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Dynamic transmissions between main stock markets and SME stock markets: evidence from tropical economies

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Abstract

This paper investigates the dynamic return and asymmetric volatility transmissions between main stock markets and Small and Medium Enterprise (SME) stock markets in Hong Kong, Singapore, Thailand, and Malaysia under the joint impacts of volatility breaks, thin trading, and trading volume. For the analysis, a linear state-space AR model with Kalman filter and an augmented bivariate VAR asymmetric BEKK-GARCH model were adopted. The results reveal that only Hong Kong showed evidence of return transmission from the SME market to the main market. Controlling for the joint effects of the three factors considerably reduced the magnitude and significance level of this return transmission and, in essence, eliminates the volatility transmission. Moreover, Hong Kong's main market return exhibited a causal relationship and a long-run equilibrium relationship with the country's economic development. Therefore, the SME market arguably can make an indirect contribution to economic development in Hong Kong via its return transmission across the main market. Consequently, any policies that facilitate the development of the SME market in this country would promote long-term economic stimulation indirectly through its transmission mechanism with the main market.

Keywords: SME stock market, return and asymmetric volatility transmissions, volatility break, thin trading, trading volume, augmented bivariate VAR asymmetric BEKK-GARCH

JEL codes: C32, C58, G15

1. Introduction

Acting as a second-tier listing option to the main stock market in a country, a Small and Medium Enterprise (SME) stock market, also known as an alternative stock market, provides a new fundraising channel and a credible identity for SMEs that are unqualified to be listed on the main market. Although SME stock markets are a significant component of the SME financing ecosystem (World Federation of Exchanges, 2015) and are increasingly being established worldwide, they have received limited academic attention. On the other hand, several studies have documented the influence of the main stock market return and volatility on economic development. A legal bond also exists between the main stock market and SME stock market, in which the SME market is often housed under the main market and serves as a pathway for SMEs to become listed on the main market (Harwood & Konidaris, 2015). Accordingly, given the existing contribution of the main stock market to economic development and the legal relationship between the two stock markets, the SME stock market could potentially make an indirect contribution to economic development through its return and volatility transmissions across the main market channel. However, these dynamic transmissions between the two stock markets have been disregarded in the financial economics literature.

Furthermore, it is noted that financial time series often encounter large shocks that can instigate changes in the unconditional variance, also known as structural breaks in volatility or volatility breaks. The existence of deterministic volatility breaks in the return series may cause the underlying volatility persistence to be overestimated by a standard Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model (Lamoureux & Lastrapes, 1990b). Thin trading, which occurs when stocks are traded at low volume due to a lack of buy or sell orders, can cause spurious autocorrelation in the return series (Lo & MacKinlay, 1990). Neglecting to adjust for thin trading can induce biased empirical outcomes. Moreover, trading volume can affect the price movements and the clustering pattern of return volatility according to the Mixture of Distributions Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIAH). Although the studies on return and volatility transmissions among size-based stock portfolios are numerous, very few of them accounted for either volatility breaks or trading volume when examining these transmission effects. As such, there is a paucity of research on cross-market transmissions of return and volatility that accounts for the joint effects of volatility breaks, thin trading, and trading volume. Ignoring the impacts of these factors while modelling cross return and volatility transmissions may distort the true corresponding estimates that mislead policymakers and investors.

Consequently, this paper aims to explore the dynamic return and asymmetric volatility transmissions between the main stock market and SME stock market while considering the joint effects of volatility breaks, thin trading, and trading volume on these dynamic transmissions. The findings of this research provide further knowledge about a potential indirect influence of the SME stock market on economic development through the main market channel. This paper focuses on the main markets and SME markets in Hong Kong, Singapore, Thailand and Malaysia because of their important roles in corporate financing and growth stimulation for tropical economies, which are discussed in the next section.

To the extent of the authors' awareness, this study is the first to explore the dynamic return and asymmetric volatility transmissions between the main stock market and SME stock market. Unlike previous studies, this paper investigates the joint impacts of volatility breaks, thin trading, and trading volume on these cross-market transmissions by augmenting the bivariate Vector Autoregressive (VAR) Asymmetric Baba-Engle-Kraft-Kroner (BEKK) Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model. Our augmented model further contributes to the existing empirical models by incorporating both volatility breaks and trading volume into a standard VAR Asymmetric BEKK-GARCH procedure, which is described in detail in Section 4.4.

2. Key aspects of tropical economies and SME stock markets

Recent decades have witnessed substantial changes in the global political economy as the world begins to reformulate its global development agenda. Among these changes, the Global Financial Crisis (GFC) during 2007-2009, the Paris agreement on climate-change action in 2015, and the policies enacted by Donald Trump's administration since 2017 have further diversified the multifaceted perceptions of the world geopolitical landscape. While the world's geopolitical regions are classified primarily into east and west, north and south, and developed and developing areas, the lateral perception of world geopolitical regions has been emphasised in the recent State of the Tropics (2014) Report[1]. This report has acknowledged the Tropics as a critical geopolitical entity owing to its unique features and contribution to the future global economy. Situated between the Tropics of

[1] State of the Tropics (2014) Report is the initiation of cooperation among prominent research organisations with an interest in tropical issues. This report brings in a wide range of indicators and aspects of the ecosystem, human system, and economy to shed light on a unique set of characteristics of the Tropics.

Cancer and the Tropics of Capricorn (see Figure 1), the tropical zone with 60 countries currently accommodates 40% of the world's population and this percentage is expected to increase to 50% by 2050, indicating a substantial growth rate of consumption and labour force.

Tropic of Cancer

Equator

Tropic of Capricorn

Central America
Caribbean
South America
Northern Africa & Middle East
Central & South Africa
South Asia
Southeast Asia
Oceania

Source: State of the Tropics (2014) Report

In 2010, the value of tropical economies was reported to be US$12 trillion and predicted to reach US$40 trillion by 2025 (Harding, 2011), which represents 19% and 23% of the world's GDP, respectively (PricewaterhouseCoopers, 2015). Within 30 years to 2010, the economic growth rate in the Tropics surpassed the rest of the world by 20% and even remained positive during the GFC. South Asia and Southeast Asia[2] have emerged as the key growth drivers of the Tropical economies and contributed 10.3% to the world's GDP in 2010. Additionally, almost half of all G20 members, representing 85% of the global economy, are located completely or partially in the Tropics. As part c… lvocated for private investment and structural r… ystem in the region (Hockey, 2014).

Governments of tropical nations have long recognised SMEs as a growth engine for their tropical economies (World Bank, 2015). However, these growing aspirant enterprises are facing a significant credit gap of US$196.3 billion due to issues of information asymmetries, low credit-worthiness, and high level of risk associated with small businesses (International Finance Corporation, 2013). Although bank loans remain the primary source of funds for SMEs, alternative sources of financing, such as SME stock markets, has been identified recently as an important component of the financing ecosystem of SMEs (World Federation of Exchanges, 2015). Since the 1990s, an increasing number of SME stock markets have been established around the world, reaching a total of 51 markets in 2016, of which nearly a quarter are located in the Tropics (see Figure 2). In this region, the SME stock markets in Hong Kong – Growth Enterprise Market (GEM), Singapore – CATALIST Market, Thailand – Market for Alternative Investment (MAI), and Malaysia – Access, Certainty, and Efficiency Market (ACE), effectively dominate other peers in terms of active operation and the number of listings.

[2] South Asia consists of Bangladesh*, India*, Maldives, and Sri Lanka. South East Asia consists of Brunei, Cambodia, China*, Hong Kong, Macau, Indonesia, Laos, Malaysia, Myanmar, Singapore, Thailand, Vietnam, and Timor-Leste. (* These nations have large areas that bestride the Tropics.)

In general, stock markets in Hong Kong, Singapore, Thailand, and Malaysia have been recognised as the primary sources of capital for the Asia region (Ong & Lipinsky, 2014) and have played a critical role in driving economic growth of the region (Azam, Haseeb, Samsi, & Raji, 2016). In addition, these four countries are developed and emerging economies in Southeast Asia, which is one of the key growth drivers of the Tropics as mentioned earlier. Consequently, the stock markets of these countries (including the main market and SME market) may be a major source of funding and a critical driving force for tropical economies. Indeed, capital mobilisation from the SME stock markets of these countries over the period 1999-2016 was around US$28.1 billion, which effectively fulfilled 75.8% of SMEs credit gaps in the four countries or 14.3% of SMEs credit gaps in the Tropics. Although the SME stock markets in China and Korea are the second and the third largest in the world with regard to the number of listed companies, they just covered approximately 26.2% and 11.5% of SMEs credit gaps in China and Korea, respectively. Therefore, arguably, the GEM (Hong Kong), CATALIST (Singapore), MAI (Thailand), and ACE (Malaysia), given their activeness and significant contribution to closing the credit gap for SMEs in the Tropics, would play a prominent role in SMEs' finance and growth stimulation for the region.

Pertinent facts regarding the stock exchanges in Hong Kong, Singapore, Thailand, and Malaysia are as follows. While the Hong Kong Stock Exchange (HKEX) is the world's sixth- and Asia's third-largest market, the Singapore Stock Exchange (SGX) is the largest market in Southeast Asia with regard to market capitalisation. The Stock Exchange of Thailand (SET) has emerged as an ASEAN volume leader that has consistently recorded the highest trading volume among other regional peers. More intriguingly, Bursa Malaysia (BM) is one of the few international exchanges that offer an investment opportunity in the listed subsidiaries of several large multinational corporations (MNCs), i.e. Carlsberg, Heineken, and British American Tobacco.

In addition, the main markets of HKEX, SGX, SET, and BM operate on the philosophy of neoclassical growth theory which allows for government intervention, while their SME markets (i.e. the GEM, CATALIST, MAI, and ACE) follow two principles of "buyer beware" and "let the market decide", which are grounded in the philosophy of classical growth theory. Compared to the main markets, these SME markets adhere to less onerous rules and regulations and offer flexible requirements for listing and information disclosure. The sponsors and market makers, which act as corporate finance advisers for potential listed firms and liquidity providers for the markets, respectively, are also involved in the operation of these SME markets.

The GEM, CATALIST, MAI, and ACE are characterised by small capitalisation and thin trading because they represent a very small fraction of the main markets in terms of capitalisation and trading value, and a relatively low trading volume (see Table 1). Compared to the CATALIST, MAI, and

ACE, the GEM can be seen as the largest and the most liquid SME market and makes the most significant contribution to GDP (12.6%).

3. Literature review

Following the principles of Arbitrage Pricing Theory[3] (Ross, 1976), a large body of studies on the dynamic linkage between the main stock market returns and economic development has begun to emerge. For examples, Lee (1992) noted that stock market returns affect the macroeconomic indicators in the US using multivariate VAR analysis. Choi, Hauser, and Kopecky (1999) and Nasseh and Strauss (2000) reported a long-run nexus between stock market returns and industrial manufacturing for G7 and six other European countries using Vector Error-correction (VEC) model. Mauro (2003) showed a positive correlation between output growth and stock market returns in 10 advanced economies and 5 emerging economies, including Singapore and Thailand. Henry, Olekalns, and Thong (2004), using a panel data of 27 countries including Hong Kong and Singapore, concluded that stock market returns are most helpful in anticipating output growth during recession periods. Tang, Habibullah, and Puah (2008) documented a bidirectional Granger causality between stock market returns and real GDP in China, Hong Kong, Indonesia, Malaysia, and Thailand, as well as a long-term relationship between the two variables in China, the Philippines, Singapore and Taiwan. Liu and Sinclair (2008) reported a unidirectional causality running from stock market returns to economic growth in the short run and the reverse causality in the long run in China, Hong Kong, and Taiwan. Mahmood and Dinniah (2009) found the presence of a long-term equilibrium nexus between stock market indices and economic variables (foreign exchange rates, consumer price index, and industrial production index) in Japan, Korea, Hong Kong, and Australia. Forson and Janrattanagul (2014) also showed a long-term equilibrium nexus between the Stock Exchange of Thailand index (SETI) and macroeconomic indicators (money supply, industrial production index, and consumer price index).

Since the introduction of ARCH and GARCH models, several studies have adopted a multivariate GARCH model to analyse the dynamic between the main stock market return volatility and economic development. Schwert (1989) indicated that US macroeconomic volatility can be predicted by stock market return volatility. Liljeblom and Stenius (1997) presented evidence of reciprocal spillover between stock market return volatility and macroeconomic volatility using the data from Finland. Caporale and Spagnolo (2003) showed that stock market return volatility has a significant influence on GDP growth volatility in both emerging economies (Thailand, Malaysia, and the Philippines) and

[3] Arbitrage Pricing Theory (APT) refers to a linear relationship between the expected stock market returns and various macroeconomic variables which accounts for market risk or un-diversifiable risk. This is a helpful mechanism for identifying mispriced assets and formulate a value investing strategy.

developed economies (US, UK, and Canada). Ahn and Lee (2006) employed a bivariate VAR-GARCH process and reported that increased stock market return volatility is likely to instigate high volatility in industrial production and vice versa in the US, UK, Canada, Italy, and Japan. Kanas and Ioannidis (2010) further showed Granger causality from stock market returns to industrial output growth in a fairly low volatile stock market using the Markov switching VAR model and data from the UK. More recently, Guo (2015), who applied a non-uniform weighting two-step causality test and a multivariate GARCH process, revealed one-way causality from real economic growth to stock market returns and from the market return volatility to real economic growth in China.

Turning now to the existing legal relationship between the main market and SME market, most SME stock markets are structured as a separate board that is legally housed under the main stock market. This is due mainly to an SME market being able to benefit from (i) the reputation and credentials of the main market, which assures both securities issuers and investors, and (ii) the subsidies from the main market because they need to maintain low costs for issuers with smaller issue sizes and lower liquidity, which translates to low listing and trading costs (Harwood & Konidaris, 2015). In return, the SME market is considered a supplier of pipeline companies for the main market to increase its liquidity (World Federation of Exchanges, 2015). Legally, the main market is categorised as a regulated market, which is administered by national securities regulators and conforms to stricter standards for listing and disclosure. An SME market is classified as an Alternative Trading Platform (ATP), which is a separate board managed by the regulated market operator (management of the main market) and adheres to less stringent regulations. The regulated market operator is required to submit the regulatory framework for the ATP to the national securities regulators for approval. The ATP is wholly owned and regulated by the main market.

As discussed above, the main stock market return and volatility have a significant influence on economic development. A legal bond also exists between the main stock market and SME stock market. Accordingly, it is arguable that the SME market could potentially make indirect contributions to economic development through its return and volatility transmissions across the main market channel. However, these dynamic transmissions between the two markets have yet to be explored.

Stock markets often encounter sporadic structural breaks in the unconditional variance. These breaks may have been triggered by various events such as macroeconomic and political events, major changes in market sentiments, or financial crises. The presence of structural breaks in volatility has been proved to have effects on volatility clustering and volatility persistence according to several studies in the literature on financial economics. For examples, Lamoureux and Lastrapes (1990b) postulated that persistence in variance can be overestimated by a standard GARCH process if one fails to account for structural shifts in variance. Mikosch and Starica (2004) emphasised the importance of modelling the changing unconditional variance for long return series due to the fact that long return series usually have a changing volatility structure rather than a constant structure. Hillebrand (2005) provided solid evidence on the strong bias towards unity of the summations of the estimated ARCH and GARCH parameters when breaks in the unconditional volatility are neglected. Stărică and Granger (2005) contended that most of the dynamics of return series are attributed to breaks in the unconditional variance and their nonstationary unconditional model produces better forecasts than the stationary GARCH model. Ewing and Malik (2005) argued that if structural shifts in unconditional variance of one series can affect the volatility persistence in the series itself, then they may also affect the volatility persistence across two series. In addition, the presence of structural breaks in unconditional variance can give rise to volatility asymmetry and volatility clustering (Ewing & Malik, 2005).

Thin trading-induced autocorrelation in the return series, as indicated by Dimson (1979) and Lo and MacKinlay (1990), may lead to seriously biased cross transmissions of return and volatility. Despite numerous studies on the cross-market return and volatility transmissions, there are very few research studies that accounted for the effect of thin trading. For instance, Kuttu (2014) examined the effect of thin trading on return and volatility transmissions between stock markets in Ghana, Kenya, Nigeria, and South Africa. Using a thin-trading adjustment method recommended by Miller, Muthuswamy, and Whaley (1994), this author concluded that neglect of adjusting for thin trading can lead to inconsistent and unreliable model estimation. Nonetheless, the assumption of Miller et al. (1994) of a fixed AR coefficient for thin-trading adjustment is implausible to hold in emerging markets or newly established markets because these markets are known to be highly volatile. Therefore, to adjust for thin trading while capturing the volatile feature of these markets, Harrison and Moore (2012) suggested using a state-space AR model with Kalman filter that allows for time-varying AR coefficient. Compared to other models, state-space model can identify the temporal dynamics of a system more precisely and be more flexible when modelling univariate and multivariate with structural shifts, missing data or other data abnormalities (Chukhrova & Johannssen, 2017). Kalman filter, which is a distribution-free algorithm, offers the best linear estimators in the sense that mean squared errors are minimised (Kalman, 1960). In addition, the method of adjustment for thin trading suggested by Harrison and Moore (2012) has also been adopted in recent studies on market efficiency and long memory such as Ngene, Tah, and Darrat (2017), Abakah, Alagidede, Mensah, and Ohene-Asare (2018), and Robinson, Glean, and Moore (2018).

As mentioned earlier, the volume-volatility nexus is grounded theoretically on either the MDH or the SIAH. The MDH, which was first introduced by Clark (1973) and later modified by Andersen (1996), posits that conditional variance of return or return volatility and trading volume are ascertained simultaneously by a stream of information. This hypothesis indicates a positive concurrent linkage between these two variables, and this linkage is a function of the information stream distribution. In contrast, according to the SIAH, as suggested by Copeland (1976), new information appears in the market in a sequential random manner and is not obtained by all market participants instantaneously. The response of each market participant to new information, i.e., changing their trading positions, stands for one in a set of preliminary market equilibria. The ultimate market equilibrium is determined once all market participants have a similar set of information. The SIAH implies that given the sequential response of traders to information, return volatility can be predicted from trading volume information. Empirically, Lamoureux and Lastrapes (1990a), Gallo and Pacini (2000), and Girard and Biswas (2007) used stock market data from several developed and emerging countries and found that incorporating trading volume into the volatility model decreased or eliminated the persistence in return volatility. Recently, Chakraborty and Kakani (2016) noted that trading volume can provide endogenous dynamic information evolving together with return volatility.

There exists a substantial body of literature on return and volatility transmissions between different size stock portfolios, for examples, McQueen, Pinegar, and Thorley (1996), Harris and Pisedtasalasai (2006), Karmakar (2010), and Hung and Lin (2013). These studies revealed a unidirectional asymmetric return transmission from the large-stock portfolios to the small-stock portfolios and bidirectional asymmetric volatility transmission between these two portfolios. Nevertheless, a very few of studies in this body of literature accounted for either volatility breaks or trading volume when examining these transmission effects. For instances, Ewing and Malik (2005) studied the small- and large-cap stock returns in the New York and American stock markets and showed that volatility breaks significantly weaken the volatility spillover and, in some instances, wipe out the spillover effects. Koulakiotis, Babalos, and Papasyriopoulos (2016) reported volatility transmissions among large-, medium-, and small-cap stocks in the Athens stock market with feedback effect after taking trading volume into account. Therefore, the joint impacts of volatility breaks, thin trading, and trading volume on return and volatility transmissions between size-based stock portfolios have largely been ignored in the literature on dynamic transmissions between small- and large-cap stocks.

Overall, two research gaps have been identified from the existing bodies of literature. First, dynamic return and volatility transmissions between the main market and SME market have been neglected. This gap implies a potential indirect influence of the SME market to economic development via the main market channel given the existing connection between the main market and economic development. Second, the joint effects of volatility breaks, thin trading, and trading volume on cross-market return and volatility transmissions have yet to be examined. As previously discussed, failure to address the effects of these factors while modelling cross return and volatility transmissions may result in overestimated volatility persistence. Therefore, this study aims to investigate the dynamic return and asymmetric volatility transmissions between the main stock market and SME stock market while taking into account the joint effects of volatility breaks, thin trading, and trading volume to avoid biased results.

4. Empirical models

As mentioned earlier, this paper aims to investigate dynamic transmissions of return and asymmetric volatility between the main stock market and SME stock market. These dynamic transmissions would result in a potential indirect contribution of the SME stock market to economic development through the main market channel. Simultaneously, the joint impacts of volatility breaks, thin trading, and trading volume on these cross-market transmissions were also accounted for (because ignoring these effects may result in overestimated volatility persistence). To test the presence of volatility breaks, the Iterated Cumulated Sum of Squares (ICSS) algorithm were adopted. To avoid the pitfall of autocorrelation instigated by thin trading, the SME market return series were de-thinned using a linear state-space AR model with Kalman filter estimation. The thin trading-adjusted return series, dummy variables indicating volatility breaks, and trading volume variable were then incorporated into an augmented bivariate VAR asymmetric BEKK-GARCH model to investigate the return and asymmetric volatility dynamics between the two markets. The econometric models used in this study are demonstrated in the following subsections.

4.1 Iterated cumulative sum of squares (ICSS) algorithm

Iterated cumulative sum of squares (ICSS) algorithm was introduced by Inclan and Tiao (1994) to detect multiple structural shifts in the unconditional variance of returns (volatility breaks). The ICSS algorithm offers the beginning and the end of return volatility regimes and is robust to heteroscedasticity. Suppose that ε_t is a series with zero mean and unconditional variance (σ_t^2). Within each interval between the breaks, the variance is given by σ_j, where $j = 1, 2, \dots, N_T$ and N_T is the total number of volatility breaks in the T observations. A set of breakpoints is given by $1 < K_1 < K_2 < \dots < K_{N_T}$. The unconditional variance over the N_T intervals is expressed as below:

$$\sigma_t^2 = \begin{cases} \sigma_0^2 \text{ for } 1 < t < K_1 \\ \sigma_1^2 \text{ for } K_1 < t < K_2 \\ \vdots \\ \sigma_{N_T}^2 \text{ for } K_{N_T} < t < T \end{cases} \tag{1}$$

To estimate the number of volatility breaks, the cumulative sum of squared observations from the beginning of the series to the kth point in time is determined as follows:

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 , \quad \text{for } k = 1, 2, \dots, T \tag{2}$$

where ε_t is the residuals series obtained from the AR(1) process of return series (R_t),

$$R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t \tag{3}$$

The statistic D_k is then defined as

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, \quad \text{with } D_0 = D_T = 0 \tag{4}$$

where C_T is the cumulative sum of squared observations for the entire sample.

The statistic D_k will oscillate around zero if there are no volatility breaks. When plotting the D_k against k, it is a horizontal line. In contrast, if there are volatility breaks, the D_k statistic departs from zero. Critical values achieved from the distribution of D_k are used to identify the significant breaks in the variance under the null hypothesis of constant variance. When the maximum absolute value of D_k exceeds the critical value, the null hypothesis is rejected. Thus, if $\{\max_k \sqrt{T/2}|D_k|\}$ is greater than the predetermined boundary, then k*, which is the value at which $\max_k |D_k|$ is reached, is considered as an estimate of volatility breakpoint.

4.2 Linear state-space AR model with Kalman filter estimation

To adjust the SME market returns (R_{2t}) for thin trading, the linear state-space AR(1) model (Harvey, 1989; Hamilton, 1994; Koopman, Shephard, & Doornik, 1999) with a Kalman filter estimation (Kalman & Bucy, 1961) was adopted. This model allows for the time-varying AR(1) coefficient and can be expressed in the following space and state equations.

$$R_{2t} = \beta_0 + \beta_{1t} R_{2,t-1} + e_t \tag{5}$$

$$\beta_{1t} = \beta_{1t-1} + v_t \tag{6}$$

where e_t and $v_t \sim N(0, \sigma_t^2)$.

Parameter β_{1t} in Equation (5) represents the time-varying AR(1) coefficient. The dynamics of the AR(1) coefficient was estimated using Equation (6) with a Kalman recursive filter. Principally, the Kalman filter estimates the one-step-ahead coefficient sequentially to produce a set of β_{1t} and the corresponding standard deviations over time. In other words, the Kalman filter generates a set of measurements observed through time to estimate the unknown parameter (β_{1t}). The time path of this parameter is an indicator of the time-varying thin-trading adjustment.

As suggested by Harrison and Moore (2012), to obtain the de-thinned SME market returns (R_{2t}^{d}), the time-varying coefficient (β_{1t}) and residuals (e_t) were extracted from the above model and used to estimate R_{2t}^{d} as follows:

$$R_{2t}^{d} = \frac{e_t}{1-\beta_{1t}} \tag{7}$$

4.3 Bivariate VAR asymmetric BEKK-GARCH model

Multivariate asymmetric BEKK-GARCH model was developed by Engle and Kroner (1995) and Kroner and Ng (1998) to capture the asymmetric volatility transmission across multiple markets. The variance-covariance matrix of this model is built on the vector of innovation term (ε_{it}) of a VAR model. Suppose that $R_t = (R_{1t}, R_{2t})'$ denotes a (2x1) vector of the main market return series and the SME market return series at day t, and p represents the lag order, a bivariate VAR(p) model can then be stated in the following matrix:

$$\begin{pmatrix} R_{1t} \\ R_{2t} \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \varphi_{11}^{1} & \varphi_{12}^{1} \\ \varphi_{21}^{1} & \varphi_{22}^{1} \end{pmatrix} \begin{pmatrix} R_{1,t-1} \\ R_{2,t-1} \end{pmatrix} + \cdots + \begin{pmatrix} \varphi_{11}^{p} & \varphi_{12}^{p} \\ \varphi_{21}^{p} & \varphi_{22}^{p} \end{pmatrix} \begin{pmatrix} R_{1,t-p} \\ R_{2,t-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{8}$$

where $\mu_i (i = 1,2)$ denotes constants or drift coefficients for the return series i (where 1 and 2 stands for the main market returns and SME market returns, respectively) and $\varepsilon_{it} (i = 1,2)$ denotes the innovation term (shock) for the return series i at day t. The diagonal parameters $\varphi_{ij}^{p} (i = j)$ gauge the effect of return spillover within individual return series (own return spillover) whereas the off-diagonal parameters $\varphi_{ij}^{p} (i \neq j)$ quantify the effect of return spillover between return series (cross return spillover). The vector of error terms is then used to model a bivariate asymmetric BEKK-GARCH(1,1) process, which can be expressed as

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon_{t-1}')A + B'H_{t-1}B + D'(\kappa_{t-1}\kappa_{t-1}')D \tag{9}$$

where C denotes a (2x2) lower triangular matrix of constants, A denotes (2x2) squared matrix of coefficients measuring the impact of past shocks on present volatility (short-run volatility spillover), B denotes (2x2) squared matrix of coefficients measuring the influence of past volatility on present volatility (long-run volatility spillover), D denotes (2x2) matrix of coefficients capturing the asymmetry of the conditional variance-covariance (asymmetric volatility spillover), H_{t-1} denotes a (2x2) conditional variance matrix, ε_{t-1} denotes a (2x1) vector of squared error terms and cross product of error terms, and κ_{t-1} denotes a (2x1) vector of squared asymmetric terms and cross products of asymmetric terms.

Alternatively, a bivariate asymmetric BEKK-GARCH(1,1) model can be expanded in the following conditional variance equations, which show how past shocks and volatility are transmitted within and across the main market ($h_{11,t}$) and the SME market ($h_{22,t}$).

$$\begin{aligned} h_{11,t} = {} & c_{11}^2 + b_{11}^2 h_{11,t-1} + 2b_{11}b_{21}h_{12,t-1} + b_{21}^2 h_{22,t-1} + a_{11}^2 \varepsilon_{1,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + a_{21}^2 \varepsilon_{2,t-1}^2 + \delta_{11}^2 \kappa_{1,t-1}^2 + 2\delta_{11}\delta_{21}\kappa_{1,t-1}\kappa_{2,t-1} + \delta_{21}^2 \kappa_{2,t-1}^2 \end{aligned} \tag{10}$$

$$\begin{aligned} h_{22,t} = {} & c_{21}^2 + c_{22}^2 + b_{12}^2 h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + b_{22}^2 h_{22,t-1} + a_{12}^2 \varepsilon_{1,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + a_{22}^2 \varepsilon_{2,t-1}^2 + \delta_{12}^2 \kappa_{1,t-1}^2 + 2\delta_{12}\delta_{22}\kappa_{1,t-1}\kappa_{2,t-1} + \delta_{22}^2 \kappa_{2,t-1}^2 \end{aligned} \tag{11}$$

As suggested by Kearney and Patton (2000), the standard errors of these coefficients are computed using a first-order Taylor expansion of the function around its mean, which involves the estimated variance-covariance matrix of the coefficients together with vectors of the mean and standard error. Assuming normally distributed errors, the model is estimated using the following maximum-likelihood function.

$$L(\theta) = -\frac{T}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \tag{12}$$

where T indicates the number of observations and θ indicates the vector of estimated coefficients.

4.4 Augmented bivariate VAR asymmetric BEKK-GARCH model

To observe the joint impacts of volatility breaks, thin trading, and trading volume on the dynamic transmissions between the main market and SME market, the bivariate VAR asymmetric BEKK-GARCH model was augmented with these factors. As discussed in the literature review section, there were very few studies on the dynamic spillovers between large- and small-cap stocks portfolios that accounted for either volatility breaks or trading volume in the model. While Ewing and Malik (2005) introduced a set of dummies indicating volatility breaks into a bivariate BEKK-GARCH model, Koulakiotis et al. (2016) included trading volume in a trivariate VAR-EGARCH model. Putting these forward, in this paper, both factors, volatility breaks and trading volume, were incorporated into a bivariate VAR asymmetric BEKK-GARCH model. Accordingly, our augmented model further contributes to the existing empirical models by including both volatility breaks and trading volume in a standard VAR Asymmetric BEKK-GARCH procedure. In particular, a set of dummies for volatility breaks in each market was entered into variance equation while the aggregate trading volume of the two markets was included in both mean and variance equations. The aggregate volume series can be a better variable than individual volume series because idiosyncratic buying or selling pressure does not initiate systematic risk for market makers (Campbell, Grossman, & Wang, 1993). In addition, using a single aggregate series help accounts for a large disparity in trading volume between the main markets and the SME markets in each country (as shown in Table 1). This approach has been used in some of studies such as those by Gallant, Rossi, and Tauchen (1992), Hussain (2011), and Koulakiotis et al. (2016).

The augmented model was then used to fit the main market return series (R_{1t}) and the de-thinned SME market return series (R_{2t}^d). It can be written in the following mean and variance equations.

$$\begin{pmatrix} R_{1t} \\ R_{2t}^d \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \varphi_{11}^1 & \varphi_{12}^1 \\ \varphi_{21}^1 & \varphi_{22}^1 \end{pmatrix} \begin{pmatrix} R_{1,t-1} \\ R_{2,t-1}^d \end{pmatrix} + \cdots + \begin{pmatrix} \varphi_{11}^p & \varphi_{12}^p \\ \varphi_{21}^p & \varphi_{22}^p \end{pmatrix} \begin{pmatrix} R_{1,t-p} \\ R_{2,t-p}^d \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} + \begin{pmatrix} \gamma_1 \\ \gamma_2 \end{pmatrix} ATV_t \quad (13)$$

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon_{t-1}')A + B'H_{t-1}B + D'(\kappa_{t-1}\kappa_{t-1}')D + \sum_{i=1}^{n} V_i'(X_iX_i')V_i + T'ATV_tT \quad (14)$$

where $\gamma_i (i = 1,2)$ quantifies the impact of aggregate trading volume on the return spillover in return series i, ATV_t denotes the aggregate trading volume of the main market and the SME market at day t, T denotes $(2x2)$ lower triangular matrix of parameters measuring the effect of aggregate trading volume on the conditional variance of return series i, V_i is a $(2x2)$ lower triangular matrix of parameters measuring the effect of volatility breaks on the conditional variance of return series i, X_i is a $(1x2)$ vector of dummies for volatility breaks in return series i, if the series is subjected to a volatility break at time t, X_i will take a value of 0 before time t and a value of 1 from time t onwards, n is the number of breakpoints detected in variance, all other variables and parameters were described in the preceding subsection.

5. Data sources and characteristics

Data used in this study were daily index closing prices and trading volumes of the main stock markets and SME stock markets in Hong Kong, Singapore, Thailand, and Malaysia. The corresponding main markets and SME markets are represented by the following pairs of indices: (i) Hong Kong Hang Seng Composite Index (HSI) and S&P/HKEX GEM Index, (ii) FTSE Strait Times All-Share Index (FSTAS) and FTSE Strait Times CATALIST Index, Stock Exchange of Thailand Index (SETI) and MAI Index, and FTSE Bursa Malaysia EMAS Index (FBMEMAS) and FTSE Bursa Malaysia ACE Index. The datasets were downloaded from the Bloomberg Database from 01/07/2009 to 30/12/2016 and then filtered for valid trading days (because there exist several non-trading days which duplicate the values of the previous trading day in the raw series), yielding 1,832-1,884 observations. The sample period started from the launch of the ACE market, which replaced the former MESDAQ in Malaysia. The data were analysed using RATS9.2 and Eviews10, which are among the most prevailing econometrics software packages and, importantly, offer integrated solutions for time series analysis.

The daily price series of the main markets (P_{1t}) and SME markets (P_{2t}) were transformed to daily logarithmic return series as, $R_{1t} = ln\left(P_{1t}/P_{1,t-1}\right)$ and $R_{2t} = ln\left(P_{2t}/P_{2,t-1}\right)$, where P_t and P_{t-1} denote the index closing prices at day t and $t-1$. The daily trading volume series of the main markets and SME markets were rescaled and combined into one single aggregate trading volume series (ATV_t) for each country.

Appendix A presents the characteristics of the returns and trading volumes of the main markets and SME markets in Hong Kong, Singapore, Thailand, and Malaysia. Compared to Thailand and Malaysia, Hong Kong and Singapore experienced negative mean returns but higher standard deviations in the SME markets, suggesting no risk and return trade-off in these markets. Hong Kong and Singapore also exhibited lower mean returns in the main markets than those in Thailand and Malaysia. All return series, except for the R_t^S in Hong Kong, had fatter tails and longer left tails compared to the Gaussian distribution due to negative skewness. In contrast, all trading volume series were highly positively skewed, indicating that they have fatter tails and much longer right tails than the Gaussian distribution. The substantial kurtosis indicated that all return and volume series were leptokurtic and had a sharp peak. The Jarque and Bera (1980) statistics further confirmed that all return and volume series were non-Gaussian distributed. The significant Ljung and Box (1979) Q and Q^2 statistics up to lag 10 and 20 indicated the presence of autocorrelation in the mean and variance of all return and volume series. The Engle (1982) ARCH statistics up to lag 5 and 10 provided evidence of conditional heteroscedasticity in all return and volume series, suggesting that these series should be fit by a model that accommodates the ARCH/GARCH processes.

6. Empirical findings and discussion

6.1 Preliminary analysis

Before modelling the return and volatility transmissions between the main stock market and SME stock market in Hong Kong, Singapore, Thailand, and Malaysia, all return and aggregate trading volume series were tested for stationarity to avoid spurious regression (see Appendix B). Tests of the asymmetric return volatility and cross-correlations of the returns and residuals were performed to determine the appropriate mean and variance models that might be a good fit for the data. The presence of structural breaks in volatility of the return series was also tested to identify whether a set of dummy variables representing volatility breaks should be included in the model. The tests results are presented in the following subsections.

6.1.1 Asymmetric return volatility

To test the presence of asymmetric return volatility, the size and sign bias tests introduced by Engle and Ng (1993) were adopted. Table 2 displays the asymmetric test statistics for the return series of the main markets and SME markets in Hong Kong, Singapore, Thailand, and Malaysia. These results showed that in Hong Kong, the GEM exhibited both size bias and sign bias (negative and positive) in return volatility, whereas the HKEX exposed only positive sign bias in return volatility. In Singapore, there was no size bias in return volatility of the SGX and CATALIST, but there existed positive sign bias in the SGX return volatility and negative sign bias in the CATALIST return volatility.

In Thailand, the SET and MAI only experienced positive sign bias in return volatility. In Malaysia, the BM return volatility had size bias whereas the ACE return volatility showed negative sign bias. Although the evidence of the individual size and sign bias in return volatility was inconsistent between the main markets and SME markets in the four countries, the joint test of size and sign bias for all market returns was highly significant, indicating the presence of asymmetric return volatility. These results suggest that an asymmetric volatility model might fit the return series of the two markets in all countries.

6.1.2 Cross-correlations of returns and residuals

Following the procedure proposed by Conrad, Gultekin, and Kaul (1991), the first-order lagged cross-correlation matrices of returns and residuals between the main markets and SME markets in Hong Kong, Singapore, Thailand, and Malaysia were generated from a VAR(1) process (see Table 3). As shown in Panel A, the absolute values of the first lagged cross-correlations between the previous day's return on the main market ($R_{1,t-1}$) and the current day's return on the SME market (R_{2t}) were 5.6% (for Hong Kong), 10.6% (for Singapore), 11.2% (for Thailand), and 11.3% (for Malaysia). Meanwhile, the absolute cross-correlations between the previous day's return on the SME market ($R_{2,t-1}$) and the current day's return on the main market (R_{1t}) were only 3.3% (for Hong Kong), 0.5% (for Singapore), 4.1% (for Thailand), and 1.2% (for Malaysia). These results indicate the presence of an asymmetric cross-correlation of returns, which is important because variations in the returns of each individual market may exert a different asymmetric influence on the cross-market correlation of returns. In addition, the return cross-correlations between the two markets in Singapore and Thailand were positive while those in Hong Kong and Malaysia were negative.

Panel B reports the first lagged cross-correlations of the residuals of the model, in which the returns of the main market and SME market follow a VAR(1) process. The results showed that the asymmetry of residuals between the two markets was reduced dramatically in all four countries. For examples, in Hong Kong, approximately 0.5% of variation in the residual of VAR(1) model for the HKEX return can be explained by that of the GEM lagged return, and 0.1% of variation in the residual of VAR(1) model for the GEM return can be explained by that of the HKEX lagged return. Accordingly, the above results suggest that a VAR process that incorporates asymmetric features might be a good fit for the returns of the main markets and SME markets in Hong Kong, Singapore, Thailand, and Malaysia.

6.1.3 Detected structural breaks in volatility

The presence of volatility breaks in the return series of the main market and the SME market was tested using the procedure of the ICSS algorithm. The results reported in Table 4 show different volatility breakpoints in the two markets' return series in Hong Kong, Singapore, and Malaysia. In Thailand, there was one common volatility breakpoint in both return series because a critical event would instigate volatility break in different markets simultaneously. The detected breakpoints appear to correspond to major political, macroeconomic and financial events as presented in Table 4.

6.2 Modelling return and volatility transmissions

Following preliminary analysis, the bivariate VAR asymmetric BEKK-GARCH model was adopted to model the dynamic transmissions of return and asymmetric volatility between the main market and SME market in Hong Kong, Singapore, Thailand, and Malaysia. As mentioned before, the presence of volatility breaks can reduce or even remove volatility spillover effects, thin trading can induce spurious autocorrelation in the return series, and trading volume can affect the price movements and the pattern of volatility clustering. Ignoring these factors would most likely lead to biased estimation of dynamic return and volatility transmissions. Therefore, the joint impacts of volatility breaks, thin trading (of the SME markets), and aggregate trading volume (of the main markets and SME markets) on the return and asymmetric volatility dynamics were accounted for using the augmented bivariate VAR asymmetric BEKK-GARCH model.

To begin with, the optimal lag lengths in the mean (VAR) and variance (Asymmetric BEKK-GARCH) models were selected based on the following three criteria: minimum AIC value, parsimonious model, and the convergence of coefficient estimation. Accordingly, in the VAR model, lag 2 was selected for Hong Kong and Malaysia whereas lag 3 was chosen for Singapore and Thailand. In the Asymmetric BEKK-GARCH model, order 1 was selected for both ARCH and GARCH terms for all four countries. Since this study was intended to explore a dynamic relationship between the main market and SME market, the statistical significance, sign, and size of coefficients for the mean, conditional variance, covariance, and squared error terms which represent direct and indirect cross-market transmissions were on the focus in the subsequent analysis. Tables 5-7 report the model estimations for Hong Kong, Singapore, and Thailand in the following four cases:

- Case 1: analysis using raw return series in modelling;
- Case 2: analysis incorporating detected volatility breaks into the model;
- Case 3: analysis using thin trading adjusted return series and incorporating detected volatility breaks into the model;
- Case 4: analysis using thin trading adjusted return series and incorporating detected volatility breaks and aggregate trading volume into the model.

Table 8 reports the model estimation for Malaysia up to Case 3 only, Case 4 was not reported because the model did not satisfy the condition of covariance stationarity and the ARCH effect persisted in the residuals (see Table 9).

The results indicate that in Hong Kong, there was a unidirectional return transmission from the GEM to the HKEX and its magnitude and significance level declined from 0.049 (1%) to 0.034 (5%) (equation $R_{1,t}$, coefficients of $R_{2,t-2}$) when volatility breaks, thin trading, and aggregate trading volume were included in the model. By contrast, Singapore and Thailand exhibited a reverse return transmission from the SGX and the SET to the CATALIST and the MAI, respectively, after the inclusion of the three factors. Malaysia also showed a reverse return transmission from the BM to the ACE after accounting for volatility breaks and thin trading. Interestingly, the size and/or significance level of these return transmissions increased from 0.138 (1%) to 0.146 (1%) for Singapore (equation $R_{2,t}$, coefficient of $R_{1,t-3}$), from 0.049 (5%) to 0.070 (1%) for Thailand (coefficient of $R_{1,t-1}$), and from 0.158 (1%) to 0.180 (1%) for Malaysia (coefficient of $R_{1,t-2}$). Among the countries, the return transmission from the SME market to the main market is only visible in Hong Kong mainly because the GEM is much larger in size and has higher liquidity compared to the CATALIST, MAI, and ACE (see Table 1). In addition, cross-market transmission effect is often attributed to hedging activities between large and small markets and the sharing of common information between these two markets as suggested by Fleming, Kirby, and Ostdiek (1998).

Turning to variance equations ($h_{11,t}$ and $h_{22,t}$), the results reveal no short- and long-run volatility spillovers and asymmetric volatility spillover between the main market and the SME market in Thailand and Malaysia. In Hong Kong, direct short-run volatility spillover from the GEM to the HKEX became insignificant after controlling for the three factors (equation $h_{11,t}$, coefficient of $\varepsilon_{2,t-1}^2$), making cross-market volatility dynamics invisible in Hong Kong as well. However, in Singapore, while there was no short- and long-run volatility spillovers between the two markets, the asymmetric volatility spillover from the SGX to the CATALIST was getting stronger in significance level and larger in magnitude from 0.070 (10%) to 0.108 (5%) (equation $h_{11,t}$, coefficient of $\varepsilon^2_{2,t-1}$). This asymmetric volatility transmission implies that volatility in the CATALIST responding to a negative shock in the SGX is higher than that responding to a positive shock in the SGX. The presence of an asymmetric response in volatility of the small-cap stocks in the CATALIST may have been due to the infamous 2013 penny stock manipulation in the SGX that wiped out S$8 billion (US$5.8 billion) in less than two days of trade.

Post-estimation diagnostics for Hong Kong, Singapore, Thailand, and Malaysia are shown in Table 9. The results reveal that multivariate portmanteau statistics of Ljung-Box test (M-Q) and Engle ARCH test (M-ARCH) up to lag 10 and 20 were insignificant in Case 4 for Hong Kong, Singapore, and Thailand. This indicates the absence of serial correlation and heteroscedasticity in the residuals after incorporating volatility shifts, thin trading, and aggregate trading volume into the model. Covariance stationarity of the models for those three countries are also ensured because the summation of (α_{ii}^2 + β_{ii}^2) were all less than unity (α_{ii} and β_{ii} are diagonal elements of the A and B matrices of the model). The models were thus well-specified for Hong Kong, Singapore, and Thailand. For Malaysia, the model specification is valid in Cases 1 to 3 because the residuals contained no serial correlation and satisfied the condition of covariance stationarity; the ARCH effect in the residuals also dissipated when the test was performed up to lag 20. The model estimation for Malaysia was thus reported up to Case 3 as in Table 8.

Thus far, the study found that the SME market can exert influence on the main market through the effect of return transmission and this influence is visible in the case of Hong Kong only. As previously discussed in the literature review section, a causal relationship and a long-run equilibrium relationship exist between the main market return and economic development in Hong Kong. To ensure the existence of these relationships in Hong Kong during the studied period, Pairwise Granger Causality test and Johansen Cointegration Rank test were performed. A set of different macroeconomic indicators including real GDP growth (RYG), growth of real physical capital stock (RKG), real productivity growth (RPG), and real wage growth (RWG)[4] were used as the proxies for economic development. The results of Pairwise Granger Causality test, as reported in Table 10, show a one-way causality running from the main market return to each of the four economic development indicators in Hong Kong. The results of Johansen Cointegration Rank test (see Table 11) also provide evidence that the pairs of variables are cointegrated, implying the presence of a long-run equilibrium nexus between the main market return and economic development in Hong Kong.

Overall, only Hong Kong exhibits a return transmission from the SME market (the GEM) to the main market. Moreover, the main market return also exposes a causal relationship and a long-run relationship with the economic development of Hong Kong. Therefore, it can be inferred that the GEM can contribute indirectly to Hong Kong's economic development via the main market channel. This inference is related only to Hong Kong and it can be justified by the fact that the GEM's market

[4] Real Productivity is measured by dividing real GDP by labour force. The data were obtained from various issues of Hong Kong Census and Statistics Department, International Financial Statistics (IFS-IMF), World Bank Database (WDI), for the period of 2009:Q2 to 2016:Q4. Quarterly data were adjusted for seasonality and then converted into monthly data using Eviews10 interpolation techniques, where appropriate, quadratic with sum or average matched to the source data.

capitalisation accounts for a significant 12.6% of Hong Kong's GDP while the ratios for the CATALIST, MAI, and ACE are very modest, ranging from 0.8% to 3.0% of GDP (see Table 1). Accordingly, any policies that facilitate the development of the GEM would indirectly promote long-term economic stimulation in Hong Kong through its return transmission mechanisms with the main market. Furthermore, the results of cross-market return and asymmetric volatility transmissions potentially benefit several applications in finance which depend on the forecasts of these dynamic relationships, i.e. value-at-risk and hedging, derivatives pricing, and portfolio management.

7. Conclusions and future research

This paper reported the results of a study on the return and asymmetric volatility transmissions between the main stock markets and the SME stock markets under the joint impacts of volatility breaks, thin trading, and trading volume in Hong Kong, Singapore, Thailand, and Malaysia. The study has provided a further understanding of an indirect contribution of the SME markets to macroeconomic stimulation via the main market channel. A set of time series econometrics adopted in this study was: (i) Iterated Cumulated Sum of Squares (ICSS) algorithm to identify volatility breaks (ii) linear state-space AR model with the Kalman filter to adjust for thin trading, and (iii) augmented bivariate VAR asymmetric BEKK-GARCH model to estimate the return and asymmetric volatility transmissions under the joint effects of volatility breaks, thin trading, and trading volume.

The results determined that the incorporation of volatility breaks, thin trading, and trading volume in modelling return and asymmetric volatility transmissions proved to have at least one of the following consequences. First, in Hong Kong, the magnitude and significance level of unidirectional return transmission from the SME market to the main market have decreased. Second, however, in Singapore, Thailand, and Malaysia, the magnitude and/or significance level of the return transmissions from the main markets to the SME markets have increased. Third, in Hong Kong, direct short-run volatility transmission from the SME market to the main market has dissipated. Fourth, in Singapore, asymmetric volatility transmission from the main market to the SME market has become stronger in significance level and larger in magnitude. Accordingly, several important consequences on return and asymmetric volatility transmissions between the main market and SME market would be hidden if one fails to consider the joint effects of volatility breaks, thin trading, and trading volume.

The results also indicated that among the studied countries, evidence of return transmission from the SME market to the main market was found to be substantial in Hong Kong only. The main market return also exhibit a causal nexus and a long-run equilibrium nexus with the economic development in Hong Kong. Consequently, it can be argued that the SME market can make an indirect contribution to economic development in Hong Kong via its dynamic return transmission with the main market.

Therefore, any policies that facilitate the development of the SME market would indirectly promote long-term economic stimulation in Hong Kong through its transmission mechanisms with the main market. Moreover, the results of cross-market return and asymmetric volatility transmissions have important implications for several applications in finance which depend on the forecast of these dynamic relationships, i.e. value-at-risk and hedging, derivatives pricing, and portfolio management.

Finally, while return and asymmetric volatility transmissions between the main stock market and SME stock market were investigated in this paper, liquidity transmission between the two markets is also worthwhile to explore. Future research can examine this dynamic effect using different liquidity measures such as Amihud (2002) illiquidity ratio and relative quoted bid-ask spreads. These two measures of liquidity proved to be effective in capturing price impact, premium for illiquidity, and spread cost over time as suggested by Goyenko and Ukhov (2009), Goyenko, Holden, and Trzcinka (2009), and Hasbrouck (2009). Moreover, unlike the main markets, the SME markets in Hong Kong, Singapore, Thailand, and Malaysia are currently functioning on the principals of the classical growth theory, which casts out the government intervention. This paper was not intended to explore the potential impacts of government intervention on the dynamic cross-market transmissions and the indirect contribution of the SME market to economic development, and these remain areas for future research.

Declaration of interest: none

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Figure 1: The Tropical economies

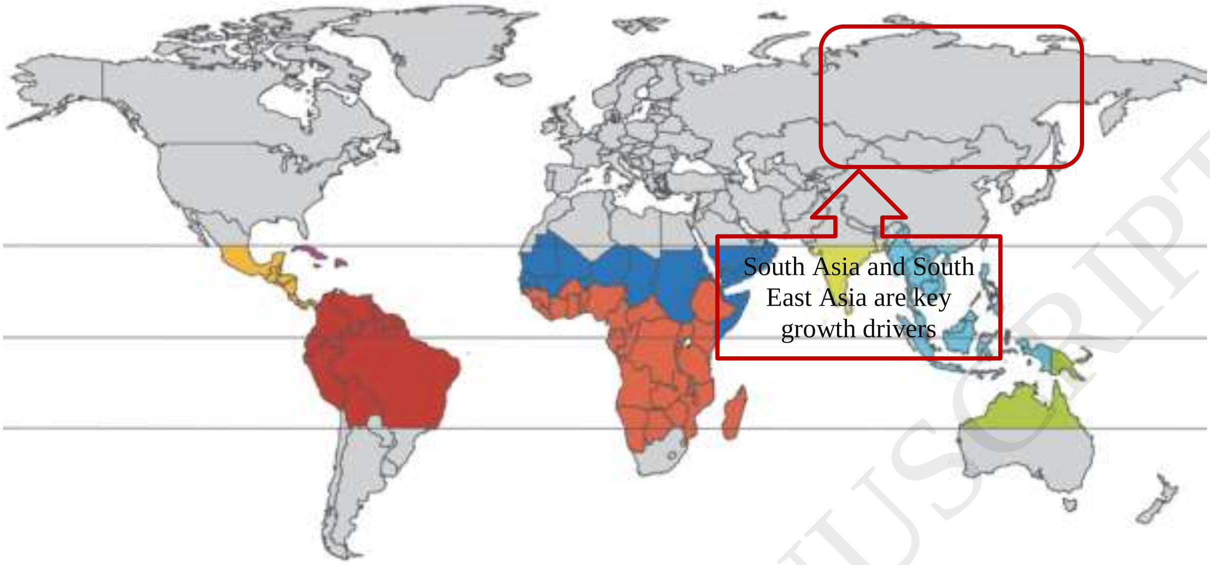
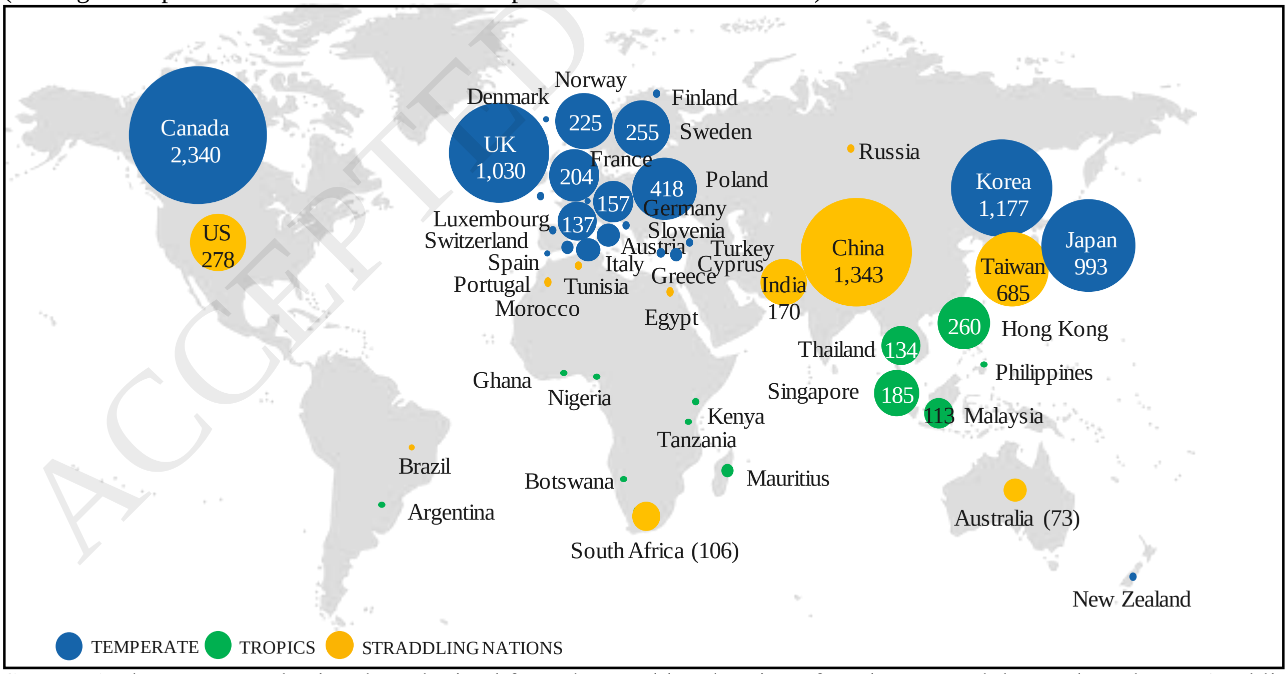


Figure 2: SME stock markets worldwide
(The figures represent the number of listed companies as of December 2016)



Source: Authors generated using data obtained from the World Federation of Exchanges and the stock exchanges' public domains

Table 1: Facts and figures (2016)

	Hong Kong		Singapore		Thailand		Malaysia	
Main market – SME market	HKEX	GEM	SGX	CATALIST [c]	SET	MAI	BM	ACE [c]
Market opened	1986	1999	1973	2007	1975	2001	1976	2009
No. of listed companies	1,713	260	572	185	522	134	791	113
Representative Index	HSI	GEM	FSTAS	CATALIST	SETI	MAI	FBMEMAS	ACE
Market capitalisation [a]	1,720.7	40.1	423.8	6.4	383.5	11.9	313.6	2.3
Percentage of GDP (%)	542.7%	12.6%	149.4%	2.3%	95.8%	3.0%	112.9%	0.8%
Percentage of Main Index (%)		2.3%		1.5%		3.1%		0.7%
Trading value [a]	745.7	19.0	175.4	4.9	341.7	15.5	103.5	3.2
Percentage of Main Index (%)		2.5%		2.8%		4.5%		3.1%
Trading volume [b]	424.7	231.9	164.4	88.5	1,297.5	200.6	142.8	55.3
Percentage of Main Index (%)		54.6%		53.8%		15.5%		38.7%

Source: Exchange factbooks. Notes: (a) in US$ billion; (b) in billion shares; (c) CATALIST and ACE are the replacements for the SESDAQ and MESDAQ, respectively, to improve the quality of listed companies and the market liquidity; HSI is Hang Seng Composite Index; FSTAS is FTSE Strait Times All Shares Index; SETI is Stock Exchange of Thailand Index; FBMEMAS is FTSE Bursa Malaysia EMAS Index.

Table 2: Asymmetric tests for the return series

	Hong Kong		Singapore		Thailand		Malaysia	
	R_{1t}	R_{2t}	R_{1t}	R_{2t}	R_{1t}	R_{2t}	R_{1t}	R_{2t}
Size bias (t-test)	0.03	2.37**	0.94	0.68	0.30	0.11	2.68*	1.16
Negative sign bias (t-test)	0.63	5.40*	0.97	2.35**	1.10	0.42	0.24	1.38***
Positive sign bias (t-test)	2.16**	1.84***	1.71***	0.81	3.30*	2.16**	0.18	0.75
Joint effect (F-test)	10.37**	33.51*	15.72*	6.21**	20.30*	8.47**	17.68*	2.50**

*, **, *** indicate the test statistic is significant at 1%, 5% and 10%, respectively; R_{1t} and R_{2t} denote daily returns of the main market and SME market, respectively.

Table 3: Cross-correlations of the returns and residuals

	Hong Kong		Singapore		Thailand		Malaysia	
Panel A: Return cross-correlations	R_{1t}	R_{2t}	R_{1t}	R_{2t}	R_{1t}	R_{2t}	R_{1t}	R_{2t}
$R_{1,t-1}$	-0.008	-0.056	0.062	0.106	0.063	0.112	0.114	-0.113
$R_{2,t-1}$	0.033	0.168	-0.005	-0.186	-0.041	0.018	0.012	0.100
Panel B: Residual cross-correlations	ε_{1t}	ε_{2t}	ε_{1t}	ε_{2t}	ε_{1t}	ε_{2t}	ε_{1t}	ε_{2t}
$\varepsilon_{1,t-1}$	-0.001	-0.001	-0.002	-0.006	0.000	0.005	-0.011	-0.034
$\varepsilon_{2,t-1}$	-0.005	-0.003	0.003	-0.003	-0.001	-0.007	0.003	0.007

Notes: R_{1t} and R_{2t} denote daily returns of the main market and SME market, respectively; ε_{1t} and ε_{2t} denote residuals from estimates of VAR(1) process for daily returns of the main market and SME market, respectively.

Table 4: Structural breaks in volatility

Market	Breakpoint	Corresponding event	Break regime	SD
HSI			02/07/2009 - 26/11/2009	0.0158
Hong Kong	27/11/2009	Dubai debt standstill due to a massive renovation	27/11/2009 - 18/08/2010	0.0126
		projects and the Great Recession	19/08/2010 - 21/09/2011	0.0122
	22/09/2011	The US Federal Reserve's Operation Twist failed	22/09/2011 - 18/02/2014	0.0122
		to calm financial markets after the crash in August	19/02/2014 - 30/12/2016	0.0115
GEM			02/07/2009 - 10/11/2010	0.0132
Hong Kong	11/11/2010	Chinese Central Bank announced an increase in the	11/11/2010 - 08/07/2015	0.0133
		monetary policy rate	09/07/2015 - 21/08/2015	0.0562
	24/08/2015	Black Monday of Chinese stock market	24/08/2015 - 13/06/2016	0.0167
			14/06/2016 - 30/12/2016	0.0095
FSTAS			01/07/2009 - 14/08/2009	0.0138
Singapore	16/08/2009	Singapore's Prime Minister announced "the worst	17/08/2009 - 29/08/2014	0.0080
		is over for Singapore economy"	01/09/2014 - 30/12/2016	0.0074
CATALIST			01/07/2009 - 25/09/2009	0.0209
Singapore	28/09/2009	Singapore's unemployment rate peaked at 3.3%	28/09/2009 - 24/06/2016	0.0147
		since September 2003 (4.8%)	27/06/2016 - 30/12/2016	0.0089
SET			02/07/2009 - 07/04/2010	0.0150
Thailand	07/04/2010	Thai Prime Minister ordered state of emergency	08/04/2010 - 14/12/2015	0.0109
			15/12/2015 - 30/12/2016	0.0113
MAI			02/07/2009 - 05/04/2010	0.0094
Thailand	07/04/2010	Thai Prime Minister ordered state of emergency	07/04/2010 - 16/08/2013	0.0124
			19/08/2013 - 30/12/2016	0.0131
FBMEMAS			01/07/2009 - 26/09/2011	0.0061
Malaysia	27/09/2011	Asian and European stock markets opened lower in	27/09/2011 - 02/08/2012	0.0060
		response to the ongoing sovereign debt crisis in EU	03/08/2012 - 20/01/2016	0.0058
	21/01/2016	Central Bank of Malaysia retained the overnight	21/01/2016 - 07/04/2016	0.0060
		policy rate at 3.25%, meeting the market's expectation	08/04/2016 - 30/12/2016	0.0043
ACE			01/07/2009 - 12/09/2012	0.0112
Malaysia	13/09/2012	S&P warned to cut Malaysia's sovereign credit	13/09/2012 - 12/12/2014	0.0115
		rating	15/12/2014 - 26/08/2015	0.0173
	27/08/2015	Malaysian government declared the Bersih rallies	27/08/2015 - 28/03/2016	0.0119
		illegal	29/03/2016 - 30/12/2016	0.0088

Notes: The usual 5% level of significance was used to detect volatility breaks in the return series; SD denotes standard deviation for each break regime.

Table 5: Augmented bivariate VAR asymmetric BEKK-GARCH model estimation for Hong Kong

Case 1: Raw return series																				
R_{1t}	=	-5E-06	+	$0.021R_{1,t-1}$	+	$0.01R_{2,t-1}$	−	$0.036R_{1,t-2}$	+	$0.049\ R_{2,t-2}$										
		(-0.03)		(1.00)		(0.45)		(-1.65)***		(2.59)*										
R_{2t}	=	-0.0004	+	$0.025R_{1,t-1}$	+	$0.067\ R_{2,t-1}$	−	$0.004R_{1,t-2}$	+	$0.058\ R_{2,t-2}$										
		(-1.51)		(1.34)		(3.11)*		(-0.23)		(2.25)**										
$h_{11,t}$	=	3E-06	+	$0.939h_{11,t-1}$	−	$0.014\ h_{12,t-1}$	+	5E-05$h_{22,t-1}$	+	$0.001\varepsilon^2_{1,t-1}$	+	$0.003\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	$0.003\ \varepsilon^2_{2,t-1}$	+	$0.076\ \kappa^2_{1,t-1}$	−	$0.0002\ \kappa_{1,t-1}\kappa_{2,t-1}$	+	2E-07$\kappa^2_{2,t-1}$
		(3.13)*		(75.99)*		(-0.33)		(0.82)		(0.28)		(0.09)		(1.75)***		(3.60)*		(-0.02)		(0.01)
$h_{22,t}$	=	6E-06	+	4E-06$h_{11,t-1}$	+	$0.004\ h_{12,t-1}$	+	$0.809\ h_{22,t-1}$	+	$0.004\varepsilon^2_{1,t-1}$	−	$0.041\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	$0.120\ \varepsilon^2_{2,t-1}$	+	$0.013\ \kappa^2_{1,t-1}$	+	$0.055\ \kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.055\ \kappa^2_{2,t-1}$
		(1.68)***		(0.05)		(0.08)		(19.05)*		(0.44)		(-0.51)		(4.67)*		(0.48)		(0.30)		(1.10)
Case 2: Volatility breaks in volatility incorporated																				
R_{1t}	=	1.5E-05	+	$0.019R_{1,t-1}$	+	$0.010\ R_{2,t-1}$	−	$0.037R_{1,t-2}$	+	$0.047\ R_{2,t-2}$										
		(0.07)		(1.12)		(0.70)		(-1.87)***		(3.62)*										
R_{2t}	=	-0.0004	+	$0.024R_{1,t-1}$	+	$0.065\ R_{2,t-1}$	−	$0.005R_{1,t-2}$	+	$0.057\ R_{2,t-2}$										
		(-1.28)		(1.31)		(3.90)*		(-0.43)		(3.00)*										
$h_{11,t}$	=	4E-06	+	$0.944h_{11,t-1}$	−	$0.019\ h_{12,t-1}$	+	1E-04$h_{22,t-1}$	+	$0.0004\ \varepsilon^2_{1,t-1}$	+	$0.002\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	$0.004\ \varepsilon^2_{2,t-1}$	+	$0.072\ \kappa^2_{1,t-1}$	+	$0.002\ \kappa_{1,t-1}\kappa_{2,t-1}$	+	9E-06$\kappa^2_{2,t-1}$
		(3.23)*		(76.49)*		(-0.27)		(1.19)		(0.19)		(0.09)		(2.16)**		(2.88)*		(0.06)		(0.09)
$h_{22,t}$	=	1E-05	+	$0.0001\ h_{11,t-1}$	+	$0.018\ h_{12,t-1}$	+	$0.789\ h_{22,t-1}$	+	$0.006\varepsilon^2_{1,t-1}$	−	$0.054\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	$0.127\ \varepsilon^2_{2,t-1}$	+	$0.008\ \kappa^2_{1,t-1}$	+	$0.046\ \kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.066\ \kappa^2_{2,t-1}$
		(1.85)***		(0.21)		(0.20)		(18.38)*		(0.43)		(-0.34)		(4.64)*		(0.24)		(0.26)		(1.08)
Case 3: Volatility breaks in volatility incorporated and Thin trading adjusted																				
R_{1t}	=	3.5E-06	+	$0.019R_{1,t-1}$	+	$0.009\ R_{2,t-1}$	−	$0.036R_{1,t-2}$	+	$0.040\ R_{2,t-2}$										
		(0.02)		(0.86)		(0.76)		(-1.87)***		(2.56)*										

R_{2t}	=	-0.0002	+	$0.028R_{1,t-1}$	−	0.079 $R_{2,t-1}$	−	$0.003R_{1,t-2}$	+	0.040 $R_{2,t-2}$										
		(-0.58)		(0.99)		(-3.56)*		(0.99)		(1.62)										
$h_{11,t}$	=	4E-06	+	$0.944h_{11,t-1}$	−	0.016 $h_{12,t-1}$	+	7E-05$h_{22,t-1}$	+	0.0005 $\varepsilon^2_{1,t-1}$	+	0.002 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.003 $\varepsilon^2_{2,t-1}$	+	0.072 $\kappa^2_{1,t-1}$	+	0.001 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	2E-06$\kappa^2_{2,t-1}$
		(2.82)*		(71.79)*		(-0.19)		(0.88)		(0.27)		(0.07)		(2.47)**		(2.90)*		(0.04)		(0.06)
$h_{22,t}$	=	1.5E-05	+	0.0002 $h_{11,t-1}$	+	0.021 $h_{12,t-1}$	+	0.789 $h_{22,t-1}$	+	$0.007\varepsilon^2_{1,t-1}$	−	0.061 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.127 $\varepsilon^2_{2,t-1}$	+	0.010 $\kappa^2_{1,t-1}$	+	0.052 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.065 $\kappa^2_{2,t-1}$
		(1.72)***		(0.20)		(0.18)		(15.81)*		(0.45)		(-0.36)		(4.25)*		(0.25)		(0.26)		(1.11)
Case 4: Volatility breaks in volatility and Aggregate trading volume incorporated and Thin trading adjusted																				
R_{1t}	=	0.001	+	$0.020R_{1,t-1}$	+	0.006 $R_{2,t-1}$	−	$0.027R_{1,t-2}$	+	0.034 $R_{2,t-2}$										
		(1.16)		(0.92)		(0.29)		(-1.31)		(2.00)**										
R_{2t}	=	0.0002	+	$0.025R_{1,t-1}$	−	0.074 $R_{2,t-1}$	+	$0.007R_{1,t-2}$	+	0.031 $R_{2,t-2}$										
		(0.22)		(1.11)		(-2.67)*		(0.38)		(1.45)										
$h_{11,t}$	=	4.4E-07	+	$0.946h_{11,t-1}$	−	0.031 $h_{12,t-1}$	+	3E-04$h_{22,t-1}$	+	$0.001\varepsilon^2_{1,t-1}$	−	0.003 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.002 $\varepsilon^2_{2,t-1}$	+	0.074 $\kappa^2_{1,t-1}$	+	0.015 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.001 $\kappa^2_{2,t-1}$
		(0.44)		(42.05)*		(-0.23)		(0.77)		(0.16)		(-0.06)		(1.55)		(2.50)**		(0.14)		(0.54)
$h_{22,t}$	=	6E-06	+	$0.002h_{11,t-1}$	+	0.081 $h_{12,t-1}$	+	0.714 $h_{22,t-1}$	+	$0.004\varepsilon^2_{1,t-1}$	−	0.037 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.084 $\varepsilon^2_{2,t-1}$	+	0.001 $\kappa^2_{1,t-1}$	−	0.022 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.169 $\kappa^2_{2,t-1}$
		(0.41)		(0.31)		(0.31)		(5.66)*		(0.19)		(-0.30)		(3.18)*		(0.04)		(-0.11)		(1.10)

Notes: *, **, *** indicate the t-statistic is significant at 1%, 5% and 10%, respectively; R_{1t} and R_{2t} are the mean equations for the main market return series and the SME market return series, respectively; $h_{11,t}$ and $h_{22,t}$ are the conditional variance equations for the main market return series and the SME market return series, respectively. Numbers below the estimated coefficients are the corresponding t-statistics (in parentheses).

Table 6: Augmented bivariate VAR asymmetric BEKK-GARCH model estimation for Singapore

Case 1: Raw returns																				
R_{1t}	=	-8E-05	+	$0.053R_{1,t-1}$	+	0.0003 $R_{2,t-1}$	+	$0.028R_{1,t-2}$	+	0.004 $R_{2,t-2}$	+	$0.058R_{1,t-3}$	−	0.010 $R_{2,t-3}$						
		(-0.60)		(2.51)**		(0.03)		(1.45)		(0.34)		(3.98)*		(-1.37)						
R_{2t}	=	-0.001	+	$0.042R_{1,t-1}$	−	$0.078R_{2,t-1}$	+	$0.145R_{1,t-2}$	−	0.001 $R_{2,t-2}$	+	$0.138R_{1,t-3}$	+	0.019 $R_{2,t-3}$						
		(-4.08)*		(1.35)		(-2.20)**		(3.58)*		(-0.04)		(7.60)*		(0.88)						
$h_{11,t}$	=	8.4E-07	+	$0.934h_{11,t-1}$	−	0.028 $h_{12,t-1}$	+	0.0002 $h_{22,t-1}$	+	$0.002\varepsilon^2_{1,t-1}$	+	0.004 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.003 $\varepsilon^2_{2,t-1}$	+	0.126 $\kappa^2_{1,t-1}$	−	0.011 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.0002 $\kappa^2_{2,t-1}$
		(3.39)*		(109.08)*		(-0.40)		(1.44)		(0.40)		(0.08)		(1.97)**		(3.97)*		(-0.11)		(0.19)
$h_{22,t}$	=	2.8E-06	+	0.0001 $h_{11,t-1}$	−	0.022 $h_{12,t-1}$	+	$0.876h_{22,t-1}$	+	0.0002 $\varepsilon^2_{1,t-1}$	−	0.009 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.111 $\varepsilon^2_{2,t-1}$	+	0.072 $\kappa^2_{1,t-1}$	−	0.014 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.001\kappa^2_{2,t-1}$
		(1.68)***		(0.64)		(-0.38)		(24.35)*		(0.60)		(-0.09)		(2.77)*		(1.59)		(-0.25)		(0.30)
Case 2: Volatility breaks incorporated																				
R_{1t}	=	-7E-05	+	$0.052R_{1,t-1}$	+	$0.001R_{2,t-1}$	+	$0.027R_{1,t-2}$	+	0.004 $R_{2,t-2}$	+	$0.058R_{1,t-3}$	−	0.010 $R_{2,t-3}$						
		(-0.51)		(2.17)**		(0.07)		(1.88)***		(0.51)		(3.53)*		(-1.45)						
R_{2t}	=	-0.001	+	$0.039R_{1,t-1}$	−	$0.079R_{2,t-1}$	+	$0.145R_{1,t-2}$	−	0.002 $R_{2,t-2}$	+	$0.140R_{1,t-3}$	+	0.018 $R_{2,t-3}$						
		(-3.25)*		(1.04)		(-1.64)		(7.65)*		(-0.09)		(3.71)*		(0.82)						
$h_{11,t}$	=	1E-06	+	$0.933h_{11,t-1}$	−	0.028 $h_{12,t-1}$	+	0.0002 $h_{22,t-1}$	+	$0.002\varepsilon^2_{1,t-1}$	+	0.004 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.003 $\varepsilon^2_{2,t-1}$	+	0.128 $\kappa^2_{1,t-1}$	−	0.010 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.0002 $\kappa^2_{2,t-1}$
		(2.55)**		(96.42)*		(-0.34)		(1.53)		(0.41)		(0.08)		(2.14)**		(3.50)*		(-0.11)		(0.14)
$h_{22,t}$	=	3E-06	+	0.0001 $h_{11,t-1}$	−	0.019 $h_{12,t-1}$	+	$0.873h_{22,t-1}$	+	0.0001 $\varepsilon^2_{1,t-1}$	−	0.007 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.110 $\varepsilon^2_{2,t-1}$	+	0.070 $\kappa^2_{1,t-1}$	−	0.013 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.001\kappa^2_{2,t-1}$
		(1.69)***		(0.51)		(-0.71)		(28.68)*		(0.05)		(-0.09)		(3.44)*		(1.68)***		(-0.17)		(0.31)
Case 3: Volatility breaks incorporated and Thin trading adjusted																				
R_{1t}	=	-6E-05	+	$0.052R_{1,t-1}$	−	$0.008R_{2,t-1}$	+	$0.029R_{1,t-2}$	−	0.002 $R_{2,t-2}$	+	$0.056R_{1,t-3}$	−	0.013 $R_{2,t-3}$						
		(-0.43)		(2.37)**		(-0.73)		(1.73)***		(-0.23)		(3.19)*		(-1.23)						
R_{2t}	=	-0.0003	+	$0.029R_{1,t-1}$	−	$0.043R_{2,t-1}$	+	$0.139R_{1,t-2}$	−	0.054 $R_{2,t-2}$	+	$0.134R_{1,t-3}$	+	0.011 $R_{2,t-3}$						
		(-1.51)		(0.91)		(-1.61)		(7.13)*		(-1.85)***		(5.01)*		(0.57)						
$h_{11,t}$	=	9E-07	+	$0.935h_{11,t-1}$	−	0.026 $h_{12,t-1}$	+	0.0002 $h_{22,t-1}$	+	$0.002\varepsilon^2_{1,t-1}$	+	0.004 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.002 $\varepsilon^2_{2,t-1}$	+	0.136 $\kappa^2_{1,t-1}$	−	0.022 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.0009 $\kappa^2_{2,t-1}$
		(1.97)**		(62.28)*		(-0.21)		(1.20)		(0.29)		(0.07)		(1.54)		(4.42)*		(-0.17)		(0.53)

$h_{22,t}$	=	2E-06	+	2E-05$h_{11,t-1}$	−	0.008 $h_{12,t-1}$	+	0.861$h_{22,t-1}$	+	0.001$\varepsilon^2_{1,t-1}$	+	0.025 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.105 $\varepsilon^2_{2,t-1}$	+	0.085 $\kappa^2_{1,t-1}$	−	0.034 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.003$\kappa^2_{2,t-1}$
		(2.08)**		(0.18)		(-0.25)		(34.64)*		(0.26)		(0.20)		(4.19)*		(1.81)***		(-0.28)		(0.74)
Case 4: Volatility breaks and Aggregate trading volume incorporated and Thin trading adjusted																				
R_{1t}	=	-0.0003	+	0.051$R_{1,t-1}$	−	0.009$R_{2,t-1}$	+	0.030$R_{1,t-2}$	−	0.002 $R_{2,t-2}$	+	0.059$R_{1,t-3}$	−	0.014 $R_{2,t-3}$						
		(-1.36)		(2.37)**		(-0.81)		(1.39)		(-0.20)		(3.47)*		(-1.64)						
R_{2t}	=	-0.003	+	0.042$R_{1,t-1}$	−	0.068$R_{2,t-1}$	+	0.145$R_{1,t-2}$	−	0.062 $R_{2,t-2}$	+	0.146$R_{1,t-3}$	−	0.006 $R_{2,t-3}$						
		(-10.37)*		(1.38)		(-3.07)*		(3.78)*		(-1.61)		(7.33)*		(-0.30)						
$h_{11,t}$	=	6E-07	+	0.939$h_{11,t-1}$	−	0.030 $h_{12,t-1}$	+	0.0002 $h_{22,t-1}$	+	0.001$\varepsilon^2_{1,t-1}$	+	0.003 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.002 $\varepsilon^2_{2,t-1}$	+	0.139 $\kappa^2_{1,t-1}$	−	0.027 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.001$\kappa^2_{2,t-1}$
		(1.37)		(57.22)*		(-0.19)		(1.70)		(0.17)		(0.06)		(1.53)		(5.58)**		(-0.20)		(0.97)
$h_{22,t}$	=	1E-06	+	2E-05$h_{11,t-1}$	−	0.009 $h_{12,t-1}$	+	0.860$h_{22,t-1}$	+	0.002$\varepsilon^2_{1,t-1}$	+	0.025 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.097 $\varepsilon^2_{2,t-1}$	+	0.108 $\kappa^2_{1,t-1}$	−	0.053 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.007$\kappa^2_{2,t-1}$
		(0.42)		(0.17)		(-0.17)		(30.36)*		(0.22)		(0.18)		(4.31)*		(2.40)**		(-1.58)		(0.89)

Notes: *, **, *** indicate the t-statistic is significant at 1%, 5% and 10%, respectively; R_{1t} and R_{2t} are the mean equations for the main market return series and the SME market return series, respectively; $h_{11,t}$ and $h_{22,t}$ are the conditional variance equations for the main market return series and the SME market return series, respectively. Numbers below the estimated coefficients are the corresponding t-statistics (in parentheses).

Table 7: Augmented bivariate VAR asymmetric BEKK-GARCH model estimation for Thailand

Case 1: Raw returns																				
R_{1t}	=	0.0004	+	$0.014R_{1,t-1}$	+	$0.007R_{2,t-1}$	+	$0.013R_{1,t-2}$	+	0.006 $R_{2,t-2}$	+	$0.034R_{1,t-3}$	−	0.022 $R_{2,t-3}$						
		(2.27)**		(0.58)		(0.33)		(0.93)		(0.36)		(1.61)		(-1.12)						
R_{2t}	=	0.0005	+	$0.049R_{1,t-1}$	+	$0.090R_{2,t-1}$	+	$0.022R_{1,t-2}$	+	0.038 $R_{2,t-2}$	+	$0.022R_{1,t-3}$	+	0.044 $R_{2,t-3}$						
		(1.84)***		(1.96)**		(2.87)**		(1.17)		(2.30)**		(0.77)		(2.02)**						
$h_{11,t}$	=	3E-06	+	0.917 $h_{11,t-1}$	−	0.081 $h_{12,t-1}$	+	0.002 $h_{22,t-1}$	+	0.044 $\varepsilon^2_{1,t-1}$	+	0.016 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.001 $\varepsilon^2_{2,t-1}$	+	0.099 $\kappa^2_{1,t-1}$	+	0.030 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.002\kappa^2_{2,t-1}$
		(3.52)*		(32.27)*		(-0.30)		(0.85)		(1.89)***		(0.14)		(0.34)		(1.84)***		(0.21)		(0.50)
$h_{22,t}$	=	1E-05	+	0.001 $h_{11,t-1}$	+	0.051 $h_{12,t-1}$	+	0.719 $h_{22,t-1}$	+	0.003 $\varepsilon^2_{1,t-1}$	−	0.028 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.067 $\varepsilon^2_{2,t-1}$	+	0.019 $\kappa^2_{1,t-1}$	+	0.102 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.137\kappa^2_{2,t-1}$
		(2.22)**		(0.99)		(0.24)		(9.85)*		(0.48)		(-0.20)		(1.43)		(0.59)		(0.47)		(2.84)*
Case 2: Volatility breaks incorporated																				
R_{1t}	=	0.0004	+	$0.016R_{1,t-1}$	+	$0.005R_{2,t-1}$	+	$0.012R_{1,t-2}$	+	0.004 $R_{2,t-2}$	+	$0.036R_{1,t-3}$	−	0.023 $R_{2,t-3}$						
		(2.13)**		(0.58)		(0.27)		(0.63)		(0.32)		(1.67)***		(-1.21)						
R_{2t}	=	0.0005	+	$0.054R_{1,t-1}$	+	$0.088R_{2,t-1}$	+	$0.021R_{1,t-2}$	+	0.034 $R_{2,t-2}$	+	$0.024R_{1,t-3}$	+	0.045 $R_{2,t-3}$						
		(2.07)**		(1.79)***		(3.35)*		(0.97)		(1.58)		(1.06)		(2.49)**						
$h_{11,t}$	=	4E-06	+	0.913 $h_{11,t-1}$	−	0.092 $h_{12,t-1}$	+	0.002 $h_{22,t-1}$	+	0.039 $\varepsilon^2_{1,t-1}$	+	0.017 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.002 $\varepsilon^2_{2,t-1}$	+	0.126 $\kappa^2_{1,t-1}$	+	0.021 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.0009 $\kappa^2_{2,t-1}$
		(2.54)**		(25.34)*		(-0.32)		(0.68)		(1.92)***		(0.14)		(0.39)		(2.07)**		(0.18)		(0.30)
$h_{22,t}$	=	1E-05	+	0.001 $h_{11,t-1}$	+	0.062 $h_{12,t-1}$	+	0.685 $h_{22,t-1}$	+	0.004 $\varepsilon^2_{1,t-1}$	−	0.032 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.063 $\varepsilon^2_{2,t-1}$	+	0.032 $\kappa^2_{1,t-1}$	+	0.130 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.133\kappa^2_{2,t-1}$
		(1.41)		(1.21)		(0.27)		(8.72)*		(0.59)		(-0.20)		(1.41)		(0.74)		(0.50)		(3.07)*
Case 3: Volatility breaks incorporated and Thin trading adjusted																				
R_{1t}	=	0.0004	+	$0.016R_{1,t-1}$	+	$0.007R_{2,t-1}$	+	$0.011R_{1,t-2}$	+	0.004 $R_{2,t-2}$	+	$0.032R_{1,t-3}$	−	0.019 $R_{2,t-3}$						
		(1.87)***		(0.74)		(0.40)		(0.73)		(0.32)		(1.27)		(-0.95)						
R_{2t}	=	-0.0001	+	$0.064R_{1,t-1}$	+	$0.019R_{2,t-1}$	+	$0.023R_{1,t-2}$	+	0.033 $R_{2,t-2}$	+	$0.017R_{1,t-3}$	+	0.053 $R_{2,t-3}$						
		(0.24)		(3.03)*		(0.98)		(1.38)		(1.49)		(0.55)		(2.47)**						
$h_{11,t}$	=	4E-06	+	0.908 $h_{11,t-1}$	−	0.081 $h_{12,t-1}$	+	0.002 $h_{22,t-1}$	+	0.041 $\varepsilon^2_{1,t-1}$	+	0.014 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.001 $\varepsilon^2_{2,t-1}$	+	0.125 $\kappa^2_{1,t-1}$	+	0.022 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.001\kappa^2_{2,t-1}$
		(2.86)*		(31.57)*		(-0.30)		(0.82)		(1.93)		(0.14)		(0.37)		(2.16)**		(0.19)		(0.39)

$h_{22,t}$	=	1E-05	+	0.001 $h_{11,t-1}$	+	0.058 $h_{12,t-1}$	+	0.683 $h_{22,t-1}$	+	0.002 $\varepsilon^2_{1,t-1}$	−	0.025 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.062 $\varepsilon^2_{2,t-1}$	+	0.031 $\kappa^2_{1,t-1}$	+	0.136 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.149$\kappa^2_{2,t-1}$
		(1.61)		(1.04)		(0.27)		(9.64)*		(0.43)		(-0.21)		(1.49)*		(0.65)		(0.50)		(3.54)*
Case 4: Volatility breaks and Aggregate trading volume incorporated and Thin trading adjusted																				
R_{1t}	=	0.001	+	0.029$R_{1,t-1}$	−	0.003$R_{2,t-1}$	+	0.008$R_{1,t-2}$	+	0.010 $R_{2,t-2}$	+	0.031$R_{1,t-3}$	−	0.007 $R_{2,t-3}$						
		(2.40)**		(1.40)		(-0.19)		(0.42)		(0.56)		(1.82)***		(-0.33)						
R_{2t}	=	0.0003	+	0.070$R_{1,t-1}$	+	0.002$R_{2,t-1}$	+	0.022$R_{1,t-2}$	+	0.040 $R_{2,t-2}$	+	0.003$R_{1,t-3}$	+	0.081 $R_{2,t-3}$						
		(0.73)		(3.82)*		(0.10)		(0.71)		(1.40)		(0.11)*		(3.66)*						
$h_{11,t}$	=	4E-06	+	0.900 $h_{11,t-1}$	−	0.107 $h_{12,t-1}$	+	0.003 $h_{22,t-1}$	+	0.055 $\varepsilon^2_{1,t-1}$	−	0.061 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.017 $\varepsilon^2_{2,t-1}$	+	0.169 $\kappa^2_{1,t-1}$	+	0.048 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.003$\kappa^2_{2,t-1}$
		(2.10)**		(28.17)*		(-0.37)		(1.14)		(2.75)*		(-0.32)		(0.97)		(3.44)*		(0.24)		(0.64)
$h_{22,t}$	=	6E-06	+	0.002 $h_{11,t-1}$	+	0.062 $h_{12,t-1}$	+	0.626 $h_{22,t-1}$	+	0.004 $\varepsilon^2_{1,t-1}$	−	0.017 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.017 $\varepsilon^2_{2,t-1}$	+	0.046 $\kappa^2_{1,t-1}$	+	0.181 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.177$\kappa^2_{2,t-1}$
		(2.18)**		(0.83)		(0.30)		(11.71)*		(0.35)		(-0.14)		(0.43)		(1.38)		(0.52)		(3.43)*

Notes: *, **, *** indicate the t-statistic is significant at 1%, 5% and 10%, respectively; R_{1t} and R_{2t} are the mean equations for the main market return series and the SME market return series, respectively; $h_{11,t}$ and $h_{22,t}$ are the conditional variance equations for the main market return series and the SME market return series, respectively. Numbers below the estimated coefficients are the corresponding t-statistics (in parentheses).

Table 8: Augmented bivariate VAR asymmetric BEKK-GARCH model estimation for Malaysia

Case 1: Raw returns																				
R_{1t}	=	0.0001	+	$0.121R_{1,t-1}$	+	$0.009R_{2,t-1}$	+	$0.074R_{1,t-2}$	−	0.006 $R_{2,t-2}$										
		(1.17)		(6.93)*		(0.82)		(3.15)*		(-0.38)										
R_{2t}	=	-1E-04	−	$0.070R_{1,t-1}$	+	$0.079R_{2,t-1}$	+	$0.158R_{1,t-2}$	+	0.026 $R_{2,t-2}$										
		(-0.39)		(-1.61)		(3.75)*		(3.69)*		(1.12)										
$h_{11,t}$	=	1E-06	+	$0.903h_{11,t-1}$	−	0.045 $h_{12,t-1}$	+	$0.001h_{22,t-1}$	+	$0.011\varepsilon^2_{1,t-1}$	+	0.012 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.003 $\varepsilon^2_{2,t-1}$	+	0.141 $\kappa^2_{1,t-1}$	−	0.005 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	4E-05$\kappa^2_{2,t-1}$
		(3.38)*		(39.78)*		(-0.27)		(0.75)		(0.71)		(0.16)		(1.40)		(2.23)**		(-0.10)		(0.11)
$h_{22,t}$	=	9E-06	+	0.0003 $h_{11,t-1}$	−	0.031 $h_{12,t-1}$	+	$0.781h_{22,t-1}$	+	$0.001\varepsilon^2_{1,t-1}$	−	0.021 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.138 $\varepsilon^2_{2,t-1}$	+	0.201 $\kappa^2_{1,t-1}$	+	0.045 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.002\kappa^2_{2,t-1}$
		(1.55)		(0.20)		(-0.19)		(9.94)*		(0.19)		(-0.17)		(4.02)*		(1.63)		(0.37)		(0.25)
Case 2: Volatility breaks incorporated																				
R_{1t}	=	0.0001	+	$0.121R_{1,t-1}$	+	$0.009R_{2,t-1}$	+	$0.075R_{1,t-2}$	−	0.006 $R_{2,t-2}$										
		(1.30)		(6.46)		(1.01)		(3.10)*		(-0.48)										
R_{2t}	=	-0.0001	−	$0.072R_{1,t-1}$	+	$0.080R_{2,t-1}$	+	$0.160R_{1,t-2}$	+	0.026 $R_{2,t-2}$										
		(-0.46)		(-1.84)		(4.40)*		(3.89)*		(1.38)										
$h_{11,t}$	=	1E-06	+	$0.910h_{11,t-1}$	−	0.045 $h_{12,t-1}$	+	$0.001h_{22,t-1}$	+	$0.008\varepsilon^2_{1,t-1}$	+	0.011 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.004 $\varepsilon^2_{2,t-1}$	+	0.141 $\kappa^2_{1,t-1}$	−	0.006 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.0001 $\kappa^2_{2,t-1}$
		(4.46)*		(43.15)*		(-0.27)		(0.87)		(0.44)		(0.12)		(1.17)		(1.80)***		(-0.10)		(0.15)
$h_{22,t}$	=	9E-06	+	0.0002 $h_{11,t-1}$	−	0.025 $h_{12,t-1}$	+	$0.784h_{22,t-1}$	+	$0.001\varepsilon^2_{1,t-1}$	−	0.022 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.135 $\varepsilon^2_{2,t-1}$	+	0.200 $\kappa^2_{1,t-1}$	+	0.045 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	$0.003\kappa^2_{2,t-1}$
		(1.57)		(0.16)		(-0.17)		(10.00)*		(0.16)		(-0.16)		(3.40)*		(1.64)		(0.45)		(0.31)
Case 3: Volatility breaks incorporated and Thin trading adjusted																				
R_{1t}	=	0.0001	+	$0.125R_{1,t-1}$	+	$0.007R_{2,t-1}$	+	$0.073R_{1,t-2}$	−	0.004 $R_{2,t-2}$										
		(1.15)		(6.21)*		(0.93)		(2.62)**		(-0.35)										
R_{2t}	=	-0.0003	−	$0.063R_{1,t-1}$	−	$0.004R_{2,t-1}$	+	$0.180R_{1,t-2}$	+	0.016 $R_{2,t-2}$										
		(-0.99)		(-1.41)		(-0.19)		(6.02)*		(0.75)										
$h_{11,t}$	=	1E-06	+	$0.915h_{11,t-1}$	−	0.042 $h_{12,t-1}$	+	0.0005 $h_{22,t-1}$	+	$0.005\varepsilon^2_{1,t-1}$	+	0.008 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.003 $\varepsilon^2_{2,t-1}$	+	0.132 $\kappa^2_{1,t-1}$	+	0.002 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	1E-05$\kappa^2_{2,t-1}$

		(4.73)*		(32.50)*		(-0.24)		(0.69)		(0.22)		(0.10)		(0.81)		(1.53)		(0.07)		(0.05)
$h_{22,t}$	=	1E-05	+	2E-05$h_{11,t-1}$	−	0.008 $h_{12,t-1}$	+	0.775$h_{22,t-1}$	+	0.003$\varepsilon^2_{1,t-1}$	−	0.041 $\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	+	0.146 $\varepsilon^2_{2,t-1}$	+	0.212 $\kappa^2_{1,t-1}$	+	0.071 $\kappa_{1,t-1}\kappa_{2,t-1}$	+	0.006$\kappa^2_{2,t-1}$
		(1.45)		(0.05)		(-0.09)		(10.82)*		(0.24)		(-0.24)		(4.06)*		(1.31)		(0.38)		(0.41)

Notes: *, **, *** indicate the t-statistic is significant at 1%, 5% and 10%, respectively; R_{1t} and R_{2t} are the mean equations for the main market return series and the SME market return series, respectively; $h_{11,t}$ and $h_{22,t}$ are the conditional variance equations for the main market return series and the SME market return series, respectively. Numbers below the estimated coefficients are the corresponding t-statistics (in parentheses). Case 4 (analysis using thin trading adjusted return series and incorporating detected volatility breaks and aggregate trading volume into the model) is not reported because the model did not satisfy the condition of covariance stationarity and the ARCH effect in the residuals persists (see Table 9).

Table 9: Augmented bivariate VAR asymmetric BEKK-GARCH model diagnostics

Country	Case	M-Q(10)	M-Q(20)	M-ARCH(10)	M-ARCH(20)	$\alpha_{11}^2 + \beta_{11}^2$	$\alpha_{22}^2 + \beta_{22}^2$
Hong Kong	1	41.14	91.42	133.73*	210.21***	0.94	0.93
	2	45.06	94.83	131.35*	202.34	0.94	0.92
	3	45.39	95.43	131.68*	202.52	0.94	0.92
	4	42.82	87.87	104.46	172.45	0.95	0.80
Singapore	1	42.04	70.48	70.81	185.13	0.94	0.99
	2	42.65	71.77	70.38	186.68	0.93	0.98
	3	45.64	72.57	77.90	186.21	0.94	0.97
	4	43.41	71.94	76.85	184.22	0.94	0.96
Thailand	1	41.69	82.74	61.18	106.05	0.96	0.79
	2	39.78	80.94	64.34	108.41	0.95	0.75
	3	41.38	81.91	63.80	108.87	0.95	0.74
	4	36.25	76.13	67.90	111.34	0.96	0.64
Malaysia	1	39.69	77.54	131.37*	202.75	0.91	0.92
	2	39.93	77.65	132.26*	203.23	0.92	0.92
	3	41.49	79.28	132.12*	200.89	0.92	0.92
	4	46.90	86.76	162.85*	258.33*	1.06	0.25

*, *** indicate the test statistic is significant at 1% and 10%, respectively; Case 1 refers to analysis using raw return series in modelling; Case 2 refers to analysis incorporating detected volatility breaks into the model; Case 3 refers to analysis using thin trading adjusted return series and incorporating detected volatility breaks into the model; Case 4 refers to analysis using thin trading adjusted return series and incorporating detected volatility breaks and aggregate trading volume into the model; M-Q(q) is multivariate statistics of the Ljung-Box test for serial correlation up to lag q in the residuals; M-ARCH(q) is multivariate statistics of the Engle ARCH test for conditional heteroscedasticity up to lag q in the residuals; α_{ii} and β_{ii} are diagonal elements of the A and B matrices of the model.

Table 10: Pairwise Granger Causality Test for Hong Kong

Null Hypothesis	Observation (monthly)	F-Statistic	Causal relation
RM does not Granger Cause RYG	75	1.98**	RM → RYG
RYG does not Granger Cause RM		0.52	
RM does not Granger Cause RKG	74	2.14**	RM → RKG
RKG does not Granger Cause RM		0.63	
RM does not Granger Cause RPG	75	1.83***	RM → RPG
RPG does not Granger Cause RM		0.77	
RM does not Granger Cause RWG	88	2.85***	RM → RWG
RWG does not Granger Cause RM		1.95	

, * indicate the test statistic is significant at 5% and 10%, respectively; RM is the main market return; RYG is real GDP growth; RKG is growth of real physical capital stock; RPG is real productivity growth; RWG is real wage growth.

Table 11: Johansen Cointegration Rank test for Hong Kong

Hypothesised	RM – RYG		RM – RKG		RM – RPG		RM – RWG	
No. of Cointegration Equation(s)	Trace Statistic	Max-Eigen Statistic	Trace Statistic	Max-Eigen Statistic	Trace Statistic	Max-Eigen Statistic	Trace Statistic	Max-Eigen Statistic
None	34.59*	25.61*	28.92*	24.73*	46.37*	27.39*	42.43*	26.12*
At most 1	8.98*	8.98*	4.19**	4.19**	18.98*	18.98*	16.31*	16.31*

*, ** indicate the test statistic is significant at 1% and 5%, respectively; RM is the main market return; RYG is real GDP growth; RKG is growth of real physical capital stock; RPG is real productivity growth; RWG is real wage growth. Both Trace test and Max-eigenvalue test indicate 2 cointegrating equations at 5% level.

Appendix A: Descriptive statistics

	Hong Kong			Singapore			Thailand			Malaysia		
	R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t
Obs.	1,853	1,853	1,853	1,884	1,884	1,884	1,832	1,832	1,832	1,849	1,849	1,849
Mean	0.0001	-0.0003	0.0255	0.0001	-0.0005	0.0118	0.0005	0.0006	0.0058	0.0003	0.0001	0.0081
Median	0.0002	0.0003	0.0229	0.0004	-0.0005	0.0100	0.0009	0.0014	0.0050	0.0005	0.0001	0.0074
Std. Dev.	0.012	0.015	0.011	0.008	0.015	0.006	0.011	0.012	0.003	0.006	0.012	0.003
Skewness	-0.3	1.0	2.5	-0.4	-0.3	2.8	-0.3	-0.9	1.6	-0.4	-0.5	1.2
Kurtosis	5.0	75.3	13.8	5.3	7.0	17.6	6.4	9.9	6.3	6.3	7.2	5.5
Jarque-Bera	332*	403,695*	10,868*	473**	1,254*	19,207*	922*	3,816*	1,592*	884*	1,399*	900*
Q(10)	6.3	79.6*	4,614.0*	22.8*	80.9*	7,980.3*	12.8	25.5*	10,829.5*	41.1*	31.6*	7,086.0*
Q(20)	27.4**	108.9*	6,930.4*	39.1*	91.7*	12,335.1*	26.7**	32.0**	18,892.3*	49.5*	46.2*	10,981.7*
$Q^2(10)$	307.2*	502.3*	2,829.7*	584.5*	416.1*	5,079.7*	408.6*	329.0*	8,238.5*	371.2*	313.9*	5,083.5*
$Q^2(20)$	514.8*	509.6*	4,204.0*	916.5*	771.4*	7,712.1*	515.3*	338.0*	13,590.8*	506.7*	351.7*	7,608.2*
ARCH(5)	24.8*	78.1*	209.6*	40.1*	44.8*	453.9*	38.2*	38.5*	837.0*	38.9*	31.7*	463.7*
ARCH(10)	16.1*	40.1*	108.9*	27.7*	24.7*	270.2*	21.9*	19.4*	432.1*	21.3*	19.2*	235.0*

*, ** indicate the test statistic is significant at 1% and 5%, respectively; R_{1t} and R_{2t} denote daily returns of the Main market and SME market, respectively; ATV_t denotes daily aggregate traded volumes of the Main market and the SME market (in trillion shares for Thailand and 100 billion shares for other countries); JB represents Jarque-Bera statistic; Q and Q^2 are statistics of the Ljung-Box test for autocorrelation in return series and squared return series, respectively; ARCH represents the Engle's Autoregressive Conditional Heteroscedasticity statistic.

Appendix B: Tests for stationarity

		Hong Kong			Singapore			Thailand			Malaysia		
		R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t	R_{1t}	R_{2t}	ATV_t
ADF	C	-42.41*	-25.79*	-7.13*	-40.95*	-51.03*	-4.79*	-41.50*	-39.29*	-4.76*	-37.74*	-27.24*	-7.86*
	C&T	-42.40*	-25.79*	-7.34*	-40.98*	-51.06*	-4.79*	-41.55*	-39.29*	-5.07*	-37.85*	-27.24*	-8.89*
PP	C	-42.40*	-37.19*	-28.56*	-41.22*	-50.54*	-13.46*	-41.49*	-39.41*	-9.80*	-37.81*	-40.63*	-13.65*
	C&T	-42.40*	-37.19*	-28.88*	-41.21*	-50.57*	-13.46*	-41.56*	-39.40*	-10.92*	-37.95*	-40.60*	-15.61*
NP – C	MZ_{α}^{d}	-12.01**	-14.48*	-71.36*	-15.24*	-75.64*	-130.41*	-71.22*	-26.42*	-90.39*	-20.75*	-8.28**	-215.24*
	MZ_{t}^{d}	-2.38**	-2.69*	-5.96*	-2.73*	-6.15*	-8.07*	-5.95*	-3.59*	-6.72*	-3.22*	-1.99**	-10.37*
	MSB^{d}	0.20**	0.19*	0.08*	0.18**	0.08*	0.06*	0.08*	0.14*	0.07*	0.16*	0.24**	0.05*
	MP_{T}^{d}	2.34**	1.70*	0.36*	1.74**	0.33*	0.19*	0.39*	1.07*	0.28*	1.18*	3.13**	0.12*
NP – C&T	MZ_{α}^{d}	-26.89*	-30.33*	-181.05*	-38.25*	-18.98**	-212.31*	-184.67*	-66.39*	-191.80*	-120.22*	-20.04**	-370.33*
	MZ_{t}^{d}	-3.66*	-3.89*	-9.50*	-4.37*	-3.07**	-10.30*	-9.61*	-5.76*	-9.78*	-7.75*	-3.16**	-13.60*
	MSB^{d}	0.14**	0.13*	0.05*	0.11*	0.16**	0.05*	0.05*	0.09*	0.05*	0.06*	0.16**	0.04*
	MP_{T}^{d}	3.40*	3.06*	0.53*	2.40*	4.89**	0.45*	0.50*	1.38*	0.51*	0.77*	4.58**	0.25*

*, ** indicate the test statistic is significant at 1% and 5%, respectively; R_{1t} and R_{2t} denote daily returns of the Main market and SME market, respectively; ATV_t denotes daily aggregate traded volumes of the Main market and SME market; C represents constant; C&T represents constant and trend; MZ_{α}^{d}, MZ_{t}^{d}, MSB^{d} and MP_{T}^{d} represents the four test statistics of the Ng-Perron unit root test.