

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

Lena Körber (LSE and Bank of England)






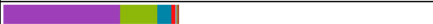


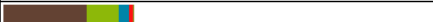

Oliver Linton (University of Cambridge)

Michael Vogt (University of Konstanz)

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The views expressed in this paper are our own and not those of the
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Motivation

	BATS	Market	% of Mkt	Breakdown
FTSE 100	€889,182,377	€3,455,419,995	25.73%	
CAC 40	€708,725,326	€3,191,382,128	22.21%	
DAX	€711,424,895	€3,023,343,945	23.53%	
FTSE MIB	€363,370,939	€2,435,319,496	14.92%	
IBEX 35	€232,540,490	€1,511,767,523	15.38%	
SMI	€303,883,228	€1,428,822,998	21.27%	
CHERI Nordic	€292,339,071	€1,195,727,382	24.45%	
AEX	€216,393,111	€1,098,005,711	19.71%	
OMXS30	€258,454,677	€1,079,182,566	23.95%	
FTSE 250	€154,538,448	€754,827,260	20.47%	

- The implementation of MiFID in 2007 created a competitive environment for equity trading in Europe
- in July 2014, the volume of the FTSE 100 stocks traded via the London Stock Exchange had declined to about 54%

This paper

- What are the effects of fragmentation in equity markets on the quality of trading outcomes in the UK?
- To answer this question, we extend the common correlated effects estimator (Pesaran, 2006) to quantile regression
 - ▶ Control for unobserved common factors such as HFT
 - ▶ Characterize the whole conditional distribution
 - ▶ Robust to outliers in the dependent variable

Main findings

- Fragmentation in visible order books lowers trading volumes at the LSE but dark trading increases LSE and overall volumes
- Visible fragmentation and dark trading lower volatility
- Dark trading increases the variability of volatility and trading volumes
- Visible fragmentation reduces the variability of volatility
- The level of optimal fragmentation varies across individual firms and is positively related to market capitalization

Related Literature: Fragmentation in equity markets

- Theoretical

- ▶ Why competition can harm market quality (Pagano, 1989)
 - Security exchanges can be natural monopolies
 - A single, consolidated exchange market creates network externalities (but: SORT)
- ▶ Why competition can improve market quality (Biais et. al., 2000)
 - Higher competition generally promotes technological innovation, improves efficiency and reduces fees

- Empirical

- ▶ Europe: Gresse (2011), De Jong et al. (2012)
- ▶ US: O'Hara and Ye (2011), Boehmer and Boehmer (2003)

Related Literature: Quantile regression in heterogeneous panels

- Estimation in linear heterogeneous panels with unobserved common factors: Pesaran (2006)
- Quasi-ML estimator for homogeneous, dynamic panels with unobserved common factors: Moon and Weidner (2010)
- Panel quantile regression: Koenker (2004), Lamarche (2010)
- Quantile estimation in homogeneous panels with unobserved common factors and endogeneity: Harding and Lamarche (2013)
- Bias-corrected quantile panel estimators with endogeneous regressors: Arellano and Weidner (2014)
- A semiparametric estimator for large heterogeneous panels: Körber, Linton and Vogt (2013)

Outline

- 1 Markets in Financial Instruments Directive (MiFID)
- 2 Econometric Model
- 3 Estimation
- 4 Data
- 5 Empirical results
- 6 Conclusions

1. Markets in Financial Instruments Directive

The fast speed of innovation in the financial industry called for a new regulation to replace the Investment Services Directive of 1993



1. Markets in Financial Instruments Directive

A new structure for equity markets in Europe

- Since 2007, MiFID provides a common regulatory framework for security markets across the EEA
- MiFID abolished the concentration rule in the EEA and 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

2. Econometric model

... for the level of market quality (1)

- We observe a sample of panel data $\{Y_{it}, X_{it}, Z_{it}, d_t\}_{i=1, \dots, N; t=1, \dots, T}$
- We assume that the data come from the model

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

- $Q_\tau(\varepsilon_{it} | X_{it}, Z_{it}, d_t, f_t) = 0$ but ε_{it} is allowed to be serially correlated or weakly cross-sectionally correlated

2. Econometric model

... for the level of market quality (2)

- The regressors $W_{it} = (X_{it}, Z_{it}^T)^T$ are assumed to have the factor structure (Pesaran, 2006)

$$W_{it} = a_i + D_i d_t + K_i f_t + u_{it}$$

- $E(u_{it}) = 0$ but u_{it} is also allowed to be serially correlated or weakly cross-sectionally correlated
- The individual parameters follow the random coefficient specification

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

2. Econometric model

... for the variability of market quality

- Regulators aim at constructing a robust market structure that contributes to a resilient functioning of equity markets
- We assume the conditional variance of market quality can be modelled by the conditional variance specification

$$\text{Var}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) = \alpha_j + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}^T Z_{it} + \delta_j^T d_t + \kappa_j^T f_t$$

- Or by the conditional IQR

$$q_{0.75}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) - q_{0.25}(Y_{it}|X_{it}, Z_{it}, d_t, f_t) = \\ \alpha_j + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}^T Z_{it} + \delta_j^T d_t + \kappa_j^T f_t$$

3. Estimation

Individual coefficients β_i

- Taking cross-sectional averages of the factor model for regressors,

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

→ Unknown factors f_t can be approximated by d_t and \overline{W}_t

- β_i can be consistently estimated by the quantile regression in the regression model

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

- $\hat{\beta}_i$ minimize the objective functions

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

where $\rho_\tau(x) = x(\tau - 1(x < 0))$ (Koenker, 2005)

3. Estimation

Asymptotic theory for $\widehat{\beta}_i$ (sketch)

- We interpret \overline{W}_t as a preliminary estimator of the function $h_{0t} = \delta + \rho f_t$
- By Theorems 1 and 2 in Chen, Linton and van Keilegom (2003), $\widehat{\beta}_i$ are consistent and asymptotically normal
- Important condition: \overline{W}_t is uniformly consistent:
 $\sup_t \|\overline{W}_t - h_{0t}\| = o_p(1)$

3. Estimation

Quantile CCE mean group estimator

- The quantile common correlated effects (CCE) mean group estimator is defined as

$$\hat{\beta} = n^{-1} \sum_{i=1}^n \hat{\beta}_i$$

- Under suitable regularity conditions,

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

where the covariance matrix Σ can be estimated by (Pesaran, 2006)

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

3. Estimation

Parameter of interest

- What is the difference of market quality (the variability of market quality) between a high (H) and low (L) degree of fragmentation or dark trading?

$$\Delta_X = \frac{E_{X=H}Y - E_{X=L}Y}{H - L} = \beta_1 + \beta_2 \frac{(H^2 - L^2)}{H - L} = \beta_1 + \beta_2(H + L)$$

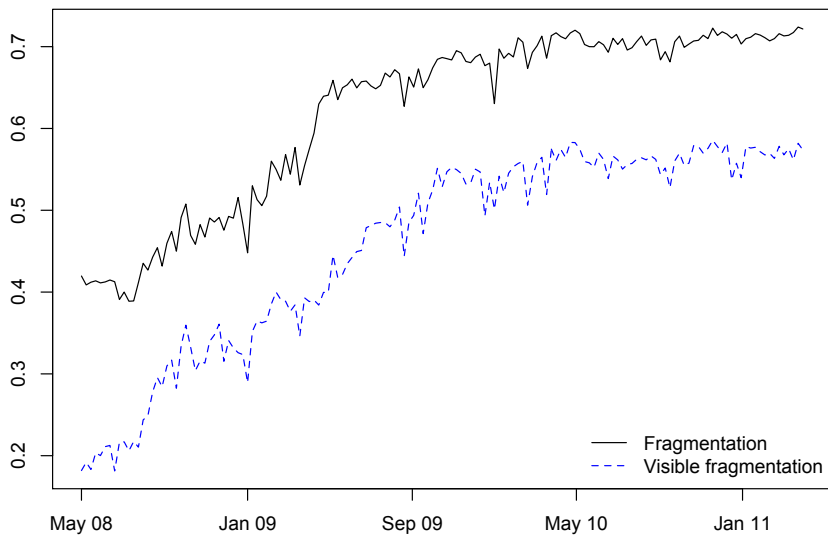
4. Data

Overview

- FTSE 100 and 250 stocks
- Sample period: 2008-2011
- Weekly frequency
- Fragmentation is measured by $1 - \text{Herfindahl Index}$
- Dark trading is measured by fraction of shares traded on regulated dark pools, OTC venues and systematic internalizers
- Market quality is measured by
 - ▶ (Rogers-Satchel) volatility at the LSE
 - ▶ Temporary volatility at the LSE
 - ▶ Bid-ask spreads at the LSE
 - ▶ Trading volume at the LSE
 - ▶ Overall trading volume

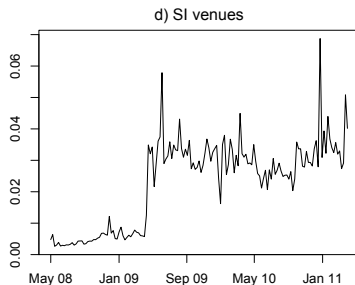
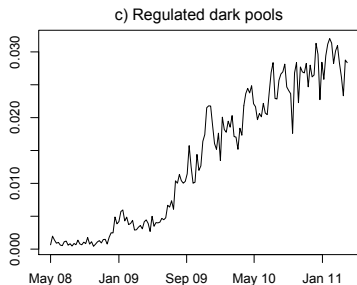
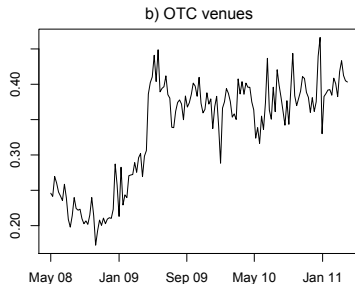
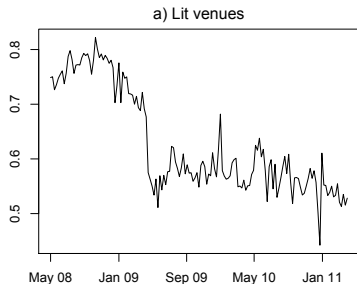
4. Data

Fragmentation



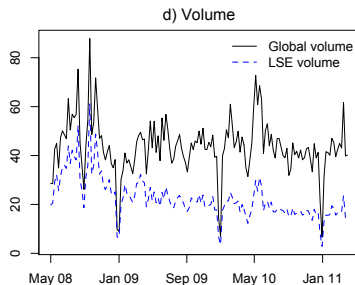
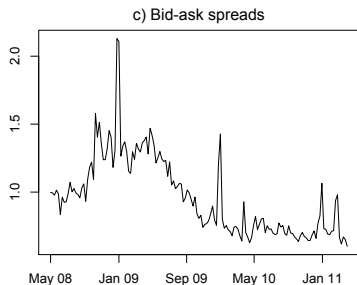
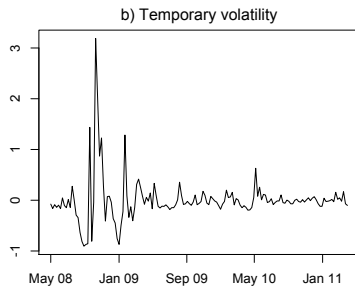
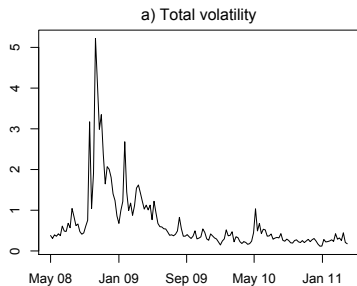
4. Data

Share of volume traded by category



4. Data

Market quality



5. Empirical results

Regression specifications

$$Y_{it} = \alpha_i + \beta_{1i}X_{it} + \beta_{2i}X_{it}^2 + \beta_{3i}Z_{it} + \delta_{1i}^T d_t + \kappa_i^T \overline{W}_t + \epsilon_{it}$$

$$Var(Y_{it}|X_{it}, Z_{it}, d_t, f_t) = a_i + b_{1i}X_{it} + b_{2i}X_{it}^2 + b_{3i}Z_{it} + d_{1i}^T d_t + k_i^T \overline{W}_t$$

where $Var(\cdot)$ is replaced by the squared residuals from the median regression and

- Y_{it} is a measure of the level or variability of market quality
- $X_{it} = (\text{VisFrag}_{it}, \text{Dark}_{it})^T$
- $Z_{it} = \log \text{MarketCap}_{it}$
- $\overline{W}_t = (\overline{X}_t, \overline{Z}_t)^T$
- $d_t = (\log \text{VIX}_t, \text{FTSEreturn}_{t-1}, \text{Christmas}_t)^T$

5. Empirical results

The effect of visible fragmentation and dark trading on the **level** of market quality

	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Vis.frag.}(0.25)$	0.01 (0.09)	-0.263 (-2.879)	0.081 (0.959)	-0.034 (-0.41)	-0.917 (-11.698)
$\Delta_{Vis.frag.}(0.5)$	-0.181 (-1.523)	-0.342 (-3.537)	0.139 (1.86)	-0.157 (-1.85)	-0.988 (-11.891)
$\Delta_{Vis.frag.}(0.75)$	-0.487 (-3.483)	-0.61 (-5.432)	0.112 (1.309)	-0.22 (-2.036)	-1.094 (-10.128)
$\Delta_{Dark}(0.25)$	-0.286 (-3.735)	-0.463 (-6.63)	-0.004 (-0.07)	2.022 (32.67)	0.986 (16.361)
$\Delta_{Dark}(0.5)$	-0.171 (-2.518)	-0.315 (-5.446)	-0.035 (-0.689)	2.055 (34.419)	1.217 (20.626)
$\Delta_{Dark}(0.75)$	-0.005 (-0.061)	-0.064 (-0.935)	0.048 (0.785)	2.072 (29.979)	1.374 (19.166)

Notes: t-statistics are shown in parenthesis. $\Delta_X^T(\tau) = \hat{\beta}_1(\tau) + \hat{\beta}_2(\tau)(H + L)$
 where $\hat{\beta}_k$ is the average of individual quantile coefficients

5. Empirical results

The effect of visible fragmentation and dark trading on the **variability** of market quality

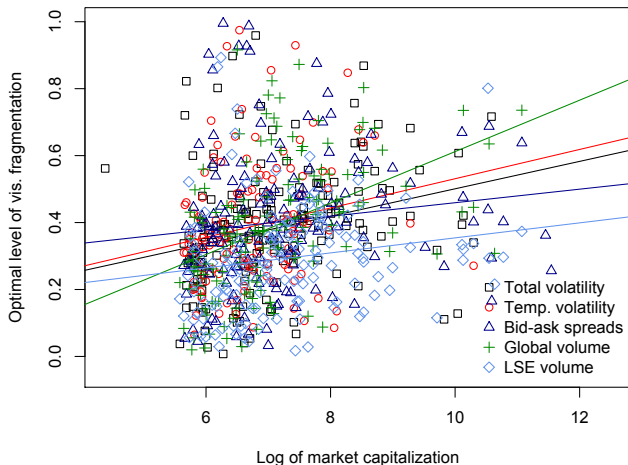
	Total volatility	Temp. volatility	BA spreads	Global volume	LSE volume
$\Delta_{Vis.frag.}(0.25)$	0.052 (1.701)	-0.007 (-0.224)	0.007 (0.387)	0.009 (1.273)	0.019 (2.095)
$\Delta_{Vis.frag.}(0.5)$	-0.055 (-1.359)	-0.073 (-1.231)	0.017 (0.636)	0.017 (1.213)	0.032 (1.403)
$\Delta_{Vis.frag.}(0.75)$	-0.614 (-3.145)	-0.244 (-1.955)	0.201 (1.566)	-0.169 (-1.324)	-0.162 (-1.228)
$\Delta_{Dark}(0.25)$	0.03 (1.771)	0.022 (1.853)	0.011 (1.211)	0.013 (1.966)	0.024 (2.599)
$\Delta_{Dark}(0.5)$	0.098 (3.554)	0.055 (2.49)	-0.001 (-0.064)	-0.024 (-0.853)	0.012 (0.619)
$\Delta_{Dark}(0.75)$	0.19 (2.054)	0.223 (2.66)	0.028 (0.387)	-0.07 (-1.667)	-0.046 (-0.687)

Notes: t-statistics are shown in parenthesis. $\Delta_X^T(\tau) = \hat{\beta}_1(\tau) + \hat{\beta}_2(\tau)(H + L)$ where $\hat{\beta}_k$ is the average of individual quantile coefficients. Variability is measured by the conditional variance.

5. Empirical results

Turning points and market capitalization

“... there may be a point at which too much visible fragmentation leads to deteriorating market quality, and this turning point may vary depending on the market capitalization of a stock” (SEC, 2013, p.9)



Conclusions

- This paper develops a quantile CCE estimator for heterogeneous panels
- The estimator is applied to investigate the effects of fragmentation in equity markets on the quality of trading outcomes in the UK