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

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Appendix A The regulatory framework under MiFID

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 It replaces the "Investment Services Directive (ISD)" of 1993 that has become outdated by the fast speed of innovation in the financial industry.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

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

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

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

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

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

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

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

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

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

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

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

Appendix B Trading venues

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

- **Lit venues:** Bats Europe, Chi-X, Equiduct, LSE, Nasdaq Europe, Nyse Arca, and Turquoise[4]
- **Regulated dark pools:** BlockCross, Instinet BlockMatch, Liquidnet, Nomura NX, Nyfix, Posit, Smartpool, and UBS MTF.
- **OTC venues:** Boat xoff, Chi-X OTC, Euronext OTC, LSE xoff, Plus, XOFF, and xplu/o.
- **Systematic internalizers:** Boat SI and London SI.

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

Appendix C System latency at the LSE

Table C: System latency at the LSE

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

Source: Brogaard et al. (2013) and own calculations.

Appendix D Econometric justification for quantile CCE estimation

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

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

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

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

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

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

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

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

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

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

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

Taking cross-sectional averages we have

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

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

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

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

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

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

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

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

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

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

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

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

by the estimator

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

we have

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

It follows that for each i

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

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

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

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

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

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

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

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

because the averaging over i reduces the orders, for example

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

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

Appendix E: Robustness

Alternative measures of market quality

Measuring market quality is inherently difficult, and there is an ongoing debate on what constitutes a good measure of market quality. In view of this controversy, this section investigates the robustness of the main results in the main paper to a variety of alternative measures of market quality. The particular measures we consider are total (Parkinson) volatility, idiosyncratic volatility, within day and overnight volatility, efficiency, and Amihud illiquidity. Table 14 reports summary statistics of these measures together with the variable used in the regressions in the main paper.

Market quality measures

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

$$V_{it_j}^{P} = \frac{1}{4\ln 2}\left(\ln P_{it_j}^{H} - \ln P_{it_j}^{L}\right)^2 \tag{24}$$

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

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

$$V_{it_j}^{day} = (\ln P_{it_j}^{C} - \ln P_{it_j}^{O})^2 \tag{25}$$

$$V_{it_j}^{night} = (\ln P_{it_j}^{O} - \ln P_{it-1_j}^{C})^2 \tag{26}$$

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

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

Liquidity. While in the main paper, liquidity is measured by the bid-ask spread, this ap-

[5] 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.

pendix considers a measures of liquidity based on daily transaction data. In particular, we use the Amihud (2002) measure that is defined as

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

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

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

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

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

Results for alternative measures of market quality

Our finding that visible fragmentation and dark trading have a negative effect on total and temporary volatility is robust to using alternative measures of volatility such as Parkinson or within-day volatility (Tables 1-2). If we measure market quality by the Amihud (2002)

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

illiquidity measure, we find that a higher degree of overall or visible fragmentation is associated with less liquid markets. Dark trading is found to improve liquidity. Because the Amihud (2002) liquidity measure is closely related to LSE volume, these results probably in part reflect our findings for LSE volume in the main paper. For efficiency, we cannot find significant effects.

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

FTSE 100 and FTSE 250 subsamples

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

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

Methods used in Related Research

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

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

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

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

Gresse (2011) considered the following two equation specification

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

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

Zhang (2010) considered panel regressions of the form

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

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

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

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

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

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

We re-estimate our results using a heterogeneous panel data model without common factors. This model can be obtained as a special case of our econometric model where f_t is a vector of ones and there are no observed common factors d_t. A version of this model with homogenous coefficients has been used by Gresse (2011), among others. However, that model cannot account for unobserved, common shocks in the data and gives inconsistent results in the presence of common shocks that are correlated with the regressors (Pesaran, 2006). As reported in Table 13, omitting observed and unobserved common factors leads to results that differ in magnitude and statistical significance with the exception of LSE volume. However, the large increase in our measure of cross-sectional dependence (CSD) indicates that this model is misspecified because unobserved common shocks such as changes in trading technology or high frequency trading are omitted that are likely to affect both market quality and fragmentation.

Stochastic Dominance

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

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

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

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

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

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

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of idiosyncratic volatility and efficiency. Market capitalization, index return and VIX are in logs too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H+L)$ and evaluated at $H = \max(\text{X})$ and $L = \min(\text{X})$, for $X = \{\text{Vis. frag, Dark}\}$ with $\max(\text{Vis. frag}) = 0.698, \min(\text{Vis. frag}) = 0, \max(\text{Dark}) = 1, \min(\text{Dark}) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

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

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

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

Notes: Dependent variables are squared median regression residuals. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. Δ_X is defined as $\widehat{\beta} + \widehat{\gamma}(H + L)$ and evaluated at $H = \max(\text{X})$ and $L = \min(\text{X})$, for $X = \{\text{Vis. frag, Dark}\}$ with $\max(\text{Vis. frag}) = 0.0698, \min(\text{Vis. frag}) = 0, \max(\text{Dark}) = 1, \min(\text{Dark}) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

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

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

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

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

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

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

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of idiosyncratic volatility and efficiency. Market capitalization, index return and VIX are in logs too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.0698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of idiosyncratic volatility and efficiency. Market capitalization, index return and VIX are in logs too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H+L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

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

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

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

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

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

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

Notes: Dependent variables are squared median regression residuals. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

Notes: Dependent variables are squared median regression residuals. Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Market capitalization, index return and VIX are in logs. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

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

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

Notes: Coefficients are median CCE mean group estimates. t-statistics are shown in parenthesis. Dependent variables are in logs with the exception of idiosyncratic volatility and efficiency. Market capitalization, index return and VIX are in logs too. Δ_X is defined as $\widehat{\beta}_1 + \widehat{\beta}_2(H + L)$ and evaluated at $H = \max(X)$ and $L = \min(X)$, for $X = \{Vis.frag, Dark\}$ with $\max(Vis.frag) = 0.698, \min(Vis.frag) = 0, \max(Dark) = 1, \min(Dark) = 0$. The adjusted R^2 is the R^2 calculated from pooling the individual total and residual sums of squares, adjusted for the number of regressors.

Table 14: Summary statistics

a) Market quality measures

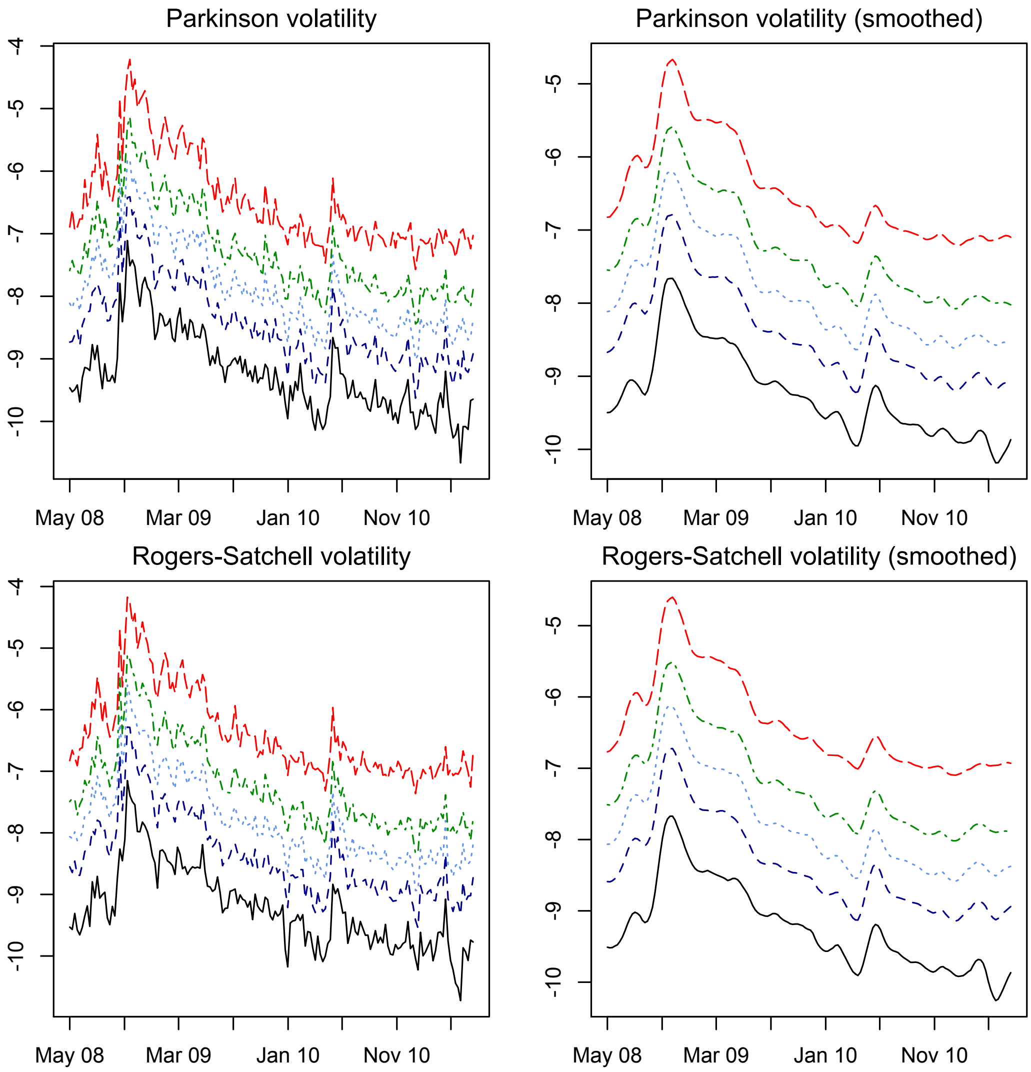
	Obs.	Min	Max	Median	Mean	St. dev.
Total volatility	51038	-14.827	-1.917	-7.879	-7.820	1.142
Temp. volatility	51038	-5.307	7.431	-0.014	-0.003	0.574
BA spreads	51141	-9.196	-2.023	-6.351	-6.247	1.037
Global volume	51141	-7.049	8.388	3.222	3.079	0.982
LSE volume	51117	-8.198	7.988	2.594	2.523	0.941
Total (Parkinson) volatility	51129	-20.360	-2.001	-7.932	-7.875	1.131
Idiosync. Volatility	51141	0.000	0.076	0.000	0.000	0.001
Daily volatility	50927	-16.986	-2.332	-8.831	-8.886	1.521
Overnight volatility	50722	-18.465	-2.492	-10.124	-10.153	1.559
Illiquidity	50974	-17.990	-2.428	-11.172	-11.121	1.786
Efficiency	51131	0.000	0.792	0.224	0.267	0.176

b) Fragmentation, dark trading and observed common factors

	Obs.	Min	Max	Median	Mean	St. dev.
Fragmentation	51141	0.000	0.834	0.568	0.522	0.188
Visible fragmentation	51141	0.000	0.698	0.366	0.335	0.199
Dark trading	51141	0.000	1.000	0.463	0.474	0.186
Dark fragmentation	51112	0.000	0.842	0.526	0.496	0.154
Market capitalization	51141	3.383	11.769	6.850	7.122	1.386
Index return	162	7.751	8.399	8.188	8.155	0.172
VIX	162	2.738	4.273	3.164	3.244	0.369

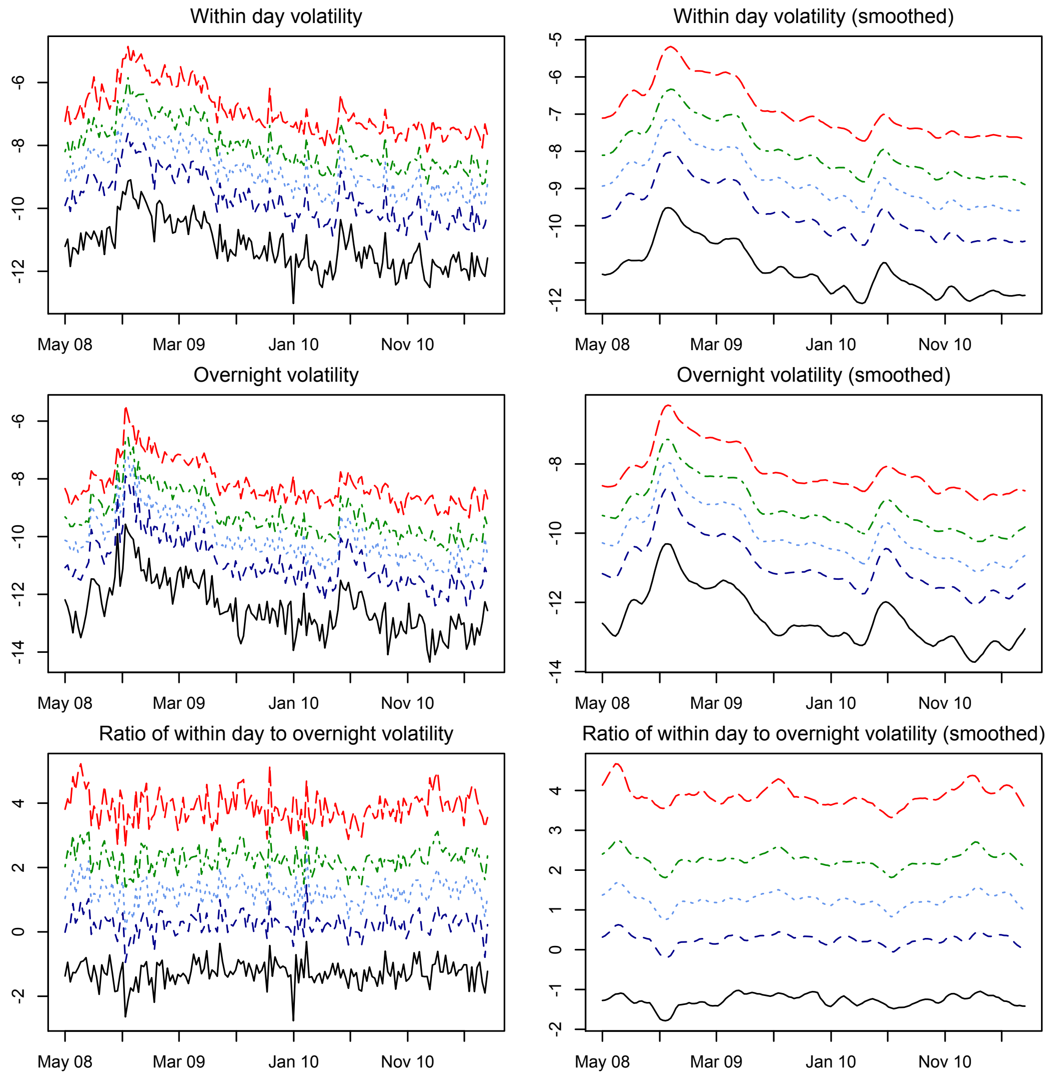
Notes: Market quality measures are in logs with the exception of temporary volatility, idiosyncratic volatility and efficiency. Market capitalization, index return and VIX are in logs too.

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



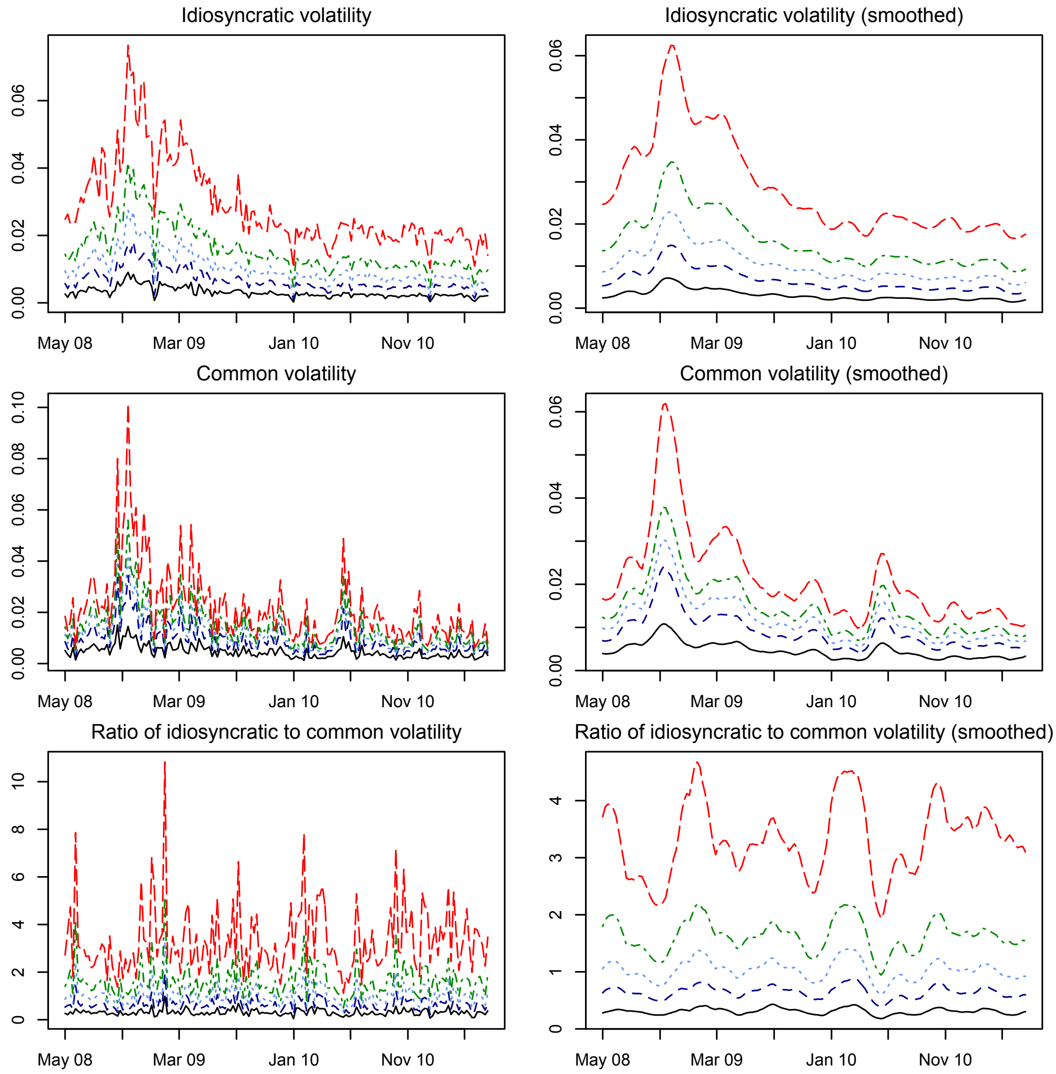
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Volatilities are in logs. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

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



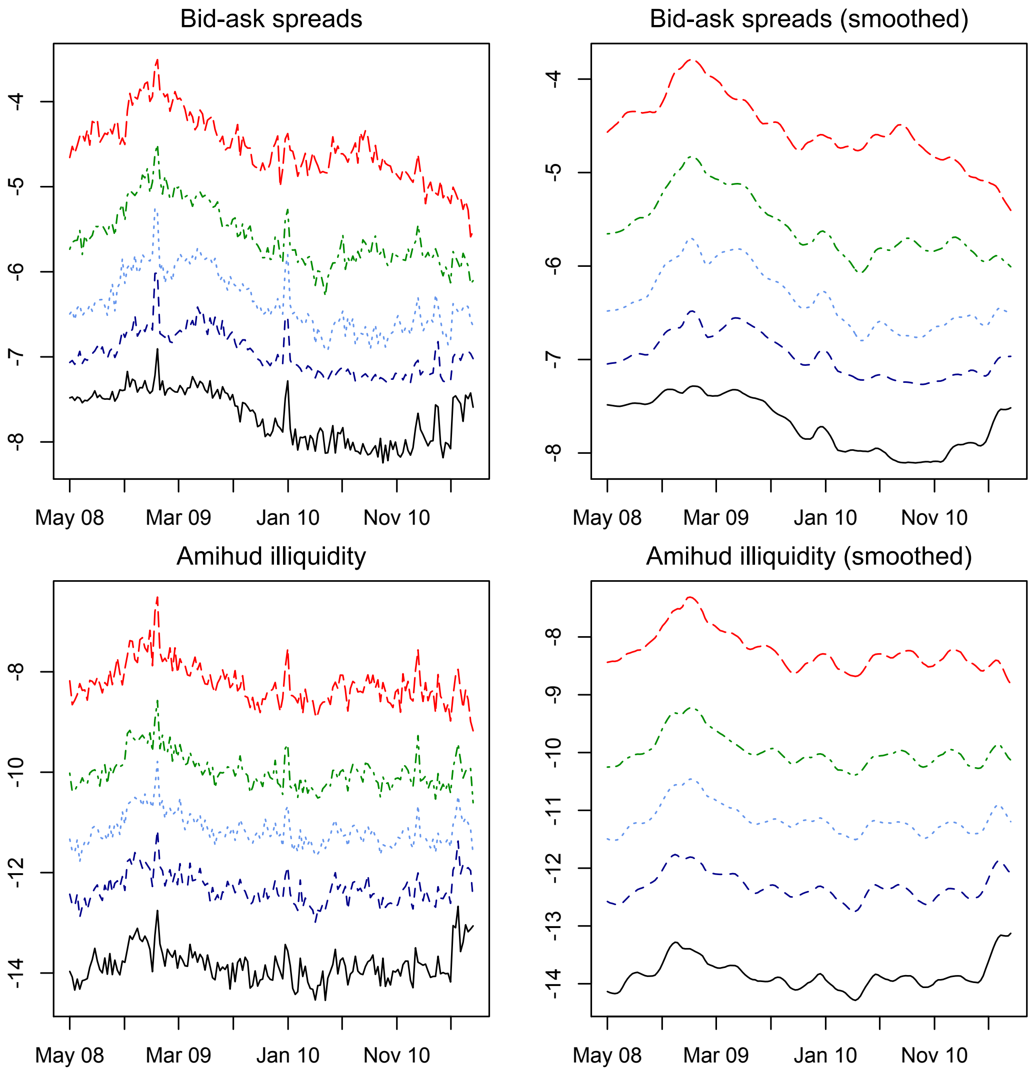
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. Within day and overnight volatilities are in logs and the ratio is the difference between the two logged variables. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter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

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



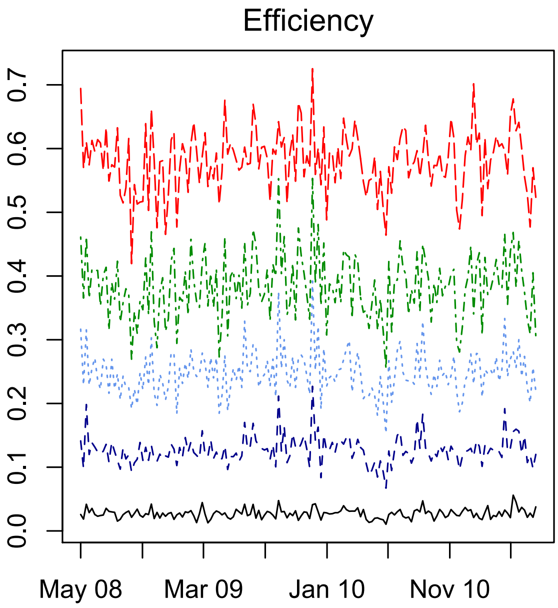
Notes: 5th, 25th, 50th, 75th and 95th percentiles of the cross-sectional distribution are shown. We took square roots of idiosyncratic and common volatilities. The panels on the right hand side show a nonparametric trend $m_i(t/T)$ with bandwidth parameter 0.03.

Figure 4: Cross-sectional quantiles for illiquidity measures



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

Figure 5: Cross-sectional quantiles for market efficiency measures



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