Illiquidity and Volatility Spillover effects in Equity Markets during and after the Global Financial Crisis: an MEM approach

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Abstract

Even though volatility spillover effects in global equity markets have been documented extensively, the transmission of illiquidity across national borders has not. In this paper, we propose a multiplicative error model (MEM) for the dynamics of illiquidity. We empirically study the illiquidity and volatility spillover effects in eight developed equity markets during and after the recent financial crisis. The results indicate that equity markets are interdependent, both in terms of volatility and illiquidity. Most markets show an increase in volatility and illiquidity spillover effects during the crisis. Furthermore, we find volatility and illiquidity transmission are highly relevant. Illiquidity is a more important channel than volatility in propagating the shocks in equity markets. Our results show an overall crucial role for illiquidity in the US market in influencing other equity markets' illiquidity and volatility. These findings are of importance for policy makers as well as institutional and private investors.

JEL Classification: C32, C52, G14

Key words: Illiquidity Spillover, Volatility Spillover, Multiplicative Error Model

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1. Introduction

For many years, especially following the global financial crisis, much has been made of the nature of financial market interdependence, mainly in terms of returns and return volatilities (King and Wadhwani 1990; Forbes and Rigobon, 2002; Diebold and Yilmaz, 2009; Engle et al., 2012). However, market liquidity, as an equally important risk factor as volatility, has attracted less attention in the financial market interdependence literatures.

The recent global financial crisis (2007-2009), suggests that, at times, market conditions can be severe and liquidity can decline or even disappear. Such illiquidity can spread to other markets if the liquidity shocks are systematic. The systematic nature of shocks in illiquidity across markets is due to: a) financial constraints affecting liquidity providers in different securities/markets simultaneously (Comerton-Forde et al., 2010); or b) a decline in the capital available to financial intermediaries active in multiple securities that triggers an increase in risk aversion, impairing the supply of liquidity in these securities/markets (Kyle and Xiong, 2001). Either way, this suggests that understanding the multivariate dynamics of financial markets' liquidity is of importance to policy makers as well as institutional and private investors.

In this paper, we propose a multiplicative error model (MEM) for the dynamics of illiquidity, and study the illiquidity spillover effects in global equity markets during and after the recent financial crisis. Furthermore, we model the dynamics of illiquidity and volatility jointly, so that we can investigate the interdependence between illiquidity and volatility among the equity markets. An MEM-based model is chosen as it is preferred to alternative ways of modelling volatility/illiquidity spillover effects in the literature. First, relative to a VAR model (as used by Diebold and Yilmaz, 2009), an MEM does not suffer from problems caused by zero-valued observations and ensures that only non-negative predictions are permitted. Second, relative to the multivariate GARCH model (as used by Bauwens et al., 2006), an MEM does not suffer from limitations in the number of markets that can be considered, since it can be estimated equation by equation. Third, relative to the GARCHX model of absolute returns, an MEM is more flexible, since a more flexible distribution (i.e., the general gamma distribution) can be adopted for nonnegative valued financial time series (i.e., absolute return, illiquidity or realized volatility).

We apply our analysis to eight developed equity markets over the period 2007-2016, devoting particular attention to the treatment of the 2007-2009 global financial crisis period. We find that equity markets are significantly interdependent, both in terms of volatility and illiquidity; with no markets independent of others. The global financial crisis brings significant changes to the volatility and illiquidity dynamics. Most markets show an increase in volatility and illiquidity spillover effects during the crisis. Furthermore, the volatility and illiquidity transmission are highly relevant. By comparing the spillover balance index between illiquidity and volatility, we find that illiquidity is a more important channel than volatility in propagating shocks in equity markets. Our results show that the illiquidity of US markets plays a crucial role in influencing illiquidity and volatility in other equity markets.

The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the model and methodology. Section 4 introduces the dataset. Section 5 contains the empirical results. Section 6 concludes.

2. Literature Review

This section reviews the theoretical explanations of illiquidity and volatility spillover effects and the associated empirical evidence.

2.1 Liquidity spillovers

Liquidity is defined as the ability to buy or sell large quantities of assets quickly and at a low cost. The comovements or commonalities in liquidity across markets are known in the literature as liquidity spillovers. Understanding the reasons for such liquidity spillovers is of broad interest because it throws light on the causes of sudden unexpected systematic liquidity crises.

Theoretical economic explanations for liquidity spillovers rely on systematic variations in liquidity across borders. When a liquidity shock originates in one country, the interdependence of the real and financial economies induce systematic liquidity shocks across borders (Kaminsky and Reinhart, 1998, and van Rijckeghem and Weder, 2001). In addition, global phenomena or common shocks such as (unexpected/large) changes in US interest rates, exchange rates, and/or oil prices may adversely affect the economic fundamentals and market liquidity in several economies simultaneously, and potentially cause a systematic liquidity shock (Eichengreen et al., 1996).

Liquidity spillover can also be explained using demand or supply side theories. The demand side theories argue that liquidity commonality arises from information asymmetries or the behaviour of international investors (Diamond and Dybvig, 1983, King and Wadhwani, 1990, and Kodres and Pritsker, 2002). Information asymmetries make investors more uncertain about the actual economic fundamentals of a country. A crisis in one country may give a “wake-up call” to international investors to reassess the risks in other countries, and uninformed or less informed investors may find it difficult to extract the informed signal from the falling price. Consequently, they all follow the strategies of better informed investors, generating excess co-movements in price and liquidity across the markets (Calvo and Mendoza, 2000, Pasquariello, 2007, and Yuan, 2005). Other studies that adopt demand side theories include Koch et al. (2010), Kamara et al. (2008) and Karolyi et al. (2012). The supply-side theories suggest that liquidity commonality arises from liquidity providers’ information sharing and capital constraints. An example would be Comerton-Forde et al. (2010) who argue that financial constraints constitute a systematic liquidity factor because they affect liquidity providers in different securities/countries at the same time. Similarly, Kyle and Xiong (2001) suggest that a decline in the capital available to financial intermediaries active in multiple securities/countries can trigger an increase in risk aversion, impairing the supply of liquidity in these securities. Brunnermeier and Pedersen (2009) also suggest that a huge market-wide decline in prices reduces the aggregate collateral of the market making sector, which feeds back as higher comovement in market liquidity. Similar studies also include Chordia et al. (2005), Coughenour and Saad (2004), Kamara et al. (2008) and Hameed et al. (2010).

In terms of the empirical evidence, studies initially focused mainly on cross-sectional analysis of liquidity spillovers, primarily because of data availability and computation techniques. More recent and relevant work on liquidity spillovers has been dominated by time series analysis. Chordia, Roll and Subrahmanyam (2000) study the co-movements in liquidity. They indicate that quoted spreads, quoted depth, and effective spreads co-move with market and industry-wide liquidity. Huberman and Halka (2001) document the presence of a systematic, time-varying component of liquidity. Korajczyk and Sadka (2008) propose a latent factor models of liquidity, aggregated across various liquidity measures, suggest that systematic liquidity is a pricing factor. Corwin and Lipson (2011) find that commonality in liquidity is driven by the correlated trading decisions of professional traders. There is also a tranche of the literature in which trading volume is used as a measure of liquidity. These studies focus on volume spillover effects across different financial markets, and deliver somewhat mixed empirical findings (cf. Gebka, 2012; Gebka and Wohar, 2013, and Lin, 2013).

Despite the number and breadth of previous studies of liquidity dynamics, they are still limited in the sense that they focus only on illiquidity spillovers in different financial markets within a particular country. By contrast, studies of illiquidity spillovers in global equity markets represent a relatively unexplored avenue of research.

2.2 Volatility spillovers

The literature on volatility spillovers is extensive. Theories that explain volatility transmission mechanisms belong to two groups. One group argue that the economic fundamentals of different countries are interconnected by their cross-border flows of goods, services, and capital. When a crisis originates in one country, this interdependence of economies through real and financial linkages becomes a carrier of crisis (Kaminsky and Reinhart, 1998; van Rijckeghem and Weder, 2001). Another group of theories argue that financial crises spread from one country to another due to market imperfections or the behaviour of international investors (Diamond and Dybvig, 1983; King and Wadhwani, 1990; Kodres and Pritsker, 2002).

The empirical studies investigating these effects include Engle, Ito and Lin (1990), Forbes and Rigobon (2002), Edwards and Susmel (2001, 2003), Fratzscher (2003), Gallo and Otranto (2007), Diebold and Yilmaz (2009) and Engle et al. (2012). Generally, they can be categorized according to the three types of empirical model employed: viz. GARCH, VAR and MEM. Typically, these authors find significant and substantial cross-market volatility spillovers. They often find a dominant role for the US market as a source for volatility transmission in global equity markets.

2.3 Interaction between illiquidity and volatility

The relationship between asset liquidity and return volatility has been addressed both theoretically and empirically. Market microstructure theories predict that higher return volatility increases illiquidity (e.g., Stoll, 1978a). A simplified description of the mechanism behind these theories runs as follows. In the one direction, market-makers, who must hold the stock, bear higher inventory risk for more volatile stocks. Higher volatility increases inventory risk and leads to higher bid-ask spreads (e.g., Benston and Hagerman, 1974). In the reverse direction, decreasing liquidity could increase asset price fluctuation (e.g., Subrahmanyam, 1994). These theories are supported by empirical studies that have confirmed the predicted positive relation between illiquidity and return volatility (e.g., Stoll, 1978b, 2000; Amihud and Mendelson, 1989; Statman et al., 2006; Bao and Pan, 2013).

There is also reason to believe that cross market effects between illiquidity and volatility may be significant. For example, if there are leads and lags in trading activity in response to systematic information shocks, then trading activity in one market may predict trading activity, and, in turn, liquidity in another. Similarly, leads and lags in volatility and liquidity shocks may have cross-effects. Thus, if systematic shocks to liquidity and volatility get reflected in one market before another, then liquidity in one market could influence future liquidity in another. More generally, the above variables in one market may forecast the corresponding variables in the other markets. Empirically, Chordia et al. (2005) study the spillover effect between US stock and bond markets, but find no evidence of a causal relationship between liquidity in one market and volatility on another. By contrast, Lee and Rui (2002) find that trading volume (a measure of liquidity) in the US influences return volatility in Japan and the UK. Furthermore, Gebka (2012) show that absolute stock returns (a measure of return volatility) in the US has a strong influence on trading volume in Asian markets. Despite this attention, little if any relevant research has been done on the spillover effects between illiquidity and volatility across global equity markets.

2.4 Summary

Volatility spillover effects have been studied extensively in the literature; however, the dynamics of illiquidity and illiquidity spillovers have received less attention from an empirical perspective. There is also no relevant research on the interaction between illiquidity and volatility across global equity markets. We focus on these two issues in this paper. Specifically, we empirically study the illiquidity spillover effects in global equity markets during and after the recent financial crisis. Furthermore, we model the dynamics of illiquidity and volatility jointly, so that we can investigate the interdependence between illiquidity and volatility in equity markets. The empirical model we adopt is an MEM-type model, which is close to that used by Engle et al. (2012). We innovate by using a realized volatility and illiquidity proxy in each market.

3. The Methodology Framework

3.1 Liquidity proxy and model

The illiquidity measure we employ here is the daily ratio of absolute stock return to its dollar volume, as proposed by Amihud (2002). It can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact.[1] The daily illiqidity lq_t is defined as:

$$lq_t = \frac{abs(r_t)}{P_t \times volume_t}. \tag{1}$$

Since the illiquidity is non-negatively valued, and highly persistent over time (as shown in Figure 1 and Table 1 in section 4), we follow Engle et al. (2012) and use the MEM to model the dynamics of illiquidity. The MEM was initially proposed by Engle (2002) and has been widely used to model the dynamics of non-negative valued highly persistent financial time series (i.e., absolute return, daily range, realized volatility, trading duration, trading volume and bid-ask spread). Conditional on the information set I_{t-1}, illiqidity in market i, $lq_{i,t}$, is modelled as

$$lq_{i,t} \mid I_{t-1} = \mu_{i,t}^{lq} \varepsilon_{i,t}^{lq}, \qquad i = 1, 2, \cdots k. \tag{2}$$

where the innovation term $\varepsilon_{i,t}^{lq}$ is a unit mean random variable, such that $\varepsilon_{i,t}^{lq} \mid I_{t-1} \sim i.i.d(1, \sigma_i^{lq})$, and k is the number of markets included in the analysis. The conditional expectation of $lq_{i,t}$, $\mu_{i,t}^{lq}$, can be specified as a base MEM (1,1),

$$\mu_{i,t}^{lq} = w_i^l + \alpha_{ii}^l lq_{i,t-1} + \beta_i^l \mu_{i,t-1}^{lq}, \tag{3}$$

To study the illiquidity spillovers, we include the lagged daily illiquidity observed in other markets in the base specification:

$$\mu_{i,t}^{lq} = w_i^l + \alpha_{ii}^l lq_{i,t-1} + \beta_i^l \mu_{i,t-1}^{lq} + \sum_{j \neq i} \alpha_j^l lq_{j,t-1}. \tag{4}$$

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[1] There are finer and better measures of illiquidity, such as the bid-ask spread (quoted or effective), transaction-by-transaction market impact, or the probability of information-based trading. These measures, however, require a lot of microstructure data that are not available in many stock markets. And, even when available, the data do not cover very long periods of time. The measure used here enables us to construct a long time series of illiquidity that is necessary to test illiquidity spillover effects in equity markets. This would be very hard to do with the finer microstructure measures of illiquidity.

The other terms that are of interest in the framework can be included. For example:

- Time dummies: DC_t (during crisis = 1)
- Interaction terms between illiquidity of all markets and DC_{t-1} to accommodate the possibility of changing links during the crisis
- Asymmetric effects (Glosten et al, 1993): $S_{i,t-1}=1$ if $r_{i,t-1}<0$; $S_{i,t-1}=0$ if $r_{i,t-1}>=0$, denoting $lq^*_{i,t-1}=S_{i,t-1}lq_{i,t-1}$

The general model is thus:

$$\mu^{lq}_{i,t}=w^l_i+\alpha^l_{ii}lq_{i,t-1}+\beta^l_i\mu^{lq}_{i,t-1}+\sum_{j\neq i}\alpha^l_{ij}lq_{\mathrm{j},t-1}+\delta^l_iDC_{t-1}+\lambda^l_ilq^*_{i,t-1}+\sum_{i,j}\gamma^l_{ij}lq_{j,t-1}DC_{t-1}\ . \quad (5)$$

3.2 Volatility model

Rather than using a high-low range, as in Engle et al. (2012), we use realized volatility based on 5-min intra-day squared returns to build a volatility proxy. The evidence presented by Patton et al. (2013) shows that it is difficult to beat the simple 5 min realized variance by other realized measures of volatility. The 5-min realized volatility can be obtained from the Oxford-Man Institute of Realized Volatility lab. As realized volatility is non-negative valued and highly persistent over time, we follow Engle and Gallo (2006) and Shephard and Sheppard (2010) and use an MEM to model the dynamics of realized volatility. Conditional on the information set I_{t-1}, realized volatility in market *i*, $rv_{i,t}$, is modelled as

$$rv_{i,t}\mid I_{t-1}=\mu^{rv}_{i,t}\varepsilon^{rv}_{i,t},\qquad i=1,2,\cdots k. \quad (6)$$

where the innovation term $\varepsilon^{rv}_{i,t}$ is a unit mean random variable. The conditional expectation of $rv_{i,t}$, $\mu^{rv}_{i,t}$, can be specified as a base MEM (1,1),

$$\mu^{rv}_{i,t}=w^v_i+\alpha^v_{ii}rv_{i,t-1}+\beta^v_i\mu^{rv}_{i,t-1}\,. \quad (7)$$

We then include the lagged realized volatility observed in other markets, asymmetric effects, a crisis period dummy, and the interaction terms between volatility and time dummy of all markets; the general model is then:

$$\mu^{rv}_{i,t}=w^v_i+\alpha^v_{ii}rv_{i,t-1}+\beta^v_i\mu^{rv}_{i,t-1}+\sum_{j\neq i}\alpha^v_{ij}rv_{\mathrm{j},t-1}+\delta^v_iDC_{t-1}+\lambda^v_irv^*_{i,t-1}+\sum_{i,j}\gamma^v_{ij}rv_{j,t-1}DC_{t-1} \quad (8)$$

3.3 Liquidity and volatility spillover model

To study the illiquidity and volatility interaction in financial markets, we add lagged volatility (illiquidity) and the interaction between lagged volatility (illiquidity) to DC_{t-1} in all markets to the illiquidity (volatility) model. The liquidity-volatility model is then: [2]

$$\begin{aligned}\mu_{i,t}^{lq} &= w_i^l + \alpha_{ii}^l lq_{i,t-1} + \beta_i^l \mu_{i,t-1}^{lq} + \sum_{j\neq i} \alpha_{ij}^l lq_{j,t-1} + \sum_{i,j} \alpha_{ij}^{lv} rv_{j,t-1} \\ &+ \delta_i^l DC_{t-1} + \lambda_i^l lq_{i,t-1}^{*} + \sum_{i,j} \gamma_{ij}^l lq_{j,t-1} DC_{t-1} + \sum_{i,j} \gamma_{ij}^{lv} rv_{j,t-1} DC_{t-1}\end{aligned} \tag{9}$$

$$\begin{aligned}\mu_{i,t}^{rv} &= w_i^v + \alpha_{ii}^v rv_{i,t-1} + \beta_i^v \mu_{i,t-1}^{rv} + \sum_{j\neq i} \alpha_{ij}^v rv_{j,t-1} + \sum_{i,j} \alpha_{ij}^{vl} lq_{j,t-1} \\ &+ \delta_i^v DC_{t-1} + \lambda_i^v rv_{i,t-1}^{*} + \sum_{i,j} \gamma_{ij}^v rv_{j,t-1} DC_{t-1} + \sum_{i,j} \gamma_{ij}^{vl} lq_{j,t-1} DC_{t-1}\end{aligned} \tag{10}$$

To estimate the model, we assume that the innovation term $\varepsilon_{i,t}^{lq} \mid I_{t-1}$ follows a generalized gamma distribution with a shape ϕ_1 and scale parameter ϕ_2 to ensure a large degree of flexibility. Then the log-likelihood function for the illiquidity model is:

$$L = \sum_{t=1}^{T} \left\{ -\log[\Gamma(\phi_1)] + \log(\phi_2) + (\phi_2\phi_1 - 1)\log\left(\frac{lq_{i,t}}{\mu_{i,t}^{lq}}\right) - \left(\frac{lq_{i,t}}{\mu_{i,t}^{lq}}\right)^{\phi_2} \right\} \tag{11a}$$

Following Engle et al. (2012), the illiquidity model in (9) can be estimated equation by equation. The same log-likelihood function and estimation approach can be obtained for the volatility model. The likelihood function is:

$$L = \sum_{t=1}^{T} \left\{ -\log[\Gamma(\phi_1)] + \log(\phi_2) + (\phi_2\phi_1 - 1)\log\left(\frac{rv_{i,t}}{\mu_{i,t}^{rv}}\right) - \left(\frac{rv_{i,t}}{\mu_{i,t}^{rv}}\right)^{\phi_2} \right\}. \tag{11b}$$

3.4 Spillover analysis

Engle et al. (2012) propose a quantitative measure of volatility spillover effects for several markets, based on the measure of spillovers as a response to shocks. Following their lead, we derive similar measures for our liquidity-volatility model.

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[2] A second (or more) own lags could be added in models (9) and (10), but the empirical results (as shown in Table 3 and 4) show that the first lag captures most of the persistence for all the illiquidity and volatility series except the realized volatility of the Australian market. For simplicity, we use one lag in model (9) and (10).

Let $lq_t = (lq_{1,t}, lq_{2,t}, \cdots lq_{k,t})'$, $\mu_t^{lq} = (\mu_{1,t}^{lq}, \mu_{2,t}^{lq}, \cdots \mu_{k,t}^{lq})'$ and $\varepsilon_t^{lq} = (\varepsilon_{1,t}^{lq}, \varepsilon_{2,t}^{lq}, \cdots \varepsilon_{k,t}^{lq})'$, where k is the number of markets included in the analysis. Let $rv_t = (rv_{1,t}, rv_{2,t}, \cdots rv_{k,t})'$, $\mu_t^{rv} = (\mu_{1,t}^{rv}, \mu_{2,t}^{rv}, \cdots \mu_{k,t}^{rv})'$ and $\varepsilon_t^{rv} = (\varepsilon_{1,t}^{rv}, \varepsilon_{2,t}^{rv}, \cdots \varepsilon_{k,t}^{rv})'$. Conditional on the information available at time t, (9) and (10) can be stacked in a compact matrix form as:

$$\begin{aligned} \begin{pmatrix} \mu_t^{lq} \\ \mu_t^{rv} \end{pmatrix} &= \begin{pmatrix} \omega^l \\ \omega^v \end{pmatrix} + \begin{pmatrix} \delta^l \\ \delta^v \end{pmatrix} DC_{t-1} + \begin{pmatrix} A^l & A^{lv} \\ A^{vl} & A^v \end{pmatrix} \begin{pmatrix} lq_{t-1} \\ rv_{t-1} \end{pmatrix} + \begin{pmatrix} \Lambda^l & \\ & \Lambda^v \end{pmatrix} \begin{pmatrix} lq_{t-1}^* \\ rv_{t-1}^* \end{pmatrix} \\ &+ \begin{pmatrix} B^l & \\ & B^v \end{pmatrix} \begin{pmatrix} \mu_{t-1}^{lq} \\ \mu_{t-1}^{rv} \end{pmatrix} + \begin{pmatrix} \Pi^l & \Pi^{lv} \\ \Pi^{vl} & \Pi^v \end{pmatrix} \begin{pmatrix} lq_{t-1} DC_{t-1} \\ rv_{t-1} DC_{t-1} \end{pmatrix} \end{aligned} \tag{12}$$

Further assuming that $x_t = (lq_t', rv_t')$, $\mu_t = (\mu_t^{lq}', \mu_t^{rv}')$, and $\varepsilon_t = (\varepsilon_t^{lq}', \varepsilon_t^{rv}')$, (12) can be expressed as:

$$\begin{aligned} x_t &= \mu_t \odot \varepsilon_t \\ \mu_t &= W + \delta DC_{t-1} + A x_{t-1} + \Lambda x_{t-1}^* + B \mu_{t-1} + \Pi x_{t-1} DC_{t-1} \end{aligned} \tag{13}$$

where $\odot$ denotes the Hadamard (element by element) product.

We will use MEM-based forecasts to derive a spillover balance index later. To this end we require a formula for $E(x_{t+\tau} | I_t)$, where $\tau > 0$. $x_{t+\tau}$ is not known and needs to be substituted with its corresponding conditional expectation $\mu_{t+\tau} = E(x_{t+\tau} | I_t)$. The dummy DC_t is fixed to the value that it had in t, so $E(DC_{t+\tau} | I_t) = DC_t$, and forecasts of the asymmetric effect is $E(S_{t+\tau} | I_t) = 0.5$ [3], hence for

$$\begin{aligned} \mu_{t+2} &= W + \delta DC_t + A\mu_{t+1} + 0.5\Lambda\mu_{t+1} + B\mu_{t+1} + \Pi\mu_{t+1} DC_t \\ &= W + \delta DC_t + \lambda PC_t + (A + 0.5\Lambda + B + \Pi DC_t)\mu_{t+1} \end{aligned} \tag{14}$$

And then, for $\tau > 2$,

$$\mu_{t+\tau} = W + \delta DC_t + (A + 0.5\Lambda + B + \Pi DC_t)\mu_{t+1-1} \tag{15}$$

which can be solved recursively for any horizon τ.

Following Engle et al. (2012), let us recall the MEM in a system,

$$x_t = \mu_t \odot \varepsilon_t, \quad \varepsilon_t | \mathcal{F}_{t-1} \sim D(I, \Sigma) \tag{16}$$

The innovation vector ε_t has a mean vector I with all components' unity and general variance-covariance matrix Σ, i.e. $\varepsilon_t | \mathcal{F}_{t-1} \sim D(I, \Sigma)$. We can interpret $\mu_{t+\tau} = E(x_{t+\tau} | I_t, \varepsilon_t = 1)$, i.e., the expectation of $x_{t+\tau}$ conditional on ε_t being equal to the

[3] See the discussion associated with the asymmetric GARCH model (Glosten et al., 1993).

unit vector I: this is the basis for the dynamic forecast obtained before. Let us now derive a different dynamic solution, $\mu_{t+\tau}^{(i)} = E(x_{t+\tau} | I_t, \varepsilon_t = 1 + s^{(i)})$, for a generic i th element $s^{(i)}$. The i th element equal to the unconditional standard deviation of ε_{it} and the other terms $j \neq i$ equal to the linear projection $E\left(\varepsilon_{j,t} \middle| \varepsilon_{i,t} = 1 + \sigma_i\right) = 1 + \sigma_i \frac{\sigma_{i,j}}{\sigma_i^2}$. The element-by-element division ($\oslash$) of the two vectors, $\rho_{t,\tau}^{(i)}$, is given by

$$\rho_{t,\tau}^{(i)} = \mu_{t+\tau}^{(i)} \oslash \mu_{t+\tau} - 1, \ \tau = 1, \ldots, K \tag{17}$$

where K is the number of periods that shocks can last. Given the multiplicative nature of the model, $\rho_{t,\tau}^{(i)}$ gives us the set of responses (relative changes) in the forecast profile starting at time t for a horizon τ brought about by a 1 standard deviation shock in the i th market.

We use $\psi_{t,\tau}^{j,i}$ to denote the cumulated impact of the shock from market i to market j:

$$\psi_{t,\tau}^{j,i} = \sum_{\tau=1}^{K} \rho_{t,\tau}^{j,i}. \tag{18}$$

So $\phi_{t,\tau}^{j,i}$ is a way to assess the total change induced by the shock. The volatility/illiquidity spillover balance (ζ_i) is expressed as the ratio of the average responses "from" to the average response "to" (excluding one's own):

$$\zeta_i = \frac{\sum_{j \neq i} \sum_{t=1}^{T} \psi_t^{j,i}}{\sum_{j \neq i} \sum_{t=1}^{T} \psi_t^{i,j}}. \tag{19}$$

Suppose i is one's own market, and j (where $j \neq i$) are all other markets (excluding its own market), then the numerator is interpreted as the average responses "to", or the average responses of all other markets to the shocks that happened in one's own market. The denominator is interpreted the average response "from", or the average responses of one's own market to the shocks that happened in other markets. A value of ζ_i bigger than 1 signals that market as a net creator of spillover. It is notable that the effect of shocks to its own market is not included, so the effect on the size of a shock (i.e., one standard deviation shock) between different markets is trivial.

4. Dataset

In the empirical analysis, we choose eight developed international stock markets. The US: SP500, Canada (CA): TSE300, UK: FTSE100, Germany (GE): DAX30, France (FR): CAC40, Japan (JP): Nikkei225, Hong Kong (HK): Hang Seng, and Australia (AU): ATX, for the period from January 3, 2007 to October 18, 2016. The global financial crisis that started in the US sub-prime mortgage market in February 2007 reached its climax in mid-September 2008 with the disastrous collapse of the Lehman Brothers (on August 9, 2007). As the global financial crisis unfolded in several stages, financial markets all around the world went through wild fluctuations, with volatility/illiquidity spreading across markets at an unprecedented speed. It was not until 2009 that the main developed countries showed any recovery. Therefore, we define the crisis period from August 9, 2007 to June 30, 2009 (where August 9, 2007 was the date that Lehman Brothers went bankrupt which is considered as the start of the financial crisis, and June 30, 2009 was the date that the Business Cycle Dating Committee of the National Bureau of Economic Research announced the end of the financial crisis).[4] The remaining time is the post crisis period.

We obtain the daily stock index and daily turnover by volume for the eight stock indices from Datastream. The realized volatility is obtained from the Oxford Man Institution of Realized Volatility lab. The daily return is calculated as the log daily price change. The daily return and the realized volatility series are transformed into percentage and squared percentage terms by multiplying by 100 and 10,000 respectively. We standardize the dollar volume by dividing by its mean for each market, in order to be in the same magnitude for all markets. We then calculate the illiquidity according to Amihud (2002), given in (1).

The data are from three different time zones: Europe (UK, GE, FR), East Asian (JP, HK, AU) and America (US, CA). The trading time on one trading day are illustrated as following:

East Asia (JP, HK, AU)[5]	Europe (UK, GE, FR)[6]	America (US, CA)
0:00 – 6:00 GMT	8:00 – 16:30 GMT	14:30 – 21:30 GMT

[4] The recession in US is officially announced to be ended in the second quarter of 2009 by Business Cycle Dating Committee, National Bureau of Economic Research. http://www.nber.org/cycles/sept2010.html

[5] The Hong Kong Stock Exchange trading time is 0:30 – 8:00 GMT

[6] The Frankfurt Stock Exchange trading time is 8:00 – 16:45 GMT

Table 1: Statistics of illiquidity for all markets

Mean	US	CA	UK	GE	FR	JP	HK	AU
Whole period	0.82	0.83	0.94	1.13	1.11	1.35	1.14	0.87
Crisis	1.21	1.47	1.28	1.50	1.32	2.24	1.76	1.47
Post-crisis	0.73	0.68	0.90	1.07	1.11	1.19	0.97	0.73
Statistics								
Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	10.72	10.80	8.92	70.85	8.88	16.86	10.30	8.66
S.D.	0.83	0.93	0.94	1.87	1.03	1.49	1.05	0.90
Skewness	3.04	3.38	2.56	22.94	2.05	3.37	2.23	2.96
Kurtosis	22.74	22.17	13.86	802.85	10.00	22.93	11.62	17.46
LB(12)	979.19	3471.14	1534.28	250.51	1000.15	3063.68	2501.70	2919.08

Note: S.D. denotes the standard deviation. LB(12) denotes the Ljung Box statistics up to order 12.

There is no overlapping trading between East Asia and Europe (or America). However, there are two hours overlapping between Europe and America trading. The protocol of Fleming and Lopez (1999) and Clements et al. (2015) is adopted to delimit the global trading day effects. Specifically, the close time in the East Asian and Australian exchanges is ahead of the open time in the Europe and America exchanges, so we use "same trading day" to denote the lagged effect from JP, HK and AU to Europe (or America). As there is overlapping trading between Europe and America, we treat them as the same trading zone.

Table 1 provides summary statistics for the illiquidity series. The average illiquidity during the crisis period is about 50% larger than that in the whole sample period for all the markets. This suggests that market liquidity declines during the crisis and that it happens for all the markets. The skewness and kurtosis statistics show that all illiquidity series are positively skewed and highly leptokurtic. The Ljung Box (LB) statistics for up to 12 lags for illiquidity series indicate the presence of high serial autocorrelations; thus models that are capable of allowing for such dynamics are required. The standard deviation is appropriately the same magnitude as the mean, indicating no overdispersion for the illiquidity series.

A similar pattern can be observed for volatility series in Table 2. The mean of realized volatility during the crisis period is three times larger than the mean of volatility in the whole sample period. The LB statistics indicate that realized volatility has strong serial autocorrelations. The overdispersion (the ratio of standard deviation to mean) is about 2 to 3. A large degree of overdispersion requires a large value of "alpha" (ARCH coefficient). The skewness and kurtosis show that all realized volatility series are positively skewed and highly leptokurtic. These, together with the observed

Table 2: Statistics of realized volatility for all markets

Mean	US	CA	UK	GE	FR	JP	HK	AU
Whole period	1.34	0.81	0.86	1.58	1.52	1.12	0.94	0.64
Crisis	3.75	2.11	2.21	3.30	3.06	2.46	2.75	1.47
Post-crisis	0.79	0.52	0.55	1.21	1.20	0.84	0.62	0.45
Statistics								
Minimum	0.02	0.02	0.04	0.05	0.04	0.05	0.05	0.04
Maximum	77.48	35.96	31.18	58.83	51.22	32.29	43.73	15.25
S.D.	3.22	1.90	1.57	2.93	2.56	2.13	1.94	0.97
Skewness	9.77	9.49	8.70	9.72	9.42	7.47	12.14	6.19
Kurtosis	162.12	128.15	119.27	147.68	141.05	77.73	209.13	62.01
LB(12)	8580.98	7899.30	8000.19	7089.62	6619.17	6321.64	3816.29	6348.43

Note: S.D. denotes the standard deviation. LB(12) denotes the Ljung Box statistics up to order 12.

overdispersion, suggest that a more flexible distribution such as the generalized gamma distribution rather than the exponential distribution, which has been used in Engle et al. (2012), is needed for the modelling of realized volatility.

Their features are also reflected in Figure 1. The stock indices decline and the market illiquidity and return volatility increase during the crisis for all the markets. After the crisis, the stock indices soon recover, market liquidity improves and is persistent (that is, it remains high in the future). The realized volatility is much lower than that in the crisis period but there are a few jumps. The graph shows that the illiquidity and realized volatility are very persistent over time. Large illiquidities/volatilities tend to be followed by large illiquidities/volatilities. These features, together with the LB statistics in Tables 1 and 2, suggest that MEM models (incorporating structural change during a crisis) are suitable for the dynamics of the illiquidity and realized volatility.

5. Empirical Results

Based on the equation by equation estimation results, we proceed to select a more parsimonious specification, based on the significance of zero restrictions.[7] Given the large number of coefficients in the general specification in (9) and (10), leaving all coefficients regardless of their significance results in inefficient estimates and therefore less precise spillover forecasts (Engle et al., 2012). We only report the coefficients estimates that are significant at the 5% level. The effects, which are significant in each

[7] The parameters are significantly different from zero at 5% significant level.

market, are reported in Tables 3 and 4; the model diagnostics are summarized in the lower panels. We report the estimated shape parameters for the generalised gamma distribution, the values of the log-likelihood functions, Bayesian Information Criteria (BIC) and LB statistics for autocorrelation in the model residuals. The detailed estimation results are reported in the Appendix.

5.1 Are there illiquidity spillover effects in equity markets?

From Table 3, we can find significant illiquidity spillover effects. Six out of eight markets show significant interaction in liquidity with other markets; four of them show an extra illiquidity spillover effect during the crisis. CA is an exception, it is independent from other markets' illiquidity, but significantly interacted with other markets' volatility during the crisis. Overall, all markets show significant interactions with one another in terms of illiquidity. This suggests that when there is a sudden shortage of liquidity in one market (either arising from demand or supply side factors), the illiquidity shock can spread to other markets, which leads to the decline of liquidity in other markets, causing the comovement in illiquidity across equity markets. The results confirm the effect of equity market comovements in liquidity.

Interestingly, we find that no casual effects from volatility to illiquidity within its own market, which is contrast to Statman et al. (2006). However, four out of eight markets show a significant transmission from volatility of other markets to illiquidity in its own market. These effects are enhanced during the crisis (seven out of eight markets are significant). Only the US market is independent from other markets. These results are consistent with Gebka (2001). [8] These results confirm the existence of causal effects from return volatility to illiquidity (e.g., Stoll, 1978a). However, these casual effects are only significant across borders.

Lastly, all markets exhibit significant degrees of asymmetry in terms of the transmission of illiquidity associated with good and bad news. Bad news tends to increase illiquidity more than good news.

[8] Gebka (2001) shows that absolute return (a proxy for return volatility) in the US market has a significant influence on the volume (a proxy for liquidity) in Asian markets.

Table 3: Summary of the illiquidity model for each market

	US	CA	UK	GE	FR	JP	HK	AU
Other markets illiquidity	×		×	×	×		×	×
Other markets illiquidity during crisis					×	×	×	×
Own volatility								
Other markets volatility				×	×	×	×	
Other markets volatility during crisis		×	×	×	×	×	×	×
Shift during crisis	×			×		×		
Own asymmetric effect	0.156	0.093	0.118	0.129	0.105	0.118	0.109	0.119
Model Diagnostics								
ϕ_1	1.322	1.629	1.881	0.870	1.757	1.354	2.082	1.691
ϕ_2	0.765	0.622	0.509	1.576	0.589	0.776	0.494	0.635
-Loglik	1236.5	954.7	1319.6	1699.6	1680.3	1966.7	1593.6	1151.1
BIC	2540.5	1976.9	2706.7	3496.6	3473.0	4023.4	3299.7	2414.7
LB(12)	18.98	9.30	8.46	7.21	9.23	22.92	21.48	10.98

Note: A cross (×) indicates the presence of significant additional links relative to the own market specification. ϕ_1 and ϕ_2 are estimated shape parameters for the generalised gamma distribution. Loglik denotes the values of the log-likelihood. BIC is Bayesian Information Criteria. LB(12) denotes the Ljung Box statistics up to order 12.

The lower panel of Table 3 summarizes the model diagnostics. The estimated gamma parameters ϕ_1 and ϕ_2 for the illiquidity process are fairly similar across markets (ϕ_1 ranges from 1.2 to 2 and ϕ_2 ranges from 0.5 to 1), showing that the illiquidity processes have similar characteristics in different markets. The LB statistics are small and insignificant, suggesting that our model captures the dynamics of the illiquidity processes successfully.

5.2 Are there volatility spillover effects in equity markets?

From Table 4, we observe a similar pattern as in Table 3. We find significant volatility spillover effects. All markets show significant interaction in volatility with other markets; five of them show increased volatility spillover effects during the crisis. Therefore, equity markets are interdependent in terms of return volatility, and the level of interdependence increases during the financial crisis. These empirical results are consistent with previous empirical studies (i.e., Gallo and Otranto, 2007; Diebold and Yilmaz, 2009; Engle, Gallo and Velucchi, 2012).

Table 4: Summary of the volatility model for each market

	US	CA	UK	GE	FR	JP	HK	AU
Other markets volatility	×	×	×	×	×	×	×	×
Other markets volatility during crisis	×	×	×	×	×			
Own illiquidity				×				
Other markets illiquidity	×	×	×		×	×	×	×
Other markets illiquidity during crisis	×		×	×	×	×		×
Shift during crisis				×				
Own asymmetric effect	0.253	0.193	0.000	0.078	0.092	0.113	0.059	0.112
Model Diagnostics								
ϕ_1	0.561	0.610	0.730	0.678	0.674	0.507	0.655	0.575
ϕ_2	7.589	7.502	8.273	7.630	8.775	9.958	7.915	8.750
-Loglik	624.3	184.9	187.7	1173.8	1129.6	844.5	538.7	177.0
BIC	1368.6	257.4	277.8	2452.5	2356.7	1763.9	1167.4	234.1
LB(12)	8.49	7.71	19.70	12.45	19.88	9.00	5.16	91.21**

Note: A cross (×) indicates the presence of significant additional links relative to the own market specification. ϕ_1 and ϕ_2 are estimated shape parameters for the generalised gamma distribution. Loglik denotes the values of the log-likelihood. BIC is Bayesian Information Criteria. LB(12) denotes the Ljung Box statistics up to order 12. ** denote significance at 5% level.

Interestingly, no significant casual effects from illiquidity to volatility within a market are found. However, the causal effects from the illiquidity of other markets to the volatility of the own market are significant and these effects are increased during the crisis.

Finally, all markets exhibit significant degrees of asymmetry in terms of the transmission of volatility associated with good and bad news. Bad news tends to increase volatility more than good news.

From the model diagnostics, it can be seen that the estimated gamma parameters ϕ_1 and ϕ_2 are also similar across markets, but ϕ_1 ranges from 0.5 to 0.7 and ϕ_2 ranges from 7 to 9, showing that the volatility series have different characteristics from that of the illiquidity series. Again, ϕ_1 and ϕ_2 are significantly different from 1, suggesting that the generalized gamma distributions are the most suitable distribution for realized volatility (cf. the exponential distribution adopted in Engle et al. 2012). The LB statistics are small and insignificant for all the markets except AU, suggesting that our model captures the dynamics of the volatility process.

5.3 Which effects play a more important role in spreading the shocks across markets – illiquidity or volatility spillover effects?

From Tables 3 and 4, there are two channels of shocks transmissions in equity markets: illiquidity and volatility spillovers. The illiquidity spillovers are due to systematic variation in the demand or supply of liquidity, which affects the liquidity in different markets at the same time. The volatility spillover is due to fundamental-based reasons or to investor behaviour-based reasons.

Our empirical results show that there are significant interactions between the two effects. The shocks in illiquidity affect the volatility of other markets, and vice versa. The question is which one plays a more important role in transmitting the shocks to other markets. We use the spillover balance index derived in section 3.4 to explore this question. The spillover balance index that has a value bigger than 1 signals that market as a net creator of spillovers. The results are reported in Table 5.

From Table 5, it can be seen that US and German markets are the main illiquidity spillover providers, as the illiquidity spillover balances for the US and Germany are 4.9 and 1.7, respectively. Canada, France, and Hong Kong are more or less balanced, while the UK, Japan and Australia are the main illiquidity spillover takers. The US market has the largest spillover balances index, implying that it plays a central role in illiquidity spillover to other markets; Germany is the second most important market.

Regarding volatility spillovers, the US and Japan are the only markets that have a spillover balance index more than 1, as all the other markets' spillover balance indices are less than 1. This suggests all the other markets are volatility spillover takers.

Table 5: Summary of the volatility/illiquidity impacts of **a one-standard deviation** shock to the market in the column heading [9]

	From illiquidity								From volatility								
	US	CA	UK	GE	FR	JP	HK	AU	US	CA	UK	GE	FR	JP	HK	AU	
To	illiquidity/volatility								illiquidity/volatility								
US	9.47	2.89	1.21	0.77	0.90	0.19	0.09	0.71	2.57	1.14	0.86	0.74	0.67	1.00	0.35	0.18	14.26
CA	13.19	24.78	7.43	4.36	6.79	0.35	2.14	1.57	6.01	6.51	2.19	1.94	1.94	2.56	2.20	0.72	59.89
UK	6.90	9.96	46.68	24.09	29.89	2.31	6.70	6.64	12.34	8.86	4.92	5.55	4.72	3.56	1.22	2.15	129.81
GE	3.23	3.47	5.48	4.78	3.42	3.54	2.57	2.28	4.68	4.11	2.63	2.63	2.49	3.27	1.80	2.01	47.61
FR	7.14	12.18	13.36	11.82	17.81	2.60	3.15	5.68	5.45	4.17	1.48	1.74	1.63	2.64	1.22	2.00	76.25
JP	3.41	3.47	22.01	10.15	12.65	26.29	6.28	9.84	5.82	5.11	2.98	4.41	3.79	5.91	0.69	4.19	100.71
HK	3.77	5.98	2.54	0.90	1.10	4.00	5.09	1.26	3.44	3.47	1.99	1.87	1.87	2.30	1.37	1.36	37.22
AU	6.76	13.16	8.53	4.02	6.21	7.04	2.60	9.15	3.96	3.89	1.32	0.88	0.90	1.97	1.54	3.20	65.97
US	2.33	1.37	4.82	1.30	1.71	11.70	3.82	2.42	8.45	7.25	4.03	4.01	3.95	6.71	3.78	3.38	62.56
CA	2.97	2.34	14.96	6.50	8.07	8.37	3.15	3.52	7.80	7.37	3.76	4.08	3.72	5.79	2.73	3.01	80.77
UK	3.30	0.86	6.38	2.62	3.20	7.96	2.12	1.32	7.04	5.93	4.13	4.18	3.99	5.84	2.58	2.73	60.03
GE	4.70	1.63	5.78	2.90	3.38	1.24	0.82	0.81	5.45	4.09	3.96	5.81	4.49	4.81	2.23	2.28	48.54
FR	3.12	0.77	3.94	1.59	1.87	4.60	1.45	0.68	6.51	5.23	3.87	4.28	4.28	5.19	2.60	2.47	48.16
JP	2.07	0.82	6.79	3.08	3.92	3.76	0.82	1.75	4.49	3.90	2.02	2.16	2.05	9.87	2.44	2.90	42.96
HK	1.67	1.02	7.31	3.26	4.10	3.64	1.58	1.34	5.12	4.64	2.99	3.08	2.48	5.62	4.84	2.45	50.30
AU	5.60	1.78	5.39	2.77	3.26	1.11	0.61	0.48	4.94	3.75	2.64	2.97	2.40	4.35	2.18	1.94	44.23
	70.15	61.71	115.90	80.10	90.44	62.40	37.88	40.29	85.63	72.04	41.64	44.52	41.08	61.51	28.93	35.06	0.00
Spillover Balance	4.92	1.03	0.89	1.68	1.19	0.62	1.02	0.61	1.37	0.89	0.69	0.92	0.85	1.43	0.58	0.79	

Note: Spillover balance index bigger than 1 signals that market as a net creator of spillover.

[9] Following Engle et al. (2012), we choose K=200 in eq (17) to allow the shocks to disappear completely.

Table 6: Summary of the **standardised** volatility/illiquidity impacts of **a one-unit** shock to the market in the column heading

	From illiquidity								From volatility								
	US	CA	UK	GE	FR	JP	HK	AU	US	CA	UK	GE	FR	JP	HK	AU	
To	illiquidity/volatility								illiquidity/volatility								
US	8.11	3.40	2.65	2.41	3.81	0.36	0.39	0.25	2.95	1.51	0.78	0.85	0.82	1.06	0.45	0.11	21.81
CA	5.66	6.69	13.41	7.44	9.99	2.15	5.00	3.23	9.10	6.94	3.78	3.63	3.57	3.51	2.59	2.58	82.59
UK	19.38	13.90	51.71	25.95	34.39	2.15	7.75	6.45	18.15	11.66	5.50	5.72	5.27	3.49	2.20	2.67	164.63
GE	3.21	2.81	8.48	2.26	1.51	1.78	3.30	2.31	7.44	6.21	4.58	4.50	4.25	3.44	2.63	2.70	59.14
FR	17.28	12.22	35.62	32.39	48.67	1.29	6.34	4.60	16.12	9.11	3.96	5.46	4.59	5.44	2.36	2.48	159.26
JP	13.90	11.22	36.95	22.63	33.07	18.44	9.43	8.19	15.81	10.55	4.44	4.20	4.52	5.66	1.02	3.58	185.17
HK	1.82	2.44	5.81	0.90	1.23	0.75	7.00	2.08	5.15	4.29	2.73	1.98	2.21	1.84	1.83	1.80	36.88
AU	5.97	3.79	9.89	4.59	6.04	0.98	2.36	4.03	6.70	4.65	3.04	3.48	3.03	3.09	2.28	2.92	62.83
US	6.49	5.20	15.04	7.18	9.85	4.48	6.07	3.90	13.38	9.72	5.12	4.27	4.68	5.80	4.19	3.62	95.60
CA	6.37	5.46	16.06	6.62	8.08	3.96	4.83	3.82	12.46	10.07	5.44	4.74	5.07	5.71	4.00	3.96	96.59
UK	5.15	3.91	10.59	4.27	5.09	3.35	3.90	2.74	11.75	9.03	6.32	5.15	5.64	5.95	3.92	3.80	84.24
GE	5.45	3.81	11.42	3.99	4.42	2.31	3.67	2.58	10.96	8.61	6.15	7.21	6.51	5.80	4.09	4.01	83.78
FR	6.07	4.55	13.15	6.25	7.79	2.86	4.10	2.91	11.87	8.99	5.87	5.87	6.09	5.77	3.75	3.77	93.57
JP	5.14	4.13	14.38	6.37	8.42	2.42	2.39	2.63	9.05	6.79	3.74	2.68	3.21	6.73	2.43	2.61	76.40
HK	2.61	2.21	7.05	2.42	3.50	0.61	2.57	1.99	6.88	5.40	3.70	3.28	3.15	4.58	5.12	2.94	52.86
AU	5.37	3.09	6.55	2.55	3.56	0.67	1.90	1.75	7.64	5.78	3.99	3.81	3.68	4.74	3.34	3.20	58.41
	109.87	82.15	207.05	135.93	140.74	30.13	64.01	49.45	152.01	109.24	62.81	59.63	60.20	65.89	41.08	43.55	0.00
Spillover Balance	5.04	0.99	1.26	2.30	0.88	0.16	1.74	0.79	1.59	1.13	0.75	0.71	0.64	0.86	0.78	0.75	

Note: Spillover balance index bigger than 1 signals that market as a net creator of spillover

Comparing the illiquidity and volatility spillover balance index, it is found that the former is much larger than the latter. Most illiquidity spillover indices are greater than 1, while the opposite holds for volatility spillover indices. These indicate that it is illiquidity which plays a more important role in spreading the shocks to the other markets, either through illiquidity spillover effects or through the interaction between illiquidity and volatility. Moreover, the illiquidity of US markets plays a central role in influencing other equity markets' illiquidity and volatility.

A concern of the spillover balance index is that illiquidity and volatility are measured in different units such that they may have different variances and distributions, and thereby may not be comparable directly.[10] However, the spillover balance derived in this paper (also in Engle et al. 2012) is an index. As defined in formula (19), the own effect (the effect of a one standard deviation shock to its own market) is excluded in calculating the spillover balance index. Therefore, the effect of the illiquidity and volatility measures having different variances in different markets should not affect the spillover balance index. Nevertheless, we conduct a robustness test on the spillover balance index. Specifically, we firstly standardise all the volatility and illiquidity series, so that they have the same mean. We then calculate the impact of a one unit (rather than a one standard deviation) shock on the original market. By doing this, volatility and illiquidity are necessarily measured in the same units. The shocks on volatility and illiquidity also have the same units. Consequently, the spillover balance index between illiquidity and volatility are comparable directly. We then re-estimate the model and calculate the spillover balance index in the same way. The results are reported in Table 6. The main conclusions remain unchanged. Illiquidity is a more important channel than volatility in spreading shocks across global equity markets. Moreover, US market illiquidity plays a central role in this process.

5.4 Contemporaneous cross-correlation of the illiquidity and volatility innovations

We examine the cross-correlations of innovations obtained from the MEM estimation. The unexpected arrival of information, as well as unexpected shocks to investors' liquidity, can cause unanticipated trading needs, and, in turn, unanticipated

[10] We thank an anonymous referee for his suggestion.

fluctuations in liquidity and volatility. It is of interest to examine whether such fluctuations are correlated across equity markets. We obtain the illiquidity and volatility innovations from the MEM estimation in (9) and (10), and calculate their cross-correlation matrix. The Spearman's correlation matrix is adopted, as it is more general and can account for possible nonlinearity and outliers in the volatility and illiquidity series. The results are summarized in Table 7.

We first find that the UK, GE, and FR markets have a relatively large correlation (0.53 to 0.70) in illiquidity between each other, while the illiquidity correlations between them and other markets are small, Similarly, the volatility correlations between the three European markets are large (0.71 to 0.79), while the volatility correlations between them and other markets are small. These suggest a certain degree of illiquidity and volatility commonality in the European equity markets.

We also see that innovations between illiquidity and volatility of their own markets are positively correlated. This suggests that higher return volatility is associated with higher illiquidity (Stoll, 1978a; Subrahmanyam, 1994). However, the correlation is relatively small (between 0.02 and 0.36). The cross-correlation between illiquidity of one market and volatility of other markets is very low for all the eight markets, suggest no contemporaneous cross-correlation between liquidity of one market and volatility of other markets.

Overall, these results indicate that there is a certain degree of commonality in European stock markets, in terms of both illiquidity and volatility. However, there would appear to be no commonalities in the global markets.

Table 7: Spearman's Correlation coefficients matrix of illiquidity/volatility residuals for all markets

	US	CA	UK	GE	FR	JP	HK	AU	US	CA	UK	GE	FR	JP	HK	AU
	Illiquidity and Illiquidity															
US	1.00															
CA	0.40	1.00														
UK	0.27	0.22	1.00													
GE	0.26	0.16	0.53	1.00												
FR	0.29	0.21	0.60	0.70	1.00											
JP	-0.05	0.02	-0.01	-0.05	-0.02	1.00										
HK	0.03	0.08	0.11	0.06	0.09	0.20	1.00									
AU	-0.01	0.06	0.09	-0.03	0.04	0.25	0.24	1.00								
	Volatility and Illiquidity								Volatility and Volatility							
US	0.25	0.13	0.24	0.25	0.23	-0.02	-0.01	-0.03	1.00							
CA	0.09	0.17	0.12	0.13	0.11	0.01	0.03	0.01	0.55	1.00						
UK	0.06	0.04	0.08	0.07	0.04	0.00	0.03	-0.01	0.48	0.40	1.00					
GE	0.08	0.03	0.07	0.12	0.08	0.04	0.06	-0.04	0.39	0.31	0.71	1.00				
FR	0.04	0.03	0.05	0.07	0.05	0.06	0.03	-0.01	0.42	0.34	0.79	0.79	1.00			
JP	0.02	0.01	0.01	-0.01	0.00	0.15	0.05	0.06	0.09	0.04	0.09	0.09	0.10	1.00		
HK	0.00	0.04	0.00	-0.01	-0.02	0.00	0.02	-0.03	0.04	0.04	0.10	0.11	0.10	0.25	1.00	
AU	-0.05	-0.03	0.02	-0.01	0.00	0.17	0.16	0.36	0.02	0.02	0.00	0.02	0.01	0.23	0.11	1.00

5.5 *Shock propagations for three crucial events*

Lastly, we use the MEM-based impulse response to show how the shocks propagate to other markets for a few events. We investigate the evolution of volatility and illiquidity as a consequence of three crucial episodes (events).

The first episode we report is the bankruptcy of Lehman Brothers on August 9, 2007, which is regarded as the beginning of the global financial crisis. The second episode we report is on July 13, 2010, which is the beginning of the Eurozone debt crisis, as pointed out by Righi and Geretta (2011) based on structural change tests. The third episode that we report is the UK Brexit referendum on June 23, 2016.

First, let us take the US as the market to be shocked, considering August 9, 2007, as the starting date. Applying our procedure in (17) and taking K=200 to allow the shocks disappear completely[11], we obtain the curves in Figure 2. We observe that shocks on illiquidity and volatility in the US have a lagged impact on illiquidity and volatility in the other markets. On the response to the US illiquidity shock, we observe a high impact on US illiquidity (about 0.8) with a monotonically declining response and a few days ahead lower impact (mostly between 10% and 20%) on JA, HK, GE and AU markets. The latter response grows over time and reaches its peak between ten and thirty days (hump shape or momentum). On the response to US volatility shocks, we observe a high impact on US volatility (about 0.8) with a monotonically declining response and a few days ahead lower impact (mostly between 0.3 and 0.5) in the other markets. The latter response grows over time and reaches its peak between two and ten days (hump shape or momentum).

Second, taking GE as the market to be shocked, and considering July 13, 2010 (EU Sovereign debt crisis), as the starting date, by applying our procedure, we obtain the curves in Figure 3. We observe that shocks on the illiquidity and volatility of GE markets have little impact on the illiquidity and volatility of other markets, as the impulse response functions for other markets decline monotonically.

Third, we take the UK as the market to be shocked, considering June 23, 2016 (Brexit referendum), as the starting date, by applying our procedure, we obtain the curves in Figure 4. We observe similar patterns as in Figure 3. Again the shocks on illiquidity and have little impact on the illiquidity and volatility of other markets, as the impulse response functions for other markets are almost monotonically declining.

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[11] We follow Engle et al. (2012) and choose K=200 to allow the shock to disappear completely.

By comparing the three sets of events, the US market and the global financial crisis seem to have played a major role in the evolution and interdependence of the volatility and illiquidity in global equity markets. The regional crisis and regional market has little impact on the evolution of volatility and illiquidity globally.

6. Conclusion

In this paper, we propose an MEM for the dynamics of illiquidity and volatility. We empirically study the illiquidity spillover effects in eight developed equity markets during and after the recent financial crisis. Furthermore, we model dynamics of the illiquidity and volatility jointly, so that we can investigate interdependence between illiquidity and volatility among the equity markets.

We apply our analysis to the equity markets for the period 2007-2016, devoting particular attention to the treatment of the 2007-2009 global financial crisis period. We find that equity markets are significantly interdependent, both in terms of volatility and illiquidity. No markets are independent from others. The global financial crisis brings significant changes in the volatility and illiquidity; most markets show an increase in volatility and illiquidity spillover effects during the crisis. Furthermore, volatility and liquidity transmission are highly relevant. There are significant causal effects from illiquidity to volatility across borders, and vice versa. However, the causal effects from illiquidity to volatility (and from volatility to illiquidity) of its own markets are insignificant.

By comparing the spillover balance index between illiquidity and volatility, we find that illiquidity is a more important channel than volatility in propagating the shocks in global equity markets. The results also indicate that there are contemporaneous commonalities in regional stock markets, both in terms of illiquidity and volatility. The US market and global financial crisis seem to have played a major role in the evolution and interdependence of volatility and illiquidity in global equity markets.

Our results show an overall crucial role for illiquidity in the US market in influencing other equity markets' illiquidity and volatility. These findings are of importance for policy makers as well as institutional and private investors in the following way:

1) Markets are highly interdependent in terms of both volatility and illiquidity. Consequently, international portfolio managers should not only consider the linkage in terms of return and return volatility, but also the linkage in illiquidity in international equity markets when constructing their portfolios.

2) There are causal effects from illiquidity to volatility across borders, but no casual effects from illiquiidy to volatility within the same market. This has implications for risk managers because they can build more accurate forecasting models of volatility by incorporating past illiquidity from overseas markets into their specification.
3) Illiquidity in the US market plays a crucial role in spreading shocks across global equity markets, with the global financial crisis most likely caused by illiquidity shocks originating in the US. Regulators should therefore focus on ensuring that markets in the US have sufficient liquidity in order to avoid future crises.

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Figure 1: Stock indices, illiquidity proxies and realized volatilities for all markets.

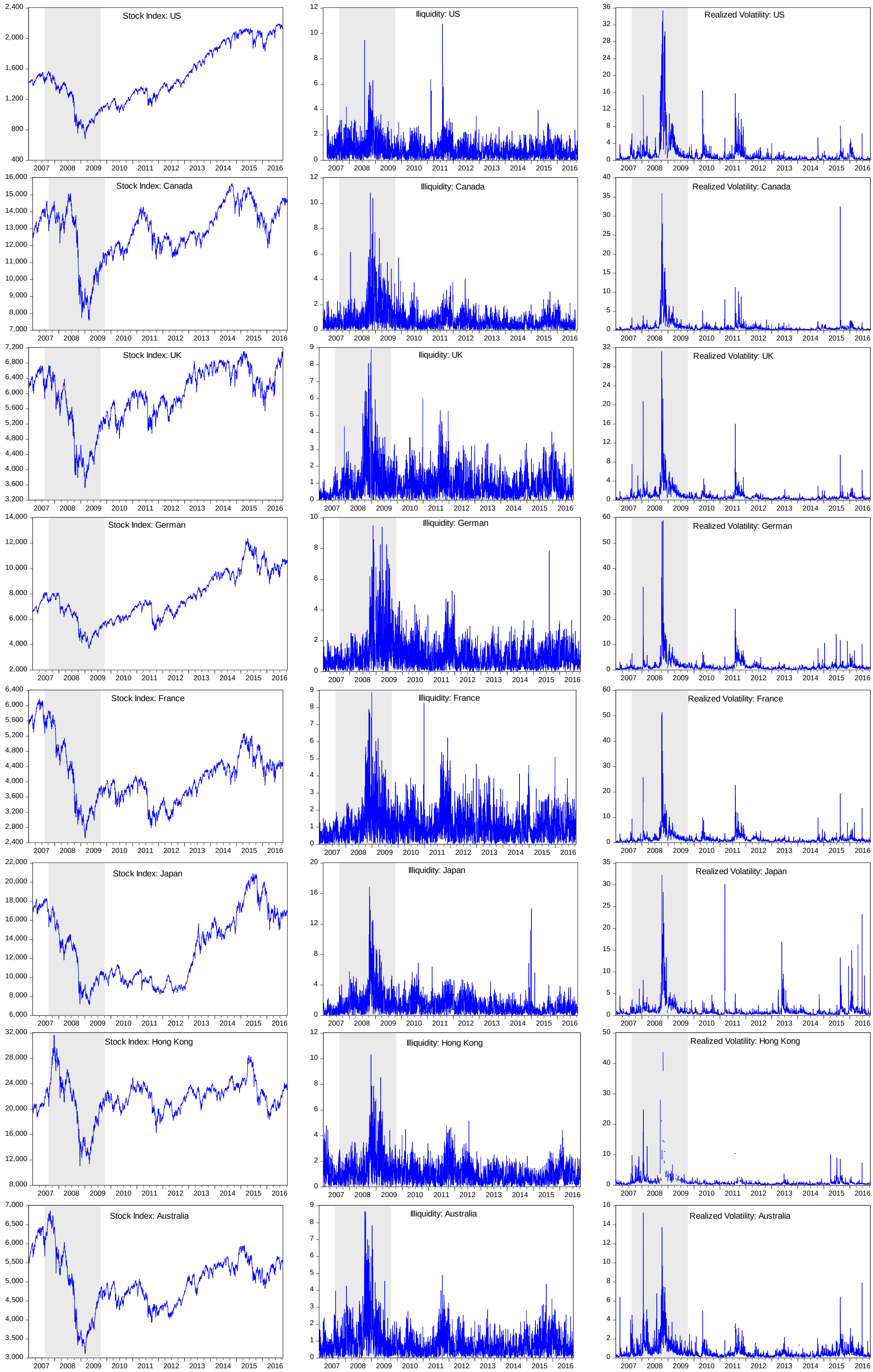


Figure 2: MEM Impulse Response Functions: Originating Markets: US- Starting data: 16/09/2008 (Lehman Brothers bankruptcy).

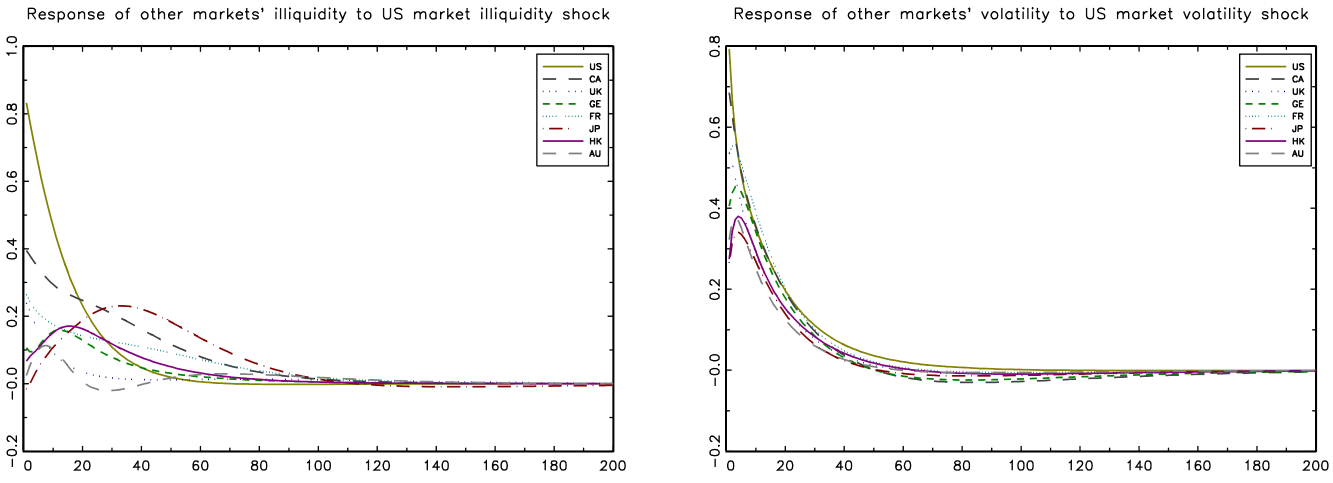


Figure 3: MEM Impulse Response Functions: Originating Markets: GE- Starting data: 13/07/2010 (EU Sovereign debt crisis)

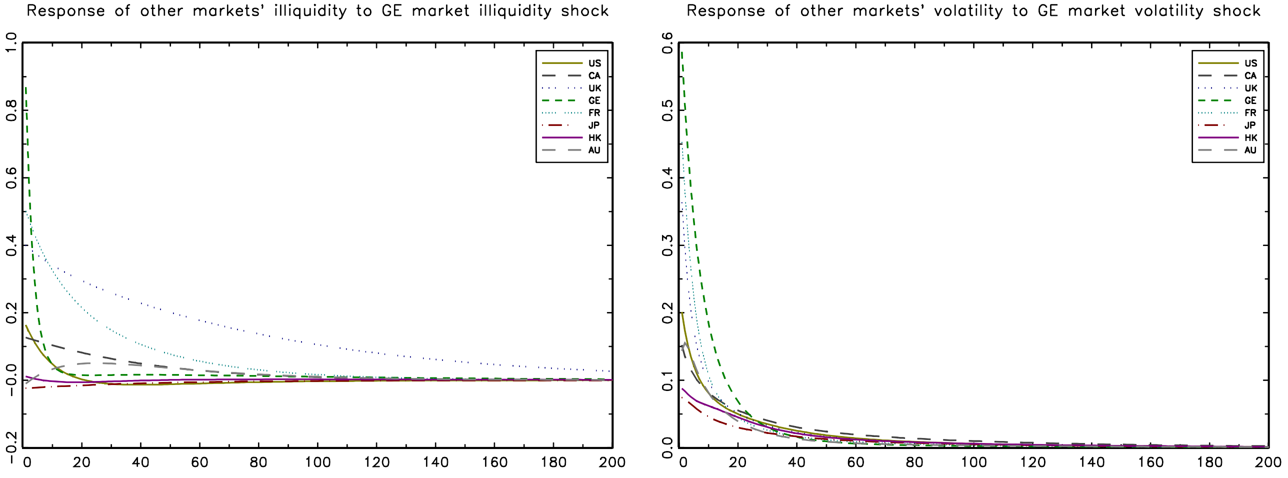
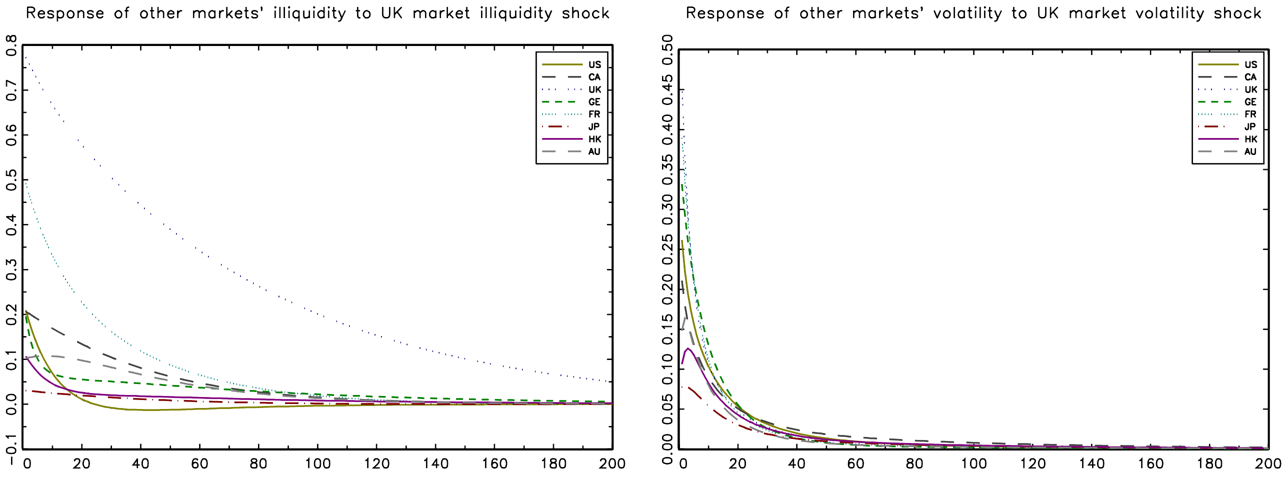


Figure 4: MEM Impulse Response Functions: Originating Markets: UK- Starting data: 23/06/2016 (Brexit).



Note: the confident interval is not reported due to the lack of space. However, all the IRF are in the 95% significant interval.

Appendix A: Estimation results from MEM

Table 7: Estimated Coefficients – illiquidity model

		US	CA	UK	GE	FR	JP	HK	AU
	w	0.066	0.019	0.025	0.067	0.041	0.032	0.084	0.038
	α			0.011			0.005		
	β	0.846	0.924	0.915	0.626	0.904	0.908	0.808	0.877
	DC	0.025			0.063		0.066		
Illiquidity	US_{t-1}			-0.017		-0.019			
	CA_{t-1}					0.006		0.057	0.037
	UK_{t-1}			0.011					
	GE_{t-1}								
	FR_{t-1}	-0.007						-0.017	
	JP_{t-1}						0.005		-0.014
	HK_{t-1}				0.069				
	AU_{t-1}				0.062	0.027			
Volatility	US_{t-1}								
	CA_{t-1}							-0.021	
	UK_{t-1}				0.232			0.100	
	GE_{t-1}						0.008		
	FR_{t-1}								
	JP_{t-1}								
	HK_{t-1}				0.051				
	AU_{t-1}					-0.013	-0.018	-0.038	
Illiquidity *DC	US_{t-1}	0.005				-0.001			
	CA_{t-1}		-0.018			0.062			
	UK_{t-1}			-0.004					0.203
	GE_{t-1}							0.093	-0.030
	FR_{t-1}					-0.079			-0.058
	JP_{t-1}								0.033
	HK_{t-1}							-0.082	-0.072
	AU_{t-1}						-0.142		-0.040
Volatility *DC	US_{t-1}								
	CA_{t-1}								
	UK_{t-1}				-0.136				
	GE_{t-1}		-0.013	0.005					
	FR_{t-1}		0.025						
	JP_{t-1}							-0.037	0.003
	HK_{t-1}				-0.097	-0.007			
	AU_{t-1}					0.022	0.088	0.034	
	γ	0.156	0.093	0.118	0.129	0.105	0.118	0.109	0.119
	ϕ_1	1.322	1.629	1.881	0.870	1.757	1.354	2.082	1.691
	ϕ_2	0.765	0.622	0.509	1.576	0.589	0.776	0.494	0.635
Loglik		-1236.5	-954.7	-1319.6	-1699.6	-1680.3	-1966.7	-1593.6	-1151.1
BIC		2540.5	1976.9	2706.7	3496.6	3473.0	4023.4	3299.7	2414.7
LB(12)		18.98	9.30	8.46	7.21	9.23	22.92	21.48	10.98

Table 8: Estimated Coefficients – realized volatility model

		US	CA	UK	GE	FR	JP	HK	AU
	w		0.008	0.021	0.046	0.087	0.083	0.084	0.044
	α	0.305	0.302	0.299	0.378	0.366	0.403	0.269	0.206
	β	0.417	0.380	0.388	0.452	0.337	0.389	0.510	0.197
	DC				-0.100				
Illiquidity	US_{t-1}		-0.017			-0.021		-0.024	0.108
	CA_{t-1}								
	UK_{t-1}		0.029						
	GE_{t-1}								
	FR_{t-1}	-0.019	-0.011						
	JP_{t-1}	0.031	0.021	0.013				-0.011	-0.016
	HK_{t-1}	0.034					-0.022		-0.013
	AU_{t-1}			-0.023		-0.022			
Volatility	US_{t-1}	0.305		0.048		0.115			
	CA_{t-1}		0.302	0.089			0.125	0.082	0.068
	UK_{t-1}			0.299				0.218	0.124
	GE_{t-1}				0.378			0.026	0.053
	FR_{t-1}					0.366		-0.094	-0.051
	JP_{t-1}						0.403		0.016
	HK_{t-1}	0.094	0.045					0.269	0.047
	AU_{t-1}		0.096	0.155	0.229	0.311			0.206
Illiquidity *DC	US_{t-1}						0.176		0.112
	CA_{t-1}								
	UK_{t-1}				-0.159				
	GE_{t-1}			0.070	0.195	-0.056			
	FR_{t-1}								
	JP_{t-1}	-0.100							
	HK_{t-1}								
	AU_{t-1}	0.121			0.009				
Volatility *DC	US_{t-1}	-0.271							
	CA_{t-1}	0.352			0.279	0.047			
	UK_{t-1}								
	GE_{t-1}			-0.169	-0.311				
	FR_{t-1}								
	JP_{t-1}	0.330	0.104	0.201	0.115	-0.027	-0.078		
	HK_{t-1}	-0.106	-0.040						
	AU_{t-1}		-0.078						
	γ	0.253	0.193	0.000	0.078	0.092	0.113	0.059	0.112
	ϕ_1	0.561	0.610	0.730	0.678	0.674	0.507	0.655	0.575
	ϕ_2	7.589	7.502	8.273	7.630	8.775	9.958	7.915	8.750
Loglik		-624.3	184.9	187.7	-1173.8	-1129.6	-844.5	-538.7	177.0
BIC		1368.6	-257.4	-277.8	2452.5	2356.7	1763.9	1167.4	-234.1
LB(12)		8.49	7.71	19.70	12.45	19.88	9.00	5.16	91.21*

Appendix B: Generalized gamma distribution

The density for Generalized Gamma distribution is:

$$f(\varepsilon_t \mid \phi_1, \phi_2) = \frac{\phi_1 (\varepsilon_t)^{\phi_1 \phi_2 - 1}}{\Gamma(\phi_1)} \exp(-\varepsilon_t^{\phi_2}), \qquad \varepsilon_t \geq 0$$

So, $E(\varepsilon_t) = 1$.