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# The effect of fragmentation in trading on market quality in the UK equity market

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**cemmap** working paper CWP42/13

# 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 trading on the quality of the trading outcomes specifically, volatility, liquidity and volume. We use panel regression methods on a weekly dataset following the FTSE350 stocks over the period 2008-2011, which provides a lot of cross-sectional and time series variation in fragmentation. 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 a version of the common correlated effects estimator (Pesaran, 2006). One finding is that volatility is lower in a fragmented market when compared to a monopoly. Trading volume at the London Stock Exchange is lower too, but global trading volume is higher if order flow is fragmented across multiple venues. When separating overall fragmentation into visible fragmentation and dark trading, we find that the decline in LSE volume can be attributed to visible fragmentation, while the increase in global volume is due to dark trading.

**JEL codes:** C23, G28, L10

**Keywords:** Heterogenous panel data, quantile regression, MiFID

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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 specific 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.<sup>1</sup> 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%.<sup>2</sup> 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. In 2007, Euronext merged with NYSE and LSE with Borsa Italiana, and NYSE Euronext is about to be taken over by ICE at the time of writing. In 2011, Chi-X was acquired by BATS.

There are reasons to think that the observed consolidation fosters market quality. Security exchanges perhaps qualify as natural monopolies: consolidated exchanges enjoy economies of scale because a security exchange operating in a monopolistic market has lower costs compared to the combined costs of a competitive market place. In addition, a single, consolidated exchange market creates network externalities: the larger the market, the more trading opportunities exist, which attracts even more traders.

On the other hand, there are theoretical explanations for why competition between trading venues can improve market quality. Higher competition generally promotes the adoption of technological innovation, improves efficiency and reduces the fees that have to be paid by investors.<sup>3</sup> Furthermore, traders that use Smart Order Routing Technologies can still benefit from network externalities in a fragmented market place.

In view of the ambiguous theoretical predictions, whether the net effect of fragmentation on “market quality” is negative or positive is an empirical question. There is a growing literature that has attempted to answer this question (e.g. O’Hara and Ye, 2011, Gresse, 2011, De Jong et. al., 2011). We contribute to this literature by investigating the effect of market fragmentation on measures of market quality such as volatility, liquidity, and trading volume in the UK. Our analysis distinguishes between the effect on average market quality on the one hand and on

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<sup>1</sup>The different pillars of MiFID are summarized in Appendix B.

<sup>2</sup>[http://www.batstrading.co.uk/market\\_data/market\\_share/index/](http://www.batstrading.co.uk/market_data/market_share/index/), assessed on August 24, 2013

<sup>3</sup>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. Appendix C). Chesini (2012, 2013) reports a reduction in explicit trading fees on exchanges around Europe due to the competition between them for order flow.

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 frequent market crashes and volatile episodes.

We employ a novel dataset that allows us to calculate weekly measures for overall fragmentation, visible fragmentation and dark trading 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) model for heterogeneous panels. That model is suitable for our dataset because it can account for multiple common shocks to the market such as were observed during the global financial crisis. It also allows for certain types of endogeneity which could for example represent the activity of high frequency traders whose activity has generated so much scrutiny.<sup>4</sup> Compared to Pesaran (2006), we allow for a quadratic effect of fragmentation on market quality. This functional form is justified by the data and has been used before in this literature (De Jong et. al., 2011). Importantly, it does not impose monotonicity of the effect of interest. We employ quantile estimators 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 also estimate a model for the squared residuals that has a similar structure and which allows us to address the question of whether market quality has become more variable in response to increases in competition. We provide a justification of these econometric extensions in the appendix D.

Our main findings are that most market quality measures improve under a competitive fragmented market when compared to a monopoly. Volatility and in particular temporary volatility are lower. Trading volume at the LSE is lower, too, but global volume is higher if order flows are fragmented. When separating visible fragmentation from dark trading, we find that the increase in global volume can be attributed to dark trading, while the decline in LSE volume is due to visible fragmentation, that is, competition between trading venues with a publicly visible order book. We find no evidence that liquidity and efficiency are worse in a fragmented market.

Turning to the effect of fragmentation on the variation in market quality, our estimates suggest that a market with a high degree of visible fragmentation is associated with less variability in volatility but the opposite is observed for dark trading. While average effects are useful to summarize the information in large panels, we also illustrate that there is a large amount of heterogeneity between individual firms that cannot be well explained by observable characteristics.

In addition to investigating the difference in market quality of a competitive market compared to a monopoly, we also assess the transition between these extremes. We find that the transition between monopoly and competition is non-monotonic in particular for overall

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<sup>4</sup>See the UK Government Office for Science report, henceforth, (Foresight, 2012), and associated reports available at the web site <http://www.bis.gov.uk/foresight/our-work/projects/published-projects/computer-trading/reports-and-publications>

and visible fragmentation while there is less evidence for a non-monotonic relationship for dark trading.

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. 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.<sup>5</sup>

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.<sup>6</sup> The literature has assessed this question using data from different countries and time periods and has applied different empirical methods. The remainder of this section summarizes some theoretical predictions and existing empirical evidence for both Europe and the US.<sup>7</sup>

**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. For example, in a monopolistic market there is no need to invest in expensive technology upgrades. 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.

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<sup>5</sup>A trade-through occurs if an order is executed at a price that is higher than the best price quoted in the market.

<sup>6</sup>See Foresight (2012) for a review of the literature on competition and market quality.

<sup>7</sup>In Appendix E, we survey the methodology used in related research and relate them to our econometric framework.

On the other hand, there are reasons why competition between trading venues can improve market quality. Higher competition generally promotes technological innovation, improves efficiency and reduces the fees that have to be paid by investors. Biais et. al. (2000) propose a model for imperfect competition in financial markets that is consistent with the observation that traders earn positive profits and that the number of traders is finite. Their model also assumes that traders have private information on the value of financial assets, giving rise to 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. She finds that increased competition between trading venues creates more liquidity – measured by effective and realized spreads and best-quote depth – in a sample of stocks listed on the LSE and Euronext exchanges in Amsterdam, Paris and Brussels.

De Jong et. al. (2011) study the effect of fragmentation on market quality in a sample of Dutch stocks from the AEX index. 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. Dark trading is found to have a negative effect on liquidity. In a sample of Swiss data, Kohler and von Wyss (2012) provide evidence for lower spreads and higher depth in a more fragmented market. Studying UK data, Linton (2012) finds that fragmentation reduces volatility using data for the FTSE 100 and FTSE250 indices for the period from 2008 to 2011, although the effect is not statistically significant. 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.

Using data from different European countries, Gentile and Fioravanti (2011) find that fragmentation does not harm liquidity, but reduces price information efficiency. In addition, price discovery migrates from regulated exchanges to MTF's in some cases. 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. The NYSE gained a market share of about 15% after starting to trade ETFs. Prior to the entry of the NYSE, the American Stock Exchange (AMEX), 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) and Kohler and von Wyss (2012) 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 (2011) argued that the impact of the Flash Crash across stocks is systematically related to prior market fragmentation, suggesting 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. De Jong et al. (2011) and 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 both mean regression and 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.



Although O’Hara and Ye (2011) provide evidence that the effect of fragmentation on market quality varies significantly across stocks, many previous studies (e.g. Gresse, 2011, De Jong et al., 2011) assume that the effect of fragmentation on market quality is homogeneous across firms. In contrast, the heterogenous panel data methods we apply in this paper are suitable to account for the heterogeneity that is apparently present in the data.

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. During our sample period, many changes occurred at the market level and at the individual stock level, for example the rank order of stock by stock fragmentation changed substantially.

### 3 Data and Measurement Issues

This section introduces our dataset and discusses how we measure fragmentation and market quality. Our dataset includes the individual FTSE 100 and FTSE 250 firms. 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. Data on market quality and fragmentation are at a weekly frequency and cover the period from May 2008 to June 2011.

#### 3.1 Fragmentation and Dark Trading

Weekly data on the volume of the individual FTSE 100 and FTSE 250 firms traded on each equity venue was supplied to us by Fidessa.<sup>8</sup> For venue  $j = 1, \dots, J$ , denote by  $w_j$  the market share (according to the number of shares traded) of that venue. We measure fragmentation by 1-Herfindahl index, where the Herfindahl index is calculated as  $\sum w_j^2$ .

In May 2008, equity trading in the UK was consolidated at the LSE as reflected by a fragmentation level of 0.4 or a Herfindahl index of 0.6 (left panel of 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 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.

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<sup>8</sup>In the appendix we give a full list of the trading venues in our sample.

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”).<sup>9</sup> We use this information in our analysis to distinguish between fragmentation in visible order books (right panel in Figure 1) and the amount of dark trading where we define dark trading as the market share of OTC, SI and regulated dark pools. Figure 2 shows the evolution of volume traded at the different venue categories. 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. Figures 3 and 4 report traded volumes for the different venues in our dataset. For both the FTSE 100 and the FTSE 250 stock indices, we observe that the market share of the LSE is declining over the sample period after the entry of the new trading venues.

Finally, Figure 5 shows kernel regression estimates of fragmentation, visible fragmentation and dark trading on the (log of) market value. We find that fragmentation and visible fragmentation are higher for larger stocks. This finding is consistent with Hengelbrock and Theissen (2009) who document that Turquoise gained higher market shares in larger stocks. Dark trading, in contrast, decreases with market capitalization.

## 3.2 Market Quality

We measure market quality by (several types of) volatility, liquidity, and volume of the FTSE 350 stocks. We also experimented with a variety of alternative market quality measures such as efficiency and Amihud (2002) illiquidity that are discussed in Appendix E. 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.

With the exception of volume, our measures of market quality are calculated using data from the LSE. In that sense, our measures are local as compared to global measures that are constructed by consolidating measures from all markets. Global measures are relevant for investors that have access to 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.<sup>10</sup> 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.

We compared bid-ask spreads and volatility at the LSE with the same measures at Chi-X, which has the largest volume after the LSE in our dataset. While volatility is similar across

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<sup>9</sup>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).

<sup>10</sup>Under MiFID, investment firms are required to seek best execution for their clients, cp, Appendix A for details.

venues, bid-ask spreads differ significantly (cp. Appendix B). Fiovaranti and Gentile (2011) also find that bid-ask spreads are higher at Chi-X when compared to regulated markets.

**Volatility.** Volatility is often described in negative terms, but its interpretation should depend on the perspective and on the type of volatility. 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. We consider several different types of volatility. There is a vast econometric literature on volatility measurement and modelling that is summarized by Anderson, Bollerslev and Diebold (2010).

We first consider total (ex post) volatility based on intraday transactions data. Our main results are based around the following method where we estimate total daily volatility by the Rogers and Satchell (1991) estimator

$$V_{it_j} = (\ln P_{it_j}^H - \ln P_{it_j}^C)(\ln P_{it_j}^H - \ln P_{it_j}^O) + (\ln P_{it_j}^L - \ln P_{it_j}^C)(\ln P_{it_j}^L - \ln P_{it_j}^O) \quad (1)$$

where  $V_{it_j}$  denotes volatility of stock  $i$  on day  $j$  within week  $t$ , and  $P^O, P^C, P^H, P^L$  are daily opening, closing, high and low prices that are obtained from datastream. The upper left panel of Figure 6 shows the weekly time series for total volatility for both the FTSE 100 and FTSE 250 indices. Total volatility increased dramatically during the financial crisis in the latter half of 2008. Figure 7 plots 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 on September 22, 2008 and October 31, 2008 (upper left panel). However, this analysis is misleading because many other events took place at the same time, most importantly, the global financial crisis. Also, the LSE upgraded its system to Trade Elect 3 on September 1, 2008 which can also confound a visual analysis.

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. 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.<sup>11</sup> It subsequently recovered all the losses when it became clear that no such explosion had occurred.

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

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<sup>11</sup>See <http://blueandgreentomorrow.com/2013/04/24/twitter-hoax-wipes-200bn-off-dow-jones-for-five-minutes/>

(rescaled) time (this is effectively a moving average of volatility with declining weights over 32 weeks). The evolution of temporary volatility is shown in the upper right panel of Figure 6. Temporary volatility co-moves with total volatility, as it can be seen more clearly from Figure 7. As for total volatility, temporary volatility seems to decline around the market entry of Turquoise and Chi-X but this decline may reflect other factors as discussed above.

**Liquidity.** Liquidity is a fundamental property of a well-functioning market, and lack of liquidity is generally at the heart of many financial crises and disasters. Defining liquidity, however, is problematic. 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.

Since we do not have access to the order book data for this period for all the stocks, our main measure of liquidity is the percentage bid-ask spread. As illustrated in Figure E4, bid-ask spreads are highly correlated with the Amihud (2002) illiquidity measure that has been put forward by Goyenko et al. (2009) as a good proxy for the price impact. Also, Mizzen (2010) documents that trends in quoted bid-ask spreads are similar to trends in effective bid-ask spreads. The quoted bid ask spread for stock  $i$  on day  $t_j$  is defined as

$$BA_{it_j} = \frac{P_{it_j}^A - P_{it_j}^B}{\frac{1}{2}(P_{it_j}^A + P_{it_j}^B)}. \quad (2)$$

where daily ask prices  $P^A$  and bid prices  $P^B$  are obtained from datastream. The time series of weekly bid-ask spreads is reported in the bottom left panel of Figure 6. Bid-ask spreads are significantly higher for FTSE 250 stocks when compared to FTSE 100 stocks. Inspection of Figure 7 seems to suggest that bid-ask spreads declined at the entry of Chi-X but this decline can also be 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.<sup>12</sup>

**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

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<sup>12</sup>cp. Appendix C.

and that this would reflect a deepening of the intermediation chain rather than real benefits to investors. Statistically, volume is a highly persistent and heavy tailed process, as documented by Lo and Wang (2010) and Gopikrishnan, Gabaix, and Stanley (2000).

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 (Lo and Wang, 2010). The volume data is obtained from fidessa.

Time series of both global volume and LSE volume are shown in the bottom right panel of Figure 6. Volume is higher on the FTSE 100 and there is a relatively stable level of global volume for the FTSE 100, whereas the FTSE 250 has seen some secular decline over the period. Towards the end of the sample period, global and LSE volume diverge, as alternative venues gain market share. The same trend can also be observed in Figure 7.

## 4 Econometric Methodology

Figure 6 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 use panel regression methods with weekly data to identify the effect of fragmentation on market quality. We adopt a methodology due to Pesaran (2006) for large panels that allows us to control for observable and unobservable factors, which is important in this context where fragmentation is likely to be endogenous and to be driven by the factors that are affecting market quality (we provide some evidence on this based on Granger causality tests below). 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.

## 4.1 A model for heterogeneous panel data with common factors

We observe a sample of panel data  $\{(Y_{it}, X_{it}, Z_{it}, d_t) : i = 1, \dots, n, t = 1, \dots, T\}$ , 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

$$Y_{it} = \alpha_i + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}^\top Z_{it} + \delta_i^\top d_t + \kappa_i^\top f_t + \varepsilon_{it}, \quad (3)$$

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  $W_{it} = (X_{it}, Z_{it}^\top)^\top$  are assumed to have the factor structure

$$W_{it} = a_i + D_i d_t + K_i f_t + u_{it}. \quad (4)$$

where  $D_i$  and  $K_i$  are matrices of factor loadings. We assume that the error terms satisfy the conditional moment restrictions  $E((u_{it}^\top, \varepsilon_{it}) | X_{it}, Z_{it}, d_t, f_t) = 0$ , but the error terms are allowed to be serially correlated or weakly cross-sectionally correlated. Equations (3) and (4) are similar to the common correlated effects (CCE) model of Pesaran (2006) except that we allow for a quadratic covariate effect in (3). The model is very general and contains many homogenous and heterogeneous panel data models as a special case. For example, it can be reduced to a heterogeneous panel data model with individual and time fixed effects under the assumption that  $f_t$  is a vector of ones and that there are no observed common factors. 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 have heterogeneous effects on the individual units.

Model (3)-(4) also allows for certain types of “endogeneity” between the covariates and the outcome variable represented by the unobserved factors  $f_t$ . For example, this could represent the activity of high frequency traders. We adopt the random coefficient specification for the individual parameters, that is,  $\beta_i = (\beta_{1i}, \beta_{2i}, \beta_{3i}^\top)^\top$  are i.i.d. across  $i$  and

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

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 a version of Pesaran’s (2006) CCE mean group estimator. Taking cross-sectional averages of (4), we obtain

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

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  $X_{it}$ .<sup>13</sup> Therefore, the effect of fragmentation on market quality can be obtained by performing (for each  $i$ ) a time series OLS estimation in the following regression model

$$Y_{it} = \pi_i + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}Z_{it} + \gamma_i^\top d_t + \xi_i^\top \bar{W}_t + \epsilon_{it}, \quad (7)$$

where we write  $\xi_i^\top = (\xi_{X_i}, \xi_{Z_i}^\top)$ , and then averaging the coefficients. In contrast to Pesaran (2006), our version of the CCE estimator does not include the cross-sectional average of  $Y$ . One reason for this is that because of the quadratic functional form,  $\bar{Y}_t$  would be a quadratic function of  $f_t$ , and so would introduce a bias. Instead, we add US variables such as the 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. Note that the parameters  $\beta_i$  in (7) are the same as in (3).

The CCE mean group estimate  $\hat{\beta} = n^{-1} \sum_{i=1}^n \hat{\beta}_i$  is defined as the average of the individual estimates  $\hat{\beta}_i = (\hat{\beta}_{1i}, \hat{\beta}_{2i}, \hat{\beta}_{3i}^\top)^\top$ . 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  $n \rightarrow \infty$ ) it follows that

$$\sqrt{n}(\hat{\beta} - \beta) \implies N(0, \Sigma), \quad (8)$$

where  $\Sigma$  is a covariance matrix. Pesaran (2006) proposes to estimate  $\Sigma$  by

$$\hat{\Sigma} = \frac{1}{n-1} \sum_{i=1}^n (\hat{\beta}_i - \hat{\beta})(\hat{\beta}_i - \hat{\beta})^\top. \quad (9)$$

This is used to form standard errors for the parameter estimates of interest.

We estimate (7) not only by OLS, but also by quantile regression methods. Quantile regression estimates are a useful tool if not only the conditional mean, but also different quantiles of the conditional distribution of the dependent variable are of interest. In addition, quantile regression estimates are robust against outliers in the dependent variable. In this case, we assume that  $\text{med}((u_{it}, \epsilon_{it}) | X_{it}, Z_{it}, d_t, f_t) = 0$ . Then, (6) still holds and the parameters in  $\beta_i$  can be consistently estimated by the median regression of (7). Let  $\hat{\beta}_i$  minimize the objective functions

$$\hat{Q}_{i\alpha T}(\theta) = \sum_{t=1}^T \rho_\alpha(Y_{it} - \pi - \beta_1 X_{it} - \beta_2 X_{it}^2 - \beta_3^\top Z_{it} - \gamma^\top d_t - \xi^\top \bar{W}_t), \quad (10)$$

where  $\rho_\alpha(x) = x(\alpha - 1(x < 0))$ , see Koenker (2005) and  $\theta = (\pi, \beta_1, \beta_2, \beta_3^\top, \gamma^\top, \xi^\top)$ . We argue in the appendix that, under suitable regularity conditions, (8) holds in this case with the same covariance matrix  $\Sigma$ .

The regression models above concentrate on the average effect, or the effect in “normal times”. We are also interested in the effect of fragmentation on the variability of market

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<sup>13</sup>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.

quality. Does greater fragmentation lead to more variable market quality? We can address this issue by looking at the conditional variance of market quality. We adopt a symmetrical specification whereby

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

where the parameters  $b_i = (b_{1i}, b_{2i}, b_{3i}^\top)^\top$  have a random coefficient specification like (5). We estimate this by mean or median regression of the squared residuals  $\hat{\epsilon}_{it}^2$  from (7) on  $X_{it}, X_{it}^2, Z_{it}, d_t, \bar{W}_t$ . We argue in the Appendix D that, under suitable regularity conditions, (8) holds in this case with a covariance matrix  $\Sigma$  (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  $\hat{\beta}(0.75) - \hat{\beta}(0.25)$ , where  $\hat{\beta}(\alpha)$  denotes the level  $\alpha$  quantile regression from (10).

## 4.2 Parameters of Interest

We are particularly interested in measuring the market quality at different levels of competition, holding everything else constant. For example, we should like to compare monopoly with perfect competition. In our context, the level of competition is measured by the Herfindahl index computed from recorded trading venues. 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 (averaged across firms) between a high (H) and low (L) degree of fragmentation or dark trading (on all firms). We normalize this by  $H - L$ . We therefore obtain the measure

$$\Delta_X = \frac{E_{X=H}Y - E_{X=L}Y}{H - L} = \beta_1 + \beta_2(H + L), \quad (11)$$

where the coefficients are estimated by the CCE method.<sup>14</sup> For comparison, we also report the marginal effect  $\beta_1 + 2\bar{X}\beta_2$ . 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. To assess the heterogeneity across individual firms, we also define the individual differences (setting the other firms fragmentation to the same level),  $\Delta_{X,i}^{HL} = \beta_{1i} + \beta_{2i}(H_i + L_i)$ .

An alternative way of comparing the outcomes under monopoly and competition is to compare the marginal distributions of market quality (holding other factors constant) between the two cases. Specifically, we should compare the distribution of  $\beta_{1i}H + \beta_{2i}H^2$  with the distribution of  $\beta_{1i}L + \beta_{2i}L^2$  by means of stochastic dominance tests. We report these results in the Appendix E.

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<sup>14</sup>This measures abstracts from the dependence of  $Z$  variables such as market value on fragmentation, cp. Figure 5.



## 5 Results

Before reporting our regression results, we investigate a few characteristics of our dataset in more detail. The particular characteristics we are interested in are the question of causality between market quality and fragmentation and unit roots. As pointed out by De Jong (2012) among others, fragmentation and market quality may be both cause and effect of each other, which is why our main results are reported within a regression framework that allows for some endogeneity. We investigated the two way causality issue by carrying out univariate Granger causality tests for each stock and for each market quality measure. Our results are reported in Table 1.<sup>15</sup> We find evidence of two way causation, but formally we can reject the null hypothesis that fragmentation or visible fragmentation do not Granger cause market quality more often than the reverse hypothesis. We interpret this finding as evidence that market quality is more likely to be determined by fragmentation when compared to the opposite case, but the results are more mixed for dark trading.

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.<sup>16</sup> We carried out unit roots on the variables using augmented Dickey Fuller tests of two types, and we report in Table 2 the fraction of tests that are significant at 1%,5%, and 10%. The results indicate little support for a unit root in fragmentation. 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. In any case, our regression results are robust to trends in the covariates, since this would make the time series estimates have even smaller error.

### 5.1 Regression Results

**The effect of total fragmentation, visible fragmentation and dark trading on the level of market quality.** Here, we report estimates based on the individual median regressions. The results for the individual mean regressions are qualitatively similar and are available upon request. Table 4 reports CCE coefficients based on individual quantile regressions together with our parameter of interest  $\Delta_{Frag}$ . As observable factors, we include VIX, the lagged index return, and a dummy variable that captures the decline in trading activity around Christmas and New Year.<sup>17</sup>  $\Delta_{Frag}$  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. Table 3a) provides a summary of  $\Delta_{Frag}$ ,  $\Delta_{Vis.frag}$  and  $\Delta_{Dark}$  from various specifications.

Inspecting  $\Delta_{Frag}$ , we find that a fragmented market is associated with higher global volume

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<sup>15</sup>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 313 firms for visible fragmentation.

<sup>16</sup>Formally, Kapetanios et al. (2007) have shown that the CCE estimator remains consistent if the unobserved common factors follow unit root processes.

<sup>17</sup>The coefficients on observed common factors and on cross-sectional averages do not have a structural interpretation because they are a combination of structural coefficients, cf. Section 4.1.

but lower volume at the LSE when compared to a monopoly. For comparison, we also report marginal effects and we find that they agree with  $\Delta_{Frag}$  in most specifications. The increase in global volume in a fragmented market place is consistent with the theoretical prediction 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 while there is no significant effects for overall volatility and bid-ask spreads.

Figure 8 illustrates  $\Delta_{Frag}$  for both individual OLS (red line) and quantile regressions (black points).<sup>18</sup> However,  $\Delta_{Frag}$  does not vary significantly across quantiles. The same observation can be made from Figure 11 that shows the kernel density estimates of the individual measures  $\Delta_{i,Frag}$  where the individual coefficients are estimated by quantile regression. While man group estimates are useful to summarize the information in large panels, the kernel density estimates of individual effects illustrate that there is a significant degree of heterogeneity across individual firms.

It is also interesting to split the total level of fragmentation into visible fragmentation and dark trading. When measured by  $\Delta_{Vis.frag.}$ , we find that visible fragmentation reduces temporary volatility and lowers trading volume both globally and locally at the LSE. In addition, a market with a high degree of visible fragmentation has larger bid-ask spreads when compared to a monopoly. Since our market quality measures are defined at the traditional exchange with exception of global volume, our result for bid-ask spreads is consistent with the findings of De Jong et al. (2011) who 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.

Turning to dark trading, our results suggest that dark trading reduces volatility and increases volume while it does not has a significant effect on bid-ask spreads. In contrast to overall fragmentation, both  $\Delta_{Vis.frag.}$  and  $\Delta_{Dark}$  vary significantly across quantiles.  $\Delta_{Vis.frag.}$  is higher for low volatility and low volume stocks, while the opposite pattern can be observed for  $\Delta_{Dark}$  (Figures 9-10, 12-13).

While the difference measure  $\Delta_{Frag.}$  for example, measures the difference between perfect competition and a monopolistic market, it is also interesting to assess the transition between these extremes. Figures 14-15 illustrate the estimated relationship between market quality on the one hand and overall fragmentation, visible fragmentation and dark trading on the other. We observe that the transition between monopoly and competition is non-monotonic in

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<sup>18</sup>Because the dependent variable is in logs, it is difficult to interpret Figures 8-10 in terms of location and scale shifts: For a semi-logarithmic specification as considered here, a horizontal line is a pure scale shift. A non-horizontal line can be either a location or skewness shift (Hao and Naiman, 2007).

particular for overall and visible fragmentation. For visible fragmentation (panel a) in Figure 14), for example, we observe an inverted U-shape for most measures of market quality, where the maximum occurs at a level of visible fragmentation of about 0.35.

Our tables also report two different measures of cross-sectional dependence, CSD absolute and CSD squared. CSD absolute (squared) is defined as the mean of the absolute value (square) of the off-diagonal elements in the cross-sectional dependence matrix. To obtain a better understanding whether our model is able to account for the cross-sectional dependence in the data, Figures 16-20 compare kernel density estimates of both autocorrelation and cross-sectional correlation in the dependent variables and the median regression residuals. Consistent with the small values for CSD absolute and CSD squared, we find that cross-sectional correlations higher than 0.5 are rare between residuals while the dependent variables itself are strongly correlated in the cross-section. We observe a similar reduction in residual autocorrelations when compared to the dependent variables.<sup>19</sup>

**The effect of total fragmentation, visible fragmentation and dark trading on the variability of market quality.** So far, we discussed the effect of fragmentation on the level of market quality. In this section, we investigate whether there is any evidence that fragmentation of trading has led to an increase in the volatility of market quality as for example, more frequent market crashes or large price moves. Tables 6-7 contain the results from regressing the variability of market quality – constructed as squared median regression residuals – on market fragmentation. While  $\Delta_{Frag.}$  is not statistically significant for any market quality measure, we find that visible fragmentation reduces the variability of temporary volatility but dark trading increases the variability of both overall and temporary volatility. These results are summarized in Table 3b).

**Heterogeneity.** The kernel density estimates of the individual difference measures in Figures 11-13 indicate that the effect of fragmentation on market quality varies significantly across individual firms. Table 8 investigate possible explanations of the observed heterogeneity by regressing the individual effects of fragmentation on market quality on a number of firm characteristics.

While most regression coefficients are statistically not different from zero, some interesting results can be observed: For temporary volatility,  $\Delta_{Vis.frag.}$  is lower if the average trade size at venues other than the LSE is smaller. Turning to global volume,  $\Delta_{Frag.}$  increases in the average trade size at venues other than the LSE and  $\Delta_{Vis.frag.}$  is higher for stocks that are traded at a larger number of venues. The latter results is also found for volume at the LSE.

**Robustness.** In Appendix E, 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

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<sup>19</sup>We also tried to formally test for cross-sectional dependence in the residuals using the test of Pesaran (2004). However, due to the large cross-sectional dimension of our dataset, this test did not perform well.

estimation methods.<sup>20</sup>

Our finding that overall fragmentation, visible fragmentation and dark trading have a negative effect on total and temporary volatility is robust to using a variety of alternative measures of volatility such as Parkinson volatility, idiosyncratic volatility, within-day and overnight volatility. However, the effect of dark trading on idiosyncratic and overnight volatility is not statistically significant. If we measure market quality by the Amihud (2002) illiquidity measure, we find that a higher degree of fragmentation is associated with less liquid markets. This finding can be mainly attributed to visible fragmentation, whereas dark trading is found to improve liquidity. For efficiency, we cannot find a significant effect.

When comparing the effect of market fragmentation on market quality for FTSE 100 and FTSE 250 firms, some interesting differences emerge: We find that the positive effect of overall fragmentation on market quality can be attributed to the FTSE 100 firms. When splitting overall fragmentation into visible fragmentation and dark trading, our results suggest that dark trading increases volatility for FTSE 100 firms, but has the opposite effect for FTSE 250 firms. The negative effect of visible fragmentation on volatility is only significant for FTSE 100 stocks. Investigating the effect of fragmentation on the variability of market quality, we document that overall fragmentation has a negative effect on the variability of LSE volume for FTSE 250 firms, while dark trading increases the variability of LSE volume for FTSE 100 firms.

Finally, we re-estimate our results using a heterogeneous panel data model with individual and time fixed effects that can be obtained as a special case of model (3)-(4) where  $f_t$  is a vector of ones and that there are no observed common factors  $d_t$ . A version of this model with homogenous coefficients has been used in related work by De Jong (2011) and 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). In line with our main results, both fixed effects and difference in difference estimates suggest that fragmentation depresses trading volume at the LSE. In addition, the difference-in-difference results confirm our main findings that fragmentation lowers total volatility but increases global volume.

## 6 Conclusions

After the introduction of MiFID in 2007, the equity market structure in Europe underwent a fundamental change as newly established venues such as Chi-X started to compete with traditional exchanges for order flow. For the UK, this development is illustrated by Figures 3 and 4 that show the decline of the market share of the LSE. This change in market structure has been a seedbed for High Frequency Trading, which has benefited from the competition between

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<sup>20</sup>In addition to the sensitivity analysis reported here, our results are robust to including a) additional observed factors such as the spread between a BBB and AAA corporate bond or system latency at the LSE, b) the cross-sectional average of the dependent variable, c) monthly dummies, d) a time trend. These results are available upon request.

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. At the same time, a trend towards consolidation was observed as exemplified by the merger between LSE and Borsa Italiana in 2007, and markets experienced a period of turmoil after the Lehman shock in 2008.

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 that can represent 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 the researcher to characterize the whole conditional distribution of the dependent variable rather than just its conditional mean. This estimator is suitable for heterogeneous financial datasets 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.

Our main findings are that the competitive fragmented UK market is characterized by lower volatility and LSE trading volume, but higher global volume when compared to a monopoly. When separating visible fragmentation from dark trading, we find that the decline in LSE volume can be attributed to visible fragmentation, while the increase in global volume is due to dark trading. Turning to the effect of fragmentation on the variation in market quality, our estimates suggest that visible fragmentation lowers the variability in volatility while dark trading has the opposite effect.

These results are broadly consistent with earlier studies that used different methods and different datasets. In general, competition has brought improvements in both the average level of most market quality measures and its variability. The magnitude of the effect is not large, but it is robust to many specifications. At the least, we can confirm that there is no evidence that competition and fragmentation of liquidity has by itself worsened market quality. The one finding of concern may be that the increase in dark trading is associated with an increase in the variability of some market quality measures.

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**Table 1:** Granger causality tests: Fraction of p-values less than 5%

	Total volatility	Temp. volatility.	Bid-ask spreads	Global volume	LSE volume
$H_0$ : Fragmentation $\nrightarrow$ Y	0.540	0.056	0.290	0.170	0.425
$H_0$ : Y $\nrightarrow$ Fragmentation	0.161	0.056	0.147	0.155	0.158
$H_0$ : Vis. fragmentation $\nrightarrow$ Y	0.626	0.045	0.470	0.252	0.572
$H_0$ : Y $\nrightarrow$ Vis. fragmentation	0.144	0.064	0.131	0.141	0.118
$H_0$ : Dark $\nrightarrow$ Y	0.482	0.042	0.214	0.294	0.511
$H_0$ : Y $\nrightarrow$ Dark	0.233	0.074	0.086	0.419	0.510

Notes:  $X \nrightarrow Y$  means that X does not help to predict market quality. Granger causality tests are carried out for each individual stock and the fraction of p-values less than 5% is shown. Lag length is chosen by AIC.

**Table 2:** Dickey-Fuller tests for selected individual time series

a) No lags included

	Fraction significant at 1%	Fraction significant at 5%	Fraction significant at 10%
Fragmentation	0.979	0.994	0.997
Vis. fragmentation	0.808	0.942	0.971
Dark	0.994	1	1
Total volatility	1	1	1
Temp. volatility	1	1	1
Bid-ask spreads	0.988	0.994	0.997
Global volume	0.991	0.997	1
LSE volume	0.991	0.997	1

b) 3 lags included

	Fraction significant at 1%	Fraction significant at 5%	Fraction significant at 10%
Fragmentation	0.328	0.455	0.548
Vis. fragmentation	0.109	0.208	0.288
Dark	0.553	0.754	0.847
Total volatility	0.402	0.786	0.927
Temp. volatility	0.953	0.982	0.991
Bid-ask spreads	0.592	0.786	0.865
Global volume	0.839	0.93	0.959
LSE volume	0.836	0.93	0.959

Notes:  $H_0$ : Y is nonstationary. In both panels, intercept and time-trend are included.

**Table 3:** The difference in market quality between the maximum and minimum level of fragmentation and dark trading:  
Summary of results

a) Level of market quality

	Total volatility	Temp. volatility.	Bid-ask spreads	Global volume	LSE volume
$\Delta_{Frag.}$	-0.15 (-0.735)	-0.323 (-1.822)	0.014 (0.154)	0.166 (1.918)	-0.973 (-10.108)
$\Delta_{Vis.frag.}$	-0.181 (-1.523)	-0.339 (-3.279)	0.139 (1.86)	-0.157 (-1.85)	-0.988 (-11.891)
$\Delta_{Dark}$	-0.171 (-2.518)	-0.287 (-4.802)	-0.035 (-0.689)	2.055 (34.419)	1.217 (20.626)

b) Variability of market quality

	Total volatility	Temp. volatility.	Bid-ask spreads	Global volume	LSE volume
$\Delta_{Frag.}$	0.021 (0.581)	0.005 (0.111)	-0.002 (-0.096)	-0.057 (-1.488)	-0.032 (-1.178)
$\Delta_{Vis.frag.}$	-0.055 (-1.359)	-0.091 (-1.658)	0.017 (0.636)	0.017 (1.213)	0.032 (1.403)
$\Delta_{Dark}$	0.098 (3.554)	0.084 (3.797)	-0.001 (-0.064)	-0.024 (-0.853)	0.012 (0.619)

Notes: The table shows  $\Delta_X^{HL}$  that is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  and evaluated at  $H = \max(X)$  and  $L = \min(X)$ , for  $X = \{\text{frag.}, \text{vis. frag.}, \text{dark}\}$ .

**Table 4:** The effect of fragmentation on market quality

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-7.745 (-9.97)	-12.167 (-19.099)	4.468 (5.803)	1.713 (2.552)	2.365 (3.497)
Fragmentation	0.45 (0.805)	-0.754 (-1.526)	0.195 (0.726)	0.064 (0.22)	0.413 (1.338)
Fragmentation sq.	-0.719 (-1.619)	0.516 (1.299)	-0.217 (-0.933)	0.122 (0.426)	-1.662 (-5.752)
Market cap.	-0.475 (-6.372)	-0.288 (-5.694)	-0.343 (-4.951)	-0.214 (-3.172)	-0.236 (-3.492)
Lagged index return	0.11 (0.862)	1.157 (11.213)	-0.909 (-9.697)	0.031 (0.318)	-0.056 (-0.543)
VIX	1.126 (36.039)	0.914 (35.829)	0.016 (0.642)	0.231 (9.586)	0.245 (9.366)
Christmas and New Year	-0.237 (-10.867)	-0.207 (-10.589)	0.38 (21.269)	-1.212 (-50.056)	-1.21 (-49.658)
Fragmentation (avg.)	-1.885 (-8.142)	0.431 (2.289)	-0.533 (-3.693)	0.131 (0.569)	-0.126 (-0.556)
Market cap. (avg.)	-0.008 (-0.091)	0.29 (4.065)	-0.089 (-1.175)	0.307 (5.62)	0.322 (5.36)
Marginal effect	-0.301 (-2.312)	-0.215 (-1.917)	-0.031 (-0.458)	0.191 (2.552)	-1.321 (-17.249)
$\Delta_{Frag.}^T$	-0.15 (-0.735)	-0.323 (-1.822)	0.014 (0.154)	0.166 (1.918)	-0.973 (-10.108)
Adjusted $R^2$	0.732	0.137	0.775	0.78	0.758
CSD abs.	0.152	0.133	0.084	0.158	0.166
CSD sq.	0.032	0.026	0.011	0.036	0.039

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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. CSD abs. (CSD sq.) is the mean of the absolute value (square) of the off-diagonal elements in the cross-sectional dependence matrix.

**Table 5:** The effects of visible fragmentation and dark trading on market quality

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-8.475 (-10.602)	-12.699 (-20.183)	1.28 (1.615)	1.189 (1.89)	2.333 (2.988)
Vis. fragmentation	0.817 (2.663)	-0.483 (-1.733)	0.436 (2.085)	0.158 (0.759)	-0.151 (-0.682)
Vis. fragmentation sq.	-1.429 (-3.937)	0.206 (0.624)	-0.425 (-1.536)	-0.451 (-1.728)	-1.199 (-4.323)
Dark	-0.212 (-0.946)	0.471 (2.262)	-0.212 (-1.068)	0.332 (1.673)	0.232 (1.11)
Dark sq.	0.041 (0.178)	-0.759 (-3.54)	0.177 (0.897)	1.724 (9.605)	0.986 (4.867)
Market cap.	-0.399 (-5.328)	-0.287 (-4.975)	-0.32 (-4.851)	-0.243 (-4.29)	-0.293 (-4.595)
Lagged index return	0.298 (2.469)	1.244 (12.508)	-0.65 (-7.308)	0.307 (3.465)	0.231 (2.317)
VIX	1.082 (31.337)	0.942 (31.869)	0.083 (3.061)	0.276 (11.248)	0.228 (8.433)
Christmas and New Year	-0.345 (-14.356)	-0.256 (-11.817)	0.426 (19.393)	-1.273 (-52.092)	-1.289 (-49.603)
Vis. fragmentation (avg.)	-1.151 (-5.873)	0.059 (0.364)	-1.179 (-8.686)	-0.661 (-4.338)	-0.479 (-2.944)
Dark (avg.)	-1.159 (-7.44)	0.181 (1.421)	0.606 (4.05)	-1.531 (-12.27)	-1.815 (-13.94)
Market cap. (avg.)	-0.175 (-1.56)	0.247 (2.704)	-0.005 (-0.055)	0.14 (2.182)	0.129 (2.264)
Marg. effect (vis. frag)	-0.193 (-1.637)	-0.337 (-3.287)	0.136 (1.812)	-0.161 (-1.899)	-0.999 (-12.063)
Marg. effect (dark)	-0.174 (-2.63)	-0.226 (-3.878)	-0.049 (-0.959)	1.914 (29.99)	1.137 (18.729)
$\Delta_{Vis.frag.}$	-0.181 (-1.523)	-0.339 (-3.279)	0.139 (1.86)	-0.157 (-1.85)	-0.988 (-11.891)
$\Delta_{Dark}$	-0.171 (-2.518)	-0.287 (-4.802)	-0.035 (-0.689)	2.055 (34.419)	1.217 (20.626)
Adjusted $R^2$	0.751	0.158	0.754	0.852	0.8
CSD abs.	0.144	0.137	0.08	0.195	0.171
CSD sq.	0.029	0.027	0.01	0.05	0.04

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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. CSD abs. (CSD sq.) is the mean of the absolute value (square) of the off-diagonal elements in the cross-sectional dependence matrix.

**Table 6:** The effect of fragmentation on the volatility of market quality

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.536 (-1.893)	-0.315 (-1.081)	0.28 (1.429)	0.275 (1.15)	0.498 (2.662)
Fragmenation	-0.029 (-0.256)	-0.048 (-0.412)	-0.037 (-0.463)	-0.215 (-1.716)	-0.128 (-1.522)
Fragmentation sq.	0.06 (0.565)	0.063 (0.635)	0.041 (0.548)	0.189 (1.73)	0.115 (1.455)
Market cap.	-0.01 (-0.477)	-0.019 (-1.007)	-0.009 (-0.482)	-0.035 (-2.302)	-0.034 (-2.312)
Lagged index return	0.039 (1.021)	0.076 (1.923)	0.014 (0.542)	0.024 (0.809)	-0.019 (-0.677)
VIX	0.033 (2.709)	0.007 (0.586)	0.002 (0.229)	-0.007 (-0.616)	-0.014 (-1.447)
Christmas and New Year	0.06 (3.931)	0.063 (5.425)	0.095 (4.186)	0.104 (6.128)	0.088 (5.756)
Fragmentation (avg.)	-0.097 (-1.602)	-0.111 (-1.425)	0.049 (0.95)	-0.022 (-0.243)	-0.04 (-0.505)
Market cap. (avg.)	0.048 (2.137)	0.001 (0.062)	-0.029 (-1.62)	-0.006 (-0.34)	0.013 (0.705)
Marginal effect	0.033 (1.173)	0.018 (0.59)	0.006 (0.302)	-0.018 (-0.77)	-0.007 (-0.329)
$\Delta_{Frag.}^T$	0.021 (0.581)	0.005 (0.111)	-0.002 (-0.096)	-0.057 (-1.488)	-0.032 (-1.178)
Adjusted $R^2$	-0.013	-0.013	-0.041	0.056	0.064
CSD abs.	0.087	0.074	0.074	0.09	0.088
CSD sq.	0.015	0.011	0.01	0.016	0.016

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  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. CSD abs. (CSD sq.) is the mean of the absolute value (square) of the off-diagonal elements in the cross-sectional dependence matrix.

**Table 7:** The effect of visible fragmentation and dark trading on the volatility of market quality

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.708 (-2.005)	-0.075 (-0.244)	0.208 (0.917)	-0.145 (-0.972)	0.054 (0.287)
Vis. fragmentation	-0.237 (-1.745)	-0.355 (-1.9)	0.006 (0.089)	0.017 (0.314)	-0.033 (-0.37)
Vis. fragmentation sq.	0.261 (1.546)	0.379 (1.712)	0.016 (0.17)	0 (-0.005)	0.094 (0.777)
Dark	0.014 (0.134)	-0.02 (-0.228)	-0.073 (-1.13)	-0.157 (-1.931)	-0.185 (-2.551)
Dark sq.	0.084 (0.885)	0.104 (1.206)	0.072 (1.106)	0.133 (2.267)	0.197 (3.262)
Market cap.	0.02 (1.065)	-0.001 (-0.054)	0.004 (0.197)	-0.037 (-2.752)	-0.021 (-1.378)
Lagged index return	0.015 (0.35)	-0.004 (-0.101)	0.019 (0.69)	0.042 (1.938)	0.029 (1.087)
VIX	0.043 (3.063)	0.014 (1.021)	-0.006 (-0.541)	-0.004 (-0.753)	-0.016 (-2.465)
Christmas and New Year	0.038 (3.304)	0.022 (2.301)	0.031 (3.801)	0.03 (4.537)	0.036 (4.094)
Vis. fragmentation (avg.)	0.133 (1.787)	0.159 (2.135)	0.045 (0.882)	-0.02 (-0.579)	0.062 (1.763)
Dark (avg.)	-0.028 (-0.443)	-0.101 (-1.801)	0.061 (1.525)	-0.018 (-0.576)	-0.04 (-1.126)
Market cap. (avg.)	0.048 (1.647)	0.028 (1.269)	-0.034 (-1.954)	0.024 (1.646)	0.002 (0.145)
Marg. effect (vis. frag)	-0.052 (-1.317)	-0.087 (-1.625)	0.017 (0.641)	0.017 (1.213)	0.033 (1.441)
Marg. effect (dark)	0.091 (3.057)	0.075 (3.272)	-0.007 (-0.392)	-0.035 (-1.097)	-0.004 (-0.164)
$\Delta_{Vis.frag.}$	-0.055 (-1.359)	-0.091 (-1.658)	0.017 (0.636)	0.017 (1.213)	0.032 (1.403)
$\Delta_{Dark}$	0.098 (3.554)	0.084 (3.797)	-0.001 (-0.064)	-0.024 (-0.853)	0.012 (0.619)
Adjusted $R^2$	-0.011	-0.018	-0.028	0.03	0.021
CSD abs.	0.082	0.075	0.073	0.108	0.097
CSD sq.	0.013	0.011	0.01	0.022	0.018

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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. CSD abs. (CSD sq.) is the mean of the absolute value (square) of the off-diagonal elements in the cross-sectional dependence matrix.

**Table 8:** Explaining heterogeneity

## b) Fragmentation

	Total volatility	Temporary volatility	Bid-ask spreads	Volume	LSE volume
Constant	4.274 (2.071)	2.267 (1.295)	0.961 (0.603)	-6.436 (-4.04)	-3.843 (-2.183)
N. of venues	0.466 (0.558)	0.172 (0.242)	0.28 (0.434)	0.335 (0.52)	0.991 (1.391)
Avg. trade size off LSE	-1.319 (-1.641)	-0.49 (-0.719)	-0.363 (-0.585)	2.088 (3.366)	0.869 (1.268)
Price	-0.818 (-1.642)	-0.694 (-1.641)	-0.123 (-0.319)	0.455 (1.184)	-0.296 (-0.698)
Adjusted $R^2$	0.009	0.003	-0.008	0.092	0.036

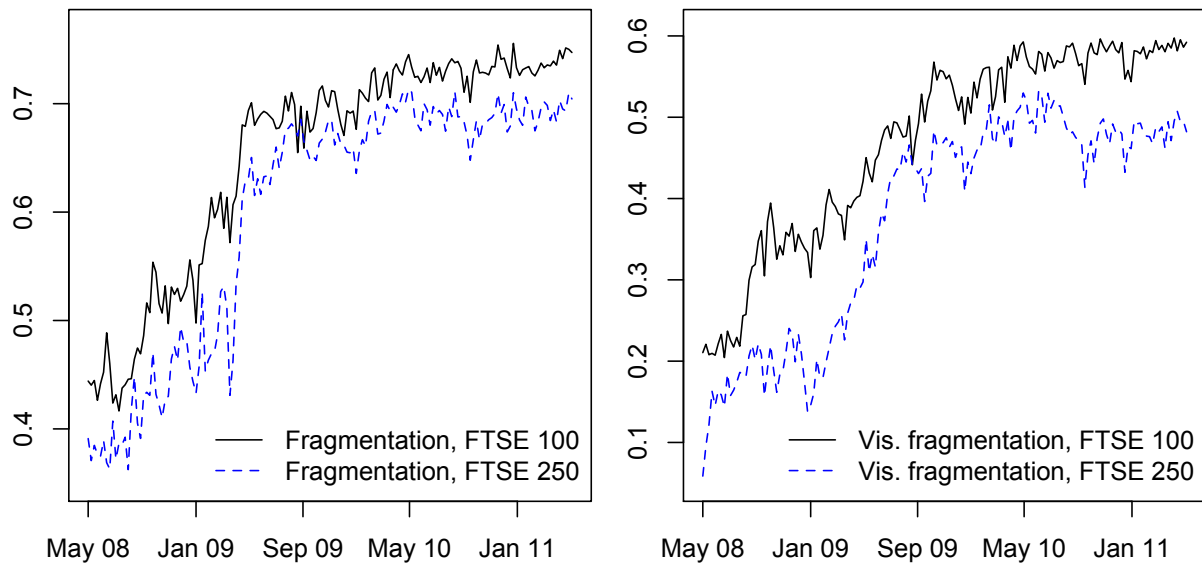
## c) Visible fragmentation

	Total volatility	Temporary volatility	Bid-ask spreads	Volume	LSE volume
Constant	1.345 (0.428)	8.245 (3.225)	-0.824 (-0.316)	-4.985 (-2.057)	-4.007 (-1.493)
N. of venues	1.115 (0.523)	-0.016 (-0.009)	0.187 (0.106)	7.027 (4.27)	3.891 (2.135)
Avg. trade size off LSE	-1.519 (-1.045)	-2.756 (-2.329)	-0.122 (-0.101)	-0.585 (-0.522)	-0.226 (-0.182)
Price	0.845 (1.168)	-0.795 (-1.348)	0.637 (1.061)	0.37 (0.662)	0.246 (0.397)
Adjusted $R^2$	0.011	0.07	-0.003	0.189	0.053

Notes: OLS regressions. In panel a) the dependent variable is the difference between a high and low degree of fragmentation  $\Delta_{Frag.}^{HL}$  from the model in Table 4. In panel b), the dependent variable is the difference between a high and low degree of visible fragmentation  $\Delta_{Vis.frag.}^{HL}$  from Table 5.

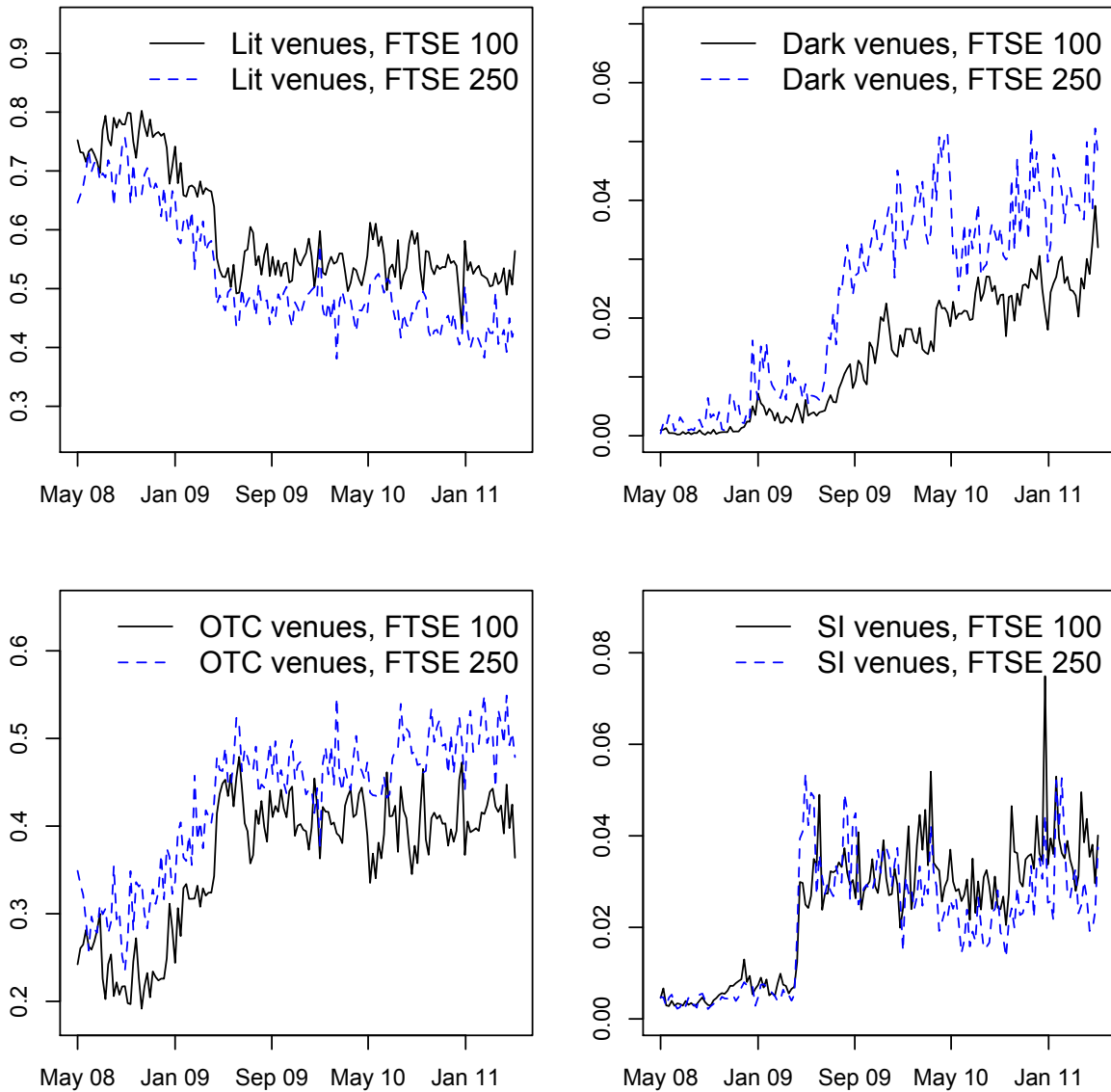


**Figure 1:** Fragmentation and visible fragmentation for the FTSE 100 and FTSE 250 indices



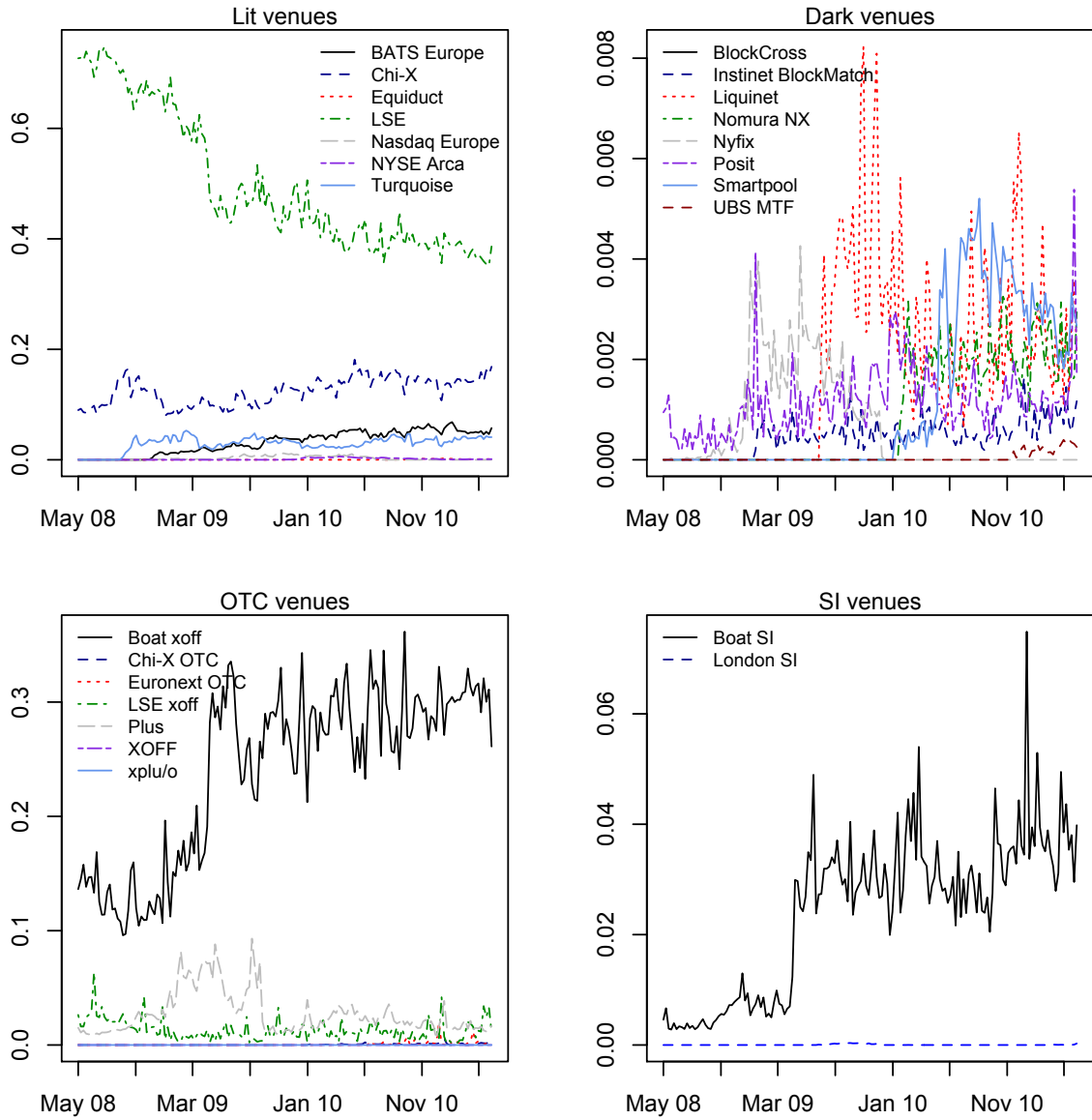
Notes: Fragmentation is defined as 1-Herfindahl index and visible fragmentation as 1-visible Herfindahl index. Data source: Fidessa.

**Figure 2:** Share of volume traded by venue category.



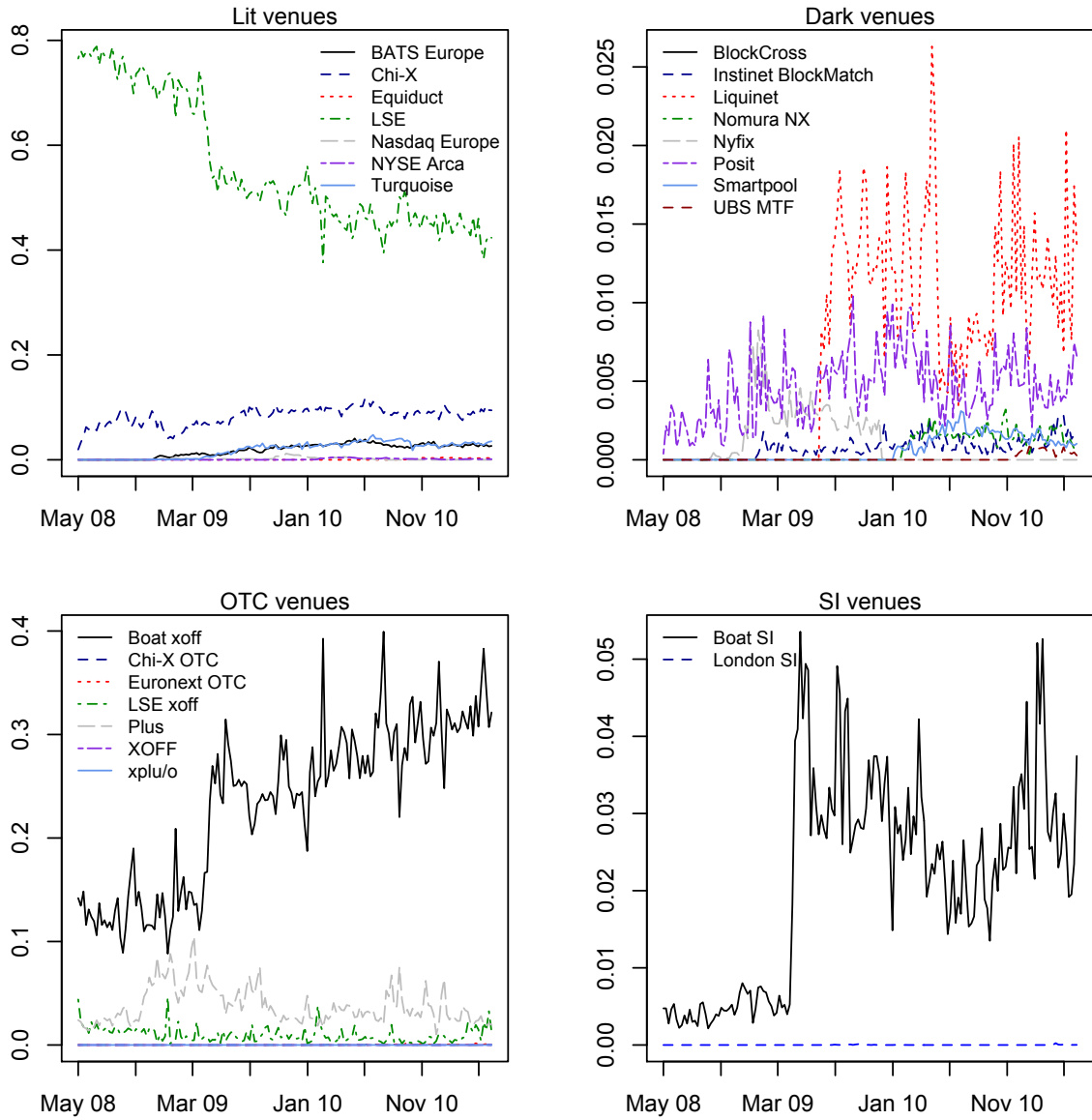
Data source: Fidessa.

**Figure 3:** Share of volume traded by venue for the FTSE 100 index



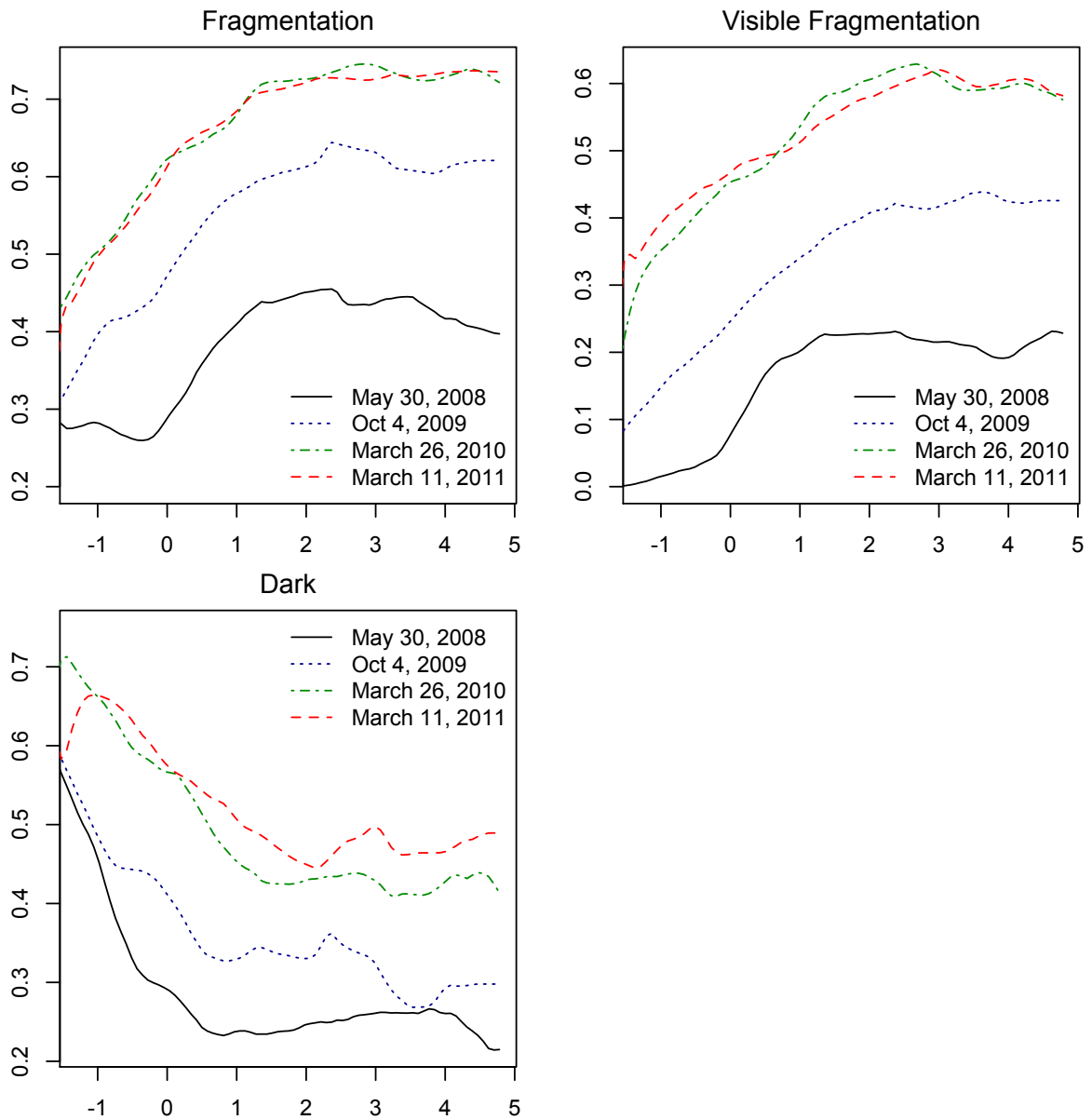
Data source: Fidessa.

**Figure 4:** Share of volume traded by venue for the FTSE 250 index



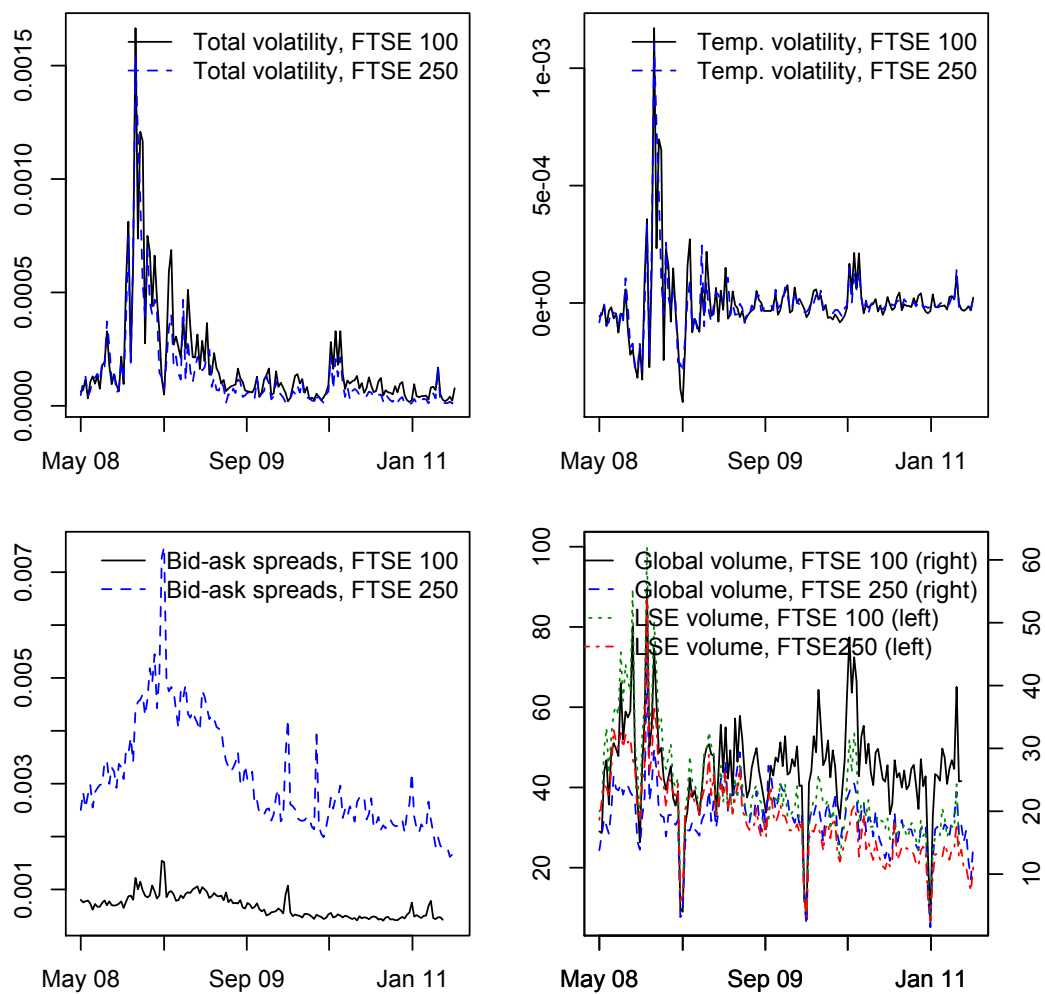
Data source: Fidessa.

**Figure 5:** Nonparametric kernel regression estimates of fragmentation, visible fragmentation and dark trading on the log of market value



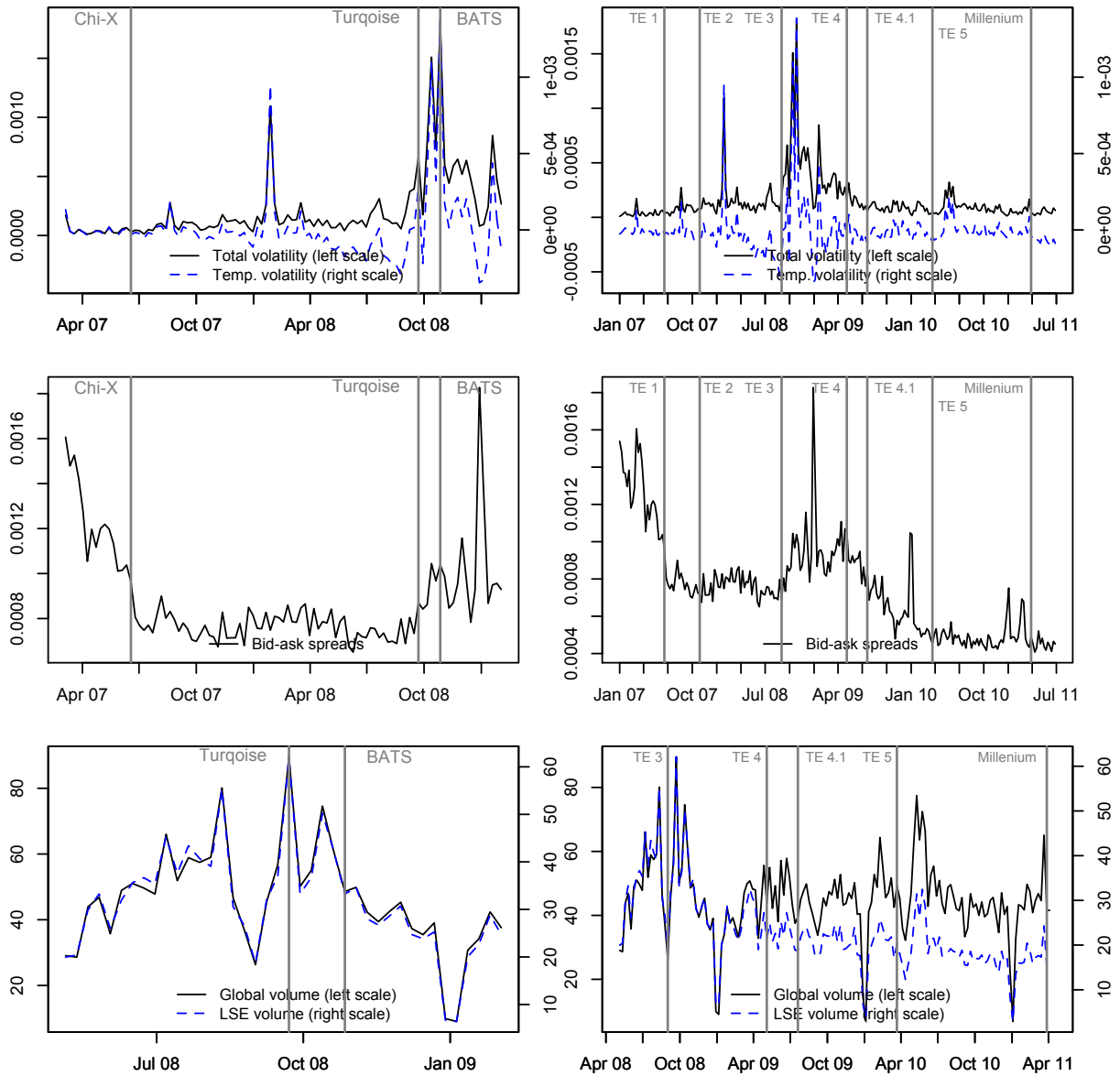
Note: The figure shows cross-sectional kernel regressions of fragmentation on market value at 4 different times for all firms.

**Figure 6:** Market quality measures of the FTSE 100 and FTSE 250 indices



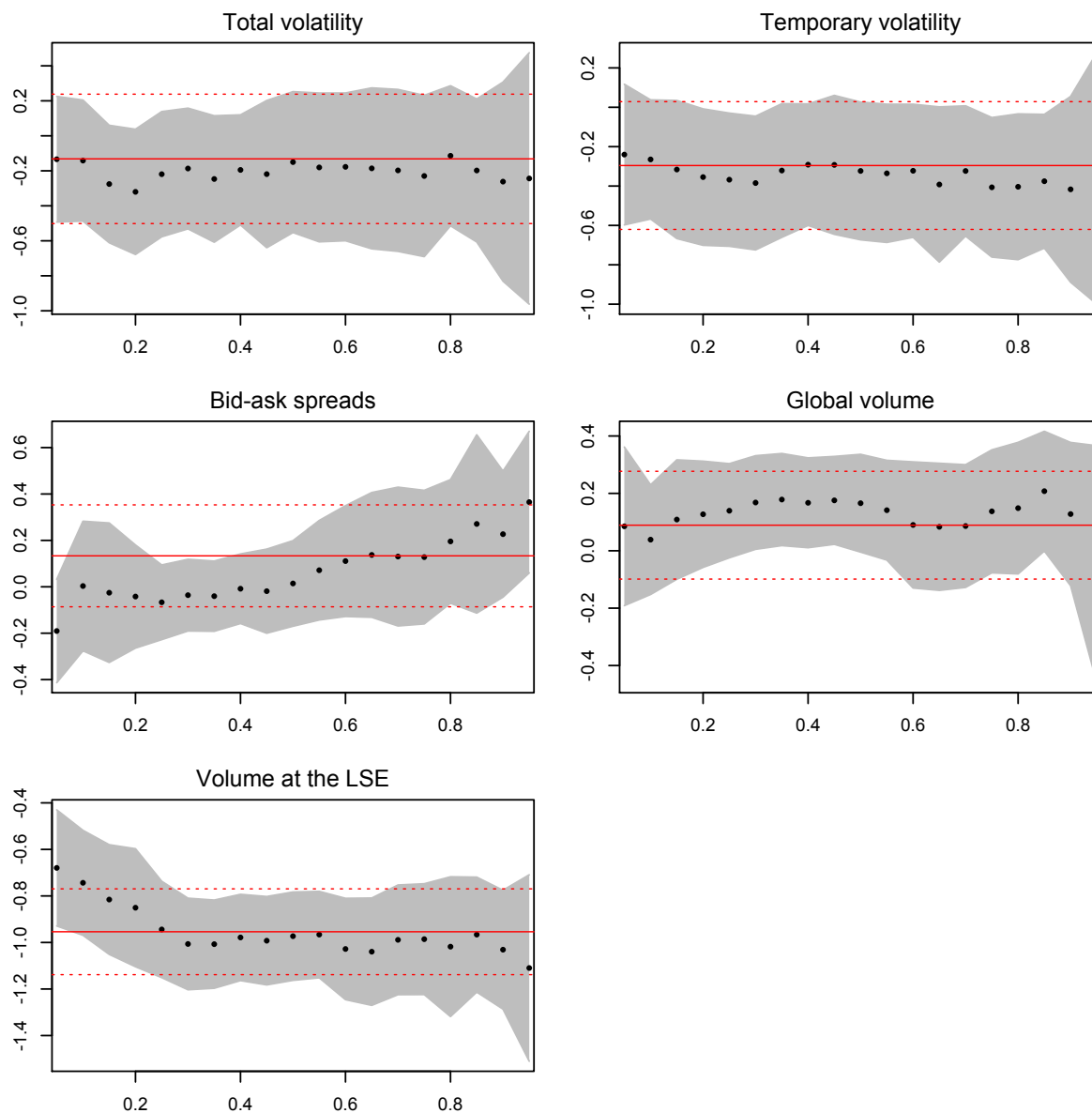
Notes: Market quality measures are calculated from index data with exception of bid-ask spreads where no index data is available. The series for bid-ask spreads show averages of the individual bid-ask spreads weighted by market capitalization. The downside spike in the series is due to the Christmas and New Year holiday. Data source: Datastream and Fidessa.

**Figure 7:** 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 (cp. Appendix C). The downside spike in the series is due to the Christmas and New Year holiday. Series for volume are shorter due to data availability. Data source: Datastream, Fidessa and own calculations.

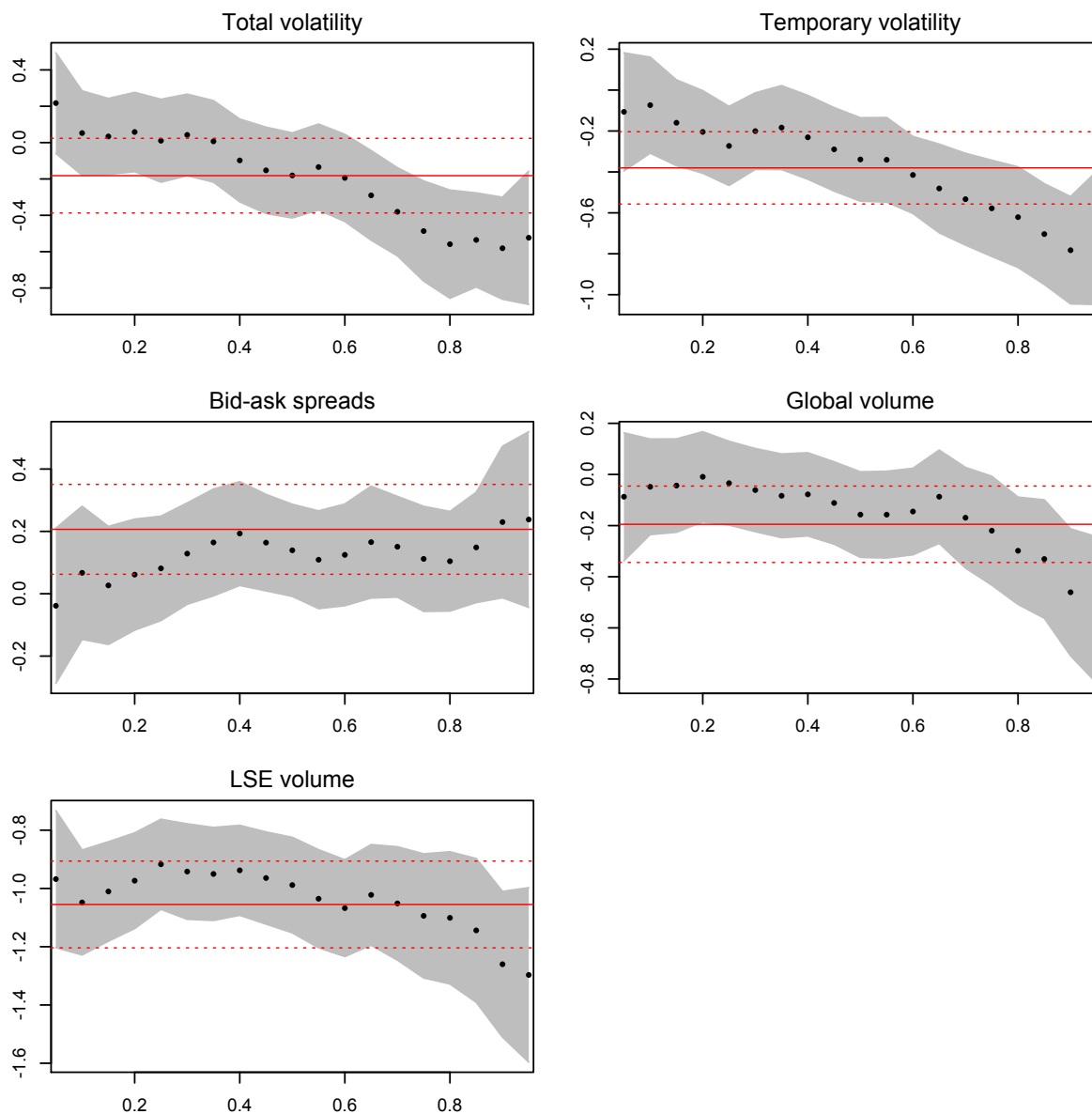
**Figure 8:** Difference in market quality between high and low degrees of competition



Notes: The figure shows  $\Delta_{Frag.}^{HL}$  that is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  and evaluated at  $H = \max(Frag.) = 0.834$  and  $L = \min(Frag.) = 0$ . Differences constructed from CCE estimates that are based on individual OLS regressions are shown as a red line (the dashed lines correspond to a 95% confidence interval). Differences constructed from CEE estimates that are based on individual quantile regressions for  $\tau \in \{0.05, 0.1, \dots, 0.9, 0.95\}$  are shown as black dots (the shaded area corresponds to a 95% confidence interval).

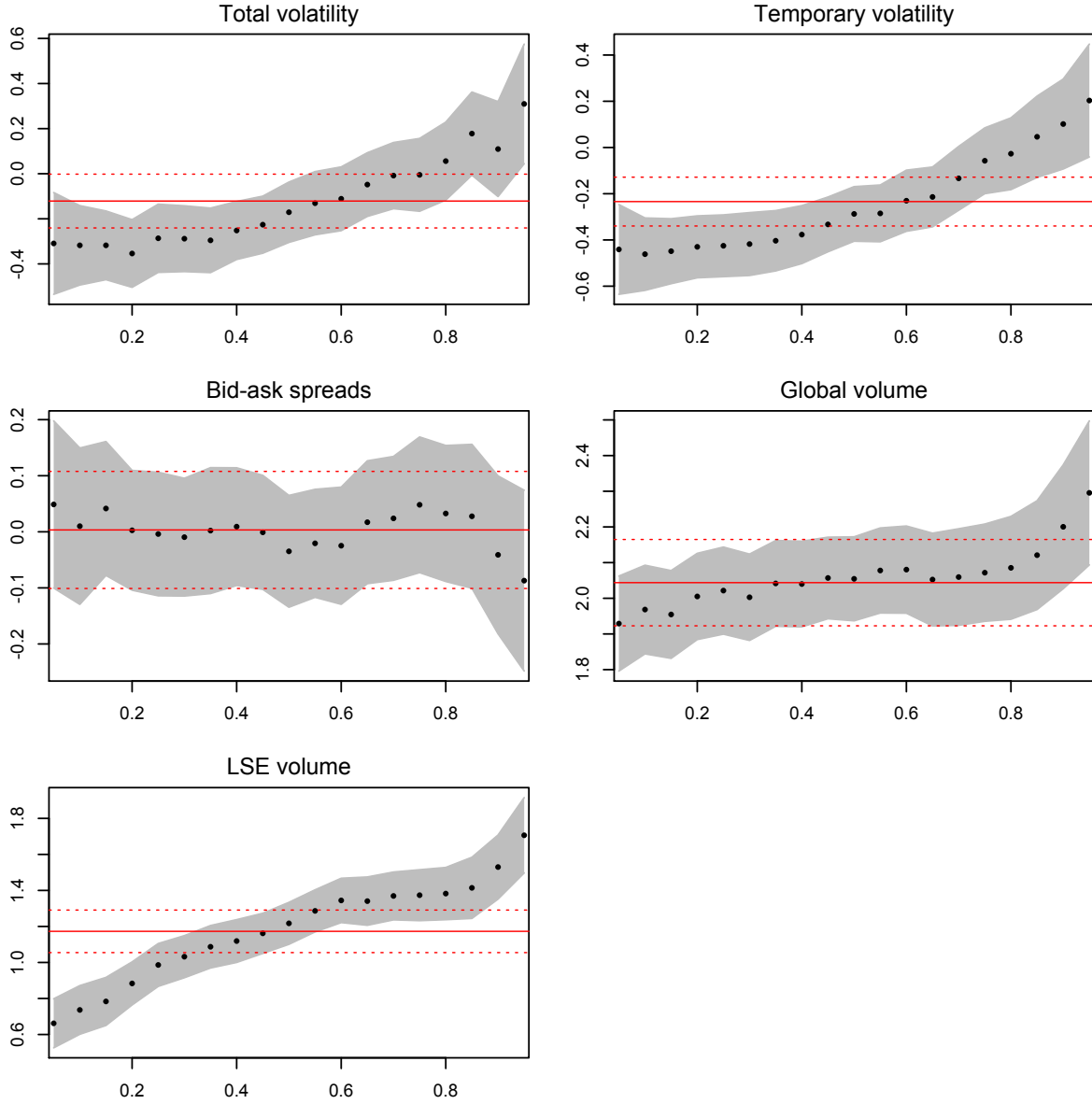


**Figure 9:** Difference in market quality between high and low degrees of visible competition



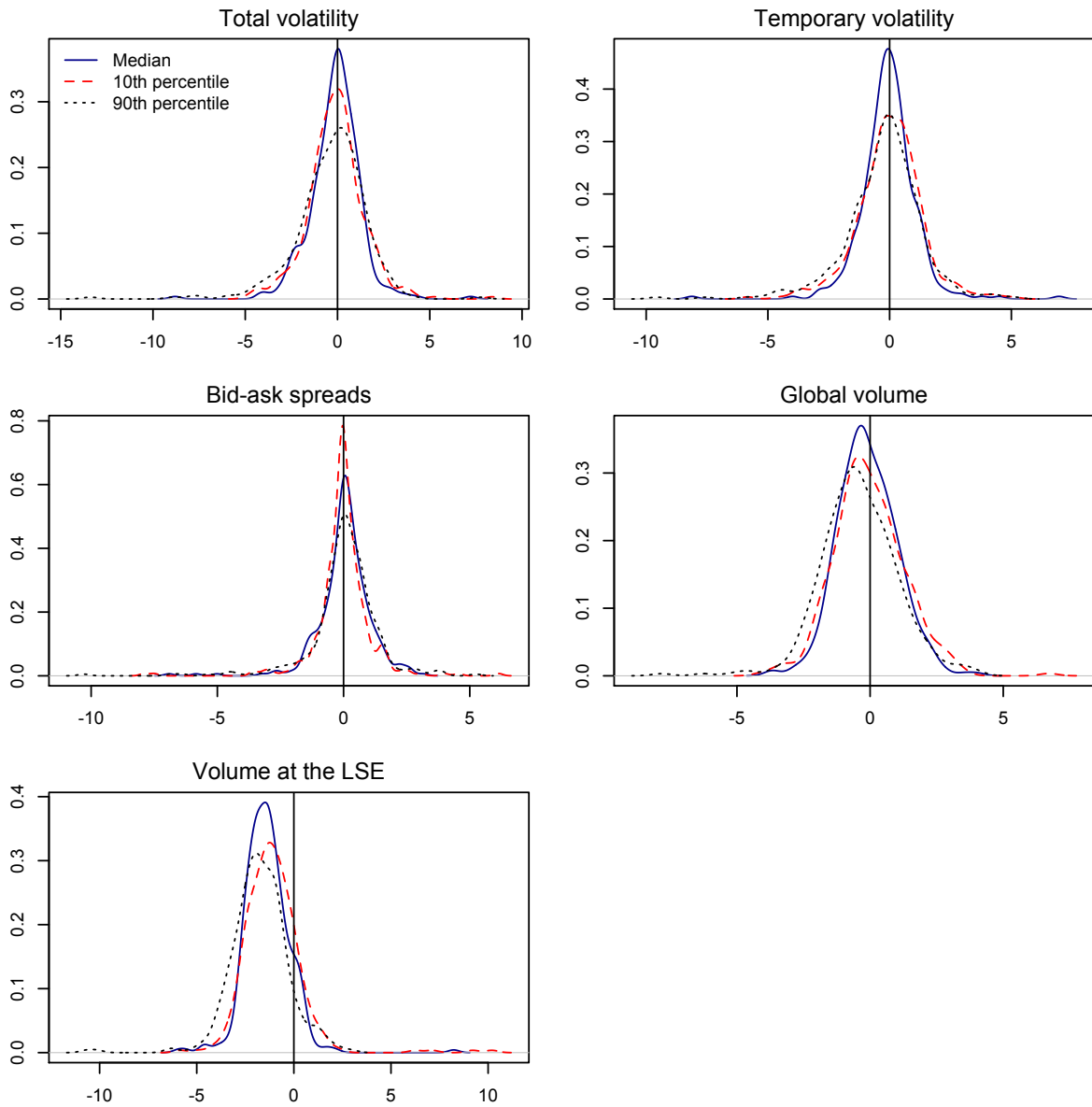
Notes: The figure shows  $\Delta_{Vis.frag.}^{HL}$  that is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  and evaluated at  $H = \max(Vis.frag.) = 0.698$  and  $L = \min(Vis.frag.) = 0$ . Differences constructed from CCE estimates that are based on individual OLS regressions are shown as a red line (the dashed lines correspond to a 95% confidence interval). Differences constructed from CEE estimates that are based on individual quantile regressions for  $\tau \in \{0.05, 0.1, \dots, 0.9, 0.95\}$  are shown as black dots (the shaded area corresponds to a 95% confidence interval).

**Figure 10:** Difference in market quality between high and low degrees of dark trading



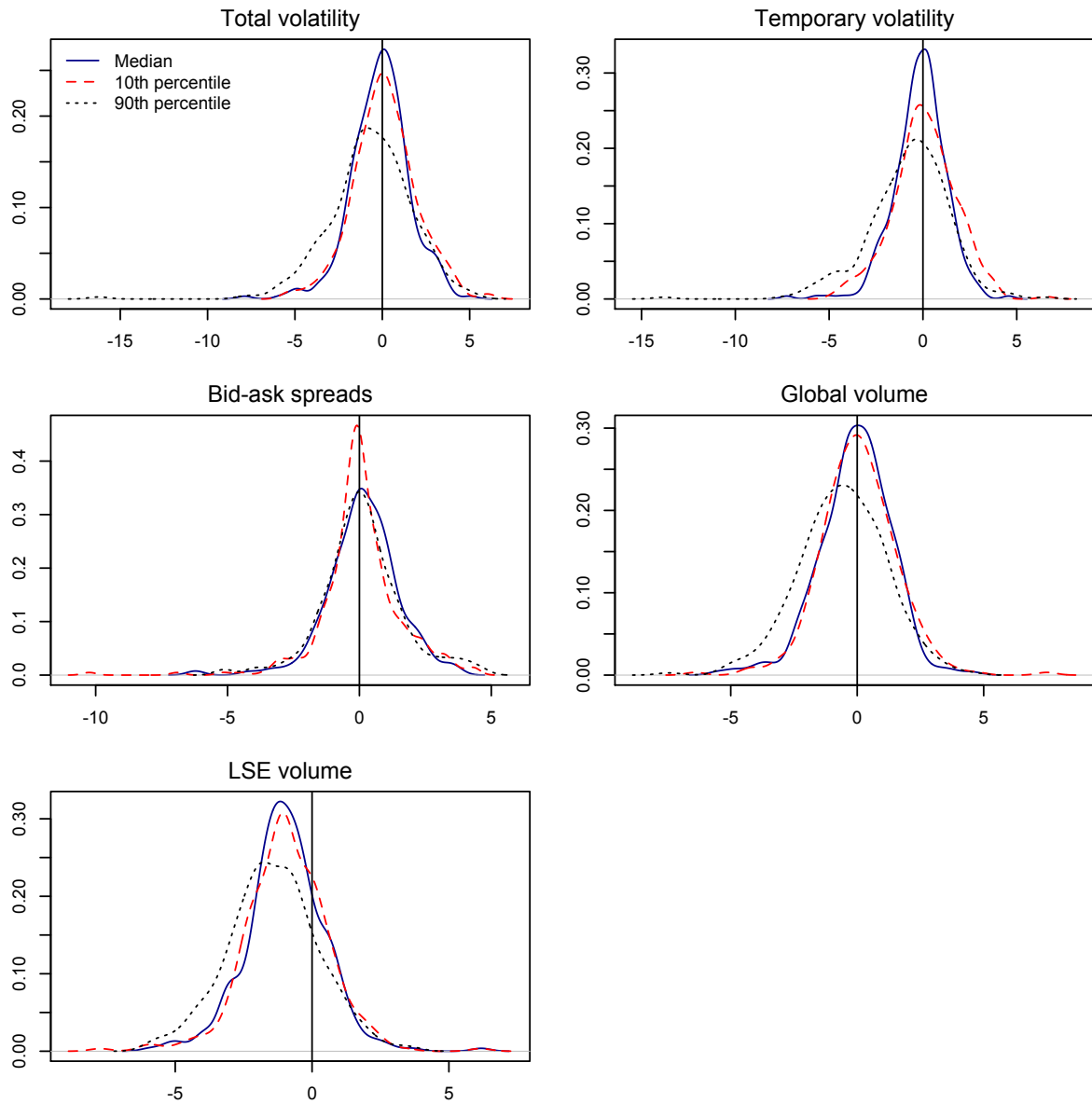
Notes: The figure shows  $\Delta_{Dark}^{HL}$  that is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  and evaluated at  $H = \max(Dark) = 1$  and  $L = \min(Dark) = 0$ . Differences constructed from CCE estimates that are based on individual OLS regressions are shown as a red line (the dashed lines correspond to a 95% confidence interval). Differences constructed from CEE estimates that are based on individual quantile regressions for  $\tau \in \{0.05, 0.1, \dots, 0.9, 0.95\}$  are shown as black dots (the shaded area corresponds to a 95% confidence interval).

**Figure 11:** Heterogeneity in individual differences in market quality between a high and low degree of fragmentation



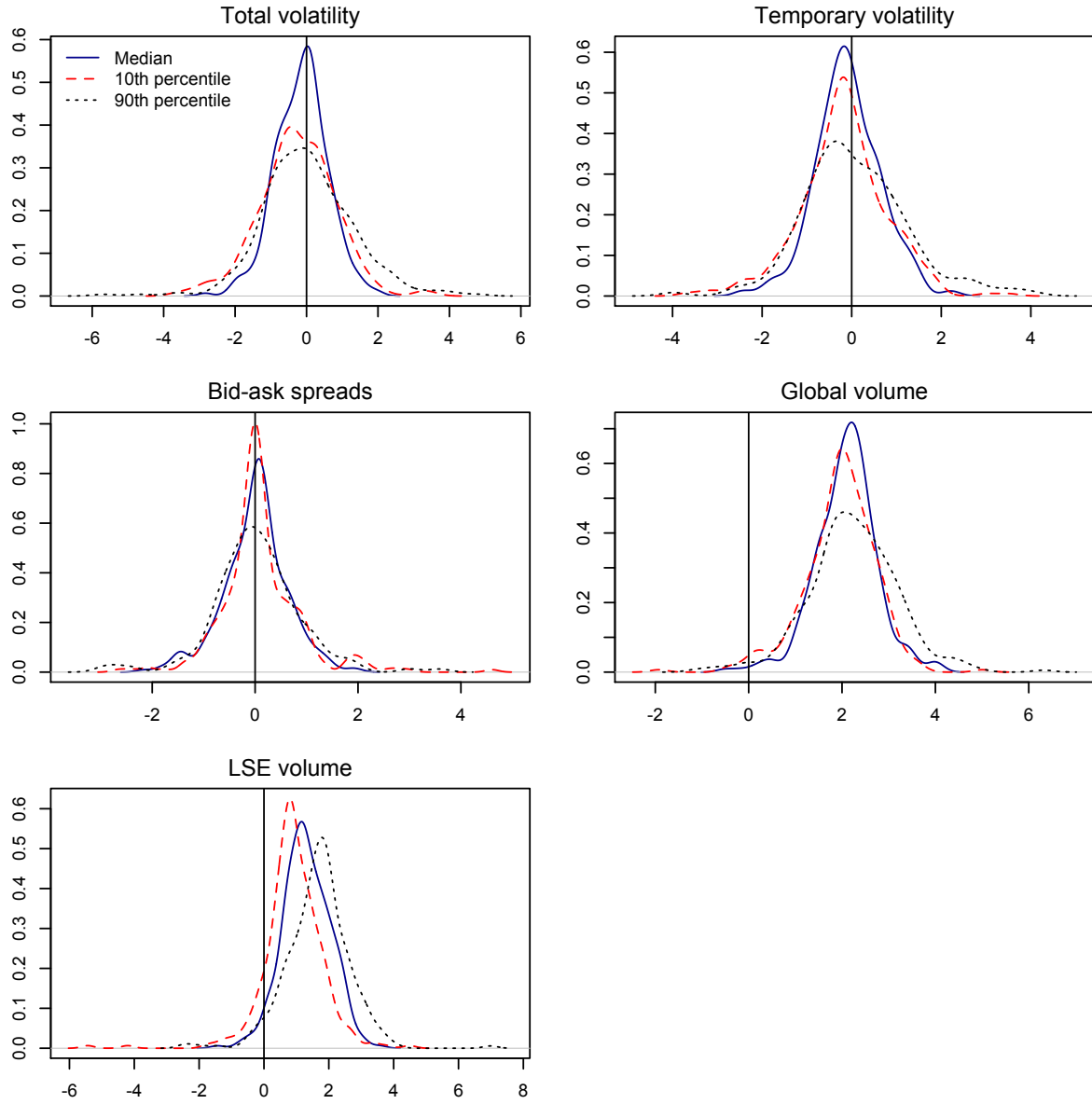
Notes: The figure shows  $\Delta_{Frag.,i}^{HL}$  that is defined as  $\hat{\beta}_{1i} + \hat{\beta}_{2i}(H_i + L_i)$  and evaluated at  $H_i = \max(Frag._i)$  and  $L_i = \min(Frag._i)$ . Individual coefficients are estimated by quantile regressions.

**Figure 12:** Heterogeneity in individual differences between a high and low degree of visible fragmentation



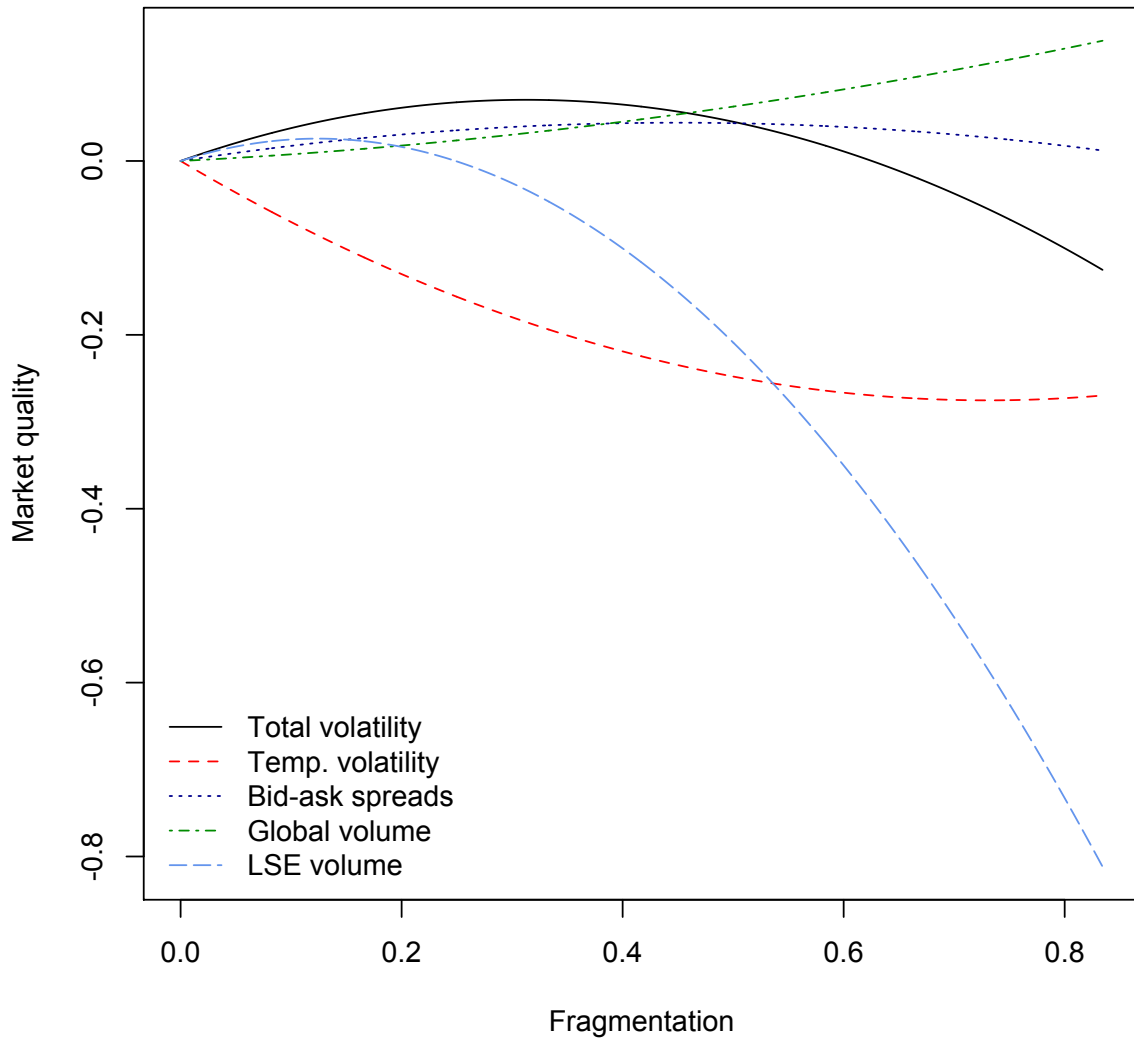
Notes: The figure shows  $\Delta_{Vis.frag.,i}^{HL}$  that is defined as  $\hat{\beta}_{1i} + \hat{\beta}_{2i}(H_i + L_i)$  and evaluated at  $H_i = \max(Vis.frag._i)$  and  $L_i = \min(Vis.frag._i)$ . Individual coefficients are estimated by quantile regressions.

**Figure 13:** Heterogeneity in individual differences between a high and low degree of dark trading



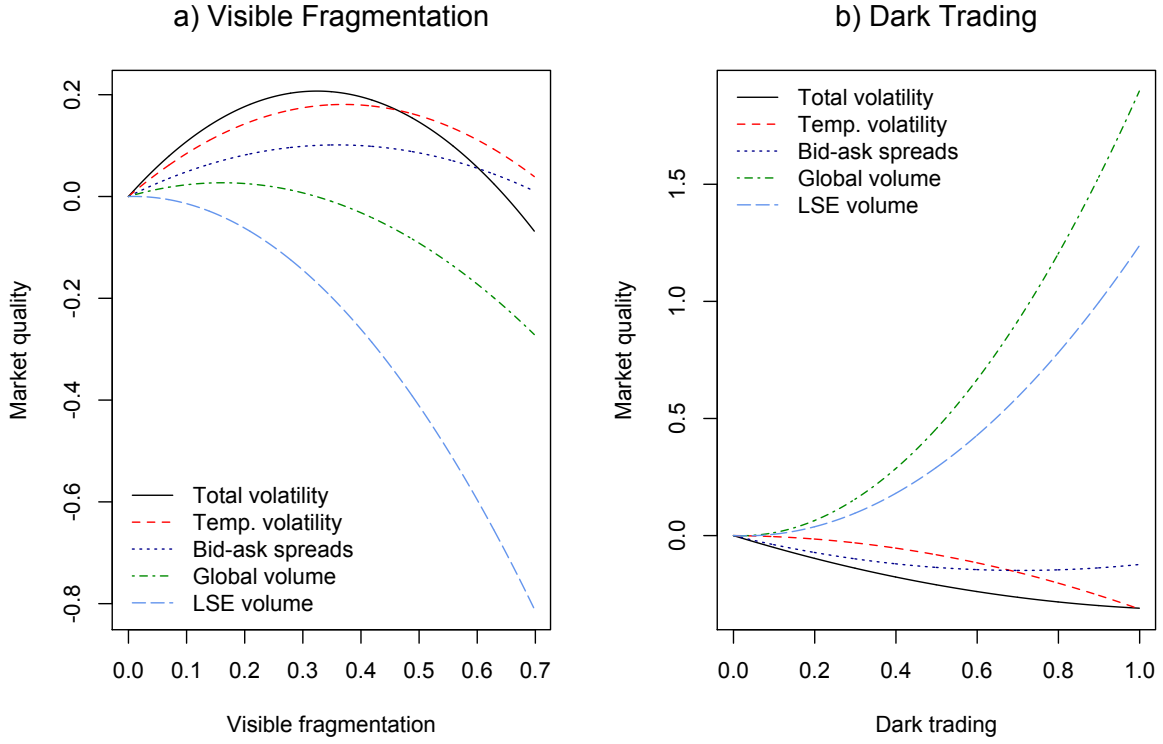
The figure shows  $\Delta_{Dark,i}^{HL}$  that is defined as  $\hat{\beta}_{1i} + \hat{\beta}_{2i}(H_i + L_i)$  and evaluated at  $H_i = \max(Dark_i)$  and  $L_i = \min(Dark_i)$ . Individual coefficients are estimated by quantile regressions.

**Figure 14:** Fragmentation and market quality



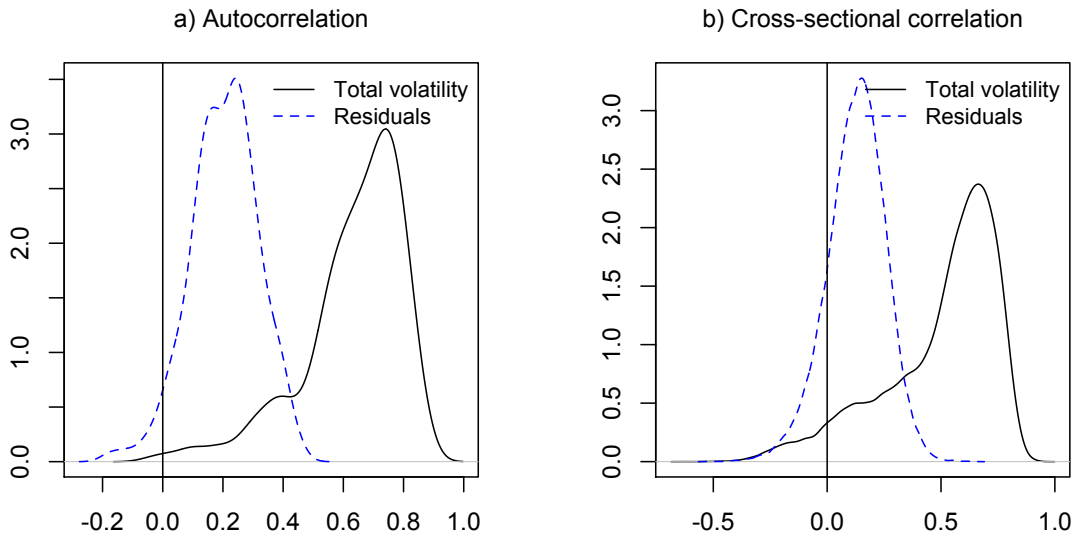
The figure shows  $Y = \hat{\beta}_1 Frag + \hat{\beta}_2 Frag^2$ , where  $Y$  is market quality, and  $\hat{\beta}_j$  are the median CCE estimates from Table 4.

**Figure 15:** Visible fragmentation, dark trading and market quality



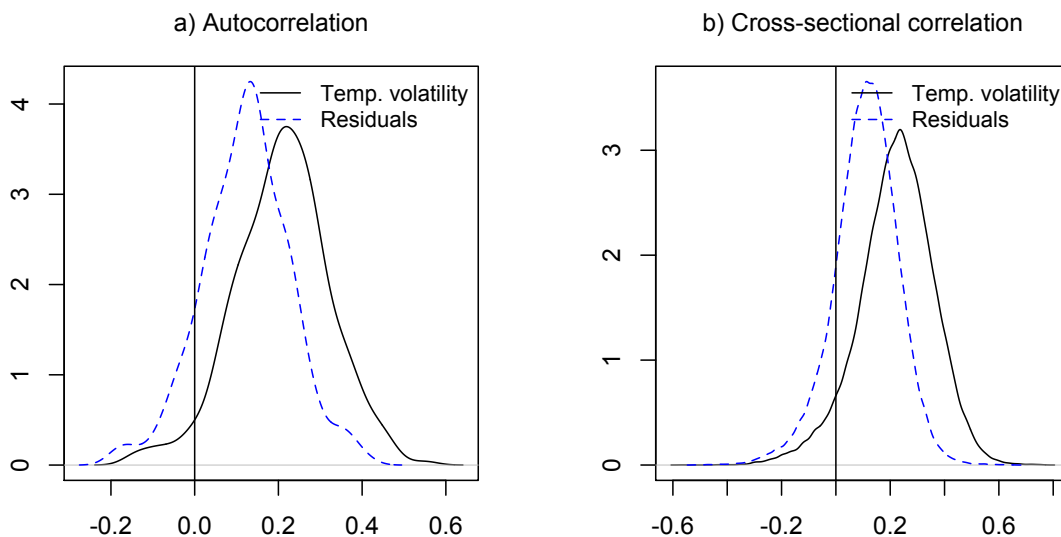
The figure shows  $Y = \hat{\beta}_1 X + \hat{\beta}_2 X^2$ , where  $Y$  is market quality,  $X$  is either visible fragmentation or dark trading, and  $\hat{\beta}_j$  are the median CCE estimates from Table 5.

**Figure 16:** Autocorrelation and cross-sectional correlation in total volatility and residuals



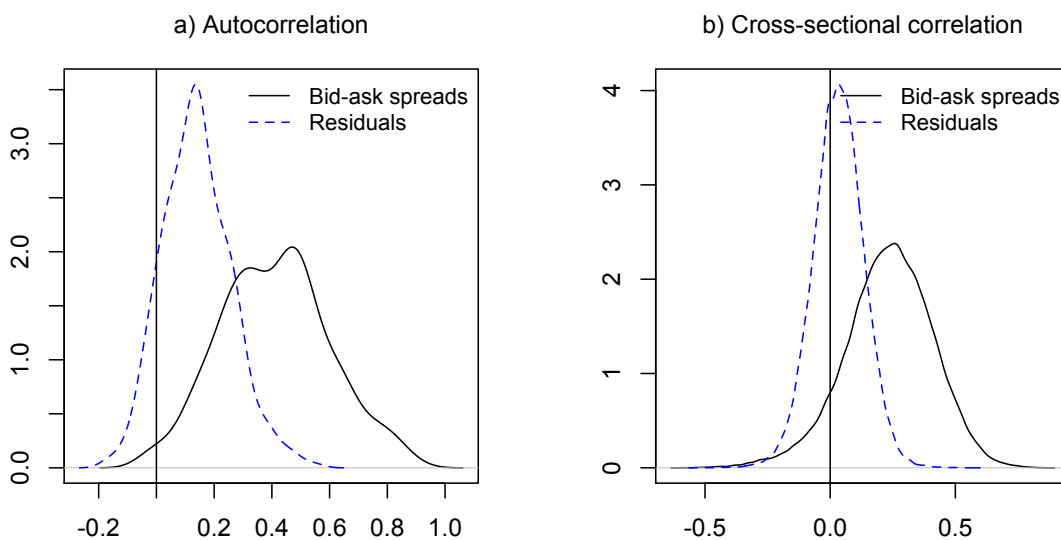
The figures show the kernel density estimates of autocorrelations and cross-sectional correlations in the pooled time-series for total volatility and the median regression residuals.

**Figure 17:** Autocorrelation and cross-sectional correlation in temporary volatility and residuals



The figures show the kernel density estimates of autocorrelations and cross-sectional correlations in the pooled time-series for temporary volatility and the median regression residuals.

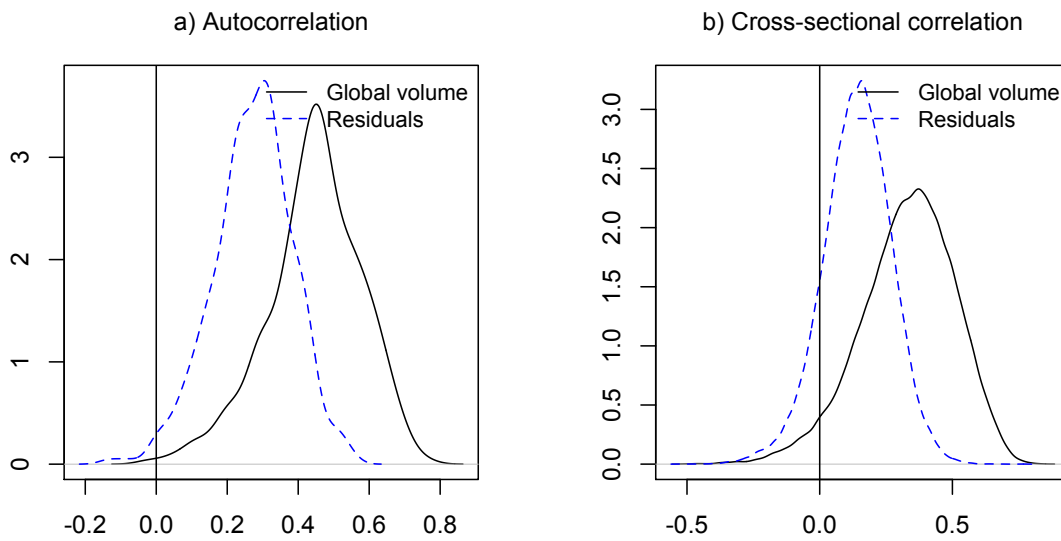
**Figure 18:** Autocorrelation and cross-sectional correlation in bid-ask spreads and residuals



The figures show the kernel density estimates of autocorrelations and cross-sectional correlations in the pooled time-series for bid-ask spreads and the median regression residuals.

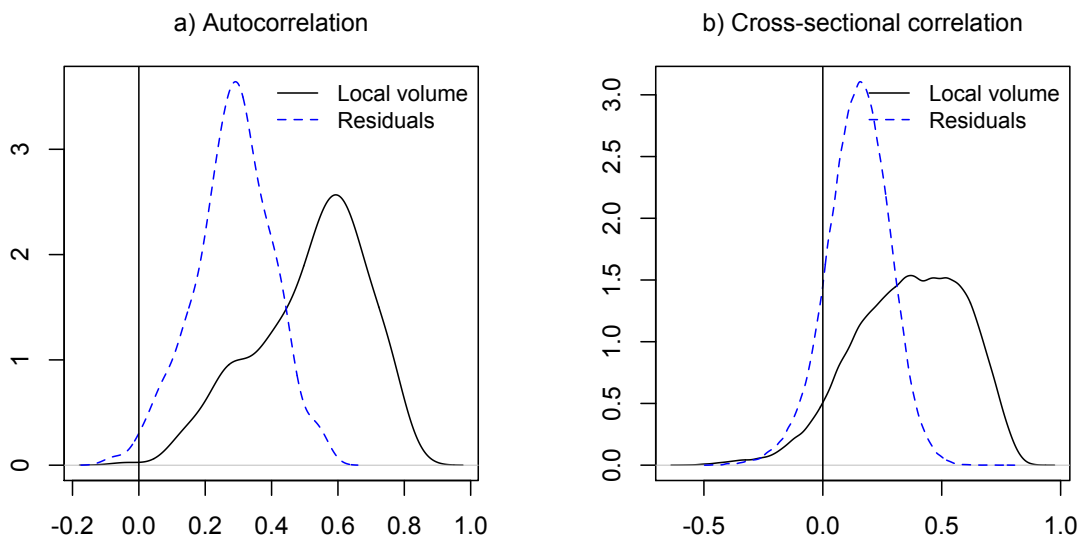


**Figure 19:** Autocorrelation and cross-sectional correlation in global volume and residuals



The figures show the kernel density estimates of autocorrelations and cross-sectional correlations in the pooled time-series for global volume and the median regression residuals.

**Figure 20:** Autocorrelation and cross-sectional correlation in LSE volume and residuals



The figures show the kernel density estimates of autocorrelations and cross-sectional correlations in the pooled time-series for local volume and the median regression residuals.

## 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<sup>21</sup> 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.<sup>22</sup> 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 the 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.<sup>23</sup>

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

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<sup>21</sup>The European Economic Area consists of the 27 member states of the European Union as well as Norway, Iceland, and Liechtenstein.

<sup>22</sup>There are other, unregulated categories of dark pools that are registered as OTC venues or brokers (Gresse, 2012)

<sup>23</sup><http://mifidatabase.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

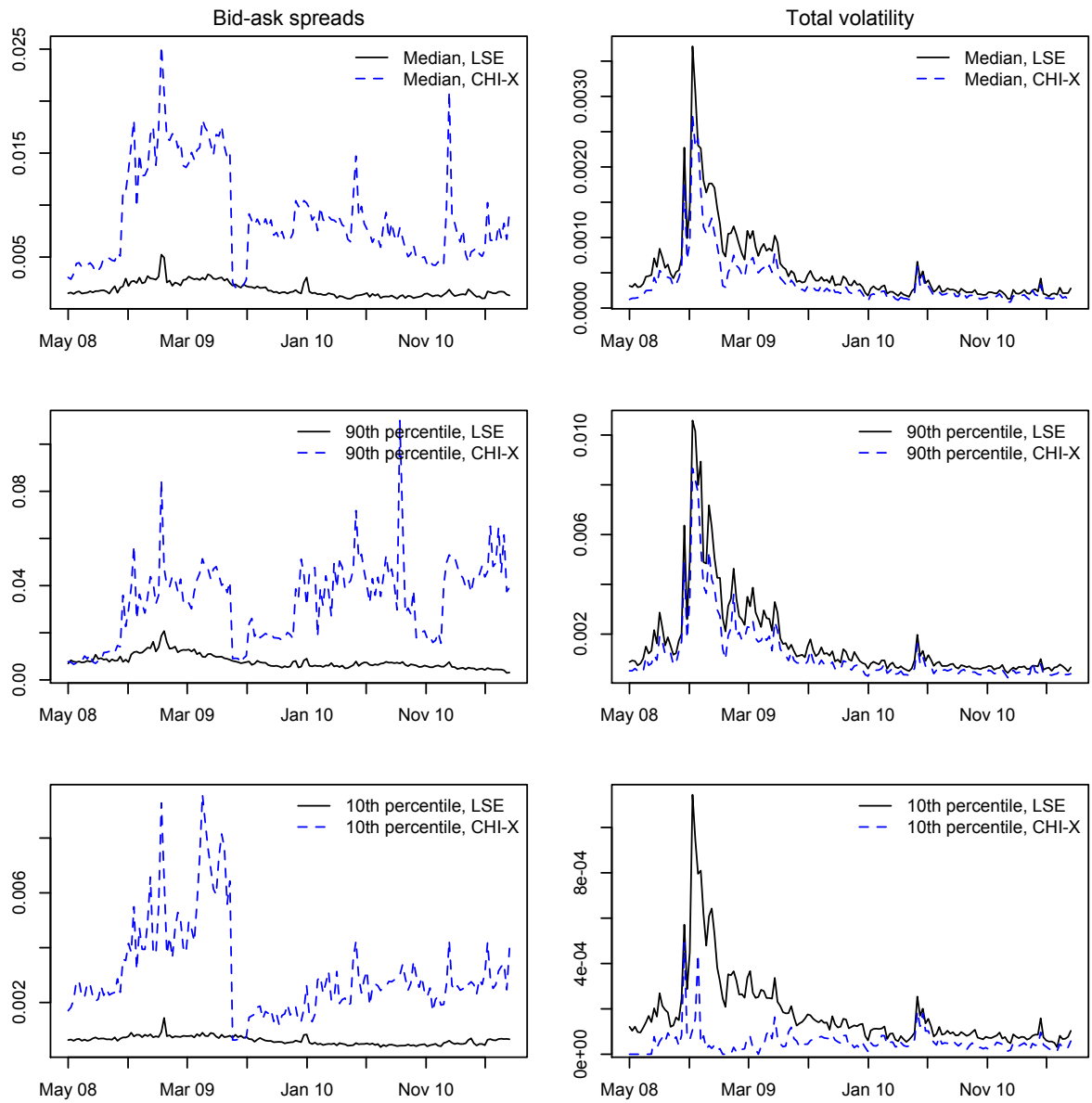
This appendix lists the individual trading venues that are used in our study.

- **Lit venues:** Bats Europe, Chi-X, Equiduct, LSE, Nasdaq Europe, Nyse Arca, and Turquoise<sup>24</sup>
- **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.

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<sup>24</sup>On 21 December 2009, the London Stock Exchange Group agreed to take a 60% stake in trading platform Turquoise.

**Figure B:** Bid-ask spreads and volatility at the LSE and Chi-X



Data source: Datastream.

## 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  $\{(Y_{it}, X_{it}) : i = 1, \dots, n, t = 1, \dots, T\}$ . We first assume that the data come from the linear panel regression model

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

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

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

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

$$\theta_i = \theta + \eta_i,$$

where  $\theta_i = (\alpha_i, \beta_i, \kappa_i, \delta_i, \rho_i)^\top$ ,  $\theta = (\alpha, \beta, \kappa, \delta, \rho)^\top$  and  $\eta_i$  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  $\rho \neq 0$ )

$$Y_{it} = \alpha_i^* + \beta_i X_{it} + \kappa_i^* h_{0t} + \varepsilon_{it}, \quad (12)$$

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

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

since  $\bar{u}_t = O_p(n^{-1/2}) = \bar{\delta} - \delta = \bar{\rho} - \rho$ . Therefore, we may consider the least squares estimator that minimizes  $\sum_{t=1}^T \{Y_{it} - a - bX_{it} - c\bar{X}_t\}^2$  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  $\bar{Y}_t$  here (in this special case, it would introduce approximate multicollinearity here, since  $\bar{Y}_t = \bar{\alpha} + \bar{\beta}\bar{\delta} + (\bar{\beta}\rho + \bar{\kappa})f_t + \bar{\varepsilon}_t + (\bar{\beta}u)_t$ ). Moon and Weidner (2010) advocate a QMLE approach, which would involve optimizing a pooled objective function over  $\theta_i$ ,  $i = 1, \dots, n$  and  $f_t$ ,  $t = 1, \dots, T$ . 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  $\text{med}(\varepsilon_{it} | X_{it}, f_t) = 0$  and maintain the assumptions that  $E(u_{it}) = 0$  with  $u$  independent of  $\varepsilon$ , so that  $\bar{X}_t = \delta + \rho f_t + \bar{u}_t = h_{0t} + O_p(n^{-1/2})$  as before. We consider a more general class of estimators based on minimizing the objective function

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

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

$$M_{Ti}(\psi; \bar{X}_1, \dots, \bar{X}_T) = \frac{1}{T} \sum_{t=1}^T \begin{pmatrix} 1 \\ X_{it} \\ \bar{X}_t \end{pmatrix} \text{sign}(Y_{it} - \alpha - \beta X_{it} - \gamma \bar{X}_t) = \frac{1}{T} \sum_{t=1}^T m_{it}(\psi, \bar{X}_t)$$

We discuss now the properties of  $\hat{\psi}_i$ , the zero of  $M_{Ti}(\psi; \bar{X}_1, \dots, \bar{X}_T)$ . For this purpose we can view  $\hat{\psi}_i$  as an example of a semiparametric estimator as considered in Chen, Linton, and Van Keilegom (2003). That is,  $\bar{X}_t$  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

$$\max_{1 \leq t \leq T} |\bar{X}_t - \delta - \rho f_t| \leq \max_{1 \leq t \leq T} |\bar{u}_t| + |\bar{\delta} - \delta| + (\max_{1 \leq t \leq T} |f_t|) |\bar{\rho} - \rho| = o_p(1).$$

By elementary arguments we have  $\max_{1 \leq t \leq T} |\bar{u}_t| = o_p(T^\kappa n^{-1/2})$  for some  $\kappa$  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  $M_{Ti}(\psi; \bar{X}_1, \dots, \bar{X}_T)$  by  $M_{Ti}(\psi, \hat{h})$ , where  $\hat{h} = (\bar{X}_1, \dots, \bar{X}_T)$ .

The approach of CLV is to approximate the estimator

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

by the estimator

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

where  $h_0 = (h_{01}, \dots, h_{0T})$  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

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

which is uniquely minimized at the true value of  $\psi$ . Here,  $E_i$  means expectation conditional on  $\psi_i$ .

In fact, because of the independence of  $u, \varepsilon$ , 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

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

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  $h^* = (h_1^*, \dots, h_T^*)$

$$E_i [m_{it}(\psi, h_i^*)|f_t] = E_i [m_{it}(\psi, h_{0t})|f_t] + \frac{\partial}{\partial h} E_i [m_{it}(\psi, h_{0t})|f_t] [h_i^* - h_{0t}] + \frac{\partial^2}{\partial h^2} E_i [m_{it}(\psi, \bar{h}_t)|f_t] [h_i^* - h_{0t}]^2$$

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

expectation and so

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

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

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

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

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

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

we have

$$\sqrt{T}(\widehat{\psi}_i - \psi_i) \implies \mathcal{N}[0, \Omega], \text{ where } \Omega = (\Gamma_1^\top \Gamma_1)^{-1} \Gamma_1^\top V_1 \Gamma_1 (\Gamma_1^\top \Gamma_1)^{-1}. \quad (13)$$

It follows that for each  $i$

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

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

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

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

$$\sqrt{n}(\widehat{\beta} - \beta) \implies N(0, \Sigma_{\beta\beta}),$$



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

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

because the averaging over  $i$  reduces the orders, for example

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

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 Amihid 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).<sup>25</sup> The Parkinson estimator of total volatility can be computed as

$$V_{it_j}^P = \frac{1}{4 \ln 2} \left( \ln P_{it_j}^H - \ln P_{it_j}^L \right)^2$$

As shown in Figure E1, the Parkinson volatility estimator is highly correlated with the Rogers-Satchell estimator.

We also decompose volatility into overnight volatility and intraday volatility. 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 E2 reports the time

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<sup>25</sup>We also measured total volatility by the simple range estimator  $V_{it_j} = \frac{P_{it_j}^H - P_{it_j}^L}{P_{it_j}^L}$ . The results for this estimator are very similar to the Parkinson estimator and are available upon request.

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 E3. 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

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

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 E4 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  $\rho_{it}(k) = \text{corr}(R_{it_j}, R_{it_{j-k}})$ ,  $k = 1, 2$ , 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)

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

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 E5 reports cross-sectional quantiles of our efficiency measure. The median inefficiency is around 0.3 quite high.<sup>26</sup> 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

In the main paper, we find that overall fragmentation, visible fragmentation and dark trading have a negative effect on total and temporary volatility. Tables E1-E2 document that these findings are robust to using alternative measures of volatility, albeit the effect of dark trading on idiosyncratic and overnight volatility is not statistically significant. In addition, we find that Amihud illiquidity increases if the level of overall or visible fragmentation increases, while dark trading has the opposite effect. There is no statistically significant effect on efficiency.

Turning to the effect of fragmentation on the variability of market quality (Tables E3-E4), we find that dark trading increases the variability of total (Parkinson) volatility, which is consistent with our main results in the main paper. However, there is no significant effect for visible fragmentation and the other volatility measures. Furthermore, we document that higher fragmentation reduces the variability of Amihud illiquidity.

### 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 across the different subsamples, some interesting differences between FTSE 100 and FTSE 250 firms emerge: We find that the positive effect of overall fragmentation on market quality can be attributed to the FTSE 100 firms (Tables E5-E6). When splitting overall fragmentation into visible fragmentation and dark trading, our results in Tables E7-E8 suggest that dark trading increases volatility for FTSE 100 firms, but has the opposite effect for FTSE 250 firms. The negative effect of visible fragmentation on volatility is only significant for FTSE 100 stocks.

Investigating the effect of fragmentation on the variability of market quality, we document that overall fragmentation has a negative effect on the variability of LSE volume for FTSE 250 firms (Tables E9-E10), while dark trading increases the variability of LSE volume for FTSE

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<sup>26</sup>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.

100 firms (Tables E11-E12).

## Alternative Panel Data Estimators

### Results for fixed effects and difference-in-difference estimators

In the paper, we estimate the effect of fragmentation in equity trading on market quality using the heterogenous regression model

$$\begin{aligned} Y_{it} &= \alpha_i + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}^\top Z_{it} + \delta_i^\top d_t + \kappa_i^\top f_t + \varepsilon_{it} \\ W_{it} &= a_i + D_id_t + K_if_t + u_{it} \end{aligned} \quad (14)$$

where  $f_t$  denotes the unobserved common factor or factors and  $W_{it} = (X_{it}, Z_{it}^\top)^\top$ .

In this section, we re-estimate our results using a heterogeneous panel data model with individual and time fixed effects that can be obtained as a special case of (14) where  $f_t$  is a vector of ones and that there are no observed common factors  $d_t$ :

$$Y_{it} = \alpha_i + \lambda_t + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}^\top Z_{it} + \varepsilon_{it} \quad (15)$$

Compared to the more general model (14), (15) cannot account for common shocks in the data and gives inconsistent results in the presence of common shocks that are correlated with the regressors (Pesaran, 2006).

The difference-in-difference method results in the following model:

$$Y_{it} - Y_{Ft} = \alpha_{iF} + \beta_{1i}X_{it} - \beta_{1F}X_{Ft} + \beta_{2i}X_{it}^2 - \beta_{2F}X_{Ft}^2 + \beta_{3i}^\top Z_{it} - \beta_{3F}^\top Z_{Ft} + u_{iFt} \quad (16)$$

where variables with a subscript F are for the corresponding index (i.e. FTSE 100 or FTSE 250), and  $\alpha_{iF} = \alpha_i - \alpha_F$ . The fixed effects model is given by

$$Y_{it} - \bar{Y}_t = \alpha_i + \beta_{1i}(X_{it} - \bar{X}_t) + \beta_{2i}(X_{it}^2 - \bar{X}_t^2) + \beta_{3i}^\top(Z_{it} - \bar{Z}_t) + u_{it} \quad (17)$$

where  $\bar{Y}_t = \frac{1}{N} \sum_i Y_{it}$  and correspondingly for the other variables. Both (16) and (17) can be estimated by OLS or median regression for each stock. Individual estimates are then averaged and the covariance is estimated as:

$$\hat{\Sigma} = \frac{1}{N-1} \sum_{i=1}^N (\hat{\beta}_i - \hat{\beta})(\hat{\beta}_i - \hat{\beta})^\top. \quad (18)$$

We restrict attention to the effect of overall fragmentation on the level of market quality. Inspecting Tables E13-E14, we find that fragmentation depresses trading volume at the LSE, a finding that is consistent with our main results. This result holds for both fixed effects and difference in difference estimates. In addition, the difference-in-difference results confirm our main findings that fragmentation lowers total volatility but increases global volume. However, the fixed effects estimates also imply that fragmentation increases bid-ask spreads.

## 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

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

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

$$Y_{it} = \alpha_i + \beta_1 X_{it} + \beta_2^T Z_{it} + \varepsilon_{it}$$

$$X_{it} = a + b \overline{MV}_i + c^T W_{it} + \eta_{it}$$

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

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

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. (2012) considered a specification of the form

$$Y_{it} = \alpha_i + \gamma_i t + \beta_1 X_{it} + \beta_3 Z_{it} + w d_t + \varepsilon_{it}$$

$$X_{it} = a_i + b_i t + c L_t + e Z_{it} + \eta_{it}$$

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 ( $i = 1, \dots, 7$ ) 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.

## 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 measured 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.

**Table E1:** The effect of fragmentation on market quality for alternative measure of market quality

	Total (Parkinson) volatility	Idiosync. volatility	Daily volatility	Overnight volatility	Efficiency	Illiquidity
Constant	-7.713 (-8.817)	-6.987 (-4.855)	-5.507 (-3.025)	-14.926 (-10.13)	0.562 (2.738)	-13.652 (-14.019)
Fragmentation	0.208 (0.383)	0.416 (0.518)	-0.11 (-0.134)	-1.916 (-1.919)	-0.025 (-0.23)	-0.524 (-1.112)
Fragmentation sq.	-0.534 (-1.269)	-0.988 (-1.446)	-0.368 (-0.55)	1.1 (1.356)	0.056 (0.579)	1.341 (3.315)
Market cap.	-0.499 (-6.936)	-0.48 (-3.694)	-0.591 (-5.561)	-0.48 (-4.238)	-0.039 (-2.539)	-0.322 (-4.528)
Lagged index return	0.13 (1.094)	-0.236 (-1.042)	-0.303 (-1.293)	-0.048 (-0.226)	0.037 (1.2)	0.415 (3.381)
VIX	1.126 (39.602)	1.022 (19.726)	1.153 (20.79)	1.845 (28.379)	-0.018 (-2.507)	0.556 (19.476)
Christmas and New Year	-0.267 (-12.004)	-0.976 (-19.751)	-0.135 (-3.704)	0.166 (4.78)	0.016 (3.157)	0.588 (19.262)
Fragmentation (avg.)	-1.991 (-10.776)	-2.514 (-6.743)	-2.777 (-8.061)	-1.57 (-4.449)	0.058 (1.492)	-1.026 (-4.086)
Market cap. (avg.)	-0.004 (-0.062)	0.174 (1.139)	0.227 (1.758)	0.607 (4.329)	-0.044 (-1.79)	-0.033 (-0.465)
Marginal effect	-0.349 (-2.634)	-0.615 (-3.146)	-0.495 (-2.478)	-0.768 (-3.43)	0.033 (1.303)	0.875 (8.422)
$\Delta_{Frag.}^T$	-0.238 (-1.154)	-0.408 (-1.457)	-0.418 (-1.402)	-0.998 (-2.821)	0.021 (0.592)	0.595 (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. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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 E2:** The effects of visible fragmentation and dark trading on market quality for alternative measure of market quality

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

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  and evaluated at  $H = \max(X)$  and  $L = \min(X)$ , 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 E3:** The effect of fragmentation on the volatility of market quality for alternative measure of market quality

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

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta} + \hat{\gamma}(H+L)$  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 E4:** The effect of visible fragmentation and dark trading on the volatility of market quality for alternative measure of market quality

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

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  is defined as  $\hat{\beta} + \hat{\gamma}(H + L)$  and evaluated at  $H = \max(X)$  and  $L = \min(X)$ , 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 E5:** The effect of fragmentation on market quality for FTSE 100 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-2.74 (-2.296)	-10.733 (-11.668)	9.955 (5.771)	1.286 (1.032)	3.546 (3.332)
Fragmentation	1.141 (1.181)	-2.636 (-2.851)	-0.02 (-0.035)	1.711 (3.076)	2.197 (4.326)
Fragmentation sq.	-1.216 (-1.616)	2.122 (2.917)	0.184 (0.38)	-1.232 (-2.457)	-3.115 (-7.203)
Market cap.	-0.44 (-3.857)	-0.405 (-4.82)	-0.335 (-2.952)	-0.533 (-6.469)	-0.52 (-6.71)
Lagged index return	1.675 (7.51)	1.896 (8.497)	-0.099 (-0.949)	0.9 (6.024)	1.153 (8.29)
VIX	1.102 (21.961)	0.941 (21.181)	-0.239 (-4.642)	0.283 (6.563)	0.217 (5.529)
Christmas and New Year	-0.352 (-10.879)	-0.343 (-11.752)	0.387 (11.849)	-1.332 (-50.646)	-1.346 (-57.374)
Fragmentation (avg.)	-0.971 (-2.458)	1.278 (3.667)	-0.169 (-0.909)	0.913 (1.578)	0.364 (0.968)
Market cap. (avg.)	-2.01 (-7.536)	-0.447 (-2.099)	-1.386 (-4.634)	-0.257 (-1.312)	-0.722 (-4.294)
Marginal effect	-0.38 (-1.936)	0.019 (0.103)	0.211 (1.534)	0.169 (1.243)	-1.702 (-16.012)
$\Delta_{Frag.}^T$	0.087 (0.245)	-0.795 (-2.394)	0.14 (0.752)	0.642 (4.153)	-0.506 (-3.223)
Adjusted $R^2$	0.777	0.204	0.605	0.801	0.831

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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 E6:** The effect of fragmentation on market quality for FTSE 250 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-8.503 (-8.268)	-11.781 (-14.881)	3.584 (3.743)	2.195 (2.639)	2.18 (2.336)
Fragmentation	-0.193 (-0.282)	-0.091 (-0.168)	0.072 (0.258)	-0.658 (-1.876)	-0.276 (-0.837)
Fragmentation sq.	-0.162 (-0.297)	-0.07 (-0.162)	-0.164 (-0.651)	0.707 (2.012)	-1.091 (-3.298)
Market cap.	-0.437 (-4.379)	-0.359 (-5.414)	-0.326 (-3.772)	-0.058 (-0.682)	-0.084 (-0.979)
Lagged index return	0.297 (1.965)	0.753 (6.049)	-0.921 (-6.442)	-0.359 (-2.043)	-0.385 (-2.118)
VIX	1.042 (26.254)	0.947 (29.374)	0.095 (2.745)	0.264 (7.134)	0.295 (7.461)
Christmas and New Year	-0.182 (-6.693)	-0.139 (-5.728)	0.395 (17.525)	-1.144 (-37.005)	-1.134 (-35.65)
Fragmentation (avg.)	-1.424 (-5.659)	0.187 (1.039)	-0.758 (-4.471)	-0.273 (-0.915)	-0.351 (-1.224)
Market cap. (avg.)	-0.219 (-1.285)	0.758 (5.45)	0.033 (0.201)	0.556 (3.103)	0.571 (3.244)
Marginal effect	-0.348 (-1.775)	-0.158 (-1.066)	-0.085 (-1.066)	0.019 (0.193)	-1.322 (-13.856)
$\Delta_{Frag.}^T$	-0.328 (-1.301)	-0.149 (-0.772)	-0.065 (-0.682)	-0.069 (-0.635)	-1.186 (-11.469)
Adjusted $R^2$	0.714	0.117	0.706	0.738	0.714

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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 E6:** The effects of visible fragmentation and dark trading on market quality for FTSE 100 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-2.643 (-1.852)	-9.287 (-8.125)	8.131 (4.587)	4.08 (4.744)	5.067 (5.14)
Vis. fragmentation	-0.3 (-0.445)	-4.476 (-7.695)	0.221 (0.628)	-0.87 (-2.12)	-0.734 (-1.825)
Vis. fragmentation sq.	-0.597 (-0.903)	4.228 (7.189)	0.001 (0.002)	0.916 (2.015)	-0.679 (-1.498)
Dark	-0.003 (-0.009)	1.216 (3.583)	0.052 (0.14)	0.98 (3.189)	0.864 (2.185)
Dark sq.	0.315 (0.676)	-1.404 (-3.337)	-0.015 (-0.037)	1.504 (4.333)	0.546 (1.269)
Market cap.	-0.332 (-2.539)	-0.337 (-3.13)	-0.326 (-3.094)	-0.46 (-5.995)	-0.47 (-5.859)
Lagged index return	1.552 (7.909)	1.478 (7.759)	0.061 (0.638)	1.081 (7.074)	1.052 (8.273)
VIX	1.031 (22.721)	0.955 (24.949)	-0.174 (-3.981)	0.271 (7.556)	0.207 (5.648)
Christmas and New Year	-0.398 (-11.033)	-0.358 (-11.325)	0.43 (13.148)	-1.386 (-56.478)	-1.372 (-54.94)
Vis. fragmentation (avg.)	0.591 (1.488)	1.948 (5.233)	-0.676 (-2.988)	0.11 (0.453)	0.408 (1.385)
Dark (avg.)	-1.453 (-7.065)	-0.229 (-1.303)	0.362 (2.516)	-1.111 (-7.48)	-1.568 (-10.632)
Market cap. (avg.)	-1.973 (-7.426)	-0.288 (-1.437)	-1.356 (-5.426)	-0.68 (-3.809)	-0.756 (-5.124)
Marg. effect (vis. frag)	-0.853 (-4.368)	-0.558 (-3.043)	0.222 (1.305)	-0.021 (-0.187)	-1.363 (-12.007)
Marg. effect (dark)	0.227 (2.024)	0.189 (1.855)	0.041 (0.322)	2.081 (20.762)	1.263 (9.424)
$\Delta_{Vis.frag.}^T$	-0.715 (-2.67)	-1.536 (-6.604)	0.222 (1.585)	-0.233 (-1.731)	-1.206 (-9.234)
$\Delta_{Dark}^T$	0.303 (2.02)	-0.148 (-1.122)	0.038 (0.321)	2.442 (23.905)	1.394 (11.101)
Adjusted $R^2$	0.784	0.224	0.617	0.846	0.848

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  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 E7:** The effects of visible fragmentation and dark trading on market quality for FTSE 250 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-9.696 (-9.159)	-12.84 (-13.846)	0.588 (0.465)	1.368 (1.692)	3.05 (3.456)
Vis. fragmentation	1.277 (3.855)	0.977 (3.649)	0.565 (2.107)	0.334 (1.511)	0.03 (0.115)
Vis. fragmentation sq.	-1.969 (-4.665)	-1.319 (-3.766)	-0.787 (-2.222)	-1.035 (-3.561)	-1.706 (-5.192)
Dark	-0.531 (-1.775)	-0.014 (-0.05)	-0.42 (-1.446)	-0.071 (-0.275)	-0.073 (-0.28)
Dark sq.	0.221 (0.879)	-0.3 (-1.256)	0.297 (1.137)	1.972 (9.367)	1.312 (5.59)
Market cap.	-0.487 (-5.184)	-0.405 (-5.395)	-0.318 (-3.531)	-0.343 (-4.021)	-0.311 (-3.494)
Lagged index return	-0.166 (-1.151)	0.616 (4.69)	-0.999 (-6.243)	-0.597 (-4.071)	-0.427 (-2.599)
VIX	1.142 (28.397)	1.031 (28.084)	0.2 (4.458)	0.374 (12.267)	0.286 (7.619)
Christmas and New Year	-0.27 (-8.899)	-0.179 (-6.964)	0.466 (17.456)	-1.192 (-37.077)	-1.222 (-34.246)
Vis. fragmentation (avg.)	-1.631 (-8.201)	-0.482 (-2.831)	-1.245 (-7.958)	-0.824 (-5.024)	-0.771 (-4.02)
Dark (avg.)	-0.669 (-3.334)	0.285 (1.877)	0.599 (3.367)	-1.777 (-11.211)	-1.992 (-11.218)
Market cap. (avg.)	0.557 (3.501)	1.094 (8.133)	0.48 (2.412)	1.256 (7.844)	0.794 (4.817)
Marg. effect (vis. frag)	0.085 (0.6)	0.178 (1.536)	0.088 (0.844)	-0.293 (-2.605)	-1.003 (-8.736)
Marg. effect (dark)	-0.309 (-4.184)	-0.315 (-4.726)	-0.122 (-1.654)	1.908 (26.269)	1.245 (18.449)
$\Delta_{Vis.frag.}^T$	-0.097 (-0.728)	0.056 (0.501)	0.015 (0.155)	-0.389 (-3.472)	-1.161 (-10.722)
$\Delta_{Dark}^T$	-0.31 (-4.162)	-0.314 (-4.669)	-0.123 (-1.665)	1.899 (25.949)	1.238 (18.291)
Adjusted $R^2$	0.736	0.139	0.672	0.831	0.765
CSD abs.	0.12	0.114	0.08	0.172	0.149
CSD sq.	0.021	0.019	0.01	0.041	0.032

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  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 E8:** The effect of fragmentation on the volatility of market quality for FTSE 100 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.58 (-1.958)	-0.359 (-1.059)	0.585 (1.834)	-0.175 (-1.324)	-0.122 (-0.662)
Fragmenation	-0.092 (-0.452)	0.127 (0.573)	0.135 (1.164)	0.229 (2.329)	0.174 (1.874)
Fragmentation sq.	0.088 (0.463)	-0.116 (-0.616)	-0.111 (-1.09)	-0.215 (-2.532)	-0.142 (-1.766)
Market cap.	0.043 (1.627)	0.027 (1.088)	-0.027 (-0.861)	-0.006 (-0.442)	-0.007 (-0.626)
Lagged index return	0.099 (1.386)	-0.058 (-0.974)	0.116 (2.743)	0.018 (0.506)	0.037 (1.219)
VIX	0.035 (2.58)	0.026 (2.056)	-0.001 (-0.086)	-0.002 (-0.304)	-0.002 (-0.212)
Christmas and New Year	0.017 (1.767)	0.034 (2.883)	0.052 (4.416)	0.049 (5.578)	0.033 (4.577)
Fragmentation (avg.)	0.098 (0.815)	-0.012 (-0.124)	0.144 (2.31)	0.054 (1.748)	-0.025 (-0.375)
Market cap. (avg.)	-0.073 (-0.867)	0.07 (1.006)	-0.15 (-3.37)	0.006 (0.151)	-0.01 (-0.253)
Marginal effect	0.018 (0.299)	-0.018 (-0.318)	-0.004 (-0.108)	-0.039 (-1.649)	-0.003 (-0.126)
$\Delta_{Frag.}^T$	-0.016 (-0.277)	0.026 (0.356)	0.039 (0.978)	0.043 (1.387)	0.051 (1.732)
Adjusted $R^2$	-0.061	-0.066	-0.037	-0.023	-0.022

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  is defined as  $\hat{\beta}_1 + \hat{\beta}_2(H + L)$  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 E9:** The effect of fragmentation on the volatility of market quality for FTSE 250 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.021 (-0.041)	-0.683 (-1.29)	0.346 (1.485)	0.607 (1.204)	0.178 (0.53)
Fragmenation	-0.171 (-1.24)	-0.086 (-0.709)	-0.068 (-0.745)	-0.457 (-2.165)	-0.412 (-2.676)
Fragmentation sq.	0.147 (1.168)	0.105 (0.902)	0.087 (0.926)	0.432 (2.409)	0.333 (2.475)
Market cap.	-0.043 (-1.31)	-0.05 (-1.757)	0.004 (0.196)	-0.081 (-3.734)	-0.084 (-4.271)
Lagged index return	-0.035 (-0.401)	0.185 (2.105)	0.053 (0.958)	0.026 (0.331)	-0.003 (-0.058)
VIX	0.021 (1.154)	-0.007 (-0.458)	-0.01 (-0.754)	-0.011 (-1.019)	-0.004 (-0.264)
Christmas and New Year	0.08 (3.916)	0.062 (3.885)	0.111 (3.26)	0.115 (4.652)	0.104 (4.637)
Fragmentation (avg.)	-0.018 (-0.162)	-0.085 (-0.827)	0.02 (0.331)	-0.196 (-1.584)	-0.082 (-1.061)
Market cap. (avg.)	0.107 (1.321)	-0.046 (-0.697)	-0.098 (-1.539)	0.015 (0.241)	0.107 (1.841)
Marginal effect	-0.031 (-0.808)	0.015 (0.48)	0.015 (0.667)	-0.043 (-0.812)	-0.093 (-2.147)
$\Delta_{Frag.}^T$	-0.049 (-1.069)	0.002 (0.062)	0.004 (0.157)	-0.097 (-1.383)	-0.134 (-2.526)
Adjusted $R^2$	-0.009	-0.01	-0.06	0.048	0.055

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_{Frag.}^T$  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 E10:** The effect of visible fragmentation and dark trading on the volatility of market quality for FTSE 100 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.879 (-2.133)	-0.477 (-1.013)	0.663 (2.255)	0.01 (0.079)	0.2 (1.355)
Vis. fragmentation	0.366 (2.588)	-0.083 (-0.275)	-0.045 (-0.474)	0.264 (3.244)	0.259 (2.709)
Vis. fragmentation sq.	-0.498 (-2.845)	-0.111 (-0.398)	0.047 (0.462)	-0.318 (-3.699)	-0.308 (-3.078)
Dark	-0.095 (-0.74)	-0.138 (-1.524)	-0.046 (-0.542)	-0.037 (-0.838)	-0.042 (-0.909)
Dark sq.	0.252 (1.552)	0.277 (2.458)	0.038 (0.387)	0.057 (1.076)	0.109 (1.855)
Market cap.	0.012 (0.41)	0.012 (0.457)	0.005 (0.237)	-0.003 (-0.284)	0.005 (0.381)
Lagged index return	0.069 (0.922)	-0.114 (-1.943)	0.095 (1.952)	-0.012 (-0.51)	-0.063 (-1.88)
VIX	0.045 (2.594)	0.037 (2.02)	-0.002 (-0.192)	-0.009 (-1.66)	-0.013 (-2.194)
Christmas and New Year	0.009 (0.932)	0.004 (0.48)	0.044 (3.836)	0.015 (3.344)	0.017 (2.927)
Vis. fragmentation (avg.)	0.195 (2.157)	0.189 (1.985)	0.073 (1.505)	0.024 (0.82)	0.035 (0.978)
Dark (avg.)	-0.127 (-1.723)	-0.202 (-3.655)	0.112 (2.278)	-0.035 (-1.632)	-0.056 (-2.214)
Market cap. (avg.)	0.006 (0.063)	0.151 (1.734)	-0.161 (-3.217)	0.016 (0.686)	0.038 (1.252)
Marg. effect (vis. frag)	-0.095 (-1.572)	-0.186 (-2.204)	-0.001 (-0.033)	-0.03 (-1.522)	-0.026 (-1.216)
Marg. effect (dark)	0.09 (2.322)	0.064 (1.996)	-0.018 (-0.66)	0.005 (0.418)	0.038 (2.458)
$\Delta_{Vis.frag.}^T$	0.02 (0.378)	-0.16 (-1.29)	-0.012 (-0.331)	0.043 (1.56)	0.045 (1.403)
$\Delta_{Dark}^T$	0.15 (2.869)	0.131 (3.233)	-0.009 (-0.305)	0.019 (1.225)	0.064 (3.137)
Adjusted $R^2$	-0.049	-0.056	-0.022	-0.012	-0.003

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  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 E11:** The effect of visible fragmentation and dark trading on the volatility of market quality for FTSE 250 firms

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-0.436 (-1.004)	-0.138 (-0.341)	0.163 (0.412)	0.294 (1.316)	0.054 (0.185)
Vis. fragmentation	-0.333 (-2.897)	-0.243 (-1.7)	0.064 (0.668)	-0.126 (-1.457)	-0.145 (-1.377)
Vis. fragmentation sq.	0.379 (2.169)	0.261 (1.36)	-0.013 (-0.107)	0.153 (1.275)	0.173 (1.192)
Dark	0.046 (0.328)	-0.103 (-0.716)	-0.139 (-1.645)	-0.183 (-2.7)	-0.283 (-3.58)
Dark sq.	0.029 (0.238)	0.175 (1.38)	0.125 (1.527)	0.149 (2.749)	0.268 (4.031)
Market cap.	-0.042 (-1.359)	-0.054 (-1.952)	0.026 (1.085)	-0.053 (-3.301)	-0.052 (-2.272)
Lagged index return	-0.02 (-0.206)	0.062 (0.907)	0.004 (0.067)	0.013 (0.321)	0.043 (0.631)
VIX	0.041 (1.796)	0.006 (0.232)	-0.007 (-0.433)	-0.023 (-2.483)	-0.018 (-1.477)
Christmas and New Year	0.053 (3.639)	0.039 (2.934)	0.02 (1.799)	0.042 (3.575)	0.029 (3.191)
Vis. fragmentation (avg.)	0.143 (1.624)	0.078 (1.27)	-0.039 (-0.678)	0.017 (0.404)	-0.003 (-0.067)
Dark (avg.)	0.118 (1.824)	-0.01 (-0.152)	-0.018 (-0.265)	-0.014 (-0.377)	0.019 (0.416)
Market cap. (avg.)	0.119 (0.968)	0.013 (0.169)	-0.023 (-0.358)	0.028 (0.821)	0.026 (0.318)
Marg. effect (vis. frag)	-0.103 (-2.213)	-0.085 (-1.76)	0.056 (1.524)	-0.033 (-1.441)	-0.04 (-1.452)
Marg. effect (dark)	0.076 (2.224)	0.073 (2.328)	-0.014 (-0.727)	-0.034 (-1.788)	-0.014 (-0.7)
$\Delta_{Vis.frag.}^T$	-0.068 (-1.372)	-0.06 (-1.375)	0.055 (1.608)	-0.019 (-0.946)	-0.024 (-1.032)
$\Delta_{Dark}^T$	0.075 (2.203)	0.072 (2.284)	-0.014 (-0.757)	-0.034 (-1.809)	-0.015 (-0.755)
Adjusted $R^2$	-0.011	-0.017	-0.044	0.04	0.015

Notes: Coefficients shown are averages of individual median regression coefficients. Dependent variables are squared median regression residuals. Market capitalization and VIX are in logs, too.  $\Delta_X^T$  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 E12:** Fixed effects estimation

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	0.074 (0.939)	0.031 (1.018)	-0.048 (-1.027)	0.126 (2.029)	0.111 (1.754)
Fragmentation	1.802 (5.81)	0.108 (0.543)	0.129 (0.526)	0.49 (1.898)	1.04 (4.023)
Fragmentation sq.	-1.903 (-6.524)	-0.106 (-0.623)	0.005 (0.02)	-0.556 (-2.309)	-2.547 (-10.946)
Market cap.	-0.327 (-7.852)	-0.104 (-5.385)	-0.407 (-12.532)	0.028 (0.85)	0.049 (1.448)
Marginal effect	-0.183 (-2.027)	-0.003 (-0.067)	0.133 (2.077)	-0.091 (-1.361)	-1.618 (-23.064)
$\Delta_{Frag.}$	0.215 (2.053)	0.019 (0.278)	0.132 (1.618)	0.026 (0.312)	-1.085 (-12.224)

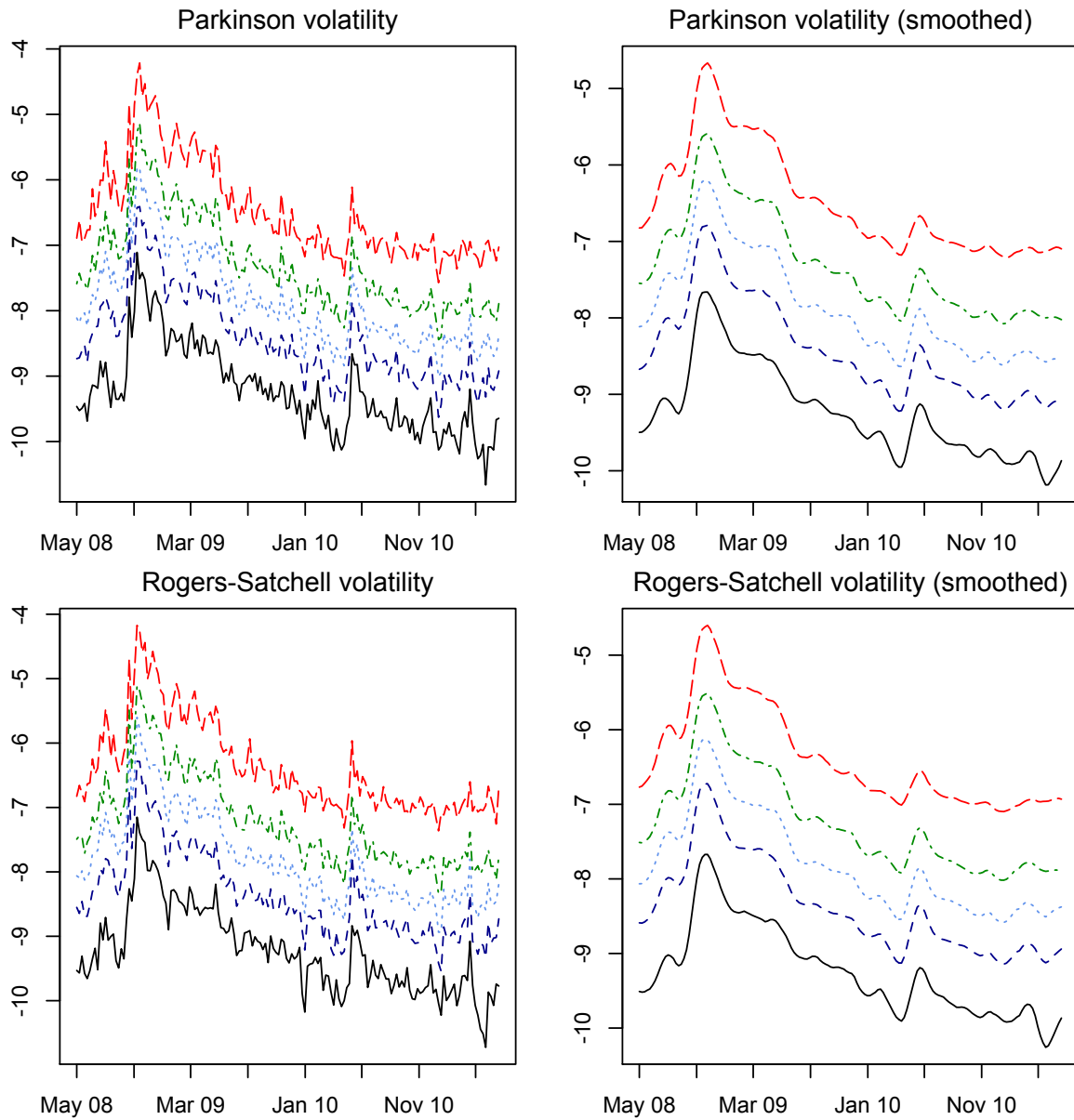
Notes: Coefficients shown are averages of individual OLS coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization and VIX are in logs, too.

**Table E13:** Difference-in-difference estimation

	Total volatility	Temp. volatility	Bid-ask spreads	Global volume	LSE volume
Constant	-2.237 (-0.695)	9.511 (3.67)	0.983 (0.361)	0.069 (0.026)	1.565 (0.488)
Fragmentation	0.139 (0.258)	-0.041 (-0.107)	-0.223 (-0.872)	0.133 (0.416)	0.535 (1.696)
Fragmentation (index)	-24.434 (-2.606)	0.761 (0.104)	-4.277 (-0.587)	-5.875 (-0.905)	-8.703 (-1.098)
Fragmentation sq.	-0.487 (-1.112)	0.061 (0.189)	0.262 (1.193)	0.074 (0.249)	-1.683 (-5.817)
Fragmentation sq. (index)	16.651 (2.435)	1.237 (0.233)	2.145 (0.405)	3.247 (0.691)	6.852 (1.194)
Market cap.	-0.078 (-0.916)	-0.295 (-6.168)	-0.274 (-5.083)	0.019 (0.34)	0.035 (0.601)
Market cap. (index)	1.081 (9.141)	-0.643 (-8.325)	0.233 (2.976)	0.138 (1.786)	0.07 (0.805)
Marginal effect	-0.328 (-2.269)	0.017 (0.162)	0.029 (0.401)	0.204 (2.438)	-1.078 (-13.03)
$\Delta_{Frag.}$	-0.267 (-1.411)	0.009 (0.069)	-0.004 (-0.043)	0.195 (1.947)	-0.869 (-8.61)

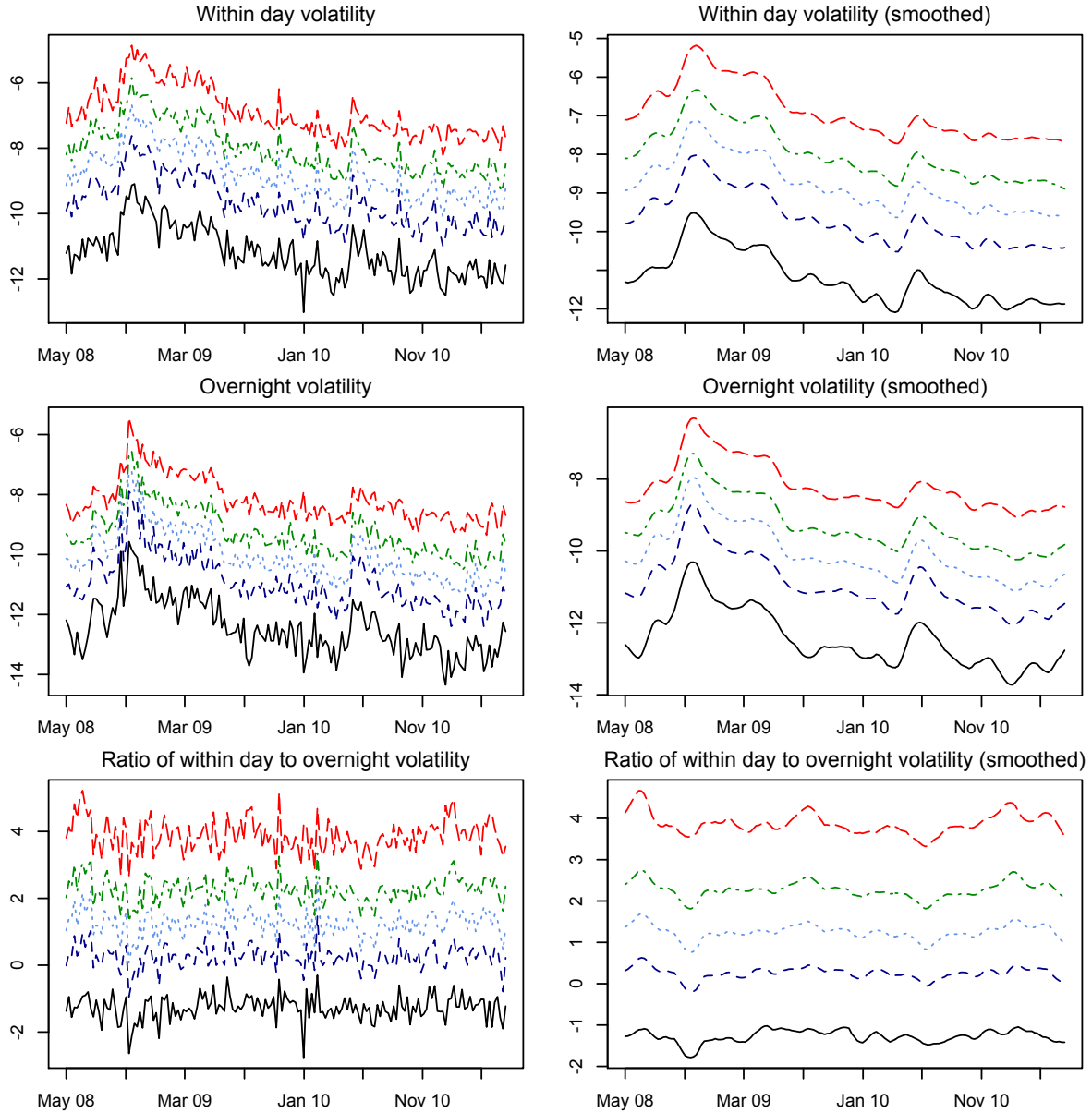
Notes: Coefficients shown are averages of individual OLS coefficients. Dependent variables are in logs with exception of temporary volatility. Market capitalization is in logs, too.

**Figure E1:** Cross-sectional quantiles for Parkinson and Rogers-Satchell volatility



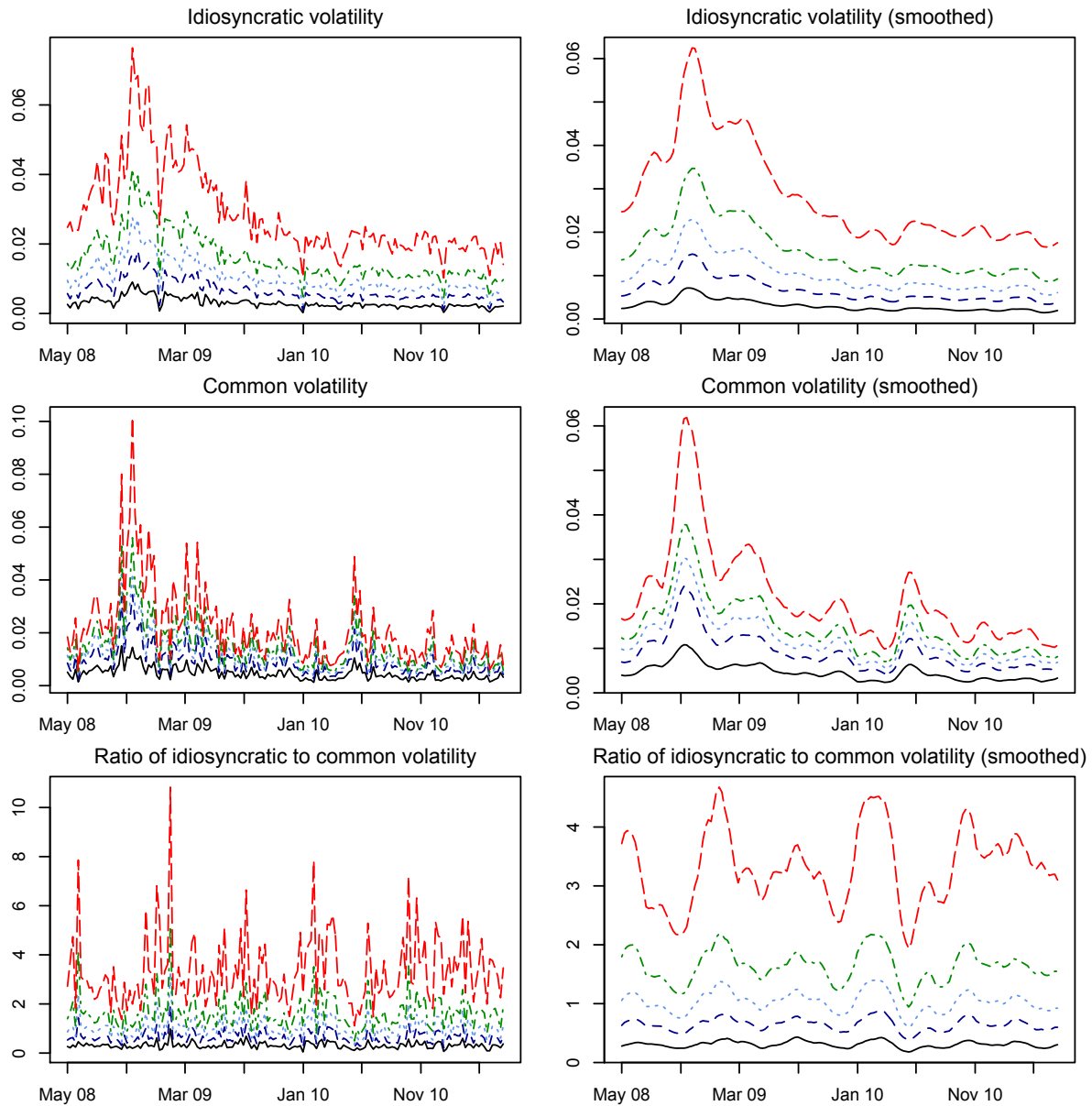
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Volatilities are in logs. The panels on the right hand side show a nonparametric trend  $m_i(t/T)$  with bandwidth parameter 0.03. Data source: Datastream.

**Figure E2:** Cross-sectional quantiles for within day and overnight volatility



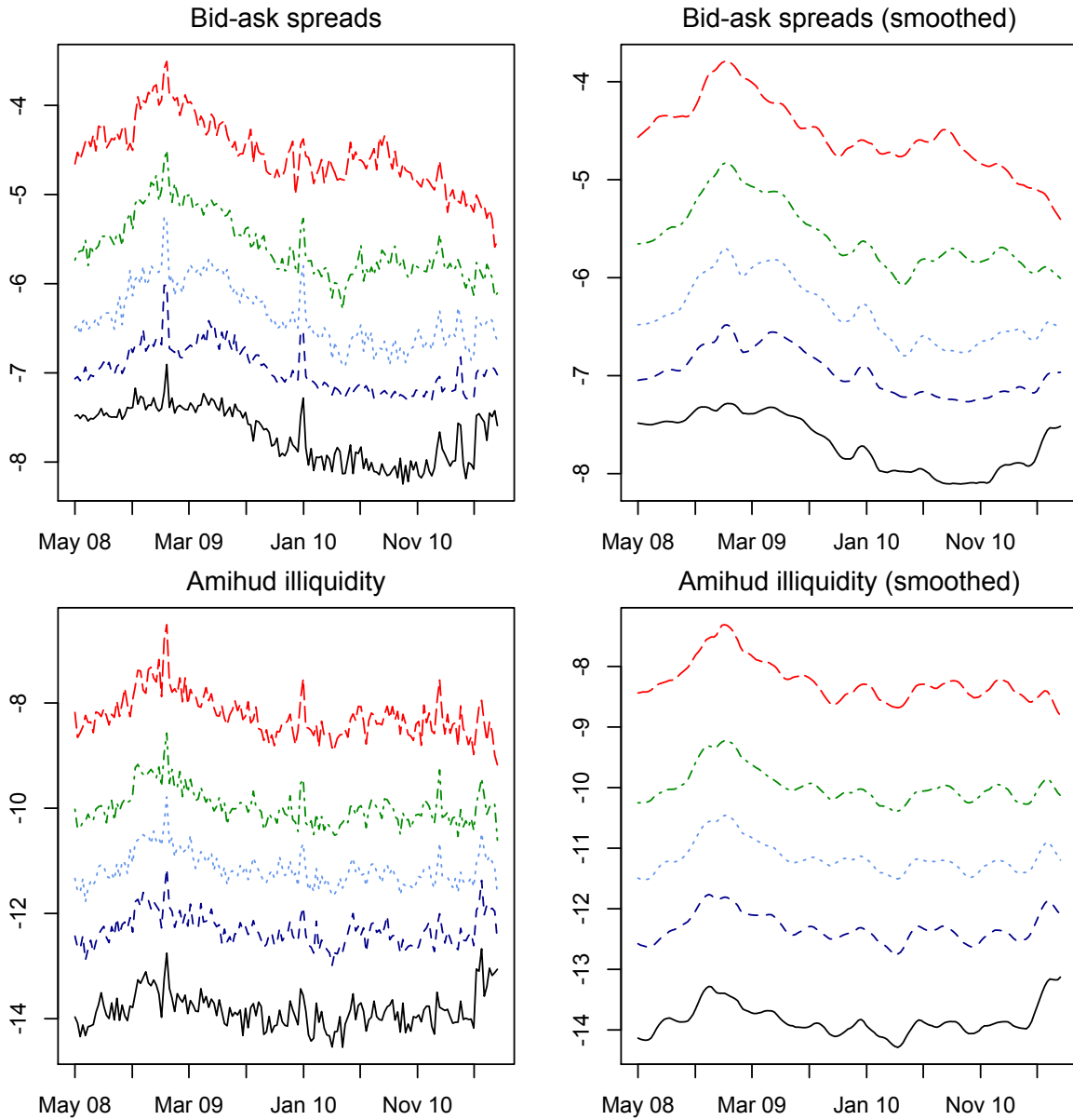
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Within day and overnight volatilities are in logs and the ratio is the difference between the two logged variables. The panels on the right hand side show a nonparametric trend  $m_i(t/T)$  with bandwidth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

**Figure E3:** 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. Data source: Datastream.

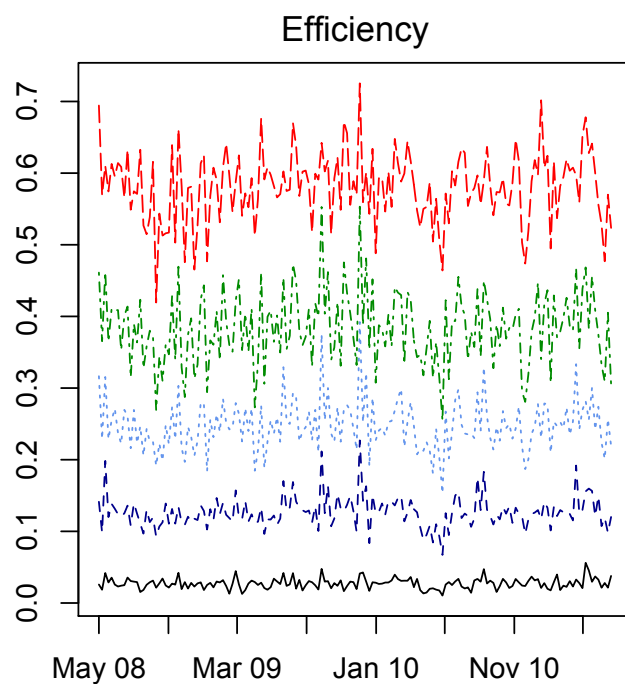
**Figure E4:** Cross-sectional quantiles for illiquidity measures



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. Data source: Datastream.



**Figure E5:** 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). Data source: Datastream.