Volatility Modelling on the Use of Structural Breaks

A Thesis Submitted for the Degree of

Master of Philosophy

at the University of Leicester

By

Yuhan Zhang

Department of Management

School of Business

University of Leicester

2018

Abstract

This thesis focuses on examining potential impacts that structural breaks impose on volatility modelling via GARCH models. After incorporating structural breaks detected by the modified ICSS of Sanso et al. (2004) into conventional GARCH models, reduced volatility persistence is obtained for stock and foreign exchange returns in both China and the UK. A unidirectional volatility spillover is found going from stock to foreign exchange market for both countries, and ignoring structural breaks can lead to biased spillover patterns. These findings are well supported by comprehensive Monte Carlo simulations.

Acknowledgement

My sincere thanks goes to my supervisors, Alexandra Dias and Emmanuel Haven, for their continuous support and guidance.

Contents

List of Tables

List of Figures

Thesis Introduction

Volatility has widely been used as one of the most important indicators in many financial activities, including asset pricing, hedging and devising other trading strategies; it also provides economic implications for regulatory policies. As a result, volatility has become one of the most crucial factors that have drawn considerable attention to both academics and practitioners. Moreover, according to Ross (1989), in an arbitrage free economy, the volatility of prices is directly related to the degree to which the information flows to the market. Therefore, by studying the volatility of financial markets, it also helps to better understand and forecast how markets react by the arrival of new information.

It is well known that volatility measures the variation of individual observation from its average in one data series; high-volatility indicates a more volatile financial market than low-volatility of which a market is recognized as relatively stable. One stylized feature of this time-varying volatility is the volatility clustering, describing a phenomenon where large movements tend to be followed by ones with similar scale, forming temporal clusters within certain length of time. This feature is commonly captured by the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model introduced by Bollerslev (1986). Developed on the basis of the Autoregressive Conditional Heteroskedasticity (ARCH) model (Engle, 1982), GARCH not only takes account of the previous error terms as the way in an ARCH model, it is also built conditionally on the previous volatilities when modelling the current volatility. This entitles GARCH with more attractive properties permitting a parsimonious structure yet providing convincing statistical inferences. Literature in this area is substantial (see, for instance, Mandelbrot, 1963; Oh et al., 2008; Tseng and Li, 2011).

On the other hand, it is necessary not only to study one single financial asset, but also to perceive the interactions across various financial markets. Due to the rising interdependence between financial markets, the impacts caused by significant events or shocks to one market can be passed onto another market in the form of volatility. Such volatility spillover effects can be described as the causality-in-variance in the

sense of Granger (1969), which defines the causality between two variables as how much of the current value of one variable can be explained by the past values of the other variable (Mantalos and Shukur, 2010). Therefore, by investigating such transmission of information, it can directly benefit investors holding multiple assets positions to gain alternative strategies to manage the potential exposures. In this context, a large number of research has been carried out on investigating this type of linkage between two financial markets. One type of interest lies in evaluating the transmission of influences between stock markets in different nations. Chou et al. (1999) studied the interactions between stock markets of Taiwan and the US; analysing the daily close-to-open and open-to-close stock returns from 1991 to 1994 by GARCH models and a bivariate BEKK model of Engle and Kroner (1995), a one-way causality was pinned to flow from the US market to Taiwan, especially for the case using open-to-close returns. Using similar approach, Lee (2009) assessed daily stock prices over the period from 1985 to 2004 of six Asian countries, namely, Taiwan, Japan, Singapore, India, Hong Kong and South Korea; volatility spillover effects were found within five countries except India, the reason of which was postulated to be geographic. Moreover, Moon and Yu (2010) investigated the spillover effects of stock markets between the US and China via variations of a GARCH (1,1)-M model (Engle and Granger, 1987); results from examining daily stock prices from 2005 to 2007 showed evidences of volatility spillovers in both direction between markets in study. They further noted that the more volatile the US market tended to lead to a less volatile market in China.

With respect to the recent studies, focuses have extended to study such causal relationship between stock markets and foreign exchange markets. In addition to the fact that both stock prices and foreign exchange rates are important indicators of economic strengths and degree of development, it is believed that a causal relationship exists between the two assets based on two models for determination of the exchange rate (see Ali and Anwar, 2012; Tsai, 2012). One is the Portfolio Balance Model, which takes currency as an asset, thereby the price of which is determined by the demand. Thus, as a sign of increasing growth of wealth, an increase of the stock prices would trigger an increasing demand for money, leading to an increase of interest rate; more capital inflows are attracted under such circumstances, boosting an increase in foreign demand for this currency in the short-term, which eventually leads to an appreciation of this currency. The other is the Balance of Trade Model, which states that the changes in the exchange rate affect the stock market by affecting the incomes of companies. A depreciation of the domestic currency means more competitive advantages for an export-focused company, while less than good news to an import-oriented company; either case will affect their stock prices. Such

theoretical evidences can be found in Dornbusch and Fischer (1980); Solnik (1987); Koseoglu and Cevik (2013).

Based on the theoretical models, a great number of empirical studies have been carried out on investigating the volatility spillover effects between stock markets and foreign exchange markets, in order to determine whether they are causal-related and the behaviour of such causation. Richer literature in this area can be found in, for example, Yang and Doong (2004); Francis et al. (2006); Tai (2007); Yang and Chang (2008).

It is worth noting that, most of the techniques involved in such subject are in the framework of GARCH models; however, it is argued that a considerate upward bias of the estimations derived from the conventional GARCH models could be produced due to the ignorance of the structural breaks in the volatility of the examined financial series (Bollerslev and Engle, 1993; Ding et al., 1993; Ding and Granger, 1996; Andersen and Bollerslev, 1997; Engle and Sheppard, 2001; Mikosch and Stărică, 2004). The occurrence of structural breaks has long been conjectured in volatility of financial markets, the trigger of which may involve with the mechanism change of exchange rate systems, evolution of the stock markets, or a global financial crisis. Induced by these significant economic or political events, the shocks may cause the behaviour of financial time series to deviate from its tranquil time (Andreou and Ghysels, 2002; Wang and Moore, 2009). As is further confirmed through the likelihood ratio test, a decrease of the sum of the parameters in GARCH models happened after the structural change effects are eliminated (Lamoureux and Lastrapes, 1990; Arago-Manzana and Fernandez-Izquierdo, 2007; Wang and Nguyen Thi, 2007; Ewing and Malik, 2010). In addition, by Monte Carlo simulations, Hillebrand (2005) further documents that this error would occur for all common estimators of GARCH. Meanwhile, Wang and Nguyen Thi (2007) examine the sudden changes in volatility in the stock markets of new EU members by adopting an ICSS (Iterative Cumulative Sum of Squares) algorithm developed by Inclan and Tiao (1994) and point out that the persistence of volatility could be reduced dramatically when taking into account the sudden shifts in the GARCH models. They further suggest that overestimation of the degree of volatility persistence may have happened in many previous studies. In such circumstances, as Rodrigues and Rubia (2007) argues, failure to accommodate the structural breaks could eventually lead to biased causality results. Moreover, based on an extensive set of Monte Carlo simulations, Dijk and Sensier (2005) provide evidence that the causality-in-variance test developed by Cheung and Ng (1996) and Hong (2001) suffers from considerable size distortions when structural breaks are ignored. Therefore, it is absolutely necessary to detect possible structural

breaks before examining the causality in variance.

So far, extensive evidences have been found supporting that equity markets and currency markets are causal-related, yet no consensus has reached either theoretically or empirically. Nevertheless, the spotlight of the majority of existing literature has been put on the developed financial markets, leaving few studies targeting such causality towards the emerging markets. Among the scarce research of the latter, even fewer have concentrated on the markets in the mainland of China. Motivated as such, this research will investigate the volatility spillover with consideration of the potential presence of structural breaks between two financial time series, namely, stock prices and foreign exchange rates, over the recent two decades; moreover, it will be conducted in both the UK and China, offering a comparison between markets with different levels of development. Proposed as such, this research will employ the causality in variance test of Hong (2001), taking into consideration the structural breaks in the targeted series, which will be identified by the modified ICSS algorithm of Sanso et al. (2004). Moreover, in order to well understand the mechanism of the selected models, Monte Carlo simulation study will be adopted prior to the application to the research data. Designed as such, the contribution of this thesis is twofold. First, by targeting the financial markets in two countries discussed above, this research not only can help to establish insightful knowledge on the fundamentals of financial markets, it also seeks the possibility to build customized models dealing with markets with specific characteristics. Next, through a comprehensively well-designed simulation study, this research attempts to produce more accurate estimates of structural change dates and volatility spillover pattern, in order to make efforts for the further investigation on exploring any particular volatility patterns as potential early warnings of any forthcoming fluctuations in the targeted financial markets. Therefore, this research is of interest to both investors and financial managers to devise proper investment strategies especially over the period such as a financial crisis; it can also provide policy makers with invaluable information and advanced econometric techniques to ensure economic stability.

The remainder of this thesis proceeds as follows: Chapter 1 provides an overview of several well applied methods in the area of structural breaks detection and volatility spillover investigation, together with a general discussion on the empirical applications; Chapter 2 examines stock returns in China and the UK for potential structural breaks, and provide detailed analysis on the modification of GARCH model with structural breaks; Chapter 3 focuses on studying the volatility spillover between stock and foreign exchange markets in China and the UK, especially evaluates the influence of structural breaks toward the detected volatility spillover pattern.

Chapter 1

Structural Breaks in Volatility Modelling

1.1 Introduction

This chapter introduces several popular techniques in the area of structural breaks detection and volatility spillover investigation. To be more specific, the methods of Bai and Perron (2003), Andrews (1993), Inclan and Tiao (1994) and Sanso et al. (2004) are discussed with regard to identify the presence of structural breaks; Cheung and Ng (1996), Hong (2001), Hafner and Herwartz (2006) and Engle and Kroner (1995) are reviewed in the topic of studying the volatility spillover pattern. By documenting the construction of each selected model and its empirical application, this chapter aims at creating a collection of the most popularly applied methods with respect to structural breaks in volatility modelling. Moreover, by discussing each model, this chapter justifies the choice of methods selected for the later chapters.

This chapter proceeds as the following: Section 1.2 briefly reviews the conventional GARCH specifications; Section 1.3 introduces several widely employed methods for identifying the structural breaks; Section 1.4 discusses a few popular techniques for determining the volatility spillover pattern; Section 1.5 provides the concluding remarks of this chapter.

1.2 Overview of the Conventional GARCH (p,q) Process

GARCH models have been widely applied to model the time-varying nature of volatility in empirical finance. Introduced by Bollerslev (1986), GARCH grants a more flexible lag structure of the ARCH (Engle, 1982) class models. The standard

GARCH (p, q) for the return series r_t can be reviewed as:

$$
\begin{aligned}
r_t &= \mu + \varepsilon_t, \;\; \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) && (1.1)\\
\varepsilon_t &= z_t \sqrt{\sigma_t^2}, \;\; z_t \sim N(0,1) && (1.2)\\
\sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 && (1.3)
\end{aligned}
$$

σ_t^2 is the conditional variance, with $\omega > 0$, $\alpha_i > 0$ and $\beta_i > 0$ to ensure the positivity of σ_t^2. z_t is an independent and identically distributed error term with zero mean and unit variance. Moreover, $p \geq 0, q > 0$; it is an ARCH (q) process when $p = 0$. The volatility persistence is measured by the sum of α_i and β_i; the more it approaches unity the greater the persistence of shocks to the volatility. Moreover, according to Hansen and Lunde (2005), GARCH (1,1) is recognised to perform quite sufficiently when forecasting volatility. Consider the GARCH (1,1) process and rewrite (1.3):

$$
\begin{aligned}
\sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \alpha \sigma_{t-1}^2 - \alpha \sigma_{t-1}^2 && (1.4)\\
\sigma_t^2 &= \omega + \alpha(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) + (\alpha + \beta)\sigma_{t-1}^2 && (1.5)
\end{aligned}
$$

Thus, from (1.5), let $v_{t-1} = \varepsilon_{t-1}^2 - \sigma_{t-1}^2$ represent the shock, and $\lambda = \alpha + \beta$, then

$$
\sigma_t^2 = \omega + \alpha v_{t-1} + \lambda \sigma_{t-1}^2 \qquad (1.6)
$$

Continue decomposing σ_{t-1}^2 in the form shown in (1.6) and then replace σ_{t-1}^2 in (1.6) with its new form in the following manner:

$$
\begin{aligned}
\sigma_{t-1}^2 &= \omega(1 + \lambda + \lambda^2 + \lambda^3 + \cdots) + \alpha(v_{t-1} + \lambda v_{t-2} + \lambda^2 v_{t-3} + \cdots)\\
\sigma_{t-1}^2 &= \omega \frac{1-\lambda^t}{1-\lambda} + \alpha(v_{t-1} + \lambda v_{t-2} + \lambda^2 v_{t-3} + \cdots) && (1.7)
\end{aligned}
$$

Therefore, in (1.7), $\omega \frac{1-\lambda^t}{1-\lambda} = \frac{\omega}{1-\lambda}$ is the unconditional variance when $\lambda < 1$. When $\lambda = 1$, the variance contains a unit root, thus the process has no unconditional variance and is defined as an integrated GARCH or I-GARCH process (Engle and Bollerslev, 1986). Furthermore, it can also be noticed from (1.7) that, the effect imposed by the shock on the conditional variance σ_t^2 relies on the degree of λ; that is to say, the larger the sum of α and β, the longer the shock lasts, i.e. the more persistent of the volatility. Therefore, the volatility persistence for a certain shock is

measured by the sum of α and β, and it is argued that the high volatility persistence of financial assets series is caused by the structural breaks in the unconditional variance in terms of $\frac{\omega}{\alpha+\beta}$ from the conventional GARCH models. More specifically, this biased volatility persistence implies that the current information will still impose significant impacts on the conditional variance forecast for all horizons because of the very close to permanent influence on volatility. In this sense, this phenomenon can be defined as the spurious IGARCH effects (Hillebrand, 2005). Under such circumstances, many tests have been developed in order to identify the structural breaks in the conditional volatility process.

1.3 Structural Breaks Detection

The occurrence of structural breaks has long been conjectured in the volatility of financial markets. The trigger of such structural breaks may involve with the introduction of new currency, the mechanism change of exchange rate systems, the evolution of the stock markets, or a global financial crisis, see, for instance, (see, for instance, Aggarwal et al., 1999; Andreou and Ghysels, 2002). Induced by these significant economic or political events, the "shocks" may trigger an abrupt change in the volatility structure and thus cause parameters inconsistency of the model. Ignoring such effect can lead to biased volatility forecasting. This section will introduce several of the most popular methods in the literature on structural breaks detection, along with their empirical applications.

1.3.1 Structural Breaks Test of Bai and Perron (2003)

For a data series $Y_t, t = 1, ..., T$, consider a system of linear regression equations regarding a set of segments determined by the locations of potential structural breaks, namely, $[T_1, ..., T_m]$, with m being the number of potential breaks:

$$
\begin{aligned}
Y_t &= \boldsymbol{\varphi_t'}\beta + \boldsymbol{z_t'}\delta_1' + \varepsilon_t, \;\; t = 1, ..., T_1, && (1.8)\\
Y_t &= \boldsymbol{\varphi_t'}\beta + \boldsymbol{z_t'}\delta_2' + \varepsilon_t, \;\; t = T_1 + 1, ..., T_2, && (1.9)\\
&\vdots && (1.10)\\
Y_t &= \boldsymbol{\varphi_t'}\beta + \boldsymbol{z_t'}\delta_{m+1}' + \varepsilon_t, \;\; t = T_m + 1, ..., T. && (1.11)
\end{aligned}
$$

where Y_t in each equation represents a segment of observations from the total series $Y_t, t = 1, ..., T$. $\boldsymbol{\varphi_t'}$ and $\boldsymbol{z_t'}$ are two vectors of covariants, with dimensions of $p \times 1$ and $q \times 1$ respectively. The former has a dimension of $p \times 1$, indicating the start of one segment; while the latter is of $q \times 1, q = 1, ..., T$, and it indicates the

end of that segment. In each equation in the system above, the coefficients β and $\delta_i', i = 1, ..., m+1$ are then obtained by minimizing the sum of squared residuals $\sum_{i=1}^{m+1} \sum_{T_i}^{t=T_{i-1}+1} [Y_t - \boldsymbol{\varphi_t'}\beta - \boldsymbol{z_t'}\delta_1']$. And the estimates of the locations of structural breaks are $[\bar{T_1}, ..., \bar{T_m}]$, which makes the smallest sum of these minimized sum of squared residuals obtained in each segment. Moreover, T_m will be determined via an algorithm which is designed by the authors to calculate the estimates of break points as global minimizers of the sum of squared residuals (SSR) in each of the m segment.

With this key concept discussed above, Bai and Perron (2003) develop several approaches to test each partition choice to find the breaks. One is via a Supremum F-test with the null hypothesis of no break versus the alternative of the presence of break with a number of a fixed finite positive integer. That means the number of breaks needs to be known in advance. Another approach is through a double maximum procedure, with the null hypothesis of no break and the alternative of an unspecified number of breaks. This approach consists of two tests, one is called the $UD\ max$ test with all weights equal to unity, and the other is the $WD\ max$ test with varying weights. The last approach is known as the sequential test, with the null hypothesis of m break(s) against $m+1$ break(s). More detail can be found in Bai and Perron (1998) and Bai and Perron (2003), including the construction of confidence intervals and information on optimisation methods. Most research usually adopts one or more of these approaches, and refer to their methods as "the test of Bai and Perron (2003)"; we use "the BP test" hereafter to avoid over referencing.

Kirkulak-Uludag and Lkhamazhapov (2016) investigate Russian gold market for potential structural breaks from June 2008 to May 2013 using the BP test. Each of the spot and futures return series under study is found to experience one break very close to the 2007-2008 financial crisis. The possible cause of these breaks could be the largely increased gold reserves made by the Russian Central Bank in 2009. Particularly, the break found in the futures returns occurred two weeks earlier than that found in the spot returns. It can be inferred that Russian futures gold market reacts faster than its spot market to the negative world news induced by the recent global financial crisis. Caporale et al. (2018) examine bonds series from the EMBI (Emerging Market Bond Index) from January 1997 to June 2015 for Argentina, Brazil, Mexico, and Venezuela. Via the BP test, several breaks are found in all the countries corresponding to the country-specified factors, for instance, GDP growth, the establishment of new economic policies, presidential election. More applications of BP test involve Mongi and Haj Ali (2016), where the stock and commodity markets in the US are checked for structural breaks. From

January 2000 to March 2014, a number of breaks are found in each of the return series. Also, Tule et al. (2017) study the bond and oil markets in Nigeria from March 2011 to April 2016. The BP test finds one break for each return series, and these breaks can be associated with events that relate to oil supply. Moreover, Ahmed (2017) investigates the major stock index in Egypt along with its oil and gas markets over the sample period from February 2006 to June 2016. Several breaks are found via the BP test in all the series; most of these breaks are clustered around 2008-2009, indicating the huge influence this country received from the recent financial crisis. More studies can be found in, for instance, Huang and Yang (2001); Jouini and Boutahar (2003); Christopher and Wohar (2006); Rapach and Wohar (2006); Belkhouja and Boutahar (2009); Budd (2018); Antonakakis et al. (2018).

1.3.2 Lagrange Multiplier Tests of Andrews (1993)

Andrews (1993) proposes a structural break test based on the Lagrange Multiplier (LM) to locate a one-time unknown change point in non-linear parametric models. Consider an econometric model that fits to time series $Y_t, t = 1, ..., T$ with parameter vector $\boldsymbol{\theta_t}$; define π as the location of a potential break near the known events with $\pi \in (0, 1)$; take $[\pi T]$, where $[\cdot]$ is the integer part operator, as the proportion of sample observations before the break occurs at the $[\pi T]th$ observation. In this way, the model parameters before and after the break then become θ_1 for $t = 1, ..., [\pi T]$ and θ_2 for $t = [\pi T] + 1, ..., T$ respectively. Thus the null hypothesis of no structural break with alternative being the presence of such at $[\pi T]$ in the parameter are formulated as below:

$$H_0 : \boldsymbol{\theta_t} \quad = \quad \boldsymbol{\theta_0} \tag{1.12}$$

versus

$$H_A : \boldsymbol{\theta_t} = \begin{cases} \boldsymbol{\theta_1}(\pi), & \text{for } t = 1, ..., [\pi T] \\ \boldsymbol{\theta_2}(\pi), & \text{for } t = [\pi T] + 1, ..., T \end{cases} \tag{1.13}$$

In particular, for a normal linear regression model, if the location of structural break is known, the LM test that is constructed under the above hypotheses is equivalent to F test, which is also referred to as Chow test (Chow, 1960) in the literature.

Moreover, under the null hypothesis of no structural break, there is only one set of the parameter vector and it can be estimated via maximum likelihood; when there is one structural break, in other words, H_A is true, and the location of it is known at $[\pi T]$ in a non-linear model, then the LM test statistic $LM(\pi)$ is calculated as

below:

$$LM(\pi) = \frac{T}{\pi(1-\pi)}\overline{\boldsymbol{g}}_{\boldsymbol{1T}}(\hat{\boldsymbol{\theta}},\pi)'\boldsymbol{S_T}^{-1}\boldsymbol{D_T}(\boldsymbol{D_T}'\boldsymbol{S_T}^{-1}\boldsymbol{D_T})^{-1}\boldsymbol{D_T}'\boldsymbol{S_T}^{-1}\overline{\boldsymbol{g}}_{\boldsymbol{1T}}(\hat{\boldsymbol{\theta}},\pi) \quad (1.14)$$

where

$$\overline{\boldsymbol{g}}_{\boldsymbol{1T}}(\hat{\boldsymbol{\theta}},\pi) = \frac{1}{T}\sum_{t=1}^{\pi T} g(Y_t;\hat{\boldsymbol{\theta}}) \quad (1.15)$$

$$\boldsymbol{S_T} = \frac{1}{T}\sum_{t=1}^{T}[g(Y_t;\hat{\boldsymbol{\theta}}) - \overline{\boldsymbol{g}}_{\boldsymbol{T}}(\hat{\theta})][g(Y_t;\hat{\boldsymbol{\theta}}) - \overline{\boldsymbol{g}}_{\boldsymbol{T}}(\hat{\boldsymbol{\theta}})]' \quad (1.16)$$

$$\boldsymbol{D_T} = \frac{1}{T}\sum_{t=1}^{T}\frac{\partial(Y_t;\theta)}{\partial\hat{\boldsymbol{\theta}}'} \quad (1.17)$$

In (1.15), $g(Y_t;\hat{\boldsymbol{\theta}}) = \partial log f(Y_t;\hat{\boldsymbol{\theta}})/\partial\hat{\boldsymbol{\theta}}$ is the score in terms of the partial derivative of the log density with respect to the parameter vector $\hat{\boldsymbol{\theta}}$. $\boldsymbol{D_T}$ in (1.17) is the restricted estimator that is used to construct weight matrices for LM test statistics. And in (1.16), $\overline{\boldsymbol{g}}_{\boldsymbol{T}} = \frac{1}{T}\sum_{t=1}^{T} g(Y_t;\hat{\boldsymbol{\theta}})$. Constructed as such, the $LM(\pi)$ statistic asymptotically follows a chi-squared distribution with degrees of freedom of the number of the parameters in the model.

Often the location of the break is unknown and the standard distributional theory is no longer applicable to financial time series. Therefore, based on the work of Davies (1977) and Davies (1987), Andrews (1993) modifies the LM test to a $supLM(\pi)$ form that requires $\pi \in \Pi$, defining Π as a pre-specified subset of $[0,1]$ that is not close to the boundary value zero and one. In fact, according to Andrews (1993), $supLM(\pi)$ would perform badly when $\Pi \in [0,1]$, as $supLM(\pi)$ test statistic diverges as the sample size increases to the boundary region. Such drawback could be amended by choosing a proper π_0, which is the proportion of observations that are taken out from two ends of the sample. Therefore, when the subset proportion is selected far away from zero and one, it is possible to calculate a well defined asymptotic distribution for the $supLM(\pi)$ test statistic. In fact, Andrews (1993) suggest a restricted interval for Π as $\Pi = [0.15, 0.85]$ to avoid unnecessary reduction of test power. Since the $supLM(\pi)$ test can only check the presence of structural break within a pre-determined sample period, therefore, this requirement restricts Andrews (1993)'s method to only be applicable to the cases where an event is known to have caused a structural break in the data series.

Empirical studies of LM type tests of Andrews (1993) can be found in Smith (2008).

The author tests for structural breaks in twelve financial return series from 1990 to 2002 including one stock exchange index, five foreign exchange series, and seven company stocks. With the $supLM(\pi)$ test of Andrews (1993), strong evidence is found for the presence of structural breaks in the unconditional volatility of GARCH models for eight return series. Moreover, Moon and Yu (2010) investigate the daily returns from the major stock index in China via the structural break test of Andrews (1993). Over a sample period January 1999 to June 2007, one structural break is identified on 2 December 2005. This break is very likely induced by the reform on the non-tradable shares of the state-owned company in December 2005. This break might also be associated with the RMB appreciation against the US Dollar since December 2005 due to the adoption of new Chinese exchange rate regime. More research with regard to Andrews (1993) can be found in Bec and Bastien (2007), Morales-Zumaquero and Sosvilla-Rivero (2010), Chen et al. (2017), Georgiev et al. (2018).

1.3.3 Iterative Cumulative Sum of Squares of Inclan and Tiao (1994) and the Modified Version of Sanso et al. (2004)

Consider a series of uncorrelated random variables $Y_t, t = 1, ..., T$ with mean 0 and variance $\sigma_t^2, t = 1, 2, ..., T$. Define the following expression:

$$D_k \quad = \quad C_k/C_T - k/T, \;\; k = 0, 1, 2, ..., T \tag{1.18}$$

D_k is the centred and normalized cumulative sum of squares; $C_{k+1} = \sum_{i=1}^{k} Y_t^2, \;\; k = 0, 1, 2, ..., T$ is the cumulative sum of $k + 1$ squares of the data observations. The underlying concept of this Iterated Cumulative Sums of Squares (ICSS) algorithm of Inclan and Tiao (1994) is to assume the variability of $\sigma_t^2, t = 1, 2, ..., T$ is made of constant σ^2 at different time periods over the whole sample period T. In other words, the variance stays constant for some time, until it takes up a new value at k^*; the variance then stays at this new value for some other time until another variance value occurs. It is then said that one structural break has occurred at k^*. Within this context, the construction of D_k in expression (1.18) will oscillate around zero until the occurrence of a structural break where D_k varies away distinguishably from zero. Therefore, an IT test is developed to find the variation of D_k that is statistically significant, which takes the form as below:

$$IT = \max \sqrt{T/2}|D_k| \tag{1.19}$$

where $\sqrt{T/2}$ is to standardize the distribution. Under a null hypothesis of no structural break against the alternative of presence of one break, when IT exceeds the critical value at a selected confidence level, one structural break is detected in the variance or volatility of this data series. In order to find multiple unknown breaks in the whole series, an iterative scheme is specifically designed to systematically search for change points by applying the IT test to sub-samples created consecutively after a possible change point is identified.

As Inclan and Tiao (1994) further point out, this Iterative Cumulative Sum of Squares algorithm (ICSS hereafter) has certain advantages over other alternative methods such as a Bayesian approach or a likelihood ratio test, since it is free of the heavy computations required by the latter methods, yet provides adequately powerful inferences. In addition, according to Andreou and Ghysels (2002), ICSS can provide good statistical inference when applying to even strongly dependent data with minor size distortions. Therefore, ICSS has been widely employed in the literature. Earlier studies involve Aggarwal et al. (1999), where the large shifts in the volatility of emerging stock markets were examined. By investigating daily returns covering the period May 1985 to April 1995 for ten emerging markets in Asia and Latin America, several structural breaks were detected around the significant economic or political events via ICSS. In particular, for three targeted stock markets, one break was located two days later after the occurrence of stock market crash on 19 October in 1987. More recent research can be found in Malik and Hassan (2004), who examine the volatility for five Dow Jones sector indices, namely, financial, industrial, consumer, health and technology. Via the ICSS algorithm, they conclude that most detected structural breaks are associated with big events. Wang and Nguyen Thi (2007) investigate the major stock indices in Taiwan and the US over a period from January 1997 to October 2001. Via ICSS algorithm, structural breaks are found in all the series in study. Moreover, Kang and Yoon (2010) investigate the exchange rates in Singaporean Dollar, Korean Won, New Taiwan Dollar and Thai Baht series by the ICSS algorithm. Sudden change is detected immediately after the 1997 Asian currency crisis and the 2008 financial crisis in all the series.

Despite that the ICSS of Inclan and Tiao (1994) has received its popularity for its straightforward implementation and satisfactory statistical inferences, however, recent studies have argued that the IT test would deliver false detections especially

when applied to financial time series (Andreou and Ghysels, 2002; Sanso et al., 2004). The underlying assumption of IT test is that the disturbances of the targeted series are independent and normally distributed, which is highly unlikely for financial time series as they evidently show fat-tailed distributions comparing to a normal distributed data sequence. Known as being leptokurtic, this fat-tailed distribution manifests greater chances for large fluctuations to occur. When dealing with data of such distribution, IT test tends to overestimate the number of change points. In light of such situation, Sanso et al. (2004) modified the ICSS by proposing a κ_2 test substituting the IT test shown in (1.19), under the same iteration procedure as of ICSS. κ_2 is defined as in Equations (1.20):

$$\begin{aligned} \kappa_2 &= \sup|\sqrt{1/T}G_k| \\ G_k &= \sqrt{1/\hat{\omega}_4}(C_k - \frac{k}{T}C_T) \\ \hat{\omega}_4 &= \frac{1}{T}\sum_{t=1}^{T}(\epsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t=l+1}^{T}(\epsilon_t^2 - \hat{\sigma}^2)(\epsilon_{t-1}^2 - \hat{\sigma}^2) \end{aligned} \tag{1.20}$$

where $\omega(l,m) = 1 - \frac{l}{m+1}$ (Newey and West, 1994).

Sanso et al. (2004) further provide simulation evidence to show much appealing properties of this modified version of ICSS algorithm of Sanso et al. (2004) (MICSS hereafter). In particular, MICSS is proved to be able to correctly detect the number of simulated breaks in data series with conditional heteroskedasticity for most scenarios. On the contrary, under the same scenario, ICSS shows severe size distortion. Moreover, they re-examine the work of Aggarwal et al. (1999), where several structural breaks are identified by ICSS. However, no break is found when applying MICSS on the same data series. Thus, it is confirmed that MICSS can correct the overestimation issue of ICSS. Empirical applications of MICSS can be found in McMillan and Wohar (2011), where the FTSE All-share index is selected along with eight economic sectors over the period from 01/01/1986 to 31/03/2008. Several breaks are found in seven out of the eight selected sectors with the number of which ranging from two to eight. It is further pointed out that, more mature sectors experienced fewer breaks comparing to that of rather newer ones. For the whole market index FTSE All-share, four breaks are identified, the number of which are found to lie between the extremes of the other sectors. This could be the result of averaging out across all the sectors. Lee (2015) chooses MICSS over ICSS as a result of the latter cannot work with the data observations with strong conditional dependence. From January 1998 to February 28, two structural breaks are identified for the major stock index returns in Korea, and both of them corresponds to

either regional or global financial crisis. Surprisingly, no break is found for the US over the same sample period. He further comments that those breaks could be the reason for the long range dependence observed in the volatility. Most importantly, the break-accounted GARCH model shows significant performance in out-of-sample forecasting.

1.3.4 Volatility Persistence under the Influence of Structural Breaks

A well-received critic for the conventional GARCH model is its misspecification due to the neglect of structural breaks in the volatility (Brooks et al., 2000; Nwogugu, 2006). Diebold (1986), Hendry (1986) and Lamoureux and Lastrapes (1990) are among the first to question the spurious persistence of volatility obtained by a conventional GARCH model with the presence of structural breaks. In particular, Lamoureux and Lastrapes (1990) intentionally set up 13 mutually independent change points for a series of daily stock return data, and construct the dummy variables accordingly, which then partitions the sample of 4228 observations in total into 14 non-overlapping intervals with 302 observations in each interval. After incorporating these dummy variables into a conventional GARCH (1, 1), the estimates of this modified GARCH (1, 1) yield a dramatically decrease of the volatility persistence comparing with a conventional GARCH (1, 1) model, even under the circumstances where no structural breaks are facilitated through a formal test. Nevertheless, given the changing economic conditions, such as the transition of an exchange rate system, or the financial crises, recognisable shifts in the unconditional variance of asset returns can be provoked, and consequently leads to a different structure in a GARCH data generating process (Wang and Moore, 2009; McMillan and Wohar, 2011). As a result, failure to accommodate the structural breaks in the unconditional variance of the examined financial series could lead to a considerable upward bias in the GARCH parameters and thus affect the accuracy of modelling the volatility persistence (Ding et al., 1993; Ding and Granger, 1996; Andersen and Bollerslev, 1997; Engle and Sheppard, 2001; Mikosch and Stărică, 2004). Moreover, recent literature has also suggested that the degree of volatility persistence derived from a GARCH model could have been overestimated in most of the previous studies due to this ignorance of structural breaks in volatility (Malik, 2003; Hillebrand, 2005; Wang and Nguyen Thi, 2007).

Under such circumstances, extensive studies have focused on taking into consideration the structural breaks while modelling volatility via GARCH model. One popular approach is to modify GARCH model by incorporating the breaks detected

via ICSS as dummy variables. Wen et al. (2018) study the oil and currency markets in the US from January 2000 to July 2014. Via the ICSS test, five break dates are found for the oil market, and four are for the latter. They further compare the estimates obtained from the univariate GARCH models, one with structural breaks incorporated and the other without. Significantly reduced volatility persistence is found after the incorporation of breaks for both markets in study. Dahiru et al. (2017) examine the stock market volatility dynamics in eight countries, namely, Mexico, Indonesia, Nigeria, Turkey, Japan, USA, Germany and France. A number of structural breaks are identified via the ICSS test from January 1994 to March 2014, and many of them occur around the 2008 financial crisis. They also find decreased volatility persistence in every series after the detected breaks are accommodated in the corresponding GARCH-type models. Lian and Liao (2015) investigate the volatility dynamics of Light-Sweet oil futures returns from August 1997 to July 2007. Using ICSS, eleven breaks are found; by incorporating the detected breaks as dummy variables in the GARCH models, reduced volatility persistence is found. Zhu et al. (2015) examine the European carbon futures between 2005 and 2012. Three breaks are found via ICSS, namely, on 17/11/2008, 22/06/2011 and 10/11/2011. They can be related to the 2008 financial crisis, the 2011 European debt crisis, and the economic recession in European countries. Mansur et al. (2007) study four foreign exchange rate series, namely, the British Pound, Canadian Dollar, Japanese Yen, and Swiss Franc, from January 1975 to September 2002. All four currency returns contain a number of structural breaks detected via ICSS, and the volatility persistence decreases via ICSS-GARCH model where the breaks are accommodated. Moreover, based on the in-sample analysis, ICSS-GARCH model shows more effective hedging performance comparing to the standard GARCH; the out-of-sample analysis further reveals much significant variance reduction when using ICSS-GARCH instead of GARCH. Therefore, the authors stress that the structural breaks should not be ignored. Using the same ICSS-GARCH model but in a bivariate framework, Huang (2014) estimates the optimal hedge ratio for spot/futures portfolio. Spot and futures returns are selected from the major stock indices of the US, the UK and Japan from January 1989 to December 2006. A bivariate ICSS-GARCH model is constructed by modifying a bivariate GARCH model of Kroner and Sultan (1993) with structural breaks, which are detected by ICSS, as dummy variables. This bivariate ICSS-GARCH model is proved to outperform its standard form in all the three countries in study. Tokat (2009) examines ISE 30 and ISE 100 stock indices in Istanbul from January 1990 to April 2007. Via ICSS, two breaks are found in ISE 30 and six in ISE 100; and the timing of these breaks can be associated with EU membership, domestic announcements of new fiscal or monetary policies, and the 1997 Asian financial crisis. More importantly, reduced volatility persistence

is obtained in both series after incorporating the breaks into GARCH models. The author comments that it is important to consider the effect of structural breaks to improve the accuracy of volatility estimation.

1.4 Volatility Spillover Investigation

According to Ross (1989), a change in the volatility indicates the arrival of new information. Particularly in the financial department, volatility spillover effect describes the Granger causality between two asset series in the volatilities. Studying such spillover effect in the volatilities of financial markets not only can reveal how the new information travels across markets, but it also helps us to understand how markets respond to information originated from another market. When such effect exists, it is said that a change in the volatility of one market would cause a change in the volatility of the other causal-related market; moreover, the past innovations in the former market could help predict the behaviour of the latter. Therefore, in the context of a more and more integrated world market, by tracking this volatility transmission between financial markets, investors that hold international portfolios could greatly benefit from this subject. In the event of insufficient information when analysing one financial asset, it is still possible to predict the behaviour of this market using the information of other markets if a volatility spillover pattern is detected between them. Additionally, investors can also take advantage of the lack of such causation pattern since they can construct diversified portfolios to manage their financial exposure. Moreover, the insights gained by studying this causality in volatility/variance can also help the government to formulate and implement new policies to supervise financial markets much properly. Therefore, it is of both importance and necessity to investors, financial managers and policy makers to better understand the dynamics of financial markets via studying volatility spillover, in order to construct much proper portfolios, to better manage financial risks and to establish monetary or political policies to better maintain short term financial stability.

1.4.1 Causality in Variance Test of Cheung and Ng (1996) and the Modified Version of Hong (2001)

Cheung and Ng (1996) develop a two-stage approach to test causality pattern in variance by extending the procedures in Haugh (1976) and McLeod and Li (1983). After the first stage of estimating the univariate time series models, the cross-correlation function (CCF) is then constructed based on the squared model residuals standardised by the estimated conditional variances, in order to test the null hypothesis of

no causality in variance.

Based on the Granger Causality definition of Granger (1969) and Granger (1980), the hypotheses of causality in variance test are proposed by Hong (2001) as below:

$$H_0 : E\{Var(Y_{1t}|I_{t-1})|I_{1t-1}\} = Var(Y_{1t}|I_{t-1}) \tag{1.21}$$

vs.

$$H_A : E\{Var(Y_{1t}|I_{t-1})|I_{1t-1}\} \neq Var(Y_{1t}|I_{t-1}) \tag{1.22}$$

where $Y_{1t}, Y_{2t}, t = 1, ..., T$ are two strictly stationary time series. Define individual information set I_{1t}, I_{2t}, and the union information set $I_t = (I_{1t}, I_{2t})$. Each of the first two sets contains information of each series available at t, and I_t contains information of both series available at t. When the null hypothesis in (1.21) holds, the variance of Y_{1t} based on the union past information set I_{t-1} equals to that of its own past information set I_{1t-1}. In other words, including past information from I_{2t} does not affect the variance of Y_{1t}. Hong (2001) describes such situation as Y_{2t} does not Granger-cause Y_{1t} in the variance. When the alternative in (1.22) holds, including past information from Y_{2t} does affect the variance of Y_{1t}, thus, Hong (2001) describes this relationship as Y_{2t} Granger-causes Y_{1t} in the variance.

In order to check the volatility spillover pattern between two stationary time series $Y_{it}, i = 1, 2$, consider their conditional variances $h_{it}, i = 1, 2$, each of which follows a GARCH(p,q) process:

$$Y_{it} = \mu_{it} + \varepsilon_{it}, \quad t = 1, ..., T; i = 1, 2 \tag{1.23}$$

$$h_{it} = \omega_i + \sum_{j=1}^{p} \alpha_{ij}\varepsilon_{it-j}^2 + \sum_{j=1}^{q} \beta_{ij}h_{it-j}, \quad t = 1, ..., T; i = 1, 2 \tag{1.24}$$

Set

$$u_t = \varepsilon_{1t}^2/h_{1t} \tag{1.25}$$

$$v_t = \varepsilon_{2t}^2/h_{2t} \tag{1.26}$$

The jth cross correlation coefficient of the squared standardized residuals u_t and v_t is

$$\rho_{uv}(j) = \{C_{uu}(0)C_{vv}(0)\}^{-1/2}C_{uv}(j) \tag{1.27}$$

where $C_{uu}(0) = T^{-1}\sum_{t=1}^{T} u_t^2$ and $C_{vv}(0) = T^{-1}\sum_{t=1}^{T} v_t^2$ are the variances of Y_{1t} and Y_{2t} respectively. Moreover, $C_{uv}(j)$ calculates the jth sample cross covariance, which

takes the form

$$C_{uv}(j) = \begin{cases} T^{-1} \sum_{t=j+1}^{T} u_t v_{t-j}, & j \geq 0 \\ T^{-1} \sum_{t=-j+1}^{T} u_{t+j} v_t, & j < 0 \end{cases} \tag{1.28}$$

Test statistics S is then constructed based on the first M squared cross correlations:

$$S = T \sum_{j=1}^{M} \omega_j \rho_{uv}^2(j) \tag{1.29}$$

This test is asymptotically χ^2 under the null hypothesis of no causality; also ω_j is the sample finite correction when sample size T is small. According to Haugh (1976) and McLeod and Li (1983), two forms can be considered: $\omega_j = T/(T-j)$ or $\omega_j = (T+2)/(T-j)$. This correction enables the test to have better performance when dealing with small samples (Ljung and Box, 1978).

According to Cheung and Ng (1996), this CCF approach is much easier to implement comparing to methods which are built upon a multivariate framework, since CCF requires no simultaneously modelling of either intra or inter series dynamics. Nevertheless, as the main feature of volatility clustering, the recent past volatility is observed to have greater impact on current volatility comparing to that of distant past volatility. In this sense, the recent volatility of one asset or financial market is said to have more influence on the current volatility of the other asset or market. It can also be confirmed by the recent empirical studies, where the cross-correlations between financial assets gradually decay to zero as the lag j increases (Cheung and Ng, 1996). Therefore, when using a large M, the S test may be less efficient since it gives equal weighting to each of the M sample cross-correlations. Furthermore, strong cross-correlation may exist for some financial time series during some period, which leads to situation where the cross-correlation at each lag is small; however, the joint effect might be too significant to neglect. Therefore, it is desirable to let M grow with T or to take into consideration all $T-1$ sample cross-correlations. Based on the discussion, a Q test is proposed by Hong (2001) as shown in Equation (1.30):

$$Q = \frac{T\sum_{j=1}^{T-1} k^2(j/M)\rho_{uv}(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{1.30}$$

$$C_{1T}(k) = \sum_{j=1}^{T-1}(1-j/T)k^2(j/m) \tag{1.31}$$

$$D_{1T}(k) = \sum_{j=1}^{T-1}(1-j/T)\{1-(j+1)/T\}k^4(j/m) \tag{1.32}$$

where $k(.)$ is Bartlett kernel (Priestley, 1981), such weighting function is defined as below

$$k(z) = \begin{cases} 1-|z|\,, & \text{if } |z| \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{1.33}$$

Also, $C_{1T}(k)$ and $D_{1T}(k)$ are the mean and variance of Equation (1.30). The finite sample corrections of $(1-j/T)$ and $(1-j/T)\{1-(j+1)/T\}$ give better matches to the aforementioned mean and variance. Under the null hypothesis, Q follows an N(0,1) distribution, and it is a one-sided test, and the critical value at the 5% is 1.645.

Hu et al. (1997) carry out an investigation on the stock markets in one particular geographical region, which is the South China Growth Triangular (SCGT) containing Shanghai, Shenzhen, Hong Kong and Taiwan. To be more specific, the volatility spillover effects are examined across stock markets, both within the SCGT, and between the SCGT and the US and Japan. This comparison study can help us not only to understand the relationship of the stock markets in the same economic region but also to investigate the co-movement across international stock markets from a comparison approach between the emerging and mature markets. By examining daily returns from 05/10/1992 to 15/02/1996 via the causality in variance test of Cheung and Ng (1996), evidence is found for a causal relation in the volatilities from the Japanese stock market to the US stock market, and from Hong Kong market to the US market. Meanwhile, volatility spillover effects are found from the Hong Kong market to the US market; also, for the emerging markets located in the South China Growth Triangular, the US market is identified as the primary influence when compared to that of Japan. Moreover, within the SCGT, Shanghai and Shenzhen markets have stronger interactions with the US and Japanese markets than they do with markets in Hong Kong and Taiwan, emphasizing the fact that geographical proximity is not necessary to form a strong causal relationship in the volatility of stock markets. Last but not least, after adding the conditional variances

of the developed markets as explanatory variables to the conditional variances of the emerging markets in the SCGT, the volatility persistence of the emerging markets decreased dramatically. This finding shows us the potential to capture the arrival of new information to one market more accurately when the source is identified and accommodated appropriately. Moreover, this econometric evidence also reveals that the volatility of the developed markets can explain the excess kurtosis of the volatility of the emerging markets, in particular for those with less degree of openness.

Similarly, Xu and Hamori (2012) adopt the causality in variance test of Hong (2001), on stock markets in the BRIC countries and the United States. The BRIC countries include Brazil, Russia, Indian and China, these four countries together constitute almost half of the world population, and in the meantime, geographically cover more than a quarter of the world. The major stock price indices are selected and the daily return series are created over a period from 02/08/2004 to 30/04/2010, consisting of 1194 observations for each country in question. Moreover, in order to evaluate the potential impact of the 2008 financial crisis on the target causal relationship in question, the sample period is divided into pre-crisis and post-crisis by the date of 28/09/2008, forming subsamples of 876 and 318 observations respectively. For the pre-crisis period, the fitted models are AR(1)-EGARCH(1,1) for the US, Brazil, Russia, and India, and AR(3)-EGARCH(1,1) for China; while for the post-crisis period, the AR(1)-EGARCH(1,1) is selected for the US, Russia, India and China, and the AR(8)-EGARCH(1,2) fits the data series from Brazil. Empirical results show there is causality in mean from the US to Russia, and from the US to India in both subperiods. A two-way causality in mean exists between the US and China only in the pre-crisis period, whilst in the post-crisis period, there is no causality in mean between these two countries. It also reveals that there is no causality in mean between the US and Brazil in neither of the sub sample period. Meanwhile, the causality in variance only exists from the US to India before the 2008 financial crisis. Therefore, it can be seen that the relationship of stock markets between the US and BRIC countries varies before and after the 2008 financial crisis. Moreover, the interactions appear much stronger before the crisis. Thus it can be said that the 2008 financial crisis has weakened the transmission of stock prices in both the mean and variance between BRIC countries and the US. It can also be seen that India is the country that interacts with the US the most, while Brazil is the one interacting with the US the least. These results could imply that investment strategies should be adjusted accordingly during pre and post-crisis periods.

1.4.2 Lagrange Multiplier Test of Hafner and Herwartz (2006)

To examine the causal relationship in variance of financial returns, Hafner and Herwartz (2006) adapt the Lagrange Multiplier (LM) principle to analyse the second order causality, which is also known as causality in variance. Consider two stationary data series $\{Y_{it}, i = 1, 2\}$ with the conditional variances $\{h_{it}, i = 1, 2\}$ following a GARCH(p,q) process expressed as below:

$$\begin{aligned} Y_{it} &= \mu_{it} + \varepsilon_{it}, \;\; \varepsilon_{it} \in \mathbb{R}^{\mathbb{N}}, t \in \mathbb{N} \\ \varepsilon_{it} &= \xi_{it} h_{it}^{1/2} \\ h_{it} &= \omega_i + \sum_{j=1}^{q} \alpha_{ij} \varepsilon_{it-j}^2 + \sum_{j=1}^{p} \beta_{ij} h_{it-j} \end{aligned} \tag{1.34}$$

where each of the $\{\xi_{it}, i = 1, 2\}$ is a sequence of independent and identically distributed random variables with $\xi_{it} \sim N(0, 1)$. Moreover, the corresponding information sets are I_{1t} and I_{2t} respectively, with I_t as the information set containing all the information that is available at time t. When the information in the series of $\{\varepsilon_{2t-1}\}$ has no influence on the series of $\{\varepsilon_{1t}\}$, it is said that there is no causality in the variance from series $\{\varepsilon_{2t}\}$ to $\{\varepsilon_{1t}\}$. Therefore, the null hypothesis of the causality in variance test is formed as follows:

$$H_0 : Var(\varepsilon_{1t}|I_{1t-1}) = Var(\varepsilon_{1t}|I_{t-1}) \tag{1.35}$$

As expression (1.35) refers, no causality is found from the variance of Y_{2t} to the variance of Y_{1t} when the null hypothesis holds. Based on the formulation in expression (1.35), the Lagrange multiplier approach of Hafner and Herwartz (2006) firstly constructs an alternative parametric model to take into consideration the values from data series Y_1 at time t along with the values from data series Y_2 at time $t - 1$ as below:

$$\begin{aligned} \varepsilon_{1t} &= \xi_{1t}[h_{it}(1 + v_2'\pi)]^{1/2} \\ v_2' &= (\varepsilon_{2t-1}^2, h_{2t-1})' \end{aligned} \tag{1.36}$$

Under this new specification shown in expression (1.36), one sufficient condition for the null hypothesis shown in expression (1.35) to hold is to have $\pi = 0$. Thus, the null hypothesis of no causality in variance can be reformulated as below:

$$H_0 : \pi = 0 \tag{1.37}$$

vesus the alternative

$$H_A : \pi \neq 0 \tag{1.38}$$

Therefore, with the score of the Gaussian log-likelihood function of ε_{1t} calculated as $x_{1t}(\xi_{1t}^2 - 1)/2$, where $x_{1t} = h_{1t}^{-1}(\frac{\partial h_1 t}{\partial \theta_{1t}})$ with $\theta_{1t} = (\omega_{1t}, \alpha_{1t}, \beta_{1t})'$, the Lagrange multiplier test statistic is formed as below:

$$\lambda_{LM} = (4T)^{-1}[\sum_{t=1}^{T}(\xi_{1t}^2 - 1)v_{2t}']V(\theta_{1t})^{-1}[\sum_{t=1}^{T}(\xi_{1t}^2 - 1)v_{2t}] \tag{1.39}$$

where

$$V(\theta_{1t})^{-1} = \frac{\kappa}{4T}[\sum_{t=1}^{T} v_{2t}v_{2t}' - \sum_{t=1}^{T} v_{2t}x_{1t}'(\sum_{t=1}^{T} x_{1t}x_{1t}')^{-1}\sum_{t=1}^{T} x_{1t}v_{2t}'] \tag{1.40}$$

where

$$\kappa = T^{-1}\sum_{t=1}^{T}(\xi_{1t}^2 - 1)^2 \tag{1.41}$$

The asymptotic distribution of λ_{LM} follows an asymptotic chi-square distribution, and the number of freedom is two, which is determined by the number of misspecification indicators in $v_{2t} = (\varepsilon_{2t-1}^2, h_{2t-1})'$.

The causality in variance test of Hafner and Herwartz (2006) is argued to outperform the cross-correlation functions (CCF) approach when investigating volatility spillover, as the latter method tends to suffer from oversize greatly in small samples especially dealing with data processes that are leptokurtic. Besides, the robustness of the findings from the CCF approach is under question due to the selection of the

order of leads and lags in the test procedure, leading to a less accurate CCF test statistic (Hafner and Herwartz, 2006; Zhang et al., 2013; Yang et al., 2014; Nazlioglu and Gupta, 2015). The Monte Carlo study in Hafner and Herwartz (2006) confirms the robustness of the LM approach against asset return series that is fat-tailed or leptokurtic in small samples.

Nazlioglu and Gupta (2015) investigate the volatility spillover effect between Islamic stock market and the global markets via the causality in variance test of Hafner and Herwartz (2006) that is developed from the Lagrange multiplier test. The study is carried out from two angles; one is to investigate the volatility transmission pattern between Islamic stock market and three global major stock markets from the United States, Europe and Asia; the other is to examine the causal linkage between Islamic stock market and the global factors including the oil prices, the US economic uncertainty index, the index of volatility and fear in the US equity market, and the federal funds rate. Moreover, apart from the full sample period of 04/01/1999 to 20/09/2013, two sub sample periods are created around the 2008 financial crisis, which are the pre-crisis period dating from 04/01/1999 to 31/12/2007, and the in- and post-crisis period dating from 01/01/2008 to 20/09/2013 to be put under investigation. By examining the relationship between the Islamic stock market and each of the other global stock markets in question, a two-way volatility spillover effect is found in all the pairs of stock markets in all the three sample periods; this finding evidently points out the possibility to consider investing in the Islamic stock market when investors perceive higher volatility in the global markets especially during a financial crisis period. This finding questions the studies of Dridi and Hasan (2010) where it is argued that it is not possible for the Islamic stock market to transmit risk in terms of volatility to and from the global markets, as the structure of this market is fundamentally different from that of those global markets. Furthermore, there is no volatility spillover from any of the global variables to the Islamic stock market in any of the sample periods; however, volatility spillover is found from the Islamic stock market to all of the chosen global factors only in the in- and post-crisis period. This result strongly suggests the domestic investors could have a wide window to better respond to the financial turbulence originated from the global market.

Yang et al. (2014) study the volatility spillover effects between the major stock markets in Chinese regions taking into consideration the level of development. The market capitalization of listed companies is one major indicator in the evaluation of the development of a stock market. In this context, the interaction between three stock markets, namely, Shanghai, Hong Kong and Taiwan, are under study. As the rapid growth in the mainland of China, the market capitalization of Shanghai stock

market exceeded that of Hong Kong and Taiwan by 2000, leading towards 3.8 times of the market capitalization of Hong Kong, and 5.33 times of that of Taiwan in 2011. Moreover, the growing economy in the mainland of China also stimulated the growth of the Hong Kong stock market as many large Chinese firms rushed to go public in Hong Kong. This led to the exceeding market capitalization of Hong Kong than Taiwan from 1999. Therefore, targeting the period from July 1995 to March 2012, the study of Yang et al. (2014) employ the causality in variance test of Hafner and Herwartz (2006) on the selected stock markets, in order to understand how the market capitalization would affect the volatility transmission pattern between these markets. Empirical results show that the null hypothesis of no causality in the volatility is rejected in two pairs of stock markets out of six pairs in total, revealing a one-way volatility spillover from Shanghai stock market to Taiwan stock market, and a one-way volatility spillover from Hong Kong stock market to Taiwan stock market. This finding establishes that the larger the market capitalization is, the more influence it will pass onto the stock markets with lower market capitalization.

Zhang et al. (2013) contribute to the existing literature by investigating the volatility spillover between the domestic equity and bond markets from both the G7 (Japan, USA, Germany, Italy, UK, France, Canada) and BRICS (China, Russia, India, Brazil, South Africa) countries as to also study any different volatility transmission pattern due to different levels of development. The causality in variance test of Hafner and Herwartz (2006) is chosen over the CCF approach of Cheung and Ng (1996) and the approaches with a multivariate setting, i.e. the BEKK-GARCH of Engle and Kroner (1995), or the DCC-GARCH of Engle and Sheppard (2001). This choice overcomes the drawbacks of the decreased robustness of small samples and the inappropriate choice of lags in the former method, and the curse of dimensionality in the latter. In this regard, daily returns of stock and bond are first evaluated and GARCH(1,1) is determined to be the best model for each data series. After examining the volatility spillover effects in the G7 countries, a significant one way causality in the volatility is found to go from the bond series to the stock series in the US, the UK and Germany; a feedback volatility spillover is found between the two classes of return series in France. As for the BRICS countries, there is a two-way volatility spillover in Brazil and South Africa. No significant volatility spillover effect is found between the equity and bond markets in Japan, Italy, Canada, Russian, or China. These findings suggest idiosyncratic volatility spillover effect in individual countries; also, the authors argue that the developed countries tend to show more evidence for the efficiency of cross market information transmission and the integration of financial markets.

The study of Okur and Cevik (2013) takes consideration the influence of structural breaks when determining the volatility spillover between leptokurtic asset return series, so that the results can be more accurate. However, no clear comment nor further statistical investigation is found to mention the tendency that the causality in variance test of Hafner and Herwartz (2006) seems to be less influenced when the presence of structural breaks in the conventional GARCH (1,1) model is ignored. If this tendency could be verified, then it could mean that the causality in variance test of Hafner and Herwartz (2006) is a more suitable approach when the market was experiencing many shocks thus increasing the possibility to have many structural breaks in the volatility in a very short period of time. Without the extra effort to construct models accommodating the structural breaks and re-estimate the new model, it could save much time and resources to evaluate the causality pattern in the volatility between financial markets especially during turbulent times. Therefore, further validation of such possibility is worth pursuing in the future work.

1.4.3 BEKK Model of Engle and Kroner (1995)

The establishment of the BEKK model stems from the VEC model and the DVEC (diagonal VEC) of Kroner and Ng (1998). The VEC model was among the first to explore the relationship between financial assets in a multivariate setting, as specified below:

$$vech(H_t) = C + Avech(\varepsilon_{t-1}\varepsilon'_{t-1}) + Gvech(H_{t-1}) \tag{1.42}$$

where H_t is the conditional variance-covariance matrix, ε_{t-1} is the error terms matrix, A and G are matrices of the corresponding parameters. The $vech$ represents the vector-half operator, where the lower triangular half in a symmetric $d \times d$ matrix is stacked into a single vector with the length of $d(d+1)/2$. Therefore, each element of H_t is a linear function combining the lagged values of squared errors and cross-products of errors, as in $Avech(\varepsilon_{t-1}\varepsilon'_{t-1})$, and lagged values of H_t, as in $Gvech(H_{t-1})$. For one thing, the general VEC model requires estimating a large number of parameters; besides, according to Gourieroux (1997), the positivity of H_t could not be guaranteed without heavy restrictions on the parameters. Kroner and Ng (1998) also design the DVEC with the purpose of reducing the number of parameters to be estimated, however, the diagonal matrices A and G lead to the elements of H_t depending only on the previous values of shocks and H_t, therefore, DVEC fails to detect the volatility spillover effects across different series. In order to address the aforementioned issues, the BEKK of Engle and Kroner (1995) is proposed as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G \tag{1.43}$$

where C, A, B are parameters matrices, with C as an $n \times n$ lower triangular matrix, and A, B as $n \times n$ matrices. By using the quadratic forms, the BEKK model promises positive semi-definiteness under very week conditions. Moreover, in matrix A, the coefficients measuring the effect of shocks imposed on the volatility of its own country locate at the diagonal, in other words, the own ARCH effect, whilst the effect of shocks from country i on the volatility of country j are the off-diagonal elements. In matrix G, the diagonal elements measure the effect of the past volatility on the volatility of its own country, put it differently, the own GARCH effect, while the effect of past volatility of country i on the volatility of country j are the off-diagonal parameters. Therefore, in order to check whether there is volatility spillover from country i to country j, it is to check whether the off-diagonal estimated parameters are significant or not at the chosen confidence level. Normally, according to Engle and Kroner (1995) and Kroner and Ng (1998), the appropriate estimation technique for BEKK model is maximum likelihood estimation.

Studying the integration of international stock markets is critical for individual investors and financial institutions, as the rapidly spread of technology and the growing scale of cross-border trading opportunities ensures the integration of markets in the global economy. Moreover, the recent research focus tends to be looking into the volatility spillover between developed and emerging markets, in order to extract useful information for devising hedging strategies. For instance, if the causal linkage from the developed markets to the emerging markets is weak, this indicates that the emerging markets tend to be less influenced by the external shocks originated from the developed markets, therefore, the investors holding assets from the developed markets could diversify their position by including assets from emerging markets in the portfolio. In this context, Li and Giles (2015) investigate the volatility causality linkages between stock markets across the USA, Japan, China, India, Indonesia, Malaysia, the Philippines and Thailand. The targeted countries are divided into six groups, each of which contains the two developed countries and one developing market, and the sample period is from 01/01/1993 to 31/12/2012 covering both the 1997 Asian financial crisis and the 2008 sub prime financial crisis. In particular, as the stock market is more sensitive to negative shocks than to positive ones, the asymmetric BEKK-GARCH(1,1) of Kroner and Ng (1998) is employed in this study in the sense of the GJR (Glosten, Jagannathan and Runckle) model in Glosten

et al. (1993), in order to accommodate the asymmetric responses of volatility in the multivariate case. The specifications of the asymmetric BEKK-GARCH(1,1) are as below:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'H_{t-1}G + D'\epsilon_{t-1}\epsilon'_{t-1}D \tag{1.44}$$

where ϵ_{t-1} equals ε_{t-1} when ε_{t-1} is negative, and zero otherwise. Moreover, D measures the asymmetric response to the negative news. Empirical findings reveal strong one-way volatility spillover effects from the US stock market to both the stock markets in Japan and Asia. Particularly, during the 1997 Asia financial crisis, the volatility spillover grows more significantly between the US market and the Asian markets, and the volatility spillover becomes bidirectional.

Chkili (2012) investigate the short run causal relationship in the second moment between series of exchange rate changes and series of stock market returns between a selection of developing countries over the period of 30/12/1994 to 13/03/2009. Weekly return series are generated from the major indices in Hong Kong, Singapore, Malaysia, South-Korea, Indonesia, Argentina, Brazil and Mexico. The multivariate BEKK-GARCH (1,1) model of Kroner and Ng (1998) is adopted as suggested in Li and Majerowska (2008) and Saleem (2009) to measure the level of market integration indicated in volatility. A bidirectional volatility spillover is found between the stock and currency markets in Malaysia, Korea, Indonesia and Brazil, as indicated by the statistically significant coefficients of both g_{12} and g_{21}. Moreover, a unidirectional volatility spillover is found from the stock markets to the foreign exchange markets in Singapore, Argentina and Mexico, as indicated by the significant g_{12} with the insignificant g_{21}. These results reveal that the stock market has great impact on the foreign exchange markets in all of the selected emerging countries; moreover, four out of seven of the selected emerging countries show a strong connection between these two financial markets. In particular, the finding in the former sets the difference against the conclusion drawn from the existing literature that in the developed countries the foreign exchange markets show greater influence on the stock markets (Kanas, 2000; Yang and Doong, 2004; Aloui, 2007); possible explanations include the more effective use of derivatives for hedging currency risk (Kanas, 2000); also both Bodnar et al. (1995) and Grant and Marshall (1997) mention that the wide use of financial hedging by multinational firms could significantly weaken the impact that the exchange market imposes on the stock market, as those companies are the major components of national stock market indices. As Chkili (2012) state, since

the BEKK model is able to address not only the conditional volatility dynamics, but also the conditional covariance between the two selected financial assets, thus their empirical findings can contribute to the establishment of the optimal weights of currency and stock to minimize risk in the portfolio.

Chou et al. (1999) studied the interactions between stock markets of Taiwan and the US; analysing the daily close-to-open and open-to-close stock returns from 1991 to 1994. Under the bivariate BEKK-GARCH framework of Engle and Kroner (1995), a one-way causality was pinned to flow from the US market to Taiwan, especially for the case using open-to-close returns.

A well known drawback of BEKK is that the number of estimated parameters increases as the number of the financial assets considered in the BEKK model increases,. This has been widely agreed in many studies; however, very few study has shown comparison investigation between the performance of the major methods and of the BEKK. In other words, when the volatility spillover is considered between only two financial assets, few study has shown any evidence that the BEKK in the bivariate setting would have less satisfactory performance. Therefore, in this sense, another direction of future research could be to set up simulation studies in a way that the time of the evaluation of both methods could be compared.

1.4.4 Volatility Spillover under the Influence of Structural Breaks

From the above discussion it can be seen that most of the techniques involved in investigating volatility spillover are in the framework of GARCH models. Moreover, Section 1.3 has documented that neglecting structural breaks can lead to spurious GARCH model estimation. Such misspecification of GARCH models can eventually cause biased volatility spillover results (Rodrigues and Rubia, 2007). Moreover, based on an extensive set of Monte Carlo simulations, Dijk and Sensier (2005) provide evidence that the causality-in-variance test developed by Cheung and Ng (1996) and Hong (2001) suffers from considerable size distortions when structural breaks are ignored. Therefore, it is absolutely necessary to detect possible structural breaks before examining the causality in variance.

Huang (2012) studies the futures returns of S&P 500, FTSE 100 and Nikkei 225 from January 1989 to December 2006. All three series show structural breaks in each volatility via ICSS, also reduced persistence is obtained when those breaks are controlled for. Most importantly, via the BEKK-GARCH model, a unidirectional

spillover is found from FTSE 100 to Nikkei 225, and from S&P 500 to Nikkei 225; in addition, a bidirectional volatility spillover exists between FTSE 100 and S&P 500. Nevertheless, all these spillover effects no longer exist after the incorporation of structural breaks. This very extreme finding agrees with Ewing and Malik (2005), Arago-Manzana and Fernandez-Izquierdo (2007), and Miralles Marcelo et al. (2008) that, neglecting structural breaks could significantly cause overestimation of volatility transmission scale.

Shahrazi et al. (2014) investigate volatility spillover between Iranian gold and foreign exchange markets during a period from 2007 to 2013. Using MICSS of Sanso et al. (2004), one break is found in the gold market series, and two in the foreign exchange. Via the BEKK-GARCH model pf Engle and Kroner (1995) with detected breaks as dummy variables, a bidirectional volatility spillover is found between these two markets; however, no linkage is found when these breaks are ignored. Therefore, the authors strongly advise researchers to avoid the misleading implication caused by the ignorance of structural breaks when evaluating volatility spillover effects.

Oil prices are usually considered as a critical economic indicator. Ewing and Malik (2016) study the volatility spillover effect between daily return series of the crude oil prices and the US stock prices from 01/07/1996 to 30/06/2013. In particular, the effect of structural breaks in the volatilities of two data series is taken into consideration. MCSS method of Sanso et al. (2004) is first employed to identify the presence of possible structural breaks in the unconditional variance in each of the series. Empirical evidence indicates four change points for the oil series, and eight change points for the stock series. After taking account of the structural breaks in the corresponding conventional GARCH models, the volatility persistence has decreased in each series; to be more precisely, from 0.985 to 0.809 for the oil series and from 0.989 to 0.958 for the stock series. This significant drop is further supported by the likelihood ratio statistic, which shows the GARCH model with breaks outperforms the original one without breaks. After that, the detected structural breaks are then accommodated in the BEKK-GARCH model of Engle and Kroner (1995) to test the volatility spillover effects. Empirical findings show a bidirectional volatility spillover between these two asset series; more interestingly, in the BEKK-GARCH model where the effects of structural breaks are ignored, no significant volatility spillover is found in either direction. This finding highlights the importance of accommodating the structural breaks in the unconditional variance of financial asset series to accurately determine the volatility transmission pattern between financial markets, as well as the accurate estimation of the volatility persistence in constructing hedging strategies and derivative valuations. Moreover, in Ewing and Malik (2005), same

techniques are employed on investigating the volatility dynamics between gold and oil futures over a period of 01/07/1993 to 30/06/2010. Nine breakpoints are found in the gold series and seven in the oil futures; after those change points are incorporated in the GARCH model, reduced volatility persistence is found in both cases; moreover, a two-way volatility spillover effect is found between these two series with consideration of the structural breaks in the unconditional volatilities, yet only a one way volatility spillover is found from the oil futures to the gold market when the structural breaks are ignored. One common procedure in the methodology in both studies worth pointing out is that, residuals from both types of GARCH models pass the standard diagnosis tests, suggesting the standard diagnostic test fails to reveal the misspecification of the conventional GARCH model when the structural breaks in the volatility are ignored. This can also provide evidence for the argument in the existing literature in this area that the conditional variance could be incorrectly estimated in many studies. Furthermore, although these two studies detect a different volatility spillover pattern after the break points are taken account of, there is little empirical evidence showing the BEKK-GARCH model with structural breaks outperforms the conventional BEKK-GARCH model.

More studies combining structural breaks detection and volatility spillover investigation can be found as follows: Okur and Cevik (2013) focus on studying the volatility transmission between futures and spot markets in Turkey. This topic has been widely discussed in the literature of finance because determining the causal link in the variance between future prices and the underlying spot prices can help with hedging and budget planning, therefore, it attracts attention from not only investors but also regulators and academics. In addition, the investigation on the intra-day data set can help investors to capture the market dynamics more accurately, and thereby help them hedging their risks more efficiently so to prudently devise their investment strategies. The study of Okur and Cevik (2013) firstly detects the presence of structural breaks in the volatility of the return series of the selected future and spot prices. Via the ICSS of Inclan and Tiao (1994), sixteen structural change points are found for the spot return series, while forty are detected for the future return series. After a GARCH (1,1) is determined to be the appropriate model for both return series, the conventional GARCH (1,1) is modified by including dummy variables corresponding to the detected structural change points in both series, and empirical results show the decreased volatility persistence in both series after the accommodation of structural breaks. This is consistent with the existing literature, see, for instance, Lamoureux and Lastrapes (1990); Arago-Manzana and Fernandez-Izquierdo (2007); Ewing and Malik (2010), where it is argued to have overestimated volatility persistence when the presence of structural breaks in the volatility is ig-

nored in the conventional GARCH model. Moreover, Okur and Cevik (2013) prove that the modified GARCH (1,1) has better explanatory power than the conventional GARCH (1,1) by a likelihood ratio (LR) test. Eliminating the effect of structural breaks is essential for the later on causality in variance test because the test statistics are based on the parameters estimated from GARCH models; as a result, misleading causality results can be produced if the structural breaks exist in the volatility and are not accounted for. Next, the cross correlation function (CCF) based causality in variance test of Hong (2001) is adopted to investigate the information transmission mechanism between the two return series with two case scenarios with respect to whether the structural breaks are considered in the conventional GARCH (1,1) model. A two-way volatility spillover effect is detected between the returns of spot and the futures series when the structural breaks are taken into consideration; in addition, according to the size of cross-correlation coefficient at different lag selection, it can be determined that the spot market influences the futures market within 10 minutes, while the futures market influences the spot market within 5 minutes. When the presence of the structural breaks is ignored, only a one way volatility spillover is found from the spot market to the futures market, and the influence begins within 15 minutes. The finding of a new volatility spillover direction is consistent with the study of Dijk and Sensier (2005) and Rodrigues and Rubia (2007) that the ignorance of structural breaks will lead to the size distortion in the causality in variance test of Cheung and Ng (1996) and Hong (2001). Moreover, in order to assure the robustness of the causality results from the aforementioned test, the Lagrange multiplier based causality in variance test of Hafner and Herwartz (2006) is also employed, which is proved to overcome the lag selection problems and the small sample problems from the causality in variance test of Cheung and Ng (1996) and Hong (2001). Results of Hafner and Herwartz (2006) show a unidirectional volatility spillover from the spot to the futures market no matter the structural breaks are accommodated or not. Therefore, Okur and Cevik (2013) comment that, empirical results from both causality in variance methods can at least confirm the volatility spillover from the spot market to the futures market in Turkey over the sample period from 01/05/2006 to 31/05/2010; therefore, comparing to the futures market, the spot market plays a more dominant role in the intra-day spillover effect in Turkey. Another study considers structural breaks in volatility spillover investigation is Mensi et al. (2016). The volatility transmission patterns are examined of daily stock indices between the US and each of the BRICS countries, which includes Brazil, Russia, India, China and South Africa, over a sample period dated from September 1997 to October 2013. In order to check the impact of the 2008 financial crisis, they first examine the presence of structural breaks in each of the selected stock indices using MICSS of Sanso et al. (2004), one shared break date is

found on 15 September 2008. Based on this date, two sub-sample periods are created, and a DCC-FIAPARCH model is developed based on the FIAPARCH model of Tse (1998) under the DCC framework of Engle (2002), and adopted to the daily return series. A stronger bi-directional volatility spillover is found between the US and Brazil, India, China, and South Africa after 15 September 2008, indicating the outburst of financial crisis has increased the linkage between these markets after the financial crisis; however, volatility spillover is no longer found between the US and Russia after the crisis, implying the possibility that financial crisis has caused a disconnection of Russian stock markets from the US. This information is of great value to investors to exploit portfolio diversification benefits and risk managers to manage financial exposure and policy makers to sustain market stability.

Moreover, Güloğlu et al. (2016) examine the volatility spillover pattern between five LA stock markets Argentina, Brazil, Colombia, Chile and Mexico. The DCC-GARCH model of Engle (2002) is selected and incorporated with structural breaks detected via MICSS algorithm of Sanso et al. (2004), so to eliminate the model misspecification caused by the overlook of structural breaks. Examining the daily stock index returns over a period from January 2008 to May 2015, causality pattern is found to be very significant from Mexico to Argentina, yet very weak from Brazil to Mexico; no volatility spillover is found between the other pairs of stock markets in question. These findings suggest an independence structure between LA stock markets, which agrees with the argument raised in Korkmaz et al. (2012) that the lack of volatility spillover could be the evidence of independence between markets to some extent.

1.5 Conclusion

The ICSS test of Inclan and Tiao (1994) and its modified version of Sanso et al. (2004) are the most popular techniques when testing for structural breaks in the volatility. Although the underlying assumption of normality and i.i.d causes overestimation problems for the application of ICSS test of Inclan and Tiao (1994) to financial time series, Sanso et al. (2004) develop a modified version of ICSS (MICSS) in order to overcome such problem. In particular, both tests can be used to test for multiple structural breaks without any knowledge of the potential locations of breakpoints. This feature makes ICSS and MICSS more preferred than the $supLM(\pi)$ test of Andrews (1993), as the latter method can only detect the presence of structural break in some pre-selected time period. Despite the better size and power properties than ICSS and MICSS, the application of the $supLM(\pi)$ test could be very restrictive due to the high dependency on the choice of sample period. Therefore, it can

only produce relatively accurate timing of a structural break around known events, such as change of fiscal policy, financial crisis, or a change of CEO in a company. Nevertheless, less satisfactory results can be expected when there is no sufficient information on big events. For circumstances like this, the ICSS or MICSS test would be more reliable since it is designed to test multiple change points without asking for a specifically pre-determined time period. Also, the amount of computation required seems to make $supLM(\pi)$ less popular in the literature as not much research is found for this method. However, it is very attractive for the $supLM(\pi)$ test to have the ability to test structural breaks in the dynamics of volatility; with the appropriate design of certain algorithm in terms of a rolling window, it could be possible for $supLM(\pi)$ to find multiple breaks in the unconditional variance as well as the dynamics of volatility in GARCH models, and moreover, to create augmented models taking into consideration these breaks. This can be a future research direction in this area.

When examining volatility spillover, this chapter finds extensive applications with methods that are constructed based on GARCH models. And ignoring structural breaks in the volatility will eventually lead to incorrect spillover results. Among the selected volatility spillover tests, the causality in variance test of Cheung and Ng (1996) and its modified version of Hong (2001) are widely employed for its straightforward implementation and free of heavy computation. Moreover, the modified causality in variance test gives non-union weights when examining sample cross correlations, which is more advanced to the causality in variance test of Cheung and Ng (1996). With these considerations, this thesis will adopt the modified ICSS of Sanso et al. (2004) for structural breaks detection in stock returns in Chapter 2, and use the causality in variance test of Hong (2001) to investigate potential volatility spillover pattern between stock and foreign exchange markets in Chapter 3.

Chapter 2

Volatility Persistence: Do Structural Breaks Matter?

2.1 Introduction

The volatility of financial time series has become a popular research topic in asset pricing, portfolio selection, and investment strategy development. The accuracy of volatility modelling is a critical input in making investment decisions. The GARCH family is best known for modelling volatility of financial assets. However, recent studies have cast doubt on the accuracy of GARCH model estimation due to the presence of structural breaks in the volatility. Significant political or financial events can affect the behaviour of asset series and thereby cause parameter instability of a GARCH model, hence, a structural break in the variance/volatility. This phenomenon is also referred to as sudden changes or shifts in the variance, or in the mean level of unconditional variance. The result of neglecting such factor in a conventional GARCH model is the size distortion in volatility persistence. Thus, it is necessary to eliminate the structural breaks effect in volatility modelling. As a result, many tests are constructed to identify such breaks and accommodate them in the conventional GARCH models. Among others, the Iterative Cumulative Sums of Squares (ICSS) algorithm of Inclan and Tiao (1994) has received much attention for its simple implementation and moderate statistical power. Studies using the ICSS algorithm is substantial, see, for instance, Aggarwal et al. (1999); Malik and Hassan (2004); Wang and Nguyen Thi (2007); Wang and Moore (2009); Kang and Yoon (2010).

Nevertheless, recent studies question the robustness of this ICSS algorithm of Inclan and Tiao (1994); many studies have reported an overestimated number of structural breaks when applying ICSS to financial series (Andreou and Ghysels, 2002; Sanso

et al., 2004). According to Sanso et al. (2004), such overestimation is caused by the underlying assumption of ICSS being data series follows an independent and normal distribution. Therefore, they propose a modified version of ICSS (MICSS), which takes account of both the excess kurtosis and the time-varying dependence within the data observations. Simulation experiments further reveal severe size distortion of ICSS while good power and size properties of MICSS when employed on simulated series following a GARCH(1,1) process. Particularly, both ICSS and MICSS are adopted in Araghi and Ghazani (2015) and Koseoglu and Cevik (2013); both studies point out that more change points are found by ICSS algorithm than that of the MICSS algorithm for all data series in all the countries in question. More empirical applications of MICSS can be found in Mirovic et al. (2017); Kirkulak-Uludag and Lkhamazhapov (2017); Shahzad et al. (2017). Furthermore, extensive attempts have been made at modifying the conventional GARCH model after identifying any structural breaks in the volatility; one leading strand is to incorporate the detected structural breaks as dummy variables in a conventional GARCH model. Substantial evidence has been found that a decreased volatility persistence can be obtained after eliminating the effects caused by structural breaks (see, for instance, Lamoureux and Lastrapes, 1990; Arago-Manzana and Fernandez-Izquierdo, 2007; Ewing and Malik, 2010).

Although existing studies have well explored the topic of modelling volatility in the presence of structural breaks in various countries, however, few studies in this area have investigated the Chinese stock market. Some exceptions include the work of Ni et al. (2016), where MICSS of Sanso et al. (2004) is employed on the weekly stock returns from two major stock indices in China. Still, no research has been found to study the Chinese stock market in a comparison study with a developed country. In addition, the literature is scarce on the subject of evaluating the performance of the above mentioned two algorithms. Apart from in Inclan and Tiao (1994) and Sanso et al. (2004) where the tests are created, only two papers, Andreou and Ghysels (2002) and Kumar and Maheswaran (2012), are found to compare the two methods in a simulation study. Nevertheless, their studies are more focused on examining the size and power of the main tests from the two algorithms in the event of one structural break, leaving a gap for the case of multiple breaks. Besides, no simulation study has been done on the performance of modified GARCH models with structural breaks. Motivated as such, this chapter will carry out a comparison investigation on the stock markets in China and the UK. Whether to choose ICSS of Inclan and Tiao (1994) or MICSS of Sanso et al. (2004) will be decided after running a comprehensive Monte Carlo simulation study. Any detected structural breaks afterwards will be incorporated into the GARCH model for further evaluation on model estimation.

Also, the timing of each break will be associated with significant events. Designed as such, this chapter aims at adding a richer context to the existing literature. First of all, the identification of structural breaks allows for further analysis on the associations between break dates and significant events; moreover, it can provide insights on whether events from a particular source are more influential on the market with a certain level of development. Next, including the structural breaks in GARCH not only can improve volatility estimation, but it also builds tailored volatility models according to the unique structure of that market. Last but not least, the comprehensive simulation study can contribute to the existing literature more statistical evidence on the performance of two widely used tests for structural breaks detection.

This chapter proceeds in the following structure: Section 2.2 provides an overview of the literature regarding structural breaks detection and accommodation; Section 2.3 highlights the main research question; Section 2.4 introduces the methods, and Section 2.5 describes the research data; Section 2.6 presents the empirical results with discussions; limitation of this research and future efforts can be found in Section 2.7, followed by which is the concluding remarks in Section 2.8.

2.2 Literature Review

A vast body of empirical studies has emerged in the subject of volatility modelling for financial time series in the presence of structural breaks in the volatility. Many studies adopt the approach to first detect the occurrence of any structural break(s) in the studied financial series, then incorporate the detected breakpoint(s) as dummy variables into the variations of conventional GARCH of Bollerslev (1986).

Empirical applications of ICSS are mainly found in investigating stock index series and foreign exchange rates across various nations. Early studies can be found in Aggarwal et al. (1999), who investigates weekly stock returns from ten of the largest emerging markets at that time over the 10-year period from 1985 to 1995. Several breaks are detected via ICSS and are associated more with the local events, such as the Mexican Peso crisis, the time of hyperinflation in Latin America, and the stock market scandal in India. They further agree with the conclusion in Bailey and Chung (1995) and Bekaert and Harvey (1997) that the emerging markets are more likely to be influenced by local events.

Todea and Petrescu (2012) share similar conclusion when studying Romania stock markets. They examine weekly stock returns from five Financial Investment Companies listed on the Bucharest Stock Exchange in Romania over a period from

05/01/2000 to 30/03/2011; structural breaks are found via the ICSS in all selected company stocks. Among the significant events that are associated with the detected breaks, most are either company-specific matters or domestic financial and political policies. For instance, the decrease of inflation in 2004, the transition to a new currency, the change of the Board of Directors, the change of capital market legislation, the integration in the European Union. The 2008 financial crisis is the only global event linked to the breaks. These findings indicate that local events are most influential to these big companies in Romania's emerging stock market. Moreover, after taking account of the detected breaks in each return series, their study reports decreased volatilities in all cases. They also remove the breaks having insignificant coefficients, which correspond to events that are less influential, from each return series' best GARCH model; results show a less deducted persistence for all the sample series. Therefore, they argue that it is necessary to filter out the insignificant breaks when modifying GARCH models; otherwise, it could lead to an overestimation of the decrease in volatility persistence.

Using the same approach as Todea and Petrescu (2012), Hammoudeh and Li (2008) also leave out the breaks with insignificant coefficients when incorporating them into the best GARCH model; a less reduced volatility persistence is obtained for all the series. However, they find that the global events play a more important part with respect to the structural breaks. Several structural breaks are identified via the ICSS for five emerging stock markets in Gulf area Arab from 1994 to 2001. Comparing to domestic or regional events, the dates of the detected breaks are much closer to those in the global context; to name a few, the 1997 Asian crisis, the collapse of oil prices in 1998, the adoption of the price band mechanism by OPEC in 2000, and the 9/11 attacks.

Kang et al. (2009) also find evidence that developed markets are more likely to be affected by global events. Investigating weekly stock returns in Japan and Korea from 1986 to 2008, structural breaks are found via ICSS in both markets and are linked to global financial and political events. After incorporating the detected breaks into a fitted GARCH model and FIGARCH of Baillie et al. (1996), not only a reduced volatility persistence is observed in the modified GARCH model, long memory property also no longer exists in the modified FIGARCH model. In addition to that, smaller values are obtained from skewness, kurtosis and Jarque-Bera normality tests on the residuals from both models with breaks. This evidence suggests that including the structural breaks in the GARCH-type model can also improve its model estimation.

More application can be found in Malik and Hassan (2004) in five major Dow Jones stock indices representing five major sectors in US market from 1992 to 2003; in Malik et al. (2005) in two stock indices in Canada from 1992 to 1999, in Kasman (2009) in the stock markets of the BRIC countries (Brazil, Russia, India, China) from 1990 to 2007; in Kang and Yoon (2010) in four Asian exchange rates from 1990 to 2008; in Todea and Platon (2012) in the foreign exchange markets of four new EU countries from 1999 to 2009. All these studies have shown successful detection of structural breaks via ICSS, and reduced volatility persistence are obtained from GARCH models incorporated with structural breaks.

Despite its popularity, however, the validity of the ICSS of Inclan and Tiao (1994) has been questioned, for it is constructed under the assumption of independent and normally distributed data. This assumption is apparently contradictory to financial time series, which are with heavy-tailed distributions and also show heteroskedastic volatility. Therefore, the null hypothesis of constant variance of ICSS test is rejected too often when applied to financial time series; as a result, the number of breakpoints is very likely to be overestimated. To overcome such issue, Sanso et al. (2004) modify the ICSS test so to address the conditional heteroskedasticity.

Empirical applications of MICSS of Sanso et al. (2004) can be found in Çağli et al. (2012), where the sudden changes in the volatility are investigated in Turkish stock market. In fact, both ICSS and MICSS are employed on daily return series of the stock market index along with three major sector indices from 1997 to 2009; structural breaks are found via both tests for all the indices. However, ICSS tends to overestimate the number of change points comparing to MICSS; for instance, in return series of ISE 100 stock market index, twenty points are detected via ICSS, while only three change points are identified via MICSS. This result further supports the argument that the ICSS test suffers size distortion when applied to financial time series. They also mention that both global and local events play an influential part in these volatility shifts, for instance, government elections, changes in the monetary and fiscal policies, and improvements in the EU adaptation process. Moreover, after incorporating the detected structural breaks as dummy variables in the EGARCH model of Nelson (1992), a significant decrease in the volatility persistence is reported in all return series. Another application of MICSS can be found in Kumar and Maheswaran (2012), where weekly data of six indices in Indian stock markets are examined over a period from 1994 to 2011. Structural breaks are found in all return series and are associated with global macroeconomic and political events. Moreover, after incorporating the structural breaks in GARCH (1,1) and GJR-GARCH (1,1), both the volatility persistence and volatility asymmetry are significantly decreased. Also,

the analysis of out-of-sample forecasts suggests accommodating sudden changes in the volatility can present more satisfactory one-step-ahead forecast than that without considering regime shifts for Indian stock markets.

From the above review of the literature over the past two decades, no doubt that it is of critical importance for structural breaks detection when modelling volatility of financial time series. And clearly, MICSS algorithm of Sanso et al. (2004) is preferred over the ICSS algorithm of Inclan and Tiao (1994) when examining financial time series, since the latter method often reports more breaks than there should be. Nevertheless, of this extensive literature, few studies choose to carry out an extended investigation with respect to the performance of the discussed tests for structural breaks; only exceptions being Inclan and Tiao (1994), Sanso et al. (2004), Andreou and Ghysels (2002) and Kumar and Maheswaran (2012). Andreou and Ghysels (2002) are among the first to question the validity of the ICSS algorithm. In their study, both the size and power of the ICSS test are examined. When applied to a simulated GARCH(1,1) data sequence with no break, ICSS test is found to have size distortion. That is to say, ICSS test tends to falsely reject the null hypothesis of no break too often when no structural break is actually simulated. Regardless of the poor size property, ICSS test shows adequate power when there is one break simulated in the middle of a GARCH(1,1) data sequence. In addition, ICSS test is also able to detect very small changes in the variance of the error terms as long as the sample size is large, for example, $T = 3000$. This finding is consistent with Inclan and Tiao (1994), where simulation study shows ICSS has relatively decent power to detect structural breaks in the residuals, given that the financial series are properly modelled with very large samples. Moreover, via Monte Carlo simulations, Sanso et al. (2004) find satisfactory size and power properties for both ICSS and MICSS when applied to a normally distributed data. When the simulated data series is an ARCH(1), both algorithms still show good power property, but significant improvement in the size property is found in MICSS, and a severe size distortion is found in ICSS. Kumar and Maheswaran (2012) also evaluate the performance of ICSS and MICSS via Monte Carlo simulation study. Various scenarios are considered, including different data generating processes, such as GARCH (1,1) and stochastic volatility (SV), and different probability distributions for the error terms, such as the standard normal distribution and the Student t distribution with 5 degree of freedom. The size and power of each method are compared, where MICSS shows a more desirable overall performance while a severe size distortion is found for ICSS when applied to financial time series. Moreover, both tests show decent power properties on GARCH(1,1) series especially the change in the variance is significant.

However, one particular finding in both Sanso et al. (2004) and Kumar and Maheswaran (2012) is that, for a small sample, such as $T = 100$, both tests are less responsive to the simulated break when the change in the variance is small; yet this finding is not addressed in either study. Particularly, none of the known studies has investigated the performance of these two algorithms when more than one structural break is in presence. Furthermore, no study has conducted simulations to examine the validity and efficiency of GARCH model incorporated with the detected structural breaks. Inspired by such, this chapter will complement the literature by taking a closer look at the performance of both ICSS and MICSS by analysing the detected change points via a series of carefully designed Monte Carlo simulations. The experiments are designed to consider more factors than in the study of Kumar and Maheswaran (2012), such that the performance of both algorithms can be studied in a much broader setting. Also, a simulation study will be employed to examine GARCH models with structural breaks, in order to provide empirical evidence on the validity of such modification. Moreover, substantial studies are found to investigate stock market volatility across a number of regions, yet few research has been conducted on the Chinese stock market. One of the few exceptions is in Ni et al. (2016), where the MICSS of Sanso et al. (2004) is employed to investigate the presence of structural breaks in the volatility in Chinese stock market. In their study, weekly stock returns are obtained from two major stock indices, one of which is listed on Shanghai stock exchange and the other on Shenzhen stock exchanges, from 1990 to 2011. Three significant break dates are identified for each stock index. More importantly, the authors are able to identify the link between these dates and government policies; thus, they point out that the Chinese stock market is significantly influenced by government regulations.

To fill the gaps above, this chapter will focus on the Chinese stock market, and form a comparison study by also looking into the UK stock market, in order to compare different volatility structures because of the different level of development. More importantly, Monte Carlo simulation study will be firstly carried out, in order to comprehensively evaluate the performance of both ICSS and MICSS before application. Detailed methods of such can be found in Section 2.4.

2.3 Research Question

The primary research question of this chapter is formed as below:

Do the stock markets in China and the UK experience structural breaks in the

volatilities? And to what extent do the identified structural breaks affect volatility persistence in each stock market?

By investigating such issues, not only the timing of each structural break will be determined, but it can also reveal the relationship between break(s) and significant events, i.e. whether it is the domestic or global event that would be more likely to induce a structural break. Taking into consideration of such factor can provide investors and financial managers with insightful information when creating investment strategies. Moreover, re-examining the volatility persistence by taking account the identified structural breaks can help to obtain a more accurate volatility persistence than that obtained via the conventional GARCH models. Accurately estimated volatility persistence is of great importance since it is the detrimental factor in volatility forecasting. In addition, the comparison study conducted on one emerging and one mature market can explore the differences between volatility structure of markets of different level of development.

2.4 Methodology

This section will describe the empirical framework of this study. For structural break detection, both ICSS algorithm of Inclan and Tiao (1994) and MICSS algorithm of Sanso et al. (2004) will be reviewed again, with more detail on introducing the algorithm that both methods use. Particularly, this section also sets forth a series of carefully designed Monte Carlo experiments in order to evaluate the performance of both ICSS and MICSS algorithms, especially with multiple structural breaks in the data series. Moreover, the method of addressing the detected breaks in the volatility model will be discussed, so to eliminate the negative effect of structural breaks toward volatility persistence estimation.

2.4.1 Structural Breaks Identification

As mentioned in the previous chapter, ICSS Algorithm of Inclan and Tiao (1994) considers the data sequence to vary at a constant value for a period of time until a sudden change in the variance occurs; the data sequence then varies at this new value for another period until a next new change occurs. Thus, for an uncorrelated random data sequence $\{\varepsilon_t\}$, with mean 0 and variance $\sigma_t^2, t = 1, 2, ..., T$, the centred and normalized cumulative sum of squares D_k takes the form in Equation (2.1)

$$D_k = C_k/C_T - k/T, \;\; k = 1, 2, ..., T \tag{2.1}$$

where $C_k = \sum_{t=1}^{k} \varepsilon_t^2, \ k = 1, 2, .., T$ is the cumulative sum of squares of $\{\varepsilon_t\}$. And C_T is the sum of squares over the full sample period at T. Under the null hypothesis of no structural break in the volatility, $\sqrt{T/2}D_k$ asymptotically follows a Brownian bridge process, where $\sqrt{T/2}$ is to standardise the distribution. An IT test is created as shown in Equation (2.2) to search for one change point in interval $[1, k], k = 1, 2, ..., T$:

$$IT = \max \sqrt{T/2}|D_k| \tag{2.2}$$

According to Inclan and Tiao (1994), the critical value of IT test is 1.358 at 95% percentile. That is to say, when the maximum value of D_k from observation 1 to k exceeds 1.358 at $k^*, k^* \in [1, k]$, one break is identified at k^*.

In order to test for the potential locations of more than one breakpoint over the full sample, Inclan and Tiao (1994) propose an iterative procedure, where the IT test is successively applied to pieces of the sample series which are determined consecutively after a new change point being found. This procedure is described as below:

1. Run the IT test on the full sample series $[1, T]$. When one change point is located at $k^*(1 < k^* < T)$, the full sample is then divided into two sub-samples, $[1, k^*]$ and $[k^* + 1, T]$.

2. Run the IT test on sub-sample $[1, k^*]$. Where a new change point is detected, this then becomes the end of a new sub-sample. Run the IT test on newly formed sub-samples until no change point is found. Record each detected change points so far.

3. Run the IT test on sub-sample $[k^* + 1, T]$. When a new change point is detected, the location of this newly found change point plus one then becomes the start of a new sub-sample. Run the IT test on newly formed sub-samples until no change point is found. Record each detected change points so far.

4. Collect all the change points detected so far from the three steps above and sort them in an ascending order based on their location in the full sample series. Suppose these change points are $k_1, k_2, ..., k_n$. Define two border points $k_0 = 0$, $k_{n+1} = T$, with T as the full sample size. Run the IT test on $k_{i-1} + 1$

to k_{i+1} with $i = 1, 2, .., T-1$.

5. Collect each newly found change point from step 4 and repeat the procedure in step 4 on this new collection of change points.

6. Repeat step 1 to 5 until there is no change in the number of newly detected change points, and the location of each change point is within two observations from where it was in the previous search. Then it can be said that the algorithm has converged and the estimates of possible change points are determined.

Unlike other methods, such as the $supLM(\pi)$ test of Andrews (1993), which can only detect breaks around known events, ICSS requires no such prior information. Moreover, ICSS is easy to implement with simple computation. These features make ICSS more appealing over other breaks detection methods. Although many studies use the ICSS algorithm of Inclan and Tiao (1994) and successfully identify the structural breaks, Sanso et al. (2004) argue that ICSS can lead to inaccurate estimation of structural breaks when applied to financial time series. Since IT test in ICSS is built on independent data sequences with a normal distribution, severe size distortion occurs when applying ICSS to leptokurtic financial asset series. Sanso et al. (2004) modify the IT test with a κ_2 test by taking into consideration the fourth moment properties of the data series along with the conditional heteroskedasticity which are not properly addressed in ICSS. κ_2 function is defined in Equation (2.3):

$$\kappa_2 = \sup_k |\sqrt{1/T} G_k| \tag{2.3}$$

where

$$G_k = \sqrt{1/\hat{\omega}_4}(C_k - \frac{k}{T} C_T) \tag{2.4}$$

$\hat{\omega}_4$ in Equation (2.4) is a non-parametric estimator of the long run fourth moment of Y_t, and the expression is shown in Equation (2.5):

$$\hat{\omega}_4 = \frac{1}{T}\sum_{t=1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)^2 + \frac{2}{T}\sum_{l=1}^{m}\omega(l,m)\sum_{t=l+1}^{T}(\varepsilon_t^2 - \hat{\sigma}^2)(\varepsilon_{t-1}^2 - \hat{\sigma}^2) \tag{2.5}$$

In Equation (2.5), $\hat{\sigma}^2$ is the variance of the data sequence. Moreover, $\omega(l,m)$ represents the Bartlett kernel function, which is defined as $\omega(l,m) = 1 - \frac{l}{m+1}$ with $1 < l < m$. According to (Newey and West, 1994), m is the bandwidth that determines the number of the cross products considered in Equation (2.5); it is of particular importance for m to increase at an appropriate rate with the sample size so to ensure the consistency of this kernel function. They further suggest $4 \times (T/100)^{2/9}$ to be a choice for m based on both theoretical asymptotic and empirical Monte Carlo results. Under the null hypothesis of no structural break, the critical value of the κ_2 test is 1.329 at the 95% percentile. And MICSS algorithm follows the same iterated procedure proposed by Inclan and Tiao (1994). Sanso et al. (2004) further confirm the spurious size distortion of ICSS and the effective improvement of their modified version. Also, they re-examine the structural breaks detected via ICSS in Aggarwal et al. (1999); using MICSS on the same research data, no structural break is found.

2.4.2 Modified GARCH(p,q) with Structural Breaks

Recall the standard GARCH(p,q) of Bollerslev (1986):

$$\begin{aligned} r_t &= \mu + \varepsilon_t, \quad \varepsilon_t | I_{t-1} \sim N(0, \sigma_t^2) \\ \varepsilon_t &= z_t \sqrt{\sigma_t^2}, \quad z_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \end{aligned} \tag{2.6}$$

As it has been discussed in the previous chapter, in Equations (2.6), the sum of α_i and β_i measures the volatility persistence. According to Ross (2013), the standard GARCH model takes no account of potential structural breaks in the unconditional variance. As discussed earlier, the volatility of financial time series is very likely to experience structural breaks due to the changing economic environment or the occurrence of political events. Ignoring such factor can lead to an overestimation of the volatility persistence. Diebold (1986) and Lamoureux and Lastrapes (1990) are among the first to question such spurious GARCH estimation. In order to solve this problem, dummy variables will be constructed according to each detected break, and incorporated to the conventional GARCH model as in Equation (2.7):

$$\sigma_t^2 = \omega' + D_{1t}\delta_1 + D_{2t}\delta_2 + ... + D_{nt}\delta_n + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \tag{2.7}$$

where $D_{it}, i = 1, 2, ..., n$ are dummy variables corresponding to the number of detected change points n. Moreover, for each D_{it}, it takes the value of 1 from the detected break onwards and 0 elsewhere. $\delta_i, i = 1, 2, , n$ are the estimated coefficients of the corresponding dummy variables; $\omega^{'}$ is the new deterministic term after the elimination of the structural breaks effects. Adjusted as such, it is expected to obtain reduced volatility persistence as in the work of, for instance, Malik and Hassan (2004), Kasman (2009), Wang and Moore (2009), Kang et al. (2009), Todea and Petrescu (2012).

2.4.3 Monte Carlo Study

The purpose of conducting Monte Carlo simulations is to further understand the mechanism and performance of the ICSS of Inclan and Tiao (1994) and MICSS of Sanso et al. (2004), particularly in a setting where multiple breakpoints are simulated. Since the existing simulation studies found in Inclan and Tiao (1994), Andreou and Ghysels (2002), Sanso et al. (2004) and Kumar and Maheswaran (2012) only consider the performance of the core tests but not much has been explored on the algorithm that runs the tests. Thus, this study sees the necessity to complement in this regard and aims at revealing any specific patterns or tendencies of the performance of both algorithms by analysing breakpoints detected from much more comprehensive scenarios. Particularly, the performance of the GARCH model with structural breaks will also be studied via simulations, which is scarce in the known studies in this subject.

2.4.3.1 ICSS vs MICSS

One of the main purposes of this simulation is to evaluate the effects of multiple structural breaks to the overall performance of both ICSS and MICSS, since almost all the studies found so far are focused on the effect of one break. In order to simulate more than one break in the volatility, two data series $\{V_{1t}\}$ and $\{V_{2t}\}$ will be generated with the same parameters apart from different values of the variance. Then combine $\{V_{1t}\}$ with $\{V_{2t}\}$ by segment of equal length, where every two segments contain different variances as the variables within which are from either $\{V_{1t}\}$ or $\{V_{2t}\}$. Therefore, the presence of structural breaks is crafted to be at the joining of segments from $\{V_{1t}\}$ and $\{V_{2t}\}$. To be more specific, the simulated location of each break will be the first variable that takes a different variance from its previous value. This arrangement allows us to simulate more than one structural break while avoiding creating any trend in the simulated data. Moreover, apart from the lack of attentions on multiple breaks, even fewer studies has considered the potential

effects of the size of variance change, the order of variance change, and how often the occurrence of breaks. Thus, this study will attempt to fill such gap by looking into these factors when designing the simulation experiments:

1. The number of breakpoints
   Up to four breaks will be simulated, in order to evaluate the performance of the studied algorithms when dealing with more than one break.

2. The size of variance change
   When one structural break occurs in the volatility, it means the variance of the data series changes to a new value. And the size of variance change measures the difference between this new and the old value. Three types will then be considered: a significant size of variance change ($\Delta = 0.22$), a relatively less significant one ($\Delta = 0.11$), and an almost insignificant one ($\Delta = 0.05$). This factor aims at finding out to what extent regarding the size of the change that the two algorithms could still properly recognise a break from its adjacent ones.

3. The order of variance change
   Also, the occurrence of structural break could cause an increased new variance value or a decreased one. Therefore, it is also interesting to know whether the algorithms would react differently to upward or downward change in the new variance values. In this regard, the order of variance change is created, and the "Ascending" order indicates the variance becomes bigger than its previous value, while the "Descending" indicates the opposite.

4. The distance between adjacent breaks
   This factor represents how volatile the market is. That is to say, a large distance in terms of a large number of observations between two adjacent simulated breaks represents a "Tranquil Period", suggesting a relatively stable market. Meanwhile, the small distance with a small number of observations between the two represents a "Fluctuate Period", indicating otherwise. More specifically, this study will simulate one structural break every 300 observations for "Tranquil Period", and every 100 observations for "Fluctuate Period".

Furthermore, two types of data generating processes will be considered, namely, an independent and identically distributed (i.i.d) process and a GARCH(1,1) with the disturbances following the standard normal distribution. The former represents the application of algorithms to the residuals obtained from a fitted model, and the latter attempts to represent the direct application on the original data series which has mean zero and conditional variance of a GARCH(1,1) for simplicity. It is worth

noting that, the most common way found in the literature of detecting structural breaks is to apply the algorithm(s) to the residuals obtained from a fitted model. However, since the model estimation might have already been falsely estimated due to ignoring the breaks when modelling the data at the first place, thus, the detection would be invalid if applying the algorithm(s) to residuals obtained from a model without accommodating the structural breaks first. With such consideration, this simulation study attempts to evaluate the performance of both algorithms when applied directly to the simulated data, in order to explore the possibility of a new way which eliminates the interference of structural breaks. By taking into consideration of the above discussion, three scenarios will then be created as below:

Scenario 1: Investigating the performance of ICSS and MICSS. Both i.i.d and GARCH(1,1) series will be generated, with relatively significant variance changes ($\Delta = 3$ for i.i.d and $\Delta = 0.22$ for GARCH(1,1)). Moreover, both "Fluctuate" and "Tranquil" periods will be considered.

Scenario 2: Investigating the performance of MICSS with a less significant change ($\Delta = 0.11$) in the variance in "Fluctuate" setting.

Scenario 3: Investigating the performance of MICSS with an almost insignificant change ($\Delta = 0.05$) in the variance in "Tranquil" setting.

Scenario 1 specially contributes to the literature where evaluation of both algorithms only considers the presence of one single break. Scenario 2 and 3 are designed to mimic stress testing, that takes further investigation on MICSS under extreme conditions, i.e. breaks occur more and more frequently with less and less significant variance changes. Besides, all the scenarios will consider up to four simulated breaks; also, the Order of Variance Change is considered in each scenario. Detailed parameter values can be found in Table 2.1:

Since both algorithms are considered in Scenario 1 and only MICSS in Scenario 2 and 3, the number of experiments will be 64, 16, and 16 respectively. Therefore, this Monte Carlo study consists of 96 experiments, each of which contains 5,000 replications, in order to provide sufficient statistical evidence. This simulation design can offer the existing literature a comprehensive evaluation of the performance of the two well-known algorithms. Moreover, the existing literature has shown quite adequate evidence on the advantage of MICSS over ICSS, yet little has looked into the drawbacks of such. Therefore, the further investigation in Scenario 2 and 3 can examine the robustness of MICSS under extreme conditions. As a result, the

selected method for structural break detection is expected to be well studied before application to the stock series in this chapter.

Table 2.1: Simulation Design for Structural Breaks Detection

		i.i.d		GARCH(1,1)			
Scenarios	Interval	μ	σ^2	μ	ω	α	β
Scenario 1	300	0	$\sigma_1^2 = 1$, $\sigma_2^2 = 4$ (A)	0	$\omega_1 = 0.11$, $\omega_2 = 0.33$ (A)	0.1	0.8
	300	0	$\sigma_1^2 = 4$, $\sigma_2^2 = 1$ (D)	0	$\omega_1 = 0.33$, $\omega_2 = 0.11$ (D)	0.1	0.8
	100	0	$\sigma_1^2 = 1$, $\sigma_2^2 = 4$ (A)	0	$\omega_1 = 0.11$, $\omega_2 = 0.33$ (A)	0.1	0.8
	100	0	$\sigma_1^2 = 4$, $\sigma_2^2 = 1$ (D)	0	$\omega_1 = 0.33$, $\omega_2 = 0.11$ (D)	0.1	0.8
Scenario 2	300		—	0	$\omega_1 = 0.22$, $\omega_2 = 0.33$ (A)	0.1	0.8
	300			0	$\omega_1 = 0.33$, $\omega_2 = 0.22$ (D)	0.1	0.8
	300			0	$\omega_1 = 0.28$, $\omega_2 = 0.33$ (A)	0.1	0.8
	300			0	$\omega_1 = 0.33$, $\omega_2 = 0.28$ (D)	0.1	0.8
Scenario 3	100		—	0	$\omega_1 = 0.22$, $\omega_2 = 0.33$ (A)	0.1	0.8
	100			0	$\omega_1 = 0.33$, $\omega_2 = 0.22$ (D)	0.1	0.8
	100			0	$\omega_1 = 0.28$, $\omega_2 = 0.33$ (A)	0.1	0.8
	100			0	$\omega_1 = 0.33$, $\omega_2 = 0.28$ (D)	0.1	0.8

Note: Interval 300 indicates tranquil setting while 100 indicates fluctuate setting; (A) indicates the ascending order of variance shift while (D) indicates the descending order of variance shift.

2.4.3.2 GARCH with Structural Breaks

Apart from studying the structural break detection methods, it is also wise to study the effectiveness of modifying the conventional GARCH model by incorporating structural breaks. Two data series will be considered in this section, namely, a data sequence containing a pure GARCH(1,1) process, and a data sequence containing an autoregressive AR(1) part and a moving average MA(1) part in the mean along with a GARCH(1,1) process in the variance. Moreover, each data sequence contains one structural break located in the middle of full sample. In particular, an "MLE[Y]" estimator is programmed in R to model the modified GARCH with structural breaks, while an "MLE[N]" is programmed to model the conventional GARCH without structural breaks. Both estimators will be run on each of the simulated data series so that it can be observed whether the volatility persistence will be reduced after taking into consideration the structural breaks in the volatility and whether such decrease is significant. Besides, it can also check if the ARMA process in the mean

would affect such process. In this way, this simulation study is expected to provide an assessment of the validity of the modified GARCH with structural breaks, and it is known so far to be the first to conduct this kind of approach. This simulation will contain four experiments, each of which has 5,000 replications.

2.5 Data

As one of the main purposes of this research is to investigate how different stock markets respond to significant political, financial, and economic events in the volatility as of different development level, this chapter conducts investigation between an emerging and a mature market. With such consideration, this research will use the SSE Composite Index traded at the Shanghai Stock Exchange to represent the stock market in China, and the FTSE 100 Index listed on the London Stock Exchange for the UK. Shanghai Stock Exchange is the largest stock exchange in China, while London Stock Exchange is the most famous exchange in Europe. The world has witnessed the rapid economic growth and significant development in Chinese stock market since the establishment of Shanghai Stock Exchange on 19 December 1990; moreover, Shanghai Stock Exchange has become the biggest stock exchange in developing countries by 2016. According to WFE Annual Statistics Guide by World Federation of Exchanges (2016), Shanghai Stock Exchange was valued at $3.9 trillion at the end of 2016 in terms of market capitalisation, ranked as the fourth largest stock exchange in the world; while London Stock Exchange was valued at $3.5 trillion and ranked as the fifth in the world. In particular, as one of the major stock indices in China, SSE composite index that contains all listed stocks traded at the Shanghai Stock Exchange, is the most commonly used market index in a large body of research papers. Meanwhile, as the most widely adopted indicator measuring the performance of the stock market in the UK, FTSE 100 consists of the first one hundred largest companies in the UK that are ranked according to the scale of the market value. FTSE 100 companies issue stock shares that are listed on the London Stock Exchange and most of these companies are focused on global business. Both indices are available at Datastream, and stock prices are obtained of daily frequency covering the period from 3 January 1994 to 31 December 2014, resulting 5478 price observations in each series. Moreover, daily rate of return series from each market is firstly created as in Equations (2.8) for the following analysis:

$$\begin{aligned} r_t^{china} &= \ln s_t^{china} - \ln s_{t-1}^{china}, \;\; t = 1, ..., 5478 \\ r_t^{uk} &= \ln s_t^{uk} - \ln s_{t-1}^{uk}, \;\; t = 1, ..., 5478 \end{aligned} \tag{2.8}$$

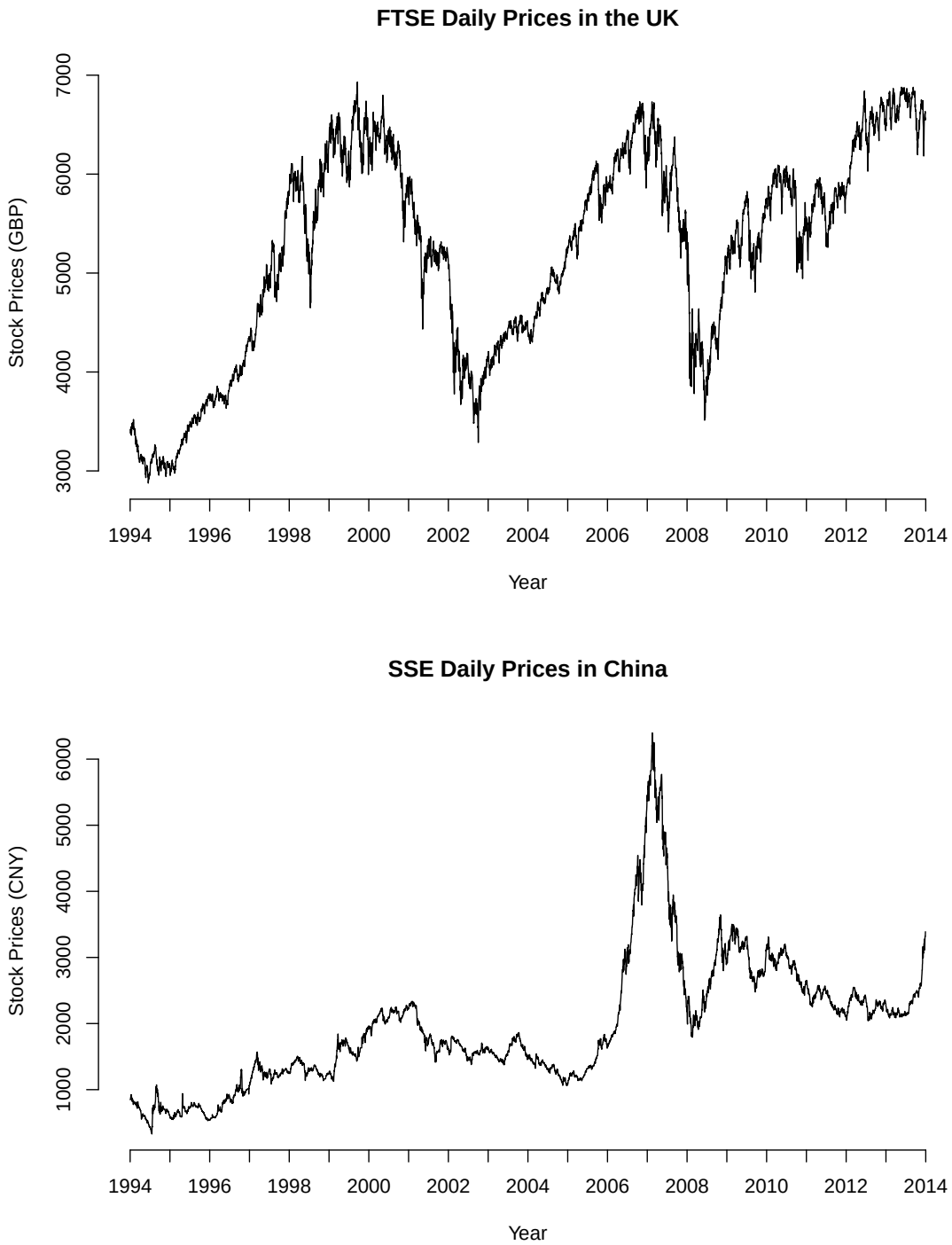


Figure 2.1: Plots for Stock Prices of the UK and China over 1994 to 2014

Table 2.2 shows the overview of basic statistics of both return series. It can be observed that each return series contains a mean value very close to 0. The positive skewness in the Chinese stock market indicates r_t^{china} is distributed with an asymmetric tail extending toward more positive values. The negative skewness in the UK suggests UK stock returns are more likely to be negative. Moreover, each

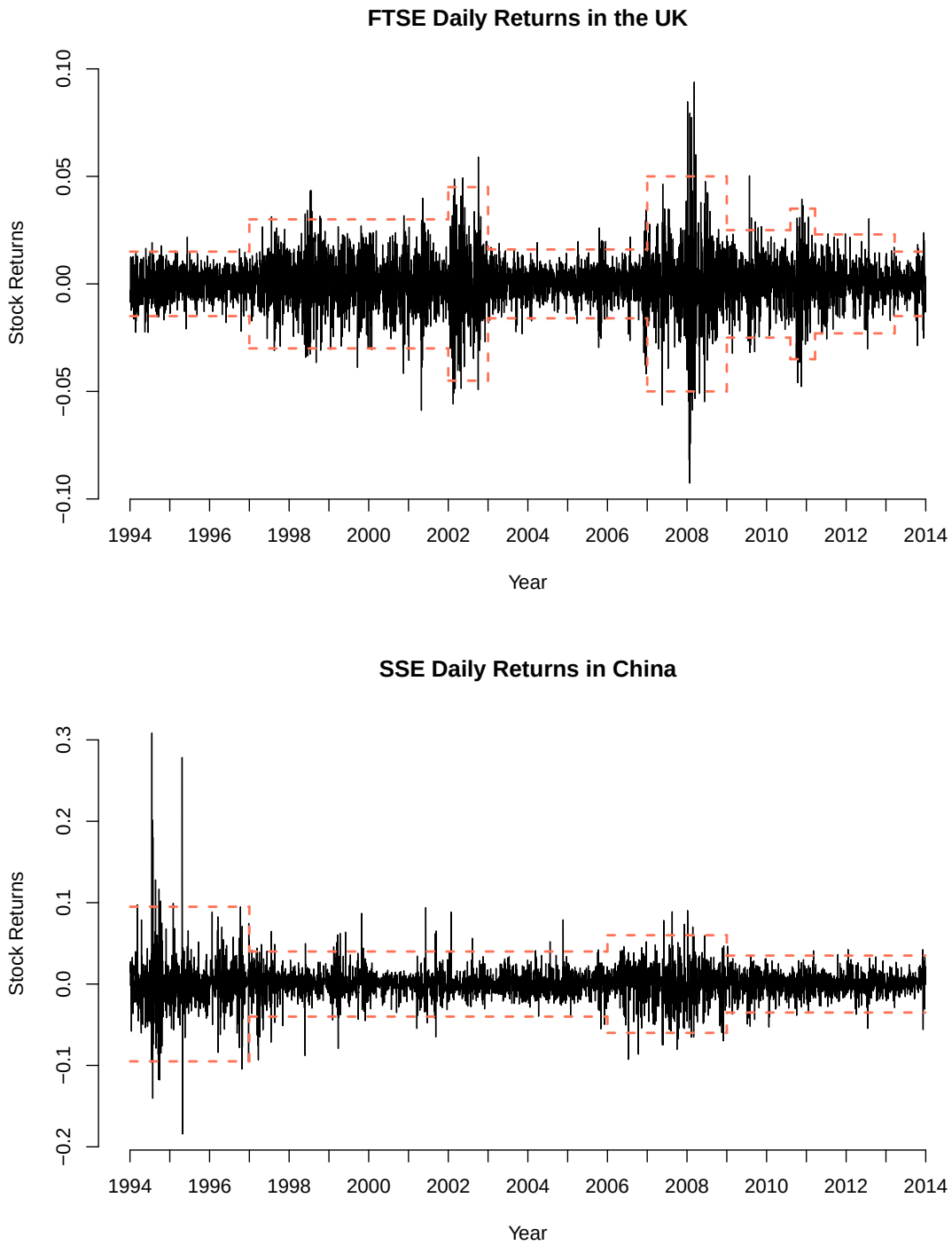


Figure 2.2: Plots for Stock Returns of the UK and China over 1994 to 2014

return series has excess kurtosis compared to a normal distribution, showing that both series have heavy tails, especially in the Chinese market. Moreover, neither return series is normally distributed as being confirmed by the Jarque-bera normality test. The absence of unit root is confirmed by the Augment Dickey-Fuller test, indicating the stationarity of both return series. Meanwhile, ARCH effect is found

Table 2.2: Descriptive Statistics of Stock Returns Series in the UK and China Markets

	China	UK
Mean	0.0003	0.0001
Standard Deviation	0.0197	0.0115
Skewness	1.4437	-0.1595
Excess Kurtosis	18.9631	6.3143
Jarque-Bera	193490[0.0000]	9131.7[0.0000]
ADF	-16.173[0.0000]	-18.502[0.0000]
ARCH LM $TR^2(12)$	1007.4[0.0000]	1274.2[0.0000]
Obs	5477	5477

Note: Return series are of daily frequency; each series contains 5477 observations; excess kurtosis indicates both return series are not normally distributed, which is also confirms by Jarque-Bera normality test where the null hypothesis of normal distributed data is rejected at 1% significant level; ADF indicates both return series are stationary as the null hypothesis of non stationarity is rejected at 1% significant level; ARCH LM test indicates both return series contains further ARCH effect in the volatility as the null hypothesis of no ARCH effect is rejected at 1% significant level; $TR^2(12)$ *indicates the ARCH LM test statistic* TR^2 *at default lag 12; p-value of each test is shown in square brackets*

in the variance of each individual return series. So far, all evidence suggests both stock return series are leptokurtic, and the variances are heteroskedastic, indicating an ARMA+GARCH model to fit the data. Figure 2.1 and 2.2 provides an overview of both prices and returns in each index over the full sample period. Figure 2.2 especially marks the returns of a similar structure by the dotted line, revealing the locations of potential structural breaks in the volatility.

2.6 Empirical Results and Interpretation

Before analysing stock returns in China and the UK, results from simulation study will be first presented to justify the choice of the structural break detection method. Next, the results of detected structural breaks will be presented in both stock markets, along with the timing and corresponding significant events reported. After that, structural breaks will be incorporated as dummy variables in the fitted model in each return series, and the results will be analysed, and implications will be presented.

2.6.1 Monte Carlo Simulation Analysis

2.6.1.1 Simulation Outputs for ICSS vs MICSS

The investigation will begin with analysing Scenario 1 via Case 1 and Case 2, where the performance of ICSS and MICSS will be compared when applied to normally distributed data and conditional heteroskedastic data. To be more specific, two settings will be considered. Namely, a tranquil setting where the breaks are simulated at every 300 observations, and a fluctuate setting where the breaks are simulated at every 100 observations. In each setting, the investigation will be conducted on data sequence containing simulated change points ranging from one to four. Moreover, the way of how the variance shifts will also be included. In particular, an ascending order of variance shift in this study represents the data sequence starts with a small variance and then the variance increases after a structural break, while the descending order of variance shift represents the opposite composition. After that, an in-depth evaluation will be conducted on MICSS according to Scenario 2 and 3, where only a conditional heteroskedastic data sequence will be considered. In particular, a relatively small and an even smaller variance change will be used to simulate the breaks in the structure of variance, in order to check under what extreme conditions that MICSS will return invalid detections. Meanwhile, other factors will be the same as those mentioned in Scenario 1, such as tranquil and fluctuate settings, a number of one to four simulated break(s), and the ascending and descending order of variance shift. This evaluation will be addressed in Case 3. This simulation study extends the scope of conducting the performance assessment of ICSS and MICSS. Under these considerations, several indicators are specially created to conduct a comprehensive analysis on the detected change points from each Case:

- Desirable Breakpoints No.: This indicator shows the total number of breakpoints detected out of 5,000 replications in each experiment, on the condition that each time each of the simulated change point(s) is correctly identified.
- Simulated Location(s): This indicator shows the locations of simulated breaks.
- Points Detected: This indicator shows the actual number of breakpoints detected out of the 5,000 replications in each experiment.
- Fail to Detect: This indicator measures out of 5,000 replications, how many times that no change point is detected.
- Detection Rate (%): This indicator is particularly created to show the accuracy of the studied algorithms, measured by how many times out of 5,000

replications that the algorithms identify a change point at a certain location. In fact, along with the simulated locations of the breaks, Detection Rate is also listed for the neighbouring observations in order to check if there is any particular pattern for the selected algorithm to recognise the structural break(s) at a certain location.

- Size Distortion Ratio (SDR): This indicator is calculated as in the following formula:

$$SDR = \frac{Points\ Detected - Success\ Detection \times Number\ of\ Simulated\ Points}{Success\ Detection} \times 100\% \tag{2.9}$$

where $Success\ Detection = 5,000 - Fail\ to\ Detect$. SDR is designed specially to measure the degree of size distortion of each algorithm. The closer SDR to 0 indicates the greater likelihood for the studied algorithm to detect the correct number of change points, i.e. a smaller chance of being size distorted. Moreover, the more positive SDR indicates more severe size distortion in an overestimated way, while the more negative SDR indicates that of an underestimated way. Designed as such, SDR can help to evaluate the effectiveness of the selected algorithms in a clear manner.

Case 1. ICSS vs MICSS in tranquil setting
Simulation results of this case study can be found in both Appendix Table A.1 and Appendix Table A.2, where the former presents the results with an ascending order of variance shift in the simulated data sequences while the latter presents that with descending order.

According to Appendix Table A.1 with Ascending Order of Variance Shift, for a normally distributed data sequence with a relatively significant change in the variance ($\Delta = 3$), Fail to Detect suggests that both algorithms have an almost 100% success rate out of 5,000 replications in all the four experiments considering change points from 1 to 4. This finding indicates both algorithms adequately respond to the presence of variance breaks. However, both algorithms start to detect fewer change points than the desirable number as the data sequence contains more breaks. For instance, when there are two change points simulated in the data sequence, ICSS finds 10,469 points, and MICSS finds 10,457 after 5,000 replications, both of which are quite close to the desirable number of 10,000. When it is the case of 4 simulated change points, ICSS finds 17,455 and MICSS finds 17,416, both of which are further away from the desirable detected number of 20,000. This finding shows that both algorithms tend to identify more than the actual number of break(s) when the data contains a small number of breaks, while to be more likely to overlook the breaks

when there is a large number of shifts in the variance. This pattern is further confirmed by SDR. In fact, both algorithms show positive SDR with relatively small values in the case of no more than two breaks; as the number of breaks increases to three, SDR starts to drop below zero and becomes more negative when it contains four breaks. These findings indicate both algorithms tend to have good size properties when there are a few structural breaks, and soon it becomes more likely for both to underestimate the presence of breaks as the number of such increases. Moreover, both algorithms show higher Detection Rate around the simulated change point(s) comparing to that of the change points that are away from the actual location(s). For instance, in the case of one change point simulated at 301, ICSS has a Detection Rate of 11.97% at 301 and of 8.69% at 302, while that of MICSS being 12.11% and 8.70% respectively. However, this significant difference in the Detection Rate starts to drop gradually as the number of simulated change points increases. For instance, in the case of four change points simulated at 301, 601, 901, 1201, a Detection Rate by ICSS becomes 3.76% at 301 and 2.61% at 302, while that of MICSS being 3.76% at 301 and 2.62% at 302. This finding indicates that both algorithms tend to be less responsive to the exact locations of structural breaks comparing to the adjacent observations as the data sequence contains more and more breaks. Very similar findings can be observed from Appendix Table A.2, where the only different factor is the Descending Order of Variance Shift; this suggests that Order of Variance Shift has little impact on the performance of both algorithms in tranquil setting. In addition, Table A.1 and A.2 further confirms that both algorithms always have a much higher Detection Rate at the previous observation of the actual break. For instance, in Table A.1 in the case of 4 simulated change points, ICSS shows a Detection Rate of 4.95% at 600 and of 1.10% at 601; the same situation can be found with MICSS; in Table A.2, when there are two simulated breaks, ICSS has a Detection Rate of 9.30% at 300 and of 1.88% at 301, while of 9.85% at 600 and of 6.30% at 601; similar results can be found with MICSS. This finding strongly suggests that both algorithms tend to determine the structural breaks one observation prior to the actual location. In short, for a normally i.i.d data sequence, ICSS present satisfactory and much alike detecting ability as MICSS. Moreover, both algorithms tend to determine the breakpoint to be one observation prior to its actual location, especially when the variance drops after the break. This can also be confirmed by Appendix Figure B.1.1 and Figure B.1.2. Both algorithms have very similar histograms on the detected change points; moreover, in both Figure B.1.1 and Figure B.1.2, (a)-(d) almost mirrors images of (e)-(h), suggesting little interference from Order of Variance Shift.

On the other hand, for a GARCH(1,1) data series with relatively big change in the variance ($\Delta = 0.22$), according to Appendix Table A.1 and Table A.2, ICSS

shows severe size distortion in the following aspects: first of all, there is an extensive amount of total change points detected against the simulated number. For instance, in the case of one simulated break at 301 with an ascending order of variance shift, ICSS finds 11610 change points out of 5000 replications; on top of that, out of 5000 replications, there are less than 30 times that ICSS finds no break. This combination guarantees that there will be at least one false identification each time when ICSS detects the presence of breaks. Moreover, the high positive SDR again reveals the spurious size distortion of ICSS. Secondly, ICSS shows passable Detection Rate at those that are around the simulated break(s), yet such Detection Rate decreases and becomes less distinguishable among neighbouring observations as the number of simulated breaks increases. For instance, in Appendix Table A.1, ICSS has a Detection Rate of 3.30% at 301 and of 2.23% at 302, when there is one break simulated at 301. And it shows 1.64% at 301 and of 1.02% at 302 when there are three breaks simulated at 301, 601, 901. Therefore, when dealing with conditional heteroskedastic data series, it is more difficult for ICSS to locate the change point(s) close to the actual one(s) as it tends to find more than the actual number of breaks plus it is less capable of singling out the actual location(s). On the contrary, MICSS shows greater advantage with conditional heteroskedastic data; SDR is quite close to zero, indicating MICSS is less likely to falsely reject the null hypothesis of no break. Meanwhile, MICSS is more capable of locating the break(s). For instance, in Appendix Table A.1, when there is one change point simulated at 301, MICSS has a Detection Rate of 5.00% to find a change point at 301, while ICSS only shows a Detection Rate of 3.30%. This advantage becomes less significant as the data series contains more breaks. This feature can also be seen from Appendix Figure B.1.3 and Figure B.1.4, where the change points detected are more centred around the simulated locations using MICSS than using ICSS. In addition, a similar tendency can be observed as to that with normally distributed data that both algorithms tend to determine one observation prior to the actual location of the structural break, and such effect becomes stronger when the variance after break takes a smaller value. From these discussions, it can be said that MICSS is much more suitable than ICSS to detect structural breaks in data series that has heteroskedastic variance. Nevertheless, MICSS shows a higher chance to find no point as the data series contains more breaks. For instance, there are 794 times out of 5000 replications that MICSS fails to find any change point when there are actually four simulated. This finding could particularly lead to a conjecture of the argument in Sanso et al. (2004), where it is claimed that MICSS outperforms ICSS as it finds no structural break in the same dataset while ICSS finds a few.

Therefore, under a tranquil setting where structural breaks occur occasionally, both

algorithms show almost identical performance when applied on a normally distributed data series. However, for data series contains conditional heteroskedasticity, MICSS outperforms ICSS. Yet this advantage tends to diminish when the data series contains more structural breaks. Moreover, both algorithms show a tendency to find break one observation prior to its occurrence, especially when variance becomes smaller after the break.

Case 2. ICSS vs MICSS in fluctuate setting

In this setting, all the other factors and simulation design remains the same as in Case 1; the only exception is the breaks are simulated at every 100 observations instead of 300. Meanwhile, comparison results between an ascending and descending order of variance shift can be found in Appendix Table A.3 and Table A.4 respectively.

For a normally distributed data sequence, ICSS shows acceptable performance which is quite similar to that in Case 1, in terms of Points Detected, Fail to Detect, SDR and Detection Rate. Moreover, when the breaks are simulated to occur more frequently, ICSS still tends to determine the break one observation prior to its actual location. For instance, when there are two simulated breaks, Table A.3 shows a Detection Rate of 10.19% at 200 and 1.84% at 201, while in Table A.4, it is 9.78% and 1.63% respectively. This can also be seen in Figure B.2.1 in Appendix, where each plot from (a)-(d) has a similar pattern as in that from (e)-(h), indicating the little impact from Order of Variance Change. In the meantime, MICSS seems to be more likely to find no break as indicated by an increasing Fail to Detect when data sequence contains more breaks. For instance, when there are four breaks simulated in the i.i.d data sequence, MICSS responds to none of the simulated breaks for 4384 times out of 5000 replications, leading to an SDR of -1.03. These results indicate that ICSS seems to outperform MICSS for a normally distributed data when breaks occur often in a short time period.

Moreover, it is interesting to notice that, for a GARCH(1,1) data sequence, ICSS seems to have less severe size distortions comparing to that in Case 1. For instance, in the event of three breaks simulated, Appendix Table A.1 shows an SDR of 1.70, while Table A.3 shows one of 0.17. Although the Fail to Detect is slightly increased, and that could be some influence on such reduction of SDR. Nevertheless, Table A.3 shows much higher Detection Rate at the simulated location comparing to that in Table A.1, suggesting ICSS actually could hold a robust performance when dealing with a GARCH(1,1) series that contains frequently occurred structural breaks in a

relatively short period of time. This can also be observed from Figure B.2.3, where very similar histograms pattern can be found as in Figure B.1.1, except for Figure B.2.3 shows a much more standing out frequency around simulated break(s), indicating a higher likelihood of finding the breaks along with less overestimation. In addition, by comparing Detection Rate between Table A.3 and Table A.4, it can be seen that ICSS reacts to the size of variance before and after the break. This means ICSS tends to be more likely to determine the break to be located one observation before its actual position in GARCH(1,1) series, especially when the new variance after a break is smaller than its previous value before the break.

Nevertheless, MICSS tends to produce a huge number of unsuccessful detections when applied on GARCH (1,1) data, especially when data contains more simulated breaks; within those successful identifications, although MICSS tends to underestimate the number of breaks, it still shows adequate ability to identify the simulated breaks. This feature can be spotted from Figure B.2.4, when the number of breaks is more than two, the frequency bars around simulated breaks of each histogram in (b)-(d) and (f)-(h) become very small but still be recognizable, along with particularly high frequency bars at zero. These observations indicate MICSS becomes less competent to locate the breaks due to a higher chance to find no break at all. This information is also detailed from Table A.3 and Table A.4, where MICSS shows uncommonly high numbers of Fail to Detect, namely, 3867 and 2581 respectively. In addition, in the event of above two simulated breaks, the Detection Rate found in both aforementioned tables is quite close to that in Case 1; however, the Points Detected is quite low due to the high Fail to Detect. This combination again confirms that the chance for to MICSS find the simulated breaks becomes even smaller, which explains Figure 2.4.4 where the frequency bars seem to disappear as the number of simulated breaks increases, and yet quite standing out at the simulated location.

In short, when structural breaks are expected to occur frequently, ICSS seems to have a robust performance toward both normally distributed and GARCH(1,1) data sequences. In the meanwhile, MICSS shows reasonable performance with normally distributed data with a small number of structural breaks (no more than three in this simulation study); however, when employed on GARCH(1,1) data sequence, MICSS can only show promising performance when there is one break; when the number of breaks exceeds one, MICSS almost performs inadequately as it is too easily to detect no break. However, once there is a successful detection by MICSS, the breaks detected by MICSS can be robust. In addition, under this fluctuate setting, both algorithms tend to determine the break one observation prior to its actual location, especially when the variance decreases after the break; however, such phenomenon

is only found in GARCH(1,1) series.

Case 3. MICSS in extremes

In order to test the limit of the performance of MICSS toward a heteroskedastic data series, extreme conditions are specially designed so to put any drawbacks of MICSS discussed earlier in perspective. Consider both a relatively small change ($\Delta = 0.11$) and an even smaller change ($\Delta = 0.05$) in the variance after break(s). When break(s) is simulated at every 300 observations, from Appendix Table A.5, MICSS shows very high Fail to Detect and relatively small Detection Rate around simulated break(s) when the variance change is 0.11 in all four investigations on different number of simulated structral breaks; moreover, when this variance change becomes 0.05, nearly two thirds replications does MICSS detect no break. Evidently, SDR is relatively high, and becomes higher as the data sequence contains more and more breaks. These findings pin to the tendency that, when the value of new variance after the break is very close to its previous one, it becomes difficult for MICSS to determine the actual location(s) of any structural break(s). This can also be observed by comparing Figure B.3.1 and B.3.2, where as the size of variance change drops, the frequency bar represents the simulated break(s) become(s) almost plateau. Moreover, this situation is worsen when the simulated break(s) locate(s) at every 100 observations. As shown in Figure B.3.3 and B.3.4, the histograms of detected change points are almost invisible, with the only bar standing out at zero. This pattern indicates that MICSS has become rather reluctant to identify the presence of any break. This finding can also be confirmed by the statistics from Appendix A.6. It can be observed that most of the Detection Rate is less than 1%. Although there are still a few incidents where the Detection Rate is above 2%, such as 2.35% at 101 when there is one break simulated, and this similar figure can be found in Case 1 and 2, however, the situation is quite different since in this case, there is also a large number of Fail to Detect. Therefore, although the figure itself is almost indifferent comparing to that in the other two cases, it represents a totally different situation that the structural breaks become less and less distinguishable for MICSS under the design of Case 3.

Thus, it can be concluded based on Case 3, MICSS will show poor performance in a period where the data series is experiencing many breaks, especially when those variance changes are insignificant.

2.6.1.2 Simulation Outputs for GARCH with Structural Breaks

In order to assess the performance when accommodating structural breaks in the conventional GARCH model, a simulation study is also employed before its application to the research data. Specifically, two maximum likelihood estimators are programmed using R project; one is "MLE[Y]" that takes into consideration the simulated structural breaks in the volatility, and the other is "MLE[N]" that takes account of none. Two GARCH(1,1) sequences are specified of an equal length 500 by $\mu = 0, \alpha_1 = 0.1, \beta_1 = 0.8$, one of which has $\omega_1 = 0.33$ and the other has $\omega_2 = 0.11$. Putting together the two GARCH(1,1) sequences to form a GARCH(1,1) containing 1000 observations with $\mu = 0, \alpha_1 = 0.1, \beta_1 = 0.8$ with a structural break located in the middle. The reason to consider a GARCH(1,1) is particularly for creating a simple and ideal case scenario where the data sequence contains mean zero and conditional heteroskedasticity, thus, to evaluate the effectiveness of modifying GARCH with structural breaks. Also as discussed in the simulation design earlier, it is common to have an ARMA process in the mean in financial data series; besides, no research work has inspected whether the ARMA process in the mean would affect modelling volatility with consideration of structural breaks. Thus, two ARMA(1,1)+GARCH(1,1) are specified of equal length 500 by $\mu = 0, \phi_1 = 0.5, \theta_1 = 0.5, \alpha_1 = 0.1, \beta_1 = 0.8$, with one sequence having $\omega_1 = 0.33$ and the other $\omega_2 = 0.11$ respectively. Then those two ARMA(1,1)+GARCH(1,1) are arranged to form an ARMA(1,1)+GARCH(1,1) with one structural break in the middle. It is worth mentioning that, this study assumes that the simulated ARMA(1,1)+GARCH(1,1) contains no structural break in the mean. Both "MLE[Y]" and "MLE[N]" are employed on each of the simulated data sequences, and each experiment runs 5000 replications. Results from this simulation can be found in Table 2.3, where each value presented is the average value from 5000 replications:

According to Table 2.3, on the one hand, when estimating GARCH (1,1) with and without the structural break, the coefficients are all significant at 1% apart from μ. Meanwhile, both models show no further ARCH effect nor serial correlations based on the insignificant LM ARCH and Ljung-Box tests; moreover, the Jarque-Bera normality test statistic is insignificant for both models, indicating a normally distributed residuals obtained. All these evidence suggests the simulated data series following a GARCH (1,1) with one structural break is sufficiently modelled by both MLE[Y] and MLE[N]. Although volatility persistence, as the sum of α_1 and β_1, is found to be decreased after the simulated break is accommodated in the GARCH (1,1) via MLE[Y], this model seems to be less a good fit to the data comparing to

Table 2.3: Results for Model Estimation by Monte Carlo Simulation

	GARCH(1,1)		ARMA(1,1)+GARCH(1,1)	
Parameters	MLE[Y]	MLE[N]	MLE[Y]	MLE[N]
μ	-0.0016	0.0016	-0.0016***	0.0013***
ϕ_1	–	–	0.5334***	0.5324***
θ_1	–	–	0.3692***	0.3755***
ω	0.3415**	0.3253**	0.4693***	0.4632***
α_1	0.0886***	0.0890***	0.0991***	0.1022***
β_1	0.8080***	0.8130***	0.7583***	0.7579***
δ_1	0.0006***	–	0.0097***	–
volatility persistence ($\alpha_1 + \beta_1$)	0.8966	0.9020	0.8574	0.8601
Log Likelihood	-1995.967	-1996.686	-2039.277	-2044.909
LR Test Statistics	1.438		11.264***	
Standardised Residuals Tests				
Jarque-Bera	4.1904	4.1626	6.4219*	6.0178
Ljung-Box $Q(10)$	8.8146	8.6633	34.986***	29.794***
Ljung-Box $Q(15)$	13.915	13.747	35.53***	31.034***
Ljung-Box $Q(20)$	23.244	23.024	38.767***	32.308**
Ljung-Box $Q^2(10)$	8.816	8.542	35.545***	30.047***
Ljung-Box $Q^2(15)$	13.915	13.623	36.05***	31.208***
Ljung-Box $Q^2(20)$	23.197	22.803	39.219***	32.491**
LM ARCH	6.8587	8.2611	20.479*	7.2535

Note: GARCH(1,1) is simulated with $\mu = 0, \alpha = 0.1, \beta = 0.8$, with $\omega_1 = 0.33, \omega_2 = 0.11$ as the volatility before and after break respectively;
ARMA(1,1)+GARCH(1,1) is simulated with $\mu = 0, \phi_1 = 0.5, \theta_1 = 0.5, \alpha = 0.1, \beta = 0.8$, with $\omega_1 = 0.33, \omega_2 = 0.11$ as the volatility before and after break respectively.
MLE[N] is the estimator that accommodates no structural break; MLE[Y] is the estimator taking account of the simulated structural break;
Structural break is simulated in the middle of the simulated data; δ_1 is the estimate coefficient of simulated break;
The null hypothesis of LR Test in this case is the better performance of model with no consideration of structural break;
*"***", "**", "*", indicates level of significant of 1%, 5%, 10% respectively.*

the conventional GARCH (1,1) estimated by MLE[N]; in fact, the insignificant LR test statistics suggests a conventional GARCH (1,1) model seems to better fit the simulated data than the modified GARCH (1,1) with structural break accommodated. On the other hand, when modelling a simulated data series containing both ARMA(1,1) and GARCH(1,1) with one structural break in the volatility, all the coefficients are found to be significant at 1%. However, different to the case in GARCH (1,1), the diagnostic tests on the standardised residuals indicate serials correlation in the standardised residuals obtained via MLE[Y]; moreover, when estimating via MLE[Y], not only serial correlation, a further ARCH effect is also found from the standardised residuals. However, the significant LR test statistics suggests a better

fit when ARMA(1,1)+GARCH(1,1) data sequence containing one structural break is modelled by MLE[Y]. These results tend to suggest that for a series only contains conditional heteroskedasticity, taking account of structural break would not necessarily improve the goodness of fit comparing to a conventional GARCH model. However, for a series with both conditional mean and variance, it is necessary to consider the effect of the structural break. Moreover, for both types of series simulated in this study, reduced volatility persistence is found after taking consideration of the structural break in the volatility, on the assumption that the conditional mean contains no structural break.

2.6.1.3 Summary of Monte Carlo Study

In all, this simulation study conducts a comparison investigation on the performance of two popular structural breaks detection methods, namely, ICSS of Inclan and Tiao (1994) and the modified MICSS of Sanso et al. (2004). Extensive evidence has been found to support some of the existing arguments in the literature; also some new findings are discovered; particularly, this study casts doubt on the well implemented MICSS especially when employed on residuals obtained from a fitted model for a data series that is heteroskedastic. First of all, both algorithms show satisfactory and almost identical performance in detecting structural breaks in a normally distributed data sequence, while ICSS is severely size distorted with GARCH(1,1) data but MICSS can retain good detecting ability. These are consistent with the existing conclusions, for instance, in Sanso et al. (2004) and Kumar and Maheswaran (2012). Nevertheless, this study finds the necessity of adding additional conditions to make sure MICSS is the better choice for heteroskedastic data. One important condition is that the interval between two consecutive breaks is relatively large and the total number of breaks is relatively small. This simulation shows that MICSS has a great chance to find fewer or even no break if this condition is not met. Therefore, this finding strongly questions the validity of the number of structural breaks found via MICSS in financial time series from majority research, and any further research work that is carried out based on it, especially during an unstable period such as a financial crisis where financial markets are expected to experience many breaks in a very short time period (see, for instance, Charles and Darne, 2014; Charles et al., 2015; Shahzad et al., 2017). This finding also calls into question the argument in Sanso et al. (2004), where MICSS finds no structural break when re-examining the work of Aggarwal et al. (1999). This finding alone cannot justify the superiority of MICSS over ICSS, as the former tends to overlook structural breaks. Surprisingly, this simulation study finds that ICSS is relatively more reliable under the circumstances when financial markets are in a more volatile structure. In fact, ICSS shows satisfactory performance in such volatile period when dealing both normally dis-

tributed and heteroskedastic data sequences, as long as the change in the variance is significant. Quite the contrary, MICSS shows dramatically decreased performance with normally distributed data containing more than three breaks in a fluctuating period, due to the problem that MICSS is easy to overlook the break. This point is particularly worth emphasising, as the approach adopted in the majority research is to apply the selected structural break test to the residuals obtained from a fitted model. Therefore, if it is MICSS, it would be very likely to have an underestimated number of breaks. On the contrary, ICSS can still possess decent performance when MICSS fails to; in fact, this finding is also supporting the conclusion from Andreou and Ghysels (2002), where ICSS is claimed to have satisfactory detecting ability with residuals from a GARCH (1,1) model. Also, as it is documented in Inclan and Tiao (1994) that, ICSS can be applied to uncorrelated series with mean zero. Moreover, Andreou and Ghysels (2002) also point out that, ICSS can have decent performance when detecting breaks in residuals even the change in the variance is small, given the sample size is large, for instance, the total sample size is 3000. All these evidence suggests potential advantages of choosing ICSS if applied to residuals when markets are expected to experience many breaks in a short period of time, such as during financial crisis. In addition, this simulation study also finds that MICSS fails to work properly when the change of variance becomes small in a fluctuating period with many breaks expected to occur. Therefore, it would be wise to carefully consider the most appropriated combination of structural break test, investigation object and data frequency, depending on whether financial time series are expected to experience many structural breaks and whether it is in the long or short run. For example, if it is to check structural breaks in financial markets around a financial crisis period, according to the previously discussed characteristics of both structural breaks algorithms, ICSS can be considered if employed on residuals from a fitted GARCH model for a daily frequency financial data series. If to consider MICSS on residuals, weekly data or high frequency data should be examined; either way, the subintervals between two consecutive breaks can be increased, such that MICSS can work properly. Furthermore, another new finding from this study is that both algorithms tend to determine the location of any detected structural break one observation prior to its actual occurrence, particularly in heteroskedastic data sequences. No previous study has made such comment because the simulation study they use is rarely based on multiple breaks but mostly in the case of one simulated break. Meanwhile, this simulation study confirms the validity of both programmed MLE[Y] and MLE[N]; particularly, MLE[Y] is confirmed to be able to distinguish the presence of structural break and make adjustment accordingly when estimating data series containing only GARCH effect; in particular, when data series contains ARMA effect in the mean and GARCH in the variance, it is necessary to fit the

data with MLE[Y] where the presence of structural break is considered, given that only conditional variance contains structural break.

Based on the above discussion, this chapter proceeds with structural breaks detection on stock returns from both China and the UK via MICSS. Despite the satisfactory properties, ICSS still has a relatively high chance to severely overestimating the structural breaks when applied on a data series with conditional heteroskedasticity.

2.6.2 The Timing of Structural Breaks in Stock Returns in China and in the UK

After applying the MICSS of Sanso et al. (2004) to the stock returns from both China and the UK market indices, the timing of each identified structural break is tabulated in Table 2.4, together with a list of significant political or economic events that could be possibly related to the occurrence of each break found.

Table 2.4: Structural Breaks Dates and Significant Events

	Dates	Significant Events
Chinese Stock Market	24 September 1997	1997 Asian financial crisis
	7 December 2006	The end of the compensation scheme to SOEs reform
	3 September 2009	The 2009 reforms in Chinese stock market
UK Stock Market	21 October 1997	1997 Asian financial crisis
	11 June 2002	The 2002 stock market crash
	2 June 2003	–
	23 July 2007	2007-2008 financial crisis
	3 April 2009	Unemployment rate reached 15-year highs
	2 August 2011	Bank of England held Interest rate
	14 December 2011	Unemployment rate reached 17-year highs
	9 July 2013	–
	19 September 2014	Scottish independence referendum

As it can be observed from Table 2.4 that, over the 10-year sample period, for the stock market in China, three breaks are found in the SSE index; while for the UK stock market, eight are found in FTSE 100 index. By comparing the number of breaks, it would initially suggest that Chinese stock market is more stable than the UK stock market. Moreover, when studying the relationship between significant events and the occurrences of structural breaks, comparing to the UK, Chinese stock market seems to be less sensitive to global financial crises. One structural

break is found on 24 September 1997 in China, which is near the time of the 1997 Asian financial crisis starting in July 1997. As for the UK stock market, a structural break occurred on 21 October 1997, 11 June 2002, and 23 July 2007, corresponding to 1997 Asian financial crisis, the 2002 stock market crash, and the 2008 financial crisis respectively. Furthermore, the domestic events play a critical role in both countries. For China, the structural break found on 7 December 2006 corresponds to the completion of the compensation scheme adopted by the Chinese government to employees made redundant due to the State-owned enterprises (SOEs) reform. This finding is consistent with Ni et al. (2016), where a break is found on 8 December 2016. Another break is found on 3 September 2009, where a series of reforms taken place to the management and supervision of stock markets, including the issue of the Rules on Supervision over Securities Companies, the Rules on Risk Disposal of Securities Companies, the Provisional Administration Measures for Stock Exchange Risk Fund, and the Rules of Contents and Format of Information Disclosure by Companies Offering Securities. These regulations are established in order to regulate the management activities that may have considerable influence over market prices, such as disclosure of relevant information by the listed companies, and to ensure the stock market avoid heavy economic losses (Geretto and Pauluzzo, 2012). For the UK, structural break found on 3 April 2009 is around the time that the unemployment rate was reported to reach 15-year highs. In 2011, the break found on 2 August is around the time that Bank of England held interest rate at a low of 0.5% for the 29th month; later on 14 December, another break is detected when the unemployment rate was announced to hit 17-year highs. After that, the break found on 19 September could be associated to the Scottish independence referendum took place on 18 September.

Therefore, these findings imply that, as an emerging stock market, China has a relatively stable structure than the mature stock market in the UK. In particular, empirical evidence shows that both markets are influenced by its domestic political, social, economic events, yet Chinese stock market seems to be less affected by significant global events. This could be the result of the fact that the Chinese stock market is more relied on government policies and regulations. A similar conclusion can also be found in Ni et al. (2016).

2.6.3 Modified ARMA-GARCH Model with Structural Breaks

After the timing of each structural break is determined, dummy variables are created corresponding to each of the detected breaks. Each dummy variable is a vector of 5477 observations with value 1 onwards from the identified location till the end of

the data series and 0 elsewhere. The best model for each research series is selected according to residuals diagnostics together with the consideration of the detected breaks [1]. Therefore, an ARMA(0,1)+GARCH(1,1) is selected to fit the Chinese stock return series best, while an ARMA(0,1)+GARCH(1,2) is determined for the UK. Estimation results of both models with and without incorporated structural breaks are presented in Table 2.5:

It can be observed from Table 2.5, after taking into consideration the detected structural breaks in the volatility, stock returns in both countries show reduced volatility persistence which is calculated as the sum of α_i and β_i. To look into more details, the Chinese stock market shows a reduced volatility persistence from very close to 1 to 0.9274, by an increase of α_1 from 0.07 to 0.10 and a more decreased β_1 from 0.9257 to 0.8243. This change then gives the rise in ω from 0.000001 to 0.000053. Similarly, for the UK, a decreased persistence of volatility is also reported from 0.9867 to 0.8554, where β_1 is decreased from 0.8077 to 0.6215 along with a slightly increased α_1 from 0.1160 to 0.1174 and an increased α_2 from 0.0637 to 0.1165. This leads to an increased ω from 0.0000008 to 0.000006. Moreover, the residual diagnosis further supports the validity of ARMA(0,1)+GARCH(1,1) model for the stock returns series in China. In fact, the Chinese stock returns seem to be modelled adequately no matter whether the structural breaks are accommodated or not. Yet, the UK stock return series shows differently. When the structural breaks are not taken account of, LM ARCH test suggests further ARCH effect in the conditional variance; this is however improved after the breaks are accommodated, although serial correlation still presents in the residuals as suggested by Ljung Box test.

2.7 Limitations and Future Work

Several issues have been raised during the investigation within this chapter. First of all, it observes a pattern where as an emerging country, Chinese stock market seems to be less sensitive to the shocks comparing to a mature stock market as in the UK, and thereby the volatility appears to be more persistence. It would be interesting to know if this pattern exists between other emerging and mature markets. However, the evidence found in this research is insufficient in supporting this conjecture. Future work could extend the scope of research to investigate on a group of markets of different level of development.

Secondly, empirical evidence has been shown via Monte Carol simulation that the

[1] Details of model selection are available on request

size of variance change has a significant impact on the robustness and effectiveness of both ICSS and MICSS. Although it reveals the tendency that both algorithms shows a diminishing power over the breaks, no further analysis has been carried out on determining the scale or threshold to which the tests would fail. Lack of such identification can lead to inadequate inference toward the choice of algorithms. In fact, the plots of both return series suggest a less volatile structural of the Chinese stock market, which indicates a smaller size of variance change for the Chinese stock returns. However, this research has taken little consideration on such feature due to the lack of a threshold. In addition, no further investigation has been conducted on how to define this size of variance change such that a break can be differentiated from an outlier of a data series. An outlier is an observation which is distant from the majority of one data series, and it can occur in a heavy-tailed distribution such as financial returns series. Yet this chapter pays little attention to such matter. These limitations tends to constrains the useful implications this research can provide for the more effective application of both algorithms in study. One suggestion for future work is to calculate the ratio of the size of variance change against the unconditional variance.

Moreover, when modelling data series containing both ARMA in the mean and GARCH effect in the variance, the underlying assumption is that no structural breaks in the mean process. It would be interesting to know the situation when there is structural break in the mean. Investigation in this aspect is worth pursuing. Also, simulation on MLE[Y] and MLE[N] is conducted only based on one simulated break; it would be worth exploring the case with multiple structural breaks.

2.8 Conclusion

This chapter has investigated the presence of structural breaks in the volatility and the potential effects it may have caused when modelling volatility via conventional GARCH models. Two stock markets are selected, namely, China and the UK, so to extend the scope to investigating markets at the different level of development. Studying this difference is critical for creating customised volatility models to fit in a specific market. This study employed MICSS algorithm of Sanso et al. (2004), and found three breaks in the Chinese stock market and eight breaks in the UK stock market over the recent two decades. The fewer structural breaks found indicate a relatively stable market structure in China. Moreover, Chinese stock market seems to be more affected by domestic economic or political events; for instance, the end of the compensation scheme to SOES reform, the 2009 reforms in Chinese stock market regulations. Nevertheless, this study finds no structural break in the Chinese stock

market either around the 2002 global stock market crash or the 2008 financial crisis. This finding is consistent with that the Chinese markets are more policy controlled. Quite to the contrary, structural breaks are found around both domestic events and global ones for the UK stock market, suggesting as a mature market, the UK stock returns are more sensitive to significant events in both local and global contexts. Moreover, after incorporating the detected structural breaks as dummy variables in the variance model, the volatility persistence of return series has dropped in both markets, with a larger scale in the UK market. This result suggests comparing to the emerging stock market in China, neglecting the structural breaks can lead to a more spurious volatility persistence in the mature stock market in the UK. Further evidence reveals that, with a relatively stable market structure such as China, the volatility tends to be more persistent, even after the negative effect of structural breaks is eliminated.

This chapter also explores the performance of both ICSS and MICSS via Monte Carlo simulations in a more comprehensive manner. Extensive evidence is found to support the well established argument in the literature that ICSS shows a severe size distortion when detecting structural breaks in financial asset series, and MICSS is thus the more suitable method in such situation. More importantly, this simulation finds the necessity to assert some additional conditions such that this argument can hold. As there has been evidence shown in this study that in a relatively fluctuate time period where structural breaks are expected to occur quite often, MICSS has strong likelihood to detect no structural breaks in a GARCH(1,1) series. Quite the contrary, ICSS shows rather sufficient detecting ability comparing to the less promising performance of MICSS in this setting, given there is a relative significant change in the variance before and after the break. Furthermore, the performance of MICSS becomes even more questionable when the change in the variance is also very small during such fluctuate period. This finding particularly casts doubt on the empirical applications of MICSS during a fluctuate time period. This study challenges the existing literature that is in favour of MICSS, as ICSS also shows some potentials when applying to residuals obtained from well fitted models. Moreover, ICSS tends to identify more change points than the simulated number in the GARCH(1,1) sequence, especially when dealing with more than one structural breaks. This finding agrees with the criticism drawn on ICSS of being spurious size distorted when employed on financial time series. Nevertheless, it is hard to neglect the fact that MICSS has a higher chance of detecting no breaks. Furthermore, as potential breaks occur more often, each estimator shows a significant drop in successful detection, especially for MICSS. In particular, when dealing with GARCH(1,1) as the variance changes are getting smaller, MICSS is no longer able to identify the

simulated breaks correctly. Therefore, this study has raised questions toward the validity of implications based on the results via MICSS.

Although this chapter reveals the Chinese stock market is less sensitive to significant global events than the UK stock market does, and the volatility is persistent in this emerging market even after eliminating the effect of structural breaks, however, this evidence is not conclusive to all emerging and mature markets. Future work can be expanded to target a group of emerging and mature markets to look for any particular pattern in this regard. Moreover, when modelling volatility with structural breaks, the insignificant breaks are kept in the model. This choice could affect the performance of MLE[Y] estimator. Therefore, it is necessary to check the validity of each detected break by the significance of each coefficient in the fitted model. Future work in this area involves constructing simulation experiments to examine whether excluding the insignificant structural breaks in the fitted model improves the performance of selected structural break test.

Table 2.5: Empirical Results for Stock Markets in China and the UK

	China		UK	
Best Model	ARMA(0,1)+GARCH(1,1)		ARMA(0,1)+GARCH(2,1)	
Action on Break(s)	Accommodated	Neglected	Accommodated	Neglected
μ	1.7258e-04	3.5465e-04**	5.0376e-05	2.3159d-04**
θ_1	0.1083***	-0.0027	0.1155***	0.0968***
ω	5.3512e-05	1.6140e-06	6.3776e-06	8.2058e-07
α_1	0.1031	0.0709	0.1174***	0.1160***
α_2	–	–	0.1165***	0.0637***
β_1	0.8243	0.9257	0.6215	0.8077
δ_1	-4.2836e-05	–	1.5225e-05***	–
δ_2	0.1031	–	4.5769e-05***	–
δ_3	0.8243	–	-4.7257e-06***	–
δ_4	–	–	3.8002e-05***	–
δ_5	–	–	1.1375e-05***	–
δ_6	–	–	5.7064e-05***	–
δ_7	–	–	6.3276e-06****	–
δ_8	–	–	-5.8317e-06***	–
δ_9	–	–	3.62e-06	–
Volatility Persistence	0.9274	0.9966	0.8554	0.9867
Log Likelihood	15000.23	14920.94	17517.23	17631
LR Test Statistics	158.58***		–	
Standardized Residuals Tests				
Jarque-Bera	18313***	38716***	332***	257***
Ljung-Box $Q(1)$	2.642	3.1231*	51.703***	33.978***
Ljung-Box $Q(5)$	15.578**	18.771 ***	58.102***	40.919***
Ljung-Box $Q(10)$	35.608***	38.049***	60.364***	42.138***
Ljung-Box $Q^2(1)$	0.28	0.1585	1.5839	4.781**
Ljung-Box $Q^2(5)$	1.4452	2.3697	27.425***	23.464***
Ljung-Box $Q^2(10)$	3.2212	3.9609	43.269***	35.378***
LM ARCH	0.2798	0.6906	0.2084	4.778**

*Note: *,**,*** represent level of significance 1%, 5%, 10% respectively;*
Volatility persistence is calculated as the sum of α_i and β_i;
Jarque-Bera checks whether the standardized residuals are normally distributed, with the null
hypothesis of normality;
Ljung-Box Q (lag order in brackets) examines the autocorrelation between standardized residuals, with null hypothesis of series being independent;
Ljung-Box Q^2 (lag order in brackets) examines the autocorrelation between squared standardized
residuals, with null hypothesis of series being independent;
LM ARCH checks for any further ARCH effect in the conditional variance, with the null hypothesis
of the absence of ARCH;
The null hypothesis of LR Test in this case is the better performance of model with no consideration of structural break.

Chapter 3

Volatility Spillover: Do Structural Breaks Matter?

3.1 Introduction

Over the past two decades, economic globalization provides investors with a broader range of investment benefits and opportunities. Meanwhile, the world markets have been experiencing more liberation and faster integration. As a consequence, information from one market can pass on to another much easily as interdependence between markets grows. Under these circumstances, it is necessary not only to study the structure and fundamentals of one single financial market but also to capture the movement and analyse the interactions between markets.

Studies of the relationship between two financial markets are well documented through studying the long run equilibrium relationship by cointegration (Granger, 1986; Engle and Granger, 1987), and the short run relationship by Granger Causality (Granger, 1969). The literature in this area is rich; see, for instance, John Wei et al. (1995), Gilmore and McManus (2002), Zhu et al. (2004), Ramlall (2009), Apergis et al. (2015), Muye and Muye (2017), Golab et al. (2018). It is worth noting that, both cointegration and Granger Causality study the relationship of two markets between the mean returns; the interaction between volatilities of the two is determined via volatility spillover, where it examines the short term cross-dependence between two volatilities. Other terms referring to volatility spillover are shock contagion (Bekaert et al., 2005, 2014) and causality in variance/volatility (Cheung and Ng, 1996; Hong, 2001) for the following reasons. Since Ross (1989) mentions that market volatility is related to the arrival of new information. Therefore, when two markets are free of volatility spillover, it implies the "shock" is asset- or market-specific, and it only affects the volatility of its own market, hence confirms the

interdependence between markets. This information is useful for constructing hedging positions. Moreover, presence of such spillover suggests "shocks" travel from the "leading" to the "led" market. Specifically, when a unidirectional volatility spillover is identified, it is said that the past volatility values of the "leading" market can contribute to explaining the current volatility of the "led" market. Therefore, the former market is described as having the incremental predictive ability for the latter market (Hong, 2001). This information is of particular help to improve volatility modelling and forecasting, especially when information on one market is insufficient. That is to say, when market experiences many shocks in a very short period of time, lack of sufficient observations could lead to efficient model estimations; nevertheless, information from another market can be used if a volatility spillover pattern can be established. Therefore, by examining information transmission patterns via volatility spillover, it offers financial participants a better understanding of the interactions between markets, hence, to devise proper strategies to adapt any unforeseen turbulence in the markets.

Moreover, recent studies find theoretical evidence for a causal relationship between equity and currency markets (Ali and Anwar, 2012; Tsai, 2012). Two models are introduced to explain such relationship, one is known as the Balance of Trade Model, or Flow Oriented Model; the other is the Portfolio Balance Model, or Stock Oriented Model. The former model suggests foreign exchange rates have influences on the stock prices by affecting the company's balance of trade. According to Dornbusch and Fischer (1980), the depreciation of the local currency will bring benefits to the export-oriented firms as they can sell their products at a lower price comparing to the foreign peer firms. This will, in turn, boost the demand for their products both locally and internationally, and thus expect more earnings in the future. On the contrary, the appreciation of local currency will then reduce the demand for the products of the export-oriented firms because of a higher cost. Therefore, it will expect less income in the future. Opposite situation occurs to the import-oriented company, where the currency depreciation will benefit the firm and the currency appreciation will damage the future income. The latter model indicates the changes in stock prices affect the changes in foreign exchange rates. According to Frankel (1983), an increase in stock prices stimulates higher demand for money, which then leads to an increase in the interest rates. Raised interest rates then attracts short-term capital inflows, resulting an increase in foreign investment, which leads to an appreciation of the currency. More theoretical evidences can be found in Branson (1981), Solnik (1987), Gavin (1989), Phylaktis and Ravazzolo (2005), Aloui (2007), Koseoglu and Cevik (2013).

Empirical studies regarding mean level relationships between stock and foreign exchange markets include Bahmani-Oskooee and Sohrabian (1992), where a two-way causal relationship is found between stock returns in the US and the effective exchange rate of the dollar July 1973 to December 1988. Pan et al. (2007) investigate main stock indices and exchange rates in seven East Asian countries, namely, Hong Kong, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand, from January 1988 to October 1998. Via the Granger causality test of Granger (1969), and variance decomposition analysis of Sims (1980), evidence is found for a significant causal relation from the currency to stock market for Hong Kong, Japan, Malaysia, and Thailand. This finding supports the Balance of Trade Model of Dornbusch and Fischer (1980). Moreover, a causal linkage is found from the stock to currency market for Hong Kong, Korea, and Singapore, supporting the Portfolio Balance Model of Frankel (1983). More studies in this area can be found in Granger et al. (2000), Smyth and Nandha (2003), Phylaktis and Ravazzolo (2005), Batori et al. (2010), Lin and Fu (2016), Tomar and Singh (2016).

Empirical work on volatility spillovers between the two markets can be found in Kanas (2000), where stock returns and exchange rates examined in several industrialised countries around the October 1987 crash. A unidirectional spillover effect is found from stock returns to exchange rates in most of the countries in question. In Caporale et al. (2002), stock and foreign exchange markets are selected in four East Asian countries around the 1997 East Asian crisis; a unidirectional causality is detected from stock prices to exchange rates in pre-crisis and bidirectional causality in post-crisis. Fedorova and Saleem (2012) examined the interaction between stock markets and foreign exchange markets within the emerging markets of Eastern Europe and Russia from January 1995 to December 2008. By utilizing the bivariate BEKK-GARCH of Engle and Kroner (1995) they reported a bidirectional causality between stock and currency markets in all the countries in question, except for the Czech Republic where they found a unidirectional causality from currency to stock markets only. Caporale et al. (2002) conduct empirical investigation on the casual relationship between local primary stock indices and exchange rates with local currency against the US dollar in Japan, South Korea, Indonesia and Thailand from January 1987 to January 2000. The 1997 Asian crisis is also taken into consideration, in a way where the full sample is divided into pre- and post-crisis periods. The bivariate BEKK-GARCH of Engle and Kroner (1995) is adopted to both the full sample and the two subsamples to determine the potential volatility spillover patterns in each country. For the more developed markets in Japan and Korea, volatility spillover is found flowing from the stock markets to the foreign exchange markets for both the full sample and the two subsamples. For Indonesia

and Thailand, the same directional volatility spillover is found over the full sample period and the pre-crisis subsample; these findings support the portfolio approach of Frankel (1983) that the stock markets affects the foreign exchange rate market. Nevertheless, evidence is found that this uni-directional spillover in Indonesia and Thailand has developed into a bi-directional pattern after the 1997 Asian financial crisis. Richer literature in this area can be found in, for example, Yang and Doong (2004); Francis et al. (2006); Tai (2007); Yang and Chang (2008); Walid et al. (2011).

So far, substantial evidence is found to support a causal relationship between equity and currency markets, yet no consensus has reached in either theoretical or empirical work. Among the volatility spillover studies, very few investigate the volatility relationship between stock and foreign exchange market in the mainland of China, and even fewer conduct a comparison study between China and other developed countries. Therefore, this chapter will focus on identifying volatility spillovers between stock and foreign exchange markets in the mainland of China using causality in variance test of Hong (2001). This test has fewer computational problems compared to other multivariate methods, for instance, the multivariate approach on the BEKK-GARCH of Engle and Kroner (1995); it is free of specific distributional assumptions and produces good inferences with conditional heteroskedastic data series. Nevertheless, recent studies argue that the presence of structural breaks could affect the volatility spillover investigation (Rodrigues and Rubia, 2007; Javed, 2011; Zivkov et al., 2015), due to the majority volatility spillover tests are constructed on GARCH models. Dijk and Sensier (2005) particularly point out that this test suffers from considerable size distortions when structural breaks are ignored. Thus this chapter will also take account of the structural breaks when examining volatility spillovers via this test, and use MICSS of Sanso et al. (2004) structural breaks detection. In addition, this chapter will conduct Monte Carlo simulations to further evaluate the performance of this volatility causality test, especially for the case of multiple structural breaks in the presence. Moreover, by conducting the causality in variance test on all the sample cross-correlations. this chapter attempts to identify not only the presence but also the start of any potential volatility spillovers. This chapter will also investigate the case in the UK markets, in order to form a comparison study when examining how differently the volatility causality patterns can be in countries at a different development level. Designed as such, this research not only can contribute to establishing insightful knowledge on the fundamentals of financial markets, it also seeks the possibility to build customized models dealing with markets with unique characteristics. Therefore, this research is of interest to both investors and financial managers to devise proper investment strategies especially over the period such as a financial crisis; meanwhile, it can also provide policy

makers with invaluable information and advanced econometric techniques to ensure economic stability.

The remainder of this chapter proceeds as follows: Section 3.2 provides a review on the recent literature with regard to investigating the volatility spillover between stock and foreign exchange markets; Section 3.3 formulates the research question; Section 3.4 presents the methodology; the data and empirical results interpretation and discussion will be found in Section 3.5 and 3.6; the limitation of this study is briefly discussed in Section 3.7; Section 3.8 concludes the chapter.

3.2 Literature Review

As the growing globalization gives rise to information transmission across financial markets, it is important to study the interactions between financial assets such that investors can make more informed investment decisions. It is particularly beneficial to financial institutions with a multinational business structure to manage exposures induced from other markets. Serving as a fundamental role in supporting the growth of one economy, the performance of stock market reflects the degree of development in one country. Meanwhile, as an important indicator of economic strength and political stability, exchange rate market is known as one of the most sensitive segments of the financial system. Those profound economic impacts of stock and exchange rate markets have drawn considerable attentions to studying the interactions between them.

In this context, a large number of empirical research has carried out investigations on the linkage between stock and foreign exchange markets. One approach is through investigating the volatility spillover. Eissa et al. (2010) study the volatlity relationship between stock returns and nominal exchange rates in Egypt, Morocco and Turkey. A bidirectional volatility spillover is found via the BEKK-GARCH model of Engle and Kroner (1995) in all three countries; in addition, this effect is much stronger in Egypt and Turkey.

Zhao (2010) studies the dynamic relationship between the currency market and stock market in China. By analysing the RMB real exchange rate and Shanghai composite stock price index of monthly frequency from January 1991 to June 2009, a bidirectional volatility spillover is found between the foreign exchange and stock markets via the MGARCH-BEKK model of Engle and Kroner (1995). This finding indicates that future volatility in stock market is greatly influenced by the past innovations in foreign exchange market in China, and vice versa.

Aloui (2007) adopts the causality in variance of Cheung and Ng (1996) to study the relationship between stock prices and foreign exchange rates for five major European countries and the United States. The sample period is from 1991 to 2005, and is divided into the pre- and post-Euro subsamples by the launch of the Euro in January 1999. The empirical results show much dynamic and complex volatility spillover patterns. In the pre-Euro period, volatility transmission is found only in two countries; France experiences a unidirectional volatility spillover from foreign exchange market to stock market in France, and same pattern is found in Germany. In the post-Euro period, unidirectional volatility spillover is found in all the countries except the United States. Apart from Germany and Italy, where the spillover effect is from foreign exchange to stock market, in France, Belgium and Spain, the spillover is from stock market to foreign exchange market.

De Las Nieves Morales (2008) employs the EGARCH model of Nelson (1992) in Spain along with in six Latin American countries from 1998 to 2006. A unidirectional volatility spillover is found from stock to foreign exchange markets. Under the same framework, Jebran and Iqbal (2016) investigate asymmetric volatility spillover between equity market and currency market in seven Asian countries, namely, Pakistan, India, Sri Lanka, China, Hong Kong and Japan. Using the EGARCH model of Nelson (1992) on daily return series from January 1999 to January 2014, a bi-directional volatility spillover is found between the two financial markets in Pakistan, and same pattern is found in China, Hong Kong, Sri Lanka; a uni-directional volatility spillover is found in India going from stock to foreign exchange market; no volatility spillover is found in Japan. They further comment that for each volatility spillover pattern being found is asymmetric in nature, meaning the volatility reacts to negative shocks more than to positive ones of same scale.

It can be seen from the above literature, that most volatility spillover methods are developed on GARCH models. Nevertheless, it has been well documented in the literature for the GARCH model misspecification due to the ignorance of the structural breaks in the volatility. Evidently, neglecting the effect structural breaks imposes on the GARCH models could lead to biased implications regarding the volatility spillover investigation. Zivkov et al. (2015) takes account the structural breaks when studying volatility spillover. The countries in study are four Eastern European emerging counties, namely, Czech Republic, Hungary, Poland and Russia; and the sample period is from 2002 to 2014. MICSS of Sanso et al. (2004) is also employed, and presence of structural breaks is found for all the return series. Moreover, incorporating the breaks as dummy variables greatly improves the GARCH

model estimations. This finding further confirms that the volatility spillover could be biased if those breaks are ignored. Under the FIGARCH framework of Baillie et al. (1996), a bidirectional spillover is found in all the countries, and the impact currency market imposes on the stock market is much stronger than the other way around, especially in Russia. Koseoglu and Cevik (2013) investigate the volatility spillover patterns between stock and foreign exchange markets in four European countries, namely, Czech Republic, Hungary, Poland, and Turkey. They also identify the presence of structural breaks by MICSS of Sanso et al. (2004). The negative effect of structural breaks is then removed before examining the volatility spillover pattern. Via the causality in variance test of Hong (2001), volatility spillover is found travelling from the stock to the foreign exchange market in every country in study.

3.3 Research Question

The primary goal of this chapter is to investigate the volatility spillover effects between stock market and foreign exchange rate market. Moreover, this research extends the scope to compare this spillover effect in two countries, namely, the UK and China, in order to explore whether the spillover effects in the volatilities between the targeted markets will be affected by the degree of the development. More importantly, the presence of structural breaks is taken into account when investigating the volatility spillover effects. Monte Carlo simulation studies will be first employed in order to understand the proposed volatility spillover test. The research question of this chapter is formed as follow:

What are the volatility spillover patterns between the stock market and foreign exchange market in China and the UK? To what extent do structural breaks affect these spillover patterns? Is it possible to identify the lag period from which the volatility of the "leading" market contributes to the volatility of the "led" market?

Addressing the above questions can help us better understand the information transmission between two important financial markets. Moreover, when information on modelling one market is scarce, investors and practitioners can use extra information from the other market if certain volatility spillover effects are found between them. Furthermore, it can also show whether taking account of structural breaks improves the identification of such pattern. Nevertheless, by investigating volatility spillovers in two countries with the different levels of development, customised models can be devised based on unique features in each country.

3.4 Methodology

This section introduces the causality in variance test of Hong (2001) developed on Cheung and Ng (1996). The establishment of test hypothesis, construction of test statistics, and test procedures will be discussed. Monte Carlo simulation design will be explained next.

3.4.1 Causality in Variance Test

The causality in variance test of Hong (2001) study the volatility spillover between two financial time series by examining their sample cross-correlations under a non-uniform weighting scheme. It is an improved version of the causality in variance test of Cheung and Ng (1996). Recall from Chapter 1, for two stationary time series $Y_{it}, i = 1, 2$ with each conditional variance following a GARCH(p,q) process:

$$Y_{it} = \mu_{it} + \varepsilon_{it}, \quad i = 1, 2 \tag{3.1}$$

$$\varepsilon_{it} = \xi_{it}\sqrt{h_{it}}, \quad \xi_{it} \sim N(0, 1), \quad i = 1, 2 \tag{3.2}$$

$$h_{it} = \omega_i + \sum_{j=1}^{p} \alpha_{ij}\varepsilon_{it-j}^2 + \sum_{j=1}^{q} \beta_{ij}h_{it-j}, \quad t = 1, ..., T, \quad i = 1, 2 \tag{3.3}$$

Let u_t and v_t represent the squared error terms $\varepsilon_{it}^2, i = 1, 2$ standardized by $h_{it}, i = 1, 2$:

$$u_t = \varepsilon_{1t}^2/h_{1t}, \quad i = 1, 2 \tag{3.4}$$

$$v_t = \varepsilon_{2t}^2/h_{2t}, \quad i = 1, 2 \tag{3.5}$$

The jth cross correlation coefficient $\rho_{uv}(j)$ between u_t and v_t is then

$$\rho_{uv}(j) = \{C_{uu}(0)C_{vv}(0)\}^{-1/2}C_{uv}(j) \quad j = 1, ..., T \tag{3.6}$$

where $C_{uu}(0) = T^{-1}\sum_{t=1}^{T} u_t^2$ and $C_{vv}(0) = T^{-1}\sum_{t=1}^{T} v_t^2$ are the variances of Y_{1t} and Y_{2t} respectively. Moreover, $C_{uv}(j)$ is the jth sample cross covariance, which takes the form

$$C_{uv}(j) = \begin{cases} T^{-1}\displaystyle\sum_{t=j+1}^{T} u_t v_{t-j}, & j \geq 0 \\ T^{-1}\displaystyle\sum_{t=-j+1}^{T} u_{t+j} v_t, & j < 0 \end{cases} \tag{3.7}$$

The test statistic Q is then calculated as below:

$$Q = \frac{T\sum_{j=1}^{T-1} k^2(j/M)\rho_{uv}(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{3.8}$$

$$C_{1T}(k) = \sum_{j=1}^{T-1}(1-j/T)k^2(j/M) \tag{3.9}$$

$$D_{1T}(k) = \sum_{j=1}^{T-1}(1-j/T)\{1-(j+1)/T\}k^4(j/M) \tag{3.10}$$

where $k(.)$ is Bartlett kernels (Priestley, 1981), such weighting function is defined as below

$$k(j/M) = \begin{cases} 1-|j/M|, & \text{if } |j/M| \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{3.11}$$

$C_{1T}(k)$ and $D_{1T}(k)$ are used to make sure Q asymptotically has N(0,1) distribution. Therefore, under the null hypothesis of no volatility spillover, Q is a one-sided test, and the critical value at the 5% is 1.645. In addition, according to equation 3.7, the range of j determines the direction of volatility spillover; the causality test with $j < 0$ identifies any causal linkage from Y_{1t} to Y_{2t}, while that of $j \geq 0$ detects any causal relation from Y_{2t} to Y_{1t}. This causality in variance test will be applied to data series twice with different range of j in order to determine the presence and the direction of volatility spillover. Moreover, M is the number of sample cross-correlations are under investigation; M can take any integer number between one and $T-1$. Therefore, the Bartlett kernel function $k(.)$ in (3.11) gives zero weight to the jth cross-correlation when j exceeds M.

It is necessary to mention that, no universal rule is found on how to determine M; the choice of M in most studies depends on intuition, and normally $M = 1, 5, 10$ (see, for instance, Koseoglu and Cevik, 2013). Moreover, assume the true volatility spillover becomes recognizable from the first $M + m$ (m is any positive integer) sample cross-correlations, it could be very likely that the causality in variance test reports no volatility spillover when only the first M cross-correlations are examined. No research has been found to consider such possibility. Nevertheless, although the existing literature shows simulation results that neglecting the structural breaks in the volatility can compromise the causality in variance test of Hong (2001) (see, for instance, Dijk and Sensier, 2005), no evaluation is conducted on the case of more than one break. Therefore, these issues call for further Monte Carlo investigation.

3.4.2 Monte Carlo Study

In order to obtain a much in-depth understanding of the causality in variance test of Hong (2001) (CinV hereafter), this simulation study is designed considering the following factors:

- The volatility spillover pattern
  Three cases will be considered, i.e., the absence of volatility spillover, lag 1 volatility spillover, lag 30 volatility spillover. The latter two patterns represent respectively an almost-immediate and a relatively-remote causality between volatilities from the "leading" to the "led" series.

- The scale of the simulated volatility spillover
  Both a strong and a weak volatility spillover will be simulated. Combining with other factors, it aims at evaluating the robustness of CinV in a more comprehensive manner.

- The relationship between M and the lag number of simulated volatility spillover
  For each of the simulated spillover patterns, $M = 1, 30, 60$ will be considered. This design is to collect evidence to support the conjuncture that CinV could overlook volatility spillover if M is smaller than the lag number.

- The presence of structural break(s)
  Up to four breaks will be considered in the paired data series, where the location of the simulated breaks will be identical in each of the individual series. Also, a comparison will be employed between accommodating and ignoring the presence of the simulated breaks. In addition, a case where no structural break in any individual data series will be set up so to study the causality in variance test without the potential disturbance caused by the structural breaks.

- The distance between two adjacent breaks
  To include this factor is to see if the test would perform differently when many structural breaks are expected to occur in a relatively short time period.

- The size of variance change
  Taking into consideration this factor is to test the sensitivity of CinV to the change of the volatility.

For simplicity, this simulation considers two GARCH(1,1) data series $Y_{it}, i = 1, 2$, and a unidirectional volatility spillover from Y_{2t} to Y_{1t}. Details can be found as below:

$$Y_{it} = \mu_{it} + \varepsilon_{it}, i = 1, 2; t = 1, 2, ..., T; \tag{3.12}$$

$$\varepsilon_{it} = \xi_{it}\sqrt{h_{it}}, \xi_{it} \sim N(0, 1); \tag{3.13}$$

$$h_{1t} = \omega_1' + \sum_{1}^{k} D_{1k}\delta_{1k} + \alpha_1\varepsilon_{1t-1}^2 + \beta_1 h_{1t-1} + \zeta_{21}\varepsilon_{2t-d}^2 + \gamma_{21}h_{2t-d}; \tag{3.14}$$

$$h_{2t} = \omega_2' + \sum_{2}^{k} D_{2k}\delta_{2k} + \alpha_2\varepsilon_{2t-1}^2 + \beta_2 h_{2t-1} \tag{3.15}$$

in the conditional variance processes h_{1t} and h_{2t}, $D_{ik}, i = 1, 2$ are dummy variables representing the simulated structural break(s). It takes value 1 from the identified structural break onwards, and value 0 elsewhere, indicating the shift in the variance caused by that break. δ_{ik} are the corresponding coefficients for the dummy variables, where k represents the number of breaks simulated. It is worth noting that, the breaks in two series are simulated to occur simultaneously; therefore, future work could be extended to investigate the performance of the test when structural breaks occur at a different time. Moreover, ζ_{21} and γ_{21} measure the scale of the causality.

In summary, this chapter will first identify the presence of structural breaks via MICSS of Sanso et al. (2004), and then accommodate the detected breaks following the same method discussed in Chapter 2. The causality in variance test of Hong (2001) is then employed to study the volatility spillover between stock and foreign exchange markets in both China and the UK. Moreover, this chapter will conduct Monte Carlo study to investigate the test performance. Under a comprehensive design, the simulation contains 270 experiments, each of which contains 5,000 replications. Two factors are particularly considered, namely, multiple structural breaks, and the choice of M; as the existing literature is scarce in evaluating the robustness of this test, especially in the case of multiple breaks. Moreover, there is no consensus or formal rule on how to choose M, despite that M is a particularly important input in this test. Structured as such, this chapter attempts to explore further on how to more accurately identify volatility spillover via causality in variance test of Hong (2001).

3.5 Data

The main stock indices are the same series as in Chapter 2, namely, the SSE A share Composite Index traded at the Shanghai Stock Exchange for China, and the FTSE 100 Index listed on the London Stock Exchange for the UK. Each of the stock series

is denoted in its home currency. As for the foreign exchange rates, the British Pound (GBP) and China Yuan Renminbi (CNY) will be used and expressed in the local currency against the US Dollar (USD). All data series are of the daily frequency and are obtained from DataStream, covering a period from 3 January 1994 to 31 December 2014, forming 5478 observations for each series. Returns from each data series are firstly created as shown in Equations (3.16) - (3.19). An initial overview of each series can be found in Figure 3.1 to 3.4.

$$rstk_t^{china} = \ln stk_t^{china} - \ln stk_{t-1}^{china} \tag{3.16}$$

$$rex_t^{china} = \ln ex_t^{china} - \ln ex_{t-1}^{china} \tag{3.17}$$

$$rstk_t^{uk} = \ln stk_t^{uk} - \ln stk_{t-1}^{uk} \tag{3.18}$$

$$rex_t^{uk} = \ln ex_t^{uk} - \ln ex_{t-1}^{uk} \tag{3.19}$$

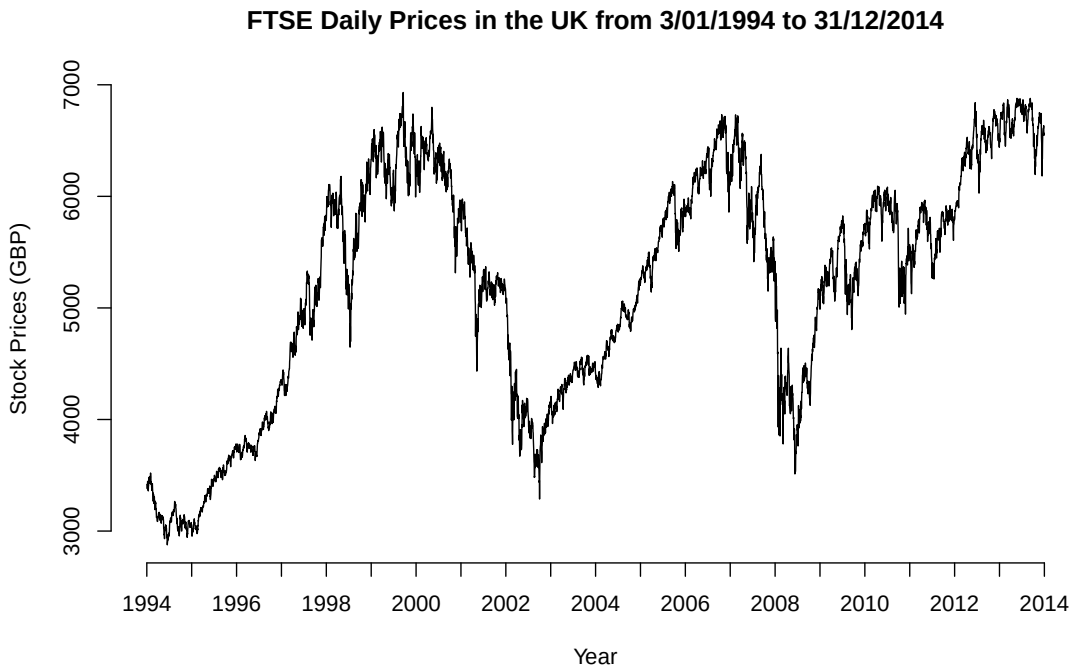
Table 3.1: Descriptive Statistics of Stock and Foreign Exchange Returns in the UK and China

	UK Markets		Chinese Markets	
	Stock Returns	FX Returns	Stock Returns	FX Returns
Mean	0.0001	0.00001	0.00047	-0.0001
Standard Deviation	0.0115	0.0054	0.0162	0.0010
Skewness	-0.1595	0.0400	-0.4231	-0.0188
Excess Kurtosis	6.3143	4.4588	4.0647	5.4974
Jarque-Bera	9131.7[0.0000]	4544.1[0.0000]	1774.6[0.0000]	3310.7[0.0000]
ADF	-18.502[0.0000]	-17.118[0.0000]	-12.315[0.0000]	-11.739[0.0000]
ARCH LM Test	1274.2[0.0000]	703.07[0.0000]	24.739[0.0000]	155.18[0.0000]
Obs	5477	5477	2464	2464

Note: Different sample is chosen for the markets in the UK and China due to the data availability caused by the change of foreign exchange regime in China; Jarque-Bera normality test significantly rejects the null hypothesis of i.i.d data for all the four data series; ADF test significantly rejects the null hypothesis of the presence of unit root, indicating stationarity for all the four series; ARCH LM test significantly rejects the null hypothesis of no ARCH effect in the conditional variance for all the data series except for the exchange rate return of China; p-value of each test is in the bracket

Figure 3.1 and 3.2 show the plot for stock [1] and foreign exchange markets in the UK in terms of prices and returns respectively. A relatively volatile structure can be observed for the price markets in the UK. Moreover, plots of returns shows several regimes in the volatility of each series as marked by the dotted line, indicating the occurrence of structural breaks. Figure 3.3 and 3.4 show the plot for prices and

[1] The plots of UK stock prices and returns are identical with the ones in Chapter 2.



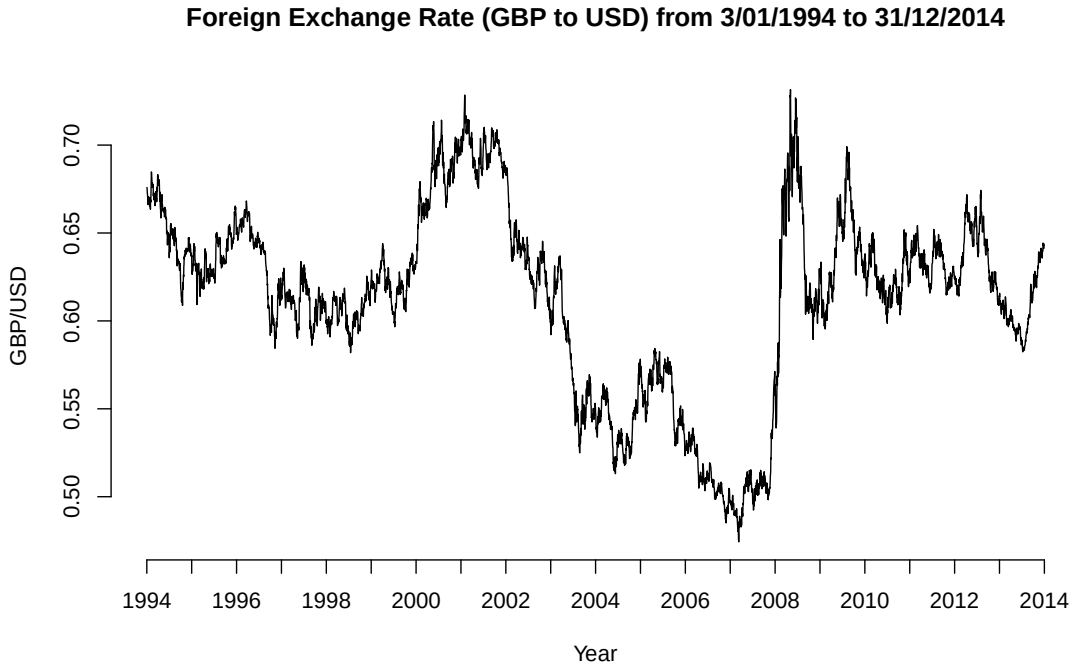


Figure 3.1: Plots for Stock Prices and Foreign Exchange Rates in the UK

returns of foreign exchange and stock market in China. It can be seen from Figure 3.3, CNY to USD exchange rates stay constant from the start of sample period to 21 July 2005, and then show variation afterwards. This is caused by the change from a pegged exchange rate system against USD to a managed floating policy on 21 July 2005. Since no structural break occurs during the pegged exchange rate

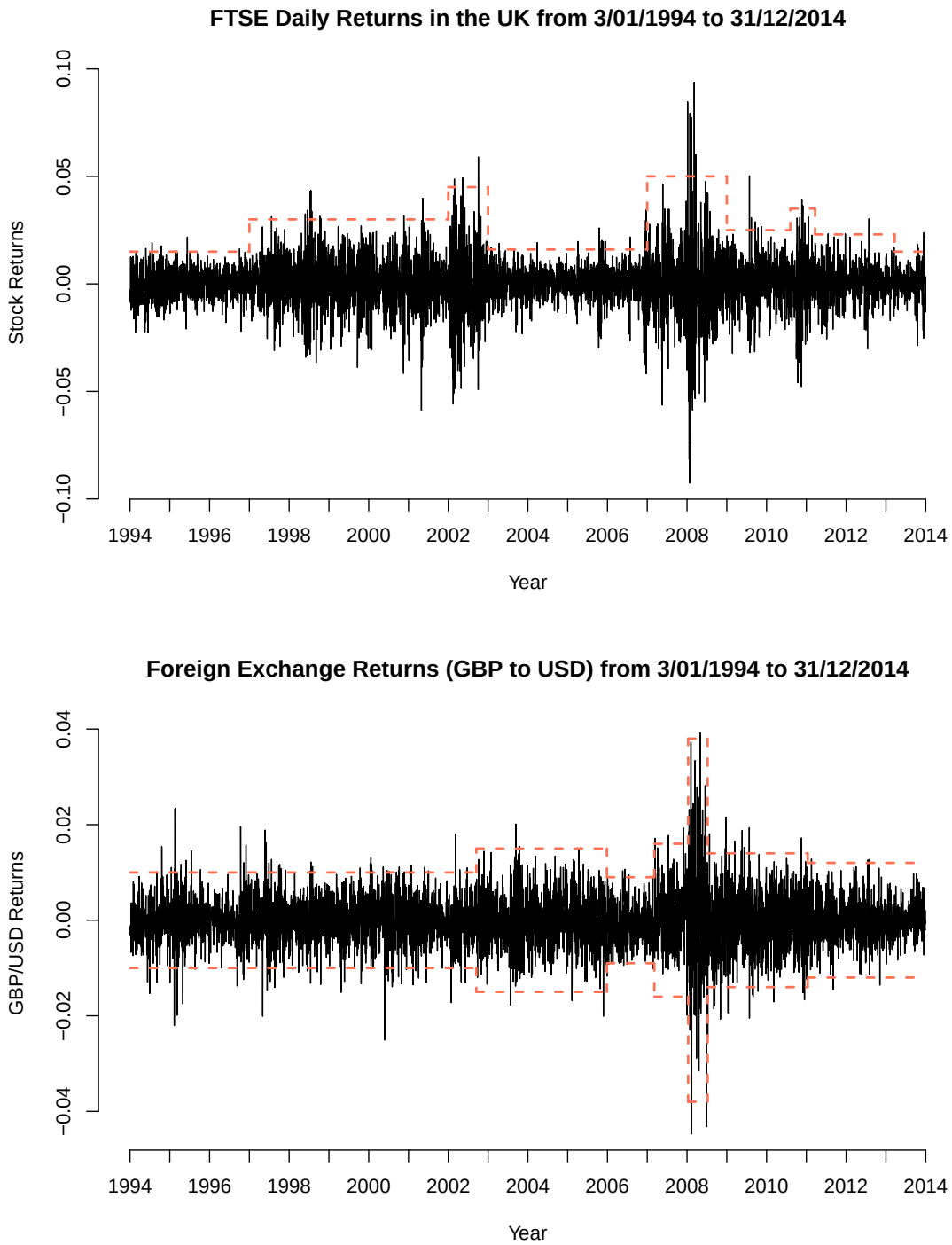


Figure 3.2: Plots for Stock and Foreign Exchange Returns in the UK

regime, and including such period interferes the detection of any structural break in the later period. Under such circumstances, this chapter will only study the sample period after the adoption of new exchange rate regime for both foreign exchange and stock series in China, namely, from 22 July 2005 to 31 December 2014. The stock prices of this new sample is plotted in Figure 3.3 and the return series

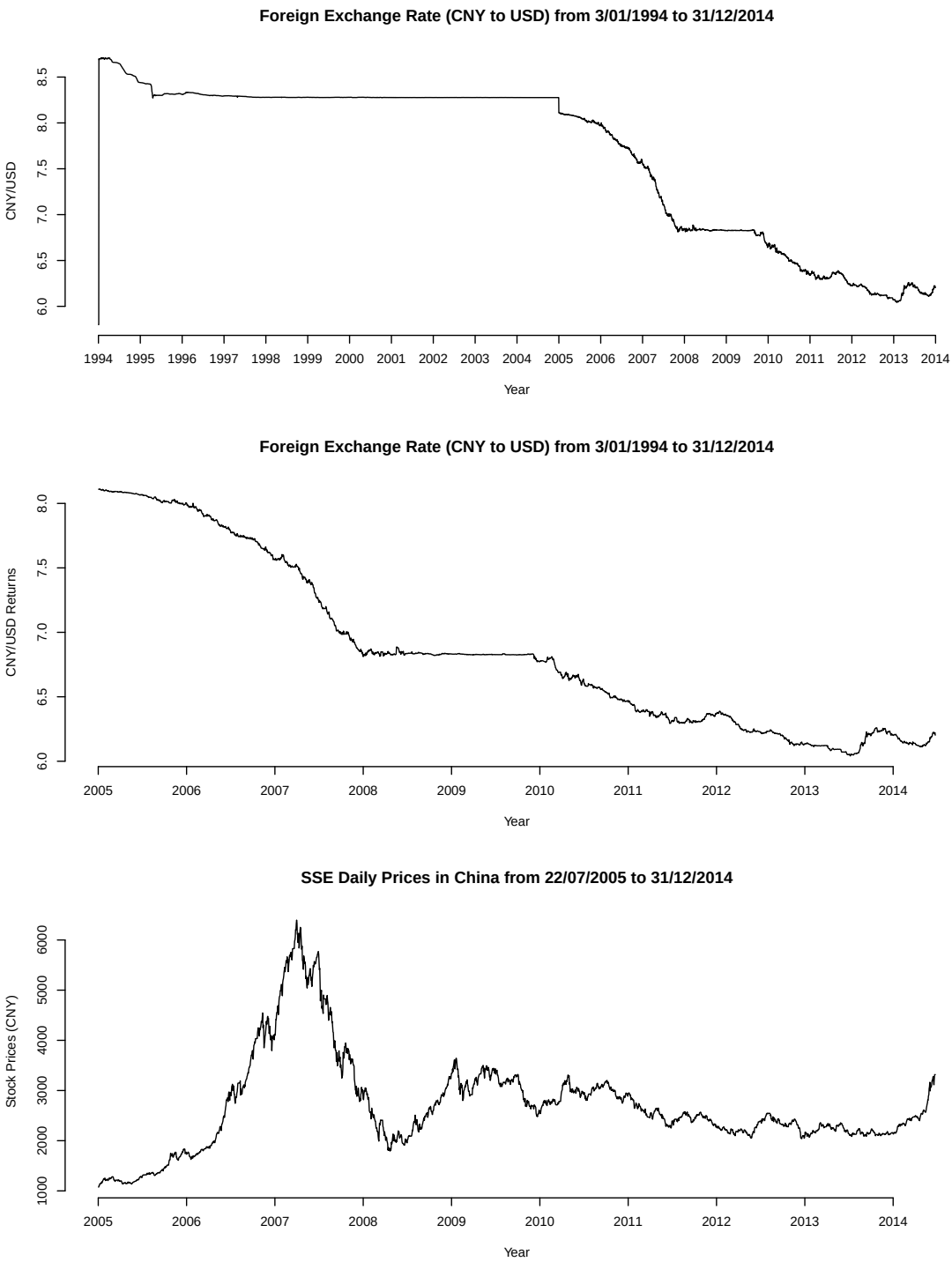


Figure 3.3: Plots for Stock and Foreign Exchange Rates in China

can be found in Figure 3.4. It can be observed that Chinese markets seem to have a rather stable structure with fewer structural breaks as indicated by the dotted line.

Descriptive statistics is presented in Table 3.1 for a different sample period between the UK and China. For the UK markets over the sample period from 3 January

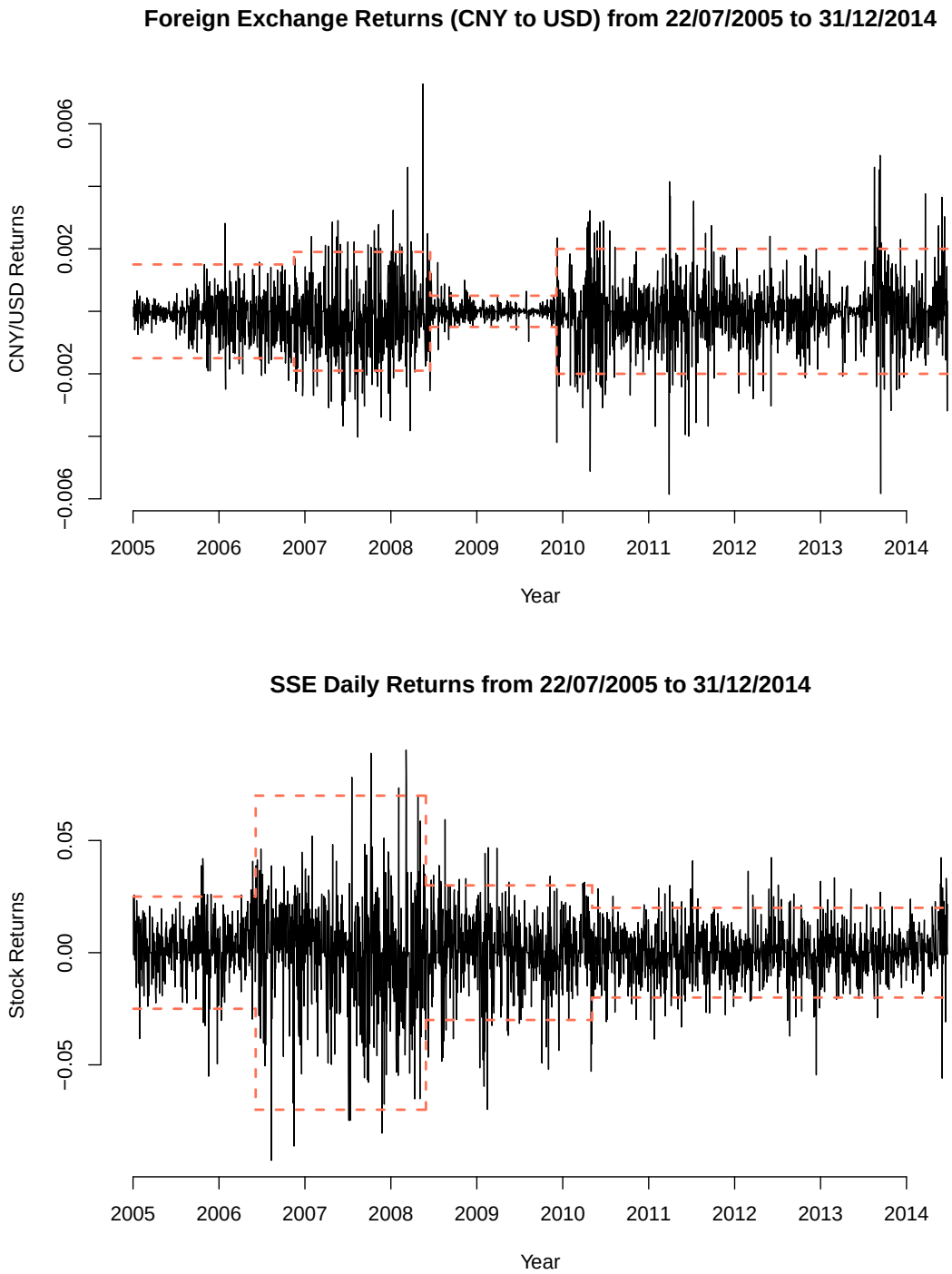


Figure 3.4: Plots for Stock and Foreign Exchange Returns in China

1994, a slightly left skewed distribution for the stock returns, and a slightly right skewed distribution for the FX returns can be observed, indicating the majority of the observations are around the mean of each series, where there is a small chance to have big negative returns in the stock and a small chance to have big positive returns in the FX. The positive excess Kurtosis indicates that neither series is normally

distributed, and it is further confirmed by Jarque-Bera normality test where the null hypothesis of normality is rejected at 1% level of significance. Similarly conclusion can be drawn for return series in China dated from 22 July 2005. Moreover, ADF test suggests all the four series are stationary and ARCH LM test indicates further GARCH effect for each of the series.

3.6 Empirical Results and Interpretation

This section will firstly analyse the simulation results to gain a more in-depth understanding of the mechanism of CinV. Next, using MICSS algorithm of Sanso et al. (2004) as discussed in the previous chapter to identify structural breaks. The best model for each data series is then presented, and CinV is employed on the most appropriate estimates to study the volatility spillover patterns between stock and foreign exchange returns in both China and UK. It is worth noting again, that the causality pattern considered in this chapter is uni-directional. Moreover, with the consideration of structural breaks, this study also discusses whether the causality pattern will be influenced by such factor.

3.6.1 Monte Carlo Simulation Analysis

Appendix Table A.7 presents the statistics of success detections returned by CinV of simulated causality patterns. Nevertheless, CinV test statistics Q are plotted from Figure B.4 to Figure **??** in every single scenario created by combining different factors, including the scale of volatility, the size of variances, and the number of structural breaks, the relationship between M and the simulated causality. Several findings are found as shown in below:

According to Panel A - Case A1, when there is no causality simulated from the variance of Y_{2t} to that of Y_{1t}, CinV shows promising performance on correctly identifying the lack of a causal linkage between the two. At $M = 10$, Pass Rate is found to be 93% when the variances of both series take a relatively large value ($\omega = 0.33$), and it then drops slightly to 92.1% when the two variances are smaller ($\omega = 0.11$). Moreover, no or very small improvement is found for the Pass Rate at $\omega = 0.33$ or $\omega = 0.11$ when increasing M to 30 and 60. These findings suggest that CinV has an impressive performance to determine the independence between two series, and neither the size of the variance ω nor the truncated number M interferes with this degree of accuracy. For Case A2, when the causality is simulated from Y_{2t-1} to Y_{1t}, CinV tends to show less satisfactory performance with regard to correctly identify-

ing the presence of such causality. At $M = 10$, CinV only shows a Pass Rate ranging from 45% to 50%, indicating CinV would detect no causality at least half the time given that the causal linkage between the two series is strong and the variances of the two series are of bigger value. And the false detection becomes worse as soon as the causality goes weak or the variances are getting small. Nevertheless, this situation can be much improved by increasing the truncated number M to 30. And this improvement appears to be more effective for the series having weak causality or smaller variances. However, continuing increasing M would not improve the Pass Rate any better. Thus, it is suggested that the choice of M critically determines whether CinV can make the correct identification of the presence of causality. Moreover, it seems that the performance of CinV can be improved by increasing M, especially for asset series with weak causality relationship while showing a relatively stable market structure. For Case A3, when the simulated causality only starts from the past 30 observations of Y_{2t} to the current value of Y_{1t}, running CinV on any truncated number M that is less than 30 will certainly detect no causality. And the Pass Rate under the category where $M = 10$ actually represents the successful detection of no causality. In this case, CinV shows promising ability under such circumstances with an above 90% Pass Rate which is not affected by either the size of variance or the scale of causality. However, it seems that CinV cannot detect causality pattern when the truncated number is of the same value of the simulated causality latency, namely 30; nevertheless, it has very limited ability to find causality even after increasing M to 60, the Pass Rate of such is barely 2%. This could indicate that CinV is very reluctant to detect the remote causality. Therefore, from the above discussion based on Panel A where no structural break is simulated, it can be concluded that CinV can most likely find the correct causality pattern when the two series have no such relation toward each other. There is still quite decent chance that CinV can detect the causality pattern when one series is very closely causal-related to the other, for instance, 1 observation; and such chance can be improved by increasing the truncated number M especially when dealing with data series of small variances or insignificant causality power, yet this improvement has its limit. Most importantly, it is confirmed that CinV will very likely detect no causality when the truncated number M is equal to or smaller than the simulated causality latency number d; in addition, CinV seems to have difficulty to find remote causality patterns. These findings are rather new in the literature.

Next, the impact of structural breaks on CinV will be examined over Panel B-E. Two types of Pass Rate will be considered, namely, Pass Rate (Y) and Pass Rate (N), representing break(s) taken into account and otherwise, in order to check whether incorporating structural breaks in CinV improves causality test results. It can be

observed from Panel B, when no causality is simulated (Case B1), or is not shown in the observations yet (Case B3, $M = 10$), CinV shows a very high level of performance both with and without incorporating breaks. Yet, it is necessary to take account the structural break as indicated by a smaller Pass Rate (N) than Pass Rate (Y). Moreover, similarly to that in Case A1 and A3, neither the size of variance change nor increasing M in these two cases have an impact on test accuracy no matter the simulated break(s) are taken into consideration or not. Another interesting finding from Case B1 is that CinV actually responds slightly better to series with a smaller difference of variances change ($\Delta = 0.11$) than that of bigger change of variances ($\Delta = 0.22$), regardless of whether the structural break is included or not. In Case B2 and Case B3 ($M = 30$, $M = 60$), when there is causality simulated in the two GARCH(1,1) series at $d = 1$ and $d = 30(M \geq 30)$, rather surprisingly, however, results show that taking structural break(s) into CinV actually compromise the test accuracy. For instance, in Case B2, CinV shows a 57.4% Pass Rate (N) comparing to a 41.2% Pass Rate (Y) at $M = 10$ when considering a strong simulated causality with a relatively large variance change ($\Delta = 0.22$) caused by the simulated break. Increasing M can improve both Pass Rate (Y) and Pass Rate (N), and this improvement appears more significant from $M = 10$ to $M = 30$ than that to $M = 60$, yet still, Pass Rate (N) is higher than Pass Rate (Y) under the same M. The results so far seem to indicate that it is unnecessary to address the presence of structural breaks in the data series when examining volatility causality patterns, which is contradictory to the existing literature. According to Dijk and Sensier (2005), the presence of structural breaks is proved to cause severe size distortions in CinV, and thus it is strongly advised to accommodate these breaks when studying volatility spillover via CinV. However, although here it finds that under the same M, CinV performs well when neglecting structural breaks, by taking a bigger M, Pass Rate (Y) of a bigger M actually exceeds Pass Rate (N) of a smaller M. This is very useful information, as it has been discussed in the previous chapter that neglecting structural breaks would cause biased volatility persistence obtained from GARCH models, therefore, it is absolutely necessary to modify conventional GARCH models with structural breaks considered. Since adding such factor would induce less power to the volatility causality test, however, by increasing M this drawback can be alleviated. Under such circumstances, the causality patterns found in the existing literature could be misleading due to an M of insufficient value, especially with the existence of structural breaks. This inference is rather a novelty in the literature known so far. Furthermore, after investigating the impact from multiple structural breaks, very similar conclusions to Panel B can be drawn for Panel C-E, indicating that the number of structural breaks has little impact on the performance of CinV. This conclusion can help to justify that impact from a relatively

volatile period where multiple structural breaks are expected to occur, such as a global financial crisis, would have a minimal impact on CinV; in other words, the performance of CinV can stay indifferent regardless of a tranquil or fluctuate period.

Last but not least, it is quite obvious that the truncated number M plays a critical role in the causality in variance test of Cheung and Ng (1996) and Hong (2001). A few methods are proposed regarding the choice of M in Hong (2001), such as, try several M or choose M via some "rule-of-thumb". However, in the real world, it would be very unlikely to know when causality starts; in fact, the unknown timing and pattern are the exact reason why we develop volatility causality test. Therefore, it would be nearly impossible to validate the choice of M. Given such circumstances, this study attempts to offer an alternative mechanism to increase the chance of correctly detecting the causality pattern. On the one hand, it is inspired by Hong (2001) that, M is permitted to choose from 1 to the full sample size; most importantly, this alternative mechanism is derived based on the implications revealed from Case 3 over Panel A-E. For Lag 30 simulated volatility spillover, even though it has been argued that CinV tends to find no causality at $M = 10$, Pass Rate actually starts to rise as M increases. Although such rising tendency is at a rather small degree and the value of Pass Rate is very small, it has already been proved in Case A2-E2 that CinV shows acceptable ability to detect the correct causality pattern, therefore, it is reasonable to believe that within the moderate range CinV will show adequate power. Therefore, it could be plausible to determine the presence and the start of volatility causality by running CinV from $M = 1, ..., T$ until causality is found.

In summary, the causality in variance test (CinV) of Cheung and Ng (1996) and Hong (2001) is very capable of finding the absence of causality between two series in terms of volatility. Such performance is hardly affected by other factors, i.e. number of structural breaks, size of variance, or differences of variances before and after the structural break, and the cross-correlations being examined in the test, namely, the truncated lag number M; however, ignoring the presence of structural breaks can compromise test accuracy. Moreover, when two series are Granger-causal related to each other in the volatilities, CinV shows a less adequate performance to detecting the correct causality pattern, and is affected by the scale of causality, the size of variance, or differences of variances before and after the structural break, and M, to some extent. Surprisingly to find that allowing for structural breaks in CinV actually worsens the performance comparing to that of without breaks. However, such drawback can be improved by increasing M to a moderate degree, as this improvement diminishes as M increases. In fact, evidence shows that CinV with breaks at a proper M is more powerful than CinV without breaks; moreover,

another distinct finding is that CinV tends to find no causality when the truncated number M takes the value that is smaller than the causality lag order d, that is to say, if CinV examines M cross-correlations before the causality starts, there is a relatively high chance that no causality will be detected. Based on this finding, this study can complement the literature on the use of the causality in variance test of Cheung and Ng (1996) and Hong (2001) that, when CinV detects no causality, two inferences could be derived: there is no causality between the two series, or the truncated number M is too small. Hence, this study also casts doubts on the existing literature where no causality is identified, see, for instance, Aloui (2007); De Las Nieves Morales (2008). A possible modification this study proposes is to run CinV with M ranging from 1 to T until causality is found at $t, 1 \leq t \leq T$. It is expected to observe the test statistics to increase until the tth observation where test statistics exceeds the critical value, and then it gradually decreases as M increase to T. This anticipation stems from the following features suggested by the simulation results: (1) CinV is powerful to detect the absence of causality; (2) CinV finds no causality when $M \leq d$ but showing signs of responding to the presence of causality when $M > d$; (3) CinV is less powerful with regard to remote causality. Therefore, this chapter will run CinV test on the selected pair of return series with $M = 1, ..., T$. Since this study only targets uni-directional causality, thus the test will be employed both from the stock to exchange rate returns and the other way around. Moreover, CinV will incorporate structural breaks if any, since taking no account of such tends to compromise the test accuracy when two series are independent. By this new way of employing CinV, this study aims to more accurately identify the volatility spillover effects; particularly, it is expected to reveal how far back one series is Granger-causally related to the other in terms of volatility; moreover, this study can also check how the presence of structural breaks would affect the detected causality patterns.

3.6.2 Structural Breaks and Model Estimations

The application of the causality in variance test of Hong (2001) requires appropriate model estimations. Since it has been discussed in the previous chapter, that it is necessary to incorporating structural breaks in the GARCH models to avoid overestimation of volatility persistence, namely, the sum of α and β. Thus the modified ICSS of Sanso et al. (2004) is employed to firstly detect any structural break in the four series in question and results are shown in Table 3.2. For Chinese markets over the sample period of 22/07/2005 to 31/12/2014, both the FX and stock returns are found to have three breaks. Although the observations are obtained from the same

stock index with the only difference being the sample period, the breaks identified here are different from that of the previous chapter. Two breaks are found at 7 December 2006 and 3 September 2009 when the sample period is from 3/01/1994 to 31/12/2014; however, this chapter has identified three new breaks at 22 December 2007, 12 December 2008, and 17 November 2010 when only using the sample period after the new foreign exchange rate regime. This finding tends to suggest the identification of breaks by MICSS of Hong (2001) is subject to the choice of sample period. In fact, this information can further support the conclusion from Monte Carlo simulation in previous chapter that, the choice of structural breaks test should be a decision on the basis of a collective evaluation on a series of factors according to the data under study, such as the size of break, the intensity of data variability, and the sample period. Nevertheless, the underlying reason for such impact calls for future investigation.

After the identification of structural breaks, dummy variables are created corresponding to each break, where taking value 1 from the break onwards and 0 elsewhere to indicate the variance shifts. The best model for each return series is selected from a number of candidate models based on a series of residuals diagnosis [2]. Therefore, a GARCH(1,0) is selected for foreign exchange returns, and ARMA(0,1)+GARCH(1,1) is for stock returns in China. Meanwhile, for the UK, an ARMA(0,1)+GARCH(2,1) tends to be the best fit for both foreign exchange and stock returns. Detailed information on model estimations can be found in Table 3.3.

Table 3.3: Empirical Estimation for Stock and Foreign Exchange Returns in China and the UK

China (from 22/07/2005 to 31/12/2014)				
	Foreign Exchange Market		Stock Market	
Best Model	GARCH(1,0)		ARMA(0,1)+GARCH(1,1)	
Action on Break(s)	Accommodated	Neglected	Accommodated	Neglected
μ	0.0000	0.0000	2.8911e-04	5.3184e-04**
θ_1	–	–	8.9693e-02***	-1.1728e-02
ω	0.0033	0.0056	6.8718e-06	1.9962e-06
α_1	0.1905	0.5095	9.7292e-02***	4.9523e-02***
β_1	–	–	8.4541e-01	9.3689e-01
δ_1	0.0112	–	3.5642e-05	–
δ_2	-0.0026	–	7.8869e-06***	–
δ_3	0.0055	–	-2.8434e-07	–
Volatility Persistence	0.1905	0.5095	0.9427	0.9864
Log Likelihood	2750.747	2421.745	6963.423	6962.151
LR Test Statistics	658.004***		2.544	

[2]Details is available on request.

Standardized Residuals Tests				
Jarque-Bera	4437***	91072***	323***	441***
Ljung-Box $Q(1)$	4.7848**	0.0059	10.353***	1.8444
Ljung-Box $Q(5)$	8.0301	3.6757	17.23***	12.387**
Ljung-Box $Q(10)$	15.402	12.608	44.398***	34.21***
Ljung-Box $Q^2(1)$	2.0165	1.9638	3.4493*	0.0004
Ljung-Box $Q^2(5)$	4.5976	2.2896	11.739**	0.3837
Ljung-Box $Q^2(10)$	8.3778	7.8083	21.806**	9.63
LM ARCH	2.0134	1.9606	3.4445*	0.0004
UK (from 03/01/1994 to 31/12/2014)				
	Foreign Exchange Market		Stock Market	
Best Model	ARMA(0,1)+GARCH(2,1)		ARMA(0,1)+GARCH(2,1)	
Action on Break(s)	Accommodated	Neglected	Accommodated	Neglected
μ	-8.0076e-05	1.4653e-05	5.0376e-05	2.3159d-04**
θ_1	2.8974e-02**	8.0526e-02***	0.1155***	0.0968***
ω	1.3749e-05	3.5545e-06	6.3776e-06	8.2058e-07
α_1	3.2474e-02**	1.0088e-01***	0.1174***	0.1160***
α_2	8.2144e-02**	1.4685e-01***	0.1165***	0.0637***
β_1	1.9037e-01***	5.6027e-01	0.6215	0.8077
δ_1	7.3971e-06***	–	1.5225e-05***	–
δ_2	-2.8344e-06*	–	4.5769e-05***	–
δ_3	1.2991e-05***	–	-4.7257e-06***	–
δ_4	1.7566e-04***	–	3.8002e-05***	–
δ_5	1.3343e-05***	–	1.1375e-05***	–
δ_6	-2.1217e-06*	–	5.7064e-05***	–
δ_7	–	–	6.3276e-06***	–
δ_8	–	–	-5.8317e-06***	–
δ_9	–	–	3.6200e-06	–
Volatility Persistence	0.305	0.808	0.8554	0.9867
Log Likelihood	21269.1	20966.8	17517.23	17631
LR Test Statistics	604.6***		–	
Standardized Residuals Tests				
Jarque-Bera	257	677	332***	257***
Ljung-Box $Q(1)$	0.301	12.678***	51.703***	33.978***
Ljung-Box $Q(5)$	2.7687	14.372**	58.102***	40.919***
Ljung-Box $Q(10)$	4.4842	16.253*	60.364***	42.138***
Ljung-Box $Q^2(1)$	0.0158	4.2454**	1.5839	4.781**
Ljung-Box $Q^2(5)$	26.083***	57.654***	27.425***	23.464***
Ljung-Box $Q^2(10)$	53.876***	87.641***	43.269***	35.378***
LM ARCH	0.0158	4.2426**	0.2084	4.778**

Note: Estimation of UK stock returns uses the results from Chapter 2 as the stock return series here and

there are the same;

Estimation of Chinese stock returns are different from the results in Chapter 2 as the same stock

return series uses a different sample period here;

Table 3.2: Structural Breaks Dates and Significant Events

Markets	Dates
Chinese Exchange Rate Market	4 June 2007
(from 22/07/2005 to 31/12/2014)	31 December 2008
	18 June 2010
Chinese Stock Market	22 December 2007
(from 22/07/2005 to 31/12/2014)	12 December 2008
	17 November 2010
UK Exchange Rate Market	21 February 2003
(from 03/01/1994 to 31/12/2014)	4 August 2006
	6 November 2007
	26 September 2008
	2 April 2009
	23 November 2011
UK Stock Market	21 October 1997
(from 03/01/1994 to 31/12/2014)	11 June 2002
	2 June 2003
	23 July 2007
	3 April 2009
	2 August 2011
	14 December 2011
	9 July 2013
	19 September 2014

Note: Due to the data availability, the sample period selected for Chinese markets starts from 22/07/2005 to 31/12/2014. Moreover, the structural breaks in Chinese stock market are re-examined due to the change of sample period. New break dates are found as shown in this table, which however are slightly different from those found between 2005 to 2014 in Chapter 2, namely, 7 December 2006, and 3 September 2009. Using the same stock series in China, structural break dates are found to be different because of the different sample periods.

*,**,*** *represent level of significance 1%, 5%, 10% respectively;*

Volatility persistence is calculated as the sum of α_i *and* β_i*;*

Jarque -Bera checks whether the standardized residuals are normally distributed, with the null

hypothesis of normality;

Ljung-Box Q (lag order in brackets) examines the autocorrelation between standardized residuals,

with null hypothesis of series being independent;

Ljung-Box Q^2 *(lag order in brackets) examines the autocorrelation between squared standardized*

residuals, with null hypothesis of series being independent;

LM ARCH checks for any further ARCH effect in the conditional variance, with the null hypothesis

of the absence of ARCH;

The null hypothesis of LR Test in this case is the better performance of model with no consideration of structural break.

3.6.3 Volatility Spillover in China and the UK markets

As discussed earlier in the methodology that, applying CinV twice between the target series with both a positive and a negative j, both the presence and direction can be determined. Therefore, after employing CinV on residuals of stock and FX returns obtained from each of the fitted models in each country, the detected volatility spillover patterns with and without accommodating the structural breaks are presented in Table 3.4 and illustrated in Figure 3.5 to 3.8. The indicator "Start of Causality" represents the appropriate selection of the truncated lag number M, one very important component in CinV. The test statistic Q is calculated based on the M cross-correlations that CinV examines. Therefore, the choice of M is one of the determinative factors to the identification of volatility causality pattern. Since the simulation study has provided justifications that CinV would very unlikely respond to the presence of volatility causality if M is smaller than the lag period d from which this causal relationship starts, therefore, it is plausible to run CinV at M taking every value from 1 to the full sample, instead of choosing M based on intuition or some "rule of thumb", in order to find the causality lag period, namely, start of causality. Simulation results also suggest that, after M is great than d, CinV tends to be able to identify the presence of volatility causality. Hereby, the start of causality will be the value that M takes which enables CinV to find causality for the very first time. In this context, if a one-way volatility causality is identified from, say, Y_2 to Y_1, and the start of causality is at m, this means that volatility spillover is found going from the lagged m observations of Y_2 to the current observation of Y_1.

According to Table 3.4, it can be firstly observed that structural breaks affect the causality pattern identified by CinV. A closer look at Chinese markets, volatility spillover is found from stock to FX returns, and the start of such spillover is found to be 67 when the breaks are accounted in the volatility model. This finding indicates the improvement of CinV with breaks, since CinV without breaks identify a causality pattern starting from 720, since it would be doubtful that the stock returns of 720 days ago would have any effect on the foreign exchange returns today. Moreover, a causality pattern is found from FX to stock returns when the breaks are accommodated as oppose to the absence of such pattern when the breaks are

Table 3.4: Volatility Causality Pattern Statistics

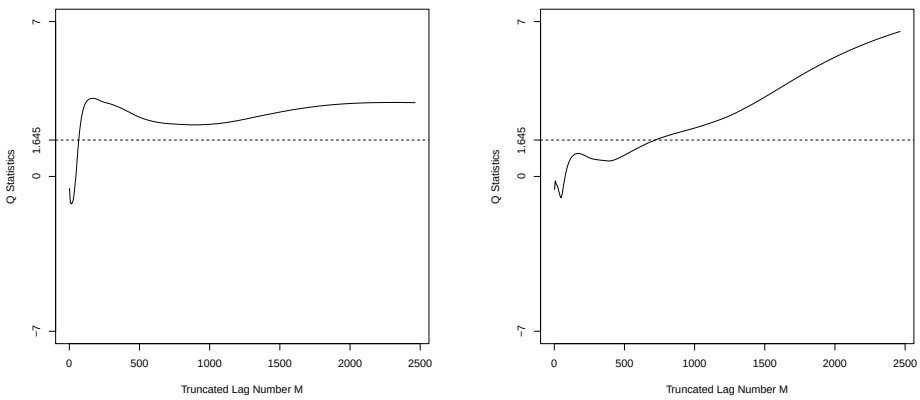
	China				UK			
	Stock → FX		FX → Stock		Stock → FX		FX → Stock	
Action for Breaks	Accounted	Ignored	Accounted	Ignored	Accounted	Ignored	Accounted	Ignored
Causality Presence	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Start of Causality	67	720	1097	–	2	82	3691	3297

Note: In "Action for Breaks", "Accounted" indicates the detected structural breaks have been accommodated in the fitted model, while "Neglected" indicates otherwise;
"Start of Causality" represents the appropriate selection of the truncated lag number M in CinV test.

ignored. However, this finding is of little practical implication since it would be unlikely for a financial series to affect or be affected by the values from another series of 1097 days ago. Therefore, based on both statistical evidence and practical considerations, it can be said that a uni-directional volatility spillover is found from stock to foreign exchange market, and the stock returns of 67 days ago have incremental predictive ability toward the current FX returns.

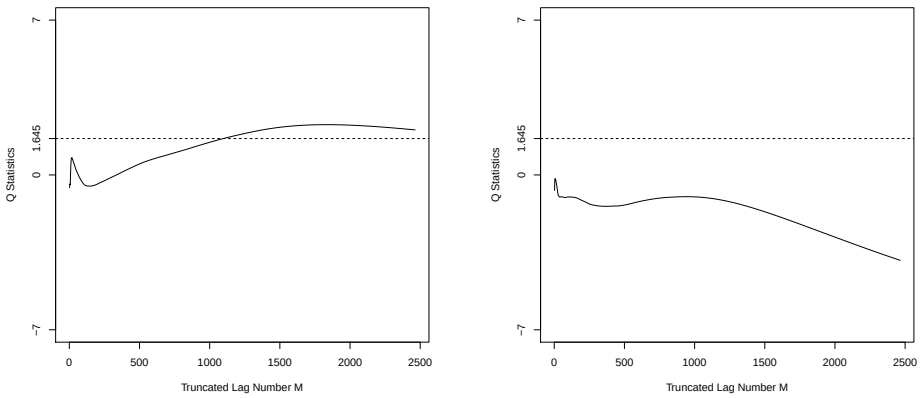
Similarly, for the UK markets, a one-way volatility spillover is found from stock to foreign exchange market. "Start of Causality" is found to be affected by whether or not the detected breaks are accommodated. To be more specific, CinV with breaks identifies the volatility spillover effect going from lagged 2 observations of stock to the current FX returns; while CinV without breaks finds it to be lagged 82. This is consistent with the former inference derived from the Chinese market that CinV without breaks tends to recognize the start of volatility causality to be a rather remote observation in the originated series. Nevertheless, CinV with breaks finds current stock returns is Granger-causally related from the lagged 3691 observations of foreign exchange returns, while without breaks, CinV finds the start of causality to be 3297. Again, it would be rare to have one series Granger-causally affected by another of, say, 3000 days ago; even if there is, the economic value toward volatility forecasting barely exists.

Based on the above discussion, whether including structural breaks appears to significantly affect the causality pattern detected by CinV, especially in determining "Start of Causality". Representing the observation at which causality is identified for the first time when employing CinV via all the cross-correlations between two target series over the full sample, this indicator is of particular importance in this study; it ensures the accurate identification of volatility spillover by avoiding choosing an M that is smaller than the lag of actual causality.



(a) Structural Breaks Accommodated (b) Structural Breaks Not Accommodated

Figure 3.5: From CN Stock to CN Foreign Exchange

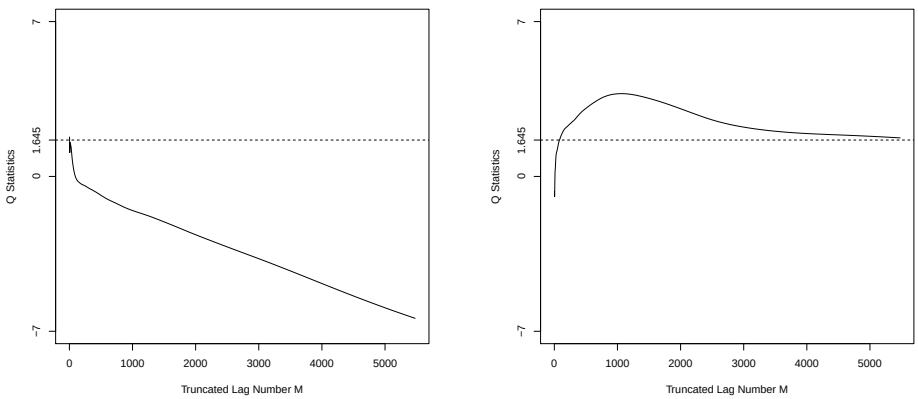


(a) Structural Breaks Accommodated (b) Structural Breaks Not Accommodated

Figure 3.6: From CN Foreign Exchange to CN Stock

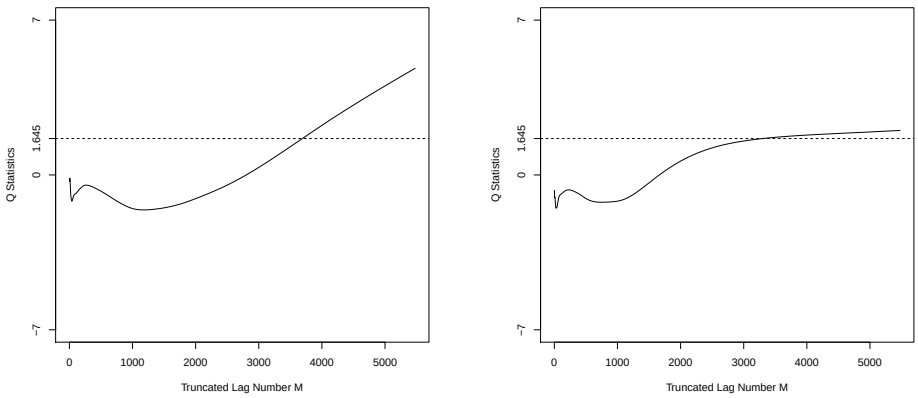
Note: Causality in variance (CinV) test statistics Q is plotted against each M from 1 to T;
When looking into volatility spillover patterns in Chinese markets, due to the availability of foreign
exchange rates, a sub-sample period is selected from 22/07/2005 to 31/12/2014 for both foreign
exchange and stock returns, which yields 2464 observations, namely, T=2464.

In short, this study argues the importance of taking account of any potential structural break when investigating volatility spillover via CinV. It then concludes that there is a uni-directional volatility spillover from stock to foreign exchange market in China, which is originated at lagged 67 of stock returns; moreover, a uni-directional volatility spillover is found from stock to foreign exchange market in the UK, which is originated at lagged 2 of stock returns. Comparing to China, the UK stock market



(a) Structural Breaks Accommodated (b) Structural Breaks Not Accommodated

Figure 3.7: From UK Stock to UK Foreign Exchange



(a) Structural Breaks Accommodated (b) Structural Breaks Not Accommodated

Figure 3.8: From UK Foreign Exchange to UK Stock

Note: Causality in variance (CinV) test statistics Q is plotted against each M from 1 to T; Sample period for investigating volatility spillover pattern in the UK markets is from 03/01/1994 to 31/12/2014, namely, T=5477.

appears to influence its currency market at a more significant level.

3.7 Conclusion

The main focus of this chapter is to examine volatility spillover effects under the influence of structural breaks between stock and foreign exchange markets in both China and the UK. Structural breaks are identified for all the return series via MCSS of Sanso et al. (2004). By employing the causality in variance test of Hong (2001)

with consideration of the detected breaks, it is found that both China and the UK experience a uni-directional volatility spillover from stock to foreign exchange markets. Moreover, this chapter is able to identify the start of volatility spillover by applying the causality in variance test at M varying from 1 to sample size. To be more specific, volatility spillover starts at the lagged 67th observation of stock returns in China, and 2nd observation of stock returns in the UK, indicating the UK currency market is led by its stock market, and such linkage is found to be more significant than that within Chinese markets. Furthermore, an extensive Monte Carlo simulation study is conducted, in order to provide in-depth information to better understand the performance of causality in variance test under a series of carefully designed scenarios. This chapter presents a relative novelty way of applying the causality in variance test of Hong (2001), thus opens up the possibility and reveals the importance of finding the start of volatility spillover effect, apart from only identifying the presence of such. Moreover, this study stresses the necessity of accounting for the structural breaks in the data volatility, as the neglect of which would generate misleading inferences toward the volatility spillover. Therefore, this study can benefit financial participants with a choice of improving volatility forecasting, especially under the circumstances where the available information is insufficient. Since if such causal relation is found and of validity, the information from the "leading" market can be used in modelling the "led" market.

Several improvements can be made to this chapter: first of all, both the simulated causality and CinV is designed to be uni-directional, which leads to a gap with examining simultaneous volatility spillover in two series. Secondly, the simulation study only run on GARCH(1,1) process, which shows little inference if data series is of ARMA(p,q) in the mean. Future work includes designing simulation regarding ARMA(1,1)+GARCH(1,1) data sequence. Most importantly, structural breaks are simulated to occur at the same time in both series, which is highly ideal. It is nearly impossible to have two financial series to have a break at the very same time, unless they have the exact same structure, at least at that time point when break occurs, which is very unlikely. Thus this is quite a flaw of the simulation design by considering only simultaneously occurrence. Extended efforts can be put on simulating different timing of structural breaks so to check any potential effect this may have.

Thesis Conclusion

Volatility modelling has drawn considerable attention to both academics and practitioners in the modern finance literature. A significant number of empirical studies has demonstrated the importance of volatility modelling in finance, for its accuracy being the essence in many financial activities, such as asset pricing, portfolio diversification, and risk management. With the proper estimation of the future volatility of financial assets obtained from the appropriate volatility models, investors and financial managers can devise suitable investment strategies dealing with different situations; also, policy makers can gain sufficient economic implications for regulatory purposes to maintain stability and stimulate the economic growth. In this context, this thesis has explored potential modifications to conventional GARCH models to either improve or enhance volatility modelling. By incorporating structural breaks, volatility persistence is found to be significantly reduced. Moreover, by eliminating the effect of structural breaks, the identified volatility spillover pattern tends to be more plausible. This thesis has conducted comprehensive Monte Carlo simulations to provide sufficient evidence to support these findings. Moreover, when examining potential volatility spillover patterns between stock and foreign exchange markets, this thesis is able to provide reasonable implications by considering both empirical and practical perspectives. This thesis attempts to shed some light on alternative ways to model volatility of financial time series with more accuracy and more reliable implications.

Word count: 35970

Appendices

Appendix: Descriptive and Graphical Statistics

Table A.1: Breakpoints Statistics via ICSS and MICSS in Tranquil Period with Ascending Order of Variance Shift (CASE 1)

Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1×5000				2×5000				3×5000				4×5000			
Simulated Location(s)	301				301 601				301 601 901				301 601 901 1201			
Data Type	i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)	
Size of the Variance Change	$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$	
Type of Algorithm	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS
Points Detected	5581	5526	11610	7675	10469	10457	17427	12469	14626	14568	23347	16706	17455	17416	28293	17382
Fail to Detect	0	0	11	10	0	0	24	84	0	1	28	78	0	1	27	794
Size Distortion Ratio	0.12	0.11	1.32	0.53	0.09	0.09	1.50	0.54	-0.07	-0.09	1.70	0.39	-0.51	-0.52	1.69	0.13
Detection Rate (%) at 299	3.14	3.13	1.15	1.60	1.62	1.63	0.76	1.02	1.34	1.35	0.64	0.80	1.02	1.00	0.43	0.60
Detection Rate (%) at 300	17.78	18.02	5.85	8.73	10.12	10.14	3.62	5.05	7.24	7.27	2.89	3.88	5.88	5.90	2.26	3.04
Detection Rate (%) at 301	11.97	12.11	3.30	5.00	6.38	6.37	2.19	2.94	4.42	4.42	1.64	2.24	3.76	3.76	1.44	2.00
Detection Rate (%) at 302	8.69	8.70	2.23	3.14	4.50	4.49	1.50	2.05	3.43	3.42	1.02	1.50	2.61	2.62	0.86	1.21
Detection Rate (%) at 303	6.04	6.08	1.72	2.61	3.32	3.31	1.12	1.58	2.41	2.44	0.88	1.21	1.91	1.94	0.80	1.08
Detection Rate (%) at 599					6.41	6.43	2.02	2.77	3.84	3.78	1.56	1.92	3.41	3.45	1.35	1.78
Detection Rate (%) at 600					9.70	9.72	3.80	5.24	5.72	5.67	2.65	3.27	4.95	4.95	2.22	2.65
Detection Rate (%) at 601					1.64	1.62	0.74	0.97	0.88	0.91	0.48	0.55	1.10	1.13	0.45	0.52
Detection Rate (%) at 602					0.83	0.84	0.46	0.58	0.42	0.43	0.36	0.35	0.40	0.42	0.27	0.30
Detection Rate (%) at 603					0.53	0.52	0.33	0.38	0.23	0.23	0.23	0.23	0.23	0.21	0.21	0.22
Detection Rate (%) at 899									0.98	0. 97	0.60	0.74	0.80	0.82	0.41	0.48
Detection Rate (%) at 900									6.36	6.36	2.64	3.45	4.52	4.53	2.03	2.48
Detection Rate (%) at 901									4.26	4.23	1.73	2.17	2.78	2.81	1.36	1.64
Detection Rate (%) at 902									2.94	2.93	1.06	1.45	1.87	1.88	0.80	1.04
Detection Rate (%) at 903									2.20	2.21	0.81	1.01	1.50	1.50	0.67	0.88
Detection Rate (%) at 1199													2.88	2.88	1.36	1.64
Detection Rate (%) at 1200													4.46	4.46	2.01	2.61
Detection Rate (%) at 1201													0.80	0.80	0.38	0.49
Detection Rate (%) at 1202													0.27	0.27	0.33	0.38
Detection Rate (%) at 1203													0.20	0.21	0.19	0.22

Table A.2: Breakpoints Statistics via ICSS and MICSS in Tranquil Period with Descending Order of Variance Shift (CASE 1)

Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1×5000				2×5000				3×5000				4×5000			
Simulated Location(s)	301				301 601				301 601 901				301 601 901 1201			
Data Type	i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)	
Size of the Variance Change	$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$	
Type of Algorithm	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS
Points Detected	5538	5485	11569	7696	10579	10565	18225	12580	15141	15131	23455	16827	18497	18144	29054	16268
Fail to Detect	0	0	8	4	0	0	16	252	1	1	24	99	1	85	23	1131
Size Distortion Ratio	0.11	0.10	1.32	0.54	0.12	0.11	1.66	0.64	0.03	0.03	1.71	0.43	-0.39	-0.31	1.83	0.20
Detection Rate (%) at 299	11.41	11.60	3.29	4.87	6.11	6.11	2.12	2.77	4.31	4.34	1.67	2.23	3.35	3.35	1.27	1.71
Detection Rate (%) at 300	18.04	18.32	5.58	8.16	9.30	9.31	3.85	5.16	6.75	6.47	2.76	3.54	5.55	5.52	2.08	2.62
Detection Rate (%) at 301	3.16	3.15	1.29	1.87	1.88	1.86	0.75	0.91	1.21	1.21	0.67	0.75	0.91	0.91	0.45	0.52
Detection Rate (%) at 302	1.66	1.66	0.61	0.92	0.82	0.83	0.49	0.67	0.47	0.48	0.42	0.48	0.33	0.33	0.28	0.31
Detection Rate (%) at 303	0.79	0.80	0.54	0.71	0.38	0.39	0.32	0.45	0.40	0.38	0.26	0.27	0.24	0.24	0.23	0.26
Detection Rate (%) at 599					1.72	1.70	0.75	0.97	1.43	1.42	0.60	0.78	0.79	0.79	0.39	0.48
Detection Rate (%) at 600					9.85	9.84	3.60	4.88	6.77	6.75	2.76	3.56	4.80	4.77	2.01	2.50
Detection Rate (%) at 601					6.30	6.35	2.18	2.84	4.09	4.12	1.68	2.25	3.01	2.99	1.20	1.28
Detection Rate (%) at 602					4.51	4.50	1.47	1.96	3.30	3.30	1.19	1.50	2.04	2.03	0.95	1.09
Detection Rate (%) at 603					3.35	3.36	1.04	1.46	2.27	2.24	0.87	1.14	1.64	1.63	0.60	0.78
Detection Rate (%) at 899									4.03	4.04	1.50	2.01	2.89	2.85	1.24	1.51
Detection Rate (%) at 900									5.96	5.97	2.60	3.40	4.41	4.41	2.00	2.37
Detection Rate (%) at 901									1.06	1.05	0.52	0.66	0.81	0.80	0.35	0.41
Detection Rate (%) at 902									0.45	0.45	0.37	0.49	0.39	0.39	0.27	0.33
Detection Rate (%) at 903									0.30	0.30	0.24	0.26	0.26	0.26	0.24	0.31
Detection Rate (%) at 1199													0.90	0.88	0.45	0.56
Detection Rate (%) at 1200													4.97	4.99	2.37	3.02
Detection Rate (%) at 1201													3.36	3.40	1.24	1.63
Detection Rate (%) at 1202													2.23	2.20	0.92	1.16
Detection Rate (%) at 1203													1.75	1.76	0.65	0.80

Table A.3: Breakpoints Statistics via ICSS and MICSS in Fluctuate Period with Ascending Order of Variance Shift (CASE 2)

Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1×5000				2×5000				3×5000				4×5000			
Simulated Location(s)	101				101 201				101 201 301				101 201 301 401			
Data Type	i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)	
Size of the Variance Change	$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$	
Type of Algorithm	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS
Points Detected	5450	5374	7157	5917	10398	6929	11620	4266	14426	10297	15348	5848	17552	1831	18244	2876
Fail to Detect	0	0	165	392	0	1640	204	2960	1	333	157	1968	2	4384	279	3867
Size Distortion Ratio	0.09	0.07	0.52	0.18	0.08	0.06	0.42	0.09	-0.11	-0.79	0.17	-1.07	-0.49	-1.03	-0.14	-1.46
Detection Rate (%) at 99	3.36	3.35	2.04	2.32	1.66	1.57	1.08	1.29	1.32	1.23	0.94	1.18	0.94	0.82	0.59	0.59
Detection Rate (%) at 100	19.27	19.48	9.83	11.56	9.96	10.67	5.64	6.24	7.33	7.60	4.36	3.68	5.55	5.30	3.34	3.37
Detection Rate (%) at 101	12.62	12.73	5.70	6.57	6.68	7.04	3.49	4.13	4.80	4.93	2.79	3.06	3.79	3.88	1.93	2.16
Detection Rate (%) at 102	8.20	8,28	3.74	4.51	4.65	4.95	2.59	2.74	3.48	3.51	1.86	1.85	2.55	3.00	1.34	1.56
Detection Rate (%) at 103	7.08	7.24	2.95	3.45	3.45	3.61	1.94	2.13	2.66	2.72	1.22	1.21	2.07	2.13	1.05	1.50
Detection Rate (%) at 199					6.66	6.84	3.21	3.61	3.55	2.83	2.14	1.61	3.19	2.89	2.00	2.09
Detection Rate (%) at 200					10.19	10.71	5.73	6.99	5.81	5.15	3.63	2.80	5.44	5.84	3.17	3.30
Detection Rate (%) at 201					1.84	1.93	1.26	1.36	0.89	0.69	0.67	0.63	0.89	1.37	0.58	0.97
Detection Rate (%) at 202					0.76	0.76	0.60	0.49	0.51	0.36	0.44	0.29	0.38	0.33	0.46	0.42
Detection Rate (%) at 203					0.44	0.61	0.48	0.59	0.28	0.25	0.35	0.24	0.22	0.16	0.29	0.38
Detection Rate (%) at 299									1.07	1.19	0.91	1.20	0.82	0.87	0.61	0.70
Detection Rate (%) at 300									6.91	8.06	4.37	6.38	4.88	5.52	3.23	3.06
Detection Rate (%) at 301									4.28	5.03	2.37	3.81	3.09	3.44	1.79	2.05
Detection Rate (%) at 302									2.99	3.44	1.73	2.56	2.14	1.80	1.24	1.63
Detection Rate (%) at 303									2.60	2.88	1.24	1.97	1.60	1.42	1.01	1.15
Detection Rate (%) at 399													2.93	2.40	1.76	2.29
Detection Rate (%) at 400													4.46	5.90	3.23	3.27
Detection Rate (%) at 401													0.80	0.93	0.63	0.49
Detection Rate (%) at 402													0.34	0.33	0.34	0.38
Detection Rate (%) at 403													0.19	0.16	0.28	0.17

Table A.4: Breakpoints Statistics via ICSS and MICSS in Fluctuate Period with Descending Order of Variance Shift (CASE 2)

Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1×5000				2×5000				3×5000				4×5000			
Simulated Location(s)	101				101 201				101 201 301				101 201 301 401			
Data Type	i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)		i.i.d		GARCH(1,1)	
Size of the Variance Change	$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$		$\Delta = 3$		$\Delta = 0.22$	
Type of Algorithm	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS	ICSS	MICSS
Points Detected	5453	5372	7272	5853	10389	6921	11814	6300	14481	10267	15668	6163	17592	1803	17811	5538
Fail to Detect	0	0	187	430	2	1643	409	2112	3	352	201	1933	10	4402	494	2581
Size Distortion Ratio	0.09	0.07	0.51	0.28	0.08	0.06	0.57	0.18	-0.10	-0.79	0.26	-0.99	-0.47	-0.98	-0.05	-1.71
Detection Rate (%) at 199	3.15	3.13	5.94	6.90	1.69	1.70	3.08	3.40	1.18	1.20	2.43	3.67	0.87	0.78	1.90	2.62
Detection Rate (%) at 100	19.66	19.97	9.27	10.78	10.71	11.72	5.46	5.56	7.52	7.57	4.15	5.91	5.79	5.66	3.63	5.13
Detection Rate (%) at 101	11.64	11.75	1.79	2.10	6.46	6.60	1.04	1.08	4.53	4.80	0.84	1.28	3.91	3.72	0.74	0.90
Detection Rate (%) at 102	8.38	8.49	1.22	1.33	4.35	4.71	0.71	0.68	2.97	3.10	0.59	0.84	2.47	2.33	0.40	0.51
Detection Rate (%) at 103	6.88	6.96	0.77	0.80	3.50	3.66	0.43	0.54	2.64	2.72	0.29	0.37	2.21	2.22	0.31	0.42
Detection Rate (%) at 199					6.29	6.57	0.99	0.95	3.83	3.56	0.64	0.60	3.64	4.44	0.353	0.43
Detection Rate (%) at 200					9.78	10.82	5.37	5.57	5.81	4.79	3.96	2.95	5.39	4.77	2.82	2.08
Detection Rate (%) at 201					1.63	1.65	3.43	3.49	0.98	0.88	2.32	1.95	0.93	1.00	1.74	1.21
Detection Rate (%) at 202					0.66	0.74	2.38	2.75	0.46	0.40	1.67	1.36	0.47	0.50	1.07	0.83
Detection Rate (%) at 203					0.62	0.66	1.68	1.75	0.23	0.22	1.27	0.99	0.31	0.11	0.97	0.67
Detection Rate (%) at 299									1.10	1.31	2.19	2.40	0.84	1.05	1.65	1.30
Detection Rate (%) at 300									6.62	7.69	4.06	3.60	4.67	5.32	2.63	1.82
Detection Rate (%) at 301									4.07	4.64	0.70	0.63	2.94	3.22	0.57	0.29
Detection Rate (%) at 302									3.20	3.62	0.36	0.44	2.09	1.72	0.27	0.22
Detection Rate (%) at 303									2.60	3.05	0.33	0.19	1.41	1.39	0.24	0.09
Detection Rate (%) at 399													2.75	2.50	0.67	0.96
Detection Rate (%) at 400													4.63	5.77	3.01	4.01
Detection Rate (%) at 401													0.68	0.55	1.85	2.55
Detection Rate (%) at 402													0.32	0.55	1.48	2.18
Detection Rate (%) at 403													0.19	0.22	0.95	1.48

Table A.5: Breakpoints Statistics via MICSS in Tranquil Period (CASE 3)

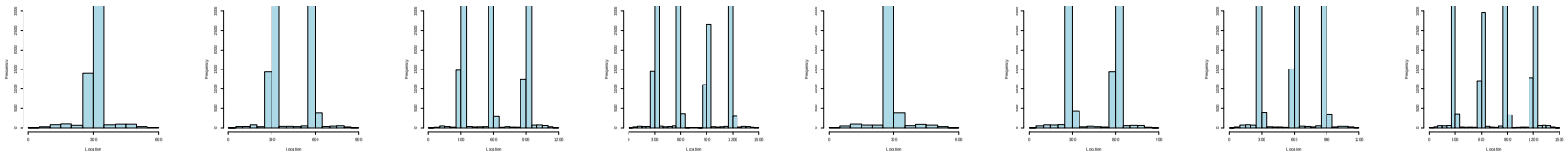
Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1×5000				2×5000				3×5000				4×5000			
Simulated Location(s)	301				301 601				301 601 901				301 601 901 1201			
Order of Variance Shift	Ascending		Descending		Ascending		Descending		Ascending		Descending		Ascending		Descending	
Size of the Variance Change	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$
Points Detected	5170	2764	5091	2752	4678	2345	5509	2883	5494	2604	5284	2808	3842	2134	4732	2606
Fail to Detect	1534	3118	1534	3163	2738	3588	2417	3327	2311	3423	2398	3349	3332	3745	2908	3449
Size Distortion Ratio	0.49	0.47	0.47	0.50	0.07	-0.34	0.13	-0.28	-0.96	-1.35	-0.97	-1.30	-1.70	-2.30	-1.74	-2.32
Detection Rate (%) at 299	0.68	0.29	1.32	0.69	0.51	0.26	0.98	0.55	0.35	0.08	0.70	0.32	0.39	0.09	0.61	0.23
Detection Rate (%) at 300	2.24	0.87	2.14	1.09	1.35	0.68	1.16	0.59	0.93	0.35	1.23	0.32	0.70	0.19	0.76	0.15
Detection Rate (%) at 301	1.61	0.83	0.69	0.65	0.77	0.51	0.45	0.24	0.60	0.12	0.49	0.21	0.34	0.05	0.49	0.19
Detection Rate (%) at 302	1.32	0.54	0.55	0.36	0.90	0.43	0.42	0.24	0.69	0.15	0.42	0.18	0.65	0.14	0.25	0.12
Detection Rate (%) at 303	1.08	0.58	0.39	0.36	0.41	0.43	0.25	0.17	0.51	0.12	0.15	0.11	0.47	0.09	0.21	0.08
Detection Rate (%) at 599					0.68	0.30	0.40	0.21	0.56	0.12	0.21	0.21	0.55	0.14	0.23	0.08
Detection Rate (%) at 600					1.77	0.72	1.60	0.55	0.75	0.42	0.91	0.36	0.73	0.37	0.38	0.27
Detection Rate (%) at 601					0.49	0.13	0.69	0.14	0.25	0.27	0.57	0.14	0.21	0.23	0.30	0.23
Detection Rate (%) at 602					0.51	0.30	0.51	0.42	0.31	0.00	0.40	0.28	0.29	0.23	0.32	0.12
Detection Rate (%) at 603					0.49	0.21	0.53	0.31	0.15	0.04	0.36	0.07	0.31	0.05	0.34	0.08
Detection Rate (%) at 899									0.51	0.27	0.62	0.21	0.26	0.09	0.36	0.15
Detection Rate (%) at 900									0.93	0.88	0.87	0.50	0.83	0.28	0.63	0.12
Detection Rate (%) at 901									0.76	0.46	0.30	0.18	0.52	0.14	0.06	0.00
Detection Rate (%) at 902									0.55	0.19	0.19	0.11	0.39	0.14	0.11	0.04
Detection Rate (%) at 903									0.44	0.27	0.13	0.07	0.36	0.28	0.17	0.08
Detection Rate (%) at 1199													0.55	0.05	0.36	0.27
Detection Rate (%) at 1200													0.73	0.28	0.97	0.15
Detection Rate (%) at 1201													0.13	0.14	0.61	0.38
Detection Rate (%) at 1202													0.29	0.05	0.36	0.27
Detection Rate (%) at 1203													0.08	0.00	0.53	0.08

Table A.6: Breakpoints Statistics via MICSS in Fluctuate Period (CASE 3)

Simulated Break(s) No.	1				2				3				4			
Desirable Breakpoints No.	1 × 5000				2 × 5000				3 × 5000				4 × 5000			
Simulated Location(s)	101				101 201				101 201 301				101 201 301 401			
Order of Variance Shift	Ascending		Descending		Ascending		Descending		Ascending		Descending		Ascending		Descending	
Size of the Variance Change	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$	$\Delta = 0.11$	$\Delta = 0.05$
Points Detected	2808	1766	2773	1787	1758	1463	2702	1880	2337	1842	2324	1802	1976	1735	2680	2149
Fail to Detect	2762	3590	2793	3582	3868	3931	3274	3630	3389	3708	3373	3695	3823	3814	3273	3536
Size Distortion Ratio	0.25	0.25	0.26	0.26	-0.45	-0.63	-0.43	-0.63	-1.55	-1.57	-1.57	-1.62	-2.32	-2.54	-2.45	-2.53
Detection Rate (%) at 199	1.99	1.02	2.88	1.90	0.80	0.34	1.70	0.74	0.43	0.05	2.28	0.78	0.30	0.35	0.82	0.56
Detection Rate (%) at 100	3.95	3.23	3.86	2.80	2.50	0.82	2.37	1.01	0.47	0.76	2.28	0.89	1.27	0.52	1.49	0.93
Detection Rate (%) at 101	2.35	1.98	1.37	1.73	1.37	0.82	0.85	0.80	0.64	0.33	0.95	0.61	0.66	0.52	0.67	0.60
Detection Rate (%) at 102	1.50	1.64	1.01	0.95	0.85	0.96	0.85	0.59	0.73	0.27	0.65	0.61	0.51	0.17	0.49	0.09
Detection Rate (%) at 103	1.82	1.13	0.83	0.67	1.25	0.48	0.56	0.37	0.34	0.60	0.52	0.28	0.46	0.17	0.15	0.09
Detection Rate (%) at 199					1.59	0.82	0.81	0,64	0.68	0.71	0.34	0.22	0.86	0.63	0.37	0.19
Detection Rate (%) at 200					2.16	1.30	1.85	1.01	0.60	0.71	1.33	0.72	0.61	0.69	0.90	0.42
Detection Rate (%) at 201					0.91	0.75	1.74	1.01	0.30	0.38	0.56	0.50	0.40	0.46	0.82	0.37
Detection Rate (%) at 202					0.74	0.27	0.93	0.64	0.30	0.27	0.43	0.22	0.46	0.63	0.26	0.23
Detection Rate (%) at 203					0.74	0.48	0.59	0.48	0.13	0.49	0.43	0.55	0.40	0.58	0.30	0.09
Detection Rate (%) at 299									1.16	0.33	0.82	0.39	0.61	0.46	0.30	0.23
Detection Rate (%) at 300									2.23	1.03	0.52	0.50	1.01	0.75	0.56	0.56
Detection Rate (%) at 301									1.75	0.87	0.52	0.11	0.86	0.52	0.41	0.47
Detection Rate (%) at 302									1.16	0.76	0.26	0.22	0.61	0.40	0.22	0.19
Detection Rate (%) at 303									0.86	0.71	0.47	0.06	0.56	0.29	0.22	0.33
Detection Rate (%) at 399													0.46	0.35	0.49	0.19
Detection Rate (%) at 400													0.96	0.58	1.57	0.88
Detection Rate (%) at 401													0.25	0.29	0.97	0.70
Detection Rate (%) at 402													0.20	0.35	0.75	0.56
Detection Rate (%) at 403													0.20	0.23	0.63	0.37

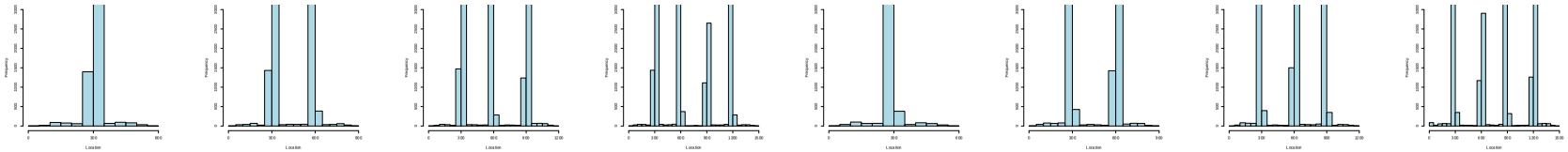
Table A.7: Pass Rate of Causality in Variance Test at 5% Significance Level from Simulation

Panel A: No Structural Break Simulated																														
Case	Case A1						Case A2												Case A3											
Simulated Causality	No Causality						Lag 1 Causality												Lag 30 Causality											
Scale of Causality	–						Strong						Weak						Strong						Weak					
Size of Variance	$\omega = 0.33$			$\omega = 0.11$			$\omega = 0.33$			$\omega = 0.11$			$\omega = 0.33$			$\omega = 0.11$			$\omega = 0.33$			$\omega = 0.11$			$\omega = 0.33$			$\omega = 0.11$		
Truncated Number m	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60
Pass Rate	0.930	0.926	0.926	0.921	0.928	0.932	0.5000	0.669	0.657	0.493	0.700	0.676	0.457	0.617	0.583	0.481	0.619	0.605	0.934	0.064	0.138	0.935	0.070	0.144	0.932	0.070	0.153	0.923	0.069	0.134
Panel B: One Structural Break Simulated																														
Case	Case B1						Case B2												Case B3											
Simulated Causality	No Causality						Lag 1 Causality												Lag 30 Causality											
Scale of Causality	–						Strong						Weak						Strong						Weak					
Difference of Variances	$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$		
Truncated Number m	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60
Pass Rate (Y)	0.930	0.925	0.929	0.933	0.935	0.934	0.406	0.575	0.547	0.407	0.552	0.539	0.439	0.583	0.547	0.429	0.553	0.523	0.941	0.069	0.113	0.939	0.073	0.119	0.937	0.062	0.124	0.930	0.698	0.118
Pass Rate (N)	0.894	0.864	0.861	0.913	0.908	0.900	0.563	0.770	0.768	0.537	0.737	0.727	0.559	0.731	0.722	0.510	0.681	0.671	0.921	0.083	0.178	0.921	0.085	0.165	0.918	0.090	0.177	0.920	0.081	0.157
Panel C: Two Structural Breaks Simulated																														
Case	Case C1						Case C2												Case C3											
Simulated Causality	No Causality						Lag 1 Causality												Lag 30 Causality											
Scale of Causality	–						Strong						Weak						Strong						Weak					
Difference of Variances	$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$		
Truncated Number m	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60
Pass Rate (Y)	0.933	0.928	0.931	0.929	0.931	0.935	0.412	0.564	0.530	0.406	0.556	0.536	0.388	0.542	0.515	0.423	0.578	0.536	0.928	0.068	0.118	0.931	0.067	0.123	0.928	0.067	0.128	0.931	0.063	0.122
Pass Rate (N)	0.877	0.864	0.852	0.915	0.911	0.906	0.574	0.768	0.766	0.527	0.719	0.709	0.529	0.732	0.726	0.492	0.677	0.668	0.912	0.085	0.174	0.921	0.079	0.168	0.910	0.087	0.167	0.924	0.077	0.157
Panel D: Three Structural Breaks Simulated																														
Case	Case D1						Case D2												Case D3											
Simulated Causality	No Causality						Lag 1 Causality												Lag 30 Causality											
Scale of Causality	–						Strong						Weak						Strong						Weak					
Difference of Variances	$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$		
Truncated Number m	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60
Pass Rate (Y)	0.923	0.927	0.935	0.926	0.926	0.924	0.428	0.572	0.546	0.412	0.569	0.541	0.439	0.565	0.522	0.433	0.569	0.553	0.939	0.057	0.117	0.936	0.066	0.120	0.935	0.071	0.122	0.935	0.065	0.118
Pass Rate (N)	0.857	0.827	0.818	0.906	0.900	0.893	0.602	0.808	0.822	0.529	0.731	0.26	0.582	0.777	0.776	0.513	0.693	0.690	0.912	0.084	0.207	0.928	0.079	0.166	0.909	0.103	0.212	0.917	0.084	0.154
Panel E: Four Structural Breaks Simulated																														
Case	Case E1						Case E2												Case E3											
Simulated Causality	No Causality						Lag 1 Causality												Lag 30 Causality											
Scale of Causality	–						Strong						Weak						Strong						Weak					
Difference of Variances	$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$			$\Delta\omega = 0.22$			$\Delta\omega = 0.11$		
Truncated Number m	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60	10	30	60
Pass Rate (Y)	0.936	0.928	0.932	0.925	0.929	0.928	0.425	0.551	0.536	0.405	0.544	0.536	0.427	0.538	0.511	0.436	0.540	0.547	0.933	0.073	0.108	0.928	0.071	0.122	0.931	0.069	0.114	0.926	0.070	0.119
Pass Rate (N)	0.861	0.822	0.809	0.915	0.908	0.902	0.588	0.802	0.814	0.522	0.718	0.710	0.585	0.767	0.779	0.519	0.663	0.673	0.918	0.094	0.191	0.924	0.086	0.168	0.908	0.103	0.183	0.918	0.077	0.194



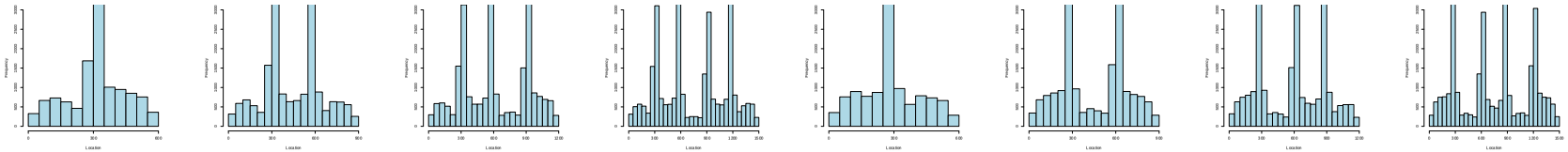
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.1.1: ICSS on i.i.d with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Tranquil)



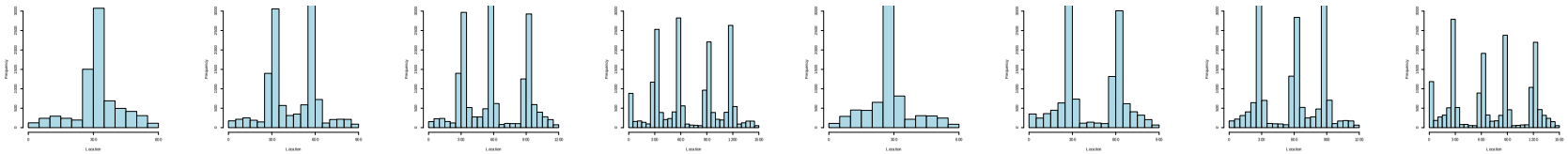
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.1.2: MICSS on i.i.d with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Tranquil)



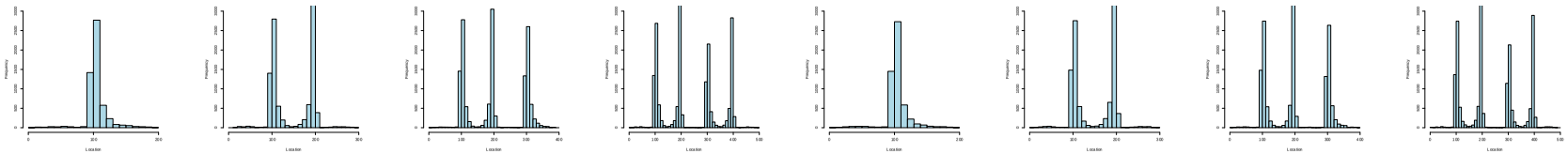
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.1.3: ICSS on GARCH(1,1) with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Tranquil)



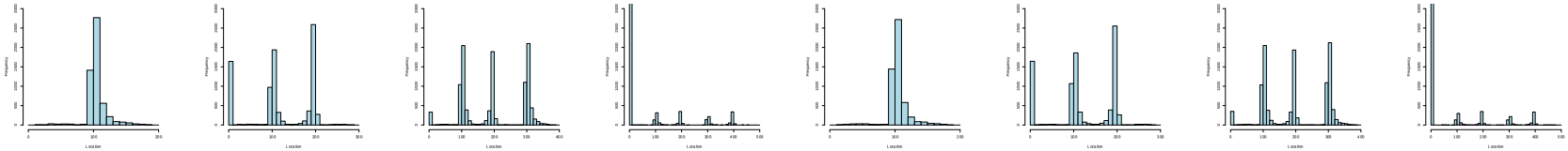
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.1.4: MICSS on GARCH(1,1) with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Tranquil)



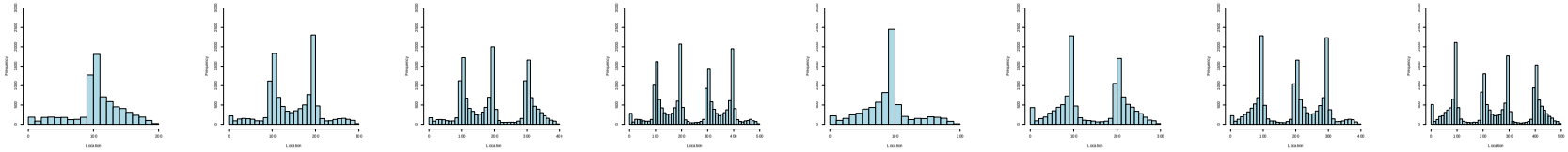
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.2.1: ICSS on i.i.d with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Fluctuate)



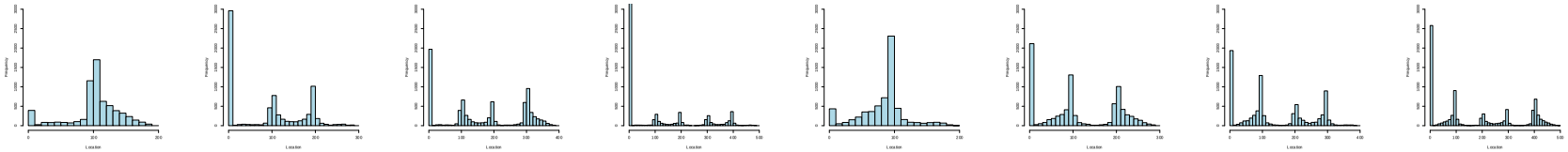
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.2.2: MICSS on i.i.d with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Fluctuate)



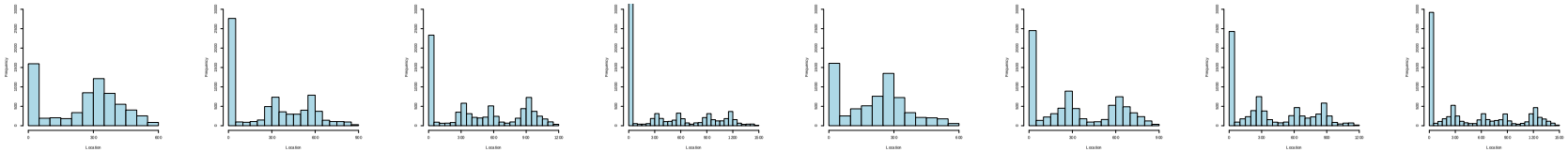
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.2.3: ICSS on GARCH(1,1) with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Fluctuate)



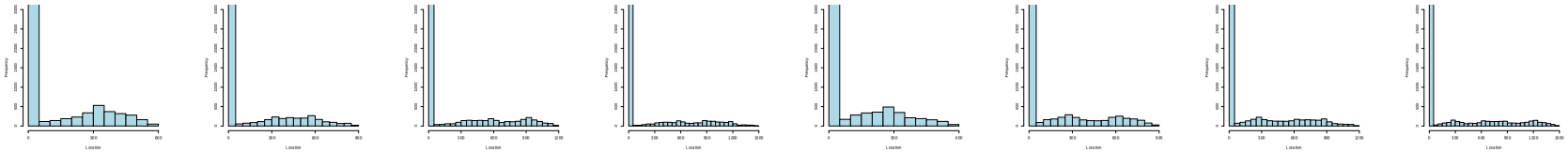
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.2.4: MICSS on GARCH(1,1) with (a)-(d) of Ascending Order and (e)-(h) of Descending Order (Fluctuate)



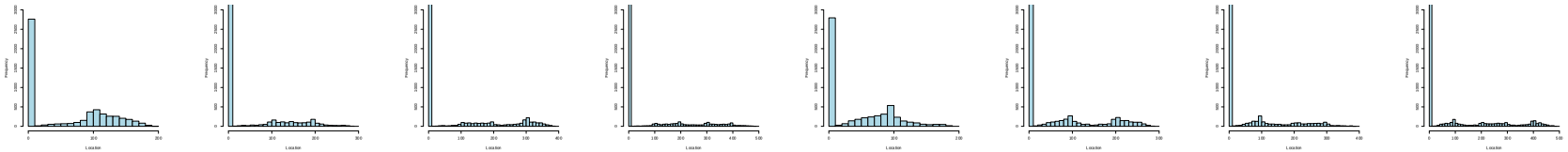
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.3.1: $\Delta = 0.11$ in Tranquil Period where (a)-(d) of Ascending Order and (e)-(h) of Descending Order



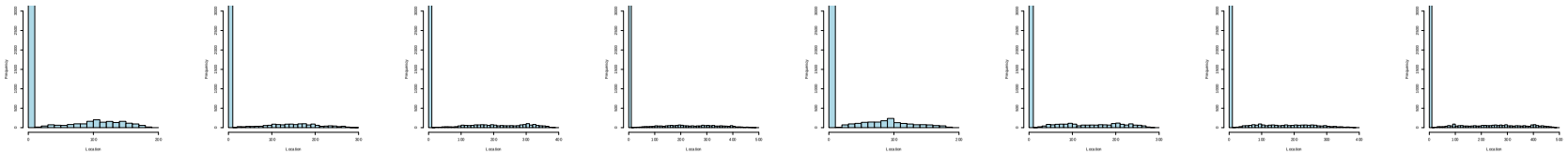
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.3.2: $\Delta = 0.05$ in Tranquil Period where (a)-(d) of Ascending Order and (e)-(h) of Descending Order



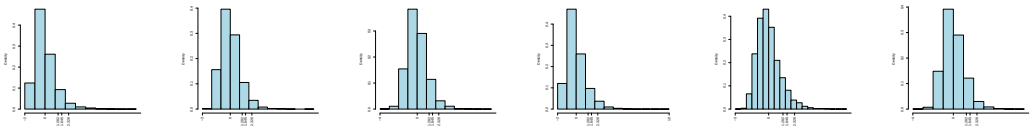
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.3.3: $\Delta = 0.11$ in Fluctuate Period where (a)-(d) of Ascending Order and (e)-(h) of Descending Order



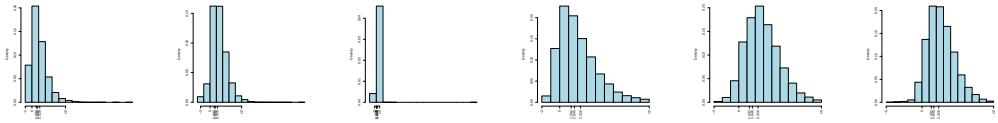
(a) One Break (b) Two Breaks (c) Three Breaks (d) Four Breaks (e) One Break (f) Two Breaks (g) Three Breaks (h) Four Breaks

Figure B.3.4: $\Delta = 0.05$ in Fluctuate Period where (a)-(d) of Ascending Order and (e)-(h) of Descending Order



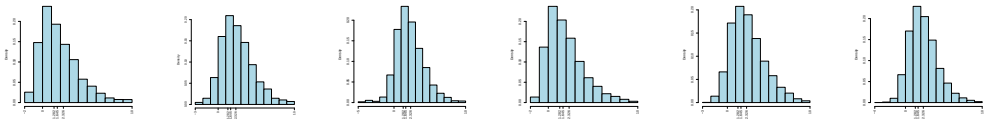
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.4.1: Case A1 - Absence of Simulated Causality with No Simulated Structural Break



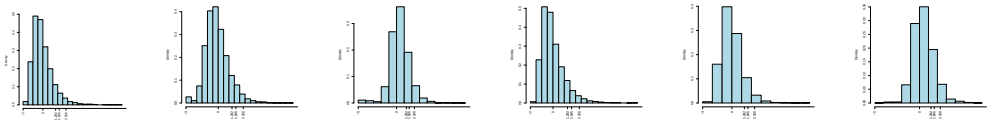
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.4.2: Case A2 - Lag 1 Simulated Strong Causality with No Simulated Structural Break



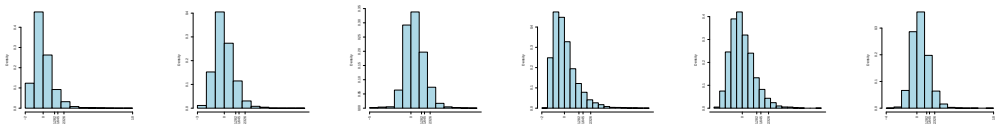
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.4.2: Case A2 - Lag 1 Simulated Weak Causality with No Simulated Structural Break



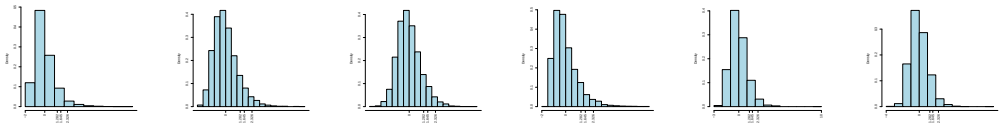
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.4.4: Case A3 - Lag 30 Simulated Strong Causality with No Simulated Structural Break



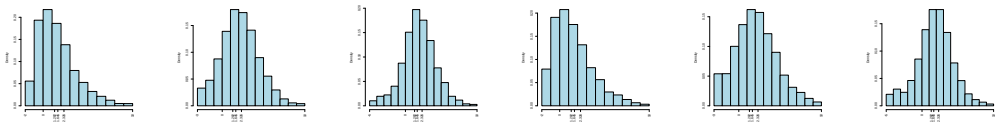
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.4.5: Case A3 - Lag 30 Simulated Weak Causality with No Simulated Structural Break



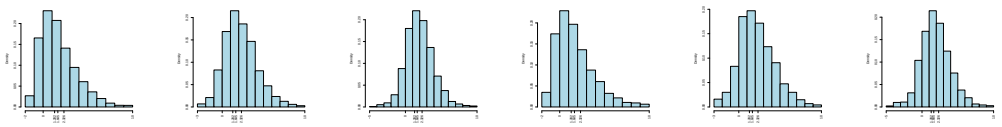
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.5.1: Case B1 - Absence of Simulated Causality with One Simulated Structural Break Accommodated



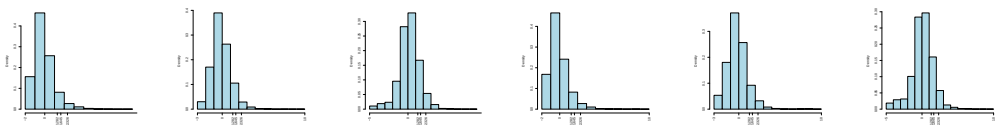
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.2: Case B2 - Lag 1 Simulated Strong Causality with One Simulated Structural Break Accommodated



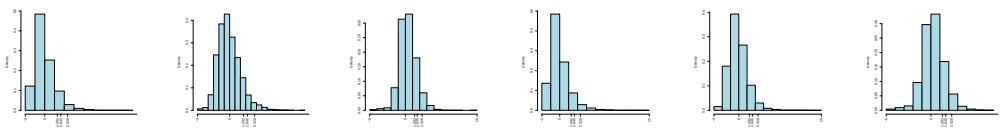
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.3: Case B2 - Lag 1 Simulated Weak Causality with One Simulated Structural Break Accommodated



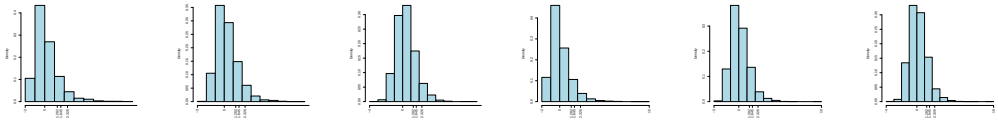
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.4: Case B3 - Lag 30 Simulated Strong Causality with One Simulated Structural Break Accommodated



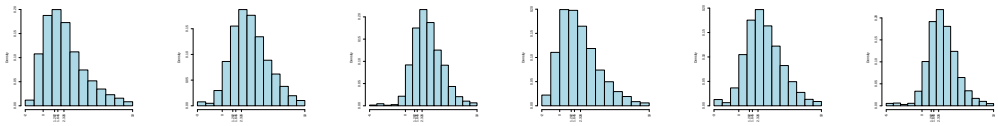
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.5: Case B3 - Lag 30 Simulated Weak Causality with One Simulated Structural Break Accommodated



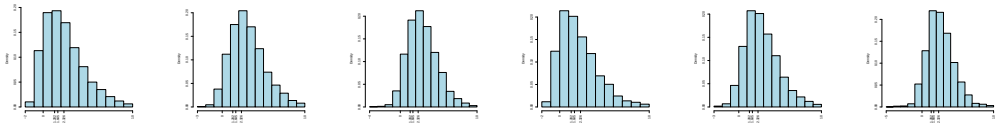
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.5.6: Case B1 - Absence of Simulated Causality with One Simulated Structural Break Neglected



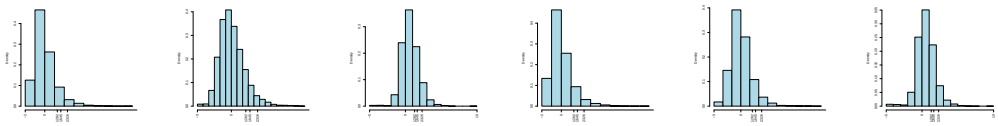
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.7: Case B2 - Lag 1 Simulated Strong Causality with One Simulated Structural Break Neglected



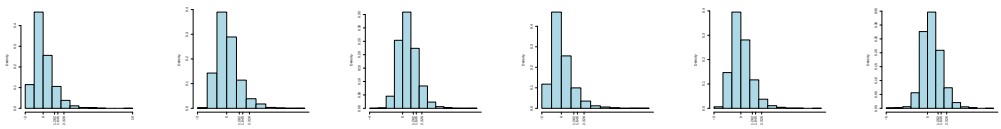
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.8: Case B2 - Lag 1 Simulated Weak Causality with One Simulated Structural Break Neglected



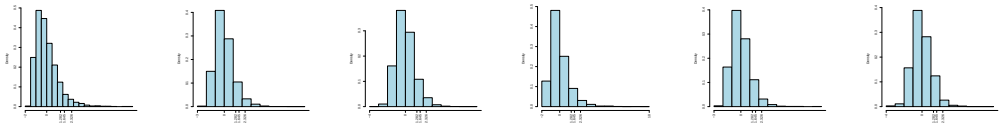
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.9: Case B3 - Lag 30 Simulated Strong Causality with One Simulated Structural Break Neglected



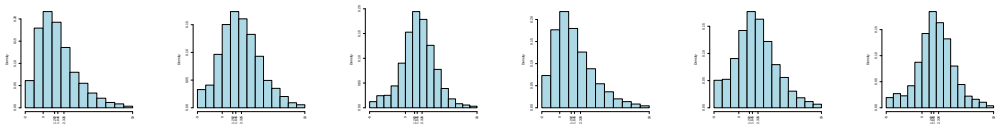
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.5.10: Case B3 - Lag 30 Simulated Weak Causality with One Simulated Structural Break Neglected



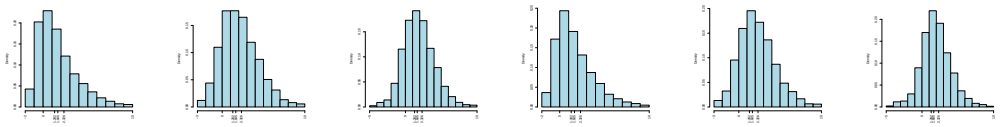
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.6.1: Case C1 - Absence of Simulated Causality with Two Simulated Structural Breaks Accommodated



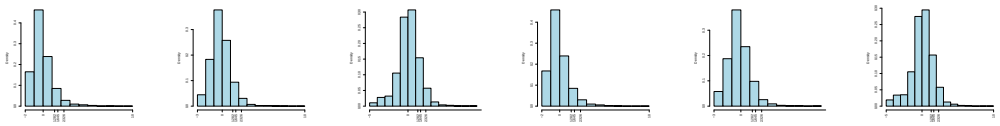
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.2: Case C2 - Lag 1 Simulated Strong Causality with Two Structural Breaks Accommodated



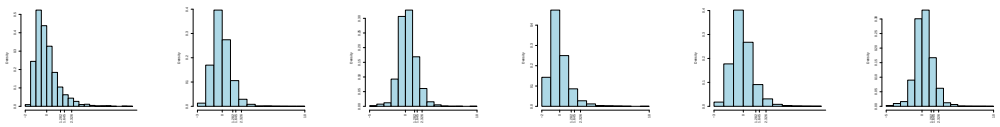
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.3: Case C2 - Lag 1 Simulated Weak Causality with Two Structural Breaks Accommodated



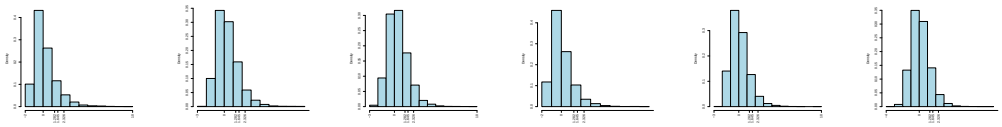
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.4: Case C3 - Lag 30 Simulated Strong Causality with Two Simulated Structural Breaks Accommodated



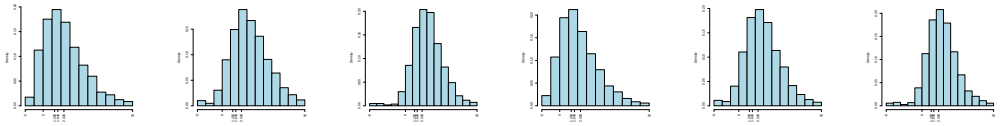
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.5: Case C3 - Lag 30 Simulated Weak Causality with Two Simulated Structural Breaks Accommodated



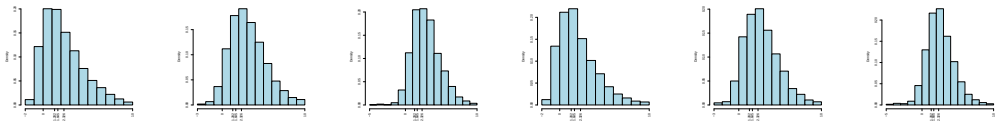
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.6.6: Case C1 - Absence of Simulated Causality with Two Simulated Structural Breaks Neglected



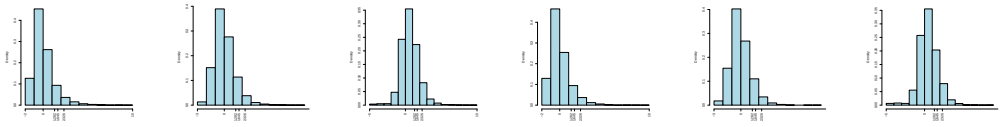
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.7: Case C2 - Lag 1 Simulated Strong Causality with Two Simulated Structural Breaks Neglected



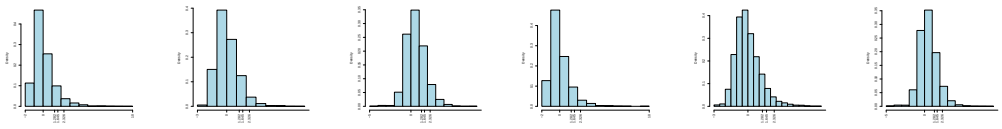
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.8: Case C2 - Lag 1 Simulated Weak Causality with Two Simulated Structural Breaks Neglected



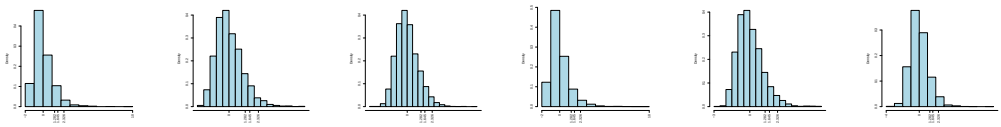
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.9: Case C3 - Lag 30 Simulated Strong Causality with Two Simulated Structural Breaks Neglected



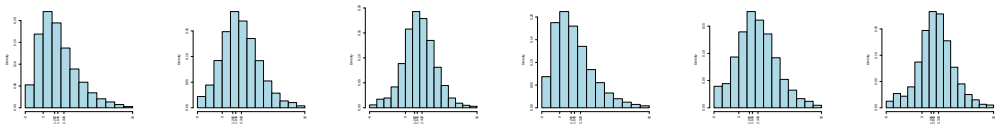
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.6.10: Case C3 - Lag 30 Simulated Weak Causality with Two Simulated Structural Breaks Neglected



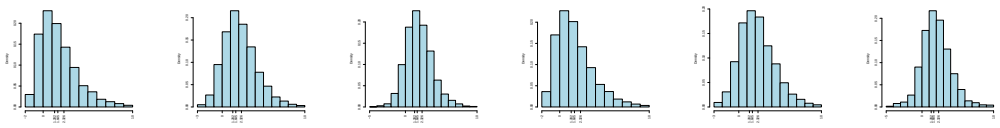
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.7.1: Case D1 - Absence of Simulated Causality with Three Simulated Structural Breaks Accommodated



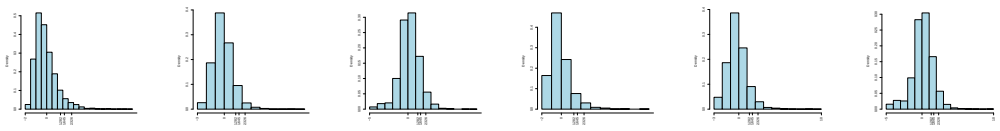
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.2: Case D2 - Lag 1 Simulated Strong Causality with Three Simulated Structural Breaks Accommodated



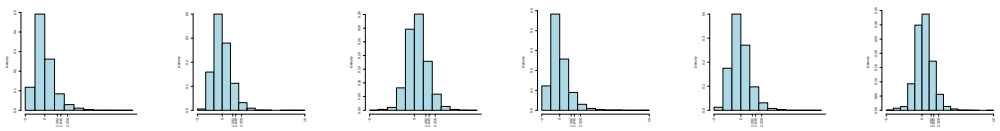
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.3: Case D2 - Lag 1 Simulated Weak Causality with Three Simulated Structural Breaks Accommodated



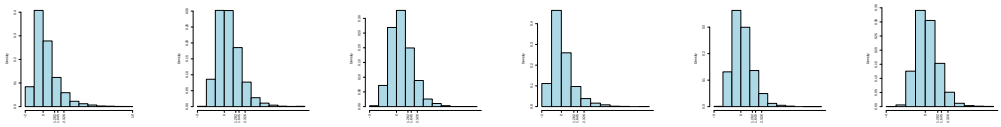
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.4: Case D3 - Lag 30 Simulated Strong Causality with Three Simulated Structural Breaks Accommodated



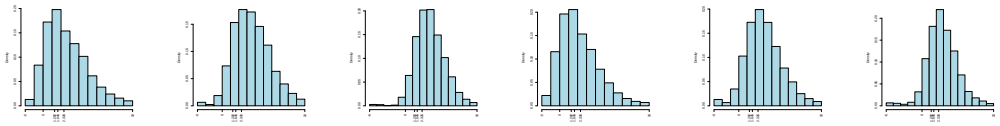
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.5: Case D3 - Lag 30 Simulated Weak Causality with Three Simulated Structural Breaks Accommodated



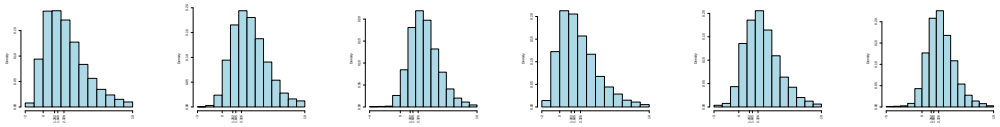
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.7.6: Case D1 - Absence of Simulated Causality with Three Simulated Structural Breaks Neglected



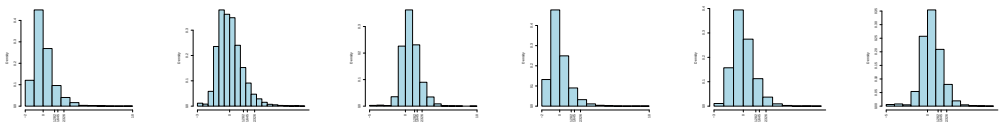
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.7: Case D2 - Lag 1 Simulated Strong Causality with Three Simulated Structural Breaks Neglected



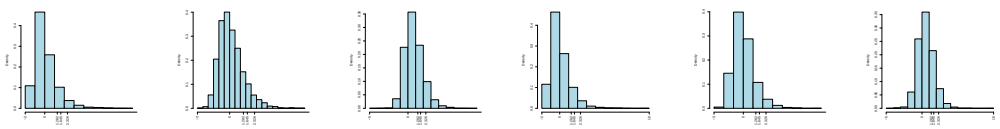
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.8: Case D2 - Lag 1 Simulated Weak Causality with Three Simulated Structural Breaks Neglected



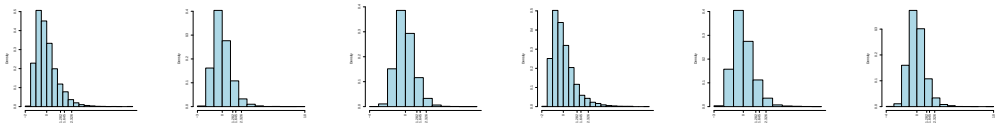
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.9: Case D3 - Lag 30 Simulated Strong Causality with Three Simulated Structural Breaks Neglected



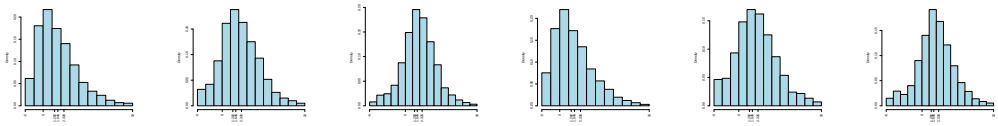
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.7.10: Case D3 - Lag 30 Simulated Weak Causality with Three Simulated Structural Breaks Neglected



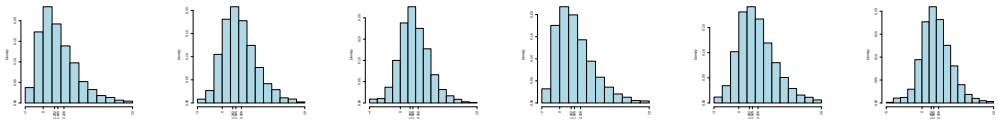
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.8.1: Case E1 - Absence of Simulated Causality with Four Simulated Structural Breaks Accommodated



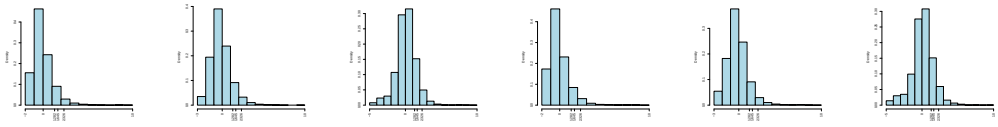
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.2: Case E2 - Lag 1 Simulated Strong Causality with Four Simulated Structural Breaks Accommodated



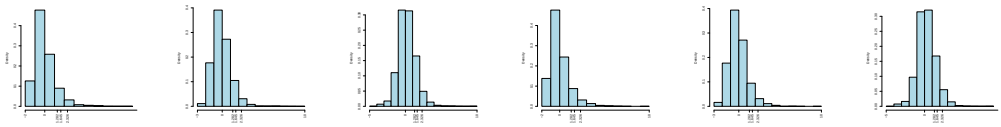
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.3: Case E2 - Lag 1 Simulated Weak Causality with Four Simulated Structural Breaks Accommodated



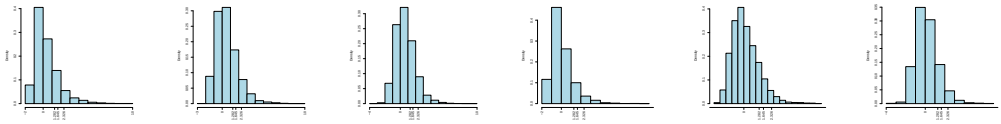
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.4: Case E3 - Lag 30 Simulated Strong Causality with Four Simulated Structural Breaks Accommodated



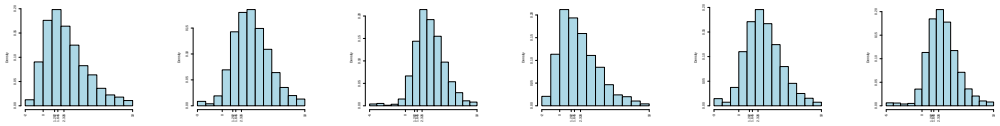
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.5: Case E3 - Lag 30 Simulated Weak Causality with Four Simulated Structural Breaks Accommodated



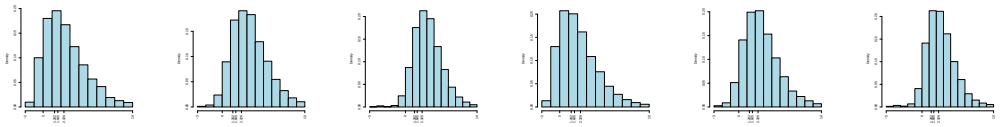
(a) $\omega = 0.33, m = 10$ (b) $\omega = 0.33, m = 30$ (c) $\omega = 0.33, m = 60$ (d) $\omega = 0.11, m = 10$ (e) $\omega = 0.11, m = 30$ (f) $\omega = 0.11, m = 60$

Figure B.8.6: Case E1 - Absence of Simulated Causality with Four Simulated Structural Breaks Neglected



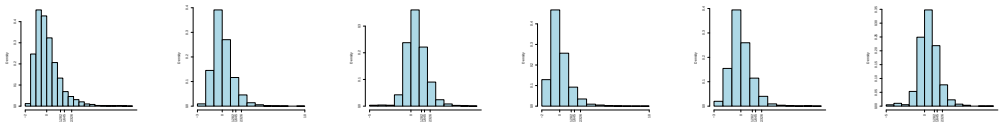
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.7: Case E2 - Lag 1 Simulated Strong Causality with Four Simulated Structural Breaks Neglected



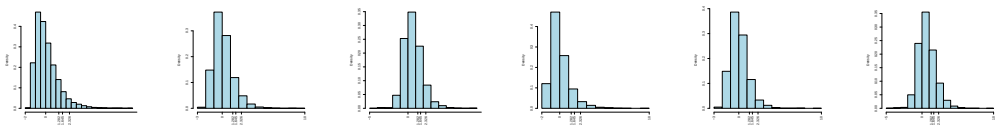
(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.8: Case E2 - Lag 1 Simulated Weak Causality with Four Simulated Structural Breaks Neglected



(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.9: Case E3 - Lag 30 Simulated Strong Causality with Four Simulated Structural Breaks Neglected



(a) $\Delta\omega = 0.22, m = 10$ (b) $\Delta\omega = 0.22, m = 30$ (c) $\Delta\omega = 0.22, m = 60$ (d) $\Delta\omega = 0.11, m = 10$ (e) $\Delta\omega = 0.11, m = 30$ (f) $\Delta\omega = 0.11, m = 60$

Figure B.8.10: Case E3 - Lag 30 Simulated Weak Causality with Four Simulated Structural Breaks Neglected

Bibliography

Aggarwal, R., Inclan, C., and Leal, R. (1999). Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis*, 34(1):33–55.

Ahmed, W. (2017). On the dynamic interactions between energy and stock markets under structural shifts: Evidence from Egypt. *Research in International Business and Finance*, 42:61–74.

Ali, G., Z. S. and Anwar, M. (2012). A bivariate causality between Brazilian stock prices and foreign exchange rates: Evidence from global financial crisis, 2007. *World Applied Sciences Journal*, 20(3):438–444.

Aloui, C. (2007). Price and volatility spillovers between exchange rates and stock indexes for the pre- and post-Euro period. *Quantitative Finance*, 7(6):669–685.

Andersen, T. and Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, 4(2-3):115–158.

Andreou, E. and Ghysels, E. (2002). Detecting multiple breaks in financial market volatility dynamics. *Journal of Applied Econometrics*, 17(5):579–600.

Andrews, D. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61(4):821–856.

Antonakakis, N., Chang, T., Cunado, J., and Gupta, R. (2018). The relationship between commodity markets and commodity mutual funds: A wavelet-based analysis. *Finance Research Letters*, 24:1–9.

Apergis, N., Simo-Kengne, B., Gupta, R., and Chang, T. (2015). The dynamic relationship between house prices and output: evidence from US metropolitan areas. *International Journal of Strategic Property Management*, 19(4):336–345.

Araghi, M. and Ghazani, M. (2015). Abrupt changes in volatility: Evidence from TEPIX index in tehran stock exchange. *Iranian Economic Review*, 19(2):377–393.

Arago-Manzana, V. and Fernandez-Izquierdo, M. (2007). Influence of structural changes in transmission of information between stock markets: A European empirical study. *Journal of Multinational Financial Management*, 17(2):112–124.

Bahmani-Oskooee, M. and Sohrabian, A. (1992). Stock prices and the effective exchange rate of the dollar. *Applied Economics*, 24(4):459.

Bai, J. and Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1):47–78.

Bai, J. and Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1):1–22.

Bailey, W. and Chung, Y. P. (1995). Exchange rate fluctuations, political risk, and stock returns: Some evidence from an emerging market. *Journal of Financial & Quantitative Analysis*, 30(4):541–561.

Baillie, R., Bollerslev, T., and Mikkelsen, H. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 74(1):3–30.

Batori, O., Tsoukalas, D., and Miranda, P. (2010). Exchange rates and equity markets: Evidence from some European countries. *International Journal of Economic Perspectives*, 4(3):501–507.

Bec, F. and Bastien, A. (2007). The transmission of aggregate supply and aggregate demand shocks in japan: Has there been a structural change? *Studies in Nonlinear Dynamics and Econometrics*, 11(4):1–18.

Bekaert, G., Ehrmann, M., Fratzscher, M., and Mehl, A. (2014). The global crisis and equity market contagion. *Journal of Finance*, 69(6):2597–2649.

Bekaert, G. and Harvey, C. (1997). Emerging equity market volatility. *Journal of Financial Economics*, 43(1):29–77.

Bekaert, G., Harvey, C., and Ng, A. (2005). Market integration and contagion. *Journal of Business*, 78(1):39–70.

Belkhouja, M. and Boutahar, M. (2009). Structural change and long memory in the dynamic of U.S. inflation process. *Computational Economics*, 34(2):195–216.

Bodnar, G., Hayt, G., Marston, R., and Smithson, C. (1995). Wharton survey of derivatives usage by U.S. non-financial firms. *Financial Management*, 24(2):104–114.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3):307–327.

Bollerslev, T. and Engle, R. (1993). Common persistence in conditional variances. *Econometrica*, 61(1):167–186.

Branson, W. (1981). Macroeconomic determinants of real exchange rates. Working Paper 801, National Bureau of Economic Research.

Brooks, C., Clare, A., and Persand, G. (2000). A word of caution on calculating market-based minimum capital risk requirements. *Journal of Banking and Finance*, 24(10):1557–1574.

Budd, B. (2018). The transmission of international stock market volatilities. *Journal of Economics and Finance*, 42(1):155–173.

Çağli, E., Mandaci, P., and Kahyaoğlu, H. (2012). Volatility shifts and persistence in variance: Evidence from the sector indices of istanbul stock exchange. *International Journal of Business and Economic Sciences Applied Research*, 4(3):119–140.

Caporale, G., Carcel, H., and Gil-Alana, L. (2018). The EMBI in Latin America: Fractional integration, non-linearities and breaks. *Finance Research Letters*, 24:34–41.

Caporale, G., Pittis, N., and Spagnolo, N. (2002). Testing for causality-in-variance: an application to the East Asian markets. *International Journal of Finance & Economics*, 7(3):235–245.

Charles, A. and Darne, O. (2014). Large shocks in the volatility of the Dow Jones Industrial Average index: 19282013. *Journal of Banking & Finance*, 43:188–199.

Charles, A., Darne, O., and Pop, A. (2015). Risk and ethical investment: Empirical evidence from Dow Jones Islamic indexes. *Research in International Business and Finance*, 35:33–56.

Chen, S., Cui, G., and Zhang, J. (2017). On testing for structural break of coefficients in factor-augmented regression models. *Economics Letters*, 161:141–145.

Cheung, Y. and Ng, L. (1996). A causality-in-variance test and its application to financial market prices. *Journal of Econometrics*, 72(1-2):33–48.

Chkili, W. (2012). The dynamic relationship between exchange rates and stock returns in emerging countries: Volatility spillover and portfolio management. *International Journal of Management Science and Engineering Management*, 7(4):253–262.

Chou, R., Lin, J., and Wu, C. (1999). Modeling the Taiwan stock market and international linkages. *Pacific Economic Review*, 4(3):305–320.

Chow, G. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica*, 28(3):591–605.

Christopher, H. and Wohar, M. (2006). Identifying regime changes in closed-end fund discounts. *Journal of Economics & Finance*, 30(1):115–132.

Dahiru, B., Jim, P., and Nwonyuku, K. (2017). Equity markets volatility dynamics in developed and newly emerging economies: EGARCH-with-skewed-t density approach. *Economics Bulletin*, 37(2):2394–2412.

Davies, R. (1977). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika*, 64(2):247–254.

Davies, R. (1987). Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika*, 74(1):33–43.

De Las Nieves Morales, L. (2008). Volatility spillovers between equity and currency markets: Evidence from major Latin American countries. *Latin American journal of economics*, 45(132):185–215.

Diebold, F. (1986). Modeling the persistence of conditional variances: A comment. *Econometric Reviews*, 5(1):51–56.

Dijk, V.D., O. D. and Sensier, M. (2005). Testing for causality in variance in the presence of breaks. *Economics Letters*, 89(2):193–199.

Ding, Z. and Granger, C. (1996). Modeling volatility persistence of speculative returns: A new approach. *Journal of Econometrics*, 73(1):185–215.

Ding, Z., Granger, C., and Engle, R. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, 1(1):83–106.

Dornbusch, R. and Fischer, S. (1980). Exchange rates and the current account. *The American Economic Review*, 70(5):960–971.

Dridi, J. and Hasan, M. (2010). The effects of the global crisis on Islamic and conventional banks; a comparative study. IMF Working Papers 10/201, International Monetary Fund. Available at: `http://EconPapers.repec.org/RePEc:imf:imfwpa:10/201`.

Eissa, M., Chortareas, G., and Cipollini, A. (2010). Stock returns and exchange rate volatility spillovers in the MENA region. *Journal of Emerging Market Finance*, 9(3):257–284.

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3):339–350.

Engle, R. and Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric Reviews*, 5:1–50.

Engle, R. and Granger, C. (1987). Co-integration and error correction: representation, estimation and testing. *Econometrica*, 55:251–276.

Engle, R. and Kroner, K. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, 11(1):122–150.

Engle, R. and Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. NBER Working Papers 8554, National Bureau of Economic Research, Inc. Available at: `http://EconPapers.repec.org/RePEc:imf:imfwpa:10/201`.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4):987–1007.

Ewing, B. and Malik, F. (2005). Re-examining the asymmetric predictability of conditional variances: The role of sudden changes in variance. *Journal of Banking & Finance*, 29(10):2655–2673.

Ewing, B. and Malik, F. (2010). Estimating volatility persistence in oil prices under structural breaks. *Financial Review*, 45(4):1011–1023.

Ewing, B. and Malik, F. (2016). Volatility spillovers between oil prices and the stock market under structural breaks. *Global Finance Journal*, 29:12–23.

Fedorova, E. and Saleem, K. (2012). Volatility spillovers between stock and currency markets: Evidence from emerging Eastern Europe. *Finance a uver-Czech Journal of Economics and Finance*, 60(6):519–533.

Francis, B. B., Hasan, I., and Hunter, D. M. (2006). Dynamic relations between international equity and currency markets: The role of currency order flow. *The Journal of Business*, 79(1):219–258.

Frankel, J. (1983). Monetary and portfolio-balance models of exchange rate determination. *Economic Interdependence and Flexible Exchange Rates*, pages 84–115.

Gavin, M. (1989). The stock market and exchange rate dynamics. *Journal of International Money and Finance*, 8(2):181–200.

Georgiev, I., Harvey, D., Leybourne, S., and Taylor, A. (2018). Testing for parameter instability in predictive regression models. *Journal of Econometrics*, 204(1):101–118.

Geretto, E. and Pauluzzo, R. (2012). Stock exchange markets in China: Structure and main problems. *Research in International Business and Finance*, 19(1):89–106.

Gilmore, C. and McManus, G. (2002). International portfolio diversification: US and central European equity markets. *Emerging Markets Review*, 3(1):69–83.

Glosten, L. R., Jagannathan, R., and Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5):1779–1801.

Golab, A., Jie, F., Powell, R., and Zamojska, A. (2018). Cointegration between the European union and the selected global markets following sovereign debt crisis. *Investment Management and Financial Innovations*, 15(1):35–45.

Gourieroux, C. (1997). *ARCH Models and Financial Applications*. Springer, New York.

Granger, C. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3):424–438.

Granger, C. (1980). Testing for causality: A personal view. *Journal of Economic Dynamics and Control*, 2:329–352.

Granger, C. (1986). Developments in the study of cointegrated economic variables. *Oxfod Bulletin of Economics and Statistics*, 48:213–228.

Granger, C. W. J., Huangb, B.-N., and Yang, C.-W. (2000). A bivariate causality between stock prices and exchange rates: Evidence from recent Asian flu. *The Quarterly Review of Economics and Finance*, 40(3):337–354.

Grant, K. and Marshall, A. (1997). Large UK companies and derivatives. *European Financial Management*, 3(2):191.

Güloğlu, B., Kaya, P., and Aydemir, R. (2016). Volatility transmission among Latin American stock markets under structural breaks. *Physica A: Statistical Mechanics and its Applications*, 406:330 – 340.

Hafner, C. and Herwartz, H. (2006). A lagrange multiplier test for causality in variance. *Economics Letters*, 93(1):137–141.

Hammoudeh, S. and Li, H. (2008). Sudden changes in volatility in emerging markets: The case of Gulf Arab stock markets. *International Review of Financial Analysis*, 17(1):47–63.

Hansen, P. and Lunde, A. (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics*, 20(7):873–889.

Haugh, L. (1976). Checking the independence of two covariance-stationary time series: A univariate residual cross-correlation approach. *Journal of the American Statistical Association*, 71(354):378–385.

Hendry, D. (1986). An excursion into conditional variance land. *Econometric Reviews*, 5:63–69.

Hillebrand, E. (2005). Neglecting parameter changes in GARCH models. *Journal of Econometrics*, 129(1-2):121–138.

Hong, Y. (2001). A test for volatility spillover with application to exchange rates. *Journal of Econometrics*, 103(1-2):183–224.

Hu, J. W. H., Chen, M. Y., Fok, R. C. W., and Huang, B. N. (1997). Causality in volatility and volatility spillover effects between US, Japan and four equity markets in the South China Growth Triangular. *Journal of International Financial Markets, Institutions and Money*, 7(4):351–367.

Huang, B. and Yang, C. (2001). The impact of settlement time on the volatility of stock market revisited: An application of the iterated cumulative sums of squares detection method for changes of variance. *Applied Economics Letters*, 8.

Huang, P. (2012). Volatility transmission across stock index futures when there are structural changes in return variance. *Applied Financial Economics*, 22.

Huang, P. (2014). The stock index futures hedge ratio with structural changes. *Investment Management and Financial Innovations*, 11.

Inclan, C. and Tiao, G. (1994). Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association*, 89(427):913–923.

Javed, F. (2011). Sensitivity of the causality in variance test to the GARCH (1,1) parameters. *Journal of the American Statistical Association.*

Jebran, K. and Iqbal, A. (2016). Dynamics of volatility spillover between stock market and foreign exchange market: evidence from Asian countries. *Financial Innovation*, 2(1):3.

John Wei, K. C., Liu, Y. J., Yang, C. C., and Chaung, G. S. (1995). Volatility and price change spillover effects across the developed and emerging markets. *Pacific-Basin Finance Journal*, 3(1):113–136.

Jouini, J. and Boutahar, M. (2003). Structural breaks in the U.S. inflation process: a further investigation. *Applied Economics Letters*, 10(15):985–988.

Kanas, A. (2000). Volatility spillovers between stock returns and exchange rate changes: International evidence. *Journal of Business Finance & Accounting*, 27(3-4):447–467.

Kang, S., Cho, H.-G., and Yoon, S.-M. (2009). Modeling sudden volatility changes: Evidence from Japanese and Korean stock markets. *Physica A: Statistical Mechanics and its Applications*, 388(17):3543–3550.

Kang, S. and Yoon, S.-M. (2010). Sudden changes in variance and volatility persistence in asian foreign exchange markets. *The Journal of the Korean Economy*, 11(1):129–143.

Kasman, A. (2009). The impact of sudden changes on the persistence of volatility: evidence from the BRIC countries. *Applied Economics Letters*, 16(7):759–764.

Kirkulak-Uludag, B. and Lkhamazhapov, Z. (2016). The volatility dynamics of spot and futures gold prices: Evidence from Russia. *Research in International Business and Finance*, 38:474–484.

Kirkulak-Uludag, B. and Lkhamazhapov, Z. (2017). Volatility dynamics of precious metals: Evidence from Russia. *Czech Journal of Economics and Finance (Finance a uver)*, 67(4):300–317.

Korkmaz, T., Cevik, E., and Atukeren, E. (2012). Return and volatility spillovers among CIVETS stock markets. *Emerging Markets Review*, 13(2):230 – 252.

Koseoglu, S. and Cevik, E. (2013). Testing for causality in mean and variance between the stock market and the foreign exchange market: An application to the Major Central and Eastern European countries. *Finance a Uver - Czech Journal of Economics and Finance*, 63(1):65–86.

Kroner, K. and Ng, V. (1998). Modeling asymmetric comovements of asset returns. *The Review of Financial Studies*, 11(4):817–844.

Kroner, K. and Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4):535–551.

Kumar, D. and Maheswaran, S. (2012). Modelling asymmetry and persistence under the impact of sudden changes in the volatility of the Indian stock market. *IIMB Management Review*, 24(3):123–136.

Lamoureux, C. G. and Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, 8(2):225–34.

Lee, H. (2015). The effect of level shift in the unconditional variance on predicting conditional volatility. *Journal of Economic Theory and Econometrics*, 26(2):36–56.

Lee, S. J. (2009). Volatility spillover effects among six Asian countries. *Applied Economics Letters*, 16(5):501–508.

Li, H. and Majerowska, E. (2008). Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. *Research in International Business and Finance*, 22(3):247–266.

Li, Y. and Giles, D. (2015). Modelling volatility spillover effects between developed stock markets and asian emerging stock markets. *International Journal of Finance & Economics*, 20(2):155–177.

Lian, Y. M. and Liao, S. (2015). The volatility structure of oil futures market returns: an empirical investigation. *Investment Management and Financial Innovations*, 12(2):16–25.

Lin, J. and Fu, S. (2016). Investigating the dynamic relationships between equity markets and currency markets. *Journal of Business Research*, 69(6):2193–2198.

Ljung, G. and Box, G. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2):297–303.

Malik, F. (2003). Sudden changes in variance and volatility persistence in foreign exchange markets. *Journal of Multinational Financial Management*, 13(3):217–230.

Malik, F., Ewing, B., and Payne, J. (2005). Measuring volatility persistence in the presence of sudden changes in the variance of Canadian stock returns. *The Canadian Journal of Economics / Revue canadienne d'Economique*, 38(3):1037–1056.

Malik, F. and Hassan, S. (2004). Modeling volatility in sector index returns with GARCH models using an iterated algorithm. *Journal of Economics and Finance*, 28(2):211–225.

Mandelbrot, B. (1963). The variation of certain speculative prices. *The Journal of Business*, 36:394.

Mansur, I., Cochran, S., and Shaffer, D. (2007). Foreign exchange volatility shifts and futures hedging:: An ICSS-GARCH approach. *Review of Pacific Basin Financial Markets & Policies*, 10(3):349–388.

Mantalos, P. and Shukur, G. (2010). The effect of spillover on the Granger Causality test. *Journal of Applied Statistics*, 37(9):1473–1486.

McLeod, A. I. and Li, W. K. (1983). Diagnostic checking ARMA time series models using squared residuals autocorrelations. *Journal of Time Series Analysis*, 4:269–273.

McMillan, D. and Wohar, M. (2011). Structural breaks in volatility: The case of UK sector returns. *Applied Financial Economics*, 21(15):1079–1093.

Mensi, W., Hammoudeh, S., Nguyen, D., and Kang, S. (2016). Global financial crisis and spillover effects among the U.S. and BRICS stock markets. *International Review of Economics & Finance*, 42:257–276.

Mikosch, T. and Stărică, C. (2004). Nonstationarities in financial time series, the long-range dependence, and the IGARCH effects. *Review of Economics and Statistics*, 86(1):378–390.

Miralles Marcelo, J., Quiros, J., and Quiros, M. (2008). Asymmetric variance and spillover effects: Regime shifts in the Spanish stock market. *Journal of International Financial Markets, Institutions and Money*, 18(1):1–15.

Mirovic, V., Zivkov, D., and Njegic, J. (2017). Construction of commodity portfolio and its hedge effectiveness gauging revisiting DCC models. *Czech Journal of Economics and Finance (Finance a uver)*, 67(5):396–422.

Mongi, A. and Haj Ali, D. (2016). Do structural breaks affect portfolio designs and hedging strategies? international evidence from stock-commodity markets linkages. *International Journal of Economics and Financial Issues*, 6(2):1–19.

Moon, G.-H. and Yu, W.-C. (2010). Volatility spillovers between the US and China stock markets: Structural break test with symmetric and asymmetric GARCH approaches. *Global Economic Review*, 39(2):129–149.

Morales-Zumaquero, A. and Sosvilla-Rivero, S. (2010). Structural breaks in volatility: Evidence for the OECD and non-OECD real exchange rates. *Journal of International Money and Finance*, 29(1):139–168.

Muye, I. and Muye, I. (2017). Testing for causality among globalization, institution and financial development: Further evidence from three economic blocs. *Borsa Istanbul Review*, 17(2):117–132.

Nazlioglu, S., H. S. and Gupta, R. (2015). Volatility transmission between Islamic and conventional equity markets: Evidence from causality-in-variance test. *Applied Economics*, 47(46):1–16.

Nelson, D. (1992). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica*, 59(2):347–370.

Newey, W. and West, K. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies*, 61(4):631–653.

Ni, J., Wohar, M. E., and Wang, B. (2016). Structural breaks in volatility: The case of Chinese stock returns. *Chinese Economy*, 49(2):81 – 93.

Nwogugu, M. (2006). Further critique of GARCH/ARMA/VAR/EVT stochastic-volatility models and related approaches. *Applied Mathematics and Computation*, 182(2):1735 – 1748.

Oh, G., Kim, S., and Eom, C. (2008). Long-term memory and volatility clustering in high-frequency price changes. *Physica A: Statistical Mechanics and its Applications*, 387(5-6):1247–1254.

Okur, M. and Cevik, E. (2013). Testing intraday volatility spillovers in Turkish capital markets: Evidence from ISE. *Ekonomska Istrazivanja*, 26(3):99–116.

Pan, M., Fok, R. C., and Liu, Y. (2007). Dynamic linkages between exchange rates and stock prices: Evidence from East Asian markets. *International Review of Economics & Finance*, 16(4):503–520.

Phylaktis, K. and Ravazzolo, F. (2005). Stock prices and exchange rate dynamics. *Journal of International Money and Finance*, 24(7):1031–1053.

Priestley, M. (1981). *Spectral Analysis and Time Series*. Academic Press, London.

Ramlall, I. (2009). Assessing the impact of US subprime crisis on SEMDEX: In quest for a change in stock market interdependence. *International Research Journal of Finance and Economics*, 30:30–44.

Rapach, D. and Wohar, M. (2006). Structural breaks and predictive regression models of aggregate U.S. stock returns. *Journal of Financial Econometrics,*, 4(2):238–274.

Rodrigues, P. and Rubia, A. (2007). Testing for causality in variance under nonstationarity in variance. *Economics Letters*, 97(2):133–137.

Ross, G. (2013). Modelling financial volatility in the presence of abrupt changes. *Physica A: Statistical Mechanics and its Applications*, 392(2):350–360.

Ross, S. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *The Journal of Finance*, 44(1):1–17.

Saleem, K. (2009). International linkage of the russian market and the russian financial crisis: A multivariate GARCH analysis. *Research in International Business and Finance*, 23(3):243–256.

Sanso, A., Arago, V., and Carrion, J. (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economa Financiera*, (4):32–53.

Shahrazi, M., Elmi, Z., Abounoori, E., and Rasekhi, S. (2014). The influence of structural changes in volatility on shock transmission and volatility spillover among Iranian gold and foreign exchange markets. *Iranian Economic Review*, 18(2):1–14.

Shahzad, S., Raza, N., Balcilar, M., Ali, S., and Shahbaz, M. (2017). Can economic policy uncertainty and investors sentiment predict commodities returns and volatility? *Resources Policy*, 53:208–218.

Sims, C. (1980). Macroeconomics and reality. *Econometrica*, 48(1):1–48.

Smith, D. (2008). Testing for structural breaks in GARCH models. *Applied Financial Economics*, 18(10):845–862.

Smyth, R. and Nandha, M. (2003). Bivariate causality between exchange rates and stock prices in South Asia. *Applied Economics Letters*, 10(11):699–704.

Solnik, B. (1987). Using financial prices to test exchange rate models: A note. *The Journal of Finance*, 42(1):141–149.

Tai, C.-S. (2007). Market integration and contagion: Evidence from Asian emerging stock and foreign exchange markets. *Emerging Markets Review*, 8(4):264–283.

Todea, A. and Petrescu, D. (2012). Sudden changes in volatility - the case of the five financial investment companies in Romania. *Procedia Economics and Finance*, 3:40–48.

Todea, A. and Platon, D. (2012). Sudden changes in volatility in Central and Eastern Europe foreign exchange markets. *Journal for Economic Forecasting*, 0(2):38–51.

Tokat, H. (2009). Re-examination of volatility dynamics in Istanbul stock exchange. *Investment Management and Financial Innovations*, 6(11):192–198.

Tomar, R. and Singh, H. (2016). Causal relationship between stock market indices, gold prices, crude oil prices, and exchange rates. *International Journal of Economic Research*, 13(1):53–65.

Tsai, I. (2012). The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. *Journal of International Financial Markets*, 22(3):609–621.

Tse, Y. (1998). The conditional heteroscedasticity of the Yen-Dollar exchange rate. *Journal of Applied Econometrics*, 13(1):49–55.

Tseng, J.-J. and Li, S.-P. (2011). Asset returns and volatility clustering in financial time series. *Physica A: Statistical Mechanics and its Applications*, 390(7):1300–1314.

Tule, M., Ndako, U., and Onipede, S. (2017). Oil price, bond market, volatility, VARMA-GARCH, spillover effect, portfolio management. *Review of Financial Economics*, 35:57–65.

Walid, C., Chaker, A., Masood, O., and Fry, J. (2011). Stock market volatility and exchange rates in emerging countries: A markov-state switching approach. *Emerging Markets Review*, 12(3):272–292.

Wang, K.-M. and Nguyen Thi, T.-B. (2007). Testing for contagion under asymmetric dynamics: Evidence from the stock markets between US and Taiwan. *Physica A: Statistical Mechanics and its Applications*, 17(3):277–290.

Wang, P. and Moore, T. (2009). Sudden changes in volatility: The case of five central European stock markets. *Journal of International Financial Markets, Institutions and Money*, 19(1):33–46.

Wen, F., Xiao, J., Huang, C., and Xia, X. (2018). Interaction between oil and US dollar exchange rate: nonlinear causality, time-varying influence and structural breaks in volatility. *Applied Economics*, 50(3):319–334.

World Federation of Exchanges (2016). WFE annual statistics guide 2016. `https://www.world-exchanges.org/home/`. [Online: accessed 30-September-2017].

Xu, J. and Hamori, S. (2012). Dynamic linkages of stock prices between the BRICs and the united states: Effects of the 200809 financial crisis. *Journal of Asian Economics*, 23(4):344–352.

Yang, G., Chang, K., Ying, Y., and Lee, C. (2014). Spillover effects of Chinese stock markets. *Economics Bulletin*, 34(1):200–205.

Yang, S. and Doong, S. (2004). Price and volatility spillovers between stock prices and exchange rates: Empirical evidence from the G-7 countries. *International Journal of Business and Economics*, 3(2):139–153.

Yang, Y. and Chang, C. (2008). A double-threshold GARCH model of stock market and currency shocks on stock returns. *Mathematics and Computers in Simulation*, 79(3):458–474.

Zhang, J., Zhang, D., Wang, J., and Zhang, Y. (2013). Volatility spillovers between equity and bond markets: Evidence from G7 and BRICS. *Romanian Journal of Economic Forecasting*, 16(4):205–217.

Zhao, H. (2010). Dynamic relationship between exchange rate and stock price: Evidence from China. *Research in International Business and Finance*, 24(2):103–112.

Zhu, B., Chevallier, J., Ma, S., and Wei, Y. (2015). Examining the structural changes of European carbon futures price 20052012. *Applied Economics Letters*, 22(5):335–342.

Zhu, H., Lu, Z., Wang, S., and Abdol, S. (2004). Casual linkage among Shanghai, Shenzhen, and Hong Kong stock markets. *International Journal of Theoretical and Applied Finance*, 07(2):135–149.

Zivkov, D., Njegic, J., and Milenkovic, I. (2015). Bidirectional volatility spillover effect between the exchange rate and stocks in the presence of structural breaks in selected eastern European economies. *Czech Journal of Economics and Finance (Finance a uver)*, 65(6):477–498.