Reexamining the time-varying volatility spillover effects: A Markov switching causality approach

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\textbf{ABSTRACT}

This paper intends to examine the volatility spillover effect between selective developed markets including U.S., U.K., Germany, Japan and Hong Kong over the sample period from 1996 to 2011. We introduce a Markov switching causality method to model the potential instability of volatility spillover relationships over market tranquil or turmoil periods. This method is more flexible as no prior information on the changing points or size of sample window is needed. From the empirical results, we find the evidence of the existence of spillover effects among most markets, and the bilateral volatility spillover effects are more prominent over turmoil or crisis episodes, especially during Asia crisis and subprime mortgage crisis periods. Moreover, the distinct role of each market is also investigated.

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1. Introduction

Financial market of one country is more likely to be influenced by others during turmoil periods, which is often labeled as the volatility spillover effect.\textsuperscript{1} In the Asian crisis of 1997–1998, researchers

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\textsuperscript{1} Another related concept is “contagion” or “volatility contagion”, for which there is no consensus on the definition in the literature so far. In Forbes and Rigobon (2002), they define “contagion” as largely unpredictable and higher correlation during

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and investors began to witness the transmission of volatility shocks from emerging markets to developed ones. More recently, the subprime mortgage crisis of 2007–2009 provided convincing evidence that volatility spillover induced widespread fears across markets, and also impacted the real economy enormously. Therefore, a careful examination of the phenomena and the mechanism behind is of great importance for market participants and policy makers.

In view of the importance of volatility spillover relationship, many approaches have been adopted in the literature to address this issue, and the most commonly used concept of volatility spillover is in the sense of Granger causality (Granger, 1969, 1980), which emphasizes the influence of past shocks of one market on the current volatility of another. First, the most common approach is the linear vector autoregressive regression (VAR) method using direct or estimated volatility proxies. For example, Eun and Shim (1989) investigate the transmission mechanism of stock market movements through a nine-market VAR model. Moreover, Soydemir (2000) utilizes a four-variable VAR model to capture the comovement between developed and emerging markets. Furthermore, Hammoudeh, Li, and Jeon (2003) find evidence of spillover effects in crude oil, gasoline, and heating oil markets, particularly in nearby futures contracts and spot prices. Using price range as volatility proxy, Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) develop the volatility spillover index under the simple or the generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). Second, parametric models for conditional variance can also be employed to account for volatility transmission between different markets. Engle, Ito, and Lin (1990) and Hamao, Masulis, and Ng (1990) are among the first to use univariate generalized autoregressive conditional heteroscedastic (GARCH) model in two stages to study the volatility spillover effect. Equipped with multivariate GARCH model, Booth, Martikainen, and Tse (1997) provide evidence on the volatility spillover among four Scandinavian stock markets, and Ng (2000) studies the volatility spillover effect from Japan and U.S. to six Pacific-Basin stock markets. Malik and Hammoudeh (2007) further explore the volatility and shock transmission mechanism among U.S. equity, global crude oil market, and equity markets of Saudi Arabia, Kuwait, and Bahrain. Chang et al. (2012) investigate the conditional correlations and volatility spillovers between crude oil returns and stock index returns. Moreover, based on a regime switching ARCH model, Edwards and Susmel (2001) find that the periods of high volatility, or the high volatility regimes, tend to roughly coincide across several emerging markets. In addition, Engle, Gallo, and Velucchi (2012) consider a range based multiplicative error model (MEM), and find that the parameters shift during the currency crisis, making the system more unstable.

However, the time-invariant spillover effect or stable Granger causality relationship assumed in most of the previous studies is problematic. In macroeconomic applications, Thoma (1994) and Swanson (1998) notice the sensitivity of causality test results with respect to different sample periods. In financial markets, the interdependence can also be unstable and even time dependent. For instance, Gallo and Velucchi (2009) emphasize the instability of the volatility spillover effects across markets before or after the 1997 crisis. If we still assume constant causality relationship, the conclusion might be unconvincing or even misleading. In practice, researchers try to deal with this issue by introducing dummy variables or splitting the samples. For example, Gallo and Velucchi (2009) adopt the MEM model to analyze the interdependence of volatility across seven East Asian markets, and estimate the model on four subperiods: early periods including and excluding the Asia crisis, and recent periods including and excluding the Asia crisis. Moreover, Engle et al. (2012) introduce two dummy variables for the crisis and the post-crisis periods during Asia crisis episode, and

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1. Crises times compared with normal times. They find that under heteroscedastic conditions, the estimates of the correlation coefficient in the high volatility regime are upward biased. After adjusting for this bias, they do not find significant increase in unconditional correlation coefficients during 1997 Asian crisis, 1994 Mexican devaluation, and 1987 U.S. market crash. For more empirical tests of contagion, please refer to Pericoli and Sbracia (2003), Dungey, Fry, González-Hermosillo, and Martin (2005) and the references therein.
2. In the literature, volatility spillover can also be interpreted as dependence between high or low volatility regimes. For instance, Sola, Spagnolo, and Spagnolo (2002) test whether a market leads the other in and out of a period of crisis, and Gallo and Otranto (2008) also define influence of past state of variable X on current state of variable Y as evidence in favor of spillover from X to Y.

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Gebka (2012) also divides the sample from January 1990 to November 2003 into three subperiods. Nevertheless, this kind of practice relies on ex post information to identify times of crisis and is inevitably arbitrary, because the time line of spillover effects dynamics may vary over different markets. Moreover, if we try to address the spillover effect over a relatively longer sample period covering many turmoil periods, this approach is much less useful due to the modeling complexity caused by too many dummy variables. As another solution to instability of spillover relationships, Diebold and Yilmaz (2009) and Diebold and Yilmaz (2012) choose the fixed window of observations to obtain the rolling sample spillover index based on VAR models. In a related study, Zhou, Zhang, and Zhang (2012) apply the method in Diebold and Yilmaz (2012) to the relationship between China and world equity markets. They conduct empirical analysis with respect to 100, 500, and 1000 days rolling sample, and find that 100-day rolling sample is too volatile to reveal any meaningful pattern, thereby primarily relying on 500-day and 1000-day rolling samples. However, this approach omits the full sample information, and a fixed window of rolling sample is still arbitrary, as the length of the window may be too short to provide reliable estimates, or too long to capture abrupt changes.

In contrast to most existing studies that rely on ex post information to identify periods of crisis, or rolling method with fixed window, we try to address how the spillover relationship vary over multiple turbulent and calm periods. In this paper, we adopt the framework of Markov switching causality (MSC) approach developed in Psaradakis, Ravn, and Sola (2005) and explore its implication in volatility spillover study. This approach relies on a VAR model with time-varying parameters to reflect changes in causality pattern between two variables of interest. As the changes in causal links are typically unknown a priori, this method avoids the choices of window size for causality, and further allows for possibly multiple structural changes. In the Markov switching framework, possible structural changes are endogenously governed by a first order hidden Markov process, and the time-varying causality pattern is reflected by the inferred probabilities of regime, which is recovered by the Hamilton filter (Hamilton, 1989). In the empirical result, we consider the interdependence of the daily log range as volatility proxy among selected developed markets, including U.S., U.K., Germany, Japan, and Hong Kong. The instability of the volatility spillover effect is firstly demonstrated through a linear Granger causality test, and the effect does vary across several subperiods. The Markov switching causality model further provides the evidence that there exist regime shifts in the causality pattern, and the spillover effect is more evident during high volatility periods, especially at times of crisis.

The rest of this paper is organized as follows. Section 2 introduces the econometric specification of the Markov switching causality model and its estimation. Sections 3 and 4 present the data and the empirical results. Finally, Section 5 concludes.

2. Econometric methodology

The Granger causality test of Granger (1969) and Granger (1980) is based on a VAR system to explore whether past information of additional variable has predictive power. Denote $h_t$ a bivariate time series consisting of the volatility proxy (log range in this study) of two markets, i.e., $h_t = (h_{1t}, h_{2t})$, which is assumed to follow the VAR model of order $p$:

$$
\begin{bmatrix}
h_{1t} \\
h_{2t}
\end{bmatrix} = \begin{bmatrix}
\omega_1 \\
\omega_2
\end{bmatrix} + \sum_{l=1}^{p} \begin{bmatrix}
\alpha_1^{(l)} \\
\alpha_2^{(l)}
\end{bmatrix} \begin{bmatrix}
h_{1t-l} \\
h_{2t-l}
\end{bmatrix} + \begin{bmatrix}
\epsilon_{1t} \\
\epsilon_{2t}
\end{bmatrix}
$$

(1)

where $t = 1, \ldots, T, \epsilon_t = (\epsilon_{1t}, \epsilon_{2t})' \sim N(0, \Sigma)$ with $\Sigma$ being positively definite variance-covariance matrix. The null hypothesis that $h_{1t}$ does not Granger cause $h_{2t}$ is equivalent to test $H_0: \beta_2^{(l)} = 0, l=1, \ldots, p$. Similarly, the null hypothesis that $h_{2t}$ does not Granger cause $h_{1t}$ can be expressed as $H_0: \beta_1^{(l)} = 0, l=1, \ldots, p$.

As mentioned in the introduction, it is well documented in empirical studies that the causal relationship is sample dependent. The instability or potentially endogenous structural breaks and/or structural changes are responsible for such phenomena, and there are several ways to deal with
it in the literature. For example, Christopoulos and León-Ledesma (2008) use a logistic smooth transition autoregressive (LSTAR) model to capture a single smooth shift in causality, which is appropriate in some macroeconomic cases when a one-off structural break would happen due to a permanent shock or change in macroeconomic policy. However, in the case of financial market over a long time span, different patterns of causality tend to occur repeatedly and changes from one regime to another can be abrupt and multiple, invalidating the application of the above approach.

In our study, the Markov switching causality model proposed by Psaradakis et al. (2005) is adopted as follows:

$$\begin{bmatrix} h_{1t} \\ h_{2t} \end{bmatrix} = \begin{bmatrix} \omega_{10} + \omega_{11} S_{1t} \\ \omega_{20} + \omega_{21} S_{2t} \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \alpha_{10} + \alpha_{11} S_{1t} & \beta_{11} S_{1t} \\ \beta_{21} S_{2t} & \alpha_{20} + \alpha_{21} S_{2t} \end{bmatrix} \begin{bmatrix} h_{1t-1} \\ h_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$  \tag{2}

where \( t = 1, \ldots, T, S_{1t} \) and \( S_{2t} \) are two discrete variables taking values of 0 or 1. We further assume that \( S_{1t} \) and \( S_{2t} \) follow time-homogeneous, first-order Markov chains with transition probabilities given as:

$$p^{(k)} = \begin{bmatrix} p_{00}^{(k)} & 1 - p_{11}^{(k)} \\ 1 - p_{00}^{(k)} & p_{11}^{(k)} \end{bmatrix}$$  \tag{3}

where \( p_{ij}^{(k)} = Pr(S_{kt} = j | S_{k,t-1} = i) \) denotes the transition probability of moving from state \( S_{k,t-1} = i \) at time \( t - 1 \) to the state \( S_{kt} = j \) at time \( t \), for \( i, j = 0, 1 \), and \( k = 1, 2 \).

The discrete state of the system, \( S_{t} \), switches between four regimes:

$$S_{t} = \begin{cases} 1 & \text{if } S_{1t} = 1 \text{ and } S_{2t} = 1 \\ 2 & \text{if } S_{1t} = 0 \text{ and } S_{2t} = 1 \\ 3 & \text{if } S_{1t} = 1 \text{ and } S_{2t} = 0 \\ 4 & \text{if } S_{1t} = 0 \text{ and } S_{2t} = 0 \end{cases}$$  \tag{4}

Under the assumption that \( S_{1t} \) and \( S_{2t} \) are independent, the transition probability matrix for \( S_{t} \) can be calculated accordingly:

$$P^{*} = \begin{bmatrix} p_{00}^{(1)} p_{00}^{(2)} & p_{00}^{(1)} (1 - p_{11}^{(1)}) & p_{00}^{(1)} (1 - p_{11}^{(2)}) & (1 - p_{11}^{(1)}) (1 - p_{11}^{(2)}) \\ p_{00}^{(2)} (1 - p_{11}^{(1)}) & p_{00}^{(2)} (1 - p_{11}^{(2)}) & (1 - p_{11}^{(1)}) (1 - p_{11}^{(2)}) & (1 - p_{11}^{(1)}) (1 - p_{11}^{(2)}) \\ p_{11}^{(1)} p_{00}^{(1)} & p_{11}^{(1)} p_{00}^{(2)} & (1 - p_{11}^{(1)}) (1 - p_{11}^{(2)}) & (1 - p_{11}^{(1)}) (1 - p_{11}^{(2)}) \\ (1 - p_{00}^{(1)}) (1 - p_{11}^{(1)}) & (1 - p_{00}^{(2)}) (1 - p_{11}^{(1)}) & (1 - p_{00}^{(1)}) (1 - p_{11}^{(2)}) & (1 - p_{00}^{(2)}) (1 - p_{11}^{(2)}) \end{bmatrix}$$  \tag{5}

Additionally, the variance–covariance matrix of the error term is specified in most general form as:

$$\Sigma_{S_{t}} = \begin{bmatrix} \sigma_{i,j} S_{t} \end{bmatrix}_{i,j = 1, 2, 3, 4}, \text{ and we rewrite } \sigma_{i,j} S_{t} \text{ as } \sigma_{i,j}^{2} S_{t} \text{ for } i = j, \text{ and } \sigma_{i,j} S_{t} \text{ as } \rho_{i,j} S_{t} S_{t} \text{ for } i \neq j, \text{ allowing the correlation coefficient } \rho \text{ to be regime dependent.}$$  \tag{6}

In order to compare with the linear VAR system of Eq. (1), the MSC model of Eq. (2) when \( S_{t} \) taking different values is explicitly expressed as:

$$\begin{bmatrix} h_{1t} \\ h_{2t} \end{bmatrix} = \begin{bmatrix} \omega_{10} + \omega_{11} \\ \omega_{20} + \omega_{21} \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \alpha_{10} + \alpha_{11} S_{1t} & \beta_{11} S_{1t} \\ \beta_{21} S_{2t} & \alpha_{20} + \alpha_{21} S_{2t} \end{bmatrix} \begin{bmatrix} h_{1t-1} \\ h_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}, \text{ if } S_{t} = 1 \text{.}$$  \tag{7}
Obviously, the causal link between $h_{1t}$ and $h_{2t}$ is captured by the latent state variable $S_{1t}$ and $S_{2t}$. In particular, under the assumption that at least one of the parameters $\beta_{l2}^{(l)}, l=1, \ldots, p$, is not zero, $h_{1t}$ is the Granger cause of $h_{2t}$ when $S_{2t} = 1$. Similarly, if at least one of the parameters $\beta_{l1}^{(l)}, l=1, \ldots, p$, is not zero, $h_{2t}$ is the Granger cause of $h_{1t}$ when $S_{1t} = 1$. Different combinations of $S_{1t}$ and $S_{2t}$, as in Eq. (4) further provide the meaning of $S_{t}$. When $S_{t} = 4$, Eq. (9) is identical to Eq. (1) under the null hypothesis that there is no causal link between $h_{1t}$ and $h_{2t}$. When $S_{t} = 3$, if at least one of the parameters of $\beta_{l1}^{(l)}$ is not zero, we say $h_{2t}$ does Granger cause $h_{1t}$, but not vice versa. The probabilities of this one-way causal link from $h_{2t}$ to $h_{1t}$, are reflected by the probabilities of the regime $S_{t} = 3$. Moreover, the constant term and the autoregressive coefficients of lag $l$ change from $\omega_{10}$ to $\omega_{10} + \omega_{11}$ and from $\alpha_{10}^{(l)}$ to $\alpha_{10}^{(l)} + \alpha_{11}^{(l)}$, respectively, to accommodate possible shifts in parameters when the regime switches from $S_{t} = 4$ to $S_{t} = 3$. In a similar vein, Eq. (7) captures the one-way causal link from $h_{1t}$ to $h_{2t}$ and the likelihood of this link is reflected by probabilities of regime $S_{t} = 2$. Lastly, when $S_{t} = 1$, Eq. (6) examines the two-way causal link between $h_{1t}$ and $h_{2t}$. The filtered or smoothed probabilities of the state can capture the time-varying spillover relationship depending on the condition of financial markets.

Finally, the parameters of the Markov switching causality model are estimated following the Expected Maximization algorithm originally introduced by Dempster, Laird, and Rubin (1977), and further illustrated for the Markov switching model in Hamilton (1990) and Kim and Nelson (1999).

3. Data and summary statistics

In the empirical analysis, we choose five markets: U.S., U.K., Germany, Japan and Hong Kong, one in North America, two in Europe, including the largest economy inside and outside the Euro Zone and two in Asia. All of those markets are popular choices as representatives of developed markets(e.g., Brière, Chapelle, & Szafran, 2012; Diebold & Yilmaz, 2009), and the role of Hong Kong in Asian financial crisis and global market has been emphasized by Forbes and Rigobon (2002), Gallo and Velucchi (2009), Diebold and Yilmaz (2009), and Engle et al. (2012), among many others. Of course, an extensive study of more international markets, especially the emerging markets is also of interest, and we leave it to further studies.

The volatility proxy considered here is log range, which is calculated as $\log(\log(H_{t}) - \log(L_{t}))$, where $H_{t}$ and $L_{t}$ denote the highest and lowest prices of stock indices within each day. As mentioned in Parkinson (1980), range is at least four times more efficient than squared return in terms of mean squared error. Moreover, Alizadeh, Brandt, and Diebold (2002) find that the range is robust
to microstructure noise and the distribution of log range is close to normal.\textsuperscript{4} We choose S&P 500, FTSE 100, DAX 30, Nikkei 255, and Hang Seng index as representative indices for each market, and sample period spans from January 2, 1996 to December 30, 2011.\textsuperscript{5} In order to deal with the issue of trading in different time zones, the ranges of the Nikkei 225 and Hang Seng indices are matched with the lagged values of others.\textsuperscript{6} It should be noted that our result is mainly based on the log range as volatility proxy and there are other choices, for example, the realized volatility measure of Andersen, Bollerslev, and Diebold (2003), among many others. However, dictated by data availability, we stick to the choice in this paper and applications using other proxies are left to further studies.

The time series plot is provided in Fig. 1. We can find that the first common insurgence of volatility level occurred in late 1997, especially in October 1997, when the crash of Hong Kong stock market caused serious worries among investors all over the world. After 2000, the burst of “internet bubble” and the 9/11 terrorist attacks kept the U.S. stock market to stay at a high volatility level and the U.K. and Germany markets were also closely correlated with U.S. market during this period. After a relatively calm period from 2004 to 2006 for most of markets, the worries of subprime mortgage market started to emerge in July–August 2007, and quickly spread to the rest following the collapse of Lehman Brothers in September 2008. Starting from late 2009 or early 2010, the European sovereign debt crisis began to influence the stock markets, but its impact differed among the selected markets. For the stock market of U.S., U.K., the volatility surged shortly after the beginning of 2010, when the fiscal deficit and sovereign debt of Greece became the concern in the market, and reached a much higher level in August 2011, when the U.S. debt ceiling issue, subsequent downgrading of U.S. credit rating by Standard & Poor’s, and renewed concern about Euro zone crisis created extreme uncertainty in the market. For Germany, its response to the early signs of European sovereign debt crisis was less pronounced, as the volatility increased significantly only in the second half of 2011. For Asian markets, Hong Kong market’s response to European sovereign debt crisis was similar to Germany. On the other hand, the volatility of Japan increased in March 2011 as a consequence of earthquake and nuclear crisis, but did not grow as much as others since then.\textsuperscript{7}

The summary statistics and Pearson correlation matrix are reported in Table 1. The average volatility level of U.S. and U.K. is relatively lower compared with Germany, Japan and Hong Kong. The skewness and excess kurtosis of all the log range series are relatively small, which confirm the approximate normality of log range series. For the correlation matrix, the three North American and European markets are closely correlated with pairwise correlation coefficients around 0.70. On the other hand, the correlation between two Asian markets is 0.43, and their correlation with the other three markets is also around 0.40.

4. Empirical results

Japan and Hong Kong markets. For example, for US–UK pair, we let $h_{1t}$ and $h_{2t}$ to be the daily log range of U.S. and U.K. markets, respectively, and estimate the linear VAR model of Eq. (1) and Markov switching causality model of Eq. (2) accordingly. This procedure is repeated for other pairs.

4.1. Linear Granger causality test

To highlight the time-varying behavior of the volatility spillover effect, Table 2 reports the result of linear Granger causality test for the full sample and six subsamples. The split of the sample is inevitably arbitrary. In general, we try to keep the periods of financial crisis together and restrict the length of subperiod to be less than or equal to three years. Row name of $X \rightarrow Y$ indicates that whether $X$ is the Granger cause of $Y$ is under investigation for this row. The figures are the $p$-values of the $F$-test under the null hypothesis that market $X$ is not the Granger cause of market $Y$. The optimal lags of the VAR model selected through Schwartz Information Criterion (SIC) are also reported. From Table 2, we can find that for the full sample, most of the $p$-values are smaller than 0.01, supporting the existence of volatility spillover relationship in the full sample. The largest $p$-value appears under the null hypothesis that there is no spillover effect from Germany to Hong Kong, which is greater than 0.10.
Table 1
Summary statistics and correlation matrix.

<table>
<thead>
<tr>
<th>Panel A: Summary statistics</th>
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<tr>
<td>Market</td>
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<tr>
<td>US</td>
</tr>
<tr>
<td>UK</td>
</tr>
<tr>
<td>GE</td>
</tr>
<tr>
<td>JP</td>
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<td>HK</td>
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<table>
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<tr>
<th>Panel B: Correlation matrix</th>
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<tbody>
<tr>
<td>Market</td>
</tr>
<tr>
<td>US</td>
</tr>
<tr>
<td>UK</td>
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<td>GE</td>
</tr>
<tr>
<td>JP</td>
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<tr>
<td>HK</td>
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</tbody>
</table>

Note: This table reports the summary statistics and correlation matrix for the daily log range of S&P 500 index of U.S. market (US), FTSE 100 index of U.K. market (UK), DAX 30 index of Germany market (GE), Nikkei 255 index of Japan market (JP), and Hang Seng index of Hong Kong market (HK).

Table 2
Linear Granger causality test.

<table>
<thead>
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<th>Market</th>
<th>Full sample</th>
<th>Subsamples</th>
</tr>
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Note: This table reports the results of linear Granger causality test for different markets over full sample and six subsample periods. US, UK, GE, JP, and HK denote the U.S., U.K., Germany, Japan and Hong Kong markets. Row name of X → Y indicate that whether X is the Granger cause of Y is under investigation for this row. The figures are the p-values of the F-test under the null hypothesis that market X is not the Granger cause of market Y. The numbers in brackets are the optimal lags of the VAR model selected through SIC.
and not decisive to reject the null. Most importantly, this table reveals that for different subperiods, the significance level of $t$-statistics is unstable. For all of the 20 pairs of Granger causality under test, the number of insignificant $t$-statistics at 10% level is 2 for 2007–2009 period, 3 for 1996–1998 period, and 5 for 2010–2011 period. For these three periods, at least one major financial crisis occurred, including the subprime mortgage crisis, Asian crisis, and European sovereign debt crisis. For the other three periods, the number of insignificant $t$-statistics increases to 6 for 2002–2004 period, 11 for 1999–2001 period, and 12 for 2005–2006 period. Overall, the results of linear Granger causality test reveal that the causal links are indeed sample dependent, and the spillover effects are more evident during periods of turmoil.

4.2. Estimation result of the Markov switching causality model

The parameters estimates of Markov switching causality model for each pair of markets are reported in Table 3. From this table, we can find that, first, for ten market pairs, the estimates of the transition probabilities $P_{11}^{(1)}, P_{00}^{(1)}, P_{11}^{(2)},$ and $P_{00}^{(2)}$ are all greater than 0.90, most of them are larger than 0.99, which indicates that both state variables are persistent and tend to stay at the same regime for a relatively long time. This finding supports the view that once a market begins to influence the other due to some financial events or shocks, the impact does not disappear shortly.

Second, most of the estimated coefficients terms are significant, indicating parameter shifts under different regimes. More specifically, $\omega_{11}$ and $\omega_{21}$ reflect shifts in constants, and $\alpha_{11}^{(l)}, \alpha_{21}^{(l)}, \beta_{1}^{(l)},$ and $\beta_{2}^{(l)}$ measure the changes of autocorrelation or spillover effect from others. To save space, we only report the sums of $\alpha_{10}^{(l)} + \alpha_{11}^{(l)} + \alpha_{20}^{(l)} + \alpha_{21}^{(l)}$, and the detailed estimates of $\beta_{1}^{(l)}$ and $\beta_{2}^{(l)}$ are presented in Table 4.

Third, the estimates of $\sigma_{i,S_t}$, $i = 1, 2$, $S_t = 1, 2, 3, 4$ demonstrate that the “volatility of volatility” is also regime dependent. This finding is broadly consistent with Corsi, Mittnik, Pigorsch, and Pigorsch (2008), who also provide evidences that the “volatility” of realized volatility is time-varying.

Fourth, the estimates of regime dependent correlation coefficient $\rho_{1}$ are almost all positively significant at 1% level with only one exception of HK–GE pair. For other regimes, the significance or the signs of $\rho$ are not consistent and less conclusive. Since the first regime ($S_t = 1$) represents the time when there exists two-way causal link between two markets, this implies that the two markets tend to be more contemporaneously correlated when interactions are intense. Edwards and Susmel (2001) also find that the correlations are state-dependent, and during the high volatility episodes related to international crises, correlations between Mexico and several other Latin American emerging equity markets increase. Our finding further confirms that there is strong evidence of transmission of contemporaneous or common shocks between two markets under turbulent market condition.

4.3. Test result of the Granger (non-) causality

Table 4 presents the estimation results of parameters determining the causal link and the Wald test statistics. The lag order of the MSC model is selected by SIC. In order to guarantee reasonable model fit and consistency with the practice in VAR literature, we keep those lag coefficients that are not significant. To be clear, we reorganize the result according to the origin of the spillover effects or the role of Granger cause. For example, for U.S. and U.K. market, the spillover from U.S. to U.K. is captured by the coefficients $\beta_{21}^{(l)}$, $l = 1, \ldots, p$, which are reported in Panel A with row name “US $\rightarrow$ UK”. Similarly, the estimates of $\beta_{11}^{(l)}$, $l = 1, \ldots, p$, in the first equation of Eq. (2) are signs of spillover from U.K. to U.S., and are labeled as “UK $\rightarrow$ US” in Panel B.

From Table 4, the coefficients are more likely to be significant and greater in magnitude in short lags rather than long lags, indicating that the spillover effects between different markets tend to be short-horizon phenomena. With efficient trading system and internationally diversified investors, developed markets are mature and respond quickly to shocks or information flow from others. Second, almost all of the significant estimates of $\beta_{11}^{(l)}$ are positive and their sums, as shown in Table 3 are also positive.
## Table 3
Estimation results of Markov switching causality model.

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Note: This table reports the estimation results of the Markov switching causality model. US, UK, GE, JP, and HK denote the U.S., U.K., Germany, Japan and Hong Kong markets. The column name of X–Y indicates that this column reports the estimation result when the daily log range of X, Y are dependent variables. The standard errors are reported in parentheses. *** denote significance at 1%, 5%, and 1% level. Log \(p\), SIC, Lag \(p\) refer to Log likelihood, Schwartz Information Criterion, and the optimal lag selected by SIC.
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Table 4 (Continued)

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Note: This table reports the estimation and test results of Granger causality. US, UK, GE, JP, and HK denote the U.S., U.K., Germany, Japan and Hong Kong markets. The row name of $X \rightarrow Y$ indicates that this row presents the estimation result of parameters determining the Granger causal link from $X$ to $Y$. For $\hat{\beta}_{i1}^{(p)}$, $i = 1$ or 2, and $l = 1, \ldots, p$, where $p$ is the maximum number of lags of the Markov switching causality model selected by SIC. If $X$ is the first variable in $X, Y$ pair, then $i = 2$, and $\hat{\beta}_{i2}^{(l)}$ are reported, where $l = 1, \ldots, p$. Otherwise, $i = 1$, and $\hat{\beta}_{i1}^{(l)}$ are reported, where $l = 1, \ldots, p$. Lag refers to the optimal lag of model, Wald refers to the Wald test statistics under the null hypothesis that $\hat{\beta}_{i1}^{(1)} = \cdots = \hat{\beta}_{i1}^{(p)} = 0$, where $i = 1$ or 2, and $p$-values are the corresponding $p$-values.
supporting the view that volatilities among markets are more likely to move in the same direction. Lastly, the magnitudes of the $\beta_i^{(1)}$ are signs of relative influence from others. For example, regarding U.S. and U.K. in Panel A, the coefficients of first three lags are all significant using conventional $t$-statistics, and the coefficient of the first lag is 0.130, which is the largest in Panel A and at least two times as large as the first order coefficient between U.S. and Germany, implying that the interdependence between U.S. and U.K. market is the strongest.

In order to formally test the existence of Granger causality, a joint test under $H_0$: $\beta_1^{(1)} = \beta_2^{(2)} = \ldots = \beta_1^{(p)} = 0$ is used to determine whether there is spillover effect from $h_{2t}$ to $h_{1t}$. Similarly, a rejection of the null hypothesis of $H_0$: $\beta_1^{(1)} = \beta_2^{(2)} = \ldots = \beta_1^{(p)} = 0$ would indicate that there exists a spillover effect from $h_{1t}$ to $h_{2t}$. Under such null hypothesis, we use Wald test statistics to test the significance of parameters, which are also employed by Lam (2004), Spagnolo, Psaradakis, and Sola (2005), Gallo and Ottanto (2008), among many others, to test multiple linear restrictions of parameters in the context of Markov switching models. The Wald test statistics and the associated $p$-values of joint significance are reported for each pair of Granger causality in Table 4. To preview the test result, except for the spillover effect from Germany to Japan and Hong Kong, all the other directions are all in favor of the presence of spillover effect during some episodes of the sample. For the two exceptions, we tend to consider that the state variable $S_t$ captures the shifts in the constant and autoregressive coefficients only.

4.4. Time-varying volatility spillover pattern

After obtaining the estimates of parameters, we further obtain the filtered probabilities of state variable $S_t$, $\Pr(S_t|\psi_T)$, which make inference about $S_t$ conditional on information up to time $t$: $\psi_T$, and the smoothed probabilities of state variable $S_t$, $\Pr(S_t|\psi_T)$, which make inference about $S_t$ conditional on information in the full sample: $\psi_T$. For detailed description of the estimation of $\Pr(S_t|\psi_T)$ and $\Pr(S_t|\psi_T)$, please refer to Hamilton (1990) and Kim (1994). In the following analysis, we focus on the smoothed probability due to the informational advantage. The pattern of those inferred probabilities can capture a variety of changes in casual links and provide direct description of the time-varying fashion of volatility spillover over relatively longer historical periods.

In this subsection, we provide the smoothed probabilities when one market has influence on other markets. For example, in Fig. 2, the solid lines represent the smoothed probabilities when there is spillover effect from U.S. to other markets. If U.S. is the first in U.S.–Y pair, then the solid line is $\Pr(S_{1t} = 1|\psi_T)$, otherwise, it would be $\Pr(S_{2t} = 1|\psi_T)$, both of which are calculated as follows:

$$\Pr(S_{1t} = 1|\psi_T) = \Pr(S_{1t} = 1, S_{2t} = 1|\psi_T) + \Pr(S_{1t} = 1, S_{2t} = 0|\psi_T) = \Pr(S_{1t} = 1|\psi_T) + \Pr(S_{t} = 3|\psi_T),$$

and

$$\Pr(S_{2t} = 1|\psi_T) = \Pr(S_{2t} = 1, S_{1t} = 1|\psi_T) + \Pr(S_{2t} = 1, S_{1t} = 0|\psi_T) = \Pr(S_{2t} = 1|\psi_T) + \Pr(S_{t} = 2|\psi_T)$$

Moreover, the shaded area represents the period when the smoothed probabilities of the first regime ($S_t = 1$) is greater than 0.5, or $\Pr(S_t = 1|\psi_T) > 0.5$, indicating the existence of the two-way causal link between U.S. and other markets.

From Figs. 2–6, an obvious observation is that the volatility spillover effect, especially two-way influence, is more likely to occur in turbulent or crises periods. In the turmoil period of 1998–2002, when Asia crisis and the burst of “internet” bubble happened, the 2007–2009 subprime crisis period, and the 2010–2011 European sovereign debt crisis episode, the smoothed probabilities of $S_{1t}$ or $S_{2t}$ or the smoothed probabilities of the first regime ($S_t = 1$) are more likely to approach 1 or remain high, showing that one-way or two-way influence also mainly concentrated at those times. As shown in Fig. 1 and the analysis in Section 3, high volatility regime mostly coincides with crisis period, showing that cross-market interaction intensifies when the overall market is volatile.\textsuperscript{8} This finding is in line with

\textsuperscript{8} Further calculations involving the intercept and autoregressive terms of Eq. (2) under different regimes do reveal that when there exists spillover effect, especially two-way influence, the average volatility levels for both markets are almost all higher than their counterparts when both are isolated.
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Fig. 4. Smoothed probabilities of volatility spillover effect originated from Germany market to other markets.

Note: This figure plots the smoothed probabilities of volatility spillover effect or Granger causal link from Germany to other markets. The red solid lines represent smoothed probabilities that there exist causal links originated from Germany to other markets, denoted by GE → X. The shaded areas represent the dates when the smoothed probabilities that there exist two way causal links between Germany and other markets are greater than 0.5.

Fig. 5. Smoothed probabilities of volatility spillover effect originated from Japan market to other markets.

Note: This figure plots the smoothed probabilities of volatility spillover effect or Granger causal link from Japan to other markets. The red solid lines represent smoothed probabilities that there exist causal links originated from U.S. to other markets, denoted by JP → X. The shaded areas represent the dates when the smoothed probabilities that there exist two way causal links between Japan and other markets are greater than 0.5.
Fig. 6. Smoothed probabilities of volatility spillover effect originated from Hong Kong market to other markets. Note: This figure plots the smoothed probabilities of volatility spillover effect or Granger causal link from Hong Kong to other markets. The red solid lines represent smoothed probabilities that there exist causal links originated from Hong Kong to other markets, denoted by HK → X. The shaded areas represent the dates when the smoothed probabilities that there exist two way causal links between Hong Kong and other markets are greater than 0.5.

literature stressing the comovement of markets at crisis times, including Edwards and Susmel (2001), Forbes and Rigobon (2002), Gallo and Otranto (2008), Diebold and Yilmaz (2009), Engle et al. (2012), among many others. For example, Diebold and Yilmaz (2009) demonstrate that the spillover index using 200-week rolling samples shows spikes at obvious crisis times. Not only does the volatility level of each individual market go up but also the correlation or comovement increases. This consensus has important implication in portfolio choice or risk management, because investors have to adjust their portfolios accordingly if different assets are more correlated with each other and become much riskier during crises as the diversification may be much less useful than previously assumed based on the variance–covariance matrix in normal times.

Another finding is that the periods of interdependence among markets usually last longer than or are at least somewhat different from the “obvious” crisis stage (e.g., Brière et al., 2012). For example, July 2, 1997 was often considered as the beginning of East Asia crisis, but as shown in Fig. 6, Hong Kong market started to influence U.S. and Japan at the beginning of sample in 1996. And from Fig. 2, the interaction between U.S. and other markets did not coincide right before the early signs of Subprime mortgage crisis period in February 2007, or subprime mortgage crisis in September 2008. For instance, U.S. and U.K. had bilateral influence with each other even before 2006. These results further highlight the complexity of interactions among financial markets, as well as the importance and advantage of data-driven method to identify the regime of interdependence. A uniform choice of sample relying on important financial events may overlook the fact that influence from other markets can be earlier or later, and comovement between different market pairs can vary substantially due to their idiosyncratic characteristics. Our approach does not rely on additional information to discover causality pattern, or uniform choice of sample splits between different market pairs, thereby providing a more realistic and accurate description of the bivariate spillover relationship. In addition to the commonality in spillover pattern, next we focus on the detailed bivariate results classified by the origin of spillover effect.

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4.4.1. U.S. market

From Fig. 2, we can have the following findings. First, the inferred probabilities of state variable governing the influence originated from U.S. were close to one covering most of the sample periods from the beginning of 1996 to the end of 2011, implying that U.S. market tended to serve as a major source of risk around the world. In view of the region of the shaded area, there also existed a joint interdependence between U.S. and other markets. Second, in spite of the similarity, the impact from U.S. varies across markets. During the subprime mortgage crisis period, the spillover effect originated from U.S. market started to appear around 2006 for U.K., Japan and Hong Kong markets, and spread to Germany shortly after 2008. In particular, when the bankruptcy of Lehman Brothers during 2008 took place, there was strong evidence of bilateral spillover between U.S. and other markets. And the two-way influence also appeared between U.S. and U.K., Germany shortly after the beginning of 2010, when the investors seemed to worry about the credit condition of Greece, especially when Standard and Poor’s downgraded the ratings of Greece’s debt below investment grade to junk bond status on April 27, 2010. However, the effect emerged for Hong Kong only during the second half year of 2011, and Japan market was still relatively less affected.

4.4.2. U.K. market

From Fig. 3, we can draw the following conclusions. First, the close relationship between U.S. and U.K. market was again confirmed. The spillover from U.K. to U.S. almost existed for the whole sample period except for some short window of relative independence. Second, the influence of U.K. market to other markets was less pronounced compared with U.S. Similar to the case from U.S. to Germany, there was little evidence of spillover from U.K. to Germany during the 1997 Asian crisis period, as well as no evidence from U.K. to Japan during the 2010–2011 European sovereign debt crisis episode. On the other hand, the interdependence between U.K. and Hong Kong was obvious during turbulent market period, but for other times, the U.K. market played a minor role.

4.4.3. Germany market

Next, we turn to Fig. 4 to identify the casual pattern between Germany and other markets. First, the spillover from Germany to other markets was most evident for U.S. market. Since the region of high probabilities for the spillover effect coincided with most of the two-way influence region, the influence between Germany and U.S. markets was reciprocal. Second, the spillover from Germany to U.K. remained from 1996 to 2001, and from 2008 to 2011, which was possibly due to the influence of Asian financial crisis, subprime mortgage crisis and European sovereign debt crisis as mentioned before. Third, from Figs. 2, 3, 5 and 6, U.S., U.K., Japan all began to influence Germany at the end of 1998, and Hong Kong’s impact took place around the end of 1997, which was the latest among all the impacts from Hong Kong to other markets shown in Fig. 6. This is consistent with the Fig. 1, as the volatility level of Germany only rose temporarily at the end of 1997 but to a less extent compared with other markets. Therefore, this tends to support the argument that Germany is less influenced by Asia crisis. Considering its late response to the subprime mortgage crisis demonstrated above together, Germany tends to play the role of late “recipient” in international financial market.

4.4.4. Japan market

Now we turn to Fig. 5 to identify the episodes of volatility spillover from Japan to other markets. First, the spillover from Japan to others mostly appeared since 1997, with only exception of Germany market from middle of 1998, and lasted until 2002 for Hong Kong market, around 2004 for U.S., U.K., and 2006 for Germany. Second, Japan market also intensely interacted with other markets before and during the subprime mortgage crisis period, when its influence firstly reached U.K. in 2006, U.S. as well as Hong Kong in 2007, and finally Germany in 2008. Third, except for Germany market, for which the influence from Japan ended at the beginning of 2011, Japan market had one-way influence on others, which was possibly related to the insurgence of volatility after the earthquake and tsunami in March 2011. Third, as mentioned previously, from Figs. 2–4, 6, Japan market was somewhat immune to shocks related to European sovereign debt crisis, because U.S., U.K. and Germany had no obvious influence on Japan during 2010, when the crisis spread to Italy, Spain, Portugal, and others. In

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line with what we observe from Fig. 1, this is also consistent with the result from linear Granger causality test. In Table 2, for the subperiod extending from 2010 to 2011, among five of the insignificant F-statistics under 10%, four of them are associated with Japan. The p-values of US \rightarrow JP, UK \rightarrow JP, GE \rightarrow JP, HK \rightarrow JP are 0.455, 0.377, 0.763, 0.994, all of which are in favor of no spillover effect to Japan.

4.4.5. Hong Kong market

Finally we turn to Fig. 6. First, Hong Kong market played the role of risk source before or at the early stage of Asian crisis. The inferred probabilities remained high since 1996 for U.S. and Japan market. The influence from Hong Kong to Germany and U.K. emerged in 1997. These evidences tend to support the importance of Hong Kong market in the crisis. Second, the influence of Hong Kong market was also prevalent at other times. For example, it had influence on U.S. and U.K. markets ever since 2006. This finding further emphasize the importance of Hong Kong market in international markets, and is also broadly consistent with several previous studies. For example, in the study of East Asian financial crisis, Engle et al. (2012) consider Hong Kong as a net generator of volatility. Furthermore, over a relatively long period from January 1992 to November 2007, Diebold and Yilmaz (2009) find that Hong Kong has the largest contribution of volatility spillover to others among all the seven developed and twelve emerging markets under investigation.

5. Concluding remarks

In this paper, we consider the volatility spillover effect from Granger causality point of view, and use the Markov switching causality model proposed in Psaradakis et al. (2005) to capture the time-varying causal pattern. The Markov switching causality method avoids the problem of arbitrarily splitting the sample with prior information about crisis periods, or relying on predetermined window size to do rolling regression, and recover the information of latent state from data-driven hidden Markov chain as the evidence of spillover effect. It is noted that the Markov switching causality method only considers the in-sample relationship. However, the out-of-sample performance of such approach in capturing casual links is of great importance, and is left for further studies.9

From the time-varying pattern of volatility spillover effect, we can have the following findings. First, the estimation result of Markov switching causality model supports the existence of distinct and persistent regimes. In addition, the shocks between two markets are more contemporaneously correlated when there exist two-way causal links. Second, the spillover effect is most evident during periods of turmoil, especially during the Asian financial crisis and subprime crisis period. Third, each market performs differently in interacting with others. We find that U.S. market served as a major risk source in the global market, and it was mostly closely related to U.K. market. For Germany, its influence on two Asian markets was not significant. Moreover, Japan was actively interconnected with other markets during Asian crisis and subprime mortgage crisis periods, but was somewhat much less influenced during European sovereign debt crisis periods. Lastly, Hong Kong played an important role in international equity market as net generator of volatility.

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