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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-monotone.

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

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Abstract

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JEL codes: C23, G28, L10
Keywords: Heterogeneous panel data, quantile regression, MiFID, dark pools, high frequency trading

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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. Additionally, security exchanges perhaps qualify as natural monopolies. On the other hand, there are theoretical explanations 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 can still benefit from network externalities in a fragmented market place.

[1] http://www.batstrading.co.uk/market_data/market_share/index/, assessed 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.

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 a stable 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 employ an extension 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 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 that provide us with a richer picture of the effect of fragmentation on market quality and which are 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. 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. The transition between monopoly and competition is non-monotonic for overall and visible fragmentation and takes the form of an inverted U. 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 the data at hand and Section 5 reports the results. Section 6 concludes.

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 exist, and trade-throughs are allowed.[3]

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

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

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 Smart Order Routing Technologies (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 entry of the LSE in the Dutch equity market. Before the entry of the 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.

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

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

[5] For example, the latency at BATS is about 8 to 10 times lower when compared to the LSE (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.

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 asymmetric information. 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 smart order routers and can access the consolidated order book. Second, from the point of view of an investor who can only access liquidity on the primary exchange. Gresse finds that increased competition between trading venues creates more liquidity both locally and globally in a sample of stocks listed on the LSE and Euronext exchanges in Amsterdam, Paris and Brussels. Dark trading does not have a negative effect on liquidity in her sample.

De Jong et. al. (2011) study the effect of fragmentation on market quality in a sample of Dutch stocks. 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 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 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 and high-frequency traders (Riordan et al., 2011). By relying on Smart Order Routing technologies, 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) who finds that the level of both trade fragmentation and quote fragmentation during the preceding 20 days is associated with larger drawdowns during the Flash Crash. This finding suggests that fragmentation may be affecting the variability of market quality. Our work below further investigates this question.

Our contribution to the literature. Our work differs from the previous literature in various dimensions. Previous work has not accounted for multiple shocks that are common to all individual stocks but are heterogeneous in effect, such as the bankruptcy of Lehman Brothers or a system latency upgrade at the LSE. If these multiple unobserved shocks do not only affect market quality, but also the level of fragmentation, then the fixed effects estimators that have been used by e.g. Gresse (2011) are biased, and remain so in large samples. In contrast, our estimation method remains consistent in such a situation.

While related studies have focused on the conditional expectation, we use quantile estimation methods that enable us to characterize the whole conditional distribution of market quality and which are robust to response variable outliers, i.e., heavy tailed distributions. In addition, we do not only examine the effect of fragmentation on the level of market quality, but also on its variability.

Finally, much of the existing evidence is obtained from high frequency data. In contrast, our study conducts regressions at a weekly frequency. This imposes some restrictions on the types of questions we can answer and the measures of market quality we can compute. Our dataset is not suitable to assess the effect of fragmentation on execution times or transaction costs. On the other hand, in contrast to O'Hara and Ye (2011), for example, we follow the market for a period of nearly three years rather than looking at performance at a single point in time.

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.

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 a 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 high frequency trading (HFT) is one explanation of the successful entry of alternative trading venues. These venues could attract a significant share of HFT order flow

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

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 in the year 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.

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 cal-

[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).

[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).

culated 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 Smart Order Routing Technologies, while local measures are important for small investment firms that are only connected to the primary exchange to save costs or for retail investors that are restricted by the best execution policy of their investment firm.[9] For example, Gomber, Pujol, and Wranik (2012) provide evidence that 20 out of 75 execution policies in their sample state that they only execute orders at the primary exchange.

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, Brown, and Stultz (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 is known to be consistent and has recently been shown to be relatively robust to microstructure noise, see Alizadeh, Brandt, and Diebold (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. Formally, the Rogers and Satchell volatility estimator can be computed as

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

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

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

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 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 analysis is misleading 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 payoff 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 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

[11]A good example is the "hash crash" of 23/4/2013 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

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). 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 liquidty.

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.

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

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 (for example, the LSE). 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 are 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 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 try and measure the relationship more reliably.

We extend the Pesaran methodology 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. This robust method is valid under weaker moment conditions for example and is robust to outliers. Third, we also model the conditional variance using the same type of regression model; we apply the median regression method for estimation based on the squared residuals from the median specification. This allows us to look at not just the average effect of fragmentation on market quality but also the variability of that effect.[13]

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 nonlinear effect of the fragmentation variable on the outcome variable by including the quadratic term. The regressors $W_{it} = (X_{it}, Z_{it}^{\intercal})^{\intercal}$ are assumed to have the factor structure

$$W_{it} = a_i + D_i d_t + K_i f_t + u_{it}, \tag{4}$$

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

where D_i and K_i are matrices of factor loadings. We assume that the error terms satisfy the conditional median restrictions $\text{med}((u_{it}, \varepsilon_{it})|X_{it}, Z_{it}, d_t, f_t) = 0.$, but the error terms are allowed to be serially correlated or weakly cross-sectionally correlated. The econometric model (3)-(4) 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 very general and contains many homogenous and heterogeneous panel data models as a special case. Körber, Linton and Vogt (2013) study a model where, in addition, there are no Z_{it} variables and the expectation of Y_{it} conditional on X_{it} is modelled as a nonparametric function $m_i(X_{it})$. In that paper, we assume that the individual functions $m_i(X_{it})$ are driven by a small number of common factors that are have heterogeneous effects on the individual units.

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

$$\beta_i = \beta + v_i, \quad v_i \sim IID(0, \Sigma_v), \tag{5}$$

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)-(4), we use Pesaran's (2006) CCE mean group estimator based on quantile regression. Taking cross-sectional averages of (4), we obtain

$$\overline{W}_t = \bar{a} + \overline{D}d_t + \overline{K}f_t + O_p(n^{-1/2}). \tag{6}$$

Equation (6) 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

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

[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 (6), we can also use an average that is e.g. weighted by market capitalization. Or we can go long in the FTSE 100 stocks and short in the FTSE 250 stocks.

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 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 estimation in the following regression model

$$Y_{it} = \pi_i + \beta_{1i} X_{it} + \beta_{2i} X_{it}^2 + \beta_{3i} Z_{it} + \gamma_i^{\intercal} d_t + \xi_i^{\intercal} \overline{W}_t + \epsilon_{it}, \tag{7}$$

where we write $\xi_i^{\intercal} = (\xi_{Xi}, \xi_{Zi}^{\intercal})$. Specifically, the parameters in β_i can be consistently estimated by the quantile regression of (7). Let $\widehat{\beta}_i$ minimize the objective functions

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

where $\rho_\tau(x) = x(\tau - 1(x < 0))$, see Koenker (2005) and $\theta = (\pi, \beta_1, \beta_2, \beta_3^{\intercal}, \gamma^{\intercal}, \xi^{\intercal})$.

At any quantile, the quantile CCE mean group estimate $\widehat{\beta} = n^{-1} \sum_{i=1}^{n} \widehat{\beta}_i$ is defined as the 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

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

where the parameters $b_i = (b_{1i}, b_{2i}, b_{3i}^\intercal)^\intercal$ have a random coefficient specification like (5). We estimate this by median regression of the squared residuals $\widehat{\epsilon}_{it}^2$ from (7) 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). Alternatively, we could examine the interquartile range associated with the quantile regression method described above, that is, compute $\widehat{\beta}(0.75) - \widehat{\beta}(0.25)$, where $\widehat{\beta}(\alpha)$ denotes the level α quantile regression from (8).

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

$$\Delta_X = \frac{E_{X=H}Y - E_{X=L}Y}{H - L} = \beta_1 + \beta_2(H + L), \tag{12}$$

where the coefficients are estimated by the quantile CCE 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]

[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.

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

Table 1 reports CCE coefficients based on individual quantile regressions together with our parameter of interest Δ_{Frag}. Δ_{Frag} is defined as the difference in market quality between a high and low level of fragmentation evaluated at the minimum and maximum level of fragmentation (equation (12)). For comparison, we also report marginal effects which tends 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) who study an imperfectly competitive financial market under asymmetric information.

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.

[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.

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. 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 the activities of high frequency traders. To mitigate these adverse effects on liquidity, investors could employ Smart Order Routing Systems 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 quartile of the conditional volatility distribution (Table 2). Dark trading also increases volume while it does not has 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 illustrate 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. 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. For temporary volatility and LSE volume, there is no interior optimum on $[0, 1]$. 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.

SEC (2013) has hypothesized that this 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 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 there is any evidence that overall fragmentation, visible fragmentation and dark trading have led to an increase in the volatility of market quality. For example, Madhavan (2012) finds that fragmentation during the preceding 20 days is associated with larger drawdowns during the Flash Crash. In addition, fragmented equity markets have been a seedbed for High Frequency Traders 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

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

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.

5.4 Dark trading and dark fragmentation

To contrast the effects of dark trading and dark fragmentation on market quality, Table 5 reports the results from including dark fragmentation as an additional regressor.[22] We find that dark fragmentation increases volatility at the median and third quartile, which contrasts with our findings for the amount of dark trading. In line with dark trading, dark fragmentation increases volume at the LSE. The variability of market quality is not affected by dark fragmentation. The only exception is an increase in the variability of total volatility for firms in the first quartile.

5.5 Robustness

In 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.

[22]The results on visible fragmentation and dark trading are not affected by including dark fragmentation in the specification.

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)-(4) 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 high frequency trading 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 fundantal 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 High Frequency Trading, 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 High Frequency Trading. Compared to Pesaran (2006), our version of the CCE 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 apply 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.

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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 averages of individual quantile regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization 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 $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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 abs.	0.145	0.135	0.08	0.194	0.17
CSD sq.	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 averages of individual quantile regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization 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 regresion

	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: Coefficients are averages of individual quantile regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization 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 $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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 abs. (CSD sq.) is the mean of the absolute value (square) 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: Coefficients are averages of individual quantile regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. $\Delta_X^T(\tau)$ 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: Dark trading and dark fragmentation

a) Level of market quality

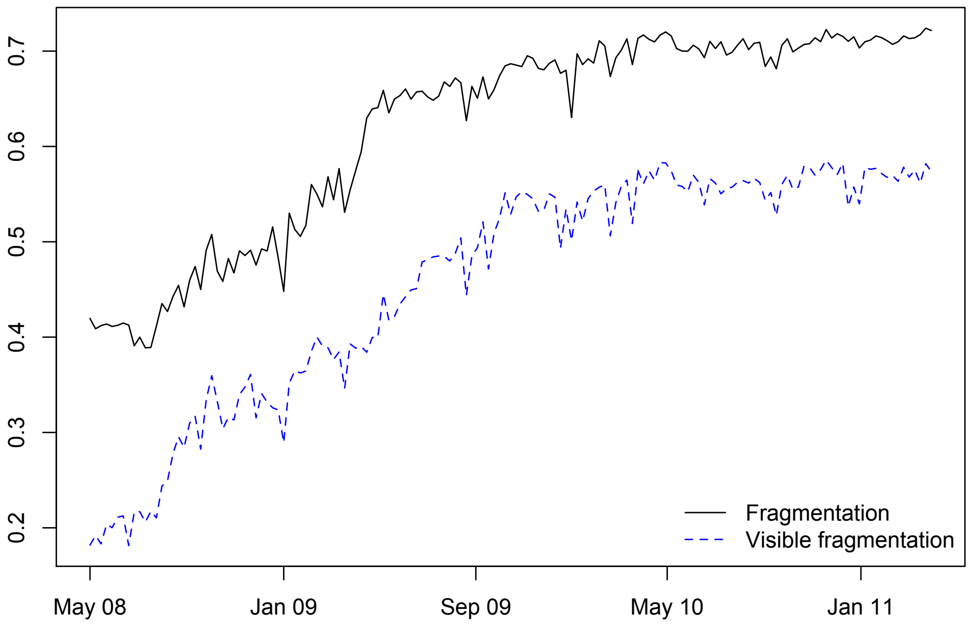
	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Dark frag.}(0.25)$	0.07	0.027	0.065	0.032	0.095
	(1.482)	(0.618)	(1.737)	(1.122)	(2.248)
$\Delta_{Dark frag.}(0.5)$	0.08	0.089	0.059	0.038	0.088
	(1.725)	(2.065)	(1.527)	(1.151)	(1.968)
$\Delta_{Dark frag.}(0.75)$	0.125	0.108	-0.021	0.031	0.021
	(2.167)	(2.187)	(-0.513)	(0.862)	(0.43)

b) Variability of market quality

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Dark frag.}(0.25)$	0.022	0.003	-0.006	0	-0.002
	(2.062)	(0.374)	(-0.783)	(0.04)	(-0.264)
$\Delta_{Dark frag.}(0.5)$	-0.01	-0.002	-0.008	0.013	0.003
	(-0.556)	(-0.135)	(-0.595)	(1.732)	(0.213)
$\Delta_{Dark frag.}(0.75)$	0.006	0.018	-0.014	0.006	-0.025
	(0.079)	(0.309)	(-0.268)	(0.178)	(-0.46)

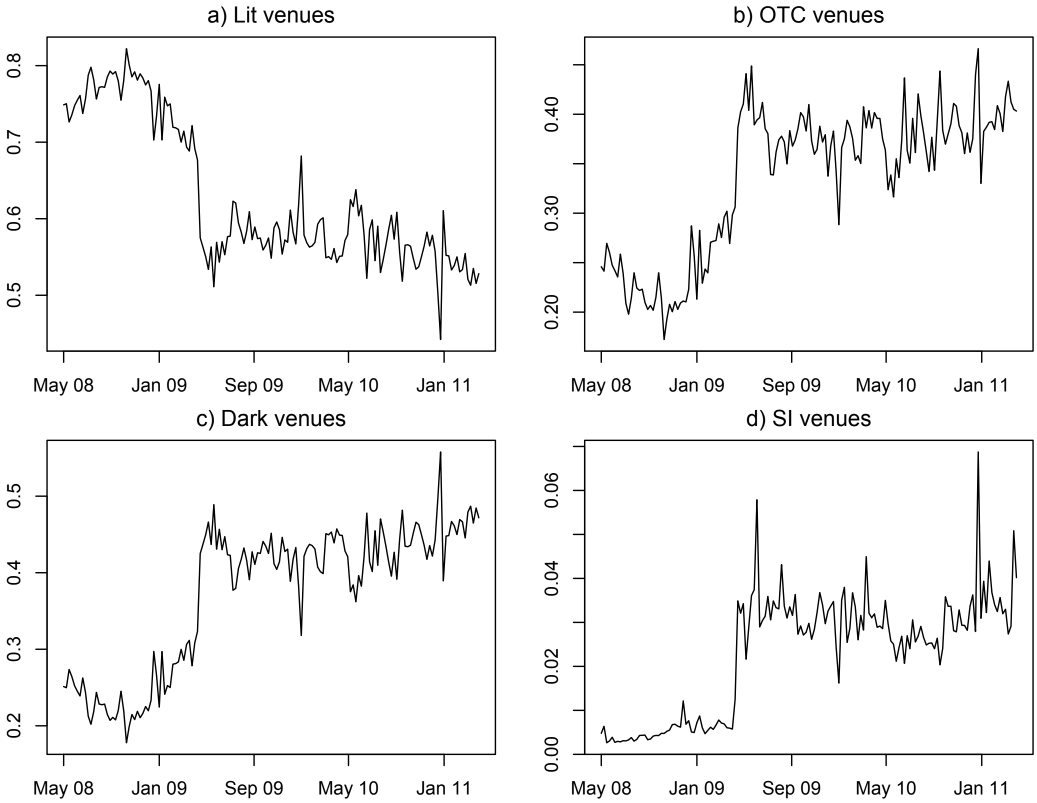
Notes: The Table reports Δ_X^T for both the level and the volatility of market quality when a measure of dark fragmentation is added to the regression in Table 2. t-statistics are shown in parenthesis. Dark fragmentation is defined as 1- dark Herfindahl index. $\Delta_X^T(\tau)$ is defined as $\widehat{\beta}_1(\tau) + \widehat{\beta}_2(\tau)(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$.

Figure 1: Fragmentation and visible fragmentation



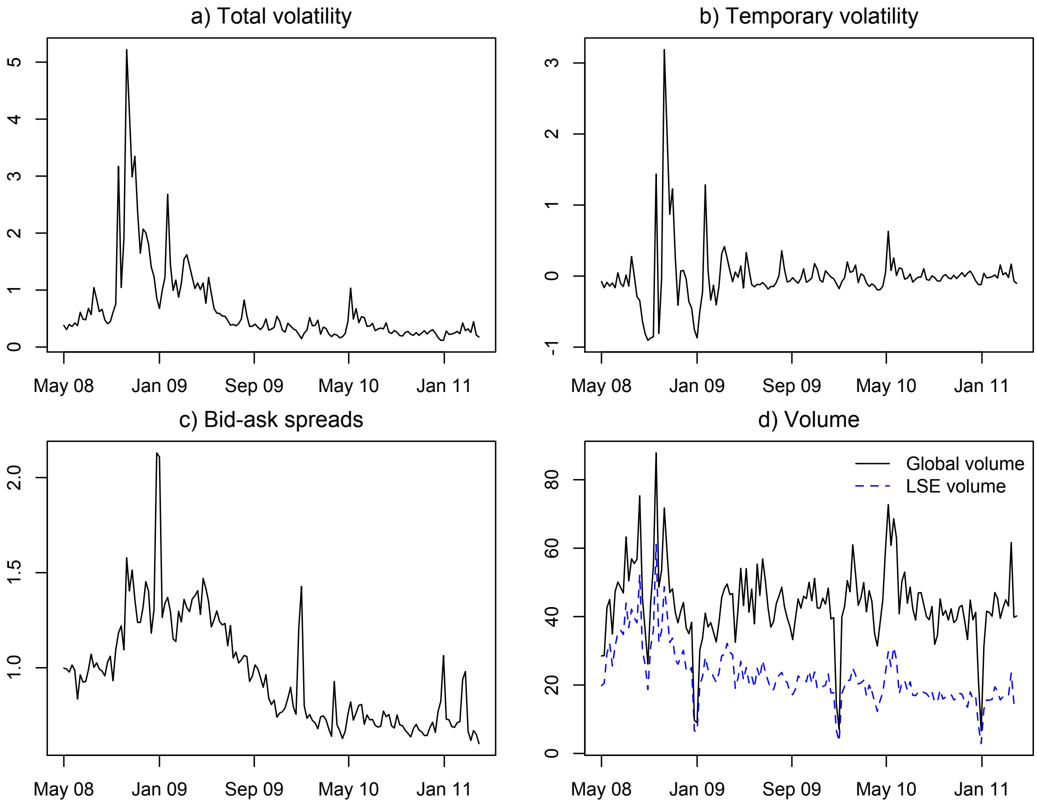
Notes: Fragmentation is defined as 1-Herfindahl index and visible fragmentation as 1-visible Herfindahl index. The time series are calculated as averages of the individual series weighted by market capitalization.

Figure 2: Share of volume traded by venue category



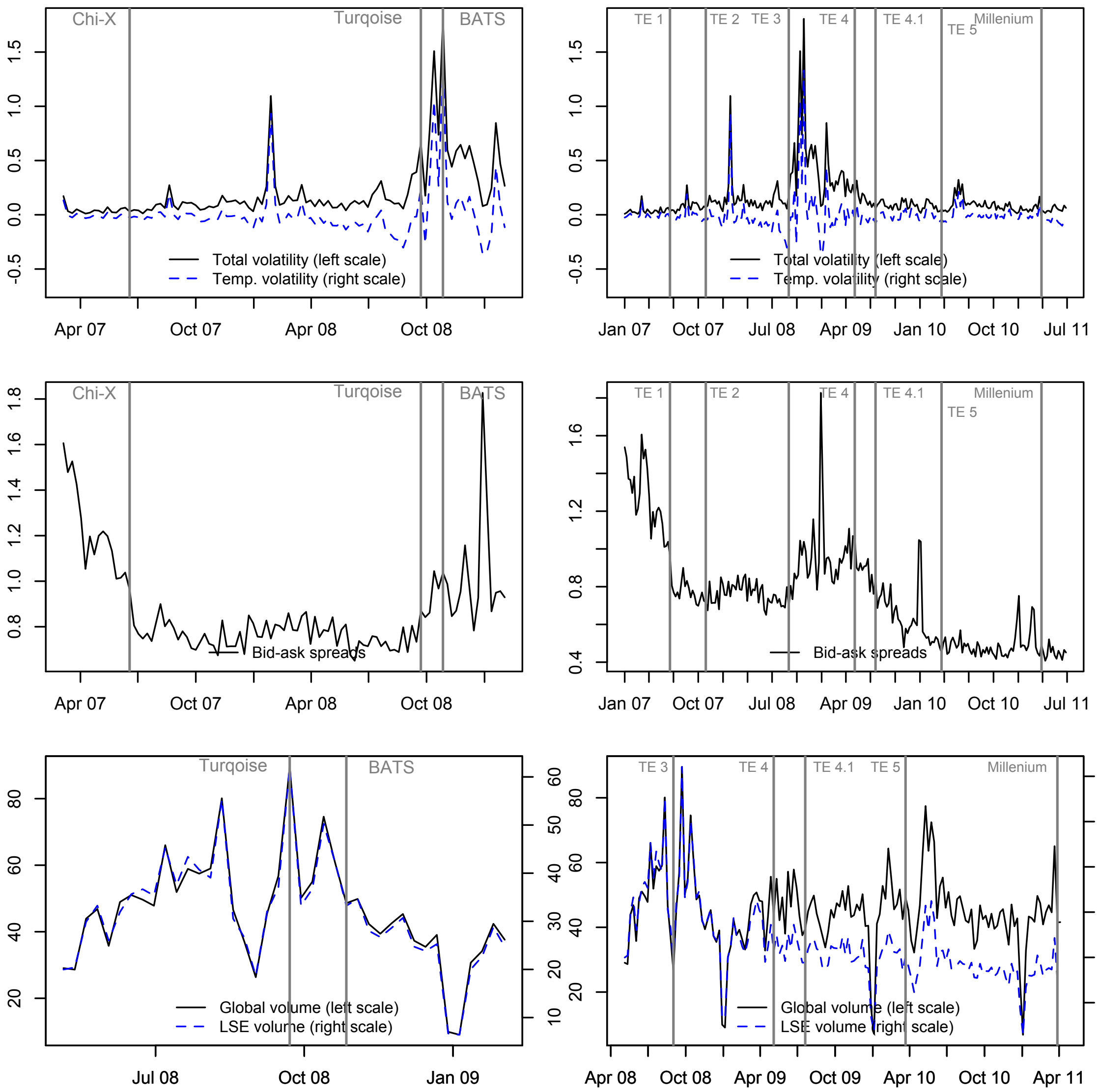
Notes: The time series are calculated as averages of the individual series weighted by market capitalization.

Figure 3: Market quality measures



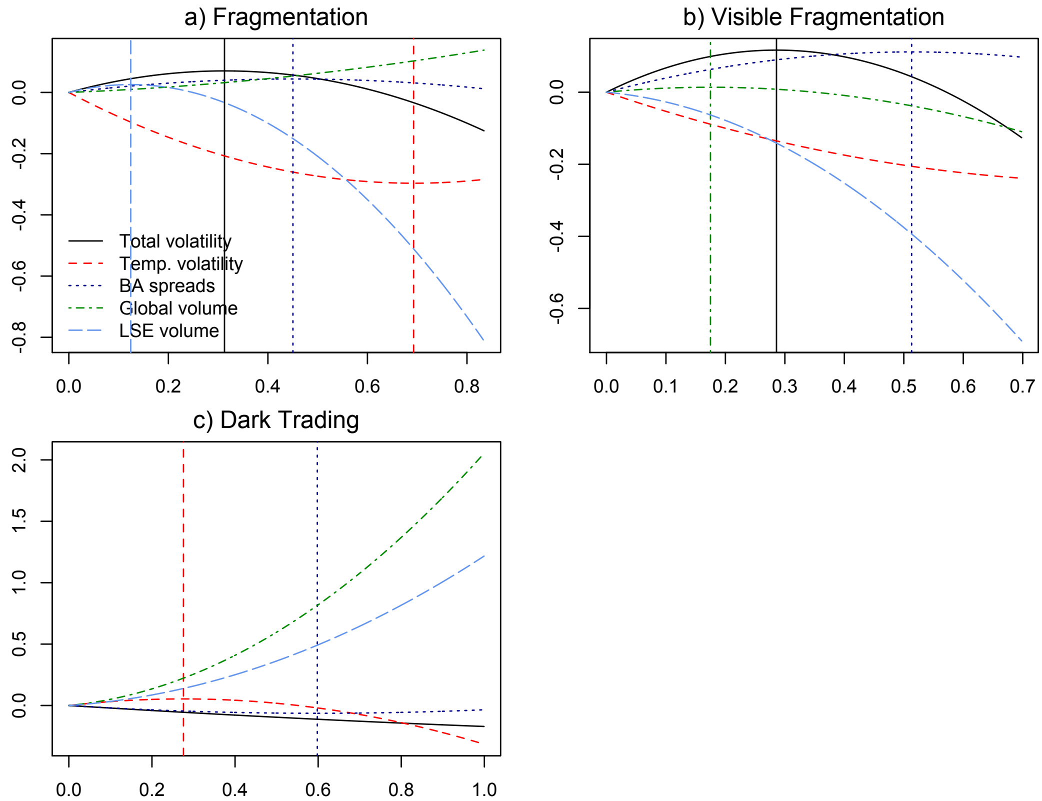
Notes: The time series are calculated as averages of the individual series weighted by market capitalization. Bid-ask spreads and volatility are multiplied by 1000. The downside spike in the series is due to the Christmas and New Year holiday.

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



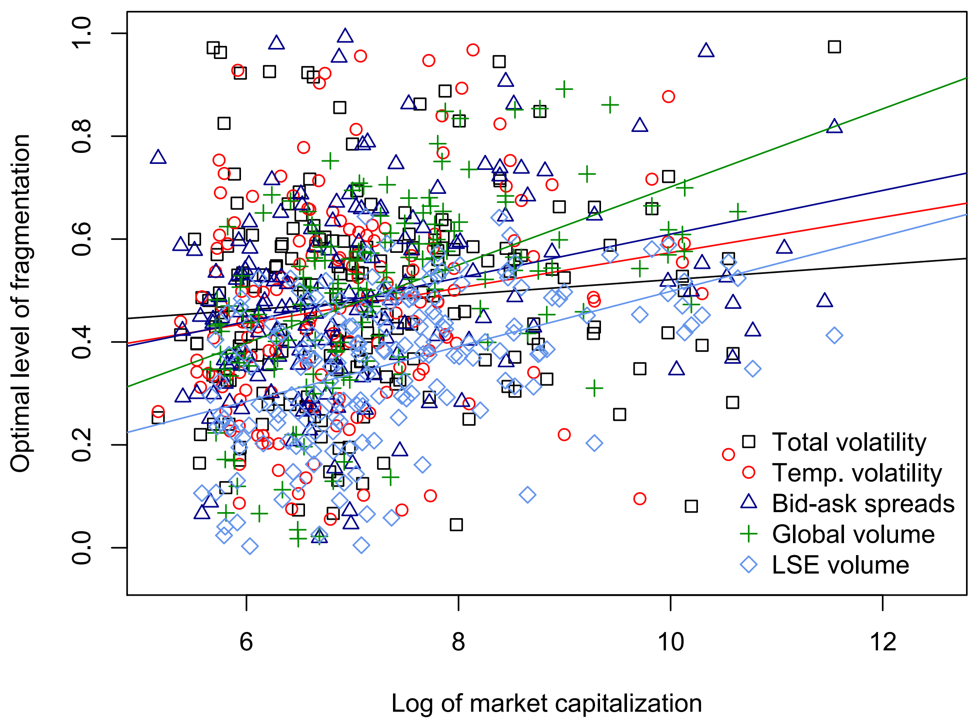
Notes: The left panels show market quality measures and venue entry and the right panels show market quality and latency upgrades at the LSE. The time series are calculated as averages of the individual series weighted by market capitalization. Bid-ask spreads and volatility are multiplied by 1000. Series 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.

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

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Appendix A The regulatory framework under MiFID

The "Markets in Financial Instruments Directive (MiFID)" is a directive of the European Union that was adopted by the Council of the European Union and the European Parliament in April 2004 and became effective in November 2007. It replaces the "Investment Services Directive (ISD)" of 1993 that has become outdated by the fast speed of innovation in the financial industry. MiFID is the cornerstone of the "Financial Services Action Plan" that aims to foster the integration and harmonization of European financial markets. It provides a common regulatory framework for security markets across the 30 member states of the European Economic Area[1] to encourage the trading of securities and the provision of financial services across borders. The main pillars of MiFID are **market access**, **transparency** and **investor protection.**

1. **Market access.** MiFID abolished the monopoly position that many primary exchanges in the European Economic Area have had in the trading of equities. Under MiFID, orders can be executed on either regulated markets (RM), multilateral trading facilities (MTF) or systematic internalizers (SI). RMs and MTFs have similar trading functionalities but differ in the level of regulatory requirements. In contrast to MTFs, RMs must obtain authorization from a competent authority. While some MTFs have a visible (lit) order book, others operate as regulated dark pools. In a dark pool, traders submit their orders anonymously and they remain hidden until execution.[2] SIs are investment firms that execute client orders against other client orders or against their own inventories.

   The new entrants differentiate themselves on quality, price and technology that are usually tailored to speed-sensitive high frequency traders. In particular, MTF's typically adopt he so-called maker-taker rebates that reward the provision of liquidity to the system, various types of orders permitted, and small tick sizes. Additionally, their computer systems offer a lower latency when compared to regulated markets.

   While the number of RMs did not significantly increase after the introduction of MiFID, a large number of MTFs and SIs emerged in the post-MiFID period and successfully captured market share from the primary markets: At the end of October 2007, the European Securities and Markets Authority (ESMA) listed 93 RMs, 84 MTFs and 4 SIs. By the end of 2012, the number of MTFs had almost doubled to 151. While SIs are rare compared to MTFs, their number had grown to 13 by December 2012. In contrast, the number of RMs had only increased to 94.[3]

   MiFID also extends the single passport concept that was already introduced in the ISD to establish a homogeneous European market governed by a common set of rules. The

[1] The European Economic Area consists of the 27 member states of the European Union as well as Norway, Iceland, and Liechtenstein.

[2] There are other, unregulated categories of dark pools that are registered as OTC venues or brokers (Gresse, 2012)

[3] http://mifiddatabase.esma.europa.eu/, accessed on November 11, 2012

single passport concept enables investment firms that are authorized and regulated in their home state to serve customers in other EU member states.

2. **Transparency.** With an increasing level of fragmentation, information on prices and quantities available in the order books of different venues becomes dispersed. In response, MiFID introduced pre- and post-trade transparency provisions to enable investors to optimally decide where to execute their trade. Pre-trade transparency provisions apply to RMs and MTFs that operate a visible order book and require these venues to publish their order book in real time. Dark venues, OTC markets and SIs use waivers to circumvent the pre-trade transparency rules. To comply with post-trade transparency regulations, RMs, MTFs including regulated dark pools and OTC venues have to report executed trades to either the primary exchange or to a trade reporting facility (TRF) such as Markit BOAT.

3. **Investor protection.** MiFID introduces investor protection provisions to ensure that investment firms keep investors informed about their execution practises in a fragmented market place. An important part of these regulations is the best execution rule: Investment firms are required to execute orders that are on behalf of their clients at the best available conditions taking into account price, transaction costs, speed and likelihood of execution. Investment firms have to review their routing policy on a regular basis.

However, the financial crisis exposed several shortcomings of MiFID and the European Commission reacted to them by proposing a revision. The most important changes include the regulation of e.g. derivatives trading on “Organised Trading Facilities”, the introduction of safeguards for HFT, the improvement of transparency in equity, bonds and derivative markets, the reinforcement of supervisory powers in e.g. commodity markets and the strengthening of investor protection (European Commission, 2011).

Appendix B Trading venues

This appendix lists the individual trading venues that are used in our study.

- **Lit venues:** Bats Europe, Chi-X, Equiduct, LSE, Nasdaq Europe, Nyse Arca, and Turquoise[4]

- **Regulated dark pools:** BlockCross, Instinet BlockMatch, Liquidnet, Nomura NX, Nyfix, Posit, Smartpool, and UBS MTF.

- **OTC venues:** Boat xoff, Chi-X OTC, Euronext OTC, LSE xoff, Plus, XOFF, and xplu/o.

- **Systematic internalizers:** Boat SI and London SI.

[4]On 21 December 2009, the London Stock Exchange Group agreed to take a 60% stake in trading platform Turquoise.

Appendix C System latency at the LSE

Table C: System latency at the LSE

System	Implementation Date	Latency (Microseconds)
SETS	<2000	600000
SETS1	Nov 2001	250000
SETS2	Jan 2003	100000
SETS3	Oct 2005	55000
TradElect	June 18, 2007	15000
TradElect 2	October 31, 2007	11000
TradElect 3	September 1, 2008	6000
TradElect 4	May 2, 2009	5000
TradElect 4.1	July 20, 2009	3700
TradElect 5	March 20, 2010	3000
Millenium	February 14, 2011	113

Source: Brogaard et al. (2013)

Appendix D Econometric justification for quantile CCE estimation

We sketch an outline of the argument for the consistency of the quantile regression estimators used above. Harding and Lamarche (2010) consider the case with homogeneous panel data models; their theory does not apply to the heterogeneous case we consider.

We consider a special case where we observe a sample of panel data $\{(Y_{it}, X_{it}) : i = 1, \ldots, n,\ t = 1, \ldots, T\}$. We first assume that the data come from the linear panel regression model

$$Y_{it} = \alpha_i + \beta_i X_{it} + \kappa_i f_t + \varepsilon_{it}, \tag{1}$$

where f_t denotes the unobserved common factor or factors. The covariates satisfy

$$X_{it} = \delta_i + \rho_i f_t + u_{it}, \tag{2}$$

where in the Pesaran (2006) model the error terms satisfy the conditional moment restrictions $E(u_{it}^{\intercal}, \varepsilon_{it} | X_{it}, f_t) = 0$ with u independent of ε. The unobserved factors f_t are assumed to be either bounded and deterministic or a stationary ergodic sequence. Then assume that

$$\theta_i = \theta + \eta_i, \tag{3}$$

where $\theta_i = (\alpha_i, \beta_i, \kappa_i, \delta_i, \rho_i)^{\intercal}$, $\theta = (\alpha, \beta, \kappa, \delta, \rho)^{\intercal}$ and η_i are iid and independent of all the other random variables in the system This is a special case of the model considered by Pesaran (2006).

Letting $h_{0t} = \delta + \rho f_t$, we can write (provided $\rho \neq 0$)

$$Y_{it} = \alpha_i^* + \beta_i X_{it} + \kappa_i^* h_{0t} + \varepsilon_{it}, \tag{4}$$

with $\alpha_i^* = \alpha_i - \delta\kappa_i/\rho$ and $\kappa_i^* = \kappa_i/\rho$, and note that $E(\varepsilon_{it}|X_{it}, h_{0t}) = 0$.

Taking cross-sectional averages we have

$$\overline{X}_t = \delta + \rho f_t + \overline{u}_t + \overline{\delta} - \delta + (\overline{\rho} - \rho) f_t = h_{0t} + O_p(n^{-1/2}), \tag{5}$$

since $\overline{u}_t = O_p(n^{-1/2}) = \overline{\delta} - \delta = \overline{\rho} - \rho$. Therefore, we may consider the least squares estimator that minimizes $\sum_{t=1}^{T} \left\{Y_{it} - a - bX_{it} - c\overline{X}_t\right\}^2$ with respect to $\psi = (a, b, c)$, which yields a closed form estimator. This bears some similarities to the approach of Pesaran (2006) except that we do not include $\overline{Y}_t$ here (in this special case, it would introduce approximate multicollinearity here, since $\overline{Y}_t = \overline{\alpha} + \overline{\beta\delta} + (\overline{\beta\rho} + \overline{\kappa}) f_t + \overline{\varepsilon}_t + \left(\overline{\beta u}\right)_t$). Moon and Weidner (2010) advocate a QMLE approach, which would involve optimizing a pooled objective function over θ_i, $i = 1, \ldots, n$ and f_t, $t = 1, \ldots, T$. In the QMLE case this may be feasible, but in the case with more nonlinearity such as quantiles as below this seems infeasible.

We now turn to quantile regression, and in particular median regression. We shall now assume that $\mathrm{med}(\varepsilon_{it}|X_{it}, f_t) = 0$ and maintain the assumptions that $E(u_{it}) = 0$ with u independent of ε, so that $\overline{X}_t = \delta + \rho f_t + \overline{u}_t = h_{0t} + O_p(n^{-1/2})$ as before. We consider a more general class of estimators based on minimizing the objective function

$$Q_{Ti}(\psi) = \frac{1}{T} \sum_{t=1}^{T} \lambda(Y_{it} - a - bX_{it} - c\overline{X}_t), \tag{6}$$

over ψ, where $\lambda(t) = |t|$. The approximate first order conditions are based on

$$\begin{aligned} M_{Ti}(\psi; \overline{X}_1, \ldots, \overline{X}_T) &= \frac{1}{T} \sum_{t=1}^{T} \begin{pmatrix} 1 \\ X_{it} \\ \overline{X}_t \end{pmatrix} \mathrm{sign}\left(Y_{it} - \alpha - \beta X_{it} - \gamma \overline{X}_t\right) \\ &= \frac{1}{T} \sum_{t=1}^{T} m_{it}(\psi, \overline{X}_t) \end{aligned} \tag{7}$$

We discuss now the properties of $\widehat{\psi}_i$, the zero of $M_{Ti}(\psi; \overline{X}_1, \ldots, \overline{X}_T)$. For this purpose we can view $\widehat{\psi}_i$ as an example of a semiparametric estimator as considered in Chen, Linton, and Van Keilegom (2003). That is, $\overline{X}_t$ is a preliminary estimator of the "function" $h_{0t} = \delta + \rho f_t$.

An important part of the argument is to show the uniform consistency of this estimate

$$\max_{1 \leq t \leq T} \left|\overline{X}_t - \delta - bf_t\right| \leq \max_{1 \leq t \leq T} |\overline{u}_t| + \left|\overline{\delta} - \delta\right| + (\max_{1 \leq t \leq T} |f_t|) \left|\overline{\rho} - \rho\right| = o_p(1). \tag{8}$$

By elementary arguments we have $\max_{1 \leq t \leq T} |\overline{u}_t| = o_p(T^{\kappa} n^{-1/2})$ for some κ depending on the number of moments that u_{it} possesses. Similarly, $\max_{1 \leq t \leq T} |f_t| = O_p(T^{\kappa})$ under the same moment conditions.

For compactness, let us denote $M_{Ti}(\psi; \overline{X}_1, \ldots, \overline{X}_T)$ by $M_{Ti}(\psi, \widehat{h})$, where $\widehat{h} = (\overline{X}_1, \ldots, \overline{X}_T)$. The approach of CLV is to approximate the estimator

$$\widehat{\psi} = \arg\min_{\psi \in \Psi} ||M_{Ti}(\psi, \widehat{h})|| \tag{9}$$

by the estimator

$$\overline{\psi} = \arg\min_{\psi \in \Psi} ||M_{Ti}(\theta, h_0)||, \tag{10}$$

where $h_0 = (h_{01}, \ldots, h_{0T})$ is the true sequence. In the case where $m_{it}(\psi, h)$ is smooth in h, this follows by straightforward Taylor expansion and using the uniform convergence result above. In the quantile case, some empirical process techniques are needed as usual, but they are standard. The estimator $\overline{\psi}$ is just the standard quantile regression estimator of the parameters in the case where h_{0t} is observed and so consistency follows more or less by a standard route, namely, the strong law of large numbers implies that

$$\begin{aligned} M_{Ti}(\psi, h_0) &= \frac{1}{T}\sum_{t=1}^{T} \begin{pmatrix} 1 \\ X_{it} \\ \delta + \rho f_t \end{pmatrix} \operatorname{sign}\left(Y_{it} - \alpha - \beta X_{it} - \gamma\delta - \rho\gamma f_t\right) \\ &\to E_i\left[\begin{pmatrix} 1 \\ X_{it} \\ \delta + \rho f_t \end{pmatrix} \operatorname{sign}\left(Y_{it} - \alpha - \beta X_{it} - \gamma(\delta + \rho f_t)\right)\right] \\ &\equiv M_i(\psi), \end{aligned} \tag{11}$$

which is uniquely minimized at the true value of ψ. Here, E_i means expectation conditional on ψ_i.

In fact, because of the independence of u, ε, the joint distribution of $\varepsilon_{it}, X_{it}, f_t$ factors into the product of the conditional distribution of $\varepsilon_{it}|f_t$ the conditional distribution of $u_{it}|f_t$ and the marginal distribution of f_t. We calculate $M_i(\psi)$. We have

$$\begin{aligned} M_{1i}(\psi) =& E_i\left[\operatorname{sign}\left(Y_{it} - \alpha - \beta X_{it} - \gamma\delta - \rho\gamma f_t\right)\right] \\ =& \int [1 - 2G((\alpha_i - \alpha) + (\beta_i - \beta)(u + \delta_i + \rho_i f) \\ & + (\gamma_i - \gamma)(\delta + \rho f)|f)]r(u|f)q(f)d\varepsilon du df, \end{aligned} \tag{12}$$

where G is the c.d.f of $\varepsilon|f$ with density g and r is the density of $u|f$ and q is the marginal density of f. It follows that $M_{1i}(\psi_0) = 0$ by the conditional median restriction. Similarly with $M_{ji}(\psi)$, $j = 2, 3$. Under some conditions can establish the uniqueness needed for consistency. We can further calculate $\partial M_{1i}(\psi)/\partial\psi$.

The next question is whether the estimation of h_0 by $\widehat{h}$ affects the limiting distribution. In this case we consider the sequence $h^* = (h_1^*, \ldots, h_T^*)$

$$E_i\left[m_{it}(\psi, h_t^*)|f_t\right] = E_i\left[m_{it}(\psi, h_{0t})|f_t\right] + \frac{\partial}{\partial h}E_i\left[m_{it}(\psi, h_{0t})|f_t\right]\left[h_t^* - h_{0t}\right] + \frac{\partial^2}{\partial h^2}E_i\left[m_{it}(\psi, \overline{h}_t)|f_t\right]\left[h_t^* - h_{0t}\right]^2 \tag{13}$$

for intermediate values $\overline{h}_t$. Then we can show that $\partial E_i\left[m_{it}(\psi, h_{0t})|f_t\right]/\partial h$ has a finite expectation and so

$$\begin{aligned} & \frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial h}E_i\left[m_{it}(\psi_0, h_{0t})|f_t\right]\left[\widehat{h}_t - h_{0t}\right] \\ = \; & \frac{1}{T}\sum_{t=1}^{T}\frac{\partial}{\partial h}E_i\left[m_{it}(\psi_0, h_{0t})|f_t\right]\left[\overline{u}_t + \overline{\delta} - \delta + (\overline{\rho} - \rho)f_t\right] = O_p(n^{-1/2}T^{-1/2}) \end{aligned} \tag{14}$$

because $E_i\left[\overline{u}_t + \overline{\delta} - \delta + (\overline{\rho} - \rho)f_t|f_t\right] = 0$. Furthermore,

$$\begin{aligned} & \frac{1}{T}\sum_{t=1}^{T}\frac{\partial^2}{\partial h^2}E\left[m_{it}(\psi, \overline{h}_t)|f_t\right]\left[\widehat{h}_t - h_{0t}\right]^2 \\ = \; & \frac{1}{T}\sum_{t=1}^{T}\frac{\partial^2}{\partial h^2}E\left[m_{it}(\psi, \overline{h}_t)|f_t\right]\left[\overline{u}_t + \overline{\delta} - \delta + (\overline{\rho} - \rho)f_t\right]^2 = O_p(n^{-1}), \end{aligned} \tag{15}$$

so that we need $T/n^2 \to 0$. It follows that the limiting distribution is the same as that of $\overline{\psi}$. The conditions of CLV Theorem 1 and 2 are satisfied. In particular, for:

$$\Gamma_1(\psi, h_o) = \frac{\partial}{\partial \psi}M(\psi) = -2 \times p\lim_{T\to\infty}\frac{1}{T}\sum_{t=1}^{T}\begin{pmatrix} 1 & X_{it} & h_{0t} \\ X_{it} & X_{it}^2 & X_{it}h_{0t} \\ h_{0t} & X_{it}h_{0t} & h_{0t}^2 \end{pmatrix} g(0|X_{it}, f_t), \tag{16}$$

$$\begin{aligned} V_1 &= \operatorname{var}[m_{it}(\psi_0, h_{0t}))] \\ &= \begin{pmatrix} 1 & \delta_i + \rho_i Ef_t & \delta + \rho Ef_t \\ \delta_i + \rho_i Ef_t & \sigma_u^2 + \delta_i^2 + \rho_i^2 Ef_t^2 + 2\delta_i\rho_i Ef_t & \delta_i\delta + \delta_i\rho Ef_t^2 + (\delta_i\rho + \delta\rho_i)Ef_t \\ \delta + \rho Ef_t & \delta_i\delta + \rho_i\rho Ef_t^2 + (\delta_i\rho + \delta\rho_i)Ef_t & \delta^2 + \rho^2 Ef_t^2 + 2\delta\rho Ef_t \end{pmatrix} \end{aligned} \tag{17}$$

we have

$$\sqrt{T}(\widehat{\psi}_i - \psi_i) \Longrightarrow \mathcal{N}[0, \Omega], \text{ where } \Omega = (\Gamma_1^\intercal\Gamma_1)^{-1}\Gamma_1^\intercal V_1\Gamma_1(\Gamma_1^\intercal\Gamma_1)^{-1}. \tag{18}$$

It follows that for each i

$$\sqrt{T}(\widehat{\beta}_i - \beta_i) \Longrightarrow N(0, \Omega_{\beta\beta i}), \tag{19}$$

where $\Omega_{\beta\beta i}$ is the appropriate submatrix of above.

In the case that $g(0|X_{it}, f_t) = g(0)$ we have

$$\Omega_i = \frac{1}{4g(0)} \begin{pmatrix} 1 & \delta_i + \rho_i E f_t & \delta + \rho E f_t \\ \delta_i + \rho_i E f_t & \sigma_u^2 + \delta_i^2 + \rho_i^2 E f_t^2 + 2\delta_i \rho_i E f_t & \delta_i \delta + \delta_i \rho E f_t^2 + (\delta_i \rho + \delta \rho_i) E f_t \\ \delta + \rho E f_t & \delta_i \delta + \rho_i \rho E f_t^2 + (\delta_i \rho + \delta \rho_i) E f_t & \delta^2 + \rho^2 E f_t^2 + 2\delta \rho E f_t \end{pmatrix}^{-1}. \tag{20}$$

Under some additional conditions we may obtain the asymptotic behaviour of the pooled estimator $\widehat{\beta} = n^{-1} \sum_{i=1}^n \widehat{\beta}_i$. Specifically, we have

$$\sqrt{n}(\widehat{\beta} - \beta) \Longrightarrow N(0, \Sigma_{\beta\beta}), \tag{21}$$

where $\Sigma_{\beta\beta} = \mathrm{var}(v_{\beta i})$. This follows because

$$\begin{aligned} \widehat{\beta} - \beta &= \frac{1}{n}\sum_{i=1}^n (\widehat{\beta}_i - \beta_i) + \frac{1}{n}\sum_{i=1}^n (\beta_i - \beta) \\ &= \frac{1}{n}\sum_{i=1}^n v_{\beta i} + O_p(T^{-1/2} n^{-1/2}) + O_p(n^{-1}), \end{aligned} \tag{22}$$

because the averaging over i reduces the orders, for example

$$\frac{1}{n}\sum_{i=1}^n \frac{1}{T}\sum_{t=1}^T \begin{pmatrix} 1 \\ X_{it} \\ h_{0t} \end{pmatrix} \mathrm{sign}\,(\varepsilon_{it}) = O_p(T^{-1/2} n^{-1/2}). \tag{23}$$

The argument extends to the more general specification considered in the text.

Appendix E: Robustness

Alternative measures of market quality

Measuring market quality is inherently difficult, and there is an ongoing debate on what constitutes a good measure of market quality. In view of this controversy, this section investigates the robustness of the main results in the main paper to a variety of alternative measures of market quality. The particular measures we consider are total (Parkinson) volatility, idiosyncratic volatility, within day and overnight volatility, efficiency, and Amihud illiquidity.

Market quality measures

Volatility. In the main paper, total volatility is measured by the Rogers-Satchell estimator. An alternative measure is due to Parkinson (2002).[5] The Parkinson estimator of total volatility

[5] We also measured total volatility by the simple range estimator $V_{it_j} = \frac{P^H_{it_j} - P^L_{it_j}}{P^L_{it_j}}$. The results for this estimator are very similar to the Parkinson estimator and are available upon request.

can be computed as

$$V^P_{it_j} = \frac{1}{4\ln 2}\left(\ln P^H_{it_j} - \ln P^L_{it_j}\right)^2 \tag{24}$$

As shown in Figure 1, the Parkinson volatility estimator is highly correlated with the Rogers-Satchell estimator.

We also decompose volatility into overnight volatility and intraday volatility that we compute as

$$V^{day}_{it_j} = (\ln P^C_{it_j} - \ln P^O_{it_j})^2 \tag{25}$$

$$V^{night}_{it_j} = (\ln P^O_{it_j} - \ln P^C_{it-1_j})^2 \tag{26}$$

Some have argued that HFT activity and the associated market fragmentation leads to higher volatility through the endogenous trading risk process, (Foresight, 2012). Therefore, we also obtained measures of overnight volatility that reflect changes in prices that occur between the closing auction and the opening auction and are therefore not subject to the influence of the continuous trading process. Unfortunately, we can't completely separate out the auction component and the continuous trading component, which would also be of interest. Figure 2 reports the time series of the cross-sectional quantiles of (the log of) overnight and within day volatility, as well as their ratio. The two series move quite closely together. There is an increase during the early part of the series followed by a decrease later, as with total volatility. The ratio of the two series shows no discernible trend at any quantile over this period. It seems that volatility increases and decreases but in no sense has become concentrated intraday relative to overnight.

In addition, we computed a measure of idiosyncratic volatility. In principle, idiosyncratic risk is diversifiable and should not be rewarded in terms of expected returns. We consider whether the effects of fragmentation take place on volatility through the common or idiosyncratic part. If it is on the idiosyncratic component of returns then it should have less impact on diversified investors, i.e., big funds and institutions. Idiosyncratic volatility is calculated as the squared residuals from a regression of individual close-to-close returns on index close-to-close returns. Common volatility is then obtained as the square of the slope coefficient multiplied by the variance of the index return. Cross-sectional quantiles of idiosyncratic and common volatility are shown in Figure 3. The sharp increase in volatility during the financial crisis is more pronounced for the common component.

Liquidity. While in the main paper, liquidity is measured by the bid-ask spread, this appendix considers a measures of liquidity based on daily transaction data. In particular, we use the Amihud (2002) measure that is defined as

$$IL_{it_j} = \frac{|R_{it_j}|}{Vol_{it_j}}, \tag{27}$$

where Vol_{it_j} is the daily turnover, and R_{it_j} are daily close to close returns. Goyenko, Holden, and Trzcinka (2009) argue that the Amihud measure provides a good proxy for the price impact. Figure 4 compared the cross-sectional quantiles of the Amihud measure and bid-ask spreads. The two measures seem to move quite closely together and share a similar trajectory with volatility measures. Towards the end of the sample there does seem to be a narrowing of the cross sectional distribution of bid ask spreads.

Efficiency. A market that is grossly "inefficient" would be indicative of poor market quality. Hendershott (2011) gives a discussion of market efficiency and how it can be interpreted in a high frequency world. We shall take a rather simple approach and base our measure of inefficiency/predictability on just the daily closing price series (weak form) and confine our attention to linear methods. In this world, efficiency or lack thereof, can be measured by the degree of autocorrelation in the stock return series. We compute an estimate of the weekly lag one autocorrelation denoted by $\rho_{it}(k) = \mathrm{corr}(R_{it_j}, R_{it_{j-k}})$, $k = 1, 2$, where R_{t_j} denotes the close to close return for stock i on day j within week t; the variance and covariance are computed with daily data within week t. Under the efficient markets hypothesis this quantity should be zero, but in practice this quantity is different from zero and sometimes statistically significantly different from zero. Since the series is computed from at most five observations it is quite noisy, we use the small sample adjustment from Campbell, Lo and MacKinlay (2012, eq. 2.4.13)

$$\widehat{\rho}_{it}^{A} = \widehat{\rho}_{it} + \frac{1}{N_{it} - 1}[1 - \widehat{\rho}_{it}^{2}], \tag{28}$$

where $\widehat{\rho}_{it}$ is the sample autocorrelation based on $N_{it} \leq 5$ daily observations. In this case, $\widehat{\rho}_{it}^{A}$ is an approximately unbiased estimator of weekly efficiency. Figure 5 reports cross-sectional quantiles of our efficiency measure. The median inefficiency is around 0.3 quite high.[6] The variation of the efficiency measures over time does not suggest that the efficiency of daily stock returns either improves or worsens over this time period.

Results for alternative measures of market quality

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 (Tables 1-2). 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.

Turning to the effect of fragmentation on the variability of market quality (Tables 3-4), we find that dark trading increases the variability of total (Parkinson) volatility, which is consistent with our main results in the main paper. We also document that a higher level of overall fragmentation reduces the variability of Amihud illiquidity.

[6] Note that when $\widehat{\rho}_{it} = 0$, $\widehat{\rho}_{it}^{A} = 0.25$ because $N_{it} = 5$ most of the time. Therefore, the bias adjusted level is quite high.

FTSE 100 and FTSE 250 subsamples

In the main paper, we only report results for a pooled sample of the FTSE 100 and 250 firms. In this appendix, we complement our main results by splitting the sample into FTSE 100 and FTSE 250 stocks. The FTSE 100 index is composed of the 100 largest firms listed on the LSE according to market capitalization, while the FTSE 250 index comprises the "mid-cap" stocks.

When comparing the effect of market fragmentation on market quality for FTSE 100 and FTSE 250 firms, interesting differences emerge: The effects of overall fragmentation on temporary volatility and global volume can be attributed to FTSE 100 firms (Tables 5-6). The negative effect of dark trading on volatility is only observed for FTSE 250 firms (Tables 7-8). 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. Inspecting the effects on the volatility of market quality, overall fragmentation reduces the variability of LSE trading volume only for FTSE 250 firms, while dark trading increases the variability of LSE volumes for FTSE 100 firms (Tables 9-12).

Methods used in Related Research

This subsection relates the econometric methods used to produce our main results to methods used elsewhere in the literature. Most authors use panel data specifications that are similar to the fixed effects and difference-in-difference estimators discussed above. Some use two stage least squares to instrument the covariate of interest (fragmentation or the related quantity, High Frequency Trading (HFT) activity). They do not however instrument other included covariates, which are just as likely to be jointly determined along with the outcome variable. Specifically, some include volume and volatility as exogenous covariates in equations for liquidity or execution cost, see below. In our case, both volume and volatility enter into their own regression equations and should be considered "as endogenous as" fragmentation and liquidity.

De Jong et al. (2011) considered a specification of the form

$$Y_{it} = \alpha_i + \gamma_{q(t)} + \beta_1 X_{it} + \beta_2 X_{it}^2 + \beta_3^{\intercal} Z_{it} + \varepsilon_{it}, \tag{29}$$

where Z contained: volatility, price level, market capitalization, volume, number of electronic messages, and the percentage of trading in the darkside. They allow only quarterly time dummies in their specification perhaps because they have more information in the time series dimension and so allowing different dummy variables for each time point would reduce the degrees of freedom in their method. They assume homogeneous coefficients on the covariates and do not investigate heterogeneity of effect in any way. Their sample was 52 firms and 1022 trading days from 2006-2009.

Gresse (2011) considered the following two equation specification

$$\begin{aligned} Y_{it} &= \alpha_i + \beta_1 X_{it} + \beta_2^{\intercal} Z_{it} + \varepsilon_{it} \\ X_{it} &= a + b\overline{MV}_i + c^{\intercal} W_{it} + \eta_{it} \end{aligned} \tag{30}$$

where Z included: volatility, price level, volume, and market value, and W included trade size and the number of markets quoting the stock. She aggregated the (high frequency) data to the monthly level for the panel regressions. The method involved two stage least squares where predicted X was used in the Y equation. The sample was 140 non-financial equities from the FTSE100, CAC40 and SBF120 for three months: January, June, and September 2009.

Zhang (2010) considered panel regressions of the form

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 X_{it} + \beta_3^{\intercal} Z_{it} + \varepsilon_{it}, \tag{31}$$

where the cross-sectional dimension was large (around 5000 stocks) and the time series dimension was low frequency (quarterly observations from 1995Q1-2009Q2). His outcome variable was volatility and X was "High Frequency Trading Activity" (measured as some residual calculated from stock turnover and institutional holdings) and Z included: price level, market value, and a number of accounting variables. For some reason he winsorized all variables at 1% and 99%, which at least bears out the relevance of robust methods.

Brogaard et al. (2013) considered a specification of the form

$$\begin{aligned} Y_{it} &= \alpha_i + \gamma_i t + \beta_1 X_{it} + \beta_3 Z_{it} + w d_t + \varepsilon_{it} \\ X_{it} &= a_i + b_i t + c L_t + e Z_{it} + \eta_{it} \end{aligned} \tag{32}$$

where X_{it} was HFT percentage, d_t was a dummy variable for the short sale ban put into place after the Lehman collapse, L_t was a measure of latency and Z_{it} was volume. The panel regressions were estimated with seven portfolios ($i = 1, \ldots, 7$) formed according to market value and the estimation was done in four event windows (separately and combined) that are defined by latency upgrades of the LSE. The method involved two stage least squares where predicted X was used in the Y equation.

O'Hara and Ye (2009) used the Davies and Kim (2007) matching methodology. Specifically, they chose every tenth stock in their dataset and matched it with a stock that was most similar in terms of a distance based on market capitalization and price level. They put the higher fragmentation stock into bucket A and the lower fragmentation stock into bucket B. Then, they tested for the difference in the mean level of market quality of stocks in bucket A versus stocks in bucket B using a Wilcoxon nonparametric test. In principle, the underlying model is nonparametric allowing different functional response of the market quality of "fragmented stocks" to observed covariates from the functional response of the market quality of "consolidated stocks" to observed covariates. The parameter of interest is the average difference of market quality between the two groups. Their data was high frequency from the first two quarters of 2008.

We re-estimate our results using a heterogeneous panel data model without common factors. This model can be obtained as a special case of our econometric model 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 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). As reported in Table 13, 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 high frequency trading are omitted that are likely to affect both market quality and fragmentation.

Stochastic Dominance

Finally, we investigated if the distribution of market quality under competition stochastically dominates its distribution in a monopolistic market using the method in Linton et al., 2006). If market quality is measures by bid-ask spreads, we find evidence of second order stochastic dominance of competition over monopoly, and vice versa for volatility. However, this evidence is only indicative as we did not formally obtain critical values for the test statistic.

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Table 1: The effect of fragmentation on market quality for alternative measures of market quality

	Total (Parkinson) volatility	Idiosync. volatility	Daily volatility	Overnight volatility	Efficiency	Illiquidity
Constant	-7.713	-6.987	-5.507	-14.926	0.562	-13.652
	(-8.817)	(-4.855)	(-3.025)	(-10.13)	(2.738)	(-14.019)
Fragmentation	0.208	0.416	-0.11	-1.916	-0.025	-0.524
	(0.383)	(0.518)	(-0.134)	(-1.919)	(-0.23)	(-1.112)
Fragmentation sq.	-0.534	-0.988	-0.368	1.1	0.056	1.341
	(-1.269)	(-1.446)	(-0.55)	(1.356)	(0.579)	(3.315)
Market cap.	-0.499	-0.48	-0.591	-0.48	-0.039	-0.322
	(-6.936)	(-3.694)	(-5.561)	(-4.238)	(-2.539)	(-4.528)
Lagged index return	0.13	-0.236	-0.303	-0.048	0.037	0.415
	(1.094)	(-1.042)	(-1.293)	(-0.226)	(1.2)	(3.381)
VIX	1.126	1.022	1.153	1.845	-0.018	0.556
	(39.602)	(19.726)	(20.79)	(28.379)	(-2.507)	(19.476)
Christmas and New Year	-0.267	-0.976	-0.135	0.166	0.016	0.588
	(-12.004)	(-19.751)	(-3.704)	(4.78)	(3.157)	(19.262)
Fragmentation (avg.)	-1.991	-2.514	-2.777	-1.57	0.058	-1.026
	(-10.776)	(-6.743)	(-8.061)	(-4.449)	(1.492)	(-4.086)
Market cap. (avg.)	-0.004	0.174	0.227	0.607	-0.044	-0.033
	(-0.062)	(1.139)	(1.758)	(4.329)	(-1.79)	(-0.465)
Marginal effect	-0.349	-0.615	-0.495	-0.768	0.033	0.875
	(-2.634)	(-3.146)	(-2.478)	(-3.43)	(1.303)	(8.422)
$\Delta_{Frag.}$	-0.238	-0.408	-0.418	-0.998	0.021	0.595
	(-1.154)	(-1.457)	(-1.402)	(-2.821)	(0.592)	(3.797)
Adjusted R^2	0.755	0.41	0.419	0.442	0.022	0.866

Notes: Coefficients shown are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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.

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

	Total (Parkinson) volatility	Idiosync. volatility	Daily volatility	Overnight volatility	Efficiency	Illiquidity
Constant	-7.061	-7.039	-3.303	-14.786	0.348	-12.065
	(-8.882)	(-4.277)	(-2.046)	(-9.409)	(1.423)	(-12.319)
Vis. fragmentation	0.263	-1.023	-0.797	0.04	0.019	-0.249
	(0.934)	(-1.878)	(-1.697)	(0.081)	(0.238)	(-0.506)
Vis. fragmentation sq.	-0.815	0.361	0.04	-0.422	-0.011	0.873
	(-2.472)	(0.547)	(0.066)	(-0.672)	(-0.106)	(1.631)
Dark	0.061	-0.237	0.98	-1.033	0.046	-0.752
	(0.264)	(-0.482)	(1.877)	(-2.467)	(0.59)	(-3.023)
Dark sq.	-0.202	0.367	-1.398	1.125	-0.031	-0.096
	(-0.858)	(0.757)	(-2.749)	(2.555)	(-0.384)	(-0.397)
Market cap.	-0.405	-0.441	-0.497	-0.3	-0.04	-0.217
	(-5.698)	(-3.066)	(-4.329)	(-2.447)	(-2.228)	(-2.989)
Lagged index return	0.13	-0.245	-0.302	-0.228	0.075	0.111
	(1.273)	(-1.149)	(-1.604)	(-1.101)	(2.285)	(0.931)
VIX	1.036	1.007	0.93	1.704	-0.011	0.474
	(32.802)	(15.204)	(15.412)	(26.517)	(-1.169)	(13.207)
Christmas and New Year	-0.407	-1.049	-0.404	-0.073	0.017	0.551
	(-17.035)	(-19.138)	(-9.463)	(-1.791)	(2.974)	(16.647)
Vis. fragmentation (avg.)	-0.84	-1.233	-0.039	-0.279	-0.062	0.712
	(-4.805)	(-4.197)	(-0.12)	(-0.838)	(-1.385)	(3.377)
Dark (avg.)	-1.742	0.088	-2.991	-3.004	0.119	-0.049
	(-11.51)	(0.279)	(-11.123)	(-10.812)	(2.685)	(-0.293)
Market cap. (avg.)	-0.133	0.062	-0.066	0.696	-0.06	-0.023
	(-1.642)	(0.393)	(-0.51)	(5.298)	(-2.125)	(-0.268)
Marg. effect (Vis. frag)	-0.313	-0.768	-0.769	-0.258	0.011	0.368
	(-2.99)	(-4.004)	(-4.029)	(-1.23)	(0.394)	(2.058)
Marg. effect (Dark)	-0.124	0.1	-0.303	0	0.018	-0.84
	(-1.891)	(0.585)	(-1.991)	(0.004)	(0.746)	(-9.526)
$\Delta_{Vis.frag.}$	-0.306	-0.771	-0.769	-0.255	0.011	0.361
	(-2.899)	(-3.991)	(-4.029)	(-1.211)	(0.396)	(1.99)
Δ_{Dark}	-0.14	0.129	-0.417	0.092	0.015	-0.848
	(-2.111)	(0.758)	(-2.804)	(0.721)	(0.62)	(-9.679)
Adjusted R^2	0.773	0.417	0.429	0.455	0.031	0.871

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{X})$ and $L = \min(\text{X})$, for $X = \{\text{Vis. frag, Dark}\}$ with $\max(\text{Vis. frag}) = 0.698, \min(\text{Vis. frag}) = 0, \max(\text{Dark}) = 1, \min(\text{Dark}) = 0$. 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.

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

	Total (Parkinson) volatility	Idiosync. volatility	Daily volatility	Overnight volatility	Efficiency	Illiquidity
Constant	-0.091	1.119	-0.38	-1.47	0.097	0.949
	(-0.366)	(0.871)	(-0.421)	(-1.503)	(3.753)	(2.679)
Fragmentation	0.015	-0.234	-0.671	-0.004	-0.031	-0.48
	(0.154)	(-0.418)	(-1.413)	(-0.007)	(-2.057)	(-2.377)
Fragmentation sq.	-0.015	0.178	0.708	0.04	0.031	0.404
	(-0.158)	(0.343)	(1.681)	(0.08)	(2.391)	(2.251)
Market cap.	-0.008	-0.152	-0.001	0.088	-0.003	-0.023
	(-0.366)	(-1.663)	(-0.018)	(1.052)	(-1.506)	(-0.915)
Lagged index return	0.03	0.249	0.129	0.091	-0.012	0.023
	(0.833)	(1.662)	(0.894)	(0.653)	(-3.349)	(0.474)
VIX	0.014	-0.069	0.014	0.067	-0.003	-0.039
	(1.336)	(-1.457)	(0.393)	(1.665)	(-2.615)	(-2.412)
Christmas and New Year	0.057	0.914	0.378	0.308	0.007	0.16
	(3.734)	(4.924)	(4.107)	(3.068)	(3.895)	(4.914)
Fragmentation (avg.)	-0.033	-0.2	0.244	-0.159	-0.001	-0.08
	(-0.498)	(-0.691)	(1.12)	(-0.616)	(-0.197)	(-0.283)
Market cap. (avg.)	0.002	-0.154	-0.04	0.064	0.007	-0.07
	(0.092)	(-1.205)	(-0.336)	(0.622)	(2.255)	(-2.154)
Marginal effect	0	-0.048	0.068	0.038	0.001	-0.058
	(-0.003)	(-0.4)	(0.59)	(0.225)	(0.172)	(-1.175)
$\Delta_{Frag.}$	0.003	-0.085	-0.08	0.029	-0.006	-0.143
	(0.095)	(-0.516)	(-0.509)	(0.139)	(-1.034)	(-2.125)
Adjusted R^2	0.002	-0.04	-0.084	-0.068	-0.088	-0.004

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta} + \widehat{\gamma}(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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.

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

	Total (Parkinson) volatility	Idiosync. volatility	Daily volatility	Overnight volatility	Efficiency	Illiquidity
Constant	-0.356	2.445	0.863	-2.094	0.089	0.547
	(-1.383)	(1.88)	(0.834)	(-2.168)	(2.686)	(1.54)
Vis. fragmentation	-0.165	-1.724	-2.016	0.268	0.005	-0.379
	(-1.374)	(-1.321)	(-2.447)	(0.747)	(0.482)	(-3.733)
Vis. fragmentation sq.	0.17	1.433	2.382	-0.299	0.001	0.591
	(1.219)	(1.213)	(2.985)	(-0.598)	(0.054)	(3.535)
Dark	0.025	-0.396	-0.65	-0.838	-0.017	-0.243
	(0.362)	(-0.963)	(-1.683)	(-2.827)	(-2.129)	(-2.465)
Dark sq.	0.056	0.544	0.711	0.927	0.022	0.257
	(0.775)	(1.356)	(1.825)	(2.757)	(2.453)	(2.671)
Market cap.	-0.005	-0.104	-0.026	-0.083	0	0.007
	(-0.253)	(-1.086)	(-0.328)	(-0.949)	(-0.074)	(0.274)
Lagged index return	0.007	0.104	0.082	0.252	-0.017	-0.02
	(0.195)	(0.632)	(0.596)	(1.812)	(-3.734)	(-0.464)
VIX	0.025	-0.112	-0.005	0.097	-0.001	-0.013
	(2.187)	(-2.361)	(-0.105)	(2.282)	(-0.97)	(-0.926)
Christmas and New Year	0.038	0.508	0.237	0.156	0.003	0.136
	(3.89)	(5.638)	(3.023)	(4.157)	(2.398)	(4.945)
Vis. fragmentation (avg.)	0.143	0.497	0.447	-0.429	-0.006	0.037
	(2.163)	(1.589)	(2.137)	(-1.981)	(-1.085)	(0.555)
Dark (avg.)	-0.005	0.106	0.087	0.373	0.008	0.177
	(-0.096)	(0.445)	(0.467)	(2.026)	(1.5)	(2.811)
Market cap. (avg.)	0.044	-0.166	-0.06	0.117	0.01	-0.029
	(1.41)	(-1.231)	(-0.496)	(1.172)	(2.54)	(-0.967)
Marg. effect (Vis. frag)	-0.045	-0.711	-0.333	0.057	0.005	0.039
	(-1.009)	(-1.394)	(-0.984)	(0.376)	(1.361)	(0.605)
Marg. effect (Dark)	0.076	0.104	0.003	0.013	0.003	-0.008
	(3.447)	(0.784)	(0.025)	(0.149)	(1.046)	(-0.256)
$\Delta_{Vis.frag.}$	-0.047	-0.724	-0.354	0.059	0.005	0.033
	(-1.033)	(-1.394)	(-1.031)	(0.395)	(1.355)	(0.531)
Δ_{Dark}	0.081	0.148	0.061	0.088	0.005	0.013
	(3.457)	(1.129)	(0.507)	(0.898)	(1.588)	(0.452)
Adjusted R^2	-0.026	-0.027	-0.074	-0.064	-0.075	-0.037

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta} + \widehat{\gamma}(H + L)$ and evaluated at $H = \max(\text{X})$ and $L = \min(\text{X})$, for $X = \{\text{Vis. frag, Dark}\}$ with $\max(\text{Vis. frag}) = 0.0698, \min(\text{Vis. frag}) = 0, \max(\text{Dark}) = 1, \min(\text{Dark}) = 0$. 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.

Table 5: The effect of fragmentation on market quality for FTSE 100 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-2.74	-8.643	9.955	1.286	3.546
	(-2.296)	(-10.29)	(5.771)	(1.032)	(3.332)
Fragmentation	1.141	-2.935	-0.02	1.711	2.197
	(1.181)	(-3.147)	(-0.035)	(3.076)	(4.326)
Fragmentation sq.	-1.216	2.365	0.184	-1.232	-3.115
	(-1.616)	(3.252)	(0.38)	(-2.457)	(-7.203)
Market cap.	-0.44	-0.38	-0.335	-0.533	-0.52
	(-3.857)	(-4.993)	(-2.952)	(-6.469)	(-6.71)
Lagged index return	1.675	1.988	-0.099	0.9	1.153
	(7.51)	(9.466)	(-0.949)	(6.024)	(8.29)
VIX	1.102	0.79	-0.239	0.283	0.217
	(21.961)	(19.127)	(-4.642)	(6.563)	(5.529)
Christmas and New Year	-0.352	-0.33	0.387	-1.332	-1.346
	(-10.879)	(-11.689)	(11.849)	(-50.646)	(-57.374)
Fragmentation (avg.)	-0.971	1.233	-0.169	0.913	0.364
	(-2.458)	(3.49)	(-0.909)	(1.578)	(0.968)
Market cap. (avg.)	-2.01	-0.731	-1.386	-0.257	-0.722
	(-7.536)	(-3.733)	(-4.634)	(-1.312)	(-4.294)
Marginal effect	-0.501	0.26	0.229	0.046	-2.012
	(-2.403)	(1.36)	(1.417)	(0.269)	(-15.503)
$\Delta_{Frag.}$	0.087	-0.883	0.14	0.642	-0.506
	(0.245)	(-2.627)	(0.752)	(4.153)	(-3.223)
Adjusted R^2	0.777	0.173	0.605	0.801	0.831

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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. .

Table 6: The effect of fragmentation on market quality for FTSE 250 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-8.503	-10.327	3.584	2.195	2.18
	(-8.268)	(-13.225)	(3.743)	(2.639)	(2.336)
Fragmentation	-0.193	-0.16	0.072	-0.658	-0.276
	(-0.282)	(-0.316)	(0.258)	(-1.876)	(-0.837)
Fragmentation sq.	-0.162	0.012	-0.164	0.707	-1.091
	(-0.297)	(0.029)	(-0.651)	(2.012)	(-3.298)
Market cap.	-0.437	-0.293	-0.326	-0.058	-0.084
	(-4.379)	(-4.599)	(-3.772)	(-0.682)	(-0.979)
Lagged index return	0.297	0.837	-0.921	-0.359	-0.385
	(1.965)	(6.876)	(-6.442)	(-2.043)	(-2.118)
VIX	1.042	0.789	0.095	0.264	0.295
	(26.254)	(25.717)	(2.745)	(7.134)	(7.461)
Christmas and New Year	-0.182	-0.149	0.395	-1.144	-1.134
	(-6.693)	(-6.713)	(17.525)	(-37.005)	(-35.65)
Fragmentation (avg.)	-1.424	0.216	-0.758	-0.273	-0.351
	(-5.659)	(1.345)	(-4.471)	(-0.915)	(-1.224)
Market cap. (avg.)	-0.219	0.438	0.033	0.556	0.571
	(-1.285)	(3.192)	(0.201)	(3.103)	(3.244)
Marginal effect	-0.359	-0.148	-0.096	0.064	-1.392
	(-2.102)	(-1.296)	(-1.258)	(0.635)	(-14.205)
$\Delta_{Frag.}$	-0.328	-0.15	-0.065	-0.069	-1.186
	(-1.301)	(-0.852)	(-0.682)	(-0.635)	(-11.469)
Adjusted R^2	0.713	0.094	0.706	0.738	0.714

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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.

Table 7: The effects of visible fragmentation and dark trading on market quality for FTSE 100 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-2.643	-7.637	8.131	4.08	5.067
	(-1.852)	(-7.171)	(4.587)	(4.744)	(5.14)
Vis. fragmentation	-0.3	-4.244	0.221	-0.87	-0.734
	(-0.445)	(-8.073)	(0.628)	(-2.12)	(-1.825)
Vis. fragmentation sq.	-0.597	4.121	0.001	0.916	-0.679
	(-0.903)	(7.412)	(0.002)	(2.015)	(-1.498)
Dark	-0.003	1.217	0.052	0.98	0.864
	(-0.009)	(3.507)	(0.14)	(3.189)	(2.185)
Dark sq.	0.315	-1.395	-0.015	1.504	0.546
	(0.676)	(-3.213)	(-0.037)	(4.333)	(1.269)
Market cap.	-0.332	-0.29	-0.326	-0.46	-0.47
	(-2.539)	(-3.069)	(-3.094)	(-5.995)	(-5.859)
Lagged index return	1.552	1.598	0.061	1.081	1.052
	(7.909)	(8.597)	(0.638)	(7.074)	(8.273)
VIX	1.031	0.81	-0.174	0.271	0.207
	(22.721)	(23.318)	(-3.981)	(7.556)	(5.648)
Christmas and New Year	-0.398	-0.344	0.43	-1.386	-1.372
	(-11.033)	(-11.343)	(13.148)	(-56.478)	(-54.94)
Vis. fragmentation (avg.)	0.591	1.746	-0.676	0.11	0.408
	(1.488)	(5.073)	(-2.988)	(0.453)	(1.385)
Dark (avg.)	-1.453	-0.154	0.362	-1.111	-1.568
	(-7.065)	(-0.935)	(2.516)	(-7.48)	(-10.632)
Market cap. (avg.)	-1.973	-0.589	-1.356	-0.68	-0.756
	(-7.426)	(-3.022)	(-5.426)	(-3.809)	(-5.124)
Marg. effect (vis. frag)	-0.91	-0.028	0.222	0.068	-1.428
	(-4.674)	(-0.16)	(1.12)	(0.525)	(-10.759)
Marg. effect (dark)	0.234	0.165	0.041	2.114	1.275
	(2.098)	(1.668)	(0.329)	(21.692)	(9.818)
$\Delta_{Vis.frag.}$	-0.715	-1.378	0.222	-0.233	-1.206
	(-2.67)	(-6.945)	(1.585)	(-1.731)	(-9.234)
Δ_{Dark}	0.303	-0.139	0.038	2.442	1.394
	(2.02)	(-1.041)	(0.321)	(23.905)	(11.101)
Adjusted R^2	0.784	0.193	0.617	0.846	0.848

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.0698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. 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.

Table 8: The effects of visible fragmentation and dark trading on market quality for FTSE 250 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-9.696	-11.53	0.588	1.368	3.05
	(-9.159)	(-12.407)	(0.465)	(1.692)	(3.456)
Vis. fragmentation	1.277	0.839	0.565	0.334	0.03
	(3.855)	(3.419)	(2.107)	(1.511)	(0.115)
Vis. fragmentation sq.	-1.969	-1.164	-0.787	-1.035	-1.706
	(-4.665)	(-3.574)	(-2.222)	(-3.561)	(-5.192)
Dark	-0.531	0.032	-0.42	-0.071	-0.073
	(-1.775)	(0.121)	(-1.446)	(-0.275)	(-0.28)
Dark sq.	0.221	-0.325	0.297	1.972	1.312
	(0.879)	(-1.403)	(1.137)	(9.367)	(5.59)
Market cap.	-0.487	-0.371	-0.318	-0.343	-0.311
	(-5.184)	(-5.328)	(-3.531)	(-4.021)	(-3.494)
Lagged index return	-0.166	0.717	-0.999	-0.597	-0.427
	(-1.151)	(5.344)	(-6.243)	(-4.071)	(-2.599)
VIX	1.142	0.886	0.2	0.374	0.286
	(28.397)	(24.714)	(4.458)	(12.267)	(7.619)
Christmas and New Year	-0.27	-0.173	0.466	-1.192	-1.222
	(-8.899)	(-7.128)	(17.456)	(-37.077)	(-34.246)
Vis. fragmentation (avg.)	-1.631	-0.461	-1.245	-0.824	-0.771
	(-8.201)	(-2.762)	(-7.958)	(-5.024)	(-4.02)
Dark (avg.)	-0.669	0.281	0.599	-1.777	-1.992
	(-3.334)	(1.928)	(3.367)	(-11.211)	(-11.218)
Market cap. (avg.)	0.557	0.799	0.48	1.256	0.794
	(3.501)	(6.149)	(2.412)	(7.844)	(4.817)
Marg. effect (vis. frag)	0.031	0.102	0.067	-0.321	-1.05
	(0.223)	(0.98)	(0.654)	(-2.879)	(-9.37)
Marg. effect (dark)	-0.308	-0.295	-0.121	1.916	1.25
	(-4.202)	(-4.625)	(-1.644)	(26.542)	(18.581)
$\Delta_{Vis.frag.}$	-0.097	0.026	0.015	-0.389	-1.161
	(-0.728)	(0.253)	(0.155)	(-3.472)	(-10.722)
Δ_{Dark}	-0.31	-0.292	-0.123	1.899	1.238
	(-4.162)	(-4.519)	(-1.665)	(25.949)	(18.291)
Adjusted R^2	0.735	0.114	0.671	0.831	0.764

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. 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.

Table 9: The effect of fragmentation on the variability of market quality for FTSE 100 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.58	-0.353	0.585	-0.175	-0.122
	(-1.958)	(-1.076)	(1.834)	(-1.324)	(-0.662)
Fragmentation	-0.092	0.211	0.135	0.229	0.174
	(-0.452)	(1.026)	(1.164)	(2.329)	(1.874)
Fragmentation sq.	0.088	-0.188	-0.111	-0.215	-0.142
	(0.463)	(-1.079)	(-1.09)	(-2.532)	(-1.766)
Market cap.	0.043	0.014	-0.027	-0.006	-0.007
	(1.627)	(0.588)	(-0.861)	(-0.442)	(-0.626)
Lagged index return	0.099	-0.052	0.116	0.018	0.037
	(1.386)	(-0.995)	(2.743)	(0.506)	(1.219)
VIX	0.035	0.025	-0.001	-0.002	-0.002
	(2.58)	(2.128)	(-0.086)	(-0.304)	(-0.212)
Christmas and New Year	0.017	0.03	0.052	0.049	0.033
	(1.767)	(2.972)	(4.416)	(5.578)	(4.577)
Fragmentation (avg.)	0.098	0.033	0.144	0.054	-0.025
	(0.815)	(0.3)	(2.31)	(1.748)	(-0.375)
Market cap. (avg.)	-0.073	0.07	-0.15	0.006	-0.01
	(-0.867)	(1.069)	(-3.37)	(0.151)	(-0.253)
Marginal effect	0.027	-0.043	-0.015	-0.06	-0.017
	(0.362)	(-0.685)	(-0.36)	(-2.138)	(-0.621)
$\Delta_{Frag.}$	-0.016	0.048	0.039	0.043	0.051
	(-0.277)	(0.685)	(0.978)	(1.387)	(1.732)
Adjusted R^2	-0.061	-0.07	-0.037	-0.023	-0.022

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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.

Table 10: The effect of fragmentation on the variability of market quality for FTSE 250 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.021	-0.381	0.346	0.607	0.178
	(-0.041)	(-0.682)	(1.485)	(1.204)	(0.53)
Fragmentation	-0.171	-0.225	-0.068	-0.457	-0.412
	(-1.24)	(-1.884)	(-0.745)	(-2.165)	(-2.676)
Fragmentation sq.	0.147	0.21	0.087	0.432	0.333
	(1.168)	(1.833)	(0.926)	(2.409)	(2.475)
Market cap.	-0.043	-0.047	0.004	-0.081	-0.084
	(-1.31)	(-1.685)	(0.196)	(-3.734)	(-4.271)
Lagged index return	-0.035	0.158	0.053	0.026	-0.003
	(-0.401)	(1.676)	(0.958)	(0.331)	(-0.058)
VIX	0.021	-0.014	-0.01	-0.011	-0.004
	(1.154)	(-0.901)	(-0.754)	(-1.019)	(-0.264)
Christmas and New Year	0.08	0.069	0.111	0.115	0.104
	(3.916)	(4.011)	(3.26)	(4.652)	(4.637)
Fragmentation (avg.)	-0.018	-0.053	0.02	-0.196	-0.082
	(-0.162)	(-0.499)	(0.331)	(-1.584)	(-1.061)
Market cap. (avg.)	0.107	-0.056	-0.098	0.015	0.107
	(1.321)	(-0.874)	(-1.539)	(0.241)	(1.841)
Marginal effect	-0.021	-0.01	0.02	-0.015	-0.071
	(-0.589)	(-0.378)	(0.883)	(-0.333)	(-1.787)
$\Delta_{Frag.}$	-0.049	-0.05	0.004	-0.097	-0.134
	(-1.069)	(-1.453)	(0.157)	(-1.383)	(-2.526)
Adjusted R^2	-0.009	-0.011	-0.06	0.048	0.055

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. $\Delta_{Frag.}$ is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(\text{Frag.}) = 0.834$ and $L = \min(\text{Frag.}) = 0$. 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.

Table 11: The effect of visible fragmentation and dark trading on the variability of market quality for FTSE 100 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.879	-0.36	0.663	0.01	0.2
	(-2.133)	(-0.851)	(2.255)	(0.079)	(1.355)
Vis. fragmentation	0.366	-0.209	-0.045	0.264	0.259
	(2.588)	(-0.518)	(-0.474)	(3.244)	(2.709)
Vis. fragmentation sq.	-0.498	0.039	0.047	-0.318	-0.308
	(-2.845)	(0.111)	(0.462)	(-3.699)	(-3.078)
Dark	-0.095	-0.23	-0.046	-0.037	-0.042
	(-0.74)	(-2.136)	(-0.542)	(-0.838)	(-0.909)
Dark sq.	0.252	0.393	0.038	0.057	0.109
	(1.552)	(2.932)	(0.387)	(1.076)	(1.855)
Market cap.	0.012	0.006	0.005	-0.003	0.005
	(0.41)	(0.22)	(0.237)	(-0.284)	(0.381)
Lagged index return	0.069	-0.073	0.095	-0.012	-0.063
	(0.922)	(-1.297)	(1.952)	(-0.51)	(-1.88)
VIX	0.045	0.029	-0.002	-0.009	-0.013
	(2.594)	(1.945)	(-0.192)	(-1.66)	(-2.194)
Christmas and New Year	0.009	0.008	0.044	0.015	0.017
	(0.932)	(0.874)	(3.836)	(3.344)	(2.927)
Vis. fragmentation (avg.)	0.195	0.15	0.073	0.024	0.035
	(2.157)	(1.626)	(1.505)	(0.82)	(0.978)
Dark (avg.)	-0.127	-0.186	0.112	-0.035	-0.056
	(-1.723)	(-3.332)	(2.278)	(-1.632)	(-2.214)
Market cap. (avg.)	0.006	0.115	-0.161	0.016	0.038
	(0.063)	(1.452)	(-3.217)	(0.686)	(1.252)
Marg. effect (Vis. frag)	-0.143	-0.17	0.004	-0.061	-0.056
	(-2.029)	(-1.914)	(0.1)	(-2.795)	(-2.382)
Marg. effect (Dark)	0.095	0.066	-0.017	0.006	0.04
	(2.477)	(2.069)	(-0.644)	(0.53)	(2.616)
$\Delta_{Vis.frag.}$	0.02	-0.182	-0.012	0.043	0.045
	(0.378)	(-1.048)	(-0.331)	(1.56)	(1.403)
Δ_{Dark}	0.15	0.152	-0.009	0.019	0.064
	(2.869)	(3.605)	(-0.305)	(1.225)	(3.137)
Adjusted R^2	-0.049	-0.055	-0.022	-0.012	-0.003

Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. 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.

Table 12: The effect of visible fragmentation and dark trading on the variability of market quality for FTSE 250 firms

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	-0.436	-0.045	0.163	0.294	0.054
	(-1.004)	(-0.101)	(0.412)	(1.316)	(0.185)
Vis. fragmentation	-0.333	-0.28	0.064	-0.126	-0.145
	(-2.897)	(-1.97)	(0.668)	(-1.457)	(-1.377)
Vis. fragmentation sq.	0.379	0.318	-0.013	0.153	0.173
	(2.169)	(1.619)	(-0.107)	(1.275)	(1.192)
Dark	0.046	-0.021	-0.139	-0.183	-0.283
	(0.328)	(-0.169)	(-1.645)	(-2.7)	(-3.58)
Dark sq.	0.029	0.082	0.125	0.149	0.268
	(0.238)	(0.752)	(1.527)	(2.749)	(4.031)
Market cap.	-0.042	-0.02	0.026	-0.053	-0.052
	(-1.359)	(-0.703)	(1.085)	(-3.301)	(-2.272)
Lagged index return	-0.02	0.046	0.004	0.013	0.043
	(-0.206)	(0.64)	(0.067)	(0.321)	(0.631)
VIX	0.041	0.005	-0.007	-0.023	-0.018
	(1.796)	(0.206)	(-0.433)	(-2.483)	(-1.477)
Christmas and New Year	0.053	0.045	0.02	0.042	0.029
	(3.639)	(3.058)	(1.799)	(3.575)	(3.191)
Vis. fragmentation (avg.)	0.143	0.059	-0.039	0.017	-0.003
	(1.624)	(0.994)	(-0.678)	(0.404)	(-0.067)
Dark (avg.)	0.118	0	-0.018	-0.014	0.019
	(1.824)	(-0.003)	(-0.265)	(-0.377)	(0.416)
Market cap. (avg.)	0.119	-0.013	-0.023	0.028	0.026
	(0.968)	(-0.157)	(-0.358)	(0.821)	(0.318)
Marg. effect (Vis. frag)	-0.093	-0.078	0.056	-0.029	-0.036
	(-1.975)	(-1.869)	(1.564)	(-1.342)	(-1.375)
Marg. effect (Dark)	0.076	0.062	-0.013	-0.033	-0.013
	(2.241)	(2.185)	(-0.701)	(-1.77)	(-0.653)
$\Delta_{Vis.frag.}$	-0.068	-0.058	0.055	-0.019	-0.024
	(-1.372)	(-1.431)	(1.608)	(-0.946)	(-1.032)
Δ_{Dark}	0.075	0.061	-0.014	-0.034	-0.015
	(2.203)	(2.135)	(-0.757)	(-1.809)	(-0.755)
Adjusted R^2	-0.011	-0.02	-0.044	0.04	0.015

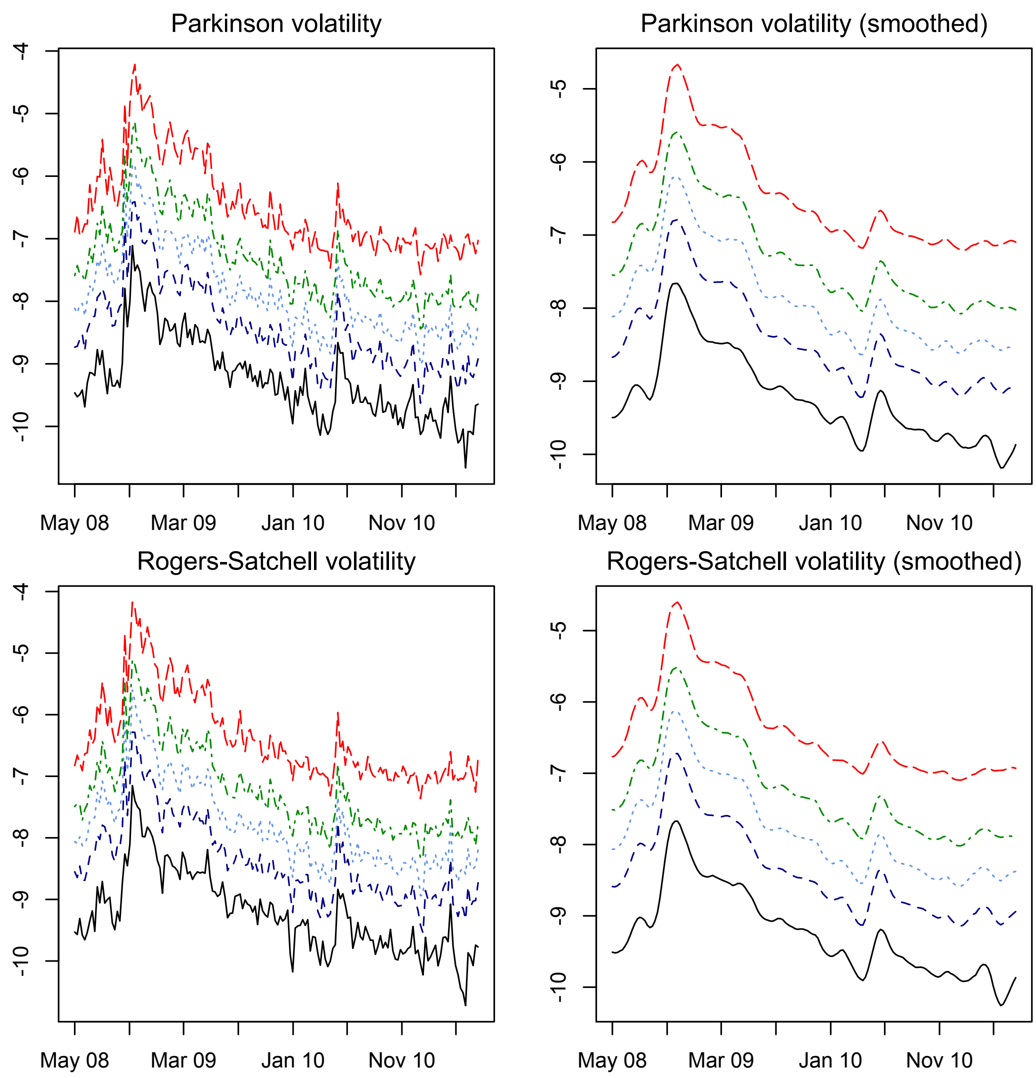
Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. 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.

Table 13: The effect of fragmentation on market quality when common factor are omitted

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
Constant	4.678	2.375	0.01	4.619	4.932
	(9.282)	(11.593)	(0.03)	(15.379)	(15.781)
Fragmentation	2.803	-0.179	0.98	0.176	0.741
	(4.749)	(-0.541)	(3.572)	(0.528)	(2.226)
Fragmentation sq.	-3.896	0.25	-1.235	-0.055	-2.22
	(-7.488)	(0.887)	(-4.929)	(-0.179)	(-7.246)
Market cap.	-1.737	-0.308	-0.901	-0.176	-0.242
	(-27.077)	(-14.912)	(-20.027)	(-4.541)	(-5.87)
Marginal effect	-1.624	0.105	-0.424	0.113	-1.782
	(-13.806)	(1.677)	(-6.188)	(1.19)	(-18.874)
$\Delta_{Frag.}$	-0.448	0.03	-0.051	0.129	-1.111
	(-2.409)	(0.275)	(-0.584)	(1.192)	(-10.003)
Adjusted R^2	0.625	0.015	0.736	0.681	0.648
CSD	0.065	0.051	0.018	0.149	0.154

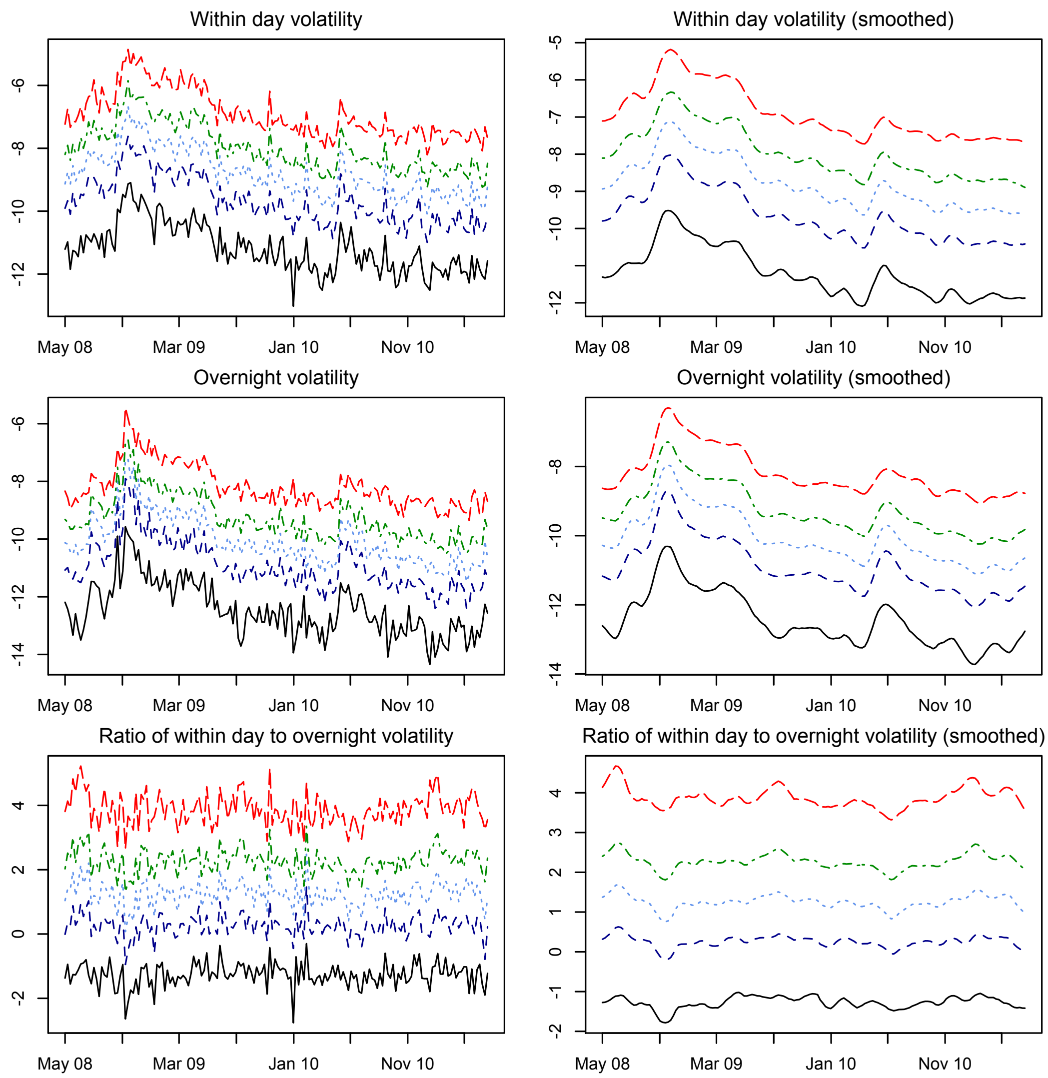
Notes: Coefficients are averages of individual median regression coefficients. t-statistics are shown in parenthesis. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. 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.

Figure 1: Cross-sectional quantiles for Parkinson and Rogers-Satchell volatility



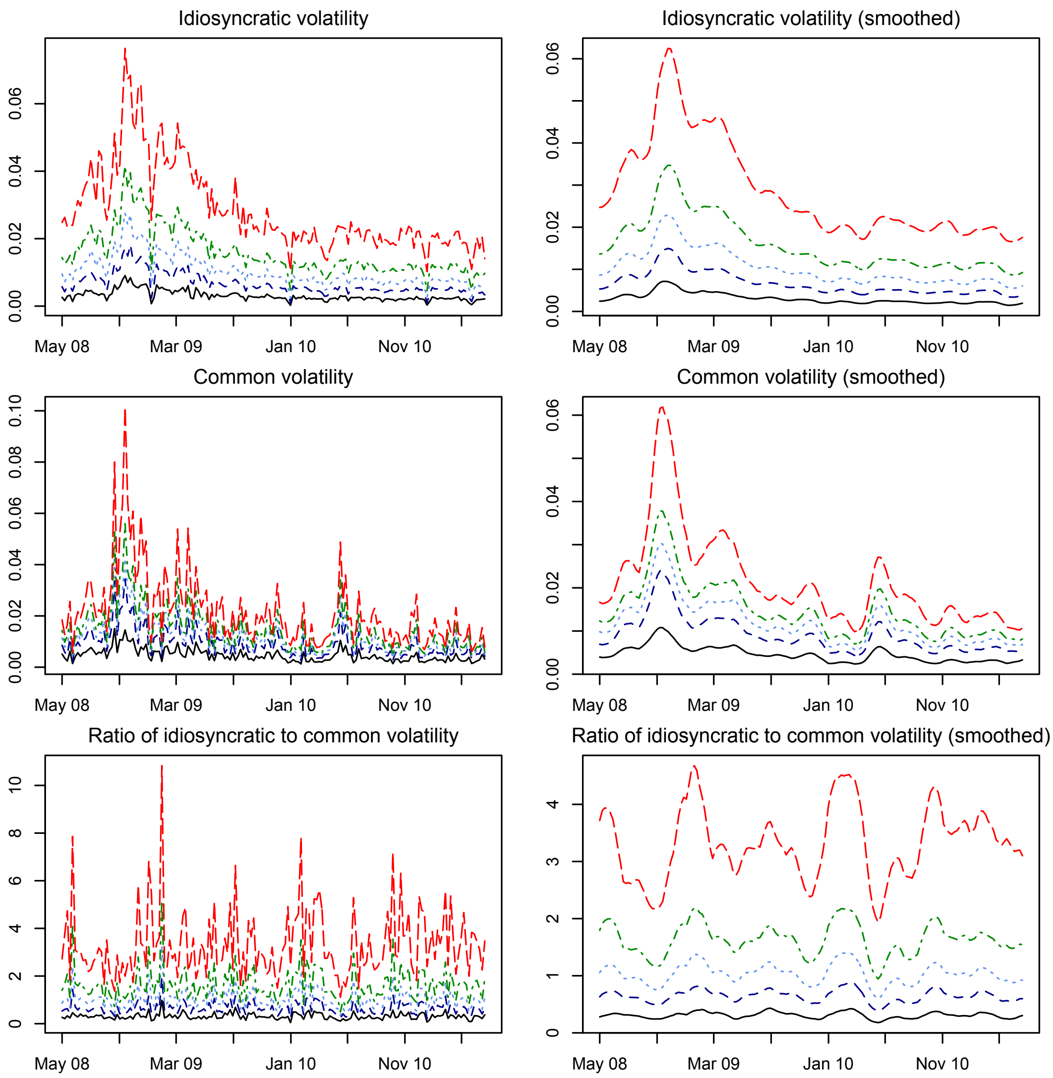
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Volatilities are in logs. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

Figure 2: Cross-sectional quantiles for within day and overnight volatility



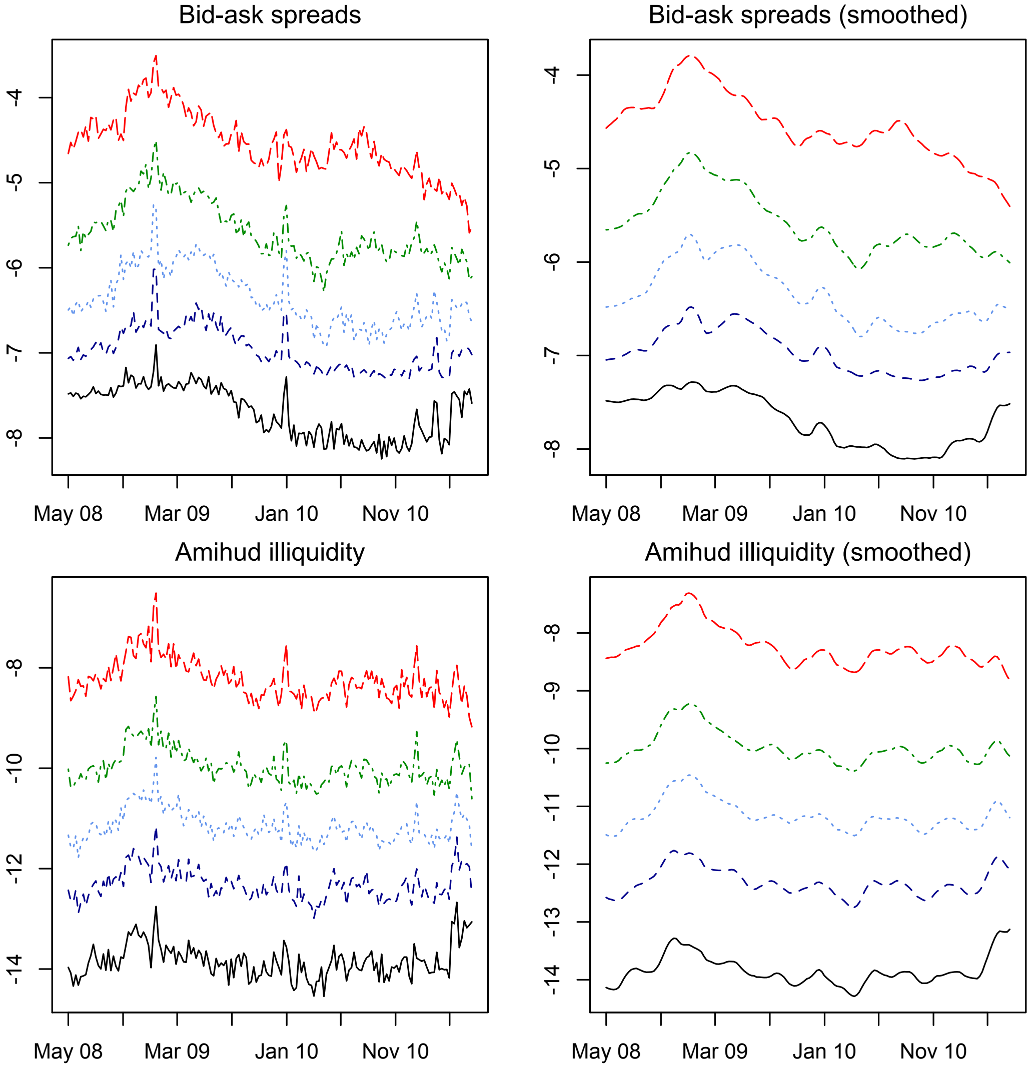
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Within day and overnight volatilities are in logs and the ratio is the difference between the two logged variables. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

Figure 3: Cross-sectional quantiles for idiosyncratic and common volatility



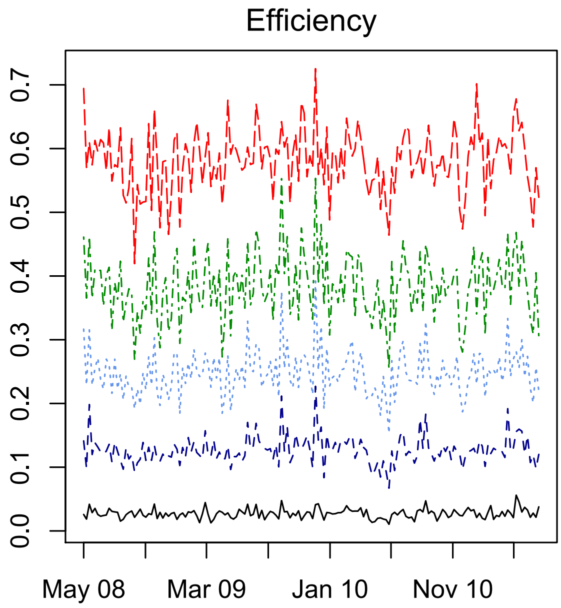
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. We took square roots of idiosyncratic and common volatilities. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

Figure 4: Cross-sectional quantiles for illiquidity measures



Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Bid-ask spreads and Amihud illiquidity are in logs. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

Figure 5: Cross-sectional quantiles for market efficiency measures



Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Efficiency is defined as weekly autocorrelations computed from daily data a small sample correction as in Campbell, Lo and MacKinlay (2012).