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Does feedback trading drive returns of cross-listed shares?

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Does Feedback Trading Drive the Returns of Cross-Listed Shares?

Abstract

This paper examines the role of cross-listing in stock return dynamics with particular reference to feedback trading based on a sample of five most frequently traded cross-listed shares. We find that a long-run equilibrium relationship among the cross-listed share prices exists, but find no evidence of long-run co-movements among different shares traded in the same exchange. Furthermore, the VAR Granger causality tests indicate bi-directional feedback relations among the returns of cross-listed shares, while there is no consistent causality among different stocks within the markets. We also find that the cross-listed shares demonstrate strong volatility spillovers, which is driven by the covariance structure that are formed by variance and correlation terms. In addition, we report liquidity spillover effects and spillovers running from liquidity to volatility for some firms but no evidence that spillover effects run from volatility to liquidity.

Key words: Feedback trading, Cross-listing, Spillover, Liquidity, Causality, Volatility

1. Introduction.

The last three decades have witnessed hundreds of companies cross-listing their shares on exchanges in London, the United States, Hong Kong and Tokyo in order to gain access to more investors, greater liquidity and a lower cost of capital. Despite the growing popularity of cross-listing, scarce evidence exists in the literature on the impact of cross-listing on the trading behaviour of investors (see Eun and Sabherwal, 2003; Karolyi, 2006). In particular, to our knowledge, there is no empirical research on the presence of feedback trading for stocks traded in multiple markets. Therefore, this paper seeks to examine the role of cross-listing in stock return dynamics with particular reference to the presence and behaviour of feedback traders. Our central premise is that where the cross listing of shares occurs then there will be a greater presence of feedback traders. Moreover, with feedback traders operating in multiple markets, the degree of spillover effects between markets are expected to be enhanced as information transmission becomes more dynamic and active across markets. In existing spillover studies, the focus has mainly been on links between volatility in different markets (e.g., Tse, 1999; Miyakoshi, 2003; Diebold and Yilmaz, 2008). We argue that the presence of feedback trading, with informational spillovers affecting volatility, may also lead to a bi-directional causal relation between liquidity and volatility as the trading dynamics often affects the liquidity spillovers, hedging strategies and ultimately market dynamics (see, for example, Subrahmanyam, 1994; Grossman, 1998). Thus, we believe that the dynamics of cross-listed shares will differ from other share returns where feedback trading is less active, where there are less avenues for volatility spillovers and where we believe that a positive unidirectional relation will exist between liquidity and volatility.

We consider a one dimension feedback-trading model based on the market equilibrium demand function and apply it to examine the existence and significance of feedback trading on some of the most frequently traded cross-listed shares in Europe. One such firm is Vodafone, which lists on LSE, BATS, Turquoise, ICE, ChiX, and Euronex. The choice of cross-listed shares forms a natural experiment in which to examine our proposed hypotheses. This is because cross-listed issuances share the same underlying asset and their price is driven by the same fundamentals, i.e., the underlying risk generating processes and exogenous shocks, such as market news. In theory, the prices of different shares in each segment would be the same if the pricing modelling can fully account for exchange rate and exogenous factors. The co-existence of market segmentation for the same fundamental share also correlates to the existence of feedback trading. Further, cross-listed shares tend to be frequently traded and their price movement would inevitably have an impact on the market.

Another important issue is the dominance of price discovery in a specific market segment, which potentially would indicate some location and/or speed advantages for traders who are interested in cross-market strategies and even arbitrage opportunities. From a trading perspective, geographic distribution leads to trade frictions, which potentially affect trading costs and therefore possibly influence the cross-market equilibrium (see Pagano, 1989; Glosten, 1994; Hasbrouck and Seppi, 2001). Moreover, considering intra-day trading activities, the risk provision, which fundamentally generates price dynamics, should become more complex. Consequently, we conduct our experiment using high frequency data on both prices and transacted volumes to observe local equity dynamics and rollover effects day to day. This means that we extend the existing literature on feedback trading based on volatility provision further to incorporate feedback from liquidity factors (e.g., Koutmos and Saidi, 2001; Antoniou, et al., 2005). Moreover, examining the causation structure between volatility and liquidity will provide a fuller understanding of the dynamics of the entire risk process. In particular, we add to the literature by focusing on cross-listed firms which provide a unique setting to examine how the informational spillovers on volatility and liquidity affect returns through feedback trading (e.g., Abhyankar et al., 1997; Angelidis and Andrikopoulos, 2010; Valenzuela et al. 2015).

The remainder of the paper is organized as follows: Section 2 briefly reviews the related literature. Section 3 outlines the theoretical model. In Section 4, we develop the hypotheses and introduce the empirical methodology. Section 5 describes the data used and Section 6 presents and analyses the main empirical results. Section 7 concludes the paper.

2. Literature.

In the literature, stock returns are widely found to display time-varying autocorrelation (see e.g., Atchison et al., 1987; Säfvenblad, 2000). Many studies argue that 'noise' traders, who make their investment decisions based on the previous price movement, partly contribute to autocorrelation in stock returns (e.g., De Long et al. 1990; Cutler et al. 1990). Sentana and Wadhwani (1992) provide evidence of positive feedback trading using index returns from the US equity market and find that, during low volatility periods, returns are positively autocorrelated but, during high volatility periods, feedback trading is more significant during market declines. Koutmos (1997) reports similar findings for six developed stock markets, while Koutmos and Saidi (2001) do so for six emerging markets. Further studies investigate the presence of feedback trading in other financial markets. This includes stock index futures (e.g., Antoniou et al., 2005; Salm and Schuppli, 2010; Hou and Li, 2014), foreign exchange markets (e.g., Vitale, 2000; Laopodis, 2005), exchange-traded fund markets (e.g., Chau et al., 2011; Charteris et al, 2014), emissions and energy markets (Chau et al., 2015) and commodity markets (Heemeijer et al., 2009).

Further, research has suggested that cross listing can affect market competition and efficiency as well as asset liquidity. Hamilton (1979) argues that the dispersion of trading may increase competition and thus improve liquidity (competition effect); but it also may prevent full realization of any economies of centralized trading on the exchange (fragmentation effect). Mendelson (1987) argues that the consolidation of the order flow creates economies of scale, while Pagano (1989) shows that when shares are traded across two markets with similar structures and investor types, more traders are seen to be active in the market. Under information asymmetry, Chowdhry and Nanda (1991) show that adverse selection costs increase with the number of markets listing an asset. Besides, when a new market opens for a stock, it may skim the least informed and consequently more profitable orders, and thus harm the liquidity of the primary market (Easley, et al, 1996; Bessembinder and Kaufman, 1997). In practice, dealers or market makers are most able to cream-skim profitable orders, and market fragmentation between competing dealers usually results in larger spreads (for theoretical proofs see the models of Biais, 1993; Madhavan, 1995).

Bennett and Wei (2006) provide empirical evidence that stock switching from the NASDAQ fragmented environment to the more consolidated NYSE structure experience an improvement in spreads. Using European data, Gajewski and Gresse (2007) show that trading costs are smaller in a centralized order book than in a hybrid market equally fragmented between an order book and competing dealers off the order book. Competition between market places often leads to improvements in liquidity (typically measured by spreads). Battalio (1997) and Boehmer and Boehmer (2003) show, across different markets, that liquidity improves (spreads fall) after entry to multiple markets. A range of other papers for both US and European markets has highlighted that multiple platforms lower trading costs and improve execution speed (e.g., Nguyen, et al., 2007; Mayhew, 2002; De Fontnouvelle et al., 2003; Lee, 2002; Huang, 2002; Foucault and Menkveld, 2008, O’Hara and Ye, 2011).

3. Theoretical Model.

In order to develop a theoretical framework to take feedback trading into account, we begin with Shiller’s (1984) and Cutler et al. (1990) ‘fads’ model that considers smart and non-smart traders. The former usually operate trades actively and lead the trading and the latter tend to follow. At the market level, the demand function of shares that smart traders is given by:

$$D_{s,t} = \frac{E_{t-1}\left(r_t\right) - \alpha}{\mu_t} \quad (1)$$

where $D_{s,t}$ is the fraction of shares demanded by smart traders at time t, which, together with the fraction of shares held by non-smart traders ($D_{ns,t}$), contributes to the overall demand for the shares D_t; r_t is the ex-post return in period t. $E_{t-1}\left(r_t\right)$ is the expectation of the return in period *t* given the information up to and including time $t-1$. The risk-free rate of return is given by α and μ_t is the risk premium needed to induce them to hold all the shares. Sentana and Wadhwani (1992) assume that:

(2) $$\mu_t = \mu \;\; \sigma_t^2$$

with $\mu^{'} > 0$,[1] where σ_t^2 is the variance of returns in period t conditional on the filtration up to time $t-1$. Therefore, equation (1) can be re-written as:

(3) $$D_{s,t} = \frac{E_{t-1}(r_t) - \alpha}{\mu(\sigma_t^2)}$$

If all investors have homogeneous demand functions then, when the market reaches equilibrium, $D_{s,t}$ takes the value 1 and we have

(4) $$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2)$$ (Merton, 1980)

Some form of feedback drives the demand from non-smart traders', such as:

(5) $$D_{ns,t} = \gamma r_{t-1}$$

where $\gamma > 0$.[2] In general, the overall demand function of a single stock will also take the value 1 when the market reaches equilibrium level

(6) $$D_t = D_{s,t} + D_{ns,t} = 1$$

Equation (6) can be re-written as:

$$D_t = \frac{E_{t-1}(r_t) - \alpha}{\mu(\sigma_t^2)} + \gamma r_{t-1} = 1$$

and multiplying by $\mu(\sigma_t^2)$ we have:

(7) $$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2) - \gamma\mu(\sigma_t^2) r_{t-1}$$

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[1] The condition $\mu' > 0$ implies that the smart traders are risk averse, so that a rise in expected volatility increases the risk premium needed to induce smart money to hold all the shares

[2] If $\gamma < 0$, then negative feedback trading is implied (see Sentana and Wadhwani, 1992).

Sentana and Wadhwani (1992) suggest γ is the feedback from volatility change into the return process. As the feedback effect usually occurs after the underlying risk process $\mu(.)$, corresponding to trading and becoming an input to the return process, we propose that the feedback parameter to be stochastic and it should reflect some form of relation between liquidity and volatility. For example, γ_{t-1} could be the causality between these two market components or could be the response function between them. Therefore, equation (7) is now written as:

(8) $$E_{t-1}(r_t) - \alpha = \mu(\sigma_t^2) - \gamma_{t-1}\mu(\sigma_t^2) r_{t-1}$$

We propose to add some novelty into a classic fad model in order to reflect equity return dynamics with consideration of feedback trading from both underlying volatility process and market liquidity provision. The theoretical model suggests that smart traders lead the price movement over the non-smart traders. Further, due to the segmentation of smart vs. non-smart traders and heterostochasticity, there exists feedback in the underlying transmission process (through volatility and autocorrelation terms).

4. Empirical Design.

4.1 The setting

We aim to study how information transmission among shares impacts price formation of financial assets. The idea of identifying feedback trading is to consider the information spillover effects not only transmitted through the covariance structure of the series but also their correlation dynamics. From the perspective of information theory on price formation, it would be ideal if we can design natural experiments, which can test the information formation and decompositions (e.g., endogenous vs. exogenous information shocks) and their impact on price. In this paper, we select five top constituents of FTSE 100: Barclays (BARC), HSBC, BHP Biliton (BLT), Tesco and Vodafone (VOD), which are traded in three different venues: London Stock Exchange (LSE), BATS Europe (BS) and Turquoise (TQ). We collect both the intra-day five-minute trade and quotes prices and volumes of these highly frequently traded shares. Except from LSE, BATS and Turquoise are the second and fourth largest Multilateral Trading Facilities (MTFs) market places in Europe.

To set up the experiment, we do not necessarily decompose the information (e.g. common vs. idiosyncratic) shocks by using some form of proxies. Instead, we utilize both the natural market segmentation and cross listing features of these shares to form systems to approximate information decomposition. For example, on the one hand, we take Barclays cross-listed in these three markets (BARCL, BARCBS and BARCTQ) to form a multivariate vector autoregression (VAR). Because these three issuances share the same fundamentals, their price movements should be affected by the same exogenous shocks, such as local market news. On the other hand, we examine all five stocks traded in the same market place (for example BARCL, HSBCL, BLTL, TESCOL and VODL), whose price increments should share the same common shocks but different trader specific shocks (idiosyncratic shocks specific to individual stocks). Therefore, in this case, it should be endogenous instead of the exogenous information flows.

We, therefore, can thoroughly test information spillovers from four angles: long-run information structure (co-movement), short-run volatility spillover, short-run causality structure and short-run liquidity spillover. This experiment provides a simple and effective way of examining our research questions and the market and product structures without making brave assumptions regarding any proxies to capture informed or speculative trading effects.

4.2 Hypotheses Formation

The aim of this paper is to examine information transmission (or spillovers) among different issuances of the same underlying shares cross-listed in a few major stock markets in Europe. This reflects the underlying features of cross-listing in two folds: 1) for the same stock, although the listing of different issuances are located in different trading venues, price moves should still be driven by the same underlying risk/price generating process and common information shocks. The only factors to drive the price difference should be from the market segment specific information shocks and trading specific constraints of the venue where the issuances are listed; 2) in the same market, the price processes for different stocks clearly should be driven by their individual trading activities and shared market news within this market. Here, we acknowledge that there may be some traders who have an information or trading advantage (e.g. speed advantage) over others. However, as we have described previously, we adopt the philosophy of 'fads' model and categorize traders into 'smart' vs. 'non-smart' traders. We assume that that all information eventually will be reflected in the pricing process through the 'fads' information transmission mechanism either in the variance and/or serial correlation dynamics. Therefore, we postulate five main hypotheses concerning the information transmission and their impact on share prices.

Cross-market shares are different issuances based on the same underlying assets of one specific firm traded in different markets while within-market shares are fundamentally different shares of different firms. Such differences stem from the nature that the cross-listed shares have same firm fundamentals and endogenous information shocks, which drive the underlying price generating process. What would affect their price changes should only be the exogenous shocks such as market news announcement in the local market and these effects usually tend to be absorbed by the market in a short while. Therefore, we expect to see long-run common trend for cross-listed shares in our sample companies (e.g. VODL, VODBS and VODTQ) but not for these shares traded in one particular market (e.g. BARCL, BLTL, HSBCL, TSCOL and VODL). Given the above, our first hypothesis is formulated as follows:

Hypothesis 1: Regarding the long-run structure, the cross-issuances tend to share at least one common trend while within-market shares would be unlikely to share co-movements in their price movements.

Within market shares, the information causation structure for each of the shares in one particular market would be driven by their own independent random walks, therefore, the short-term price discovery through causality could be uni-directional, bi-directional or random. This means that we cannot conclude the price discovery dominance of any particular share over other shares through the information spillover through mean causality. In addition, the causality represents the short-run information dynamics in the mean structure of shares. For example, for Vodafone shares listed and traded in LSE, BS and TQ, they all have the same endogenous shock system. However, the exogenous shocks in these three markets will be different and these should be efficiently reflected in the short-term price movements. With trading features, we understand the LSE is a more dominant in terms of, for example, trading volume, thereby, we expect that the trading impact would lead to more dominant causality transmission from the LSE to the other two. We thus propose the following hypotheses:

Hypothesis 2a: For the cross-market shares, causality tends to be bi-directional for each pair of the three series.

Hypothesis 2b: The causality spillover from LSE to BATS-Europe and/or Turquoise would be at higher level than the reverse direction.

We suggest that in our system, the covariance structure should be decomposed into its variance and correlation. The classic GARCH model reveals the variance structure (σ^2) or implied volatility and explains the risk-generating process of asset pricing. This is typically considered as volatility spillover effects. We argue that the correlation structure in our system also drives price updates and forms feedback trading, which specifically refers to the information shocks from the correlation structure into the underlying price evolution.

For cross-listed shares, they have the same underlying assets and it is natural that, if the correlation terms are significant, the correlation shock transmission would, together with the variance terms, drive price movements. This means that, for instance, the volatility of VODL could lead to the change in the volatility of VODBS or vice versa. At the same time, the correlation term between them would also be significant and hence lead to the overall risk level (transformed variance) to change. However, within-market shares do not possess such features. For example, TSCO and HSBC are two completely different shares in nature, which do not share any natural underlying price processes. Therefore, even if the correlation structure exists for their LSE listings, it is hard to conclude that TSCO's correlation shock would also affect HSBC's price movements. We endorse these views and express hypothesis 3 as:

Hypothesis 3: The co-existence of market segmentation for the same fundamental share correlates to the existence of the volatility spillover and feedback trading. However, shares traded in the same market have volatility spillover but not strong feedback trading relations.

Trading related information shocks should be reflected in the bid and ask profiles including both prices and volumes. Due to the cross-listing nature, when one issuance's price moves due to trading, other issuances would also be affected with possible lead-lag effects. However, different firms traded in the same market could have entirely different trading profile, risk preferences, strategies and responses to even the same market or trading news. There is not necessary any fundamental that will drive their price together. Therefore, we do not expect to see liquidity spillovers among within-market shares and hypothesis can be expressed as follows:

Hypothesis 4: The cross-market shares tend to have liquidity spillover while within-market shares' liquidity spillover tends to be in random fashion.

Finally, for the same firm cross listing their shares in three different markets, we expect to see stronger spillovers from liquidity to volatility although there might be bi-directional spillovers. When both volatility and liquidity drive prices, the different issuances would show different price movement only if their liquidity provisions are different as there is little differentiation in their volatility processes. On the contrary, if these five companies are all trading in LSE, they have their own individual volatility dynamics as well as liquidity provisions. It is harder to expect dominance from one provision to the other. For example, it is hard to conclude if or how VODL's liquidity would affect TSCO's volatility or vice versa. With consideration of intra-day trading behaviour, we propose the following hypothesis:

Hypothesis 5: The causality spillover between liquidity and volatility exists in cross-market shares not in within-market shares.

4.3 Empirical Methodology

Our empirical approach is categorised into three parts to test these five hypotheses. First, we estimate a vector error correction model (VECM) on multiple price series, both cross-issuances and cross-markets. We first use Johansen trace and maximum eigenvalues tests to examine the cointegration relation. Second, we examine the return and volatility spillovers with consideration of feedback. We construct the stationary component of the VECM over multiple price series for the same two purposes to estimate the VAR-MV-GARCH model to incorporate the ‘fads’ concept. Notably, such VAR elements with feedback can be used to examine Granger-causality effects. We further calculate the time-varying beta/factor loading for a multi-factor CAPM with the feedback dynamics through the DCC, using the VECH specification of Bollerslev et al. (1988), Kraft and Engle (1982), Engle et al. (1984) and Engle (2002). For estimation methods, we adopt the maximum likelihood estimation (MLE).

For examining long-run approximation (Hypothesis 1), we use the classic cointegration (both Johansen trace and maximum eigenvalue) tests. For the short-run dynamics (Hypotheses 2, 3, 4 and 5), we focus on spillover effects with consideration of feedback in both return, variance and liquidity; hence, we construct the Granger causality tests (spillover in return and in liquidity) and VAR-MV-GARCH (spillover in covariance, which usually can be decomposed into variance and correlation). Tables 1(a) and (b) outline our general model specifications and summarize which of the approaches outlined is applied to our data set.

Insert Table 1 here

Cointegrating Relationship

Defining a time series vector, y_t, the standard VAR model is given as follows:

$$y_t = \sum_{i=1}^{p} \Pi_i L^i y_t + c + u_t \tag{9}$$

where L is the backward shift operator, and therefore $L^i y_t = y_{t-i}$. Π_i is the autoregression coefficients matrix, c is constant vector and u_t a vector of residuals. When considering an error correction framework, the equivalent representation is given by:

$$\Delta y_t = \Phi y_{t-1} + \sum_{i=1}^{p-1} \Psi_i L^i \Delta y_t + \mu + u_t \tag{10}$$

Following Johansen (1988, 1991, 1994) and Johansen and Juselius (1990), we use a Full-Information Maximum Likelihood (FIML) test to identify cointegrating vectors. It can test for cointegration by examining the rank of the matrix Φ.

$$\Phi = \sum_{i=1}^{p} \Pi_i - I \quad \text{and} \quad \Psi_i = -\sum_{j=i+1}^{p} \Pi_j \tag{11}$$

where the rank of Π is zero then we have no long-run cointegrating relation, where the rank is full then the vector y_t only contains stationary variables. The interesting case is where the rank is greater than zero and less than full, which indicates the number of cointegrating vectors. That is, in a VAR where the number of series is given by *n* and *k* is the number of cointegrating vectors, where the rank of the matrix Π is *k* with *0 < k < n*, then cointegration exists with *n-k* the number of stochastic trends. Let $\hat{\lambda}_1 > \hat{\lambda}_2 > \hat{\lambda}_3 > \cdots > \hat{\lambda}_n$ be the eigenvalues of the estimated matrix $\hat{\Pi}$. The trace test of the null hypothesis that there are at most h cointegrating relations, i.e. $H_0 : k \leq h$, against the alternative hypothesis $H_1 : k > h$. The statistic is calculated as follows:

(12) $$\Lambda^{trace} = -T \sum_{i=h+1}^{n} \log(1 - \hat{\lambda}_i)$$

The maximum eigenvalue test of the null hypothesis is that $H_0 : k = h$, against the alternative hypothesis $H_1 : k = h + 1$. The statistic is given as:[3]

(13) $$\Lambda^{\max} = -T \log(1 - \hat{\lambda}_{h+1})$$

VAR-MV-GARCH and MLE Estimation

Starting from the initial multivariate ARCH/GARCH proposed by Kraft and Engle (1982) and Engle et al. (1984), various variations and developments have been made[4] and Bollerslev et al. (1988) model characterize the MV-GARCH (p,q) as follows:

(14) $$\Delta \mathbf{y}_t = \sum_{i=1}^{r} \Pi_i L^i \Delta \mathbf{y}_t + \mathbf{c} + \Sigma_t \boldsymbol{\omega} + \Sigma_t^{\frac{1}{2}} \varepsilon_t$$

[3] Chen et al. (2011) proposed a bootstrap approach to enhance the robustness of these two tests. The method is to collect the eigenvalues $\Lambda^{trace}, \Lambda^{\max}$ and resample them with two residual series collected from the polynomial projection process described in formula (10). Then, they re-compute the canonical correlation series and their distributions following Johansen and Juselius (1990) and MacKinnon et al. (1999). Finally, they compare the two sets of critical statistics to decide whether the results of cointegration tests are robust or not.

[4] See Gourieroux (1997), Engle (2002) and Cappiello et al. (2006).

(15) $$vech\left(\Sigma_t\right) = \mathbf{\kappa} + \sum_{i=1}^{p} \Lambda_i vech\left(\Sigma_{t-i}^{\frac{1}{2}} \varepsilon_{t-i} \left(\Sigma_{t-i}^{\frac{1}{2}} \varepsilon_{t-i}\right)'\right) + \sum_{j=1}^{q} \Gamma_j vech\left(\Sigma_{t-j}\right)$$

ε_t is an innovation white noise vector and the conditional covariance matrix is Σ_t. The vector of residuals is $\Sigma_t^{\frac{1}{2}} \varepsilon_t$ and w is a constant vector of premium loadings. The term $vech(.)$ denotes the column-stacking operator of the lower triangular portion of a symmetric matrix[5]. This, effectively, is the half-vectorization operator stacking only the different elements of a square matrix in a $\frac{1}{2}n(n+1)$ vector of constants. This $\frac{1}{2}n(n+1)$ vector is the constant array of $\mathbf{\kappa}$. Λ, Γ are symmetric coefficient matrices, both of which contain $\left(\frac{n(n+1)}{2}\right)^2$ elements.[6] Σ_t is a positive definite matrix and Engle and Kroner (1995) have provided proofs of this if all eigenvalues of $\sum_{i=1}^{p} \Lambda_i + \sum_{j=1}^{q} \Gamma_j$ are smaller than one in modulus.

For estimation, the class method is the likelihood function under the Maximum Likelihood Estimator (MLE), which is written as:

(16) $$\begin{aligned} \mathcal{L}(\theta) = & -\frac{nT}{2}\log 2\pi - \frac{1}{2}\sum_{t=1}^{T}\log\left|\Sigma_t\right| \\ & -\frac{1}{2}\sum_{t=1}^{T}\left(\Delta\mathbf{y}_t - \sum_{i=1}^{r}\Pi_i L^i \Delta\mathbf{y}_t - \mathbf{c} - \Sigma_t \mathbf{w}\right)' \Sigma_t^{-1} \left(\Delta\mathbf{y}_t - \sum_{i=1}^{r}\Pi_i L^i \Delta\mathbf{y}_t - \mathbf{c} - \Sigma_t \mathbf{w}\right) \end{aligned}$$

where the maximal values of the parameter vector are collected as:

(17) $$\theta = \left[\Pi_1, \ldots, \Pi_r, \mathbf{c}, \mathbf{w}, \mathbf{\kappa}, \Lambda_1, \ldots, \Lambda_p, \Gamma_1, \ldots, \Gamma_q\right]$$

For a given value of θ the series $\left\{\Sigma_t\right\}_{t=1}^{T}$ can be calculated recursively from equations (14) and (15) and the likelihood computed from equation (16). Then a search method can be used to obtain the

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[5] The original calculation of MVGARCH(P) is found Kraft and Engle (1982) and Engle et al. (1984).

[6] The dimensions of $\mathbf{\kappa}, \Lambda, \Gamma$ are $\frac{1}{2}n(n+1)\times 1, \frac{1}{2}n(n+1)\times\frac{1}{2}n(n+1), \frac{1}{2}n(n+1)\times\frac{1}{2}n(n+1)$.

maximal values of the parameter vector $\hat{q}$ and the associated estimated covariance matrices $\left\{ \hat{S}_t \right\}_{t=1}^{T}$. Regarding the specification of the multivariate probability distribution functions, the multivariate normal distribution can be used to obtain the density generator. Alternatively, we could apply the Quasi Maximum Likelihood Procedure to the multivariate normal MLE. From the above procedure, the volatility transmission of shocks from the j^{th} variable to i^{th} variable is the time-varying quantity derived from the estimated residual covariance matrix $\hat{S}_t$, which uses Bollerslev et al. (1988) to compute the time-varying beta β_t loading of an I-CAPM model in equation:

(18) $$b_{ij,t} = \hat{s}_{ij,t} / \hat{s}_{jj,t}$$

Liquidity approximation

A link between liquidity and stock returns was established by, among others, Amihud and Mendelson (1986), Acharya and Pedersen (2005), Amihud (2002) and Pastor and Stambaugh (2003). This work suggested that liquidity is a source of risk that should be priced in stock returns. Thus, a negative shock to liquidity would lead to fall in stock prices and current returns and an increase in expected future returns. Subsequent empirical evidence has supported this contention. This includes, for example, Amihud et al. (2013), Amihud et al. (2015) and Chiang and Zheng (2015).

As liquidity is an unobservable variable, several proxies have been suggested, including the bid-ask spread, trading costs and trading volume and turnover, here, in order to capture the effects of liquidity we implement the method of Amihud (2002), which has become a popular method (see, for example, the discussion in Chiang and Zheng, 2015). The approach of Amihud provides a measure of illiquidity and is given by:

(19) $$A_{i,t} = |R_{i,t}| / VOLD_{i,t}$$

where $|R_{i,t}|$ represents the absolute return on stock *i* at time t and $VOLD_{i,t}$ represents the corresponding cash volume. This measure implies that a higher level of volume is associated with higher liquidity (lower illiquidity) and represents the absolute return (price change) per monetary unit of trading volume. Thus, it is intended to capture price impact. In our analysis, we compute this ratio for each stock return series and examine the interactions across and within the different markets both with volatility and the illiquidity of other return series. To do this, we use a VAR framework and examine the Granger causality results.

5. Data and Sample.

In this paper, we select five top constituents of FTSE 100: Barclays, BHP Billiton, HSBC, Tesco and Vodafone, which are traded in three different venues: London Stock Exchange (LSE), BATS Europe and Turquoise. We collect both the intra-day five-minute trade and quotes prices and volumes of these highly frequently traded shares. BATS-Europe and Turquoise are the second and fourth largest MTFs (Multilateral Trading Facilities) market places in Europe.

The data sample runs from October 17, 2011 to October 15, 2013. The trading hours for three markets are synchronized to the standard GMT time: 8:00 am to 16:30pm GMT from Mondays to Fridays excluding public holidays.[7] Data outside the trading hours are also eliminated from our sample. In the end, for each company share in each market, we obtain between 50,000 and 51,300 data points over 504 trading days. The number of observations range from 50,435 to 51,027 in different markets as we have to match all cross-market shares in order to operate on the balanced VAR models (see Table 2).

As we use the intra-day data, various forms of prices for both trades and quotes are available from Thomson Reuters™ TickHistory including open, close, high and low: we use close prices in this paper. In the literature, some researchers suggest to use the average of the high and low of each interval as the 5-minute trade, bid and ask prices. Others take the halves of the previous interval's close price and the current interval's open price. We tried both methods in our initial cleaning process. However, not only do we have normal missing data problem, we also end up with quite a number of odd cases: one of the fields has missing data (for example, March 17, 2012, 12:45pm, the trade low is missing), the price for that particular interval will suddenly drop by half in comparison to the price at 12:40pm. Therefore, we decided to take the simple approach and use the close price at the end of each five minutes during the trading hours. The advantage of this is not only in its simplicity but also to avoid unnecessary nuisance data records further generated in the process of basic calculations (e.g. to avoid 'dlog0' case when calculating returns). When we use the closing price of each interval, it also shows less missing observations; especially we have not spotted any chunks of missing data. Therefore, it seems that our choice helps keep our sample 'cleaner'. We use the normal backfilling method to fill the missing data and make all series having continuous records.

From the original trade price series, we calculate log-prices and return series for all, and the descriptive statistics are reported in Table 2. Across all shares in three locations, they are all positively or negatively skewed to certain levels and the kurtoses show that these liquid shares are carrying heavy tails. However, these are typical features we would expect from financial time series, especially

[7] Christmas Eve only trades half-day.

at higher frequency. We choose five-minute frequency by following the usual practice in the literature and it has been documented that 2- or 5- minute intervals would eliminate microstructure noise effects better than using 1-minute data (see Bacry et al., 2011). We have also plotted the time-varying volume for each share and presented them in Figure 1.

Insert Table 2 Here

Insert Figure 1 Here

We run unit root tests on log-price and return series to check the non-stationarity and stationarity respectively. We have found all price series to be I (1) and returns I (0). We further utilize the information criteria (Akaike and Schwarz) to work out the optimal lag to be 2.

6. Results

6.1 Cointegration relationship cross-market vs. within-market

We hypothesise that for the same stock cross-listed in three different trading venues there will be cointegrating relations among each three issuances. From our empirical results, we have clear evidence to support the hypothesis 1. In Table 3 Panel (a), both the Johansen trace and maximum eigenvalue tests suggest that all five selected company shares demonstrate two cointegrating vectors.[8] To be more specific, Johansen trace test show that Barclays, HSBC and Vodafone have got one cointegration trend each while BHP Billiton and Tesco share two common trends among their three issuances. It is also known that these two types of cointegration tests' null hypotheses are complimentary to each other. Therefore, to obtain the consistent results from both tests, we can conclude that cross-listed (cross-market) shares share long run co-movements. This means that although individual price series of the same share follow random walks, they share at least one common trend and the price movements among the three series converge in the long run.

We also hypothesize that, when looking at one specific market (e.g. LSE), the five different company shares have their own independent price generating processes. In Table 3 Panel (b), we see no integrating vectors for these five shares traded in LSE, nor BATS-Europe or Turquoise. This is evidence to support our within-market hypothesis for the long run price movement structure. This is

[8] In Panel (a), by examining the actual figures of the test statistics, we found BHP and Tesco are significant at the step of $r \leq 2$, which indicates three cointegrating vectors. However, this is contradictory to the theory and we can see that the acceptance of significance is weak and marginal. Therefore, we should be confident in only claiming two cointegrating vectors for these firms.

presumably because these highly liquid shares have no common characteristics but are exposed to the same common shocks (exogenous); therefore, the idiosyncratic risk (or trader specific risk) would be the primary generating power leading the price changes. Clearly, all of them have different and possibly unique firm fundamentals, and hence, different trader specific risk dominating the price evolvements. Even for Barclays and HSBC in the same sector, we would think they might have completely independent price update processes as their individual specific trading impact (highly frequently traded stock) may overwhelm the impact from the shared industrial features.

The findings of the long-run information and price structure can be practically useful. For example, for cross market investments, investors can use the dominant issuance's price movement as indicators to better understand how other two issuances could behave; therefore, to form more effective and efficient cross-market hedging for risk and trading purpose. Within a market, each company share appears to behave independently from one another in the long-run. In this scenario, it may be better for investors to choose funds instead of individual stocks to better hedge risks.

Insert Table 3 Here

6.2 Granger Causality Test cross-market vs. within-market

After examining the long run dynamics for both cross-market and within-market shares, we start to study the short run structures of these series in three different ways. In our second hypothesis, we suggest that the cross-market shares tend to have bi-directional causation between each pair of the three issuances and so is the block causality ('ALL' in the results). There may not be one specific dominant information transmission series. However, we expect the LSE would be the market with higher level of causation transmission impact on the other two markets but not vice versa. If observing the shares traded within the same market, the Granger causation structure in mean may differ from the cross-market case. It could be uni-directional, bi-directional or random for each pair of the five company shares. This means that we cannot conclude the price discovery dominance of any particular share over other shares through the information spillover through mean causality.

Our estimation of different information causation structures for these shares in different multivariate settings is based on the underlying information theory of exogenous and endogenous shocks driving updates in the mean differently in a non-homogenous market. In Table 4, Panel (a) shows that strong causation (99% significance level marked as ***) for cross-market shares exists everywhere in share pairs and one series and its corresponding blocks. The information shocks in the mean process spillover to each other bi-directionally for all these companies. For the block causation, it is evident that LSE always has higher level of causality in comparison to BATS and Turquoise. For example, the 'ALL' causality statistics of BARCL, BARCBS and BARCTQ are 1249.83, 672.11 and 250.78 respectively, showing that BARCL possesses more dominance regarding causality transmission over the rest of the system.

When we study the pairs of shares, we can find bi-directional causation flows for all combinations but one flow tends to be more prominent than the other. More specifically, the stronger information causality are from TQ to LSE, TQ to BATS and LSE to BATS, (for example, BARCL to BARCBS is 168.32 while BARCBS to BARCL is 33.42; thus, LSE spills causality to BATS). The explanation for LSE overpowers BATS causation could be that LSE has been the largest trading venue in Europe by size. In a different case, TQ, is smaller in size than BATS but it has higher causality impact on LSE. It is worth to note that as the second largest trading venue in Europe, the causality transmission of BATS-Europe outflows to the other two markets appear to be weaker than its inflows from them. This means it has lower level of dominance in affecting other two markets' information structure changes. We argue this could be because this market tends to be considered riskier than LSE and BATS by traders.

Insert Table 4 Here

For within-market shares (see Table 4, Panel (b)), we still can observe the block causations for most markets apart from BHP Billiton traded on BATS and Turquoise (the 'ALL's are 6.87 (0.55) and 6.83 (0.55)). Moreover, we notice that the TSCOTQ's block causality is significant at 95% instead of 99%. For the five shares traded in the same market (LSE, BATS or Turquoise), we identify cases of bi-directional, uni-directional and no causality spillover and some examples (e.g. LSE) include:

- Bi-directional cases: 1) BARCL and HSBCL share strong bi-directional causality spillovers (both directions are ***); and 2) BLTL transmits information flows to HSBCL significantly at 99% while HSBCL does it to BLTL at 90%.
- Uni-directional case: TSCOL has causality spillover to HSBCL at 95% but HSBCL does not spill information shocks to TSCOL.
- No spillover case: TSCOL and BARCL do not have any causality spillover between them.

Similar observations can be found for BATS and Turquoise. Therefore, we can sufficiently provide evidence to support our second hypothesis. . For investors, these are particularly important. For example, if they hold shares which have the bi-directional information flows, the price changing in one could also affect the other. This means, the share price of one would respond to the price change in the other. Oppositely, if I own TSCOL and BARCL, I would not need to worry much about how their price movements could affect each other.

6.3 Volatility spillover cross-market vs. within-market

After examining the mean structures, we move on to look at variance structure through volatility spillovers with consideration of FAD's type of feedback. The third hypothesis 3 predicts that the cross-market shares would demonstrate strong volatility spillovers driven by both the covariance and correlation structures due to the co-existence of market segmentation for the same fundamental share. But such factor loading transmission for within-market companies would feature different dynamics.

Figure 2 Panels (a) to (e) show the time-varying factor loadings of five groups of cross-market shares. As expected, the multivariate factor loadings are all noisy, which indicates that the responses to information shocks through the covariance structures of these cross-listed shares are bi-directional but may be at different levels. In general, the $B_{xxxL,\ xxxBS}$ and $B_{xxxL,\ xxxTQ}$ tend to be noisier in comparison to other risk factors and usually, the fluctuations of $B_{xxxBS,\ xxxTQ}$ appears to be within a relatively smaller range. Vodafone's VAR-MV-GARCH seems slightly different from other four companies, in which the information shocks stemming from BATS and Turquoise are within narrower bounds (Panel (e), plots in the second and third rows apart from the diagonal ones). We think this makes sense if we consider the size of Vodafone traded in LSE comparing to that in BATS and Turquoise. Certainly, the size features may be common for other selected shares but we argue possibly this IT share may respond to a size factor more sensitively. It also could be due to the features of Vodafone itself. Again, the clear picture of volatility transmission directly shows investors how the underlying risk of one share (or issuance) performs relative to the other share (or issuance). The dominance and direction of volatility would benefit the risk manager to better manage their risk exposure and more efficiently decide their hedging strategies (e.g. long or short) to allocate their capitals and balance the book.

Insert Table 5 Here

In Table 5 Panel (a), we report the transformed variance coefficientsl. The coefficients of error terms and covariance matrices are stored in A and B . The covariance matrices, in theory, are formed of variance and correlation terms and proxies the information feedback trading idea described in the FAD's model. For cross-market cases, we find that both transmission vectors are significant for all five different companies. This is consistent with our hypothesis and the theory: the nature of cross-listed shares means that they share same endogenous shocks and the geographical closeness of the actual trading provide similar exogenous information. Therefore, we should not be surprised to observe that the volatility spillovers are driven by the covariance correlation matrices) jointly while the literature often suggests that covariance is the single factor evolving the price updates.

Insert Figure 2 Here

In contrast, when we examine the within-market variance transmissions in Figure 3, Panels (a) to (c) and Table 5, Panel (b). The time-varying factor loadings indicating the initiation from Barclays to other companies tend to be the noisiest (e.g. the five plots in the first row of Panel (a)) and the ones starting from Tesco and Vodafone the least in both LSE and BATS. However, the Turquoise scenario looks quite different from the other two and it is not obvious that the factor loadings initiated from one company appear to be substantially smaller than others'. The Table 5, Panel (b) indicates that the factor loading updates are driven by the covariance terms. Apart from the diagonal elements in A, all other elements are not significant, which means that the correlation transmission would not be positive indefinite. This suggests no feedback transmission among these within-market shares.

6.4 Liquidity spillover cross-market vs. within-market

In Table 6, Panel (a), we report the Granger causality tests for liquidity and between liquidity and volatility. These results follow similar logic to the volatility spillover in that we need study cross-spillover outcomes.[9]

However, the results here are a bit more complicated as we are studying more than one market provision. There should be three different scenarios: 1) cross-liquidity spillover; 2) liquidity to volatility spillover (L-to-V); and 3) volatility to liquidity spillover (V-to-L). These are essential as with more than one provision involved to affect the market structure, not only the individual factor may drive the pricing process but also the interaction or the dynamics between the two provisions would impact the underlying process. One important reason why we form the idea of examining the

[9] Following the rational of our analysis of volatility in 6.3, self-spillover refers to transmission from an observable to itself (e.g. liquidity to volatility from BARCL to BARCL; volatility to liquidity from BARCL to BARCL). while cross-spillover means the transmission from one observable to another (e.g. liquidity spillover from BARCL to BLTBS; liquidity to volatility spillover from BARCL to BARCTQ; volatility to liquidity spillover from BARCL to BLTBS).

feedback effects is exactly because the correlated behavior of two risk factors may drive the price movement in a more systematic way.

To look at the causality structure beyond volatility or liquidity individually also has practical implications. Similar to volatility studies, the liquidity spillovers explain how price movements related to trading behavior affect one another. For example, if two shares such as VODTQ and VODBS have no liquidity spillover (i.e. A0) and this can be interpreted that the price changes of VODTQ and VODBS are independent from how each other is traded in the market. In a different case, BARCBS responds to liquidity shocks in BARCL (one-way), which means that when Barclay shares traded in London have price fluctuation (usually associated with trading/quoting prices and volumes at the specific time), its cross-listed shares in BATS would respond to the London price changes. Of course, the bi-directional spillovers reveal the dynamic relations between any two price movements.

When it comes to volatility and liquidity, it is important to know the dynamic between them. If there were transmission from volatility to liquidity, this may indicate that volatility is the primary driver for price updates and it is associated with the underlying risk process; if vice versa, it could be understood that it is mainly the trading activities affecting the price movements. This could be useful in identifying some phenomena occurred in the market such as the sharp changes at the end of the trading day (the extreme case is called 'black swan'). When such phenomena happen, usually we can observe sharp price changes and volatility shoot up dramatically, however, these are usually caused by the traders deliberately pushing volatility up through buy or sell in blocks in order to figure out the true market supply and demand. This may be their utmost task as they need to balance their own books (to zero position at the end of the trading day) without exposing their positions in the market. We now shall discuss these causation structures one by one:

First, we find that for cross-liquidity spillovers, majority are not significant. However, we find both bi-directional and uni-directional spillover in liquidity among some of the shares. The details are as follows:

1) Uni-directional liquidity spillover: BARCL to BARCBS; BLTBS to BLTL; TSCOL to TSCOBS; VODTQ to VODL; and VODBS to VODL

2) Bi-directional liquidity spillover: BARCL to/from BARCTQ; BARCBS to/from BARCTQ; HSBCL to/from HSBCTQ and BLTL to/from BLTTQ.

It is, in fact, quite clear that these significant cross-spillovers are mostly from LSE to other markets, especially the bi-directional pairs.

Insert Table 6 Here

The second category (B) except for BLTBS, whilst Tesco and Vodafone only show self-L-to-V spillovers in the LSE market. Barclays, HSBC and BHP Billiton all show significant self- L-to-V spillovers (B1); whilst Tesco and Vodafone have the opposite results. Looking at all cross L-to-V spillovers, we find that the two banking shares, Barclays and HSBC, traded across three markets (LSE, BS and Turquoise) have liquidity spilled over to volatility in all combination of pairs. This means, for example, a pair of cross-traded HSBC shares, they have bi-directional L-to-V spillovers: HSBCL to/from HSBCBS.

BLT has liquidity causality transmitted into the volatility structures of all pairs apart that there is no causation in BLTL's volatility led by BLTBS' liquidity movements (Notice that L-to-V causation from BLTL to BLTBS is significant and this forms a uni-directional L-to-V spillover for this combination). In contrast, most cross-market share pairs of Tesco and Vodafone bear no cross-spillovers from liquidity to volatility. There are two different cases: TSCOL's liquidity changes lead to causality in TSCOBS' volatility and the same between VODL and VODBS, also VODL and VODTQ.

The last causality structure (C) is the spillover effects from volatility to liquidity (V-to-L). Opposite to the L-to-V spillovers, we find no cross-spillovers for all. This means that, cross shares, volatility does not intrigue causality in liquidity. For self-spillovers, we only notice one significant V-to-L spillover for each share: BARCBS to BARCBS, HSBCL to HSBCL, BLTL to BLTL, TSCOL to TSCOL and VODL to VODL. Again, we find LSE is the main destination of detecting self-spillover effects if significant.

To briefly sum up, for cross-market shares, if the causality spillovers of liquidity or between liquidity and volatility are significant, they usually more likely exist in cross-spillover effects. We also conclude that it is more possible for liquidity to drive the volatility to change but not vice versa. Finally, we find both uni-directional and bi-directional causality of liquidity or between liquidity and volatility.

In Panel (b), we run these three tests (liquidity (A), liquidity to volatility (B) and volatility to liquidity (C) spillover) for within-market shares, which are five companies traded at the same time within the same market (e.g. LSE). We continue to use the terms of self-spillover and cross-spillover to interpret our results.

For cross-spillover in liquidity, we see all in LSE, two in BATS (BARCBS to BLTBS and BLTBS to HSBCBS) and four in Turquoise (BARCTQ to BLTTQ; HSBCTQ to BARCTQ; and a bi-directional spillover between HSBCTQ and BLTTQ). Such rareness is similar to the cross-market situation.

For the L-to-V causality structure, Tesco shares traded in LSE, BATS-Europe and Turquoise present no liquidity transmitting into volatility in their own underlying processes. In BATS and Turquoise, Vodafone also shows no L-to-V causality.

In LSE, most shares spill liquidity to other shares' volatility. There are only four insignificant ones including BARCL to TSCOL; BARCL to VODL; HSBCL to TSCOL and HSBCL to VODL. This, in turn, makes the L-to-V spillovers of these two banking shares to Tesco and Vodafone shares to operate in one direction only. In BATS, less significant cross-spillover from liquidity to volatility are found and there are altogether eight null L-to-V causality transmissions including five uni-directional (BARCBS to TSCOBS, HSBCBS to TSCOBS, BLTBS to BARCBS, BLTBS to TSCOBS and VODBS to HSBCBS) and three bi-directional ones (BARCBS to VODBS, BLTBS to VODBS and TSCOBS to VODBS). For HSBCBS (or BLTBS) in particular, its volatility updates are driven substantially by some source of liquidity from itself and other shares (such as BARC, BLT and TSCO) traded in the same market. In Turquoise, there are even less significant spillovers in this kind apart from BARCTQ to HSBSTQ, BARCTQA to BLTTQ, BLTTQ to HSBCTQ and BLTTQ to BARCTQ.

Finally, for the volatility-to-liquidity spillover, there have been no cross-spillover across all five shares traded in three markets respectively. For the self-spillover, the only evidence is seen in BARCL to BARCL.

7. Conclusion

We consider a feedback-trading model that assumes two different groups of investors, i.e. risk averse expected utility maximizing investors and feedback traders, and apply it to examine the existence and significance of feedback trading through the underlying risk generating process of five most frequently traded cross-listed stocks. When the stocks are cross-listed in multiple markets, theoretically, they share the same fundamentals and therefore any price difference should be from market specific information shocks and the trading specific constraints of the exchanges. Therefore, the cross-listed shares form an empirical test with some novelty to investigate the presence and behaviour of feedback traders. This paper contributes to the literature by showing how the information spillovers on volatility and liquidity affect returns through feedback trading. Our major findings are summarized as follows.

Based on Johansen cointegration tests, we find that cross-listed (cross-market) stocks share long run co-movements, suggesting that although individual price series are characterised as random walk processes, they share at least one common trend and the price movements among the (three) prices series converge in the long run. Our Granger causality test results suggest that the cross-listed shares tend to have strong bi-directional causations among them and the LSE always has higher level of causality in comparison with BATS and Turquoise. However, we did not find the price discovery dominance of any particular share over other shares through the information spillover. Our findings also show that for cross-market shares, if the causality spillovers of liquidity or between liquidity and volatility are significant, they are usually more likely to exist in cross-spillover effects. We also conclude that it is more likely that liquidity drives volatility change but not vice versa. Finally, we find both uni-directional and bi-directional causality of liquidity or between liquidity and volatility.

To sum up, we examine the information structure of the underlying price formation process from multiple angles. The key belief is that with fluctuation in the underlying process, returns of securities will change subsequently and we argue that information formation is the primary driver, especially the short-run provisions such as volatility and liquidity. It is important is trying to understand the causes of movement in returns, to understand the information structures and the factors that cause them to change. Our main finding and contribution to the literature is that the underlying risk process does not only rely on the variance (or volatility) process but also the correlation processes. We conclude that there exists a dynamic between volatility and liquidity, which ultimately affects returns. Finally, we find that the form and nature of such interactions vary across the nature of each share's features such as cross listing. In terms of future work, we propose that we can further look into the covariance matrices and study the structure of the variance and correlation terms in order to understand the feedback structure and the volatility spillovers. The theoretical work to assist this already lies in the Dynamic Conditional Correlation method proposed by Engle (2002) and other related work such as Kim (2002), Tse and Tgui (2002) and Engle and Sheppard (2006).

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Tables

Table 1: Generic model specifications .

Model Name	**Endogenous**
(a) VECM Models	**Cross-markets**
Barclays	y_t =*[logBARCL, logBARCBS, logBARCTQ]*
HSBC	y_t =*[logHSBCL, logHSBCBS, logHSBCTQ]*
BHP Billiton	y_t =*[logBLTL, logBLTBS, logBLTTQ]*
Tesco	y_t =*[logTSCOL, logTSCOBS, logTSCOTQ]*
Vodfone	y_t=*[logVODL, logVODBS, logVODTQ]*
	Within-market
LSE	y_t=*[logBARCL, logHSBCL, logBLTL, logTSCOL, logVODL]*
BATS-Europe	y_t=*[logBARCBS, logBLTBS, logHSBCBS, logTSCOBS, logVODBS]*
Turquoise	y_t=*[logBARCBS, logBLTBS, logHSBCBS, logTSCOBS, logVODBS]*
(b)VAR-MV-GARCH Models	**Cross markets**
Barclays	y_t=*[ΔlogBARCL,Δ logBARCBS, ΔlogBARCTQ]*
HSBC	y_t=*[ΔlogHSBCL,ΔlogHSBCBS, ΔlogHSBCTQ]*
BHP Billiton	y_t=*[ΔlogBLTL, ΔlogBLTBS, ΔlogBLTTQ]*
Tesco	y_t=*[ΔlogTSCOL, ΔlogTSCOBS, ΔlogTSCOTQ]*
Vodfone	y_t=*[ΔlogVODL, ΔlogVODBS, ΔlogVODTQ]*
	Within-market
LSE	y_t=*[ΔlogBARCL, ΔlogBLTL, ΔlogHSBCL, ΔlogTSCOL, ΔlogVODL]*
BATS-Europe	y_t=*[ΔlogBARCS, ΔlogBLTBS, ΔlogHSBCBS, ΔlogTSCOBS, ΔlogVODBS]*
Turquoise	y_t=*[ΔlogBARCTQ, ΔlogBLTTQ, ΔlogHSBCTQ, ΔlogTSCOTQ, ΔlogVODTQ]*

Notes: The panel (a) of table defines the VECM model identifiers for the long run cointegration analysis described in Section 3.4. The panel (b) of table defines the model identifiers for the VAR-MV-GARCH model described in Section 3.4. *logBARC_L* is the logarithm of Barclays share price in LSE; *ΔlogBARC_L* is the logarithmic return of Barclay share traded in the LSE; The other abbreviations in the table are to be similarly interpreted.

Table 2: Descriptive statistics.

		Barclays	HSBC	BHP Billiton	Tesco	Vodafone
LSE	*Mean*	3.74E-06	2.24E-06	-6.05E-07	-9.89E-07	2.08E-06
	Std. dev.	1.23E-03	6.12E-04	8.54E-04	6.18E-04	6.77E-04
	Skewness	-0.186	-0.327	-0.113	-5.929	1.476
	Kurtosis	60.178	39.674	56.467	527.558	328.488
	Jarque-Bera	6944710	2860547	6062563	5.79E+08	2.24E+08
BATS-Europe	*Mean*	3.74E-06	2.25E-06	-6.02E-07	-9.91E-07	2.08E-06
	Std. dev.	1.168E-03	6.48E-04	8.13E-04	5.68E-04	5.83E-04
	Skewness	-0.2037	-0.363	-0.259	-8.349	2.477
	Kurtosis	63.798	47.103	56.821	690.314	425.920
	Jarque-Bera	7851863	4136411	6143577	9.93E+08	3.79E+08
Turquoise	*Mean*	3.73E-06	2.25E-06	-6.20E-07	-9.79E-07	2.07E-06
	Std. dev.	1.17E-03	6.11E-04	8.13E-04	5.64E-04	5.81E-04
	Skewness	-0.104	-0.392	-0.159	-8.664	2.397
	Kurtosis	66.709	38.735	56.748	712.515	424.262
	Jarque-Bera	8621321	2716337	6126561	1.06E+09	3.76E-08
	No. of Obs.	50979	51027	50898	50435	50834

Notes: This table reports the descriptive statistics of returns of five chosen stocks traded in three different venues. These returns are at 5-min frequency and over a period between 17/10/2011 and 15/10/2013.

Table 3: Cointegration tests.

Panel (a): Cross-markets shares Cointegration Test

Company	H0: r≤	Trace test		Max. eigenvalue test	
		Critical value (5%)	Test statistic	Critical value (5%)	Test statistic
Barclays	0	29.80	28546.29*	21.13	14606.68*
	1	15.49	13939.61*	14.26	13937.21*
	2	3.84	2.39	3.84	2.39
HSBC	0	29.80	28997.10*	21.13	14574.81*
	1	15.49	14422.29*	14.26	14420.75*
	2	3.84	1.54	3.84	1.54
BHP Billiton	0	29.80	28645.02*	21.13	14442.62*
	1	15.49	14202.40*	14.26	14192.63*
	2	3.84	9.76*	3.84	9.76*
Tesco	0	29.80	28077.02*	21.13	14181.82*
	1	15.49	13895.20*	14.26	13890.22*
	2	3.84	4.98*	3.84	4.98*
Vodafone	0	29.80	28199.75*	32.13	14349.35*
	1	15.49	13850.40*	14.26	13849.64*
	2	3.84	0.762	3.84	0.762

Panel (b): Within-Market shares Cointegration Test

Company	H0: r≤	Trace test		Max. eigenvalue test	
		Critical value (5%)	Test statistic	Critical value (5%)	Test statistic
LSE	0	69.82	64.086	33.88	23.45
	1	47.85	40.63	27.58	21.32
	2	29.80	19.31	32.13	11.88
	3	15.49	7.42	14.26	5.519
	4	3.84	1.91	3.84	1.91
Bats-Europe	0	69.82	59.99	33.88	22.96
	1	47.85	37.03	27.58	21.09
	2	29.80	15.93	32.13	8.83
	3	15.49	7.10	14.26	4.52
	4	3.84	2.57	3.84	2.57
Turquoise	0	69.82	63.43	33.88	22.89
	1	47.85	40.53	27.58	21.27
	2	29.80	19.25	32.13	11.88
	3	15.49	7.36	14.26	5.46
	4	3.84	1.91	3.84	1.90

Notes: We test the long-run cointegrating relationship 1) for the same share cross-listed in three different trading venues; and 2) five different shares within the same market. We report both Johansen Trace and Maximum eigenvalue test results in order to obtain robust results. r denotes the number of cointegrating vectors; * denotes rejection of the hypothesis at 5% significant level.

Table 4: Granger Causality Tests.

Panel (a): Cross-markets Granger Causality Test

Dependent Variable	Excluded	Chi-sq (Prob.)	Dependent Variable	Excluded	Chi-sq (Prob.)	Dependent Variable	Excluded	Chi-sq (Prob.)
BARCL	BARCBS	33.42***	*BARCBS*	BARCL	168.32***	*BARCTQ*	BARCOL	165.04***
		(0.00)			(0.00)			(0.00)
	BARCTQ	252.05***		BARCTQ	297.03***		BARCTBS	33.51***
		(0.00)			(0.00)			(0.00)
	All	1249.83***		All	672.11***		All	250.78***
		(0.00)			(0.00)			(0.00)
HSBCL	HSBCBS_R	96.77***	*HSBCBS*	HSBCL	113.99***	*HSBCTQ*	HSBCL	109.14***
		(0.00)			(0.00)			(0.00)
	HSBCTQ_R	188.63***		HSBCTQ_R	196.99***		HSBCBS	126.32***
		(0.00)			(0.00)			(0.00)
	All	1369.79***		All	468.07***		All	314.34***
		(0.00)			(0.00)			(0.00)
BLTL	BLTBS	52.36***	*BLTBS*	BLTL	135.22***	*BLTTQ*	BLTL	125.25***
		(0.00)			(0.00)			(0.00)
	BLTTQ	223.80***		BLTTQ	257.60***		BLTBS	52.43***
		(0.00)			(0.00)			(0.00)
	All	1220.81***		All	615.80***		All	223.39***
		(0.00)			(0.00)			(0.00)
TSCOL	TSCOBS	82.99***	*TSCOBS*	TSCOL	107.41***	*TSCOTQ*	BLTL	100.95***
		(0.00)			(0.00)			(0.00)
	TSCOTQ	347.56***		TSCOTQ	471.46***		BLTBS	104.72***
		(0.00)			(0.00)			(0.00)
	All	1977.52***		All	885.22***		All	251.04***
		(0.00)			(0.00)			(0.00)
VODL_R	VODBS	83.99***	*VODBS_R*	VODL	107.41***	*VODTQ*	VODL	100.95***
		(0.00)			(0.00)			(0.00)
	VODTQ	347.56***		VODTQ	471.46***		VODBS	104.72***
		(0.00)			(0.00)			(0.00)
	ALL	1977.52***		ALL	885.22***		ALL	251.04***
		(0.00)			(0.00)			(0.00)

Panel (b): Within-Market shares Granger Causality Test

Dependent Variable	Excluded	Chi-sq (Prob.)	Dependent Variable	Excluded	Chi-sq (Prob.)	Dependent Variable	Excluded	Chi-sq (Prob.)
	LSE			BATS-Europe			Turquoise	
BARCL	HSBCL	17.09***	*BARCBS*	HSBCBS	3.86	*BARCTQ*	HSBCTQ	3.86
		(0.00)			(0.15)			(0.15)
	BLTL	64.19***		BLTBS	30.73***		BLTTQ	30.92***
		(0.00)			(0.00)			(0.00)
	TSCOL	3.80		TSCOBS	5.98**		TSCOTQ	4.50
		(0.15)			(0.05)			(0.11)
	VODL	1.37		VODBS	1.06		VODTQ	0.08

		(0.50)			(0.59)			(0.96)
	All	114.74***		All	40.45***		All	33.65***
		(0.00)			(0.00)			(0.00)
HSBCL	BARCL	39.81***	*HSBCBS*	BARCBS	2.27	*HSBCTQ*	BARC	10.49***
		(0.00)			(0.32)			(0.01)
	BLTL	36.95***		BLTBS	7.37**		BLTTQ	5.57*
		(0.00)			(0.03)			(0.06)
	TSCOL	10.94**		TSCOBS	5.22*		TSCOTQ	1.45
		(0.04)			(0.07)			(0.48)
	VODL	18.80***		VODBS	2.25		VODTQ	3.78
		(0.00)			(0.32)			(0.15)
	All	167.93***		All	26.19***		ALL	33.11***
		(0.00)			(0.00)			(0.00)
BLTL	BARCL	37.84***	*BLTBS*	BARCBS	4.72*	*BLTTQ*	BARC	2.74
		(0.00)			(0.09)			(0.25)
	HSBCL	5.47*		HSBCBS	1.50		HSBCTQ	0.13
		(0.07)			(0.47)			(0.94)
	TSCOL	0.59		TSCOBS	0.78		TSCOTQ	1.61
		(0.74)			(0.68)			(0.45)
	VODL	0.46		VODBS	0.00		VODTQ	1.93
		(0.80)			(1.00)			(0.38)
	All	65.29***		All	6.87		ALL	6.83
		(0.00)			(0.55)			(0.55)
TSCOL	BARCL	2.97	*TSCOBS*	BARCBS	1.32	*TSCOTQ*	BARC	0.81
		(0.23)			(0.52)			(0.67)
	HSBCL	2.26		HSBCBS	3.30		HSBCTQ	2.46
		(0.32)			(0.19)			(0.29)
	BLTL	4.15		BLTBS	0.59		BLTTQ	1.81
		(0.13)			(0.74)			(0.40)
	VODL	6.54**		VODBS	10.93***		VODTQ	9.03***
		(0.04)			(0.00)			(0.01)
	All	20.86***		All	20.57***		ALL	16.70**
		(0.01)			(0.01)			(0.03)
VODL	BARCL	3.29	*VODBS*	BARCBS	0.97	*VODTQ*	BARC	0.59
		(0.19)			(0.61)			(0.74)
	HSBCL	8.10**		HSBCBS	1.77		HSBCTQ	0.76
		(0.02)			(0.41)			(0.68)
	BLTL	2.27		BLTBS	14.97***		BLTTQ	17.51***
		(0.32)			(0.00)			(0.00)
	TSCOL	9.77***		TSCOBS	2.08		TSCOTQ	1.68
		(0.01)			(0.35)			(0.43)
	All	33.52***		All	24.25***		ALL	33.77***
		(0.00)			(0.00)			(0.00)

Notes: We test the block causality through the Granger causality test 1) for the same share cross-listed in three different trading venues; and 2) five different shares within the same market. ***, ** and * indicate the significant causation spillovers at levels of 99%, 95% and 90%.

Table 5: Transformed variance coefficients.

Panel (a): Cross-markets Transformed variance coefficients

	Barclays		HSBC		BHP Billiton		Tesco		Vodafone	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
M(1,1)	1.20E-07	7.18E-10	1.32E-07	7.11E-10	2.99E-07	7.59E-10	1.41E-07	4.54E-10	8.77E-08	3.03E-10
M(1,2)	1.19E-07	4.58E-10	1.33E-07	5.63E-10	2.95E-07	9.20E-10	9.48E-08	2.49E-10	6.91E-08	1.97E-10
M(1,3)	1.18E-07	5.81E-10	1.37E-07	6.07E-10	3.00E-07	8.60E-10	9.65E-08	2.72E-10	6.80E-08	2.01E-10
M(2,2)	1.13E-07	3.82E-10	1.49E-07	6.51E-10	2.89E-07	1.24E-09	6.12E-08	2.20E-10	7.79E-08	2.44E-10
M(2,3)	1.20E-07	4.07E-10	1.39E-07	5.94E-10	2.87E-07	9.76E-10	6.13E-08	1.03E-10	7.45E-08	2.23E-10
M(3,3)	1.19E-07	5.98E-10	1.42E-07	7.10E-10	2.95E-07	1.06E-09	6.46E-08	1.63E-10	7.54E-08	2.48E-10
A1(1,1)*	0.128	7.42E-04	0.245	1.44E-03	0.292	80E-4	0.291	1.16E-03	0.328	1.04E-03
A1(1,2)*	0.126	5.87E-04	0.254	1.33E-03	0.288	9.40E-04	0.167	9.28E-04	0.358	1.35E-03
A1(1,3)*	0.127	7.04E-04	0.248	1.27E-03	0.296	8.53E04	0.172	8.66E-04	0.350	1.34E-03
A1(2,2)*	0.127	5.86E-04	0.272	1.42E-03	0.291	1.22E-03	0.137	9.13E-04	0.392	2.00E-03
A1(2,3)*	0.128	6.16E-04	0.258	1.28 E-03	0.294	9.77E-03	0.136	7.70E-04	0.383	1.93E-03
A1(3,3)*	0.130	7.93E-04	0.255	1.36 E-03	0.305	1.09E-03	0.145	7.96E-04	0.374	1.91E-03
B1(1,1)*	0.799	9.40E-04	0.458	2.24 E-03	0.416	5.43E-03	0.441	1.37E-04	0.588	1.13E-03
B1(1,2)*	0.798	5.54E-04	0.438	1.69 E-03	0.387	1.27E-03	0.587	9.40E-04	0.556	1.20E-03
B1(1,3)*	0.799	8.08E-04	0.429	1.83 E-03	0.379	1.08E-03	0.580	9.16E-04	0.563	1.19E-03
B1(2,2)*	0.817	3.20E-04	0.432	1.59 E-03	0.403	1.98E-03	0.720	9.03E-04	0.526	1.35E-03
B1(2,3)*	0.797	5.06E-04	0.423	1.67E-03	0.3961	1.48E-03	0.714	4.85E-04	0.533	1.29E-03
B1(3,3)*	0.799	8.40E-04	0.423	0.002031	0.391	1.58E-03	0.704	6.58E-04	0.539	1.32E-03

Panel (b): Within-Market shares Transformed variance coefficients

	LSE		Bats-Europe		Turquoise	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
M(1,1)	9.66E-08	7.07E-10	7.63E-08	7.24E-10	5.13E-08	3.54E-10
M(1,2)	4.99E-08	5.25E-10	3.07E-08	3.82E-10	2.74E-08	2.20E-10
M(1,3)	4.85E-08	7.74E-10	3.17E-08	4.86E-10	2.71E-08	2.02E-10
M(1,4)	1.27E-08	7.18E-10	8.91E-09	2.75E-10	8.52E-09	1.27E-10
M(1,5)	1.99E-08	6.12E-10	1.78E-08	5.60E-10	1.41E-08	1.96E-10
M(2,2)	7.88E-08	4.96E-10	4.02E-08	4.70E-10	4.70E-08	3.33E-10
M(2,3)	4.16E-08	6.75E-10	2.30E-08	2.81E-10	2.55E-08	1.77E-10
M(2,4)	1.02E-08	5.61E-10	6.11E-09	2.52E-10	8.95E-09	1.10E-10
M(2,5)	1.98E-08	8.50E-10	1.71E-08	4.36E-10	1.74E-08	1.39E-10
M(3,3)	9.97E-08	1.02E-09	5.96E-08	6.73E-10	5.29E-08	4.08E-10
M(3,4)	1.47E-08	6.00E-10	7.61E-09	2.13E-10	9.53E-09	1.10E-10
M(3,5)	2.18E-08	8.77E-10	2.13E-08	8.31E-10	1.72E-08	1.71E-10
M(4,4)	3.11E-08	2.11E-10	3.14E-08	4.22E-10	2.12E-08	2.08E-10

M(4,5)	6.99E-09	2.44E-10	8.32E-09	4.33E-10	8.18E-09	1.33E-10
M(5,5)	8.39E-08	2.51E-10	8.28E-08	3.24E-10	7.63E-08	3.14E-10
A1(1,1)*	0.133	0.0011	0.101	9.88E-04	0.139	8.78E-04
A1(1,2)	0.091	0.0011	0.068	8.67E-04	0.183	8.66E-04
A1(1,3)	0.069	0.0011	0.048	8.32E-04	0.143	7.68E-04
A1(1,4)	0.024	0.0014	0.024	1.01E-04	0.142	7.06E-04
A1(1,5)	0.049	0.0023	0.044	1.88E-04	0.224	1.08E-04
A1(2,2)*	0.183	0.0011	0.124	9.06E-04	0.241	0.0012
A1(2,3)	0.067	0.0010	0.050	7.85E-04	0.188	0.0008
A1(2,4)	0.020	0.0015	0.018	1.09E-04	0.187	0.0009
A1(2,5)	0.044	0.0023	0.045	1.74E-04	0.296	0.0015
A1(3,3)*	0.116	0.0013	*0.074*	9.24E-04	0.147	0.0010
A1(3,4)	0.031	0.0014	0.022	8.80E-04	0.146	0.0007
A1(3,5)	0.044	0.0020	0.044	0.0018	0.231	0.0012
A1(4,4)*	0.168	0.0009	*0.096*	0.0009	0.145	0.0009
A1(4,5)	0.041	0.0015	0.033	0.0014	0.230	0.0011
A1(5,5)*	0.306	0.0012	0.329	0.0017	0.364	0.0022
B1(1,1)*	0.822	0.0011	0.854	0.0011	0.853	0.0007
B1(1,2)*	0.781	0.0020	0.852	0.0015	0.768	0.0009
B1(1,3)*	0.830	0.0023	0.884	0.0015	0.833	0.0007
B1(1,4)*	0.889	0.0059	0.917	0.0024	0.842	0.0008
B1(1,5)*	0.792	0.0057	0.812	0.0056	0.680	0.0015
B1(2,2)*	0.652	0.0016	0.784	0.0019	0.692	0.0013
B1(2,3)*	0.765	0.0033	0.855	0.0016	0.750	0.0009
B1(2,4)*	0.863	0.0072	0.912	0.0035	0.758	0.0011
B1(2,5)*	0.736	0.0106	0.767	0.0057	0.612	0.0014
B1(3,3)*	0.764	0.0020	0.847	0.0015	0.812	0.0010
B1(3,4)*	0.851	0.0056	0.915	0.0022	0.821	0.0008
B1(3,5)*	0.771	0.0088	0.769	0.0086	0.663	0.0013
B1(4,4)*	0.774	0.0008	0.828	0.0016	0.831	0.0009
B1(4,5)*	0.842	0.0046	0.814	0.0087	0.671	0.00144
B1(5,5)*	0.604	0.0009	0.542	0.0015	0.542	0.0017

Notes: We report the transformed variance coefficients from VAR-MV-GARCH with feedback models 1) for the same share cross-listed in three different trading venues; and 2) five different shares within the same market. Coefficient vectors A1 indicates the coefficients of error terms and B1 the covariance in the multivariate settings.

Table 6: Granger causality tests for liquidity and liquidity and volatility.

Panel a for cross markets

	BARCL	BARCBS	BARCTQ
BARCL	B1, C0	A1, B1, C0	A1, B1, C0
BARCBS	A0, B1, C0	B1, C1,	A1, B1, C0
BARCTQ	A1, B1, C0	A1, B1, C0	B1, C0
	HSBCL	**HSBCBS**	**HSBCTQ**
HSBCL	B1, C1	A0, B1, C0	A1, B1, C0
HSBCBS	A0, B1, C0	B1, C0,	A0, B1, C0
HSBCTQ	A1, B1, C0	A0, B1, C0	B1, C0
	BLTL	**BLTBS**	**BLTTQ**
BLTL	B1, C1	A0, B1, C0	A1, B1, C0
BLTBS	A1, B0, C0	B0, C0	A0, B0, C0
BLTTQ	A1, B1, C0	A0, B1, C0	B1, C0
	TSCOL	**TSCOBS**	**TSCOTQ**
TSCOL	B1, C1	A1, B1, C0	A0, B0, C0
TSCOBS	A0, B0, C0	B0, C0	A0, B0, C0
TSCOTQ	A0, B0, C0	A0, B0, C0	B0, C0
	VODL	**VODBS**	**VODTQ**
VODL	B1, C1	A0, B1, C0	A0, B1, C0
VODBS	A1, B0, C0	B0, C0	A0, B0, C0
VODTQ	A1, B0, C0	A0, B0, C0	B0, C0

Panel b for stocks within the market

	BARCL	HSBCL	BLTL	TSCOL	VODL
BARCL	B1, C1	A1, B1, C0	A1, B1, C0	A1, B0, C0	A1, B0, C0
HSBCL	A1, B1, C0	B1, C0,	A1, B1, C0	A1, B0, C0,	A1, B0, C0
BLTL	A1, B1, C0	A1, B1, C0	B1, C0	A1, B1, C0	A1, B1, C0
TSCOL	A1, B1, C0	A1, B1, C0	A1, B1, C0	B0, C0	A1, B1, C0
VODL	A1, B1, C0	A1, B1, C0	A1, B1, C0	A1, B1, C0	B1, C0
	BARCBS	**HSBCBS**	**BLTBS**	**TSCOBS**	**VODBS**
BARCBS	B1, C0	A0, B1, C0	A1, B1, C0	A0, B0, C0	A0, B0, C0
HSBCBS	A0, B1, C0	B1, C0	A0, B1, C0	A0, B0, C0	A0, B1, C0
BLTBS	A0, B0, C0	A1, B1, C0	B1, C0	A0, B0, C0	A0, B0, C0
TSCOBS	A0, B1, C0	A0, B1, C0	A0, B1, C0	B0, C0	A0, B0, C0
VODBS	A0, B0, C0	A0, B0, C0	A0, B0, C0	A0, B0, C0	B0, C0

	BARCTQ	HSBCTQ	BLTTQ	TSCOTQ	VODTQ
BARCTQ	B1, C0	A0, B1, C0	A1, B1, C0	A0, B0, C0	A0, B0, C0
HSBCTQ	A1, B0, C0	B1, C0	A1, B0, C0	A0, B0, C0	A0, B0, C0
BLTTQ	A0, B1, C0	A1, B1, C0	B1, C0	A0, B0, C0	A0, B0, C0
TSCOTQ	A0, B0, C0	A0, B0, C0	A0, B0, C0	B0, C0	A0, B0, C0
VODTQ	A0, B0, C0	A0, B0, C0	A0, B0, C0	A0, B0, C0	B0, C0

Notes: A0 = no liqidity spillover; A1 = liquidity spillover; B0 = no liquidity to volatility spillover; B1 = liquidity to volatility spillover; C0 = no volatility to liquidity spillover and C1= volatility to liquidity spillover. The table only reports the outcomes of the granger causality tests. The statistics and p-values are available upon request. The rejection of the hypothesis is at 5% significant level.

Figures

Figure 1: Trading Volumes

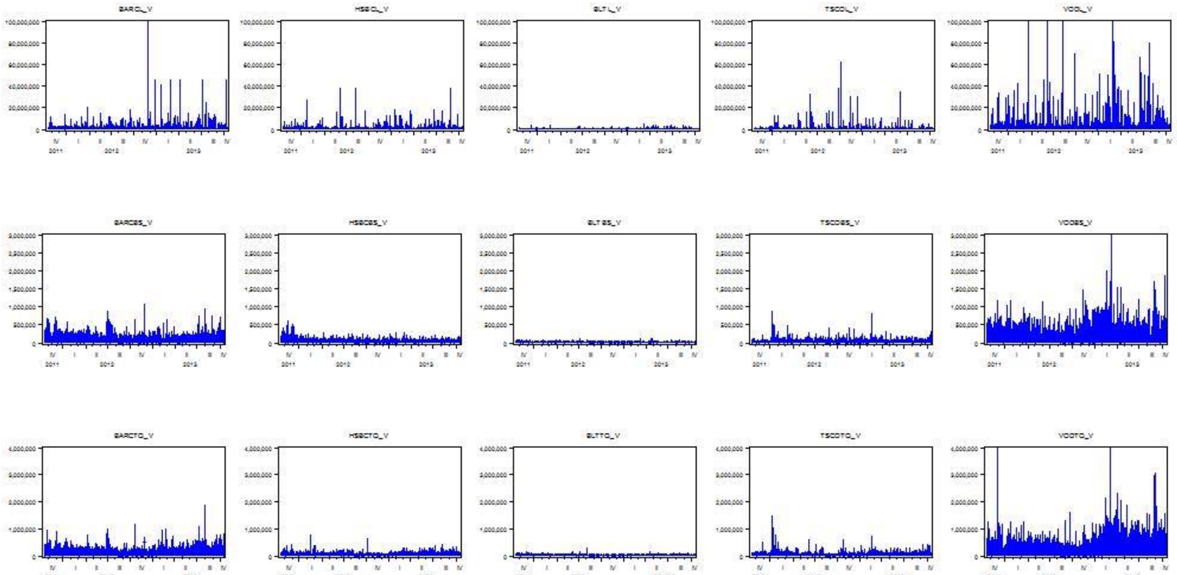
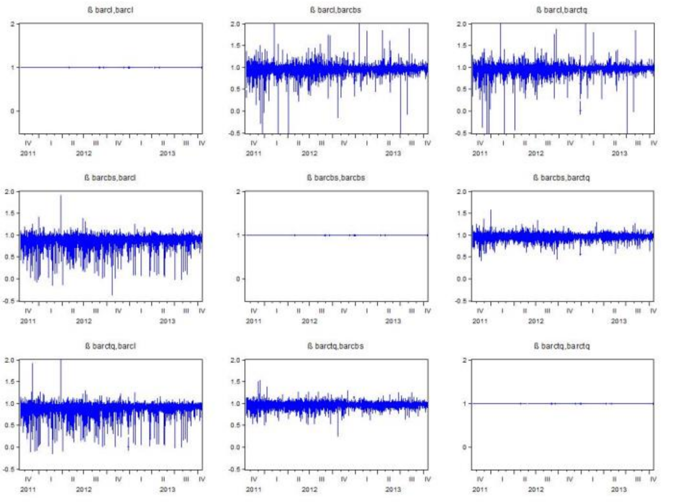
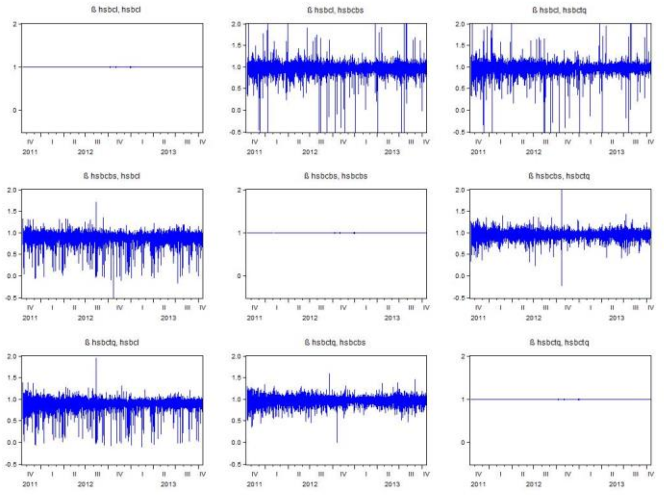


Figure 2: VAR-MV-GARCH for Cross-market Shares

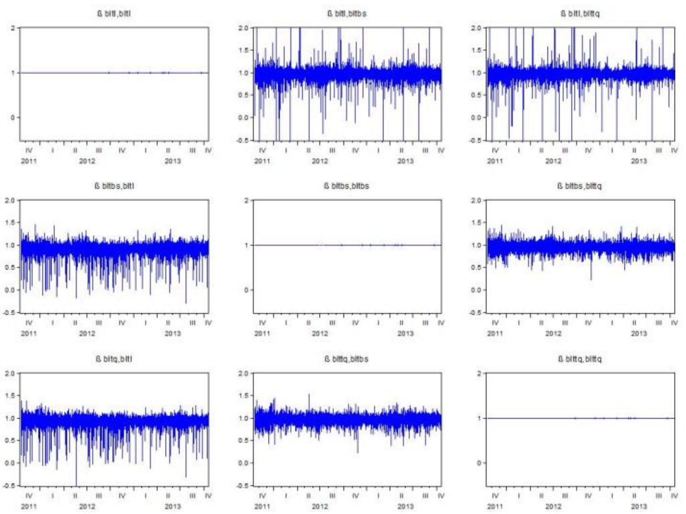
Panel (a) Barclays cross-market



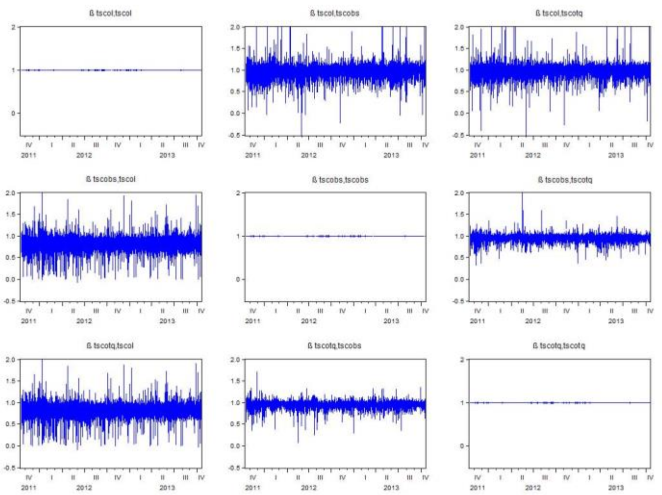
Panel (b) HSBC cross-market



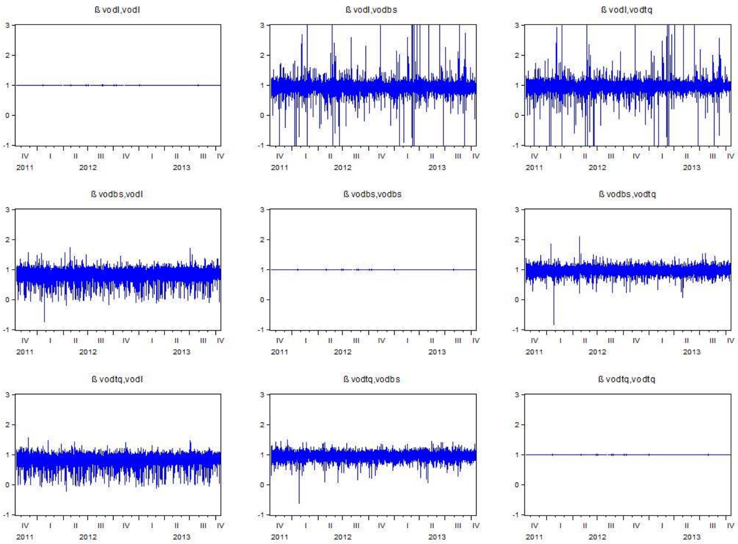
Panel (c) BHP Billiton cross-market



Panel (d) TESCO cross-market



Panel (e) Vodafone cross-market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ß vodl,vodbs
ß vodl,vodtq
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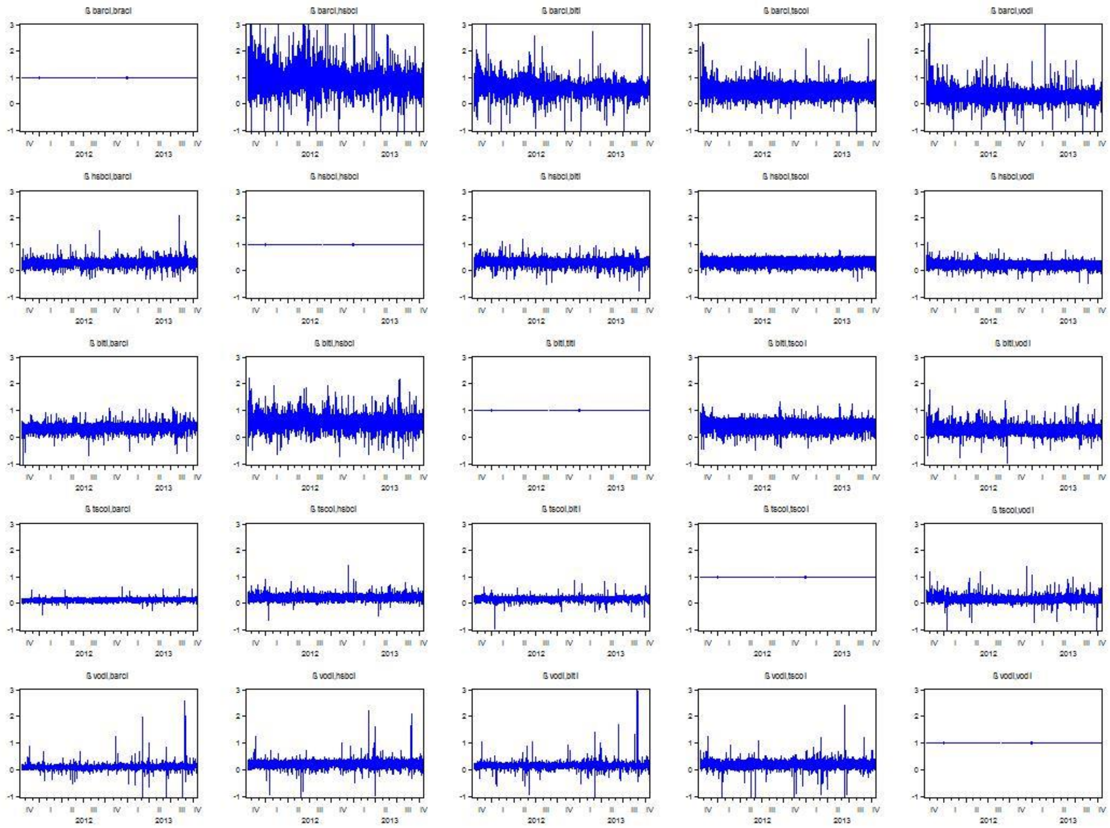
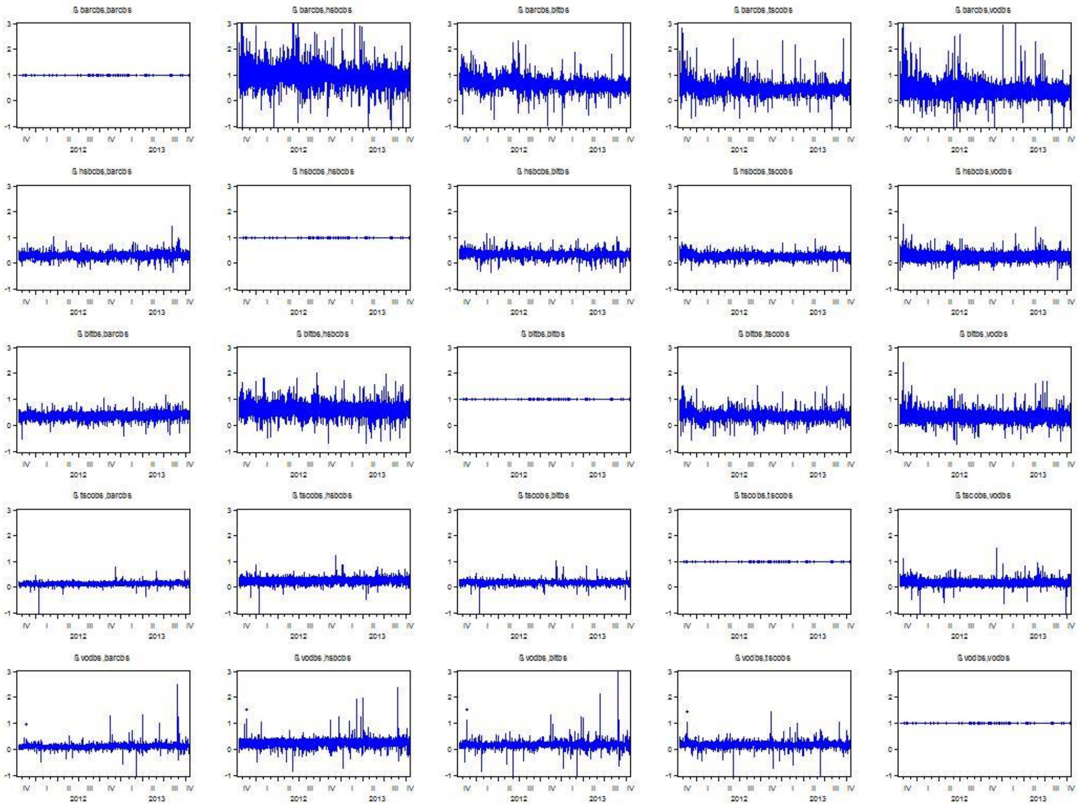
ß vodbs,vodtq
ß vodtq,vodl
ß vodtq,vodbs
ß vodtq,vodtq

Figure 3: VAR-MV-GARCH for Within-market Shares

Panel (a) LSE



Panel (b) BATS-Europe



Panel (c) Turquoise