$

where daily ask prices P^A and bid prices P^B are obtained from Datastream. P^A and P^B are measured by the last bid and ask prices before the market closes for London stock exchange at 16:35. The time series of weekly bid-ask spreads is reported in the bottom left panel of Figure 3. Inspection of Figure 4 seems to suggest that bid-ask spreads declined at the entry of Chi-X but this decline can also attributed to the introduction of Trade Elect 1 at the LSE one day before. Trade Elect 1 achieved a significant reduction of system latency at the LSE.

Volume. Volume of trading is a measure of participation, and is of concern to regulators (Foresight, 2012). The volume of trading has increased over the longer term, but the last decade has seen less sustained trend increases, which has generated concern amongst those whose business model depends on this. Some have also argued that computer based trading has led to much smaller holding times of stocks and higher turnover and that this would reflect a deepening of the intermediation chain rather than real benefits to investors.

We investigate both global volume and volume at the LSE. Global volume is defined as the number of shares traded at all venues and volume at the LSE is the number of shares traded at the LSE, scaled by the number of shares outstanding. The volume data is obtained from Fidessa. Towards the end of the sample period, global and LSE volume diverge, as alternative venues gain market share (Figures 3

[12] Mizen (2010) documents that trends in quoted bid-ask spreads are similar to trends in effective bid-ask spreads.

and 4).

4 Econometric Methodology

Figure 3 shows the time series of market quality measures for the FTSE 100 and FTSE 250 index. All measures clearly show the effect of the global financial crisis that was associated with an increase in total volatility, temporary volatility and bid-ask spreads as well as a fall in traded volumes in the early part of the sample that was followed by reversals (except for volume). As we saw in Figure 1, average fragmentation levels increased for most of the sample. If there were a simple linear relationship between fragmentation and market quality then we would have extrapolated continually deteriorating market quality levels until almost the end of the sample. We next turn to the econometric methods that we will use to exploit the cross-sectional and time series variation in fragmentation and market quality to measure the relationship more reliably.

We extend the CCE estimator of Pesaran (2006) in three ways. First, we allow for some nonlinearity, allowing fragmentation to affect the response variable in a quadratic fashion. This functional form was also adopted in the De Jong et al. (2011) study. Second, we use quantile regression methods based on conditional quantile restrictions rather than the conditional mean restrictions adopted previously.[13] This method is valid under weaker moment conditions and is robust to outliers. Third, we also model the conditional variance of market quality using the same type of regression model; we apply the median regression method for estimation based on the squared residuals from the median specification or on the conditional interquartile range. This allows us to look at not just the average effect of fragmentation on market quality but also at the variability of that effect.

[13] We provide a justification of this method in the online appendix.

4.1 A model for heterogeneous panel data with common factors

We observe a sample of panel data $\{(Y_{it}, X_{it}, Z_{it}, d_t) : i = 1, \ldots, n,\ t = 1, \ldots, T\}$, where i denotes the i-th stock and t is the time point of observation. In our data, Y_{it} denotes market quality and X_{it} is a measure of fragmentation, while Z_{it} is a vector of firm specific control variables such as market capitalization and d_t are observable common factors as for example VIX or the lagged index return. We assume that the data come from the model

$$Y_{it} = \alpha_i + \beta_{1i} X_{it} + \beta_{2i} X_{it}^2 + \beta_{3i}^{\intercal} Z_{it} + \delta_i^{\intercal} d_t + \kappa_i^{\intercal} f_t + \varepsilon_{it}, \tag{3}$$

where $f_t \in \mathbb{R}^k$ denotes the unobserved common factor or factors. We allow for a non-linear effect of the fragmentation variable on the outcome variable by including the quadratic term. We assume that the regression error term satisfies the conditional median restrictions

$$\mathrm{med}(\varepsilon_{it} | X_{it}, Z_{it}, d_t, f_t) = 0 \tag{4}$$

but is allowed to be serially correlated or weakly cross-sectionally correlated. The regressors $W_{it} = (X_{it}, Z_{it}^{\intercal})^{\intercal}$ are assumed to have the factor structure

$$W_{it} = a_i + D_i d_t + K_i f_t + u_{it}, \tag{5}$$

where D_i and K_i are matrices of factor loadings. The error term u_{it} is assumed to satisfy $E u_{it} = 0$ for all t, but is also allowed to be serially correlated or weakly cross-sectionally correlated, see Assumptions 1-2 in Pesaran (2006). The econometric model (3)-(5) also allows for certain types of "endogeneity" between the covariates and the outcome variable represented by the unobserved factors f_t.[14] The model is

[14] However, the CCE method cannot address simultaneity of Y and X at the individual level due to time varying but firm-specific determinants.

very general and contains many homogenous and heterogeneous panel data models as a special case.

We adopt the random coefficient specification for the individual parameters, that is, $\beta_i = (\beta_{1i}, \beta_{2i}, \beta_{3i}^\intercal)^\intercal$ are i.i.d. across i and

$$\beta_i = \beta + v_i, \quad v_i \sim IID(0, \Sigma_v), \tag{6}$$

where the individual deviations v_i are distributed independently of $\epsilon_{jt}, X_{jt}, Z_{jt}$ and d_t for all i, j, t.

To estimate the model (3)-(5), we extend Pesaran's (2006) CCE mean group estimator to quantile regression. Taking cross-sectional averages of (5), we obtain (under the assumption that u_{it} has weak cross-sectional dependence and some finite higher order moments)

$$\overline{W}_t = \bar{a} + \overline{D} d_t + \overline{K} f_t + O_p(n^{-1/2}). \tag{7}$$

Equation (7) suggests that we can approximate the unknown factor f_t with a linear combination of d_t and the cross-sectional average of X_{it}.[15] In contrast to Pesaran (2006), our version of the CCE estimator does not include the cross-sectional average of Y. One reason for this is that because of the quadratic functional form, $\overline{Y}_t$ would be a quadratic function of f_t, and so would introduce a bias. Instead, we add the Chicago Board Options Exchange Market Volatility Index (VIX) to the specification. Because of the high correlation between VIX and cross-sectional averages of market quality, we expect that VIX is a good and predetermined proxy for cross-sectional averages of market quality in our regressions.

The effect of fragmentation on market quality can be obtained by performing (for each i) a time series quantile regression estimation of (3) replacing f_t by $\overline{W}_t$.

[15] If f_t is a vector, i.e., there are multiple factors, then we must form multiple averages (portfolios). Instead of the equally weighted average in (7), we can also use an average that is e.g. weighted by market capitalization.

Specifically, let $\widehat{\theta}_i$ minimize the objective functions

$$\widehat{Q}_{i\tau T}(\theta) = \sum_{t=1}^{T} \rho_\alpha(Y_{it} - \pi - \beta_1 X_{it} - \beta_2 X_{it}^2 - \beta_3^\intercal Z_{it} - \gamma^\intercal d_t - \xi^\intercal \overline{W}_t) \tag{8}$$

with respect to θ, where $\theta = (\pi, \beta_1, \beta_2, \beta_3^\intercal, \gamma^\intercal, \xi^\intercal)$ and $\rho_\tau(x) = x(\tau - 1(x < 0))$, see Koenker (2005). Then $\widehat{\beta}_i$ are the estimators of the corresponding parameters of interest.

At any quantile, the quantile mean group estimator (QCCE) $\widehat{\beta} = n^{-1}\sum_{i=1}^n \widehat{\beta}_i$ is defined as the cross-sectional average of the individual quantile estimates $\widehat{\beta}_i = (\widehat{\beta}_{1i}, \widehat{\beta}_{2i}, \widehat{\beta}_{3i}^\intercal)^\intercal$. This measures the average effect. Some idea of the heterogeneity can be obtained by looking at the standard deviations of the individual effects. Following similar arguments as in Pesaran (2006), (as $n \to \infty$) it follows that

$$\sqrt{n}(\widehat{\beta} - \beta) \Longrightarrow N(0, \Sigma), \tag{9}$$

where the covariance matrix Σ can be estimated by

$$\widehat{\Sigma} = \frac{1}{n-1}\sum_{i=1}^{n}(\widehat{\beta}_i - \widehat{\beta})(\widehat{\beta}_i - \widehat{\beta})^\intercal. \tag{10}$$

The regression model above concentrates on the average effect, or the effect in "normal times". We are also interested in the effect of fragmentation on the variability of market quality. We can address this issue by investigating the conditional variance of market quality. We adopt a symmetrical specification whereby

$$\mathrm{var}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) = a_i + b_{1i}X_{it} + b_{2i}X_{it}^2 + b_{3i}^\intercal Z_{it} + w_i^\intercal d_t + q_i^\intercal f_t, \tag{11}$$

where the parameters $b_i = (b_{1i}, b_{2i}, b_{3i}^\intercal)^\intercal$ have a random coefficient specification like (6). We estimate this by median regression of the squared residuals $\widehat{\epsilon}_{it}^2$ from (3)-(5) on $X_{it}, X_{it}^2, Z_{it}, d_t, \overline{W}_t$. We argue in the online appendix that, under suitable regularity conditions, (9) holds in this case with a covariance matrix Σ (corresponding to the covariance matrix of the parameters of the variance equation).

As an alternative specification for the variability of market quality, we assume that the conditional interquartile range of market quality satisfies

$$q_{0.75}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) - q_{0.25}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) = a_i + b_{1i}X_{it} + b_{2i}X_{it}^2 + b_{3i}^\intercal Z_{it} + w_i^\intercal d_t + q_i^\intercal f_t, \tag{12}$$

where $q_\tau(Y_{it}|X_{it}, Z_{it}, d_t, f_t)$ denotes the conditional τ quantile. (12) is estimated by median regression of the conditional interquartile range on $X_{it}, X_{it}^2, Z_{it}, d_t, \overline{W}_t$.

4.2 Parameter of Interest

We are interested in measuring the market quality at different levels of competition, holding everything else constant. In particular, we would like to compare monopoly with perfect competition. In our data, the maximum number of trading venues is 24 and were trading to be equally allocated to these venues, we might achieve (fragmentation) $X = 0.96$. In fact, the maximum level reached by X is some way below that.

The parameter of interest in our study is the difference of average market quality between a high (H) and low (L) degree of fragmentation or dark trading normalized by $H - L$. We therefore obtain the measure

$$\Delta_X = \frac{E_{X=H}Y - E_{X=L}Y}{H - L} = \beta_1 + \beta_2(H + L), \tag{13}$$

where the coefficients are estimated by the QCCE method. For comparison, we also report the marginal effect $\beta_1 + 2\overline{X}\beta_2$. We estimate these parameters from the conditional variance specifications, too, in which case it is to be interpreted as measuring differences in variability between the two market structures. Standard errors can be obtained from the joint asymptotic distribution of the parameter estimates given above.[16]

5 Results

Before reporting our regression results, we investigate a few characteristics of our dataset in more detail. [17]The particular characteristics we are interested in are cross-sectional dependence and unit roots. The median value of the cross-sectional correlation for different measures of market quality ranges from 0.21 to 0.57 which points to unobserved shocks that are common to many firms. The econometric model we use can control for these common shocks.

We also investigated stationarity of the key variables as this can impact statistical performance, although with our large cross-section, we are less concerned about this.[18] The results from augmented Dickey Fuller tests indicate little support for a unit root in fragmentation or market quality. The average value of fragmentation does trend over the period of our study but it has levelled off towards the end and the type of nonstationarity present is not well represented by a global stochastic trend.[19]

5.1 The effect of total fragmentation, visible fragmentation and dark trading on the level of market quality

Table 1 reports QCCE mean group coefficients together with our parameter of interest Δ_{Frag}. Δ_{Frag} is defined as the difference in market quality between a low and high level of fragmentation evaluated at the minimum and maximum level of frag-

[16]An alternative way of comparing the outcomes under monopoly and competition is to compare the marginal distributions of market quality by means of stochastic dominance tests. We report these results in the online appendix.

[17]For our empirical analysis, we eliminate all firms with less than 30 observations and all firms where the fraction of observations with zero fragmentation exceeds 1/4. That leaves us with 341 firms for overall fragmentation and 263 firms for visible fragmentation.

[18]Formally, Kapetanios et al. (2007) have shown that the CCE estimator remains consistent if the unobserved common factors follow unit root processes.

[19]The test results are available upon request.

mentation (equation (13)). For comparison, we also report marginal effects, which tend to agree with Δ_{Frag} in most specifications. As observable common factors, we include VIX, the lagged index return, and a dummy variable that captures the decline in trading activity around Christmas and New Year.[20]

Inspecting Δ_{Frag}, we find that a fragmented market is associated with higher global volume but lower volume at the LSE when compared to a monopoly. These effects are uniform across different quartiles (Table 1b)). The increase in global volume in a fragmented market place is consistent with the theoretical prediction in Biais et al. (2000).

We also find that temporary volatility is lower in a competitive market which is in contrast with what O'Hara and Ye (2011) document using US data for 2008. O'Hara and Ye (2011) also find that fragmentation reduces bid-ask spreads while there is no significant effect in our sample. But O'Hara and Ye (2011) measure market quality globally (using the NMS consolidated order book and trade price), while our measures are local with the exception of global volume.

It is also interesting to split overall fragmentation into visible fragmentation and dark trading where we define dark trading as the sum of volume traded at regulated dark pools, OTC venues and SI (Table 2). When measured by $\Delta_{Vis.frag.}$, we find that visible fragmentation reduces temporary volatility and lowers trading volume. These effects are larger in absolute value in the third quartile of the conditional distribution (Table 2b)).

In addition, a market with a high degree of visible fragmentation has larger bid-ask spreads at the LSE when compared to a monopoly, albeit that result is only statistically significant at 10%. De Jong et al. (2011) also find that visible fragmentation has a negative effect on liquidity at the traditional exchange. The finding that visible fragmentation may harm local liquidity is also supported by survey evidence.

[20] The coefficients on the observed common factors and on the cross-sectional averages do not have a structural interpretation because they are a combination of structural coefficients, cf. Section 4.1.

According to Foresight (2012, SR1), institutional buy-side investors believe that it is becoming increasingly difficult to access liquidity and that this is partly due to: its fragmentation on different trading venues, the growth of “dark” liquidity, and to the activities of HFT. To mitigate these adverse effects on liquidity, investors could employ SORT that create a virtually integrated market place. However, the survey reports buy-side concerns that these solutions are too expensive for many investors. In contrast, Gresse (2011) finds that visible fragmentation improves local liquidity.

Turning to dark trading, our results suggest that dark trading reduces volatility in particular for firms in the first and second quartile of the conditional volatility distribution (Table 2). Dark trading also increases volume while it does not have a significant effect on bid-ask spreads. In comparison, Gresse (2011) also does not find a significant effect of dark trading on liquidity while De Jong et al. (2011) find that dark trading has a detrimental effect on liquidity.

5.2 Turning points

In addition to investigating the difference between perfect competition and a monopolistic market, it is also interesting to assess the transition between these extremes. Figure 5 illustrates the estimated relationship between market quality on the one hand and overall fragmentation, visible fragmentation and dark trading on the other. We find that the transition between monopoly and competition is non-monotonic for overall and visible fragmentation and takes the form of an inverted U shape. The maximum occurs at a level of visible fragmentation of about 0.2, 0.3 and 0.5 for global volume, total volatility and bid-ask spreads, respectively. That is, at low levels of fragmentation, fragmentation of order flow improves market quality but there is a turning point after which fragmentation leads to deteriorating market quality. For temporary volatility and LSE volume, there is no interior optimum on $[0, 1]$.

SEC (2013) has hypothesized that the turning point may depend on the market capitalization of a stock. For each individual stock, Figure 6 plots the interior maximum against the time series average of market capitalization.[21] We find that there is positive but weak relationship between the maximal level of fragmentation and market capitalization that is statistically significant with the exception of temporary volatility.

5.3 The effect of total fragmentation, visible fragmentation and dark trading on the variability of market quality

In this section, we investigate whether overall fragmentation, visible fragmentation and dark trading have led to an increase in the variability of market quality. For example, Madhavan (2012) finds that higher fragmentation prior to the Flash Crash is associated with larger drawdowns during the Flash Crash. In addition, fragmented equity markets have been a seedbed for HFT that are not obliged to provide liquidity in times of market turmoil. This development can lead to "periodic illiquidity" as for example, during the Flash Crash (Foresight, 2012).

We find that at the median, $\Delta_{Frag.}$ is not statistically significant but there is variation across quartiles (Table 3): The variability of volatility is lower in a fragmented market for firms in the third quartile of the conditional distribution. Fragmentation increases the variability of bid ask spreads at the first quartile of the distribution but this result is only marginally significant. There is also a decline in the variability of LSE volume for firms in both the first and third quartile.

Table 4 distinguishes between visible fragmentation and dark trading. The effect of visible fragmentation on the variability of volatility are similar to those of overall fragmentation. But in contrast to overall fragmentation, visible fragmentation increases the variability of LSE volume in the first quartile. Dark trading increases the variability of volatility in particular at the third quartile of the conditional distribution. Also, there is more variability of volumes when dark trading increases in the first quartile. That effect is insignificant or even negative at other quartiles.

[21] We restrict attention to interior maxima within $[0, 1]$.

Table 5 reports the results when the variability of market quality is measured by the conditional inter-quartile range of volatility (equation (12)) instead of the squared residuals. Overall, the results are similar: Visible fragmentation reduces the variability of volatility, while dark trading has the opposite effects. Also, dark trading increases the variability of LSE volume.

But there are also some differences between these alternative variability measures. The positive effect of overall and visible fragmentation on the variability in bid-ask spreads is more significant for the inter-quartile range measure of variability when compared to the residual measure. In contrast to the latter, visible fragmentation has no significant effect on the variability of LSE volume.

5.4 Robustness

In the online appendix, we assess the robustness of our results to: (i) alternative market quality measures, (ii) splitting our sample into FTSE 100 and FTSE 250 firms and (iii) different estimation methods. Our finding that visible fragmentation and dark trading have a negative effect on total and temporary volatility is robust to using alternative measures of volatility such as Parkinson or within-day volatility. If we measure market quality by the Amihud (2002) illiquidity measure, we find that a higher degree of overall or visible fragmentation is associated with less liquid markets. Dark trading is found to improve liquidity. For efficiency, we cannot find significant effects.

When comparing the effect of market fragmentation on market quality for FTSE 100 and FTSE 250 firms, interesting differences emerge: The negative effect of dark trading on volatility is only observed for FTSE 250 firms. That effect is even positive for FTSE 100 firms. But in contrast with FTSE 250 firms, visible fragmentation is associated with lower volatility for FTSE 100 firms.

Finally, we re-estimate our results using a heterogeneous panel data model without common factors. This model can be obtained as a special case of model (3)-(5)

where f_t is a vector of ones and there are no observed common factors d_t. A version of this model with homogenous coefficients has been used in related work by Gresse (2011), among others. However, that model cannot account for unobserved, common shocks in the data and gives inconsistent results in the presence of common shocks that are correlated with the regressors (Pesaran, 2006). We report in the online appendix that omitting observed and unobserved common factors leads to results that differ in magnitude and statistical significance with the exception of LSE volume. However, the large increase in our measure of cross-sectional dependence (CSD) indicates that this model is misspecified because unobserved common shocks such as changes in trading technology or HFT are omitted that are likely to affect both market quality and fragmentation.

6 Conclusions

After the introduction of MiFID in 2007, the equity market structure in Europe underwent a fundamental change as newly established venues such as Chi-X started to compete with traditional exchanges for order flow. This change in market structure has been a seedbed for HFT, which has benefited from the competition between venues through the types of orders permitted, smaller tick sizes, latency and other system improvements, as well as lower fees and, in particular, the so-called maker-taker rebates.

Against these diverse and complex developments, identifying the effect of fragmentation on market quality is difficult. To achieve this, we use a version of Pesaran's (2006) common correlated effects (CCE) estimator that can account for unobserved factors such as the global financial crisis or HFT. Compared to Pesaran (2006), our QCCE mean group estimator is based on individual quantile regressions that enable us to characterize the whole conditional distribution of the dependent variable rather than just its conditional mean. This estimator is suitable for heterogeneous panel data that are subject to both common shocks and outliers in the dependent variable.

We applied our estimator to a novel dataset that contains weekly measures of market quality and fragmentation for the individual FTSE 100 and 250 firms. We decompose the effect of overall fragmentation into visible fragmentation and dark trading, and assess their effects on both the level and the variability of market quality.

We find that trading volume is higher if visible order books are less fragmented or if there is more dark trading. Also, fragmentation and dark trading lower volatility at the LSE. But dark trading increases the variability of volatility, while fragmentation has the opposite effect in particular at the upper quantiles of the conditional distribution which gives rise to some concern.

Table 1: The effect of fragmentation on market quality

a) Median regression

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-7.745	-10.511	4.468	1.713	2.365
	(-9.97)	(-17.162)	(5.803)	(2.552)	(3.497)
Fragmentation	0.45	-0.856	0.195	0.064	0.413
	(0.805)	(-1.906)	(0.726)	(0.22)	(1.338)
Fragmentation sq.	-0.719	0.618	-0.217	0.122	-1.662
	(-1.619)	(1.694)	(-0.933)	(0.426)	(-5.752)
Market cap.	-0.475	-0.27	-0.343	-0.214	-0.236
	(-6.372)	(-5.767)	(-4.951)	(-3.172)	(-3.492)
Lagged index return	0.11	1.074	-0.909	0.031	-0.056
	(0.862)	(11.037)	(-9.697)	(0.318)	(-0.543)
VIX	1.126	0.785	0.016	0.231	0.245
	(36.039)	(32.817)	(0.642)	(9.586)	(9.366)
Christmas and New Year	-0.237	-0.21	0.38	-1.212	-1.21
	(-10.867)	(-11.255)	(21.269)	(-50.056)	(-49.658)
Fragmentation (avg.)	-1.885	0.359	-0.533	0.131	-0.126
	(-8.142)	(2.068)	(-3.693)	(0.569)	(-0.556)
Market cap. (avg.)	-0.008	0.199	-0.089	0.307	0.322
	(-0.091)	(3.108)	(-1.175)	(5.62)	(5.36)
Marginal effect	-0.367	-0.154	-0.051	0.202	-1.475
	(-3.432)	(-1.823)	(-0.782)	(2.408)	(-18.03)
$\Delta_{Frag.}(0.5)$	-0.15	-0.341	0.014	0.166	-0.973
	(-0.735)	(-2.139)	(0.154)	(1.918)	(-10.108)
Adjusted R^2	0.732	0.111	0.775	0.78	0.758
CSD	0.033	0.025	0.011	0.035	0.038

b) Difference between monopoly and competition at $\tau \in \{0.25, 0.75\}$

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Frag.}(0.25)$	-0.219	-0.356	-0.067	0.14	-0.944
	(-1.208)	(-2.255)	(-0.818)	(1.677)	(-8.988)
$\Delta_{Frag.}(0.75)$	-0.23	-0.406	0.128	0.137	-0.986
	(-0.982)	(-2.501)	(0.876)	(1.264)	(-8.161)

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of temporary volatility. Market capitalization, index return and VIX are in logs too. $\Delta_{Frag.}(\tau)$ is defined as $\widehat{\beta}_1(\tau) + \widehat{\beta}_2(\tau)(H + L)$ and evaluated at $H = \max(Frag.) = 0.834$ and $L = \min(Frag.) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors. CSD is the mean of the squared value of the off-diagonal elements in the cross-sectional dependence matrix.

Table 2: The effects of visible fragmentation and dark trading on market quality

a) Median regression

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-8.475	-11.295	1.28	1.189	2.333
	(-10.602)	(-18.629)	(1.615)	(1.89)	(2.988)
Vis. fragmentation	0.817	-0.564	0.436	0.158	-0.151
	(2.663)	(-2.171)	(2.085)	(0.759)	(-0.682)
Vis. fragmentation sq.	-1.429	0.317	-0.425	-0.451	-1.199
	(-3.937)	(1.019)	(-1.536)	(-1.728)	(-4.323)
Dark	-0.212	0.388	-0.212	0.332	0.232
	(-0.946)	(1.951)	(-1.068)	(1.673)	(1.11)
Dark sq.	0.041	-0.704	0.177	1.724	0.986
	(0.178)	(-3.47)	(0.897)	(9.605)	(4.867)
Market cap.	-0.399	-0.288	-0.32	-0.243	-0.293
	(-5.328)	(-5.364)	(-4.851)	(-4.29)	(-4.595)
Lagged index return	0.298	1.195	-0.65	0.307	0.231
	(2.469)	(12.958)	(-7.308)	(3.465)	(2.317)
VIX	1.082	0.823	0.083	0.276	0.228
	(31.337)	(30.732)	(3.061)	(11.248)	(8.433)
Christmas and New Year	-0.345	-0.241	0.426	-1.273	-1.289
	(-14.356)	(-11.828)	(19.393)	(-52.092)	(-49.603)
Vis. fragmentation (avg.)	-1.151	0.005	-1.179	-0.661	-0.479
	(-5.873)	(0.035)	(-8.686)	(-4.338)	(-2.944)
Dark (avg.)	-1.159	0.233	0.606	-1.531	-1.815
	(-7.44)	(1.944)	(4.05)	(-12.27)	(-13.94)
Market cap. (avg.)	-0.175	0.163	-0.005	0.14	0.129
	(-1.56)	(2.05)	(-0.055)	(2.182)	(2.264)
Marg. effect (vis. frag)	-0.288	-0.318	0.108	-0.191	-1.078
	(-2.511)	(-3.405)	(1.394)	(-2.233)	(-13.056)
Marg. effect (dark)	-0.175	-0.246	-0.052	1.886	1.121
	(-2.628)	(-4.311)	(-1)	(29.009)	(18.205)
$\Delta_{Vis.frag.}(0.5)$	-0.181	-0.342	0.139	-0.157	-0.988
	(-1.523)	(-3.537)	(1.86)	(-1.85)	(-11.891)
$\Delta_{Dark}(0.5)$	-0.171	-0.315	-0.035	2.055	1.217
	(-2.518)	(-5.446)	(-0.689)	(34.419)	(20.626)
Adjusted R^2	0.75	0.131	0.754	0.852	0.799
CSD	0.03	0.026	0.01	0.05	0.04

b) Difference between monopoly and competition at $\tau \in \{0.25, 0.75\}$

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Vis.frag.}(0.25)$	0.01	-0.263	0.081	-0.034	-0.917
	(0.09)	(-2.879)	(0.959)	(-0.41)	(-11.698)
$\Delta_{Vis.frag.}(0.75)$	-0.487	-0.61	0.112	-0.22	-1.094
	(-3.483)	(-5.432)	(1.309)	(-2.036)	(-10.128)
$\Delta_{Dark}(0.25)$	-0.286	-0.463	-0.004	2.022	0.986
	(-3.735)	(-6.63)	(-0.07)	(32.67)	(16.361)
$\Delta_{Dark}(0.75)$	-0.005	-0.064	0.048	2.072	1.374
	(-0.061)	(-0.935)	(0.785)	(29.979)	(19.166)

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of temporary volatility. Market capitalization, index return and VIX are in logs too. $\Delta_X(\tau)$ is defined as $\widehat{\beta}_1(\tau) + \widehat{\beta}_2(\tau)(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.695, \min(Vis.frag) = 0, \max(Dark) = 0.381, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors. CSD is the mean of the squared value of the off-diagonal elements in the cross-sectional dependence matrix.

Table 3: The effect of fragmentation on the variability of market quality

a) Median regression

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.536	-0.198	0.28	0.275	0.498
	(-1.893)	(-0.686)	(1.429)	(1.15)	(2.662)
Fragmentation	-0.029	-0.064	-0.037	-0.215	-0.128
	(-0.256)	(-0.603)	(-0.463)	(-1.716)	(-1.522)
Fragmentation sq.	0.06	0.071	0.041	0.189	0.115
	(0.565)	(0.762)	(0.548)	(1.73)	(1.455)
Market cap.	-0.01	-0.02	-0.009	-0.035	-0.034
	(-0.477)	(-1.099)	(-0.482)	(-2.302)	(-2.312)
Lagged index return	0.039	0.071	0.014	0.024	-0.019
	(1.021)	(1.747)	(0.542)	(0.809)	(-0.677)
VIX	0.033	0.002	0.002	-0.007	-0.014
	(2.709)	(0.192)	(0.229)	(-0.616)	(-1.447)
Christmas and New Year	0.06	0.058	0.095	0.104	0.088
	(3.931)	(5.023)	(4.186)	(6.128)	(5.756)
Fragmentation (avg.)	-0.097	-0.097	0.049	-0.022	-0.04
	(-1.602)	(-1.523)	(0.95)	(-0.243)	(-0.505)
Market cap. (avg.)	0.048	-0.009	-0.029	-0.006	0.013
	(2.137)	(-0.468)	(-1.62)	(-0.34)	(0.705)
Marginal effect	0.039	0.017	0.01	0	0.003
	(1.287)	(0.639)	(0.45)	(-0.001)	(0.139)
$\Delta_{Frag.}(0.5)$	0.021	-0.005	-0.002	-0.057	-0.032
	(0.581)	(-0.128)	(-0.096)	(-1.488)	(-1.178)
Adjusted R^2	-0.013	-0.014	-0.041	0.056	0.064
CSD	0.015	0.011	0.01	0.016	0.016

b) Difference between monopoly and competition at $\tau \in \{0.25, 0.75\}$

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Frag.}(0.25)$	0.028	0.021	0.03	0.011	-0.03
	(1.464)	(1.429)	(1.861)	(0.737)	(-1.847)
$\Delta_{Frag.}(0.75)$	-0.604	-0.347	-0.014	-0.194	-0.24
	(-2.28)	(-1.921)	(-0.161)	(-1.17)	(-1.82)

Notes: Dependent variables are squared median regression residuals. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. $\Delta_{Frag.}(\tau)$ is defined as $\widehat{\beta}_1(\tau) + \widehat{\beta}_2(\tau)(H + L)$ and evaluated at $H = \max(Frag.) = 0.834$ and $L = \min(Frag.) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors. CSD is the mean of the squared value of the off-diagonal elements in the cross-sectional dependence matrix.

Table 4: The effect of visible fragmentation and dark trading on the variability of market quality

a) Median regression

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.708	-0.034	0.208	-0.145	0.054
	(-2.005)	(-0.111)	(0.917)	(-0.972)	(0.287)
Vis. fragmentation	-0.237	-0.301	0.006	0.017	-0.033
	(-1.745)	(-1.545)	(0.089)	(0.314)	(-0.37)
Vis. fragmentation sq.	0.261	0.326	0.016	0	0.094
	(1.546)	(1.453)	(0.17)	(-0.005)	(0.777)
Dark	0.014	-0.044	-0.073	-0.157	-0.185
	(0.134)	(-0.471)	(-1.13)	(-1.931)	(-2.551)
Dark sq.	0.084	0.1	0.072	0.133	0.197
	(0.885)	(1.112)	(1.106)	(2.267)	(3.262)
Market cap.	0.02	0.007	0.004	-0.037	-0.021
	(1.065)	(0.334)	(0.197)	(-2.752)	(-1.378)
Lagged index return	0.015	-0.014	0.019	0.042	0.029
	(0.35)	(-0.361)	(0.69)	(1.938)	(1.087)
VIX	0.043	0.009	-0.006	-0.004	-0.016
	(3.063)	(0.644)	(-0.541)	(-0.753)	(-2.465)
Christmas and New Year	0.038	0.024	0.031	0.03	0.036
	(3.304)	(2.429)	(3.801)	(4.537)	(4.094)
Vis. fragmentation (avg.)	0.133	0.144	0.045	-0.02	0.062
	(1.787)	(1.864)	(0.882)	(-0.579)	(1.763)
Dark (avg.)	-0.028	-0.073	0.061	-0.018	-0.04
	(-0.443)	(-1.111)	(1.525)	(-0.576)	(-1.126)
Market cap. (avg.)	0.048	0.024	-0.034	0.024	0.002
	(1.647)	(1.111)	(-1.954)	(1.646)	(0.145)
Marg. effect (Vis. frag)	-0.035	-0.049	0.018	0.017	0.039
	(-0.917)	(-0.928)	(0.661)	(1.136)	(1.633)
Marg. effect (Dark)	0.09	0.046	-0.008	-0.037	-0.007
	(2.945)	(1.846)	(-0.453)	(-1.138)	(-0.296)
$\Delta_{Vis.frag.}(0.5)$	-0.055	-0.073	0.017	0.017	0.032
	(-1.359)	(-1.231)	(0.636)	(1.213)	(1.403)
$\Delta_{Dark}(0.5)$	0.098	0.055	-0.001	-0.024	0.012
	(3.554)	(2.49)	(-0.064)	(-0.853)	(0.619)
Adjusted R^2	-0.011	-0.02	-0.028	0.03	0.021
CSD	0.013	0.011	0.01	0.022	0.018

b) Difference between monopoly and competition at $\tau \in \{0.25, 0.75\}$

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Vis.frag.}(0.25)$	0.052	-0.007	0.007	0.009	0.019
	(1.701)	(-0.224)	(0.387)	(1.273)	(2.095)
$\Delta_{Vis.frag.}(0.75)$	-0.614	-0.244	0.201	-0.169	-0.162
	(-3.145)	(-1.955)	(1.566)	(-1.324)	(-1.228)
$\Delta_{Dark}(0.25)$	0.03	0.022	0.011	0.013	0.024
	(1.771)	(1.853)	(1.211)	(1.966)	(2.599)
$\Delta_{Dark}(0.75)$	0.19	0.223	0.028	-0.07	-0.046
	(2.054)	(2.66)	(0.387)	(-1.667)	(-0.687)

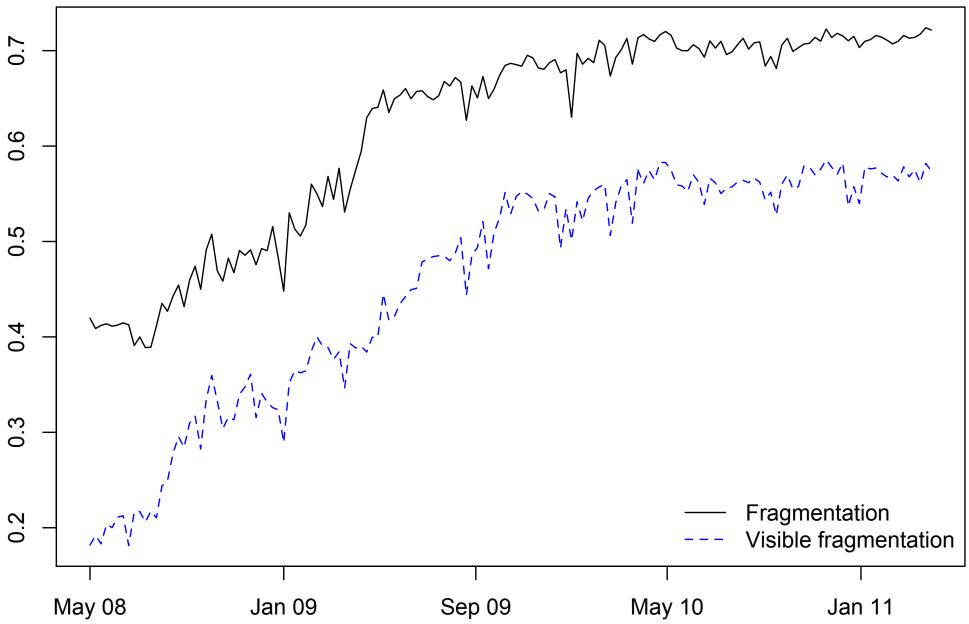
Notes: Dependent variables are squared median regression residuals. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. $\Delta_X^T(\tau)$ is defined as $\widehat{\beta}_1(\tau) + \widehat{\beta}_2(\tau)(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.695, \min(Vis.frag) = 0, \max(Dark) = 0.381, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors. CSD is the mean of the squared value of the off-diagonal elements in the cross-sectional dependence matrix.

Table 5: The effects of overall fragmentation, visible fragmentation and dark trading on the variability of market quality measured by the conditional interquartile range of market quality

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Frag.}(0.25)$	-0.021	0.021	0.214	-0.001	-0.038
	(-0.235)	(0.326)	(2.31)	(-0.021)	(-0.418)
$\Delta_{Frag.}(0.5)$	-0.084	-0.022	0.195	-0.022	-0.096
	(-0.933)	(-0.347)	(2.111)	(-0.334)	(-1.07)
$\Delta_{Frag.}(0.75)$	-0.09	-0.041	0.179	-0.058	-0.106
	(-0.975)	(-0.627)	(1.923)	(-0.873)	(-1.154)
$\Delta_{Vis.frag.}(0.25)$	-0.253	-0.162	0.084	0.004	0.001
	(-1.67)	(-1.931)	(1.257)	(0.047)	(0.008)
$\Delta_{Vis.frag.}(0.5)$	-0.23	-0.169	0.116	0.007	0.005
	(-1.524)	(-2.033)	(1.726)	(0.074)	(0.063)
$\Delta_{Vis.frag.}(0.75)$	-0.228	-0.158	0.148	0.01	0.015
	(-1.501)	(-1.881)	(2.14)	(0.109)	(0.178)
$\Delta_{Dark}(0.25)$	0.133	0.099	0.053	-0.016	0.07
	(3.13)	(2.489)	(1.257)	(-0.587)	(2.657)
$\Delta_{Dark}(0.5)$	0.14	0.152	0.053	0.003	0.087
	(3.292)	(3.911)	(1.273)	(0.12)	(3.21)
$\Delta_{Dark}(0.75)$	0.13	0.149	0.056	0.001	0.085
	(3.054)	(3.701)	(1.309)	(0.042)	(3.089)

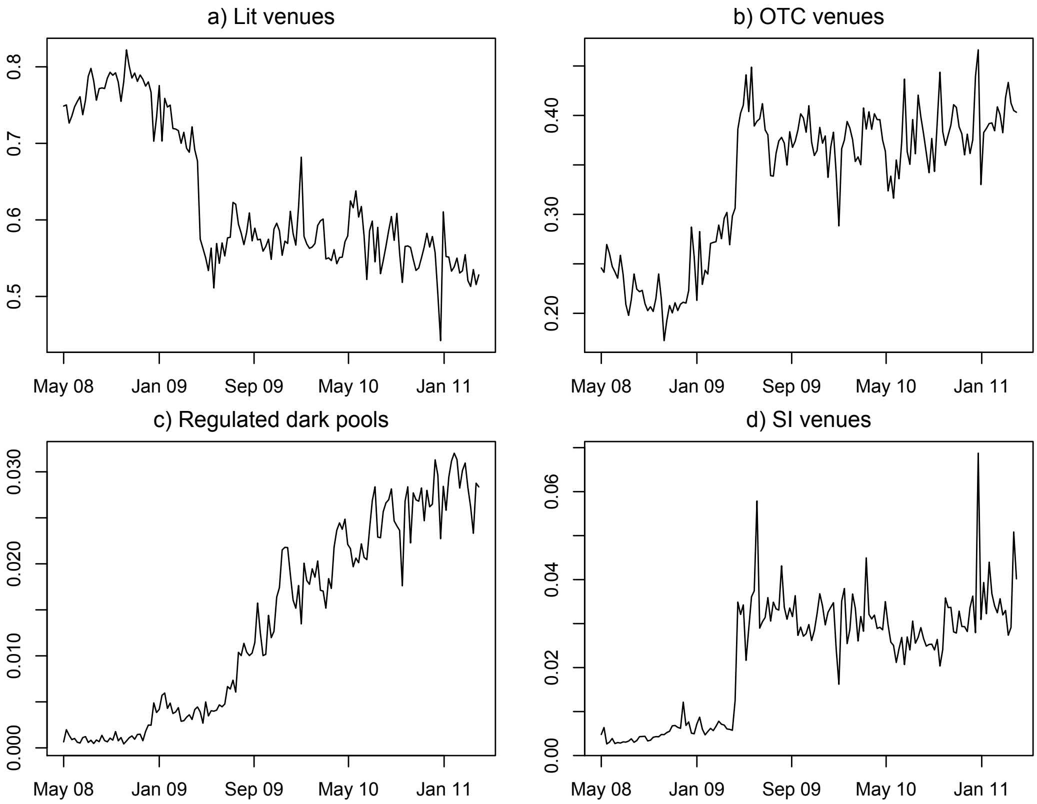
Notes: Dependent variables are the conditional interquartile range of market quality. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. $\Delta_X^T(\tau)$ is defined as $\widehat{\beta}_1(\tau)+\widehat{\beta}_2(\tau)(H+L)$ and evaluated at $H=\max(X)$ and $L=\min(X)$, for $X=\{Frag, Vis.frag, Dark\}$.

Figure 1: Fragmentation and visible fragmentation



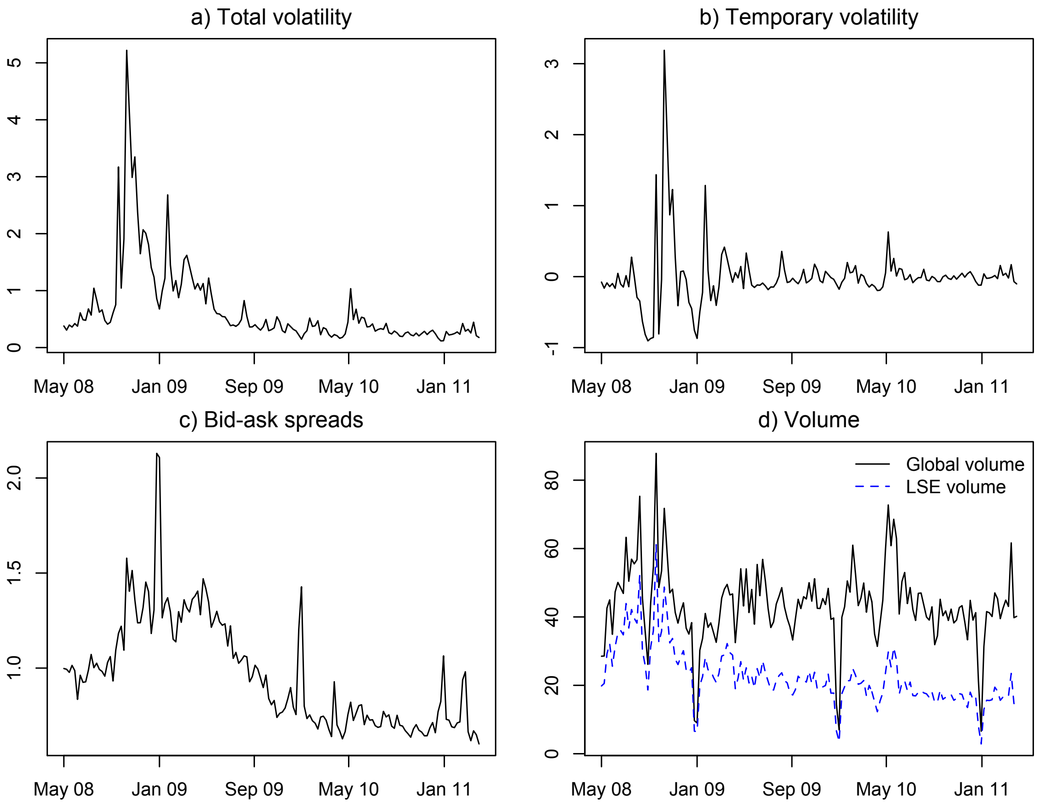
Notes: Fragmentation is defined as 1-Herfindahl index and visible fragmentation as 1-visible Herfindahl index. The time series are calculated as averages of the individual series weighted by market capitalization.

Figure 2: Share of volume traded by venue category



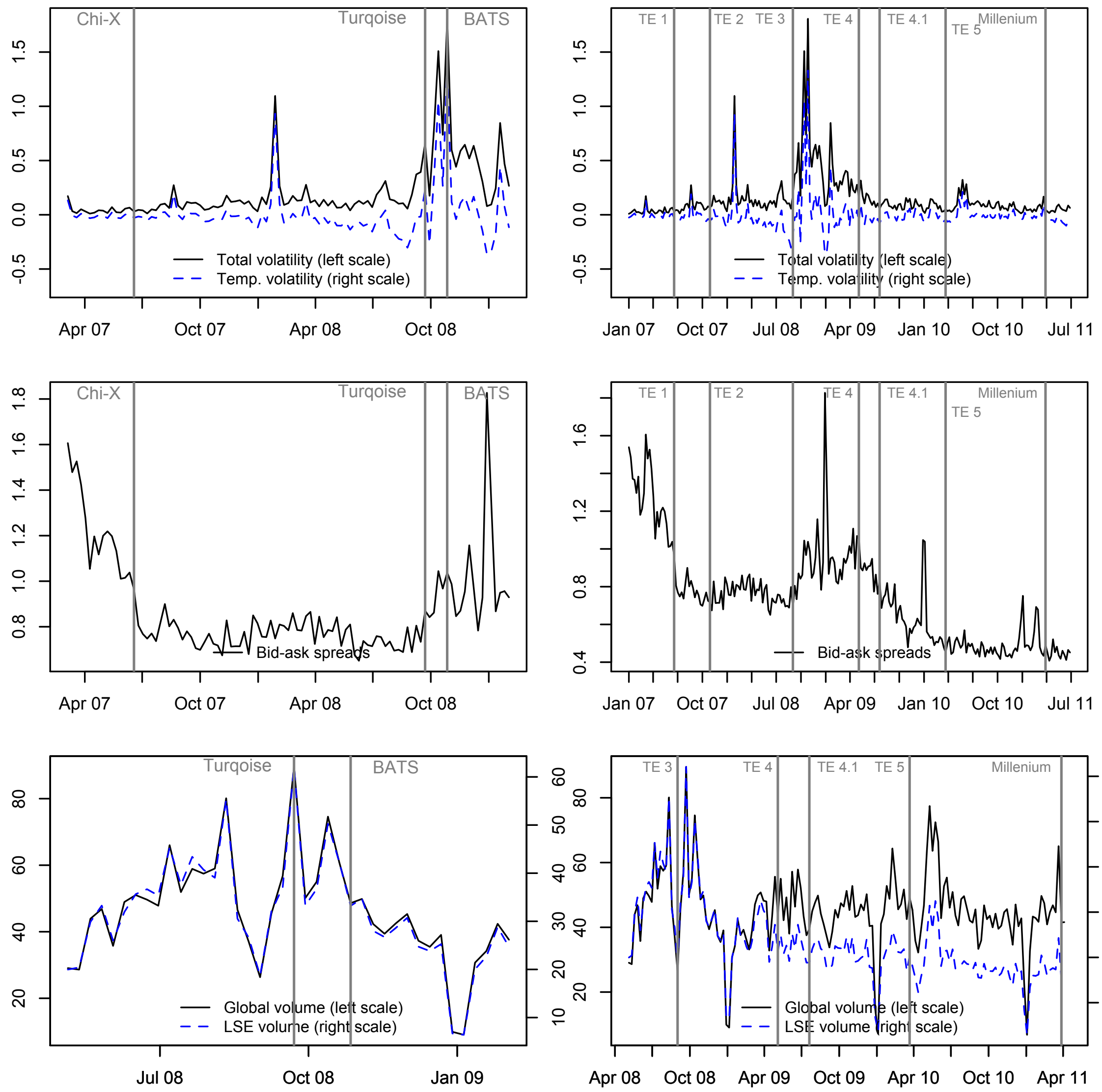
Notes: The time series are calculated as averages of the individual series weighted by market capitalization.

Figure 3: Market quality measures



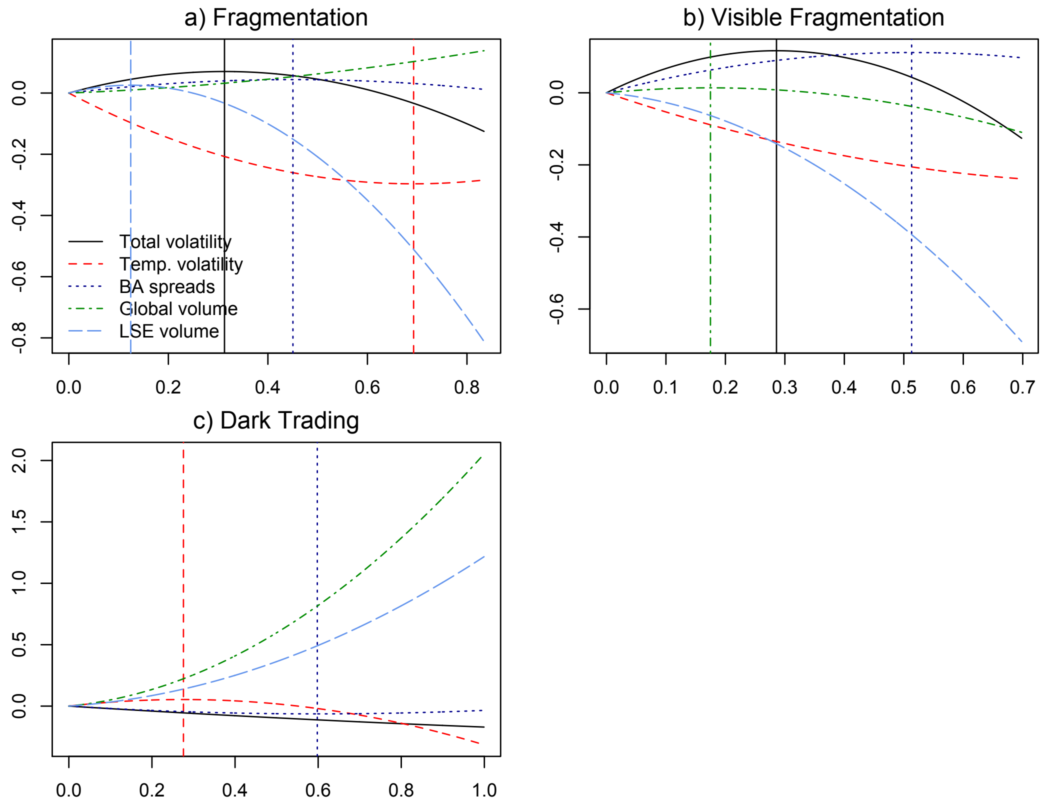
Notes: The time series are calculated as averages of the individual series weighted by market capitalization. Bid-ask spreads and volatility are multiplied by 1000. The downside spike in the series is due to the Christmas and New Year holiday.

Figure 4: Venue entry, latency upgrades at the LSE and market quality for the FTSE 100 index



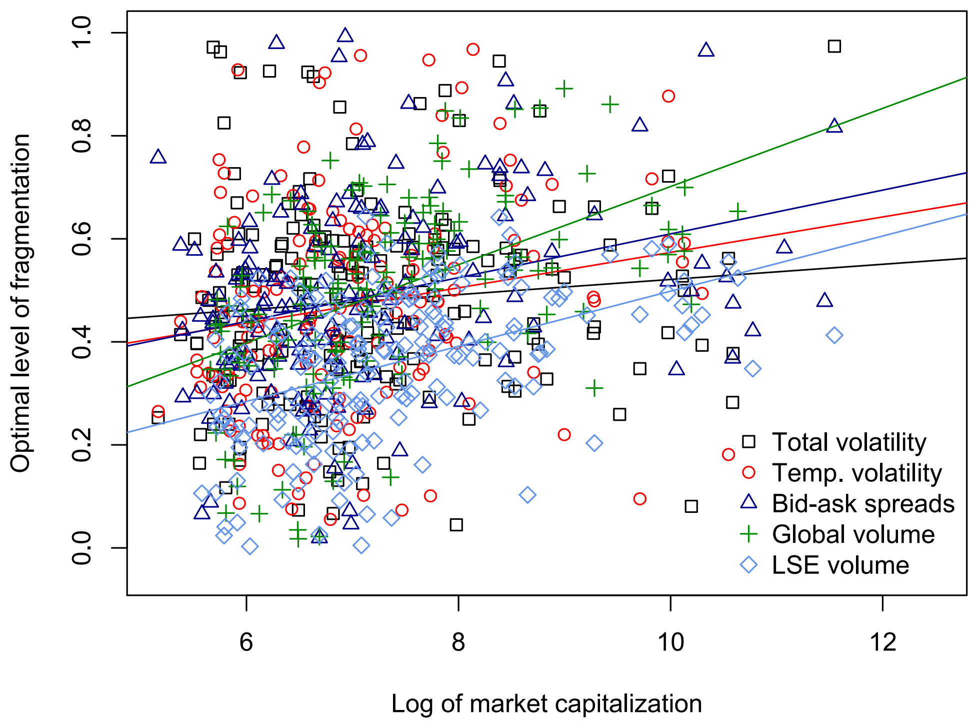
Notes: The left panels show market quality measures and venue entry and the right panels show market quality and latency upgrades at the LSE. The time series are calculated as averages of the individual series weighted by market capitalization. Bid-ask spreads and volatility are multiplied by 1000. Series for volume are shorter due to data availability. The downside spike in the series is due to the Christmas and New Year holiday.

Figure 5: Visible fragmentation, dark trading and market quality



Notes: The figure shows $Y = \widehat{\beta}_1 X + \widehat{\beta}_2 X^2$, where Y is market quality, X is either visible fragmentation, dark trading or OTC trading, and $\widehat{\beta}_j$ are the median CCE estimates from Tables 1 and 2. The vertical lines indicate interior optima.

Figure 6: The maximal level of fragmentation and market capitalization



Notes: The Figure plots the optimal level of fragmentation for each individual firm $-\frac{\beta_{1i}}{2\beta_{2i}}$ against the time-series average of the log of market capitalization. Only interior maxima within $[0, 1]$ are shown. OLS regression lines are added.