Volatility Estimation and Forecasting in the Presence of Structural Breaks

– A Case Study of BRIC Countries

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3. Abstract

This study examines the empirical relevance of structural breaks in the unconditional variance of asset returns when GARCH(1,1) model, EGARCH(1,1) model and GJR(1,1) model are employed to model and predict the conditional volatility of stock market returns of BRIC countries – Brazil, Russia, India and China. G6 countries – U.S., U.K., Japan, Italy, France and Germany – are also considered to for a comparative analysis. Two conditional densities (normal and student t) for the standardised residuals are utilised. The data covers the 20-year period from July 1993 to July 2013 and spans from the starting period of the stock market of BRIC group to the most recent period. The iterated cumulative sum of squares (ICSS) algorithm is employed to detect the structural breaks in the unconditional variance of stock returns of BRIC and G6 countries and economic as well as political events associated with each break period are identified substantially. It is found that parameter estimates (in particular volatility persistence) of all the three GARCH-family models tend to vary substantially across the sub-periods defined by the variance breaks. EGARCH(1,1) model tends to produce better results for both in-sample estimation and out-of-sample forecasting exercises. Heavy tailed density (i.e. student t) also plays an important role in estimation and forecasting practices. Overall, it is concluded that structural breaks in unconditional volatility of stock returns need to be taken into account for GARCH model estimation and forecasting practices as failure to do so can lead to huge biases in the results of both practices.

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5. Introduction

A large body of research has been conducted to model volatility, among which the most widely used method to analysing high frequency time series data is the autoregressive conditional heteroskedasticity (ARCH) model developed by (Engle, 1982). The model has later been generalised (i.e. generalised ARCH, denoted by GARCH) by (Bollerslev, 1986) and a multitude of extensions have been created to account for other features of time series data (e.g. GJR-GARCH by (Glosten, Jagannathan & Runkle, 1993), exponential GARCH (EGARCH) by (Nelson, 1991) and asymmetric power GARCH (APGARCH) by (Ding, Granger & Engle, 1993), etc.).

One issue that is of potential problem is that researchers often apply a stable GARCH process to model the volatility of return (or growth rate) of financial and economic time series, implying that a constant unconditional variance of asset returns is assumed (Rapach & Strauss, 2008). This is questionable since the economy and financial market of any country or region will periodically encounter unanticipated sudden shocks that may cause temporary spikes in market behaviour. An example of a temporary break is the worldwide stock market crash which occurred on October 19, 1987 which substantially lifted stock market volatility for a short period of time (Schwert, 1990). In addition, certain economic, political or social events can permanently alter the regime of an economy. One of the most famous examples is the collapse of the Bretton Wood System that terminated fixed currency exchange rates and controlled gold prices, making their time series begin to fluctuate. (Rapach & Strauss, 2008) stated that such events or shocks are able to bring about sudden breaks in the unconditional variance of return series which correspond to structural changes in GARCH model coefficients.

Followed by some early research from (Diebold, 1986) and (Lamoureux & Lastrapes, 1990), subsequent works by (Cai, 1994) , (Aggarwal, Inclan & Leal, 1999), (Mikosch & Starica, 2004), (Krämer, Tameze & Christou, 2012) and others show that if there are structural breaks in the unconditional variance of asset returns and they are taken into consideration in the GARCH models, the estimated degree of volatility will be biased upward significantly. Volatility persistence suggests how long a shock to volatility remains effective for the evolvement of a volatility process (Engle & Bollerslev, 1986). Their works have inspired researchers to further explore the interplay among asset (return) volatility, volatility persistence and volatility breaks and their implications on various financial activities.

(Poterba & Summers, 1986) examined the hypothesis of time-varying risk premium and reviewed the relationship between stock market fluctuations and level of stock prices. They found that, although shocks to stock market volatility tend to last only for a short period of time, share prices are negatively related to the level of volatility persistence. (Kim, Oh & Brooks, 1994) argued that sudden changes in stock returns induce risk that cannot be diversified away (i.e., systematic risk) so that it should be incorporated into the option price. It is also claimed that a constant-hedge-ratio strategy is inferior to a time-varying hedging strategy for a number of commodities, assuming no breaks in the variance of the series (Baillie & Myers, 1991). Accordingly, (Wilson, Aggarwal & Inclan, 1996) insisted that allowing for regime shifts in the variance process helps refine hedging strategies. Moreover, (Cai, 1994), (Gray, 1996) and (Starica, Herzel & Nord, 2005) pointed out that more accurate conditional volatility forecasts can be generated if sudden changes in unconditional variance are allowed for in GARCH models.

This study is dedicated to examine the empirical relevance of structural breaks in the unconditional variance of asset returns when GARCH-family models are employed to model and predict the conditional volatility of stock market returns of BRIC countries – Brazil, Russia, India and China. Data of G6 countries – U.S., U.K., Japan, Italy, France, Germany – are also analysed to form a comparative analysis.

This work is motivated mainly by two reasons. Firstly, the economy of BRIC countries have expanded rapidly and received increasing attention over the past decade since the term ‘BRIC’ was coined in 2001. More and more researchers and practitioners start to pay attention to these countries’ economy and financial market as the amount of business and investment practices between the four countries and rest of the world keep surging. Based on insights from (Hu, 1995) (Poterba, 2000) (Campbell et al., 2001) and (Cuñado Eizaguirre, Biscarri & Hidalgo, 2004)[1], studying volatility-related aspects of BRIC’s stock markets may provide crucial implications on several aspects of the world economy. Secondly, the research by (Aggarwal, Inclan & Leal, 1999) showed that it is worth inspecting emerging stock markets as they display highly different features and behaviour from those of developed markets. However, few studies concerning structural volatility changes and their effect on conditional volatility forecasting are conducted for stock markets of BRIC countries given the vital role BRIC countries play in the global market. This work attempts to contribute to the existing literature by bridging this gap.

[1] The four papers, among others, demonstrate that stock market fluctuations affect the economy through a number of ways. (Hu, 1995) documented the negative relationship between volatility of stock market and fixed business investment. (Poterba, 2000) stated that volatile stock prices could dent the consumer spending. (Campbell et al., 2001) offers evidence that stock volatility helps to forecast economic growth. Furthermore, (Cuñado Eizaguirre, Biscarri & Hidalgo, 2004) argued that excessively high level of volatility could trigger malfunction in the financial system.

Squared returns of stock prices are used as the proxy for variance. Both in-sample model tests and out-of-sample tests will be analysed in this thesis. In terms of in-sample tests the iterated cumulative sums of squares (ICSS) algorithm introduced by (Inclan & Tiao, 1994) is utilised. This algorithm is employed to detect potential structural breaks in the unconditional volatility of stock market returns of BRIC countries as well as the duration and magnitude of those identified regime shifts. Subsequently, GARCH(1,1), EGARCH(1,1) and GJR(1,1) model are estimated using the full sample and each sub-sample to analyse the empirical relevance of structural breaks in the unconditional variance. In the out-of-sample analysis, one benchmark model – the GARCH(1,1) expanding window–normal density model – and various competing models are applied to generate the forecasts of conditional volatility of stock market returns at 1-period,10-period and 30-period horizons. Forecasts produced by benchmark GARCH models are compared with forecasts generated by GARCH models accommodating possible changes in parameters. Different estimation windows – ICSS window, 0.25/0.5/0.75 rolling window – are employed for competing models to account for potential structural breaks in the unconditional volatility of stock returns.

The rest of this work is organised as follows: Section 6 introduces some background knowledge regarding the BRIC coutries, Section 7 reviewed the past studies conducted in the relevant fields, Section 8 presents the data collected and the different tests, algorithms and models applied in this study, Section 9 discuss empirical results of in-sample modelling and out-of-sample forecasting and major findings while Section 10 provides the conclusion and potential fields for future analysis.

6. Background: BRIC countries

The concept 'BRIC' countries – Brazil, Russian, Indian and China – started to attract people's attention since Jim O'Neill, the retiring chairman of Goldman Sachs Asset Management, coined the term in 2001. Over the past decade, the BRIC countries' economies have grown substantially. (Purushothaman & Wilson, 2003) predicted that the economy of BRIC countries will catch up with the six major industrial economies – USA, Japan, Germany, UK, France and Italy – in less than 40 years. The prediction was based on demographic projection techniques and a model of capital and productivity increase. More strikingly, according to the same report, China and India will dominate the world economy by 2050. Moreover, Brazil and Russia, which will grow with an annual rate of 4% and 5% respectively, will overtake the economies of Germany, UK, France and Italy over the next 50 years. Only the US and Japan are likely to stay within the top six economies in US dollar terms in 2050.

As time elapses, some of the projected figures have become realised. The table below displays the comparison between predicted and realised results of real GDP growth, obtained from (Purushothaman & Wilson, 2003) and the website of World Bank, respectively.

	Brazil		Russia		India		China	
Year	Projected	Realised	Projected	Realised	Projected	Realised	Projected	Realised
2008	4.1%	5.2%	4.5%	5.2%	6.1%	3.9%	7.1%	9.6%
2009	4.2%	-0.3%	4.3%	-7.8%	6.1%	8.5%	6.9%	9.2%
2010	4.2%	7.5%	4.1%	4.5%	6.1%	10.5%	6.6%	10.4%
2011	4.1%	2.7%	4.0%	4.3%	6.0%	6.3%	6.4%	9.3%
2012	4.1%	0.9%	3.8%	3.4%	6.0%	3.2%	6.0%	7.8%

Notes: The projected data is taken from (Purushothaman & Wilson, 2003);
The realised data is taken from the World Bank website, which is available at
http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

As can be seen from the table, there is a conspicuous difference between the projected and realised figures. However, the projection is acceptable in general given that prediction is a notoriously difficult task. It should be noted that, although the prediction overestimated the average growth rate of Brazil, it performed well for the growth of Russia and India and highly underestimate that of China.

	France		Germany		Italy		Japan		UK		US	
Year	Projected	Realised	Projected	Realised	Projected	Realised	Projected	Realised	Projected	Realised	Projected	Realised
2008	1.6%	-0.1%	1.9%	1.1%	1.5%	-1.2%	0.4%	-1.0%	2.0%	-1.0%	2.5%	-0.4%
2009	1.6%	-3.1%	1.7%	-5.1%	1.5%	-5.5%	0.4%	-5.5%	2.2%	-4.0%	2.5%	-3.1%
2010	1.6%	1.7%	1.5%	4.2%	1.6%	1.7%	0.6%	4.7%	2.2%	1.8%	2.4%	2.4%
2011	1.7%	2.0%	1.6%	3.0%	1.6%	0.4%	0.8%	-0.6%	2.2%	1.0%	2.3%	1.8%
2012	1.7%	0.0%	1.6%	0.7%	1.6%	-2.4%	1.0%	1.9%	2.2%	0.3%	2.2%	2.2%

Notes: The projected data is taken from (Purushothaman & Wilson, 2003);
The realised data is taken from the World Bank website, which is available at
http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG

The table above shows the comparison of projected and realised real GDP growth for G6 countries. It is clear that the realised growth of Germany, Japan and US roughly match with the forecasts whereas France, Italy and UK perform worse than predicted. This implies that the projections from the Goldman Sachs report in 2003 are likely to be realised by 2050 under the current trend. And the projection may become true earlier than 2040 as the economy of some BRIC countries such as China is expanding at a very fast pace while the G6 counterparts are still plagued with the prolonged recession.

7. Literature review

It is worth mentioning that many works discussed in this section may generate more contributions to the research field than the contributions documented here. However, this literature research is not necessarily exhaustive and only highlights contributions relevant to this study.

Structural breaks and volatility persistence

An increasing number of theoretical studies find that the consideration of structural breaks in volatility of asset returns tend to have a large impact on estimating GARCH models and crucial implications for various financial practices such as asset allocation, option pricing, risk hedging and volatility forecasting. When (G)ARCH models are applied to high frequency financial data it is commonly found that the level of persistence, which is suggested by the parameter estimates of conditional volatility functions, tend to be high (Cai, 1994). As a result, (Engle & Bollerslev, 1986) developed the integrated GARCH (IGARCH) model. The model has the well-known property termed ‘persistence in conditional variance’, meaning that shocks to the conditional variance will influence the forecasts of all future horizons.

However, (Diebold, 1986) started to point out that the integrated-variance disturbances of interest rate equations is likely to be caused by failure to taking into account monetary regime shifts in the conditional variance intercept of GARCH models. Three years later, (Lastrapes, 1989) studied exchange rates using ARCH model and found that the estimated volatility persistence is significantly reduced if deterministic monetary regime shifts are incorporated in the standard ARCH model, confirming (Diebold, 1986)’s claim. (Lamoureux & Lastrapes, 1990) extended the research of volatility persistence to GARCH model. They applied GARCH model to stock return data and a Monte Carlo simulation experiment to examine the consequence of a failure to include determinist structural shifts in the intercept of a GARCH model. It was concluded that this kind of model misspecification lead to sizeable upward bias in the estimated level of volatility persistence. Nonetheless, one issue relating to these works is that all the structural shifts in unconditional variance are artificially introduced by choosing subsamples arbitrarily (Lamoureux & Lastrapes, 1990). To account for this problem, (Cai, 1994) developed a Markov-ARCH model which can identify the breaks given the data. By examining monthly excess returns of the three-month Treasury bill, it is confirmed that the ARCH coefficients are diminished substantially by allowing for the endogenously determined regime changes.

(Aggarwal, Inclan & Leal, 1999) was among the earliest studies to apply a newly proposed method – the iterated cumulative sums of squares (ICSS) algorithm[2] created by (Inclan & Tiao, 1994) – to investigate breaks in volatility. They aimed to detect the multiple break points in the variance of emerging stock market returns using the ICSS algorithm as well as the length of each break period. Their results confirm previous findings that shocks to volatility become considerably less persistent when sudden changes in variance are taken into account in the GARCH model. However, one difference is that in their case the level of persistence tends to zero[3] for stock returns of many countries when 'shift dummies' are added to the GARCH (1, 1) model. Moreover, they found that large volatility changes tend to be more sensitive to regional social, political and economic events than to global ones.

Motivated by works of (Inclan & Tiao, 1994) and (Aggarwal, Inclan & Leal, 1999), increasing amount of research begins to analyse the issue of stock market volatility persistence in the existence of structural breaks using ICSS algorithm. (Malik & Hassan, 2004) applied the ICSS algorithm to identify regime shifts in volatility in returns of five major stock market sector indices and then included the dummy variables for volatility breaks in the GARCH(1, 1) framework. They showed that measured volatility persistence in those market sectors are greatly lowered when sudden changes in volatility are accounted for. (Hammoudeh & Li, 2008) utilised ICSS algorithm to study volatility shifts for Gulf Arab stock markets. They confirmed the reductions in volatility persistence for Gulf Arab stock market returns when shifts in volatility are considered[4]. (Kasman, 2009) and (Wang & Moore, 2009) proved the same finding in stock markets of BRIC countries and of five new European Union members experiencing economic transitions, respectively. While most research discussed above focuses on persistence in standard GARCH (1, 1) model, (Kang, Cho & Yoon, 2009) extended the research using fractionally integrated GARCH (FIGARCH) introduced by (Baillie, Bollerslev & Mikkelsen, 1996) and generated the same conclusion for Japanese and Korean stock markets. (Alfreedi, Isa & Hassan, 2012) supported the results of previous studies by examining volatility persistence in asymmetric GARCH frameworks (e. g. GJR-GARCH and EGARCH).

While most works covered so far involved the inclusion of dummy variables for volatility breaks in GARCH models to analyse their impact on volatility persistence, the following studies examined the effect of structural changes on long-range dependence (LRD) via different methods. (Mikosch & Starica, 2004) investigated the asymptotic behaviour of

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[2] Details of ICSS algorithm is discussed in methodology section.
[3] Furthermore, the estimated GARCH coefficients are not statistically significant in many cases. (Hammoudeh & Li, 2008) argued that (Aggarwal, Inclan & Leal, 1999) is not a good case for the study of volatility shifts.
[4] However they found that global events, rather than regional and local ones, matter more to the Gulf Arab stock markets, contrary to the results from (Aggarwal, Inclan & Leal, 1999).

Whittle estimator for the GARCH model and managed to prove theoretically that persistence of volatility can be overstated if parameter changes of GARCH process are disregarded. (Hillebrand, 2005) showed similar results for 'all common estimators of GARCH' including the most widely used maximum likelihood and quasi maximum likelihood estimators. (He. Z. & Maheu, 2010) supported the same conclusion through 'a sequential Monte Carlo method for estimating GARCH models subject to an unknown number of structural breaks.' Moreover, (Krämer, Tameze & Christou, 2012) studied the minimum distance estimator developed by (Baillie & Chung, 2001) for GARCH (1, 1) model under the condition of given structural changes and growing sample sizes. They extended previous works by demonstrating theoretically that shifts in not only GARCH parameters but also the expectation of unconditional variances can induce upward bias in the estimated volatility persistence.

Structural breaks and volatility forecasting

Structural breaks also play a crucial role in the volatility forecasting of financial time series. (Hamilton & Susmel, 1994) applied a class of Markov-switching ARCH (SWARCH) models to US weekly stock returns and claimed that their model generates better modelling and forecasting outcomes. (West & Cho, 1995) predicted exchange rate return volatility using different models. They stated that superior forecasting performance of a GARCH (1, 1) model may be obtained if breaks in the unconditional volatility of returns of exchange rates are considered, consistent with the argument by (Hamilton & Susmel, 1994). (Gray, 1996) proposed a generalised regime-switching (GRS) model to study short term interest rate and concluded that failing to take account of potential regime switches in volatility worsens the predicted volatility. Additionally, (Starica, Herzel & Nord, 2005) argued that accounting for regime changes in the unconditional volatility of stock returns will produce better long-horizon volatility forecasts than if the changes are ignored. (Rapach & Strauss, 2008) predicted the volatility of eight US dollar exchange rate returns using three benchmark GARCH-type models with stable parameters and five competing models accommodating breaks in the unconditional variance of asset returns. They pointed out that models allowing for potential breaks always produce better forecasting results than models assuming constant parameters.

Structural breaks and other financial practices

Finally, some articles also documented the effect of structural breaks on other financial practices in various fields. (Wilson, Aggarwal & Inclan, 1996) examined the impact of volatility changes on pricing and hedging activities using daily data of oil futures contracts and daily returns of a portfolio comprising oil-producing companies. They applied the then-newly-developed ICSS algorithm to identify points and magnitude of volatility shifts. The research showed that the effectiveness of hedging activities is largely weakened if breaks in volatility are neglected. In addition, there is no spillover effect of volatility changes from oil futures to stocks of oil-producing firms, invalidating the role of the oil-producing company portfolio as a tool for cross hedging. (Malik, 2003) attempted to detect the time points of variance breaks in the foreign exchange market and studied major political and economic events corresponding to those points. He suggested that correctly understanding the link between asset prices and volatility changes can help construct more accurate asset pricing models. Recently, (Ewing & Malik, 2013) explored the volatility of gold and oil futures with univariate and bivariate GARCH models. Interestingly, they found significant volatility transmission between oil and gold markets only when structural breaks in volatility were taken into account. The 'optimal portfolio weights and dynamic risk minimising hedge ratios are calculated to indicate the value of cross hedging and the use of information across asset classes to make better financial decisions.

This work concentrates on analysing the effect of structural breaks on volatility persistence and variance forecasting; while the role structural breaks play in hedging strategies and portfolio management are kept for future research.

8. Methodology and Data

8.1 In-Sample Tests

In this article, 70% of the entire sample is used for model estimation, with the rest 30% serving the out-of-sample performance tests.

8.1.1 Identification of structural breaks in variance

The cumulative sums of squares (CUSUM)-type tests are normally used to detect a single break point (Alfreedi, Isa & Hassan, 2012). However, (Inclan & Tiao, 1994) introduced an iterated cumulative sums of squares (ICSS) algorithm to detect multiple change points in variance, largely facilitating the research in the fields of volatility persistence and forecasting in GARCH models.

The analysis assumes that the variance of the data series under consideration is stationary over an initial period and begins to vary when a break in variance occurs, probably triggered by some economic, political or social news affecting the financial market. Then the variance becomes stationary again until a new sequence of news hit the market, generating another break in the variance. This process is repeated through time. Therefore, an unknown number of breaks in variance are detected for each time series.

The common procedure of the ICSS algorithm documented in the articles is specified as follows. Let $\{\varepsilon_t\}$ stand for a series of independent observations from a normal distribution with mean 0 and unconditional variance σ_t^2. The variance for each period is denoted by σ_i^2 where i = 0, 1, 2,…,N_T and N_T is the total number of breaks in variance for a sample of size T. Moreover, in the literature it is commonly denoted that $1 < K_1 < K_2 \ldots < K_{N_T} < T$ are a sequence of break points. The variance corresponding to the N_T sub-period is defined in the following way:

$$\sigma_t^2 = \begin{cases} \sigma_0^2\,, & 1 < t < K_1 \\ \sigma_1^2\,, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2\,, & K_{N_T} < t < T. \end{cases}$$

Then the CUSUM is computed in order to estimate the number of variance breaks as well as the time associated with the breaks. Let

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2\,, \qquad k = 1, 2, \ldots, T,$$

represents the cumulative sum of the squared observations from the starting point to the kth point in time. The test statistics

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad where\ D_0 = D_T = 0,$$

is then formed to facilitate the detection of breaks, where C_T denotes the sum of squared residuals for the entire sample. When the value of D_k is plotted against k, the value will fluctuate around zero if no break is found over the sample. However, the value of D_k tends to depart from zero if one or multiple breaks exist. In this situation, critical values computed from the distribution of D_k under the null hypothesis of no break in variance are used to determine whether one or more variance shifts exist. The null hypothesis of constant variance is rejected if the maximum of absolute value of D_k exceeds the critical values. Let k^* denotes the value of k that maximises $\max_k |D_k|$. If $\max_k \sqrt{T/2}|D_k|$ is greater than the critical value, k^* is chosen as an estimate of the break point. $\sqrt{T/2}$ is a factor to standardise the distribution.

It is usually pointed out that the D_k function fails to offer satisfactory results if the series suffers from (potential) multiple variance changes. (Inclan & Tiao, 1994) proposed a refined algorithm to overcome this problem by applying the D_k function recursively at different points in the sample. Initially, the D_k function is applied to the full sample to identify the first candidate of change point. Subsequently, the function is applied to the two sub-samples defined by the first break point. The whole process is repeated until no new break point is detected.

In addition to the criterion employed by most literature in this field where only the 95th percentile critical value of 1.358 is normally used, this work also tests the significance of breaks using critical values at 90th percentile of 1.224 and 99th percentile of 1.628 obtained from (Inclan & Tiao, 1994).

8.1.2 The GARCH family models

The GARCH family models provide ways to capture the volatility clustering – the famous characteristic for financial time series – where small changes in the series tend to be followed by small changes and larger changes tend to be followed by large changes, giving rise to contiguous periods of tranquillity and fluctuations. Furthermore, the GARCH class has the ability to capture the volatility persistence observed in a time series (Aggarwal, Inclan & Leal, 1999). Different from existing works where the 'shift dummies' for sudden changes in volatility detected by the ICSS algorithm are included as additional explanatory variables in GARCH models estimated using full sample data, this article applies GARCH models to both full sample and sub-samples defined by ICSS algorithm in order to analyse the effect of volatility breaks in GARCH models from a different perspective.

a. GARCH (1,1) model

The standard GARCH(1,1) model takes the form

$$y_t = \mu + e_t, \;\; e_t = \sigma_t \varepsilon_t, \;\; \varepsilon_t \sim i.i.d.\, D(0,1)$$
$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 \qquad \text{(1a;1b)}$$

where D represents a conditional density. It is generally required that $\omega > 0$ and $\alpha, \beta \geq 0$ to ensure that the conditional variance σ_t^2 is positive. The volatility persistence is controlled by $\alpha + \beta$. If $\alpha + \beta < 1$ the process is stationary and a volatility shock to the system will decay gradually as time elapses. If $\alpha + \beta = 1$, the IGARCH(1,1) should be used instead. If $\alpha + \beta < 1$, the unconditional variance for e_t is given by $\omega/(1-\alpha-\beta)$. It can be seen that β

is unidentified and set to zero when $\alpha = 0$. In this context, $\sigma_t^2 = \omega$ and e_t is conditional homoskedastic.

b. EGARCH (1,1) model

The EGARCH model is introduced by (Nelson, 1991) to account for the leverage or asymmetric effect – an unanticipated decrease in asset price resulting from bad news will increase the volatility more than an unanticipated rise in asset pricing of similar magnitude due to good news, which the standard GARCH(1,1) cannot capture. The conditional variance equation of the model is given as follows,

$$\ln(\sigma_t^2) = \omega + \alpha \frac{|e_{t-1}| + \lambda e_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) \tag{2}$$

It is worth noting that the combined effect of e_{t-1} is $(1+\lambda)|e_{t-1}|$ when there are some 'good news' (i.e. e_{t-1} is positive) while the combined effect becomes $(1-\lambda)|e_{t-1}|$ when there are some 'bad news' (i.e. e_{t-1} is negative). The leverage effect exists if λ is significant and less than zero.

c. GJR (1,1) model

As opposed to the EGARCH model, the GJR model proposed by (Glosten, Jagannathan & Runkle, 1993) is another way to model the asymmetric effect present in financial time series. The variance equation of the model takes the form,

$$\sigma_t^2 = \omega + \alpha e_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma I_{t-1}^- e_{t-1}^2 \tag{3}$$

where I_{t-1}^- is an indicator function and

$$I_{t-1}^- = \begin{cases} 1, & if \quad e_{t-1} < 0 \\ 0, & otherwise \end{cases}$$

It is clear from the setting above that the good news ($e_{t-1} > 0$) and bad news ($e_{t-1} < 0$) impact the conditional volatility differently. If γ is positive, then the negative shocks have a total effects of $(\alpha + \gamma)$ on the conditional volatility whereas the positive shocks only have an effect of α. Therefore, it is claimed that the leverage effect exists if γ is significant and greater than zero.

8.1.3 Distribution hypotheses

Two conditional densities for ε_t – Normal and Student-t – are utilised in the work. The use of normal distribution is a widely applied benchmark, while the student-t distribution is used to allow for the heavy-tailedness of financial time series, which is documented as a stylised fact in (Christoffersen, 2012: p.9). The existence of heavy-tailedness means that extreme events are more likely to occur than normal distribution would suggest. Two possible sources for heavy-tailedness are volatility clustering and breaks in asset returns (which may also imply sudden changes in volatility of returns) (Alfreedi, Isa & Hassan, 2012).

8.2 Out-of-Sample Tests

As mentioned in section 8.1, the last 30% of the whole sample is kept for out-of-sample performance tests. The number of observations in the 'in-sample' is denoted by R and the sample size for the 'out-of-sample' is denoted by P.

8.2.1 Volatility forecasting

In this work, the out-of-sample forecasts of conditional volatility of stock returns are performed by 1 benchmark model and 26 competing models – where the same type of GARCH model with normal and student-t densities are considered as two different models to investigate the impact of heavy tailed density on the conditional volatility forecasting in the presence of structural breaks. The competing models take into account structural breaks in volatility by applying various estimation windows.

a. Benchmark model

The benchmark model is the standard GARCH(1,1) model with an expanding estimation window and a normal conditional density (the GARCH(1,1) expanding window model with the student-t distribution is considered as a competing model to analyse the impact of fat-tailedness). More specifically, the GARCH(1,1) is firstly estimated using the observations 1 to R in order to product the first out-of-sample conditional volatility forecast at the 1-period horizon. The initial forecast is $\hat{\sigma}^2_{R+1|R} = \hat{\omega}_R + \hat{\alpha}_R e^2_R + \hat{\beta}_R \hat{\sigma}^2_R$, where $\hat{\omega}_R, \hat{\alpha}_R, \hat{\beta}_R, \hat{\sigma}^2_R$ are the estimates of $\omega_R, \alpha_R, \beta_R, \sigma^2_R$, respectively, in the equation (1b) estimated using the observations 1 to R. The estimation window is then expanded by 1 period to include the observations 1 to R+1 to generate a forecast for period R+2, $\hat{\sigma}^2_{R+2|R+1}$. The process is repeated until the last observation in the out-of-sample period. As a result, the total number of out-of-sample forecasts is P. According to (Rapach & Strauss, 2008), the GARCH(1,1) model with expanding window serves as a ‘natural benchmark’ which is appropriate ‘when the data are produced by a stable GARCH(1,1) process.’

b. Competing models

In addition to GARCH(1,1) expanding window model with the student-t conditional density, 25 competing models are considered in the work. One out of the 25 models is a naïve moving average model with a 0.5 rolling window using the mean of squared returns over the past periods. It is found in some literature that this model tends to have a better performance than the benchmark model, especially for forecasts at longer horizons (Starica, Herzel & Nord, 2005).

The remaining 24 models can be categorised into 3 types of models – GARCH(1,1), EGARCH(1,1) and GJR(1,1) – and each type of model is estimated with four estimation windows – ICSS window, rolling 0.25 window, rolling 0.5 window and rolling 0.75 window – and two conditional densities – normal and student-t. The process of each estimation window is explained.

ICSS window operates in the following way. The ICSS algorithm is firstly applied to the entire in-sample period. Suppose one or multiple structural breaks are detected by the algorithm and the last break is found at time T_{ICSS}. A GARCH type model is then estimated using observations from T_{ICSS} +1 to R in order to generate the first prediction. However, if no significant breaks are found or if the number of observations between T_{ICSS} +1 to R is less than 50, the expanding window is applied. This is because the author of the current thesis believes that at least 50 observations are required to generate reasonably good estimation and prediction results and mitigate the drawbacks mentioned in (Rapach & Strauss, 2008). Again, the process proceeds until the last observation of the out-of-sample period is reached.

Similar ideas are applied to the rolling window, apart from the fact that an estimation window with fixed length is used. When the first forecast is created, the whole window (i.e. the beginning and the end of the window) is moved 1-period ahead to renew the model estimation and generate the forecasts for the next period. The rolling window with different sizes is considered to analyse the trade-off between using more observations to generate more accurate parameter estimates and not relying too much on data from potentially different regimes. The 0.25, 0.5 and 0.75 window means that 25%, 50% and 75% of the in-sample period is used, respectively.

8.2.2 Combination of forecasts

The forecasts from eight models – GARCH(1,1) expanding window, GARCH(1,1) ICSS window, GARCH(1,1) 0.5 rolling window, EGARCH(1,1) ICSS window, EGARCH(1,1) 0.5

rolling window, GJR(1,1) ICSS window, GJR(1,1) 0.5 rolling window and moving average 0.5 rolling window – are employed to generate the combination forecasts.

Two combining methods are employed in the work. The first one simply averages the forecasts from 8 individual models. The second one uses a trimmed mean by taking the average after neglecting the minimum and maximum individual forecasts (Rapach & Strauss, 2008). (Stock and Watson, 2003) states that simple combining approached such as the mean and trimmed mean have satisfactory performance considering out-of-sample prediction practices. Detailed analysis will be provided in section 9.4.

8.2.3 The volatility forecast loss function

Two loss functions – the root mean squared error (RMSE) and Quasi-likelihood (QLIKE) are used in this work to evaluate the out-of-sample forecast performance. These two functions are chosen since (Patton, 2011) states that they are 'robust to noise in the volatility proxy.' According to (Christoffersen, 2012: p.85), the RMSE is given by:

$$RMSE = \sqrt{(R_{t+1}^2 - \sigma_{t+1}^2)^2}$$

In general, the RMSE will penalise more heavily large forecast errors than small ones due to the effecting of squaring.

Additionally, QLIKE is given by:

$$QLIKE = \frac{R_{t+1}^2}{\sigma_{t+1}^2} - \ln\left(\frac{R_{t+1}^2}{\sigma_{t+1}^2}\right) - 1$$

The QLIKE function tends to penalise more heavily when the model underestimates volatility. Hence, it allows for asymmetric loss (Christoffersen, 2012: p.85).

8.3 Data

The data consists of weekly closing prices for the stock market index in each of the BRIC countries – they are IBOV index for Brazil, RTS for Russia, S&P BSE SENSEX for India and SHCOMP for China. Also the weekly closing price for S&P 500 (U.S.), FTSE100 (U.K.), Nikkei 225 (Japan), FTSE MIB (Italy), CAC40 (France) and DAX (Germany) are also considered to form a comparative analysis.

The data covers the 20-year period from July 1993 to July 2013 (except for Russia and Italy, whose stock index data is available from 1995 and 1997, respectively). The sample spans from the starting period of the stock market of BRIC group to the most recent period.

Hence, most economic events and financial market reforms are taken into account. The idea of comparing the stock market behaviour between BRIC and G6 groups originates from (Purushothaman & Wilson, 2003). All the indices are obtained from the Bloomberg Terminal.

Daily and monthly closing prices for each stock market index are also collected. However, daily data contains too much noise and monthly data does not offer enough number of observations for modelling purpose. The weekly data has the best behaviour among the three data frequencies after several unit root test and autocorrelation analyses are conducted. This is consistent with (Aggarwal, Inclan & Leal, 1999) that weekly data is less noisy than daily data which suffers from issues such as non-synchronous trading and short term correlations caused by noise.

9. Empirical Analysis and Results

9.1 Unit Root Tests

It is a common and crucial practice to test the unit root for the time series of interest before conducting any regression or modelling practices. Table 1 below shows the test outputs for the price series using three unit root tests: Augmented Dickey-Fuller (ADF), Philips and Perron (PP) and Kwiatkowski, Philips, Schmidt and Shin (KPSS) tests.

Table 1 Unit Root Test for Price Series - BRIC

	Brazil	Russia	India	China
ADF (Intercept)	-1.126 [0.684]	-1.637 [0.457]	-0.275 [0.926]	-2.102 [0.251]
ADF (Intercept and Trend)	-2.288 [0.45]	-2.608 [0.292]	-2.089 [0.548]	-2.627 [0.282]
PP (Intercept)	-1.125 [0.684]	-1.455 [0.538]	-0.36 [0.913]	-1.761 [0.402]
PP (Intercept and Trend)	-2.265 [0.461]	-2.259 [0.464]	-2.125 [0.53]	-2.142 [0.522]
KPSS (Intercept)	8.611** [0.01]	6.462** [0.01]	8.032** [0.01]	4.988** [0.01]
KPSS (Intercept and Trend)	1.053** [0.01]	0.503** [0.01]	1.52** [0.01]	0.269** [0.01]
Sample Size	1048	926	1045	1009

Notes: 1. P-values are given in the square brackets.

2. * and ** denote that the test is significant under 5% and 1% significance level respectively.

As is shown in the table, the tests are conducted with two specifications: intercept only and both intercept and trend. It is suggested to investigate the behaviour of each price series in order to determine the proper options to refer to.

It is clear from the graph that all the price series have both intercept and trend. Therefore, it is easy to read from table 1 that all the four series are not stationary. Accordingly, the log return series $R_t = \log(P_t / P_{t-1})$ is calculated to convert all the series to stationary ones.

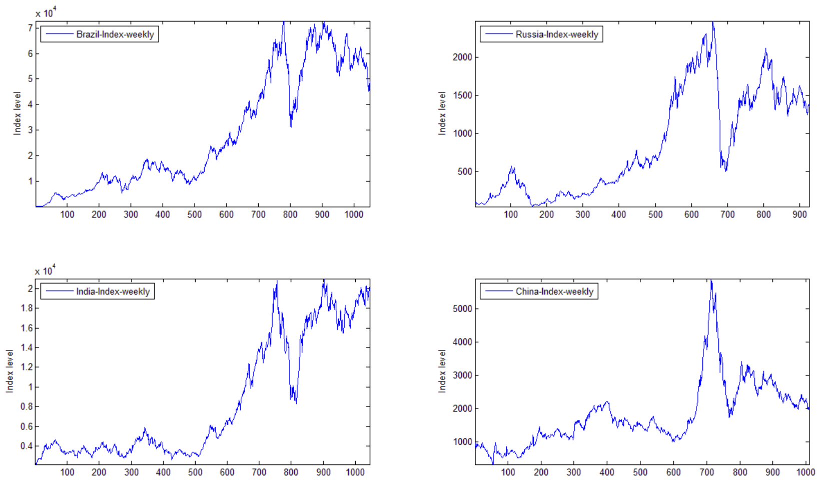

Figure 1 Price Series Plot - BRIC

It is confirmed in Appendix 1 that all the return series are stationary and are ready to use. Moreover, the results for the G6 counterparts are similar to those for the BRIC countries and are not provided in order to conserve space.

9.2 Descriptive Statistics and Diagnostic Tests

9.2.1 Descriptive statistics

Table 2 Descriptive Statistics for Return Series July 1993 – July 2013 - BRIC

	Brazil	Russia	India	China
Index	IBOV	RTS	S&P BSE SENSEX	SHCOMP
Constituents	around 50	50	30	all traded stocks (A shares&B shares)
Mean	0.0065**	0.0028	0.0021	0.0007
Std. Dev	0.0521**	0.0647**	0.0351**	0.0468**
Skew ness	0.1192	-0.399**	-0.2098**	3.9547**
Excess Kurtosis	3.3568**	4.0979**	1.8527**	58.1864**
Maximum	0.2478	0.3419	0.1317	0.7157
Minimum	-0.2506	-0.3411	-0.1738	-0.2263
Jarque-Bera test	494.04	671.77	156.97	144825.16
P-Value (JB)	0.001**	0.001**	0.001**	0.001**

Notes: 1. * and ** denote that the figure is significantly different from 0 under 5% and 1% sig

2. the value of 0.001 for P-Value (JB) indicates that it is less than 0.0005

Table 2 displays the descriptive statistics for stock return series of the BRIC group over the whole period from July 1993 to July 2013. It can be seen that all the means of returns are statistically insignificant from zero except for Brazil, whereas none of the returns of G6 countries (from Table 3) have a mean significant from zero. Furthermore, it is clear by comparing the two tables that the standard deviations of returns from BRIC countries are much higher than those from G6 countries. The standard deviations from G6 countries range from about 2.5% to 3.5% while those from BRIC countries range from 3.5% to 6.5%, indicating the generally higher risks and uncertainties contained in those (advanced) emerging markets relative to developed markets. More interesting patterns are found by investigating the skewness and kurtosis for both BRIC and G6 group. Although the skewness figures of G6 are all very close to -1, the skewness figures of BRIC are not so different from zero. And China's stock market even has a large and positive value for skewness, suggesting that positive returns are on average experienced more often than the negative ones. This can be a very attractive feature for some investors and financial institutions. More strikingly, the kurtosis values for BRIC countries, which range from 1.85 to 4.1 – are generally lower than those for G6 countries, which range from 4.97 to 10.66. This means that all the return distributions contain fat-tails as well as high peakedness but large gains and losses occur less frequently in BRIC countries than in G6 countries, except for China. Finally, Jarque-Beta normality test has been significantly rejected for all the series, suggesting that returns for both BRIC and G6 group are not normally distributed.

Table 3 Descriptive Statistics for Return Series July 1993 – July 2013 - G6

	US	UK	Japan	Italy	France	Germany
Index	S&P 500	FTSE 100	Nikkei 225	FTSE MIB	CAC 40	DAX
Constituents	500	100	225	40	40	30
Mean	0.0013	0.0008	-0.0003	-0.0005	0.0007	0.0015
Std. Dev	0.0245**	0.0243**	0.0305**	0.0347**	0.0305**	0.0324**
Skew ness	-0.7702**	-0.9947**	-0.8634**	-0.7497**	-0.7296**	-0.6571**
Excess Kurtosis	6.598**	10.6636**	7.1844**	5.9267**	5.3257**	4.9707**
Maximum	0.1136	0.1258	0.1145	0.1936	0.1243	0.1494
Minimum	-0.2008	-0.2363	-0.2788	-0.2436	-0.2505	-0.2435
Jarque-Bera test	2002.69	5133.35	2381.82	1264.48	1330.22	1153.25
P-Value (JB)	0.001**	0.001**	0.001**	0.001**	0.001**	0.001**

Notes: 1. * and ** denote that the figure is significantly different from 0 under 5% and 1% significance level respectively.
2. the value of 0.001 for P-Value (JB) indicates that it is less than 0.0005

9.2.2 Diagnostic tests

Table 4 Diagnostic Tests - BRIC Return

	Brazil	Russia	India	China
Q (1)	4.336*	7.203**	1.959	0.32
	[0.037]	[0.007]	[0.162]	[0.572]
Q (8)	99.615**	35.649**	15.254	3.75
	[0.001]	[0.001]	[0.054]	[0.879]
Q (12)	130.381**	46.834**	24.543*	8.806
	[0.001]	[0.001]	[0.017]	[0.719]
Q (16)	168.114**	48.468**	29.452*	13.038
	[0.001]	[0.001]	[0.021]	[0.67]
Q^2 (1)	71.145**	74.038**	21.418**	0.635
	[0.001]	[0.001]	[0.001]	[0.425]
Q^2 (8)	491.044**	373.131**	94.06**	7.023
	[0.001]	[0.001]	[0.001]	[0.534]
Q^2 (12)	611.599**	423.11**	109.516**	7.351
	[0.001]	[0.001]	[0.001]	[0.834]
Q^2 (16)	763.515**	461.614**	139.965**	7.837
	[0.001]	[0.001]	[0.001]	[0.954]
ARCH LM (2)	125.523**	110.937**	36.196**	1.505
	[0.001]	[0.001]	[0.001]	[0.471]
ARCH LM (12)	197.503**	157.863**	73.108**	6.329
	[0.001]	[0.001]	[0.001]	[0.899]

Note: 1. Q(lag order) and Q^2(lag order) is the Ljung-Box Q statistics for return and squared return series, respectively.
2. ARCH LM is Engles Lagrange Multiplier test for arch effect.
3. P-values are given in the square brackets.
4. * and ** denote that the test is significant under 5% and 1% significance level respectively.

Table 4 displays the diagnostic test for the returns of each BRIC country. The lag orders of 8, 12 and 16 for Q statistics are the common choices in the literature such as (Aggarwal, Inclan & Leal, 1999) and (Kang, Cho & Yoon, 2009), and the lag orders of 2 and 12 are also generally chosen by researchers, see, for example, (Rapach & Strauss, 2008). All the squared return series of BRIC countries except for China exhibit strong evidence of autocorrelation in return volatility and ARCH effects, judging from the test results of Q^2 and ARCH LM. However, the return series for Brazil and Russia are also autocorrelated, which seems to be inconsistent with the stylised fact that the return series should have little autocorrelation with its own past values (Christoffersen, 2012: p.9). A plot of autocorrelation functions for the squared return series and return series for the BRIC countries is shown in Appendix 2a and 2b, respectively. Nevertheless, it is clear from the plot that the autocorrelation for return series is considerably weaker than that for squared return series, which does not contradict the stylised fact too much. Similarly, the results for the G6 counterparts are similar to those for the BRIC countries and are not provided to conserve space. Overall, the results in table 4 justify the application of GARCH-family models to stock price returns of BRIC and G6 countries.

9.3 In-Sample Test Results

We turn to discuss the results for in-sample analyses after all the fundamental analyses are conducted. Firstly the structural breaks detected by the ICSS algorithm as well as the events associated with each sub-period will be investigated, followed by a discussion of some estimation results for GARCH model.

9.3.1 Structural breaks in variance

Table 5 Structural Breaks in Volatility and Events - BRIC

	# of breaks	Subperiod	Sample size	Stdev	%Change in Stdev	Events
Brazil	6	09-Jul-1993 to'28-Apr-1995	95	9.21%		
		05-May-1995 to'11-Jul-1997	115	3.61%	-60.80%	acknow ledgement of slavery in the country
		18-Jul-1997 to'19-Mar-1999	88	7.63%	111.36%	constitutional change to re-elect president
		26-Mar-1999 to'24-Jan-2003	201	4.78%	-37.35%	sudden change to floating foreign exchange rate system
		31-Jan-2003 to'19-Sep-2008	295	3.45%	-27.82%	rise of the middle class
		26-Sep-2008 to'24-Jul-2009	44	7.44%	115.65%	receival of first reliable S&P investment grade
		31-Jul-2009 to'26-Jul-2013	209	2.83%	-61.96%	now a creditor of the IMF funding its investments, record employment 2010
Russia	5	08-Sep-1995 to'17-Oct-1997	110	7.20%		Chechen War, Chechnya: new president in 97
		24-Oct-1997 to'16-Oct-1998	52	12.19%	69.31%	
		23-Oct-1998 to'16-Mar-2001	126	8.12%	-33.39%	rouble collapses, GDP plummeted, joins APEC (Asia Pacific Economic Corp.)
		23-Mar-2001 to'18-Jul-2008	379	3.94%	-51.48%	
		25-Jul-2008 to'17-Jul-2009	51	11.17%	183.50%	Russian stock market 50% dow n
		24-Jul-2009 to'26-Jul-2013	207	4.13%	-63.03%	GDP declines 11% over previous year
India	4	11-Jul-1993 to'17-May-1998	251	3.44%		large borrow ing from the IMF and World Bank and massive economic reforms
		24-May-1998 to'14-Oct-2001	178	4.44%	29.07%	
		21-Oct-2001 to'16-Sep-2007	309	2.69%	-39.41%	sustained high GDP grow th
		23-Sep-2007 to'19-Jul-2009	96	5.51%	104.83%	GDP at 10% grow th rate
		26-Jul-2009 to'28-Jul-2013	210	2.45%	-55.54%	
China	7	09-Jul-1993 to'08-Jul-1994	52	4.82%		Economy Reform
		15-Jul-1994 to'12-Aug-1994	5	35.29%	632.16%	Tax Reform (set up a streamlined tax system); Fiscal Reform (decentralization)
		19-Aug-1994 to'19-May-1995	39	8.73%	-75.26%	
		26-May-1995 to'03-Oct-1997	120	5.27%	-39.63%	
		10-Oct-1997 to'15-Dec-2006	456	2.95%	-44.02%	Asian Financial Crisis
		22-Dec-2006 to'27-Mar-2009	115	5.49%	86.10%	China's economy expanded by 10.7% in 2006
		03-Apr-2009 to'12-Nov-2010	84	3.42%	-37.70%	
		19-Nov-2010 to'26-Jul-2013	137	2.35%	-31.29%	China's economy grew 10.3% in 2010

Table 5 reports the number of breaks for each BRIC country, the beginning and ending time of each sub-period and the economic and political events corresponding to each sub-sample defined by the ICSS algorithm. The table for the G6 counterpart can be found in Appendix 3. It is conspicuous from the table 5 that the standard deviation in each sub-interval varies substantially across periods. And the duration of each break period for BRIC countries varies considerably, ranging from as short as 5 weeks (about 1 month) to as long as 456 weeks (about 9 years). The standard deviation changes less dramatically for G6 countries, and the duration of each break period for G6 countries tends to spread out more evenly than for the BRIC countries. The level of sub-sample standard deviation for the BRIC group is on average higher than that for the G6 counterpart, implying a higher uncertainty for BRIC countries not only for the whole sample but also for each interval. However, more breaks are detected for G6 than for BRIC, partly indicating that the stock market in those developed economies is in general more liquid and is more responsive to news.

Although it is stated that ‘as a posterior one can probably always find some event that is relatively close to a detected structural break that could conceivably have caused the break’ (Rapach & Strauss, 2008), it is still valuable to conduct an event-identification exercise for the sub-samples defined by the variance breaks. Seeing from table 5 (and Appendix 3), it seems that the ICSS algorithm has performed reasonably well in defining different sub-period of unconditional variance shifts. The algorithm successfully identified Tax reform occurred in China in 1994, Dot com crisis started in the U.S. at the beginning of 21 century and the recent financial crisis, among other events. It is worth highlighting that the recent financial crisis has a greater impact on the G6 market than on the BRIC market, judging from the percentage change in standard deviation. The percentage increase in the standard deviation of each BRIC country during the crisis period ranges from 86.1% (China) to 183.5% (Russia), whereas the percentage increase of each G6 country ranges from 143.6% (Japan) to 290.6% (Germany). Furthermore, recent years have witnessed a large decrease in standard deviation of each BRIC and G6 country by about 50% to 60% as the world’s economy is recovering from the recession.

A plot for return and 3-standard-deviation bands computed according to each sub-period is shown below to visualise the breaks.

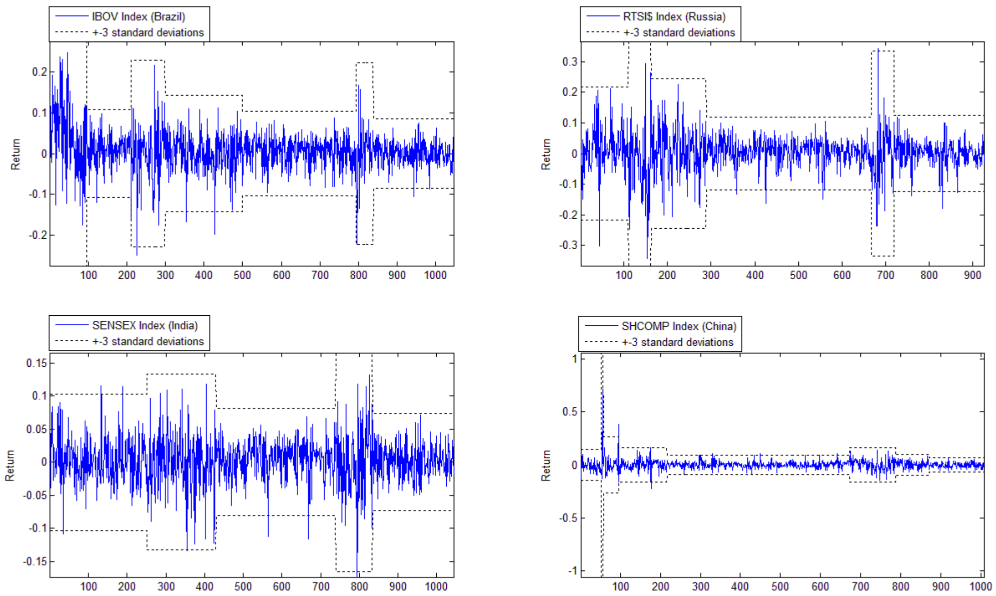

Figure 2 Return and Three-Stdev Bands - BRIC

9.3.2 GARCH model estimation and diagnostics

a. Parameter estimation

Table 6 reports the full-sample estimation results of GARCH(1,1) model for each BRIC country's stock return series, as well as the estimation results of GARCH(1,1) model for each sub-sample defined by variance breaks detected by the ICSS algorithm. Inspection of parameter estimates shows that $\hat{\alpha}+\hat{\beta}$ ranges from 0.941 to 1 in the case of full-sample. This implies that the GARCH processes are highly persistent, which is in line with the existing literature. Interestingly, the volatility persistence disappears in many sub-periods for for Brazil (sub-period 2, 4, 5-normal and 7-student t) and China (sub-period 6-student t and 7-normal). In these cases, $\hat{\alpha}=0$, meaning that these sub-periods are characterised by conditional homoskedasticity[5]. It is clear from Table 6 that the structural breaks cause substantial changes in the value of the GARCH model intercept $\hat{\omega}$, which in turn give rise to sizable shifts in the unconditional variance, $\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$, across sub-samples. In addition, the estimation results can be very different when different distributions are applied; see, for example, sub-period 5 and 7 for Brazil as well as sub-period 6, 7 and 8 for China[6]. In general, the shifts in the unconditional variance and the large variations in the parameter estimates across sub-periods indicate that it is empirically relevant to consider structural breaks in volatility of stock returns of BRIC and G6 countries (the estimation results for the G6 countries share similar patterns to the results for the BRIC countries and are not provided to conserve space).

The estimation results of EGARCH(1,1) model and GJR(1,1) model are displayed in Appendix 4a and 4b, respectively. A detailed investigation of both 4a and 4b reveals the following points. Firstly, the stock returns of all the BRIC countries (except Russia) exhibit leverage effects, suggested by the negative and significant leverage parameter $\hat{\lambda}$ of EGARCH model as well as positive and significant leverage parameter $\hat{\gamma}$ of GJR model, respectively. The EGARCH model shows more significant results of the leverage effects than the GJR model. Secondly, the EGARCH model offers more significant parameter estimates across sub-periods than the GJR model does. For the EGARCH case, there are only 3 sub-samples in which none of the ARCH ($\hat{\alpha}$), GARCH ($\hat{\beta}$) and Leverage ($\hat{\lambda}$) parameters are significant (with either normal or student t density). Whereas there are 11

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[5] In some cases, the value of $\hat{\alpha}$ is extremely small and displays as zero in the table 6 due to the rounding issue.

[6] It is still worth conducting the analysis even though the parameter estimates are not significant (under 5% level) in many sub-samples. This is probably caused by the insufficient observations in those sub-samples since the sub-samples containing significant parameter estimates all have a large number of observations.

sub-samples where none of the $\hat{\alpha}$, $\hat{\beta}$ and $\hat{\gamma}$ are significant when the GJR model is employed. This suggests that the EGARCH model has more explanatory power than the GJR model in this context. Thirdly, there are substantial variations in all the parameter estimates (including intercept term $\hat{\omega}$) across sub-samples for both EGARCH and GJR models. Fourthly, the use of different distributions (normal v.s. student t) can generate very different results in some scenarios; see, for instance, sub-period 3 for Brazil, 3 for Russia and 2 for China in Appendix 4a, and sub-period 2 and 5 for Brazil in Appendix 4b.

b. Volatility persistence

Table 7 summarises both the full-sample and sub-sample estimation results of volatility persistence measured by the GARCH(1,1), EGARCH(1,1) and GJR models. It is clear that the levels of persistence are quite high when each model is estimated using the full sample. None of the persistence level in any model is below 0.94. However, results in sub-samples show completely different pictures. In terms of GARCH model, it can be seen that the value of persistence ranges from as low as 0 in sub-period 5 for Brazil to as high as 1 in sub-period 8 for China. For EGARCH model, the persistence level ranges from 0.008 in sub-period 3 for Russia with normal distribution to 0.972 in sub-period 4 for Russia with normal distribution. For GJR model, the persistence level is between 0.003 in sub-period 5 for Brazil with normal distribution and 1 in sub-period 2 for China with student t distribution. Moreover, in many sub-samples the persistence is far lower than 1 for all the three models, and in many cases the persistence levels are different under different distributions; see, for example, sub-period 2 for China under EGARCH and 3 for Russia under GJR, among others.

Table 6 Estimation Results from GARCH(1,1) - BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample estimation output							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
$\hat{\omega}$	0.0001 (0)**	0.0001 (0)**	0.0001 (0)**	0.0001 (0)*	0 (0)**	0 (0)*	0.0001 (0)**	0.0001 (0)**
$\hat{\alpha}$	0.13 (0.019)**	0.112 (0.024)**	0.119 (0.013)**	0.158 (0.034)**	0.082 (0.015)**	0.098 (0.025)**	0.329 (0.022)**	0.184 (0.04)**
$\hat{\beta}$	0.843 (0.021)**	0.861 (0.027)**	0.87 (0.01)**	0.828 (0.029)**	0.898 (0.017)**	0.865 (0.031)**	0.671 (0.022)**	0.757 (0.047)**
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.003	0.002	0.006	0.007	0.001	0.001	53003.394	0.002
	Panel 2: subperiod estimation output							
Subperiod 1	09-Jul-1993 to28-Apr-1995		08-Sep-1995 to17-Oct-1997		11-Jul-1993 to17-May-1998		09-Jul-1993 to08-Jul-1994	
$\hat{\omega}$	0.0025 (0.0099)	0.0025 (0.0104)	0.001 (0.0012)	0.0012 (0.0019)	0.001 (0.0006)	0.001 (0.0006)	0 (0.0014)	0 (0.0015)
$\hat{\alpha}$	0.052 (0.151)	0.053 (0.169)	0.109 (0.132)	0.097 (0.14)	0.156 (0.086)	0.14 (0.089)	0 (0.087)	0 (0.093)
$\hat{\beta}$	0.65 (1.267)	0.65 (1.32)	0.692 (0.336)*	0.693 (0.441)	0 (0.481)	0 (0.536)	0.978 (0.708)	0.975 (0.786)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.008	0.009	0.005	0.005	0.001	0.001	0.002	0.002
Subperiod 2	05-May-1995 to11-Jul-1997		24-Oct-1997 to16-Oct-1998		24-May-1998 to14-Oct-2001		15-Jul-1994 to12-Aug-1994	
$\hat{\omega}$	0 (0)	0.0013 (0.4244)	0.0013 (0.0041)	0.001 (0.0032)	0.0019 (0.0052)	0.002 (0.0045)	0.0054 (4.5711)	5 (4758.4141)
$\hat{\alpha}$	0 (0.016)	0 (0.111)	0.117 (0.231)	0.153 (0.273)	0.027 (0.054)	0.039 (0.082)	0 (1.258)	0 (453.331)
$\hat{\beta}$	0.997 (0.048)**	0.015 (328.153)	0.813 (0.464)	0.804 (0.407)*	0 (2.662)	0 (2.274)	1 (40.699)	1 (8.833)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0	0.001	0.018	0.023	0.002	0.002	2704723.39	2499999932
Subperiod 3	18-Jul-1997 to19-Mar-1999		23-Oct-1998 to16-Mar-2001		21-Oct-2001 to16-Sep-2007		19-Aug-1994 to19-May-1995	
$\hat{\omega}$	0.0027 (0.0013)*	0.0007 (0.001)	0.0055 (0.0045)	0.0055 (0.0046)	0.0001 (0.0001)	0.0002 (0.0001)	0.0013 (0.3412)	0.0009 (0.0023)
$\hat{\alpha}$	0.511 (0.219)*	0.15 (0.136)	0.163 (0.154)	0.164 (0.161)	0.154 (0.076)*	0.178 (0.096)	0 (0.278)	0.251 (0.502)
$\hat{\beta}$	0.154 (0.221)	0.743 (0.239)**	0 (0.751)	0 (0.753)	0.679 (0.124)**	0.593 (0.189)**	0.822 (46.451)	0.733 (0.492)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.008	0.006	0.007	0.007	0.001	0.001	0.007	0.052
Subperiod 4	26-Mar-1999 to24-Jan-2003		23-Mar-2001 to18-Jul-2008		23-Sep-2007 to19-Jul-2009		26-May-1995 to03-Oct-1997	
$\hat{\omega}$	0.0023 (0.5606)	0.0022 (0.4792)	0.0003 (0.0002)	0.0003 (0.0003)	0.0013 (0.0034)	0.0012 (0.004)	0.0009 (0.0004)*	0.0011 (0.0008)
$\hat{\alpha}$	0 (0.092)	0 (0.1)	0.095 (0.038)*	0.089 (0.061)	0.081 (0.18)	0.082 (0.197)	0.382 (0.159)*	0.188 (0.162)
$\hat{\beta}$	0.006 (247.007)	0 (213.001)	0.707 (0.151)**	0.699 (0.226)**	0.493 (1.302)	0.517 (1.516)	0.327 (0.195)	0.396 (0.398)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.002	0.002	0.002	0.002	0.003	0.003	0.003	0.003
Subperiod 5	31-Jan-2003 to19-Sep-2008		25-Jul-2008 to17-Jul-2009		26-Jul-2009 to28-Jul-2013		10-Oct-1997 to15-Dec-2006	
$\hat{\omega}$	0.0012 (0.0743)	0.001 (0.0001)**	0.0038 (0.0062)	0.0038 (0.0068)	0.0001 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)**	0.0002 (0.0001)
$\hat{\alpha}$	0 (0.056)	0 (0.057)	0.292 (0.275)	0.292 (0.309)	0.129 (0.093)	0.129 (0.098)	0.175 (0.054)**	0.143 (0.063)*
$\hat{\beta}$	0.003 (62.519)	0.131 (0)**	0.372 (0.731)	0.372 (0.755)	0.753 (0.197)**	0.754 (0.198)**	0.566 (0.117)**	0.653 (0.156)**
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.001	0.001	0.011	0.011	0.001	0.001	0.001	0.001
Subperiod 6	26-Sep-2008 to24-Jul-2009		24-Jul-2009 to26-Jul-2013				22-Dec-2006 to27-Mar-2009	
$\hat{\omega}$	0.0002 (0.0004)	0.0002 (0.0005)	0.0001 (0.0001)	0.0001 (0.0001)			0 (0.0013)	0.0027 (0.9336)
$\hat{\alpha}$	0.222 (0.152)	0.22 (0.177)	0.096 (0.038)*	0.089 (0.061)			0 (0.057)	0 (0.079)
$\hat{\beta}$	0.686 (0.256)**	0.689 (0.32)*	0.841 (0.069)**	0.845 (0.113)**			1 (0.465)*	0.091 (312.583)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.003	0.003	0.002	0.002			1834.743	0.003
Subperiod 7	31-Jul-2009 to26-Jul-2013						03-Apr-2009 to12-Nov-2010	
$\hat{\omega}$	0.0001 (0.0001)	0.0007 (0.5382)					0.0011 (2.2707)	0.0001 (0.0041)
$\hat{\alpha}$	0.035 (0.044)	0 (0.098)					0 (0.158)	0 (0.081)
$\hat{\beta}$	0.867 (0.206)**	0.072 (673.571)					0.048 (1962.411)	0.914 (3.456)
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$	0.001	0.001					0.001	0.001
Subperiod 8							19-Nov-2010 to26-Jul-2013	
$\hat{\omega}$							0.0003 (0.0008)	0 (0.0001)
$\hat{\alpha}$							0.065 (0.105)	0 (0.048)
$\hat{\beta}$							0.332 (1.513)	1 (0.264)**
$\hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$							0.001	282.242

Note: 1. Standard errors are show n in parentheses; 2. * and ** denotes statistical significance under 5% and 1% level, respectively.

Table 7 Persistence Table - BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample results							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.972	0.973	0.989	0.986	0.980	0.964	1.000	0.941
EGARCH ($\hat{\beta}$)	0.975	0.977	0.975	0.965	0.970	0.942	0.947	0.961
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.975	0.974	0.989	0.986	0.971	0.952	1.000	0.949
	Panel 2: subperiod results							
Subperiod 1	09-Jul-1993 to'28-Apr-1995		08-Sep-1995 to'17-Oct-1997		11-Jul-1993 to'17-May-1998		09-Jul-1993 to'08-Jul-1994	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.702	0.703	0.800	0.790	0.156	0.140	0.978	0.975
EGARCH ($\hat{\beta}$)	0.958	0.953	0.874	0.867	0.261	0.309	0.856	0.848
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.310	0.311	0.858	0.857	0.171	0.139	0.803	0.799
Subperiod 2	05-May-1995 to'11-Jul-1997		24-Oct-1997 to'16-Oct-1998		24-May-1998 to'14-Oct-2001		15-Jul-1994 to'12-Aug-1994	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.997	0.015	0.929	0.957	0.027	0.039	1.000	1.000
EGARCH ($\hat{\beta}$)	0.252	0.252	0.855	0.917	0.899	0.897	0.252	0.943
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.998	0.730	0.953	0.962	0.034	0.045	0.962	1.000
Subperiod 3	18-Jul-1997 to'19-Mar-1999		23-Oct-1998 to'16-Mar-2001		21-Oct-2001 to'16-Sep-2007		19-Aug-1994 to'19-May-1995	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.665	0.893	0.163	0.164	0.833	0.771	0.822	0.983
EGARCH ($\hat{\beta}$)	0.518	0.912	0.008	0.856	0.547	0.603	0.904	0.948
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.422	0.367	0.163	0.163	0.593	0.595	0.822	0.981
Subperiod 4	26-Mar-1999 to'24-Jan-2003		23-Mar-2001 to'18-Jul-2008		23-Sep-2007 to'19-Jul-2009		26-May-1995 to'03-Oct-1997	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.006	0.000	0.802	0.788	0.574	0.599	0.710	0.583
EGARCH ($\hat{\beta}$)	0.185	0.185	0.972	0.962	0.629	0.629	0.781	0.685
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.216	0.136	0.974	0.959	0.629	0.641	0.781	0.730
Subperiod 5	31-Jan-2003 to'19-Sep-2008		25-Jul-2008 to'17-Jul-2009		26-Jul-2009 to'28-Jul-2013		10-Oct-1997 to'15-Dec-2006	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.003	0.131	0.664	0.665	0.882	0.883	0.741	0.796
EGARCH ($\hat{\beta}$)	0.260	0.260	0.806	0.796	0.819	0.820	0.785	0.840
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.003	0.190	0.756	0.757	0.851	0.853	0.770	0.813
Subperiod 6	26-Sep-2008 to'24-Jul-2009		24-Jul-2009 to'26-Jul-2013				22-Dec-2006 to'27-Mar-2009	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.908	0.909	0.937	0.935			1.000	0.091
EGARCH ($\hat{\beta}$)	0.853	0.832	0.801	0.886			0.852	0.836
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.852	0.854	0.923	0.931			0.967	0.968
Subperiod 7	31-Jul-2009 to'26-Jul-2013						03-Apr-2009 to'12-Nov-2010	
GARCH ($\hat{\alpha}+\hat{\beta}$)	0.902	0.072					0.048	0.914
EGARCH ($\hat{\beta}$)	0.949	0.302					0.261	0.261
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)	0.927	0.935					0.219	0.228
Subperiod 8							19-Nov-2010 to'26-Jul-2013	
GARCH ($\hat{\alpha}+\hat{\beta}$)							0.397	1.000
EGARCH ($\hat{\beta}$)							0.917	0.334
GJR ($\hat{\alpha}+\hat{\beta}+\hat{\gamma}/2$)							0.099	0.099

c. Diagnostics

Table 8 GARCH Model Diagnostics - BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample estimation output							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
Q(16)	44.55 [0]	46.621 [0]	32.355 [0.009]	30.092 [0.018]	26.316 [0.05]	26.64 [0.046]	26.672 [0.045]	22.371 [0.132]
Q^2(16)	14.676 [0.548]	15.557 [0.484]	5.338 [0.994]	4.106 [0.999]	19.419 [0.248]	18.197 [0.313]	2.699 [1]	1.785 [1]
LM(12)	7.998 [0.785]	7.842 [0.797]	2.67 [0.997]	2.167 [0.999]	15.354 [0.223]	13.999 [0.301]	2.09 [0.999]	1.228 [1]
AIC	-3521	-3553	-2753	-2803	-4126	-4151	-3700	-3816
BIC	-3501	-3529	-2734	-2779	-4106	-4126	-3681	-3792
LL	1764	1782	1381	1407	2067	2080	1854	1913
Sample size	1047		925		1044		1008	
	For comparison: sum across all subperiods							
AIC	-3599	-3595	-2793	-2821	-4177	-4185	-3819	-3843
BIC	-3520	-3495	-2726	-2738	-4112	-4103	-3746	-3751
LL	1828	1832	1421	1441	2109	2117	1942	1961
Sample size	1047		925		1044		1008	
	Panel 2: subperiod estimation output							
Subperiod 1	09-Jul-1993 to 28-Apr-1995		08-Sep-1995 to 17-Oct-1997		11-Jul-1993 to 17-May-1998		09-Jul-1993 to 08-Jul-1994	
Q(16)	49.13 [0]	49.136 [0]	12.496 [0.709]	12.448 [0.713]	15.538 [0.486]	15.417 [0.494]	12.583 [0.703]	12.593 [0.702]
Q^2(16)	14.34 [0.573]	14.384 [0.57]	9.387 [0.897]	9.97 [0.868]	16.91 [0.391]	17.232 [0.371]	14.506 [0.561]	14.543 [0.558]
LM(12)	12.13 [0.435]	12.151 [0.434]	7.718 [0.807]	8.278 [0.763]	11.932 [0.451]	12.739 [0.388]	18.402 [0.104]	18.539 [0.1]
AIC	-177	-175	-263	-271	-979	-978	-161	-159
BIC	-167	-162	-253	-258	-964	-960	-153	-149
LL	92	92	136	141	493	494	85	85
Sample size	95		110		251		52	
Subperiod 2	05-May-1995 to 11-Jul-1997		24-Oct-1997 to 16-Oct-1998		24-May-1998 to 14-Oct-2001		15-Jul-1994 to 12-Aug-1994	
Q(16)	16.032 [0.451]	16.711 [0.405]	20.098 [0.216]	20.586 [0.195]	12.041 [0.741]	12.052 [0.74]	1.138 [0.768]	1.117 [0.773]
Q^2(16)	14.44 [0.566]	16.016 [0.452]	10.87 [0.817]	9.693 [0.882]	15.822 [0.465]	16.286 [0.433]	1.724 [0.632]	1.334 [0.721]
LM(12)	4.727 [0.966]	4.456 [0.974]	8.92 [0.71]	6.842 [0.868]	14.572 [0.266]	14.699 [0.258]	2 [0.572]	2 [0.572]
AIC	-433	-432	-66	-65	-597	-600	11	7
BIC	-422	-418	-58	-55	-584	-584	9	5
LL	220	221	37	38	302	305	-1	1
Sample size	115		52		178		5	
Subperiod 3	18-Jul-1997 to 19-Mar-1999		23-Oct-1998 to 16-Mar-2001		21-Oct-2001 to 16-Sep-2007		19-Aug-1994 to 19-May-1995	
Q(16)	13.221 [0.657]	14.012 [0.598]	25.379 [0.063]	25.378 [0.063]	21.94 [0.145]	21.519 [0.159]	5.411 [0.993]	4.382 [0.998]
Q^2(16)	13.175 [0.66]	7.957 [0.95]	13.679 [0.623]	13.454 [0.639]	6.091 [0.987]	6.803 [0.977]	0.582 [1]	0.268 [1]
LM(12)	6.215 [0.905]	3.274 [0.993]	4.749 [0.966]	4.716 [0.967]	4.617 [0.97]	5.463 [0.941]	18.696 [0.096]	18.576 [0.099]
AIC	-200	-200	-271	-269	-1358	-1367	-73	-87
BIC	-190	-187	-259	-255	-1344	-1348	-66	-78
LL	104	105	139	139	683	688	40	48
Sample size	88		126		309		39	
Subperiod 4	26-Mar-1999 to 24-Jan-2003		23-Mar-2001 to 18-Jul-2008		23-Sep-2007 to 19-Jul-2009		26-May-1995 to 03-Oct-1997	
Q(16)	17.091 [0.38]	17.091 [0.38]	14.061 [0.594]	13.999 [0.599]	25.75 [0.058]	25.76 [0.058]	23.583 [0.099]	22.882 [0.117]
Q^2(16)	8.436 [0.935]	7.994 [0.949]	14.62 [0.553]	14.752 [0.543]	10.17 [0.858]	10.188 [0.857]	7.255 [0.968]	8.237 [0.942]
LM(12)	7.07 [0.853]	6.634 [0.881]	12.918 [0.375]	13.165 [0.357]	10.001 [0.616]	9.789 [0.634]	5.188 [0.951]	7.73 [0.806]
AIC	-645	-649	-1377	-1386	-278	-276	-374	-374
BIC	-632	-633	-1361	-1366	-268	-264	-363	-360
LL	327	330	693	698	143	143	191	192
Sample size	201		379		96		120	
Subperiod 5	31-Jan-2003 to 19-Sep-2008		25-Jul-2008 to 17-Jul-2009		26-Jul-2009 to 28-Jul-2013		10-Oct-1997 to 15-Dec-2006	
Q(16)	19.9 [0.225]	19.9 [0.225]	16.704 [0.405]	16.709 [0.405]	17.837 [0.334]	17.826 [0.334]	13.834 [0.611]	13.922 [0.604]
Q^2(16)	20.263 [0.209]	20.223 [0.21]	29.239 [0.022]	29.277 [0.022]	6.487 [0.982]	6.477 [0.982]	12.316 [0.722]	11.82 [0.756]
LM(12)	21.085 [0.049]	21.084 [0.049]	13.796 [0.314]	13.797 [0.314]	3.6 [0.99]	3.589 [0.99]	9.959 [0.62]	10.001 [0.616]
AIC	-1142	-1139	-80	-77	-965	-963	-1934	-1948
BIC	-1127	-1121	-72	-68	-952	-946	-1918	-1927
LL	575	575	44	44	487	486	971	979
Sample size	295		51		210		456	
Subperiod 6	26-Sep-2008 to 24-Jul-2009		24-Jul-2009 to 26-Jul-2013				22-Dec-2006 to 27-Mar-2009	
Q(16)	5.632 [0.992]	5.615 [0.992]	13.671 [0.623]	13.696 [0.621]			18.97 [0.27]	18.713 [0.284]
Q^2(16)	5.39 [0.993]	5.363 [0.994]	8.833 [0.92]	8.943 [0.916]			19.011 [0.268]	19.81 [0.229]
LM(12)	11.189 [0.513]	11.143 [0.517]	8.046 [0.781]	8.433 [0.75]			12.082 [0.439]	12.587 [0.4]
AIC	-112	-110	-736	-753			-335	-332
BIC	-105	-101	-723	-736			-324	-319
LL	60	60	372	382			171	171
Sample size	44		207				115	
Subperiod 7	31-Jul-2009 to 26-Jul-2013						03-Apr-2009 to 12-Nov-2010	
Q(16)	16.67 [0.407]	19.475 [0.245]					24.683 [0.076]	24.569 [0.078]
Q^2(16)	16.043 [0.45]	23.881 [0.092]					11.01 [0.809]	10.964 [0.812]
LM(12)	12.226 [0.428]	17.981 [0.116]					7.002 [0.857]	6.972 [0.859]
AIC	-891	-889					-322	-320
BIC	-877	-872					-312	-307
LL	449	450					165	165
Sample size	209						84	
Subperiod 8							19-Nov-2010 to 26-Jul-2013	
Q(16)							12.472 [0.711]	12.501 [0.709]
Q^2(16)							5.834 [0.99]	6.451 [0.982]
LM(12)							4.916 [0.961]	5.892 [0.921]
AIC							-632	-630
BIC							-620	-615
LL							320	320
Sample size							137	

Note: P-values are given in square bracket.

The results of diagnostic tests as well as model selection criteria for GARCH model are provided in table 8. Q(16) and Q^2(16) are Ljung-Box Q statistics for standardised residuals and squared standardised residuals, respectively at lag order of 16. LM(12) denotes an ARCH LM test statistics at lag order of 12 for ARCH effects. AIC and BIC represent the popular information criteria for model selection, and LL represents the log likelihood.

As is shown in the table, the estimated GARCH model does not suffer from serial correlation in squared standardised residuals for both the full-sample and each sub-sample of all BRIC countries. The model suffers from serial correlation in standardised residuals for only the full-sample (and not for each sub-sample) of all BRIC countries. Moreover, results of ARCH LM test suggest that no further signs of ARCH effects exist in all BRIC countries' estimated models for both the full-sample and each sub-sample.

One major finding is that the sum of AIC and BIC across all sub-samples are generally much lower than the full sample AIC and BIC results, while the sum of log likelihood across all sub-intervals is much higher than the log likelihood in the full-sample case. The only exceptions are the BIC for Brazil with student t distribution, the BIC for Russia with both distributions, the BIC for India with student t distribution and the BIC for China with student t distribution. This indicates an improvement in estimation results when structural breaks are taken into account and GARCH-type models are estimated under each sub-samples defined by the breaks.

Additionally, it is almost always true that the AIC and BIC are lower, and the log likelihood is higher, when the student t distribution is applied than when the normal distribution is used by the GARCH model for both the full-sample and the sum across sub-samples (with most exceptions from the BIC criterion). This implies the value of extending from normal to student t distribution which accounts for heavy tailedness. Appendix 5 provides the plots both the full-sample and sub-subsample conditional volatility estimated by the GARCH(1,1) model with normal density against the stepwise unconditional volatility defined by the variance breaks, respectively, for BRIC countries. The plots illustrate the improvement in goodness of fit when sub-samples defined by structural breaks are allowed for.

The results of diagnostic tests and model selection criteria for EGARCH and GJR model are provided in Appendix 6a and 6b, respectively. A careful comparison of the results among all the three GARCH-type models unveils the following points. Firstly, all the patterns discussed above for the GARCH model also apply to the EGARCH and GJR models. Secondly, in terms of full-sample estimation, EGARCH model outperforms GARCH and GJR only for India (with both densities) and China (with only normal density) under all three model selection criteria. GJR and GARCH models share similar estimation performance for the rest scenarios. However, when it comes to the sum of three model selection criteria across all sub-intervals, the EGARCH model outperform substantially the GARCH and GJR models.

9.4 Out-of-Sample Test Results

To recapitulate, the out-of-sample period comprises the last 30% of the whole sample observations.

9.4.1 Volatility forecasts from different models

The out-of-sample results of 1-period ahead conditional volatility forecasts are reported in table 9. The first row of each panel of the table demonstrates the value of loss function for the GARCH(1,1) expanding window–normal density model (which serves as the benchmark model), and the remaining rows display the ratios of the value of loss function from competing models to the value of loss function from benchmark model. The models generating the least forecast errors are highlighted in bold.

The figures in table 9 show that the benchmark model – GARCH(1,1) expanding window model with normal density – never delivers the lowest value of loss function for any country under either RMSE or QLIKE loss function. The competing models, which apply different estimation window to allow for potential variance breaks, are able to reduce the RMSE (QLIKE) function in most cases by 1-12% (1-3.5%) relative to the benchmark model for BRIC countries and 0.5-6.5% (0.5-10%) for G6 countries. In terms of RMSE, only two competing models – EGARCH 0.75 rolling window model (with both densities) and GJR 0.75 rolling window model (with both densities) – can outperform the benchmark model for any country in the BRIC group, while the GARCH(1,1) expanding window-student t density and EGARCH(1,1) 0.75 rolling window–student t density model are the only two that beats the benchmark model for all countries in the G6 group. With respect to the QLIKE function, the GARCH(1,1) expanding window model with student t density is the only model that outperform the benchmark model for all the countries in BRIC group. Whereas 7 models – EGARCH(1,1) 0.75 rolling window models with both densities, EGARCH(1,1) 0.5 rolling window-student t density model, GJR(1,1) ICSS models with both densities, GJR(1,1) 0.5 rolling window-normal density model and GJR(1,1) 0.25 rolling window-student t density model – perform better than the benchmark model for all the countries in the G6 group.

Appendix 7a and 7b reports the forecast results for horizons of 10 and 30 periods (i.e. weeks), respectively. Compared to the 1-period-ahead results in table 9, more sizable reductions in the value of loss function relative to the benchmark model are produced for 10- and 30-periods-ahead forecasts in Appendix 7a and 7b. Concerning 10-period-ahead forecasts in Appendix 7a, the competing models will typically lead to reductions in RMSE (QLIKE) of 3-18% (3-17%) for BRIC countries and 1.5-10% (1-9%) for G6 countries. At the

Table 9 1-Period-Ahead Forecasts - BRIC and G6

Model		Brazil	Russia	India	China	US	UK	Japan	Italy	France	Germany
Panel 1. RMSE											
GARCH(1,1)	Normal	*0.004*	*0.009*	*0.003*	*0.003*	*0.003*	*0.004*	*0.005*	*0.003*	*0.004*	*0.004*
Expanding	Student t	1.002	0.977	0.991	0.948	0.986	0.990	0.998	0.981	0.996	0.991
GARCH(1,1) ICSS	Normal	1.035	1.021	1.012	0.931	1.017	1.016	1.007	1.060	1.029	1.018
	Student t	1.051	1.007	1.010	0.934	1.005	1.001	1.006	1.045	5.290	0.999
GARCH(1,1) 0.75	Normal	1.001	0.985	0.997	0.940	1.008	1.015	1.030	1.009	1.004	1.026
Rolling	Student t	1.010	0.979	0.991	0.933	0.989	0.996	1.005	0.980	0.999	0.995
GARCH(1,1) 0.50	Normal	1.008	0.962	1.005	0.933	1.001	1.022	1.043	1.055	1.002	1.085
Rolling	Student t	1.014	0.960	1.002	0.925	0.988	0.999	1.007	0.979	0.999	0.995
GARCH(1,1) 0.25	Normal	1.024	0.991	1.029	0.935	1.066	1.052	1.098	1.079	1.011	1.226
Rolling	Student t	1.040	0.984	1.034	0.934	1.013	1.047	1.038	1.003	1.016	1.018
EGARCH(1,1) ICSS	Normal	1.040	1.006	0.982	1.004	1.003	1.007	0.997	1.067	1.009	1.080
	Student t	1.042	0.980	0.983	0.926	1.000	1.004	**0.988**	1.044	1.007	1.015
EGARCH(1,1) 0.75	Normal	0.989	0.972	**0.970**	0.931	0.948	0.976	1.007	0.945	0.984	0.988
Rolling	Student t	0.999	0.977	0.971	0.927	**0.945**	**0.974**	0.991	**0.935**	**0.982**	**0.971**
EGARCH(1,1) 0.50	Normal	1.008	0.988	0.985	0.938	0.952	0.986	1.037	0.986	0.984	1.205
Rolling	Student t	1.004	0.989	0.989	0.942	0.948	0.977	1.004	0.953	0.984	0.976
EGARCH(1,1) 0.25	Normal	1.023	0.956	0.997	0.959	0.990	1.019	1.048	1.065	1.063	2.257
Rolling	Student t	1.026	0.960	1.023	1.958	0.971	1.056	1.022	0.984	1.038	1.008
GJR(1,1) ICSS	Normal	1.001	1.007	0.985	1.013	0.993	1.002	1.015	1.046	1.015	1.009
	Student t	1.012	0.992	0.984	0.946	0.977	0.988	1.004	0.989	1.002	0.981
GJR(1,1) 0.75	Normal	**0.963**	0.976	0.989	0.940	1.009	1.018	1.028	1.084	1.030	1.057
Rolling	Student t	0.974	0.986	0.980	0.933	0.971	0.994	1.009	0.992	1.011	0.998
GJR(1,1) 0.50	Normal	0.968	**0.882**	1.007	0.934	0.997	1.060	1.074	1.182	1.046	1.216
Rolling	Student t	0.969	0.904	1.003	**0.922**	0.971	1.010	1.026	1.012	1.012	1.019
GJR(1,1) 0.25	Normal	–	–	–	–	1.147	1.105	1.218	1.263	1.190	1.307
Rolling	Student t	–	–	–	–	1.025	1.094	1.092	1.104	1.104	1.216
MovingAverage0.5	–	1.088	1.113	1.073	0.985	1.036	1.017	1.013	1.032	1.022	1.035
Panel 2. QLIKE											
GARCH(1,1)	Normal	*1.329*	*1.489*	*1.207*	*1.218*	*1.530*	*1.517*	*1.486*	*1.200*	*1.356*	*1.483*
Expanding	Student t	0.999	**0.988**	0.998	0.982	1.000	0.996	1.000	1.008	0.998	1.012
GARCH(1,1) ICSS	Normal	1.080	1.105	1.027	0.977	1.084	1.094	1.020	1.060	1.097	1.043
	Student t	1.095	1.088	1.018	0.982	1.073	1.098	1.013	1.050	1.094	1.047
GARCH(1,1) 0.75	Normal	1.000	0.993	0.980	0.986	1.007	0.985	1.076	1.015	0.995	0.986
Rolling	Student t	1.002	0.988	**0.973**	0.972	1.019	0.981	1.048	1.019	0.993	0.996
GARCH(1,1) 0.50	Normal	1.005	1.010	0.995	0.985	1.008	0.997	1.041	1.017	1.006	1.029
Rolling	Student t	1.008	1.009	1.000	0.967	1.011	1.007	1.036	1.006	1.001	1.027
GARCH(1,1) 0.25	Normal	1.038	1.019	0.995	0.974	1.038	1.035	1.058	1.026	1.024	1.049
Rolling	Student t	1.037	1.012	1.003	**0.965**	1.025	1.004	1.043	1.020	1.017	1.045
EGARCH(1,1) ICSS	Normal	1.057	1.050	1.042	1.006	1.773	1.300	1.028	1.279	1.082	0.939
	Student t	1.059	1.038	1.039	0.974	1.582	14.28	1.000	589518	46564	16.66
EGARCH(1,1) 0.75	Normal	1.006	1.009	1.002	0.985	**0.922**	**0.903**	0.949	0.997	0.909	**0.900**
Rolling	Student t	1.010	1.006	1.000	0.971	0.933	0.904	0.950	0.973	**0.906**	0.902
EGARCH(1,1) 0.50	Normal	1.001	1.054	1.064	0.993	0.981	0.934	0.978	1.018	0.915	0.927
Rolling	Student t	1.002	1.031	1.057	0.989	0.977	0.933	0.982	**0.972**	0.915	0.911
EGARCH(1,1) 0.25	Normal	1.041	1.151	1.083	1.018	1.004	0.967	1.032	1.122	1.123	0.990
Rolling	Student t	1.044	1.151	1.065	1.092	0.989	0.954	1.020	1.010	1.020	0.965
GJR(1,1) ICSS	Normal	1.023	1.024	1.021	1.002	0.946	0.952	**0.936**	0.972	0.963	0.927
	Student t	1.020	1.017	1.028	0.978	0.949	0.955	0.941	0.996	0.963	0.933
GJR(1,1) 0.75	Normal	0.978	1.010	0.993	0.981	0.929	0.934	1.006	1.004	0.944	0.922
Rolling	Student t	0.981	1.009	0.977	0.967	0.945	0.935	1.002	1.005	0.945	0.926
GJR(1,1) 0.50	Normal	**0.967**	1.027	1.020	0.987	0.945	0.955	0.959	0.997	0.953	0.949
Rolling	Student t	0.972	1.016	1.024	0.967	0.948	0.959	1.011	0.972	0.955	0.938
GJR(1,1) 0.25	Normal	–	–	–	–	0.990	0.954	0.978	1.015	0.986	0.933
Rolling	Student t	–	–	–	–	0.976	0.945	0.948	0.975	0.983	0.930
MovingAverage0.5	–	1.173	1.470	1.287	1.197	1.351	1.334	1.152	1.297	1.225	1.176

Note: Figures for the GARCH(1,1) expanding w indow model represent the value of loss function for this model. Figures for the other models provide the ratio of the value of loss function for each model to the value of loss function for the GARCH(1,1) expanding w indow model.

30-week horizon in Appendix 7b, the best performing competing models reduce the RMSE (QLIKE) by approximately 4-47.5% (4-36%) relative to the benchmark model for BRIC countries and 5-34.5% (4-16%) for G6 countries. These patterns are in line with the results in (Rapach & Strauss, 2008).

9.4.2 Combination of volatility forecasts

Table 9 along with Appendix 7a and 7b the optimal model of volatility forecasting tend to vary across different loss functions, forecast horizons and countries; therefore, it is not easy to identify a priori which model is the best to use in a given context with potential breaks in volatility.

Recently, some studies point out that combining volatility forecasts generated by different models can reduce the uncertainty regarding the selection of optional estimation window size and the uncertainty across forecasting models. (Pesaran and Timmermann, 2007) investigates the combination of volatility forecasts from various models using estimation windows of different lengths. They demonstrate that combination forecasts outperform forecasting models using an expanding estimation window in the existence of structural breaks. In this thesis, forecasts from eight models – GARCH(1,1) expanding window, GARCH(1,1) ICSS window, GARCH(1,1) 0.5 rolling window, EGARCH(1,1) ICSS window, EGARCH(1,1) 0.5 rolling window, GJR(1,1) ICSS window, GJR(1,1) 0.5 rolling window and moving average 0.5 rolling window – are employed to generate the combination forecasts.

Table 10 shows the ratios of the value of loss function for the mean and trimmed mean combination forecasts to the value of loss function for the GARCH(1,1) expanding window-normal density model, the benchmark model which is appropriate to use in the absence of variance breaks. The following points are worth mentioning. Firstly, in 143 out of 240 cases (including both mean and trimmed mean forecasts for both RMSE and QLIKE) the ratio is less than one, indicating the forecasting gains obtained by (trimmed) mean combination forecasts compared to the benchmark model forecasts. Secondly, in scenarios where there is a reduction in the loss functions (both RMSE and QLIKE), the reduction is often substantial and tends to increase as the forecast horizon becomes longer. Thirdly, there are fewer variations in the value of loss functions across countries for a given model. Fourthly, the combination forecasts works better on average for G6 than for BRIC countries. However, they perform particularly well for China and very disappointingly for Russia.

Overall, the results in table 10 show that the issue of inconsistency in volatility prediction performance suffered by individual forecasting models can be mitigated by combination forecasts. From a practical point of view, taking the average of the volatility forecasts produced by different GARCH-type models using estimation windows of various sizes can offer a reasonably reliable approach to predict conditional volatility of stock returns of BRIC and G6 countries in the presence of variance breaks. Generally, the results discussed above are consistent with those in (Rapach & Strauss, 2008), among others.

Table 10 Combination Forecasts – BRIC and G6

		Brazil	Russia	India	China	US	UK	Japan	Italy	France	Germany
A. RMSE (mean)											
h=1	Normal	1.010	0.982	0.993	0.929	0.978	0.988	1.002	0.970	0.990	1.007
	Student t	1.016	0.970	0.994	0.925	0.975	0.984	0.994	0.956	1.016	0.980
h=10	Normal	0.969	0.981	1.003	0.861	0.945	0.955	0.999	0.916	0.956	0.948
	Student t	0.970	0.982	1.002	0.865	0.943	0.954	0.999	0.919	0.957	0.948
h=30	Normal	0.969	0.911	1.011	0.553	0.946	0.944	1.006	0.727	0.952	0.975
	Student t	0.969	0.909	1.013	0.529	0.949	0.934	1.005	0.693	0.983	0.971
B. QLIKE (mean)											
h=1	Normal	1.009	1.043	1.028	0.984	1.044	1.035	1.041	1.002	1.015	0.994
	Student t	1.015	1.027	1.029	0.975	1.039	1.050	1.042	1.013	1.013	0.996
h=10	Normal	1.013	1.561	1.020	0.945	0.894	0.862	0.915	1.013	0.902	0.861
	Student t	1.012	1.604	1.015	0.949	0.885	0.852	0.914	1.035	0.898	0.856
h=30	Normal	1.012	1.219	1.064	0.712	1.161	1.209	1.172	0.906	1.176	1.202
	Student t	1.011	1.141	1.077	0.677	1.204	1.201	1.142	1.015	1.190	1.237
C. RMSE (trimmed mean)											
h=1	Normal	0.999	0.967	0.986	0.935	0.976	0.991	1.005	0.985	0.993	1.022
	Student t	1.007	0.948	0.986	0.923	0.972	0.985	0.994	0.959	0.990	0.980
h=10	Normal	0.971	0.956	1.014	0.837	0.960	0.969	1.001	0.928	0.980	0.972
	Student t	0.968	0.958	1.016	0.826	0.954	0.960	1.002	0.886	0.973	0.964
h=30	Normal	0.970	0.911	1.015	0.572	0.936	0.946	1.002	0.749	0.953	0.972
	Student t	0.964	0.912	1.016	0.535	0.939	0.934	1.004	0.691	0.945	0.968
D. QLIKE (trimmed mean)											
h=1	Normal	1.000	1.020	1.005	0.975	0.993	0.978	0.987	0.977	0.962	0.963
	Student t	1.004	1.007	1.007	0.966	0.992	0.988	0.985	0.983	0.960	0.956
h=10	Normal	0.992	1.159	1.055	0.859	1.020	1.016	1.062	0.988	1.024	1.018
	Student t	0.980	1.156	1.068	0.837	1.016	1.007	1.056	1.014	1.019	1.023
h=30	Normal	0.991	1.120	1.064	0.734	1.041	1.075	1.066	0.917	1.048	1.097
	Student t	0.973	1.107	1.072	0.681	1.086	1.065	1.128	0.956	1.042	1.100

Notes: Entries display the ratio of the value of loss function for the mean and trimmed mean combination forecasts to the value of loss function for the GARCH(1,1) expanding w indow model.

10. Conclusions

The results of this work demonstrate the empirical relevance of allowing for the structural breaks for GARCH-family models – GARCH, EGARCH and GJR model – of stock market returns of BRIC and G6 countries.

In terms of in-sample tests, the ICSS algorithm is employed to detect structural breaks in the unconditional variance of stock returns of BRIC and G6 countries and the economic as well as political events associated with each break period are identified subsequently. The results suggest that developed G6 stock markets suffer from more (temporary and prolonged) variance breaks than BRIC markets do. But the standard deviation within each sub-interval for BRIC countries is generally higher than for G6 countries.

With respect to in-sample estimation, results in Appendix 4a and Appendix 4b suggest that stock returns of all the BRIC countries (except Russia) exhibit leverage effects; thus it is worth applying asymmetric GARCH models in this study. A comparison among results in table 6, Appendix 4a and 4b shows that EGARCH model generates more reasonable parameter estimates and has more explanatory power than GARCH and GJR models do for both full-sample and sub-samples estimation exercises. Table 7, which reports the volatility persistence, reveals that persistence level is generally very high (close to 1) if full-sample is used for estimation of GARCH-type models. Whereas the volatility can become considerably less persistent if sub-samples defined by variance breaks identified by the ICSS algorithm are applied for model estimation. Moreover, the results of diagnostic tests for GARCH, EGARCH and GJR models in table 8, Appendix 6a and 6b, respectively, reveal the following points. Firstly, estimating GARCH-type models using sub-samples generates better modelling outcomes evaluated by AIC, BIC information criteria and log likelihood (LL). Secondly, EGARCH model outperforms substantially GARCH and GJR models for sub-sample estimation exercises and shares similar performance to GARCH and GJR for full-sample estimation; hence, the EGARCH(1,1) models should be preferred. Thirdly, allowing for heavy tailed density such as student t distribution for the standardised residual leads to better estimation results, again measured by AIC, BIC and LL.

In terms of out-of-sample forecasting, it is found that better out-of-sample forecasts can be obtained by accommodating potential structural breaks in the unconditional variance of stock returns of BRIC and G6 countries. In addition, employing asymmetric GARCH models (in particular the EGARCH model) and heavy tailed density (i.e. student t) for the standardised residual will also lead to better forecasts of conditional volatility of stock returns. Results in table 9, Appendix 7a and 7b demonstrate that EGARCH(1,1) 0.75 rolling window models (with both densities) produce least forecast losses in most cases for G6 countries under both RMSE and QLIKE functions. However, in the case of the BRIC countries, no single model can stand out. The best performing model for the BRIC group varies according to countries, forecasting horizons and loss functions. Finally, from a practical standpoint, taking the average of the volatility forecasts produced by different GARCH-type models using estimation windows of various sizes seems to provide a reasonably reliable way to produce more accurate conditional volatility forecasts of stock returns of BRIC and G6 countries.

Overall, it is concluded that structural breaks in unconditional volatility of stock returns need to be taken into account for GARCH model estimation and forecasting practices as failure to do so can lead to huge biases in the results of both practices.

11. References

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12. Appendices

Appendix 1 – Unit Root Test for Return Series – BRIC

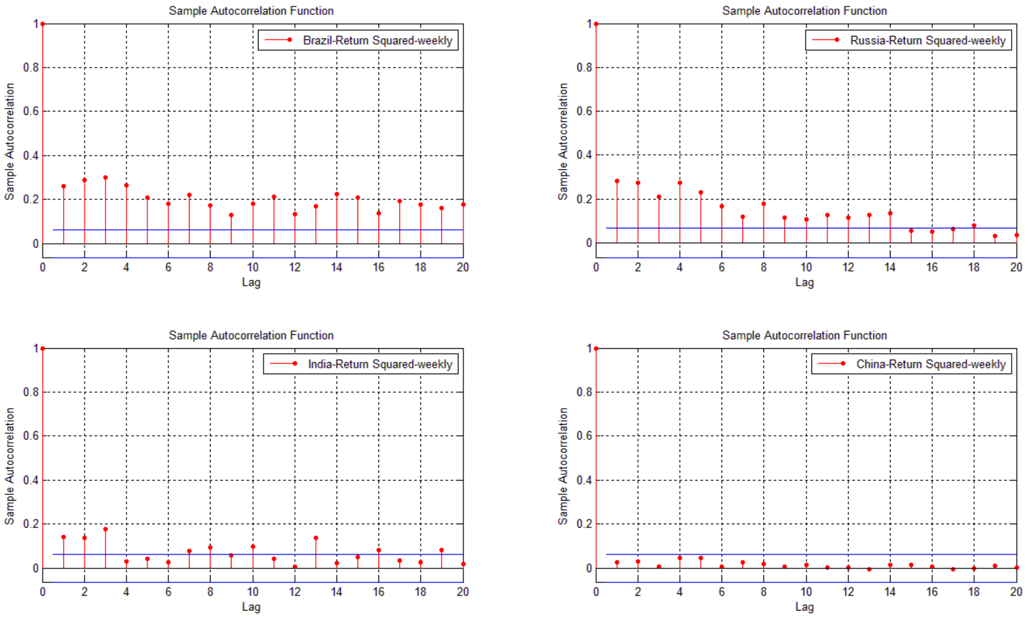
	Brazil	Russia	India	China
ADF (Intercept)	-7.317** [0.001]	-8.165** [0.001]	-9.485** [0.001]	-9.045** [0.001]
ADF (No Intercept)	-7.136** [0.001]	-8.093** [0.001]	-9.359** [0.001]	-9.033** [0.001]
PP (Intercept)	-32.226** [0.001]	-28.379** [0.001]	-31.015** [0.001]	-31.262** [0.001]
PP (No Intercept)	-32.104** [0.001]	-28.378** [0.001]	-30.964** [0.001]	-31.269** [0.001]
KPSS (Intercept)	*1.161*** *[0.01]*	0.077 [0.1]	0.062 [0.1]	0.069 [0.1]
Sample Size	1048	926	1045	1009

Notes: 1. P-values are given in the square brackets.

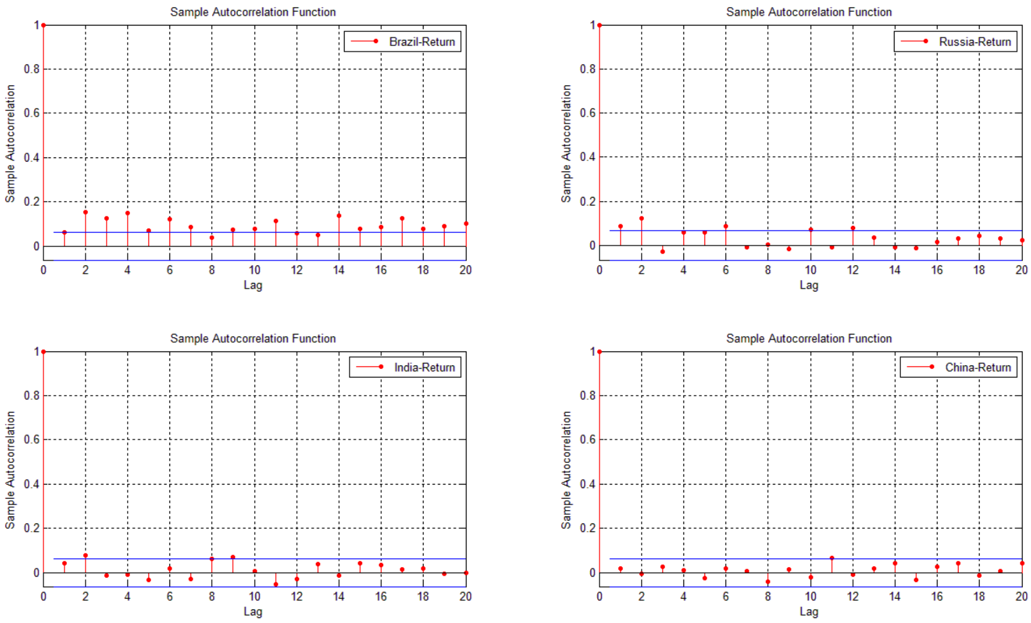
2. p-values of 0.1 for KPSS test indicate that the values are higher than 0.1

3. * and ** denote that the test is significant under 5% and 1% significance level respectively.

Appendix 2a - ACF Plot Squared Return - BRIC



Appendix 2b - ACF Plot Return – BRIC



Appendix 3 - Structural Breaks in Volatility and Events - G6

	# of breaks	Subperiod	Sample size	Stdev	%Change in Stdev	Events
US	8	09-Jul-1993 to'29-Dec-1995	130	1.14%		
		05-Jan-1996 to'17-Jul-1998	133	1.94%	70.18%	dot com bubble building up
		24-Jul-1998 to'04-Apr-2003	246	2.96%	52.58%	9/11 in 2001, dot com bubble crash, $350bn tax cut package
		11-Apr-2003 to'09-Mar-2007	205	1.45%	-51.01%	War in Iraq, then subprime mortgage bubble grow s
		16-Mar-2007 to'03-Oct-2008	82	2.49%	71.72%	subprime mortgage crisis
		10-Oct-2008 to'03-Apr-2009	26	7.03%	182.33%	Obama becomes president, Great Recession,
		10-Apr-2009 to'24-Jun-2011	116	2.28%	-67.57%	ARRA (American Recovery & Reinvestment Act)
		01-Jul-2011 to'16-Dec-2011	25	4.04%	77.19%	U.S. debt ceiling is raised
		23-Dec-2011 to'26-Jul-2013	84	1.60%	-60.40%	
UK	7	09-Jul-1993 to'06-Jun-1997	205	1.58%		1990 recession is overcome
		13-Jun-1997 to'04-Apr-2003	304	2.68%	69.62%	Britain does not join single currency 1999. Labour party in pow er
		11-Apr-2003 to'23-Feb-2007	203	1.36%	-49.25%	War in Iraq starts 2003
		02-Mar-2007 to'29-Aug-2008	79	2.25%	65.44%	subprime mortgage crisis
		05-Sep-2008 to'13-Mar-2009	28	7.29%	224.00%	
		20-Mar-2009 to'24-Jun-2011	119	2.25%	-69.14%	quantitative easing £200bn, GDP dow n by 4.9%
		01-Jul-2011 to'02-Dec-2011	23	4.02%	78.67%	
		09-Dec-2011 to'26-Jul-2013	86	1.71%	-57.46%	
Japan	4	09-Jul-1993 to'14-Nov-2003	541	2.98%		deflation policy
		21-Nov-2003 to'20-Jul-2007	192	2.14%	-28.19%	deflation policy ended 2006
		27-Jul-2007 to'29-Aug-2008	58	3.05%	42.52%	Nikkei 225 fell 50%
		05-Sep-2008 to'20-Mar-2009	29	7.43%	143.61%	subprime mortgage crisis
		27-Mar-2009 to'26-Jul-2013	227	2.84%	-61.78%	Nikkei 225 rises 42% since nov 2012
Italy	7	09-Jan-1998 to'15-Jan-1999	54	4.40%		
		22-Jan-1999 to'24-Aug-2001	136	2.47%	-43.86%	Carlo Ciampi becomes president
		31-Aug-2001 to'05-Oct-2001	6	12.61%	410.53%	Berlusconi w ins elections June 2001
		12-Oct-2001 to'18-Apr-2003	80	3.39%	-73.12%	Oct 2001:First constitutional referendum since 1946
		25-Apr-2003 to'02-Mar-2007	202	1.54%	-54.57%	Berlusconi in court
		09-Mar-2007 to'26-Sep-2008	82	2.49%	61.69%	GDP decreases 6.7% during 2007-2011
		03-Oct-2008 to'20-Mar-2009	25	8.61%	245.78%	bus cycle trough mid 2009, subprime mortgage
		27-Mar-2009 to'26-Jul-2013	227	3.75%	-56.45%	S&P and Moody's dow ngrade Italy
France	8	09-Jul-1993 to'28-Feb-1997	191	2.19%		Jacques Chirac elected president 1995,
		07-Mar-1997 to'24-Aug-2001	234	3.10%	41.55%	Lionel Jospin elected prime minister
		31-Aug-2001 to'04-Apr-2003	84	4.27%	37.74%	compulsory military service abolished
		11-Apr-2003 to'11-Jan-2008	249	1.87%	-56.21%	changes to pension system and constitution
		18-Jan-2008 to'03-Oct-2008	38	3.05%	63.10%	Ratification of Lisbon Treaty
		10-Oct-2008 to'13-Mar-2009	23	8.42%	176.07%	France pays 10.5bn euros into a french bank
		20-Mar-2009 to'24-Jun-2011	119	2.85%	-66.15%	
		01-Jul-2011 to'23-Dec-2011	26	5.33%	87.02%	Lybia conflict
		30-Dec-2011 to'26-Jul-2013	83	2.25%	-57.79%	package of austerity measures
Germany	6	09-Jul-1993 to'14-Oct-1994	67	2.43%		
		21-Oct-1994 to'31-Jan-1997	120	1.63%	-32.92%	large tax increases
		07-Feb-1997 to'10-Aug-2001	236	3.34%	104.91%	dot com bubble
		17-Aug-2001 to'13-Jun-2003	96	4.99%	49.40%	4m unemployed
		20-Jun-2003 to'26-Sep-2008	276	2.24%	-55.11%	subprime mortgage bubble
		03-Oct-2008 to'06-Mar-2009	23	8.75%	290.63%	subprime mortgage crisis
		13-Mar-2009 to'26-Jul-2013	229	3.00%	-65.71%	NBER business cycle trough reached

Appendix 4a – Estimation Results from EGARCH(1,1)-BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample estimation output							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
$\hat{\omega}$	-0.151 (0.0478)**	-0.1432 (0.0627)*	-0.1345 (0.0429)**	-0.2018 (0.0753)**	-0.2011 (0.063)**	-0.396 (0.1407)**	-0.32 (0.089)**	-0.2571 (0.1023)*
$\hat{\alpha}$	0.243 (0.027)**	0.224 (0.038)**	0.246 (0.023)**	0.298 (0.05)**	0.177 (0.029)**	0.224 (0.049)**	0.443 (0.039)**	0.233 (0.043)**
$\hat{\beta}$	0.975 (0.008)**	0.977 (0.01)**	0.975 (0.007)**	0.965 (0.013)**	0.97 (0.009)**	0.942 (0.021)**	0.947 (0.014)**	0.961 (0.015)**
$\hat{\lambda}$	-0.03 (0.011)**	-0.017 (0.017)	-0.017 (0.013)	-0.018 (0.025)	-0.048 (0.013)**	-0.066 (0.023)**	-0.1 (0.017)**	-0.031 (0.021)
	Panel 2: subperiod estimation output							
Subperiod 1	09-Jul-1993 to28-Apr-1995		08-Sep-1995 to17-Oct-1997		11-Jul-1993 to17-May-1998		09-Jul-1993 to08-Jul-1994	
$\hat{\omega}$	-0.2029 (0.347)	-0.2259 (0.3102)	-0.6878 (0.5057)	-0.7243 (0.7768)	-5 (4.0368)	-4.676 (4.1254)	-0.8317 (0.5868)	-0.8647 (0.092)**
$\hat{\alpha}$	-0.313 (0.172)	-0.395 (0.207)	-0.008 (0.078)	0.024 (0.139)	0.313 (0.156)*	0.27 (0.179)	-0.731 (0.199)**	-0.885 (0.27)**
$\hat{\beta}$	0.958 (0.071)**	0.953 (0.064)**	0.874 (0.093)**	0.867 (0.144)**	0.261 (0.595)	0.309 (0.608)	0.856 (0.091)**	0.848 (0.014)**
$\hat{\lambda}$	-0.063 (0.05)	-0.071 (0.063)	0.163 (0.054)**	0.15 (0.086)	0.005 (0.092)	0.029 (0.112)	-0.172 (0.125)	-0.274 (0.159)
Subperiod 2	05-May-1995 to11-Jul-1997		24-Oct-1997 to16-Oct-1998		24-May-1998 to14-Oct-2001		15-Jul-1994 to12-Aug-1994	
$\hat{\omega}$	-5 (3.5115)	-5 (5.6733)	-0.6175 (0.3302)	-0.3212 (0.7053)	-0.6429 (0.3987)	-0.6521 (0.5392)	-3.8263 (10.027)	-1.81 (0.0115)**
$\hat{\alpha}$	-0.348 (0.279)	-0.309 (0.294)	-0.785 (0.431)	-0.721 (0.51)	-0.195 (0.064)**	-0.188 (0.082)*	-2 (7.17)	-2 (0.002)**
$\hat{\beta}$	0.252 (0.528)	0.252 (0.852)	0.855 (0.075)**	0.917 (0.156)**	0.899 (0.063)**	0.897 (0.085)**	0.252 (3.279)	0.943 (0.043)**
$\hat{\lambda}$	-0.153 (0.173)	-0.101 (0.192)	-0.216 (0.235)	-0.127 (0.267)	-0.018 (0.055)	-0.017 (0.067)	-2 (5.545)	-2 (0.007)**
Subperiod 3	18-Jul-1997 to19-Mar-1999		23-Oct-1998 to16-Mar-2001		21-Oct-2001 to16-Sep-2007		19-Aug-1994 to19-May-1995	
$\hat{\omega}$	-2.5193 (1.4829)	-0.4763 (0.7729)	-5 (5.2171)	-0.7405 (0.2096)**	-3.3155 (1.1186)**	-2.923 (1.2904)*	-0.4728 (0.5108)	-0.2287 (0.6633)
$\hat{\alpha}$	0.39 (0.328)	0.182 (0.254)	0.256 (0.226)	-0.599 (0.177)**	0.206 (0.133)	0.241 (0.145)	-0.914 (0.433)*	-0.996 (0.663)
$\hat{\beta}$	0.518 (0.28)	0.912 (0.148)**	0.008 (1.035)	0.856 (0.041)**	0.547 (0.151)**	0.603 (0.175)**	0.904 (0.094)**	0.948 (0.117)**
$\hat{\lambda}$	-0.164 (0.142)	-0.106 (0.113)	-0.006 (0.153)	0.108 (0.088)	-0.297 (0.081)**	-0.257 (0.094)**	-0.085 (0.338)	0.008 (0.465)
Subperiod 4	26-Mar-1999 to24-Jan-2003		23-Mar-2001 to18-Jul-2008		23-Sep-2007 to19-Jul-2009		26-May-1995 to03-Oct-1997	
$\hat{\omega}$	-5 (2.2605)*	-5 (2.9308)	-0.1831 (0.1388)	-0.2463 (0.2679)	-2.1885 (1.8779)	-2.1875 (1.9098)	-1.3444 (0.7004)	-1.9214 (1.3078)
$\hat{\alpha}$	-0.152 (0.235)	-0.117 (0.252)	0.045 (0.04)	0.054 (0.056)	-0.246 (0.227)	-0.241 (0.252)	0.337 (0.196)	0.225 (0.26)
$\hat{\beta}$	0.185 (0.372)	0.185 (0.481)	0.972 (0.022)**	0.962 (0.042)**	0.629 (0.32)*	0.629 (0.326)	0.781 (0.115)**	0.685 (0.218)**
$\hat{\lambda}$	-0.334 (0.11)**	-0.29 (0.138)*	0.071 (0.027)**	0.06 (0.038)	-0.237 (0.183)	-0.236 (0.184)	0.239 (0.093)*	0.267 (0.139)
Subperiod 5	31-Jan-2003 to19-Sep-2008		25-Jul-2008 to17-Jul-2009		26-Jul-2009 to28-Jul-2013		10-Oct-1997 to15-Dec-2006	
$\hat{\omega}$	-5 (2.4558)*	-5 (2.5299)*	-0.9593 (0.4883)*	-0.9884 (0.548)	-1.3671 (0.8011)	-1.3528 (0.8495)	-1.5161 (0.6294)*	-1.1291 (0.716)
$\hat{\alpha}$	-0.275 (0.154)	-0.275 (0.156)	-0.989 (0.422)*	-1.106 (0.711)	0.221 (0.153)	0.222 (0.159)	0.298 (0.077)**	0.253 (0.093)**
$\hat{\beta}$	0.26 (0.362)	0.26 (0.371)	0.806 (0.096)**	0.796 (0.11)**	0.819 (0.106)**	0.82 (0.111)**	0.785 (0.088)**	0.84 (0.101)**
$\hat{\lambda}$	-0.182 (0.098)	-0.181 (0.101)	-0.35 (0.356)	-0.34 (0.457)	-0.209 (0.104)*	-0.209 (0.106)*	-0.038 (0.033)	-0.035 (0.044)
Subperiod 6	26-Sep-2008 to24-Jul-2009		24-Jul-2009 to26-Jul-2013				22-Dec-2006 to27-Mar-2009	
$\hat{\omega}$	-0.7629 (0.793)	-0.9368 (0.9015)	-1.2832 (0.4644)**	-0.7443 (0.6225)			-0.8896 (0.0982)**	-0.964 (0.3275)**
$\hat{\alpha}$	-0.835 (0.493)	-1.017 (0.846)	0.3 (0.114)**	0.225 (0.136)			-0.608 (0.203)**	-0.601 (0.271)*
$\hat{\beta}$	0.853 (0.136)**	0.832 (0.173)**	0.801 (0.072)**	0.886 (0.096)**			0.852 (0.016)**	0.836 (0.056)**
$\hat{\lambda}$	-0.508 (0.293)	-0.729 (0.599)	-0.193 (0.062)**	-0.09 (0.072)			-0.192 (0.061)**	-0.16 (0.055)**
Subperiod 7	31-Jul-2009 to26-Jul-2013						03-Apr-2009 to12-Nov-2010	
$\hat{\omega}$	-0.3645 (0.3824)	-5 (2.3385)*					-5 (6.5505)	-5 (6.7057)
$\hat{\alpha}$	0.02 (0.068)	-0.283 (0.288)					-0.119 (0.404)	-0.121 (0.411)
$\hat{\beta}$	0.949 (0.053)**	0.302 (0.324)					0.261 (0.967)	0.261 (0.995)
$\hat{\lambda}$	-0.088 (0.044)*	-0.233 (0.14)					-0.19 (0.188)	-0.193 (0.217)
Subperiod 8							19-Nov-2010 to26-Jul-2013	
$\hat{\omega}$							-0.6246 (2.3513)	-5 (7.2218)
$\hat{\alpha}$							0.072 (0.159)	0.039 (0.221)
$\hat{\beta}$							0.917 (0.313)**	0.334 (0.953)
$\hat{\lambda}$							-0.038 (0.059)	-0.131 (0.135)

Note: 1. Standard errors are show n in parentheses; 2. * and ** denotes statistical significance under 5% and 1% level, respectively.

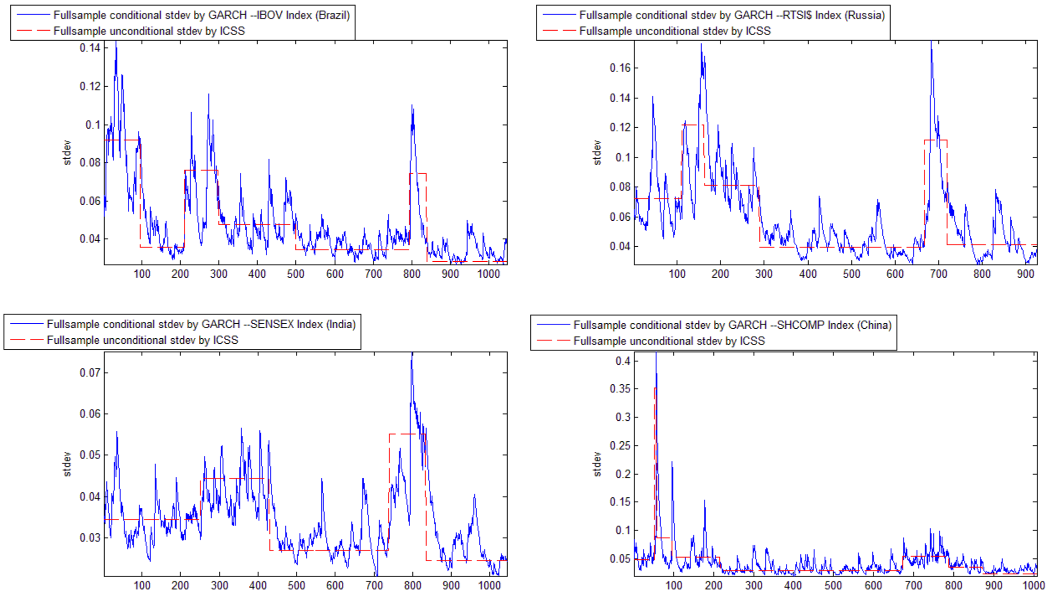
Appendix 4b – Estimation Results from GJR(1,1)-BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample estimation output							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
$\hat{\omega}$	0.0001 (0)**	0.0001 (0)*	0.0001 (0)**	0.0001 (0)*	0 (0)**	0.0001 (0)**	0.0001 (0)**	0.0001 (0)**
$\hat{\alpha}$	0.109 (0.022)**	0.103 (0.03)**	0.119 (0.02)**	0.16 (0.048)**	0.067 (0.017)**	0.075 (0.029)**	0.199 (0.03)**	0.137 (0.039)**
$\hat{\beta}$	0.844 (0.021)**	0.861 (0.028)**	0.87 (0.011)**	0.828 (0.03)**	0.875 (0.018)**	0.838 (0.034)**	0.682 (0.026)**	0.775 (0.044)**
$\hat{\gamma}$	0.042 (0.021)*	0.02 (0.029)	0.001 (0.022)	-0.003 (0.046)	0.058 (0.02)**	0.076 (0.036)*	0.238 (0.037)**	0.074 (0.05)
	Panel 2: subperiod estimation output							
Subperiod 1	09-Jul-1993 to28-Apr-1995		08-Sep-1995 to17-Oct-1997		11-Jul-1993 to17-May-1998		09-Jul-1993 to08-Jul-1994	
$\hat{\omega}$	0.0058 (0.014)	0.0058 (0.014)	0.0007 (0.0009)	0.0007 (0.001)	0.001 (0.0005)	0.001 (0.0006)	0.0004 (0.0015)	0.0004 (0.0021)
$\hat{\alpha}$	0.125 (0.334)	0.126 (0.362)	0.166 (0.165)	0.152 (0.166)	0.15 (0.087)	0.14 (0.094)	0 (0.17)	0 (0.171)
$\hat{\beta}$	0.248 (1.751)	0.247 (1.744)	0.775 (0.267)**	0.781 (0.287)**	0 (0.463)	0 (0.538)	0.769 (0.822)	0.764 (1.081)
$\hat{\gamma}$	-0.125 (0.338)	-0.126 (0.352)	-0.166 (0.129)	-0.152 (0.145)	0.041 (0.175)	-0.001 (0.196)	0.069 (0.236)	0.07 (0.281)
Subperiod 2	05-May-1995 to11-Jul-1997		24-Oct-1997 to16-Oct-1998		24-May-1998 to14-Oct-2001		15-Jul-1994 to12-Aug-1994	
$\hat{\omega}$	0 (0.0001)	0.0003 (0.1582)	0.001 (0.0023)	0.0009 (0.0023)	0.0019 (0.0031)	0.0019 (0.0028)	0 (0)**	5 (4774.5702)
$\hat{\alpha}$	0.031 (0.065)	0 (0.167)	0.003 (0.097)	0.017 (0.123)	0 (0.078)	0.01 (0.113)	0 (3.143)	0 (452.926)
$\hat{\beta}$	0.982 (0.094)**	0.73 (122.326)	0.808 (0.284)**	0.799 (0.301)**	0 (1.62)	0 (1.445)	0.462 (10.393)	1 (8.873)
$\hat{\gamma}$	-0.031 (0.068)	0 (0.166)	0.283 (0.339)	0.291 (0.401)	0.067 (0.11)	0.071 (0.153)	1 (16.352)	0 (0)**
Subperiod 3	18-Jul-1997 to19-Mar-1999		23-Oct-1998 to16-Mar-2001		21-Oct-2001 to16-Sep-2007		19-Aug-1994 to19-May-1995	
$\hat{\omega}$	0.0039 (0.001)**	0.0041 (0.0015)**	0.0055 (0.005)	0.0055 (0.0049)	0.0003 (0.0001)**	0.0003 (0.0001)*	0.0013 (0.2128)	0.0007 (0.0017)
$\hat{\alpha}$	0 (0.154)	0 (0.164)	0.165 (0.2)	0.157 (0.206)	0 (0.133)	0 (0.14)	0 (0)**	0.39 (0.768)
$\hat{\beta}$	0 (0.131)	0 (0.164)	0 (0.827)	0 (0.815)	0.389 (0.176)*	0.388 (0.202)	0.822 (28.939)	0.786 (0.518)
$\hat{\gamma}$	0.845 (0.41)*	0.734 (0.466)	-0.003 (0.259)	0.013 (0.28)	0.407 (0.198)*	0.414 (0.212)	0 (0)**	-0.39 (1.252)
Subperiod 4	26-Mar-1999 to24-Jan-2003		23-Mar-2001 to18-Jul-2008		23-Sep-2007 to19-Jul-2009		26-May-1995 to03-Oct-1997	
$\hat{\omega}$	0.0019 (0.0006)**	0.002 (0.0009)*	0.0001 (0)	0.0001 (0.0001)	0.0011 (0.0016)	0.001 (0.0017)	0.0007 (0.0003)*	0.0008 (0.0005)
$\hat{\alpha}$	0 (0.133)	0 (0.151)	0.089 (0.049)	0.093 (0.079)	0 (0.27)	0 (0.275)	0.671 (0.3)*	0.648 (0.347)
$\hat{\beta}$	0 (0.197)	0 (0.348)	0.93 (0.047)**	0.908 (0.088)**	0.529 (0.666)	0.543 (0.704)	0.446 (0.182)*	0.406 (0.232)
$\hat{\gamma}$	0.432 (0.222)	0.272 (0.258)	-0.089 (0.048)	-0.086 (0.075)	0.199 (0.269)	0.196 (0.303)	-0.671 (0.28)*	-0.648 (0.329)*
Subperiod 5	31-Jan-2003 to19-Sep-2008		25-Jul-2008 to17-Jul-2009		26-Jul-2009 to28-Jul-2013		10-Oct-1997 to15-Dec-2006	
$\hat{\omega}$	0.0012 (0.1161)	0.001 (0.0001)**	0.0026 (0.0041)	0.0026 (0.0045)	0.0001 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)**	0.0002 (0.0001)
$\hat{\alpha}$	0 (0.196)	0 (0.2)	0 (0.144)	0 (0.147)	0.015 (0.076)	0.015 (0.077)	0.14 (0.056)*	0.121 (0.068)
$\hat{\beta}$	0.003 (97.612)	0.19 (0)**	0.557 (0.529)	0.557 (0.541)	0.684 (0.157)**	0.685 (0.158)**	0.592 (0.109)**	0.666 (0.15)**
$\hat{\gamma}$	0 (0.196)	0 (0.198)	0.398 (0.452)	0.4 (0.537)	0.305 (0.191)	0.306 (0.203)	0.075 (0.066)	0.053 (0.084)
Subperiod 6	26-Sep-2008 to24-Jul-2009		24-Jul-2009 to26-Jul-2013				22-Dec-2006 to27-Mar-2009	
$\hat{\omega}$	0.0004 (0.0004)	0.0004 (0.0004)	0.0001 (0.0001)	0.0001 (0.0001)			0.0001 (0.0002)	0.0001 (0.0002)
$\hat{\alpha}$	0 (0.309)	0 (0.324)	0.068 (0.056)	0.082 (0.095)			0 (0.113)	0 (0.114)
$\hat{\beta}$	0.656 (0.272)*	0.659 (0.283)*	0.822 (0.086)**	0.841 (0.125)**			0.933 (0.13)**	0.933 (0.131)**
$\hat{\gamma}$	0.393 (0.388)	0.39 (0.389)	0.066 (0.045)	0.016 (0.085)			0.069 (0.073)	0.068 (0.074)
Subperiod 7	31-Jul-2009 to26-Jul-2013						03-Apr-2009 to12-Nov-2010	
$\hat{\omega}$	0.0001 (0.0001)	0.0001 (0.0001)					0.0009 (0.0021)	0.0009 (0.0021)
$\hat{\alpha}$	0 (0.065)	0 (0.072)					0 (0.245)	0 (0.246)
$\hat{\beta}$	0.882 (0.156)**	0.894 (0.161)**					0.146 (1.894)	0.154 (1.891)
$\hat{\gamma}$	0.091 (0.074)	0.083 (0.079)					0.147 (0.324)	0.148 (0.338)
Subperiod 8							19-Nov-2010 to26-Jul-2013	
$\hat{\omega}$							0.0005 (0.0006)	0.0005 (0.0006)
$\hat{\alpha}$							0 (0.133)	0 (0.134)
$\hat{\beta}$							0 (1.11)	0 (1.128)
$\hat{\gamma}$							0.197 (0.214)	0.197 (0.217)

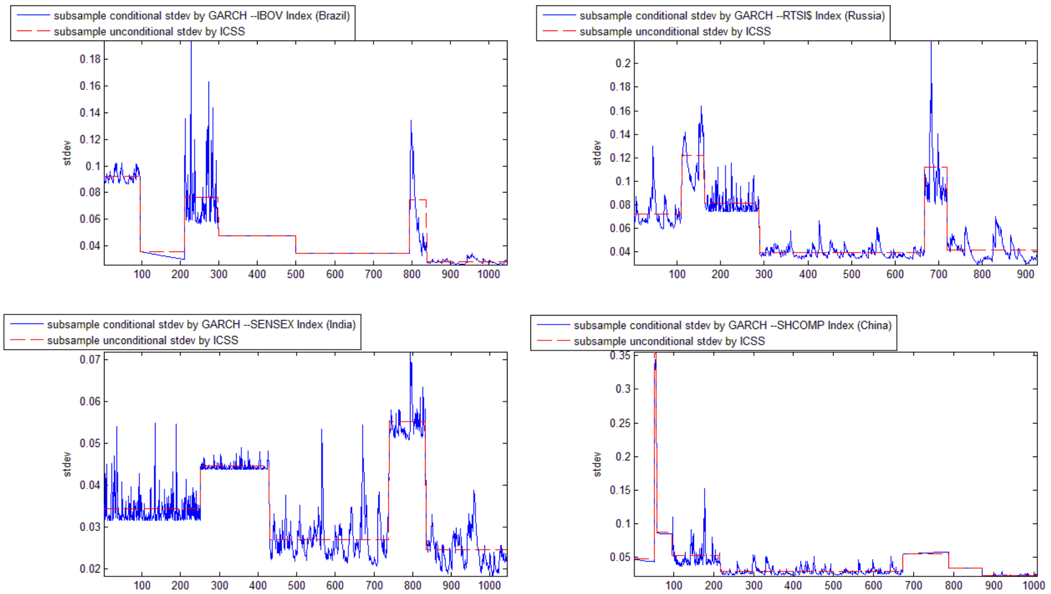
Note: 1. Standard errors are show n in parentheses; 2. * and ** denotes statistical significance under 5% and 1% level, respectively.

Appendix 5 – Plots of Conditional Volatility against Stepwise Unconditional Volatility

a. In the case of full-sample



b. In the case of sub-sample



Appendix 6a - EGARCH Model Diagnostics – BRIC

	Brazil		Russia		India		China	
	Panel 1: full sample estimation output							
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
Q(16)	50.535 [0]	50.099 [0]	31.39 [0.012]	29.488 [0.021]	26.391 [0.049]	27.191 [0.039]	27.129 [0.04]	19.983 [0.221]
Q^2(16)	15.58 [0.483]	16.067 [0.448]	6.925 [0.975]	5.252 [0.994]	18.846 [0.277]	19.569 [0.24]	3.435 [1]	2.198 [1]
LM(12)	8.006 [0.785]	8.752 [0.724]	4.653 [0.969]	3.444 [0.992]	13.499 [0.334]	11.836 [0.459]	2.227 [0.999]	1.418 [1]
AIC	-3519	-3547	-2746	-2796	-4134	-4157	-3707	-3821
BIC	-3494	-3518	-2722	-2767	-4110	-4127	-3682	-3792
LL	1764	1780	1378	1404	2072	2085	1858	1917
Sample size	1047		925		1044		1008	
	For comparison: sum across all subperiods							
AIC	-3638	-3628	-2831	-2854	-4202	-4203	-3893	-3908
BIC	-3538	-3508	-2748	-2754	-4121	-4105	-3802	-3799
LL	1854	1856	1446	1463	2126	2131	1986	2002
Sample size	1047		925		1044		1008	
	Panel 2: subperiod estimation output							
Subperiod 1	09-Jul-1993 to 28-Apr-1995		08-Sep-1995 to 17-Oct-1997		11-Jul-1993 to 17-May-1998		09-Jul-1993 to 08-Jul-1994	
Q(16)	41.546 [0]	41.657 [0]	11.839 [0.755]	11.86 [0.754]	15.727 [0.472]	15.63 [0.479]	7.969 [0.95]	8.347 [0.938]
Q^2(16)	18.682 [0.285]	20.849 [0.184]	9.433 [0.895]	9.289 [0.901]	18.435 [0.299]	18.477 [0.297]	12.262 [0.726]	11.823 [0.756]
LM(12)	14.788 [0.253]	16.273 [0.179]	8.685 [0.73]	7.985 [0.786]	12.609 [0.398]	13.317 [0.346]	10.167 [0.601]	8.602 [0.736]
AIC	-187	-185	-270	-272	-977	-976	-172	-172
BIC	-174	-170	-257	-256	-959	-955	-162	-160
LL	98	99	140	142	493	494	91	92
Sample size	95		110		251		52	
Subperiod 2	05-May-1995 to 11-Jul-1997		24-Oct-1997 to 16-Oct-1998		24-May-1998 to 14-Oct-2001		15-Jul-1994 to 12-Aug-1994	
Q(16)	17.172 [0.375]	17.45 [0.357]	18.613 [0.289]	17.341 [0.364]	12.622 [0.7]	12.697 [0.695]	1.328 [0.723]	1.122 [0.772]
Q^2(16)	10.764 [0.824]	10.839 [0.819]	18.902 [0.274]	20.212 [0.211]	15.26 [0.506]	15.153 [0.513]	1.468 [0.69]	1.357 [0.716]
LM(12)	4.082 [0.982]	4.17 [0.98]	7.337 [0.835]	8.987 [0.704]	16.276 [0.179]	16.173 [0.183]	2 [0.572]	2 [0.572]
AIC	-432	-432	-85	-79	-604	-604	1	-14
BIC	-419	-415	-75	-68	-588	-585	-1	-16
LL	221	222	48	46	307	308	5	13
Sample size	115		52		178		5	
Subperiod 3	18-Jul-1997 to 19-Mar-1999		23-Oct-1998 to 16-Mar-2001		21-Oct-2001 to 16-Sep-2007		19-Aug-1994 to 19-May-1995	
Q(16)	12.551 [0.705]	13.087 [0.666]	25.395 [0.063]	25.713 [0.058]	18.473 [0.297]	18.598 [0.29]	17.635 [0.346]	19.019 [0.268]
Q^2(16)	11.797 [0.758]	9.983 [0.868]	13.164 [0.661]	9.458 [0.893]	9.856 [0.874]	9.738 [0.88]	15.682 [0.475]	12.297 [0.723]
LM(12)	5.587 [0.935]	3.793 [0.987]	4.287 [0.978]	4.428 [0.974]	8.637 [0.734]	8.492 [0.746]	11.845 [0.458]	7.96 [0.788]
AIC	-200	-200	-268	-282	-1370	-1376	-104	-100
BIC	-187	-185	-254	-265	-1352	-1354	-95	-90
LL	105	106	139	147	690	694	57	56
Sample size	88		126		309		39	
Subperiod 4	26-Mar-1999 to 24-Jan-2003		23-Mar-2001 to 18-Jul-2008		23-Sep-2007 to 19-Jul-2009		26-May-1995 to 03-Oct-1997	
Q(16)	15.977 [0.455]	16.077 [0.448]	13.713 [0.62]	13.737 [0.618]	19.568 [0.24]	19.616 [0.238]	21.567 [0.158]	20.51 [0.198]
Q^2(16)	7.088 [0.972]	7.46 [0.963]	13.85 [0.61]	14.303 [0.576]	13.206 [0.658]	13.152 [0.662]	11.2 [0.797]	12.13 [0.735]
LM(12)	5.899 [0.921]	6.077 [0.912]	12.868 [0.379]	13.485 [0.335]	8.235 [0.767]	8.203 [0.769]	9.214 [0.685]	10.63 [0.561]
AIC	-654	-653	-1381	-1385	-281	-279	-378	-378
BIC	-637	-633	-1361	-1361	-268	-263	-364	-361
LL	332	332	695	698	145	145	194	195
Sample size	201		379		96		120	
Subperiod 5	31-Jan-2003 to 19-Sep-2008		25-Jul-2008 to 17-Jul-2009		26-Jul-2009 to 28-Jul-2013		10-Oct-1997 to 15-Dec-2006	
Q(16)	21.152 [0.173]	21.167 [0.172]	20.538 [0.197]	20.434 [0.201]	17.381 [0.361]	17.37 [0.362]	13.873 [0.608]	14.011 [0.598]
Q^2(16)	17.35 [0.363]	17.31 [0.366]	13.782 [0.615]	14.93 [0.53]	12.779 [0.689]	12.725 [0.693]	13.166 [0.661]	13.456 [0.639]
LM(12)	15.683 [0.206]	15.685 [0.206]	10.456 [0.576]	10.974 [0.531]	9.674 [0.645]	9.632 [0.648]	10.662 [0.558]	11.442 [0.492]
AIC	-1149	-1147	-89	-85	-970	-968	-1930	-1944
BIC	-1130	-1124	-79	-74	-954	-948	-1910	-1919
LL	579	579	49	49	490	490	970	978
Sample size	295		51		210		456	
Subperiod 6	26-Sep-2008 to 24-Jul-2009		24-Jul-2009 to 26-Jul-2013				22-Dec-2006 to 27-Mar-2009	
Q(16)	6.721 [0.978]	5.176 [0.995]	9.212 [0.904]	11.251 [0.794]			12.756 [0.691]	14.319 [0.575]
Q^2(16)	16.67 [0.407]	11.742 [0.762]	10.369 [0.847]	8.301 [0.939]			18.525 [0.294]	15.433 [0.493]
LM(12)	13.924 [0.306]	14.305 [0.282]	9.759 [0.637]	7.872 [0.795]			13.405 [0.34]	11.238 [0.509]
AIC	-122	-118	-738	-751			-358	-354
BIC	-113	-108	-722	-731			-345	-338
LL	66	65	374	381			184	183
Sample size	44		207				115	
Subperiod 7	31-Jul-2009 to 26-Jul-2013						03-Apr-2009 to 12-Nov-2010	
Q(16)	16.777 [0.4]	20.327 [0.206]					23.362 [0.104]	23.342 [0.105]
Q^2(16)	15.725 [0.472]	31.729 [0.011]					9.484 [0.892]	9.479 [0.892]
LM(12)	13.277 [0.349]	24.871 [0.015]					5.769 [0.927]	5.766 [0.927]
AIC	-894	-893					-321	-319
BIC	-878	-873					-309	-304
LL	452	453					165	165
Sample size	209						84	
Subperiod 8							19-Nov-2010 to 26-Jul-2013	
Q(16)							11.967 [0.746]	11.917 [0.75]
Q^2(16)							6.63 [0.98]	9.545 [0.889]
LM(12)							5.809 [0.925]	8.649 [0.733]
AIC							-630	-628
BIC							-616	-611
LL							320	320
Sample size							137	

Note: P-values are given in square bracket.

Appendix 6b - GJR Model Diagnostics – BRIC

	Brazil		Russia		India		China	
Panel 1: full sample estimation output								
	Normal	Student t	Normal	Student t	Normal	Student t	Normal	Student t
Q(16)	48.062 [0]	48.704 [0]	32.347 [0.009]	30.144 [0.017]	26.086 [0.053]	26.368 [0.049]	28.796 [0.025]	23.509 [0.101]
Q^2(16)	16.581 [0.413]	16.606 [0.412]	5.329 [0.994]	4.114 [0.999]	17.394 [0.361]	18.19 [0.313]	3.681 [0.999]	2.288 [1]
LM(12)	7.783 [0.802]	7.519 [0.821]	2.663 [0.997]	2.166 [0.999]	13.152 [0.358]	12.577 [0.401]	2.687 [0.997]	1.553 [1]
AIC	-3521	-3552	-2751	-2801	-4129	-4153	-3718	-3817
BIC	-3497	-3522	-2727	-2772	-4104	-4123	-3694	-3787
LL	1766	1782	1381	1407	2070	2082	1864	1914
Sample size	1047		925		1044		1008	
For comparison: sum across all subperiods								
AIC	-3599	-3592	-2798	-2818	-4183	-4190	-3821	-3843
BIC	-3499	-3473	-2714	-2718	-4101	-4092	-3730	-3733
LL	1834	1838	1429	1445	2117	2125	1951	1969
Sample size	1047		925		1044		1008	
Panel 2: subperiod estimation output								
Subperiod 1	09-Jul-1993 to 28-Apr-1995		08-Sep-1995 to 17-Oct-1997		11-Jul-1993 to 17-May-1998		09-Jul-1993 to 08-Jul-1994	
Q(16)	51.568 [0]	51.6 [0]	12.46 [0.712]	12.377 [0.718]	15.494 [0.489]	15.418 [0.494]	13.299 [0.651]	13.293 [0.651]
Q^2(16)	12.107 [0.737]	12.11 [0.736]	7.859 [0.953]	8.393 [0.936]	17.173 [0.374]	17.224 [0.371]	15.643 [0.478]	15.644 [0.478]
LM(12)	10.707 [0.554]	10.706 [0.554]	5.712 [0.93]	5.695 [0.931]	12.025 [0.444]	12.736 [0.389]	20.721 [0.055]	20.769 [0.054]
AIC	-175	-173	-268	-272	-977	-976	-159	-157
BIC	-163	-158	-255	-256	-959	-955	-149	-145
LL	93	93	139	142	493	494	85	85
Sample size	95		110		251		52	
Subperiod 2	05-May-1995 to 11-Jul-1997		24-Oct-1997 to 16-Oct-1998		24-May-1998 to 14-Oct-2001		15-Jul-1994 to 12-Aug-1994	
Q(16)	15.491 [0.489]	16.71 [0.405]	19.6 [0.239]	19.634 [0.237]	12.651 [0.698]	12.631 [0.699]	1.119 [0.772]	1.117 [0.773]
Q^2(16)	15.247 [0.507]	16.016 [0.452]	10.63 [0.832]	10.229 [0.854]	16.384 [0.427]	16.899 [0.392]	2.403 [0.493]	1.334 [0.721]
LM(12)	4.671 [0.968]	4.456 [0.974]	7.089 [0.852]	6.566 [0.885]	14.472 [0.272]	14.671 [0.26]	2 [0.572]	2 [0.572]
AIC	-431	-430	-66	-65	-595	-599	12	9
BIC	-417	-413	-56	-53	-579	-580	10	7
LL	221	221	38	38	303	305	-1	1
Sample size	115		52		178		5	
Subperiod 3	18-Jul-1997 to 19-Mar-1999		23-Oct-1998 to 16-Mar-2001		21-Oct-2001 to 16-Sep-2007		19-Aug-1994 to 19-May-1995	
Q(16)	12.112 [0.736]	12.266 [0.725]	25.375 [0.063]	25.39 [0.063]	19.624 [0.238]	19.064 [0.265]	5.411 [0.993]	3.786 [0.999]
Q^2(16)	14.503 [0.561]	14.834 [0.537]	13.686 [0.622]	13.415 [0.642]	8.698 [0.925]	9.289 [0.901]	0.582 [1]	0.19 [1]
LM(12)	8.229 [0.767]	8.32 [0.76]	4.749 [0.966]	4.716 [0.967]	7.273 [0.839]	7.852 [0.797]	18.696 [0.096]	16.528 [0.168]
AIC	-200	-200	-269	-267	-1363	-1372	-71	-85
BIC	-188	-185	-255	-250	-1345	-1349	-62	-75
LL	105	106	139	139	687	692	40	49
Sample size	88		126		309		39	
Subperiod 4	26-Mar-1999 to 24-Jan-2003		23-Mar-2001 to 18-Jul-2008		23-Sep-2007 to 19-Jul-2009		26-May-1995 to 03-Oct-1997	
Q(16)	13.826 [0.612]	14.4 [0.569]	14.014 [0.598]	13.983 [0.6]	24.314 [0.083]	24.288 [0.083]	23.226 [0.108]	23.26 [0.107]
Q^2(16)	11.579 [0.772]	10.416 [0.844]	15.618 [0.48]	14.789 [0.54]	10.796 [0.822]	10.803 [0.821]	13.246 [0.655]	12.815 [0.686]
LM(12)	9.009 [0.702]	8.168 [0.772]	14.865 [0.249]	14.175 [0.29]	7.169 [0.846]	7.156 [0.847]	11.096 [0.521]	10.817 [0.545]
AIC	-647	-650	-1379	-1385	-279	-277	-383	-382
BIC	-631	-630	-1359	-1361	-266	-262	-369	-365
LL	329	331	694	698	145	145	196	197
Sample size	201		379		96		120	
Subperiod 5	31-Jan-2003 to 19-Sep-2008		25-Jul-2008 to 17-Jul-2009		26-Jul-2009 to 28-Jul-2013		10-Oct-1997 to 15-Dec-2006	
Q(16)	19.9 [0.225]	19.9 [0.225]	17.649 [0.345]	17.644 [0.345]	17.347 [0.363]	17.335 [0.364]	14.113 [0.59]	14.172 [0.586]
Q^2(16)	20.263 [0.209]	20.227 [0.21]	25.898 [0.055]	25.869 [0.056]	10.507 [0.839]	10.499 [0.839]	12.751 [0.691]	12.241 [0.727]
LM(12)	21.085 [0.049]	21.084 [0.049]	13.894 [0.308]	13.895 [0.307]	7.753 [0.804]	7.751 [0.804]	10.265 [0.593]	10.314 [0.588]
AIC	-1140	-1137	-81	-79	-969	-967	-1933	-1946
BIC	-1121	-1115	-71	-67	-952	-946	-1912	-1922
LL	575	575	45	45	489	489	971	979
Sample size	295		51		210		456	
Subperiod 6	26-Sep-2008 to 24-Jul-2009		24-Jul-2009 to 26-Jul-2013				22-Dec-2006 to 27-Mar-2009	
Q(16)	6.777 [0.977]	6.756 [0.978]	12.182 [0.731]	13.278 [0.652]			18.146 [0.315]	18.154 [0.315]
Q^2(16)	9.425 [0.895]	9.332 [0.899]	7.77 [0.955]	8.534 [0.931]			19.298 [0.254]	19.324 [0.252]
LM(12)	14.266 [0.284]	14.264 [0.284]	6.582 [0.884]	7.878 [0.795]			14.985 [0.242]	14.943 [0.245]
AIC	-113	-111	-735	-751			-336	-334
BIC	-104	-100	-719	-731			-322	-318
LL	62	62	373	382			173	173
Sample size	44		207				115	
Subperiod 7	31-Jul-2009 to 26-Jul-2013						03-Apr-2009 to 12-Nov-2010	
Q(16)	14.808 [0.539]	14.787 [0.54]					24.197 [0.085]	24.162 [0.086]
Q^2(16)	13.841 [0.611]	13.497 [0.636]					10.675 [0.829]	10.649 [0.831]
LM(12)	10.575 [0.566]	10.31 [0.589]					6.785 [0.871]	6.769 [0.873]
AIC	-892	-891					-320	-318
BIC	-875	-871					-308	-304
LL	451	452					165	165
Sample size	209						84	
Subperiod 8							19-Nov-2010 to 26-Jul-2013	
Q(16)							11.82 [0.756]	11.822 [0.756]
Q^2(16)							9.682 [0.883]	9.666 [0.883]
LM(12)							8.18 [0.771]	8.168 [0.772]
AIC							-631	-629
BIC							-617	-612
LL							321	321
Sample size							137	

Note: P-values are given in square bracket.

Appendix 7a – 10-Period-Ahead Forecasts – BRIC and G6

Model		Brazil	Russia	India	China	US	UK	Japan	Italy	France	Germany
Panel 1. RMSE											
GARCH(1,1)	Normal	*0.004*	*0.011*	*0.003*	*0.003*	*0.003*	*0.004*	*0.005*	*0.003*	*0.004*	*0.004*
Expanding	Student t	0.999	1.012	1.003	0.838	0.977	0.975	1.008	0.942	0.986	0.984
GARCH(1,1) ICSS	Normal	1.015	1.043	1.014	0.835	1.029	1.017	1.080	0.992	1.022	1.009
	Student t	1.015	1.067	1.013	0.832	1.005	0.988	1.067	0.953	6.123	0.995
GARCH(1,1) 0.75	Normal	0.970	0.969	1.001	0.837	0.993	1.026	0.998	1.017	1.008	1.039
Rolling	Student t	0.973	0.965	1.001	0.832	0.967	0.985	1.013	0.941	0.996	0.992
GARCH(1,1) 0.50	Normal	0.968	0.960	1.042	0.836	0.988	1.036	1.029	1.147	1.007	1.131
Rolling	Student t	0.972	0.964	1.033	0.828	0.974	0.995	1.026	0.949	0.998	0.989
GARCH(1,1) 0.25	Normal	0.973	1.029	1.131	0.839	1.089	1.081	1.184	1.370	1.021	1.189
Rolling	Student t	1.030	1.063	1.140	0.851	1.029	1.062	1.091	0.958	1.015	0.973
EGARCH(1,1) ICSS	Normal	1.007	0.983	1.020	0.843	0.946	0.958	1.003	1.008	0.983	0.975
	Student t	1.000	0.968	1.022	**0.818**	0.944	0.961	1.003	0.969	0.982	0.971
EGARCH(1,1) 0.75	Normal	**0.950**	0.946	1.008	0.844	**0.941**	0.948	**0.997**	**0.900**	0.959	0.953
Rolling	Student t	0.951	**0.946**	1.012	0.839	0.941	**0.948**	0.997	0.901	**0.957**	**0.953**
EGARCH(1,1) 0.50	Normal	0.954	0.967	1.038	0.856	0.948	0.952	0.998	0.923	0.961	0.959
Rolling	Student t	0.953	0.968	1.038	0.862	0.944	0.952	0.999	0.912	0.962	0.957
EGARCH(1,1) 0.25	Normal	0.970	0.975	1.026	–	0.957	0.955	1.003	0.914	0.973	0.969
Rolling	Student t	0.969	0.964	1.034	–	0.955	0.955	1.004	0.916	0.973	0.966
GJR(1,1) ICSS	Normal	1.029	1.018	1.006	1.025	1.008	0.995	1.005	1.023	1.015	0.983
	Student t	1.022	1.040	1.012	0.836	0.986	0.974	1.012	0.927	0.993	0.976
GJR(1,1) 0.75	Normal	0.965	0.967	**0.999**	0.836	1.007	1.015	0.998	1.000	1.031	1.010
Rolling	Student t	0.963	0.966	1.000	0.831	0.973	0.979	1.001	0.909	1.000	0.983
GJR(1,1) 0.50	Normal	0.956	0.969	1.031	0.839	0.987	1.068	1.008	1.146	1.047	1.075
Rolling	Student t	0.956	0.970	1.028	0.837	0.974	0.989	1.007	0.914	0.993	0.985
GJR(1,1) 0.25	Normal	–	–	–	–	0.987	1.156	1.032	1.314	1.242	0.981
Rolling	Student t	–	–	–	–	1.011	1.092	1.011	1.056	1.004	0.972
MovingAverage0.5	–	0.970	0.976	1.049	0.877	0.957	0.957	0.999	0.917	0.968	0.958
Panel 2. QLIKE											
GARCH(1,1)	Normal	*1.507*	*1.894*	*1.314*	*1.449*	*1.999*	*1.975*	*1.690*	*1.396*	*1.638*	*1.935*
Expanding	Student t	0.990	**0.955**	1.019	0.891	1.010	0.991	1.006	1.030	0.991	1.005
GARCH(1,1) ICSS	Normal	1.093	1.243	1.016	0.842	1.065	1.098	1.097	1.122	1.142	1.172
	Student t	1.070	1.256	1.014	**0.830**	1.037	1.052	1.073	1.104	1.136	1.171
GARCH(1,1) 0.75	Normal	0.980	0.986	**0.992**	0.866	0.980	1.013	1.010	0.993	0.991	0.992
Rolling	Student t	0.972	0.974	0.996	0.845	1.004	0.980	1.018	1.060	0.987	0.961
GARCH(1,1) 0.50	Normal	1.003	1.128	1.077	0.860	1.052	1.070	1.070	1.057	1.034	1.063
Rolling	Student t	0.991	1.146	1.077	0.831	1.066	1.045	1.050	1.027	1.012	1.005
GARCH(1,1) 0.25	Normal	1.063	1.112	1.004	0.853	1.112	1.171	1.175	1.152	1.015	1.306
Rolling	Student t	1.062	1.094	0.993	0.843	1.072	1.055	1.068	1.014	0.995	1.123
EGARCH(1,1) ICSS	Normal	1.108	1.231	1.087	0.894	1.054	1.050	1.117	1.092	1.124	1.213
	Student t	1.086	1.206	1.110	0.840	1.003	1.037	1.116	1.569	1.106	1.177
EGARCH(1,1) 0.75	Normal	0.939	1.022	1.014	0.892	**0.949**	**0.919**	**0.989**	1.076	**0.925**	**0.910**
Rolling	Student t	**0.937**	1.017	1.029	0.870	0.989	0.939	0.998	1.088	0.935	0.915
EGARCH(1,1) 0.50	Normal	0.955	1.221	1.161	0.883	1.038	1.021	1.036	1.256	1.012	0.975
Rolling	Student t	0.946	1.219	1.176	0.872	1.031	1.034	1.050	1.112	1.028	0.970
EGARCH(1,1) 0.25	Normal	1.051	1.206	1.096	–	1.155	1.119	1.158	1.197	1.370	1.199
Rolling	Student t	1.037	1.229	1.157	–	1.133	1.145	1.170	1.172	1.340	1.218
GJR(1,1) ICSS	Normal	-	-	-	-	1.029	0.972	1.104	0.992	0.990	1.115
	Student t	-	-	-	-	1.031	0.970	1.104	1.053	0.986	1.123
GJR(1,1) 0.75	Normal	-	-	-	-	0.963	0.974	1.000	1.016	0.978	0.961
Rolling	Student t	-	-	-	-	0.992	0.966	0.996	1.113	0.981	0.949
GJR(1,1) 0.50	Normal	-	-	-	-	1.055	1.062	1.042	1.081	1.061	1.011
Rolling	Student t	-	-	-	-	1.060	1.045	1.042	1.013	1.049	0.978
GJR(1,1) 0.25	Normal	–	–	–	–	1.133	1.128	1.174	1.073	1.232	1.179
Rolling	Student t	–	–	–	–	1.084	1.042	1.133	**0.962**	1.157	1.145
MovingAverage0.5	–	1.034	1.283	1.211	1.023	1.119	1.124	1.039	1.100	1.088	0.941

Note: Figures for the GARCH(1,1) expanding w indow model represent the value of loss function for this model. Figures for the other models provide the ratio of the value of loss function for each model to the value of loss function for the GARCH(1,1) expanding w indow model.

Appendix 7b – 30-Period-Ahead Forecasts – BRIC and G6

Model		Brazil	Russia	India	China	US	UK	Japan	Italy	France	Germany
					Panel 1. RMSE						
GARCH(1,1)	Normal	*0.005*	*0.012*	*0.003*	*0.005*	*0.003*	*0.004*	*0.005*	*0.004*	*0.005*	*0.005*
Expanding	Student t	0.998	1.002	1.004	0.550	0.994	0.955	1.001	0.855	0.970	0.996
GARCH(1,1) ICSS	Normal	0.995	1.040	0.975	0.535	1.236	1.059	1.457	0.928	1.017	1.016
	Student t	0.999	1.052	**0.959**	0.530	1.233	1.014	1.254	0.854	8.272	1.014
GARCH(1,1) 0.75	Normal	0.954	0.919	1.007	0.532	0.971	1.047	1.001	1.028	1.018	1.061
Rolling	Student t	0.962	0.910	0.992	0.532	0.985	0.963	1.018	0.873	0.993	0.999
GARCH(1,1) 0.50	Normal	0.962	0.905	1.049	0.559	0.969	1.066	1.007	1.419	1.023	1.241
Rolling	Student t	0.964	0.916	1.048	0.554	0.995	0.991	1.033	0.898	0.997	1.007
GARCH(1,1) 0.25	Normal	0.978	1.015	1.204	0.548	1.096	1.172	1.232	2.629	1.052	1.817
Rolling	Student t	1.057	1.083	1.182	0.607	1.082	1.082	1.112	0.897	1.005	0.996
EGARCH(1,1) ICSS	Normal	1.007	0.942	1.012	0.567	0.940	0.951	1.007	0.927	0.960	0.992
	Student t	0.991	0.912	1.012	**0.525**	0.941	0.944	1.006	0.900	0.955	0.987
EGARCH(1,1) 0.75	Normal	0.952	0.900	1.003	0.534	**0.932**	**0.924**	1.000	0.680	**0.930**	**0.957**
Rolling	Student t	0.956	**0.899**	1.004	0.534	0.936	0.926	1.000	0.687	0.930	0.958
EGARCH(1,1) 0.50	Normal	0.955	0.908	1.027	0.574	0.941	0.929	1.002	0.675	0.935	0.960
Rolling	Student t	0.956	0.905	1.025	0.564	0.943	0.930	1.002	0.685	0.937	0.962
EGARCH(1,1) 0.25	Normal	0.970	0.918	1.036	–	0.946	0.932	1.008	**0.655**	0.941	0.971
Rolling	Student t	0.968	0.906	1.039	–	0.946	0.932	1.007	0.668	0.941	0.972
GJR(1,1) ICSS	Normal	1.028	1.014	1.002	1.036	0.960	0.955	1.002	0.883	0.987	0.970
	Student t	1.022	1.031	1.010	0.550	0.951	0.939	1.001	0.761	0.959	0.972
GJR(1,1) 0.75	Normal	**0.952**	0.908	0.982	0.532	0.957	0.974	1.000	0.742	1.000	0.974
Rolling	Student t	0.965	0.905	0.996	0.533	0.961	0.941	1.001	0.693	0.959	0.965
GJR(1,1) 0.50	Normal	0.955	0.902	1.038	0.560	0.946	1.031	1.002	1.086	1.018	0.985
Rolling	Student t	0.957	0.908	1.035	0.552	0.961	0.944	**1.000**	0.706	0.952	0.963
GJR(1,1) 0.25	Normal	–	–	–	–	0.952	1.210	1.016	1.412	1.333	1.004
Rolling	Student t	–	–	–	–	0.957	1.034	1.008	0.944	0.944	0.977
MovingAverage0.5	–	0.963	0.911	1.036	0.547	0.944	0.930	1.004	0.659	0.932	0.958
					Panel 2. QLIKE						
GARCH(1,1)	Normal	*1.633*	*2.365*	*1.445*	*1.965*	*2.059*	*2.174*	*1.715*	*1.569*	*1.832*	*1.980*
Expanding	Student t	0.986	**0.911**	1.018	0.731	1.008	0.975	**0.976**	1.002	0.976	1.006
GARCH(1,1) ICSS	Normal	1.057	1.330	1.030	0.660	1.108	1.144	1.078	0.982	1.129	1.443
	Student t	1.052	1.361	1.026	**0.643**	1.094	1.103	1.044	0.972	1.139	1.472
GARCH(1,1) 0.75	Normal	0.915	0.955	0.995	0.704	0.991	1.056	1.019	0.993	0.996	1.030
Rolling	Student t	0.927	0.936	0.987	0.693	1.022	**0.942**	1.007	1.104	0.975	0.955
GARCH(1,1) 0.50	Normal	0.962	1.082	1.148	0.741	1.048	1.126	1.064	1.141	1.062	1.095
Rolling	Student t	0.952	1.111	1.140	0.705	1.108	1.028	1.026	1.006	1.021	0.973
GARCH(1,1) 0.25	Normal	1.057	1.187	1.015	0.711	1.108	1.412	1.258	1.331	1.007	1.676
Rolling	Student t	1.072	1.209	1.002	0.728	1.105	1.148	1.061	0.956	1.014	1.305
EGARCH(1,1) ICSS	Normal	1.115	1.275	1.061	0.755	1.067	1.061	1.102	1.035	1.157	1.303
	Student t	1.070	1.169	1.074	0.673	1.134	1.065	1.103	1.007	1.108	1.345
EGARCH(1,1) 0.75	Normal	0.909	1.053	1.003	0.719	0.987	0.967	1.005	1.115	**0.920**	0.946
Rolling	Student t	0.923	1.031	1.011	0.716	1.104	1.022	1.010	1.249	0.959	0.968
EGARCH(1,1) 0.50	Normal	0.926	1.210	1.146	0.754	1.158	1.174	1.064	1.037	1.088	1.011
Rolling	Student t	0.926	1.114	1.150	0.733	1.265	1.214	1.067	1.177	1.156	1.066
EGARCH(1,1) 0.25	Normal	1.038	1.205	1.134	–	1.331	1.308	1.226	0.886	1.379	1.328
Rolling	Student t	1.022	1.291	1.206	–	1.379	1.374	1.235	0.965	1.432	1.389
GJR(1,1) ICSS	Normal	1.142	1.135	1.030	1.009	1.027	1.024	1.053	0.941	0.978	1.220
	Student t	1.123	1.136	1.061	0.729	1.047	1.030	1.038	1.071	0.972	1.234
GJR(1,1) 0.75	Normal	**0.904**	0.991	**0.959**	0.705	**0.976**	1.020	1.004	0.949	0.949	0.987
Rolling	Student t	0.963	0.953	0.992	0.698	1.044	1.003	1.000	1.286	0.962	0.961
GJR(1,1) 0.50	Normal	0.922	1.044	1.142	0.746	1.119	1.197	1.055	0.988	1.144	1.023
Rolling	Student t	0.935	1.109	1.146	0.707	1.176	1.155	1.001	1.035	1.148	0.995
GJR(1,1) 0.25	Normal	–	–	–	–	1.161	1.442	1.259	1.073	1.487	1.333
Rolling	Student t	–	–	–	–	1.092	1.287	1.192	0.922	1.295	1.294
MovingAverage0.5	–	0.964	1.127	1.163	0.768	1.168	1.110	1.075	**0.840**	0.979	**0.942**

Note: Figures for the GARCH(1,1) expanding window model represent the value of loss function for this model. Figures for the other models provide the ratio of the value of loss function for each model to the value of loss function for the GARCH(1,1) expanding window model.

Appendix 8 – Matlab Code – Unit Root Tests

```
clear
clc

[price_data,title] = xlsread('data for thesis.xlsx','rearranged data
weekly');
[r,c]              = size(price_data);


% 1.1 Unit Root tests -- ADF,PP,KPSS

% Part A. For series of price level
Unitroottable_pricelevel = zeros(12,c);

for i = 1:c

% Augmented Dickey-Fuller test
    [~,pValue,stats]     =
adftest(price_data(2:end,i),'model','ARD','Lags',10); %with intercept only
    Unitroottable_pricelevel(1,i) = stats;
    Unitroottable_pricelevel(2,i) = pValue;

    [~,pValue,stats]     =
adftest(price_data(2:end,i),'model','TS','Lags',10); %with intercept and
trend
    Unitroottable_pricelevel(3,i) = stats;
    Unitroottable_pricelevel(4,i) = pValue;

% Phillips-Perron test
    [~,pValue,stats]     =
pptest(price_data(2:end,i),'model','ARD','Lags',10); %with intercept only
    Unitroottable_pricelevel(5,i) = stats;
    Unitroottable_pricelevel(6,i) = pValue;

    [~,pValue,stats]     =
pptest(price_data(2:end,i),'model','TS','Lags',10); %with intercept and
trend
    Unitroottable_pricelevel(7,i) = stats;
    Unitroottable_pricelevel(8,i) = pValue;

% KPSS test
    [~,pValue,stats]     =
kpsstest(price_data(2:end,i),'trend',false,'Lags',10); %with intercept only
    Unitroottable_pricelevel(9,i) = stats;
    Unitroottable_pricelevel(10,i)= pValue;

    [~,pValue,stats]     =
kpsstest(price_data(2:end,i),'trend',true,'Lags',10); %with intercept and
trend
    Unitroottable_pricelevel(11,i)= stats;
    Unitroottable_pricelevel(12,i)= pValue;
end

%round to 4 decimal places
Unitroottable_pricelevel = RoundToDecimalPlace(Unitroottable_pricelevel,4);

%Organise the results in table
```

```
for i = 2:2:12
    for j = 1:c
        if Unitroottable_pricelevel(i,j) > 0.01 &&
Unitroottable_pricelevel(i,j) <= 0.05
            Pricetest_cells(i-1,j) =
{strcat(num2str(Unitroottable_pricelevel(i-1,j)),'*')};
            Pricetest_cells(i,j)   =
{strcat('(',num2str(Unitroottable_pricelevel(i,j)),')')};
        elseif Unitroottable_pricelevel(i,j) <= 0.01
            Pricetest_cells(i-1,j) =
{strcat(num2str(Unitroottable_pricelevel(i-1,j)),'**')};
            Pricetest_cells(i,j)   =
{strcat('(',num2str(Unitroottable_pricelevel(i,j)),')')};
        else
            Pricetest_cells(i-1,j) = {num2str(Unitroottable_pricelevel(i-
1,j))};
            Pricetest_cells(i,j)   =
{strcat('(',num2str(Unitroottable_pricelevel(i,j)),')')};
        end
    end
end
%% Index plot
for j = 1:c

    Price2  = price_data(2:price_data(1,j)+1,j);

    % codes below generates(sub)plot for Index series
    if j<=4
        switch j
            case 1
                figure
                subplot(2,2,1)
                plot(Price2)
                legend('Brazil-Index','Location','NorthWest')
                ylabel('Index level')
                axis tight
            case 2
                subplot(2,2,2)
                plot(Price2)
                legend('Russia-Index','Location','NorthWest')
                ylabel('Index level')
                axis tight
            case 3
                subplot(2,2,3)
                plot(Price2)
                legend('India-Index','Location','NorthWest')
                ylabel('Index level')
                axis tight
            case 4
                subplot(2,2,4)
                plot(Price2)
                legend('China-Index','Location','NorthWest')
                ylabel('Index level')
                axis tight
        end

    elseif j>=5
        switch j
            case 5
                figure
                subplot(3,2,1)
```

```
                plot(Price2)
                legend('US-Index')
                ylabel('Index level')
                axis tight
            case 6
                subplot(3,2,2)
                plot(Price2)
                legend('UK-Index')
                ylabel('Index level')
                axis tight
            case 7
                subplot(3,2,3)
                plot(Price2)
                legend('Japan-Index')
                ylabel('Index level')
                axis tight
            case 8
                subplot(3,2,4)
                plot(Price2)
                legend('Italy-Index')
                ylabel('Index level')
                axis tight
            case 9
                subplot(3,2,5)
                plot(Price2)
                legend('France-Index')
                ylabel('Index level')
                axis tight
            case 10
                subplot(3,2,6)
                plot(Price2)
                legend('Germany-Index')
                ylabel('Index level')
                axis tight
        end
    end

end
%%
% Part B. For series of return
Unitroottable_return = zeros(10,c);

for i = 1:c

    Price1  = price_data(2:price_data(1,i)+1,i);
    Return1 = log(Price1(2:end)./Price1(1:end-1)); %calculating log returns

% ADF test
    [~,pValue,stats]    = adftest(Return1,'model','ARD','Lags',10); %with
intercept only
    Unitroottable_return(1,i) = stats;
    Unitroottable_return(2,i) = pValue;

    [~,pValue,stats]    = adftest(Return1,'model','AR','Lags',10); %no
intercept
    Unitroottable_return(3,i) = stats;
    Unitroottable_return(4,i) = pValue;

% PP test
```

```
    [~,pValue,stats]    = pptest(Return1,'model','ARD','Lags',10); %with
intercept only
    Unitroottable_return(5,i) = stats;
    Unitroottable_return(6,i) = pValue;

    [~,pValue,stats]    = pptest(Return1,'model','AR','Lags',10); %no
intercept
    Unitroottable_return(7,i) = stats;
    Unitroottable_return(8,i) = pValue;

% KPSS test
    [~,pValue,stats]    = kpsstest(Return1,'trend',false,'Lags',10); %with
intercept only
    Unitroottable_return(9,i) = stats;
    Unitroottable_return(10,i)= pValue;

    % codes below generates(sub)plot for Return series
    if i<=4
        switch i
            case 1
                figure
                subplot(2,2,1)
                plot(Return1)
                legend('Brazil-Return','Location','NorthWest')
                ylabel('Return')
                axis tight
            case 2
                subplot(2,2,2)
                plot(Return1)
                legend('Russia-Return','Location','NorthWest')
                ylabel('Return')
                axis tight
            case 3
                subplot(2,2,3)
                plot(Return1)
                legend('India-Return','Location','NorthWest')
                ylabel('Return')
                axis tight
            case 4
                subplot(2,2,4)
                plot(Return1)
                legend('China-Return','Location','NorthWest')
                ylabel('Return')
                axis tight
        end

    elseif i>=5
        switch i
            case 5
                figure
                subplot(3,2,1)
                plot(Return1)
                legend('US-Return')
                ylabel('Return')
                axis tight
            case 6
                subplot(3,2,2)
                plot(Return1)
                legend('UK-Return')
                ylabel('Return')
```

```
                axis tight
            case 7
                subplot(3,2,3)
                plot(Return1)
                legend('Japan-Return')
                ylabel('Return')
                axis tight
            case 8
                subplot(3,2,4)
                plot(Return1)
                legend('Italy-Return')
                ylabel('Return')
                axis tight
            case 9
                subplot(3,2,5)
                plot(Return1)
                legend('France-Return')
                ylabel('Return')
                axis tight
            case 10
                subplot(3,2,6)
                plot(Return1)
                legend('Germany-Return')
                ylabel('Return')
                axis tight
        end
    end

end

%round to 4 decimal places
Unitroottable_return = RoundToDecimalPlace(Unitroottable_return,4);

%Organise the results in table
for i = 2:2:10
    for j = 1:c
        if Unitroottable_return(i,j) > 0.01 && Unitroottable_return(i,j) <=
0.05
            Returntest_cells(i-1,j) =
{strcat(num2str(Unitroottable_return(i-1,j)),'*')};
            Returntest_cells(i,j)    =
{strcat('(',num2str(Unitroottable_return(i,j)),')')};
        elseif Unitroottable_return(i,j) <= 0.01
            Returntest_cells(i-1,j) =
{strcat(num2str(Unitroottable_return(i-1,j)),'**')};
            Returntest_cells(i,j)    =
{strcat('(',num2str(Unitroottable_return(i,j)),')')};
        else
            Returntest_cells(i-1,j) = {num2str(Unitroottable_return(i-
1,j))};
            Returntest_cells(i,j)    =
{strcat('(',num2str(Unitroottable_return(i,j)),')')};
        end
    end
end

%% 2. Calculating the descriptive statistics
descriptive_stats = zeros(8,c);

for j = 1:c
```

```
    Price  = price_data(2:price_data(1,j)+1,j);
    Return = log(Price(2:end)./Price(1:end-1)); %calculating log returns

    descriptive_stats(1,j) = mean(Return);
    descriptive_stats(2,j) = std(Return);
    descriptive_stats(3,j) = skewness(Return);
    descriptive_stats(4,j) = kurtosis(Return)-3;
    descriptive_stats(5,j) = max(Return);
    descriptive_stats(6,j) = min(Return);
    [h, p_value, jbstat]   = jbtest(Return); %performing Jarque-Bera test
    descriptive_stats(7,j) = jbstat;
    descriptive_stats(8,j) = p_value;

end

% Estimating the significance
standard_error_matrix       = zeros(4,10);

% standard error for mean
standard_error_matrix(1,:) = descriptive_stats(2,:)./sqrt(price_data(1,:));
% standard error for standard deviation
standard_error_matrix(2,:) = (descriptive_stats(2,:).^2) .*
sqrt(2./(price_data(1,:)-1));
% standard error for skewness
standard_error_matrix(3,:) = sqrt((6*price_data(1,:).*(price_data(1,:)-
1))./...
    ((price_data(1,:)-2).*(price_data(1,:)+1).*(price_data(1,:)+3)));
% standard error for kurtosis
standard_error_matrix(4,:) = 2*standard_error_matrix(3,:).*...
    sqrt((price_data(1,:).^2-1)./((price_data(1,:)-
3).*(price_data(1,:)+5)));

pvalue_table_des_stats = descriptive_stats(1:4,:)./standard_error_matrix;

%round to 4 decimal places
descriptive_stats = RoundToDecimalPlace(descriptive_stats,4);

%Organise the results in table
for i = 1:4
    for j = 1:c
        if abs(pvalue_table_des_stats(i,j)) >= 1.96 &&
abs(pvalue_table_des_stats(i,j)) < 2.58
            descriptive_cells(i,j) =
{strcat(num2str(descriptive_stats(i,j)),'*')};
        elseif abs(pvalue_table_des_stats(i,j)) >= 2.58
            descriptive_cells(i,j) =
{strcat(num2str(descriptive_stats(i,j)),'**')};
        else
            descriptive_cells(i,j) = {num2str(descriptive_stats(i,j))};
        end
    end
end
```

Appendix 9 – Matlab Code – Diagnostic Test

```
clear
clc

[price_data,title] = xlsread('data for thesis.xlsx','rearranged data
weekly');
[r,c]              = size(price_data);

%% 3. Diagnostic tests

% 3.1 Ljung-Box statistics
% for Return level
LjungBox_table = zeros(8,c);

for j = 1:c

    Price  = price_data(2:price_data(1,j)+1,j);
    Return = log(Price(2:end)./Price(1:end-1));

    [~,pValue,stat]      = lbqtest(Return,'lags',1);
    LjungBox_table(1,j) = stat;
    LjungBox_table(2,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return,'lags',8);
    LjungBox_table(3,j) = stat;
    LjungBox_table(4,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return,'lags',12);
    LjungBox_table(5,j) = stat;
    LjungBox_table(6,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return,'lags',16);
    LjungBox_table(7,j) = stat;
    LjungBox_table(8,j) = pValue;

    % codes below generates autocorrelation (sub)plot for Return series
    if j<=4
        switch j
            case 1
                figure
                subplot(2,2,1)
                autocorr(Return)
                legend('Brazil-Return')
                axis tight
            case 2
                subplot(2,2,2)
                autocorr(Return)
                legend('Russia-Return')
                axis tight
            case 3
                subplot(2,2,3)
                autocorr(Return)
                legend('India-Return')
                axis tight
            case 4
                subplot(2,2,4)
```

```
                autocorr(Return)
                legend('China-Return')
                axis tight
        end

    elseif j>=5
        switch j
            case 5
                figure
                subplot(2,3,1)
                autocorr(Return)
                legend('US-Return')
                axis tight
            case 6
                subplot(2,3,2)
                autocorr(Return)
                legend('UK-Return')
                axis tight
            case 7
                subplot(2,3,3)
                autocorr(Return)
                legend('Japan-Return')
                axis tight
            case 8
                subplot(2,3,4)
                autocorr(Return)
                legend('Italy-Return')
                axis tight
            case 9
                subplot(2,3,5)
                autocorr(Return)
                legend('France-Return')
                axis tight
            case 10
                subplot(2,3,6)
                autocorr(Return)
                legend('Germany-Return')
                axis tight
        end
    end

end

%round to 4 decimal places
LjungBox_table = RoundToDecimalPlace(LjungBox_table,4);

%set the value to 0.001 when the rounded value is less than 0.00005
%to be consistent with the rule applied in ADF test and PP test in MatLab
%for the computed pValue
for i = 1:8
    for j = 1:c
        if LjungBox_table(i,j) == 0
            LjungBox_table(i,j) = 0.001;
        end
    end
end

%Organise the results in table
for i = 2:2:8
    for j = 1:c
```

```
        if LjungBox_table(i,j) > 0.01 && LjungBox_table(i,j) <= 0.05
            LjungBox_cells(i-1,j) = {strcat(num2str(LjungBox_table(i-
1,j)),'*')};
            LjungBox_cells(i,j)   =
{strcat('(',num2str(LjungBox_table(i,j)),')')};
        elseif LjungBox_table(i,j) <= 0.01
            LjungBox_cells(i-1,j) = {strcat(num2str(LjungBox_table(i-
1,j)),'**')};
            LjungBox_cells(i,j)   =
{strcat('(',num2str(LjungBox_table(i,j)),')')};
        else
            LjungBox_cells(i-1,j) = {num2str(LjungBox_table(i-1,j))};
            LjungBox_cells(i,j)   =
{strcat('(',num2str(LjungBox_table(i,j)),')')};
        end
    end
end

%% for Return Squared
LjungBox_table_Squared = zeros(8,c);

for j = 1:c

    Price          = price_data(2:price_data(1,j)+1,j);
    Return         = log(Price(2:end)./Price(1:end-1));
    Return_Squared = Return.^2;

    [~,pValue,stat]      = lbqtest(Return_Squared,'lags',1);
    LjungBox_table_Squared(1,j) = stat;
    LjungBox_table_Squared(2,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return_Squared,'lags',8);
    LjungBox_table_Squared(3,j) = stat;
    LjungBox_table_Squared(4,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return_Squared,'lags',12);
    LjungBox_table_Squared(5,j) = stat;
    LjungBox_table_Squared(6,j) = pValue;

    [~,pValue,stat]      = lbqtest(Return_Squared,'lags',16);
    LjungBox_table_Squared(7,j) = stat;
    LjungBox_table_Squared(8,j) = pValue;

    % codes below generates autocorrelation (sub)plot for Return Squared
    if j<=4
        switch j
            case 1
                figure
                subplot(2,2,1)
                autocorr(Return_Squared)
                legend('Brazil-Return Squared')
                axis tight
            case 2
                subplot(2,2,2)
                autocorr(Return_Squared)
                legend('Russia-Return Squared')
                axis tight
            case 3
                subplot(2,2,3)
                autocorr(Return_Squared)
```

```
                legend('India-Return Squared')
                axis tight
            case 4
                subplot(2,2,4)
                autocorr(Return_Squared)
                legend('China-Return Squared')
                axis tight
        end

    elseif j>=5
        switch j
            case 5
                figure
                subplot(2,3,1)
                autocorr(Return_Squared)
                legend('US-Return Squared')
                axis tight
            case 6
                subplot(2,3,2)
                autocorr(Return_Squared)
                legend('UK-Return Squared')
                axis tight
            case 7
                subplot(2,3,3)
                autocorr(Return_Squared)
                legend('Japan-Return Squared')
                axis tight
            case 8
                subplot(2,3,4)
                autocorr(Return_Squared)
                legend('Italy-Return Squared')
                axis tight
            case 9
                subplot(2,3,5)
                autocorr(Return_Squared)
                legend('France-Return Squared')
                axis tight
            case 10
                subplot(2,3,6)
                autocorr(Return_Squared)
                legend('Germany-Return Squared')
                axis tight
        end
    end

end

%round to 4 decimal places
LjungBox_table_Squared = RoundToDecimalPlace(LjungBox_table_Squared,4);

%set the value to 0.001 when the rounded value is less than 0.00005
%to be consistent with the rule applied in ADF test and PP test in MatLab
%for the computed pValue
for i = 1:8
    for j = 1:c
        if LjungBox_table_Squared(i,j) == 0
            LjungBox_table_Squared(i,j) = 0.001;
        end
    end
end
```

```
%Organise the results in table
for i = 2:2:8
    for j = 1:c
        if LjungBox_table_Squared(i,j) > 0.01 &&
LjungBox_table_Squared(i,j) <= 0.05
            LjungBox_cells_Squared(i-1,j) =
{strcat(num2str(LjungBox_table_Squared(i-1,j)),'*')};
            LjungBox_cells_Squared(i,j)   =
{strcat('(',num2str(LjungBox_table_Squared(i,j)),')')};
        elseif LjungBox_table_Squared(i,j) <= 0.01
            LjungBox_cells_Squared(i-1,j) =
{strcat(num2str(LjungBox_table_Squared(i-1,j)),'**')};
            LjungBox_cells_Squared(i,j)   =
{strcat('(',num2str(LjungBox_table_Squared(i,j)),')')};
        else
            LjungBox_cells_Squared(i-1,j) =
{num2str(LjungBox_table_Squared(i-1,j))};
            LjungBox_cells_Squared(i,j)   =
{strcat('(',num2str(LjungBox_table_Squared(i,j)),')')};
        end
    end
end

%% 3.2 Engle's ARCH Lagrange multiplier statistics
% for Return level only
ARCH_LM_table = zeros(4,c);

for j = 1:c

    Price  = price_data(2:price_data(1,j)+1,j);
    Return = log(Price(2:end)./Price(1:end-1));

    [~,pValue,stat]     = archtest(Return,'lags',2);
    ARCH_LM_table(1,j)  = stat;
    ARCH_LM_table(2,j)  = pValue;

    [~,pValue,stat]     = archtest(Return,'lags',12);
    ARCH_LM_table(3,j)  = stat;
    ARCH_LM_table(4,j)  = pValue;

end

%round to 4 decimal places
ARCH_LM_table = RoundToDecimalPlace(ARCH_LM_table,4);

%set the value to 0.001 when the rounded value is less than 0.00005
%to be consistent with the rule applied in ADF test and PP test in MatLab
%for the computed pValue
for i = 1:4
    for j = 1:c
        if ARCH_LM_table(i,j) == 0
            ARCH_LM_table(i,j) = 0.001;
        end
    end
end

%Organise the results in table
for i = 2:2:4
```

```
    for j = 1:c
        if ARCH_LM_table(i,j) > 0.01 && ARCH_LM_table(i,j) <= 0.05
            ARCH_LM_cells(i-1,j) = {strcat(num2str(ARCH_LM_table(i-
1,j)),'*')};
            ARCH_LM_cells(i,j)   =
{strcat('(',num2str(ARCH_LM_table(i,j)),')')};
        elseif ARCH_LM_table(i,j) <= 0.01
            ARCH_LM_cells(i-1,j) = {strcat(num2str(ARCH_LM_table(i-
1,j)),'**')};
            ARCH_LM_cells(i,j)   =
{strcat('(',num2str(ARCH_LM_table(i,j)),')')};
        else
            ARCH_LM_cells(i-1,j) = {num2str(ARCH_LM_table(i-1,j))};
            ARCH_LM_cells(i,j)   =
{strcat('(',num2str(ARCH_LM_table(i,j)),')')};
        end
    end
end
```

Appendix 10 – Matlab Code – Break Points Detection

```
clear
clc

[serialnum_Excel,title] = xlsread('data for thesis.xlsx','date weekly');
price_data              = xlsread('data for thesis.xlsx','rearranged data
weekly');
[~,c]                   = size(serialnum_Excel);

%% 4. Break Points Detection
for j = 1:c

    % convert serial date number in Excel to serial date number in Matlab
    serialnum_Matlab   =
x2mdate(serialnum_Excel(3:serialnum_Excel(1,j)+1,j));

    Return             = price2ret(price_data(2:price_data(1,j)+1,j));
    % use the ICSS algorithm to identify the position of each break point
    break_positions    = ICSS(Return,1)';

    if numel(break_positions) == 0
        NumBreakPoints(1,j)    = 0;
        continue % jump to the next pass if no break is detected
    end

    break_positions1   = [1;break_positions];
    break_serials1(1,j)= {serialnum_Matlab(break_positions1)};
    % convert the serial date number to string format showing the actual
    % date and time
    % Break_dates1 constains the beginning dates of each sub-period
    Break_dates1(1,j)  = {datestr(break_serials1{j})};

    break_positions2   = [break_positions-1;length(Return)];
    break_serials2(1,j)= {serialnum_Matlab(break_positions2)};
    % Break_dates2 constains the ending dates of each period
    Break_dates2(1,j)  = {datestr(break_serials2{j})};
    % Break_dates_all contains both beginning and ending dates of each
    % sub-period
    Break_dates_all(1,j) = {strcat(Break_dates1{j},'
to''',Break_dates2{j})};

    length_break         = length(break_positions);

    NumBreakPoints(1,j)  = length_break; % identify number of break points

    %compute 3 times standard deviation for each sub-period
    Three_std_break      = zeros(length_break+1,1);
    Three_std_break(1)   = 3*std(Return(1:break_positions(1)-1));
    Three_std_break(end) = 3*std(Return(break_positions(end):end));

    stdev_for_plot = zeros(length(Return),1);
    stdev_for_plot(1:break_positions(1)-1)    = Three_std_break(1);
    stdev_for_plot(break_positions(end):end)  = Three_std_break(end);

    for i = 1:length_break-1
```

```
        Three_std_break(i+1) =
3*std(Return(break_positions(i):break_positions(i+1)-1));
        stdev_for_plot(break_positions(i):break_positions(i+1)-1) =
Three_std_break(i+1);
    end

    StdevTable(1:length_break+1,j) = Three_std_break/3; %standard deviation
table
    StdevTable = RoundToDecimalPlace(StdevTable,4); % round to 4 decimal
places

    %PositionCell constains the 'Position' vector for each legend in plot
    PositionCell    = cell(10,1);
    PositionCell(1) = {[.145,.9022,.1,.1]};
    PositionCell(2) = {[.586,.9022,.1,.1]};
    PositionCell(3) = {[.145,.431,.1,.1]};
    PositionCell(4) = {[.586,.43,.1,.1]};
    PositionCell(5) = {[.145,.9022,.1,.1]};
    PositionCell(6) = {[.586,.9022,.1,.1]};
    PositionCell(7) = {[.145,.603,.1,.1]};
    PositionCell(8) = {[.586,.603,.1,.1]};
    PositionCell(9) = {[.145,.303,.1,.1]};
    PositionCell(10)= {[.586,.303,.1,.1]};

        if j == 1 || j == 5
            figure % generate a new figure
        end
           if j<=4
                subplot(2,2,j)
                plot(Return);hold on
                plot(stdev_for_plot,'color','k','linestyle',':'); hold on
                plot(-stdev_for_plot,'color','k','linestyle',':');
                leg=legend(title(j),'+-3 standard deviations');
                set(leg,'Position',PositionCell{j})
                hold off
                ylabel('Return')
                axis tight
            elseif j >= 5
                subplot(3,2,j-4)
                plot(Return);hold on
                plot(stdev_for_plot,'color','k','linestyle',':'); hold on
                plot(-stdev_for_plot,'color','k','linestyle',':'); hold off
                leg=legend(title(j),'+-3 standard deviations');
                set(leg,'Position',PositionCell{j})
                ylabel('Return')
                axis tight
           end

 end
```

Appendix 11 – Matlab Code – In-Sample Tests

```
clear
clc

[price_data,title] = xlsread('data for thesis.xlsx','rearranged data
weekly');
BRIC_data           = price_data(:,1:4);
[r,c]               = size(BRIC_data);

%% 5. Model Estimation using GARCH(1,1)

Parameter_Sub_Cells        = {};
GARCH_Diag_Table_N         = zeros(6,1);
GARCH_Diag_Cells           = {};
GARCH_Sub-periodDiag_Cells = {};
Para_vector_N              = zeros(8,1);
Para_Store                 = {};

GARCH_Diag_Table_T         = zeros(6,1);
Para_vector_T              = zeros(10,1);

for j = 1:c

    BRIC_return      = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    break_position   = ICSS(BRIC_return,1)';
    Index = [1;break_position;numel(BRIC_return)+1];

    for i = 1:numel(Index)-1

        % 5.1  Normal distribution for return innovation
        sub-period_ret = BRIC_return(Index(i):Index(i+1)-1);
        spec = garchset('P',1,'Q',1,'TolCon',1e-09); % normal is the
default distribution
        [Coeff,Errors,LLF,Innovations,Sigmas,~]= garchfit(spec,sub-
period_ret);

        % Step A

        % store estimation results
        Para_vector_N(1,1) = Coeff.C;
        Para_vector_N(2,1) = Coeff.K;
        Para_vector_N(3,1) = Coeff.ARCH;
        Para_vector_N(4,1) = Coeff.GARCH;
        Para_UnVar = Para_vector_N(2)/(1-Para_vector_N(3)-
Para_vector_N(4)); % unconditional variance

        Para_vector_N(5,1) = Errors.C;
        Para_vector_N(6,1) = Errors.K;
        Para_vector_N(7,1) = Errors.ARCH;
        Para_vector_N(8,1) = Errors.GARCH;

        Stats_C        = Para_vector_N(1)/Para_vector_N(5);
        Stats_K        = Para_vector_N(2)/Para_vector_N(6);
        Stats_ARCH     = Para_vector_N(3)/Para_vector_N(7);
        Stats_GARCH    = Para_vector_N(4)/Para_vector_N(8);
```

```
        Para_vector_N     = RoundToDecimalPlace(Para_vector_N,4);

        % check significance for C
        if abs(Stats_C) >= 1.96 && abs(Stats_C) < 2.58
            Para_Store(1,1) = {strcat(num2str(Para_vector_N(1)),'
(',num2str(Para_vector_N(5)),')*')};
        elseif abs(Stats_C) >= 2.58
            Para_Store(1,1) = {strcat(num2str(Para_vector_N(1)),'
(',num2str(Para_vector_N(5)),')**')};
        else
            Para_Store(1,1) = {strcat(num2str(Para_vector_N(1)),'
(',num2str(Para_vector_N(5)),')')};
        end

        % check significance for K
        if abs(Stats_K) >= 1.96 && abs(Stats_K) < 2.58
            Para_Store(2,1) = {strcat(num2str(Para_vector_N(2)),'
(',num2str(Para_vector_N(6)),')*')};
        elseif abs(Stats_K) >= 2.58
            Para_Store(2,1) = {strcat(num2str(Para_vector_N(2)),'
(',num2str(Para_vector_N(6)),')**')};
        else
            Para_Store(2,1) = {strcat(num2str(Para_vector_N(2)),'
(',num2str(Para_vector_N(6)),')')};
        end
%
        % check significance for ARCH
        if abs(Stats_ARCH) >= 1.96 && abs(Stats_ARCH) < 2.58
            Para_Store(3,1) = {strcat(num2str(Para_vector_N(3)),'
(',num2str(Para_vector_N(7)),')*')};
        elseif abs(Stats_ARCH) >= 2.58
            Para_Store(3,1) = {strcat(num2str(Para_vector_N(3)),'
(',num2str(Para_vector_N(7)),')**')};
        else
            Para_Store(3,1) = {strcat(num2str(Para_vector_N(3)),'
(',num2str(Para_vector_N(7)),')')};
        end
%
        % check significance for GARCH
        if abs(Stats_GARCH) >= 1.96 && abs(Stats_GARCH) < 2.58
            Para_Store(4,1) = {strcat(num2str(Para_vector_N(4)),'
(',num2str(Para_vector_N(8)),')*')};
        elseif abs(Stats_GARCH) >= 2.58
            Para_Store(4,1) = {strcat(num2str(Para_vector_N(4)),'
(',num2str(Para_vector_N(8)),')**')};
        else
            Para_Store(4,1) = {strcat(num2str(Para_vector_N(4)),'
(',num2str(Para_vector_N(8)),')')};
        end

        Para_UnVar = RoundToDecimalPlace(Para_UnVar,4);
        Para_Store(6,1) = {Para_UnVar};

        % Step B

        % conduct diagnostic tests: Ljung-Box and ARCH LM tests
        standardised_residuals    = Innovations./Sigmas;
        if i == 2 && j == 4
             % LB test for standardised residuals
```

```
            % use lag order of 4 and 3 here since there are only 5
observations
            % in this period
            [~,pValue,stats]         =
lbqtest(standardised_residuals,'lags',4);
            GARCH_Diag_Table_N(1,1)     = stats;
            GARCH_Diag_Table_N(2,1)     = pValue;

            % LB test for squared standardised residuals
            [~,pValue,stats]         =
lbqtest(standardised_residuals.^2,'lags',4);
            GARCH_Diag_Table_N(3,1)     = stats;
            GARCH_Diag_Table_N(4,1)     = pValue;

            % ARCH LM test for standardised residuals
            [~,pValue,stats]         =
archtest(standardised_residuals,'lags',3);
            GARCH_Diag_Table_N(5,1)     = stats;
            GARCH_Diag_Table_N(6,1)     = pValue;
        else
            % LB test for standardised residuals
            % use lag order of 16 to be in line with (Aggarwal, Inclan &
Leal, 1999),
            % (Kang, Cho & Yoon, 2009) and (Wang & Moore, 2009), among
others
            [~,pValue,stats]         =
lbqtest(standardised_residuals,'lags',16);
            GARCH_Diag_Table_N(1,1)     = stats;
            GARCH_Diag_Table_N(2,1)     = pValue;

            % LB test for squared standardised residuals
            [~,pValue,stats]         =
lbqtest(standardised_residuals.^2,'lags',16);
            GARCH_Diag_Table_N(3,1)     = stats;
            GARCH_Diag_Table_N(4,1)     = pValue;

            % ARCH LM test for standardised residuals
            [~,pValue,stats]         =
archtest(standardised_residuals,'lags',12);
            GARCH_Diag_Table_N(5,1)     = stats;
            GARCH_Diag_Table_N(6,1)     = pValue;
        end

        % round to 4 decimal places
        GARCH_Diag_Table_N      =
RoundToDecimalPlace(GARCH_Diag_Table_N,4);

        GARCH_Diag_Cells(1,1) = {strcat(num2str(GARCH_Diag_Table_N(1,1)),'
[',num2str(GARCH_Diag_Table_N(2,1)),']')};
        GARCH_Diag_Cells(2,1) = {strcat(num2str(GARCH_Diag_Table_N(3,1)),'
[',num2str(GARCH_Diag_Table_N(4,1)),']')};
        GARCH_Diag_Cells(3,1) = {strcat(num2str(GARCH_Diag_Table_N(5,1)),'
[',num2str(GARCH_Diag_Table_N(6,1)),']')};
        SubSampleSize         = numel(sub-period_ret);
        [AIC,BIC]             =
aicbic(LLF,garchcount(Coeff),SubSampleSize);
        GARCH_Diag_Cells(4,1) = {AIC};
        GARCH_Diag_Cells(5,1) = {BIC};
        LLF         = RoundToDecimalPlace(LLF,4);
        GARCH_Diag_Cells(6,1) = {LLF};
```

```
        GARCH_Diag_Cells(7,1) = {SubSampleSize};

        % 5.2 Student t distribution for return innovation

        spec = garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [Coeff,Errors,LLF,Innovations,Sigmas,~]= garchfit(spec,sub-
period_ret);

        % Step A

        % store estimation results
        Para_vector_T(1,1) = Coeff.C;
        Para_vector_T(2,1) = Coeff.K;
        Para_vector_T(3,1) = Coeff.ARCH;
        Para_vector_T(4,1) = Coeff.GARCH;
        Para_vector_T(5,1) = Coeff.DoF;
        Para_UnVar = Para_vector_T(2)/(1-Para_vector_T(3)-
Para_vector_T(4)); % unconditional variance

        Para_vector_T(6,1) = Errors.C;
        Para_vector_T(7,1) = Errors.K;
        Para_vector_T(8,1) = Errors.ARCH;
        Para_vector_T(9,1) = Errors.GARCH;
        Para_vector_T(10,1)= Errors.DoF;

        Stats_C         = Para_vector_T(1)/Para_vector_T(5);
        Stats_K         = Para_vector_T(2)/Para_vector_T(6);
        Stats_ARCH      = Para_vector_T(3)/Para_vector_T(7);
        Stats_GARCH     = Para_vector_T(4)/Para_vector_T(8);
        Stats_DoF       = Para_vector_T(5)/Para_vector_T(10);

        Para_vector_T     = RoundToDecimalPlace(Para_vector_T,4);

        % check significance for C
        if abs(Stats_C) >= 1.96 && abs(Stats_C) < 2.58
            Para_Store(1,2) = {strcat(num2str(Para_vector_T(1)),'
(',num2str(Para_vector_T(5)),')*')};
        elseif abs(Stats_C) >= 2.58
            Para_Store(1,2) = {strcat(num2str(Para_vector_T(1)),'
(',num2str(Para_vector_T(5)),')**')};
        else
            Para_Store(1,2) = {strcat(num2str(Para_vector_T(1)),'
(',num2str(Para_vector_T(5)),')')};
        end

        % check significance for K
        if abs(Stats_K) >= 1.96 && abs(Stats_K) < 2.58
            Para_Store(2,2) = {strcat(num2str(Para_vector_T(2)),'
(',num2str(Para_vector_T(6)),')*')};
        elseif abs(Stats_K) >= 2.58
            Para_Store(2,2) = {strcat(num2str(Para_vector_T(2)),'
(',num2str(Para_vector_T(6)),')**')};
        else
            Para_Store(2,2) = {strcat(num2str(Para_vector_T(2)),'
(',num2str(Para_vector_T(6)),')')};
        end
%
        % check significance for ARCH
        if abs(Stats_ARCH) >= 1.96 && abs(Stats_ARCH) < 2.58
```

```
            Para_Store(3,2) = {strcat(num2str(Para_vector_T(3)),'
(',num2str(Para_vector_T(7)),')*')};
        elseif abs(Stats_ARCH) >= 2.58
            Para_Store(3,2) = {strcat(num2str(Para_vector_T(3)),'
(',num2str(Para_vector_T(7)),')**')};
        else
            Para_Store(3,2) = {strcat(num2str(Para_vector_T(3)),'
(',num2str(Para_vector_T(7)),')')};
        end
%
        % check significance for GARCH
        if abs(Stats_GARCH) >= 1.96 && abs(Stats_GARCH) < 2.58
            Para_Store(4,2) = {strcat(num2str(Para_vector_T(4)),'
(',num2str(Para_vector_T(8)),')*')};
        elseif abs(Stats_GARCH) >= 2.58
            Para_Store(4,2) = {strcat(num2str(Para_vector_T(4)),'
(',num2str(Para_vector_T(8)),')**')};
        else
            Para_Store(4,2) = {strcat(num2str(Para_vector_T(4)),'
(',num2str(Para_vector_T(8)),')')};
        end

        % check significance for Degree of Freedom (DoF)
        if abs(Stats_DoF) >= 1.96 && abs(Stats_DoF) < 2.58
            Para_Store(5,2) = {strcat(num2str(Para_vector_T(5)),'
(',num2str(Para_vector_T(10)),')*')};
        elseif abs(Stats_DoF) >= 2.58
            Para_Store(5,2) = {strcat(num2str(Para_vector_T(5)),'
(',num2str(Para_vector_T(10)),')**')};
        else
            Para_Store(5,2) = {strcat(num2str(Para_vector_T(5)),'
(',num2str(Para_vector_T(10)),')')};
        end

        Para_UnVar = RoundToDecimalPlace(Para_UnVar,4);
        Para_Store(6,2) = {Para_UnVar};

        % arrange the results in table
        Parameter_Sub_Cells(i,j) = {Para_Store};

        % Step B

        % conduct diagnostic tests: Ljung-Box and ARCH LM tests
        standardised_residuals   = Innovations./Sigmas;
        if i == 2 && j == 4
             % LB test for standardised residuals
             % use lag order of 4 and 3 here since there are only 5
observations
             % in this period
             [~,pValue,stats]          =
lbqtest(standardised_residuals,'lags',4);
             GARCH_Diag_Table_T(1,1)    = stats;
             GARCH_Diag_Table_T(2,1)    = pValue;

             % LB test for squared standardised residuals
             [~,pValue,stats]          =
lbqtest(standardised_residuals.^2,'lags',4);
             GARCH_Diag_Table_T(3,1)    = stats;
             GARCH_Diag_Table_T(4,1)    = pValue;
```

```
            % ARCH LM test for standardised residuals
            [~,pValue,stats]        =
archtest(standardised_residuals,'lags',3);
            GARCH_Diag_Table_T(5,1)    = stats;
            GARCH_Diag_Table_T(6,1)    = pValue;
        else
            % LB test for standardised residuals
            % use lag order of 16 to be in line with (Aggarwal, Inclan &
Leal, 1999),
            % (Kang, Cho & Yoon, 2009) and (Wang & Moore, 2009), among
others
            [~,pValue,stats]        =
lbqtest(standardised_residuals,'lags',16);
            GARCH_Diag_Table_T(1,1)    = stats;
            GARCH_Diag_Table_T(2,1)    = pValue;

            % LB test for squared standardised residuals
            [~,pValue,stats]        =
lbqtest(standardised_residuals.^2,'lags',16);
            GARCH_Diag_Table_T(3,1)    = stats;
            GARCH_Diag_Table_T(4,1)    = pValue;

            % ARCH LM test for standardised residuals
            [~,pValue,stats]        =
archtest(standardised_residuals,'lags',12);
            GARCH_Diag_Table_T(5,1)    = stats;
            GARCH_Diag_Table_T(6,1)    = pValue;
        end

        % round to 4 decimal places
        GARCH_Diag_Table_T      =
RoundToDecimalPlace(GARCH_Diag_Table_T,4);

        GARCH_Diag_Cells(1,2) = {strcat(num2str(GARCH_Diag_Table_T(1,1)),'
[',num2str(GARCH_Diag_Table_T(2,1)),']')};
        GARCH_Diag_Cells(2,2) = {strcat(num2str(GARCH_Diag_Table_T(3,1)),'
[',num2str(GARCH_Diag_Table_T(4,1)),']')};
        GARCH_Diag_Cells(3,2) = {strcat(num2str(GARCH_Diag_Table_T(5,1)),'
[',num2str(GARCH_Diag_Table_T(6,1)),']')};
        SubSampleSize          = numel(sub-period_ret);
        [AIC,BIC]              =
aicbic(LLF,garchcount(Coeff),SubSampleSize);
        GARCH_Diag_Cells(4,2) = {AIC};
        GARCH_Diag_Cells(5,2) = {BIC};
        LLF          = RoundToDecimalPlace(LLF,4);
        GARCH_Diag_Cells(6,2) = {LLF};
        GARCH_Diag_Cells(7,2) = {SubSampleSize};

        % arrange the results in table
        GARCH_Sub-periodDiag_Cells(i,j) = {GARCH_Diag_Cells};

    end

end


%% 5.2 Persistence Table
Persist_vector = zeros(3,2);
Persist_cell   = {};
```

```
for j = 1:c

    BRIC_return     = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    break_position  = ICSS(BRIC_return,1)';
    Index = [1;break_position;numel(BRIC_return)+1];

    for i = 1:numel(Index)-1

        sub-period_ret = BRIC_return(Index(i):Index(i+1)-1);

     % GARCH model
        % Firstly estimate GARCH with Normal return innovation
        spec  = garchset('P',1,'Q',1,'TolCon',1e-09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with Normal return innovation
        Persist_vector(1,1) = 
RoundToDecimalPlace(Coeff.ARCH+Coeff.GARCH,4);

        % Secondly estimate GARCH with T return innovation
        spec  = garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with T return innovation
        Persist_vector(1,2) = 
RoundToDecimalPlace(Coeff.ARCH+Coeff.GARCH,4);

     % EGARCH model
        % Firstly estimate GARCH with Normal return innovation
        spec  = garchset('VarianceModel','EGARCH','P',1,'Q',1,'TolCon',1e-
09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with Normal return innovation
        Persist_vector(2,1) = RoundToDecimalPlace(Coeff.GARCH,3);

        % Secondly estimate GARCH with T return innovation
        spec  = 
garchset('VarianceModel','EGARCH','P',1,'Q',1,'Distribution','T','TolCon',1
e-09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with T return innovation
        Persist_vector(2,2) = RoundToDecimalPlace(Coeff.GARCH,3);

     % GJR model
        % Firstly estimate GARCH with Normal return innovation
        spec  = garchset('VarianceModel','GJR','P',1,'Q',1,'TolCon',1e-09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with Normal return innovation
        Persist_vector(3,1) = 
RoundToDecimalPlace(Coeff.ARCH+Coeff.GARCH+Coeff.Leverage/2,3);

        % Secondly estimate GARCH with T return innovation
```

```
        spec  =
garchset('VarianceModel','GJR','P',1,'Q',1,'Distribution','T','TolCon',1e-
09);
        Coeff = garchfit(spec,sub-period_ret);

        % persistence for GARCH with T return innovation
        Persist_vector(3,2) =
RoundToDecimalPlace(Coeff.ARCH+Coeff.GARCH+Coeff.Leverage/2,3);


        % arrange in table
        Persist_cell(i,j) = {Persist_vector};

    end

end
```

Appendix 12 – Matlab Code – Out-of-Sample Tests

```
clear
clc

[price_data,title] = xlsread('data for thesis.xlsx','rearranged data
weekly');
BRIC_data          = price_data(:,1:4); % BRIC countries
[r,c]              = size(BRIC_data);

%% 6. Volatility Forecasting

% 6.1 GARCH model - BRIC

% 6.1.1 Expanding Window

for j = 1:c

    BRIC_return      = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    % 70% observations for insample estimation
    NuminSample      = round(0.7*numel(BRIC_return));
    NumoutSample     = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    for i = 1:NumoutSample
        Return_expanding  = BRIC_return(1:NuminSample);

        % Normal
        spec               = garchset('P',1,'Q',1,'TolCon',1e-09);
        [coeff,~]          = garchfit(spec,Return_expanding);
        [SigmaForecast,~] = garchpred(coeff,Return_expanding,1);
        BRIC_GARCH_EXP_Fore_Vector_Norm(i,j) = SigmaForecast;
        % T
        spec               =
garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [coeff,~]          = garchfit(spec,Return_expanding);
        [SigmaForecast,~] = garchpred(coeff,Return_expanding,1);
        BRIC_GARCH_EXP_Fore_Vector_T(i,j) = SigmaForecast;

        NuminSample = NuminSample + 1; % expand the estimation window by 1
period

    end

    % 2 loss functions: Root Mean Squared Error (RMSE) and Quasi-likelihood
(QLIKE)

    BRIC_GARCH_EXP_RMSE(1,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_EXP_Fore_Vector_Norm(1:numel(Return_outSample),j).^2).^2)); %
Normal
    BRIC_GARCH_EXP_RMSE(2,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_EXP_Fore_Vector_T(1:numel(Return_outSample),j).^2).^2)); % T

    BRIC_GARCH_EXP_QLIKE(1,j) = mean((Return_outSample.^2)...
```

```
./(BRIC_GARCH_EXP_Fore_Vector_Norm(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_EXP_Fore_Vector_Norm(1:numel(Return_outSample),j).^2))-1);
    BRIC_GARCH_EXP_QLIKE(2,j) = mean((Return_outSample.^2)...
        ./(BRIC_GARCH_EXP_Fore_Vector_T(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...
        ./(BRIC_GARCH_EXP_Fore_Vector_T(1:numel(Return_outSample),j).^2))-
1);

end

%% 6.1.2 '0.5' Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.5 rolling window
    startpoint      = round(0.5*NuminSample)+1;
    endpoint        = NuminSample;

    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);

        % Normal
        spec                 = garchset('P',1,'Q',1,'TolCon',1e-09);
        [coeff,~]            = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL05_Fore_Vector_Norm(i,j)  = SigmaForecast;
        % T
        spec                 =
garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [coeff,~]            = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL05_Fore_Vector_T(i,j)  = SigmaForecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint    = endpoint + 1;

    end

    % 2 loss functions: Root Mean Squared Error (RMSE) and Quasi-likelihood
(QLIKE)

    BRIC_GARCH_ROLL05_RMSE(1,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ROLL05_Fore_Vector_Norm(1:numel(Return_outSample),j).^2).^2)); %
Normal
    BRIC_GARCH_ROLL05_RMSE(2,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ROLL05_Fore_Vector_T(1:numel(Return_outSample),j).^2).^2)); % T
```

```
    BRIC_GARCH_ROLL05_QLIKE(1,j) = mean((Return_outSample.^2)...
./(BRIC_GARCH_ROLL05_Fore_Vector_Norm(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...
./(BRIC_GARCH_ROLL05_Fore_Vector_Norm(1:numel(Return_outSample),j).^2))-1);
    BRIC_GARCH_ROLL05_QLIKE(2,j) = mean((Return_outSample.^2)...
./(BRIC_GARCH_ROLL05_Fore_Vector_T(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...
./(BRIC_GARCH_ROLL05_Fore_Vector_T(1:numel(Return_outSample),j).^2))-1);

end

% 6.1.3 '0.25' Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.25 rolling window
    % only use LAST 25% of the in-sample, so start from 75% of in-sample
    startpoint      = round(0.75*NuminSample)+1;
    endpoint        = NuminSample;

    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);

        % Normal
        spec                = garchset('P',1,'Q',1,'TolCon',1e-09);
        [coeff,~]           = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL025_Fore_Vector_Norm(i,j) = SigmaForecast;
        % T
        spec                =
garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [coeff,~]           = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL025_Fore_Vector_T(i,j) = SigmaForecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint    = endpoint + 1;

    end

    % 2 loss functions: Root Mean Squared Error (RMSE) and Quasi-likelihood
(QLIKE)

    BRIC_GARCH_ROLL025_RMSE(1,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ROLL025_Fore_Vector_Norm(1:numel(Return_outSample),j).^2).^2));
% Normal
    BRIC_GARCH_ROLL025_RMSE(2,j)    = sqrt(mean((Return_outSample.^2 ...
```

```
        -
BRIC_GARCH_ROLL025_Fore_Vector_T(1:numel(Return_outSample),j).^2).^2)); % T

    BRIC_GARCH_ROLL025_QLIKE(1,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ROLL025_Fore_Vector_Norm(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_ROLL025_Fore_Vector_Norm(1:numel(Return_outSample),j).^2))-
1);
    BRIC_GARCH_ROLL025_QLIKE(2,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ROLL025_Fore_Vector_T(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_ROLL025_Fore_Vector_T(1:numel(Return_outSample),j).^2))-1);

end

% 6.1.4 '0.75' Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.75 rolling window
    % only use LAST 75% of the in-sample, so start from 25% of in-sample
    startpoint      = round(0.25*NuminSample)+1;
    endpoint        = NuminSample;

    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);

        % Normal
        spec                 = garchset('P',1,'Q',1,'TolCon',1e-09);
        [coeff,~]            = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL075_Fore_Vector_Norm(i,j) = SigmaForecast;
        % T
        spec                 =
garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [coeff,~]            = garchfit(spec,Return_rolling);
        [SigmaForecast,~] = garchpred(coeff,Return_rolling,1);
        BRIC_GARCH_ROLL075_Fore_Vector_T(i,j) = SigmaForecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint   = endpoint + 1;

    end

    % 2 loss functions: Root Mean Squared Error (RMSE) and Quasi-likelihood
(QLIKE)

    BRIC_GARCH_ROLL075_RMSE(1,j)    = sqrt(mean((Return_outSample.^2 ...
```

```
        -
BRIC_GARCH_ROLL075_Fore_Vector_Norm(1:numel(Return_outSample),j).^2).^2));
% Normal
    BRIC_GARCH_ROLL075_RMSE(2,j)    = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ROLL075_Fore_Vector_T(1:numel(Return_outSample),j).^2).^2)); % T

    BRIC_GARCH_ROLL075_QLIKE(1,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ROLL075_Fore_Vector_Norm(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_ROLL075_Fore_Vector_Norm(1:numel(Return_outSample),j).^2))-
1);
    BRIC_GARCH_ROLL075_QLIKE(2,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ROLL075_Fore_Vector_T(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_ROLL075_Fore_Vector_T(1:numel(Return_outSample),j).^2))-1);

end


% 6.1.5 with ICSS algorithm

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    % 70% observations for insample estimation
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    for i = 1:NumoutSample

        break_positions = ICSS(BRIC_return(1:NuminSample),1)';

        % the author believes that at least 30 observations are required
        % in order to obtain a trustable estimation
        if numel(break_positions)~=0 && (NuminSample -
break_positions(end))>=30
            Return_ICSS = BRIC_return(break_positions(end)+1:NuminSample);
        else
            Return_ICSS = BRIC_return(1:NuminSample);
        end

        % Normal
        spec                = garchset('P',1,'Q',1,'TolCon',1e-09);
        [coeff,~]           = garchfit(spec,Return_ICSS);
        [SigmaForecast,~] = garchpred(coeff,Return_ICSS,1);
        BRIC_GARCH_ICSS_Fore_Vector_Norm(i,j) = SigmaForecast;
        % T
        spec                =
garchset('P',1,'Q',1,'Distribution','T','TolCon',1e-09);
        [coeff,~]           = garchfit(spec,Return_ICSS);
        [SigmaForecast,~] = garchpred(coeff,Return_ICSS,1);
        BRIC_GARCH_ICSS_Fore_Vector_T(i,j) = SigmaForecast;
```

```
        NuminSample = NuminSample + 1;

    end

    % 2 loss functions: Root Mean Squared Error (RMSE) and Quasi-likelihood
(QLIKE)

    BRIC_GARCH_ICSS_RMSE(1,j)   = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ICSS_Fore_Vector_Norm(1:numel(Return_outSample),j).^2).^2)); %
Normal
    BRIC_GARCH_ICSS_RMSE(2,j)   = sqrt(mean((Return_outSample.^2 ...
        -
BRIC_GARCH_ICSS_Fore_Vector_T(1:numel(Return_outSample),j).^2).^2)); % T

    BRIC_GARCH_ICSS_QLIKE(1,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ICSS_Fore_Vector_Norm(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...

./(BRIC_GARCH_ICSS_Fore_Vector_Norm(1:numel(Return_outSample),j).^2))-1);
    BRIC_GARCH_ICSS_QLIKE(2,j) = mean((Return_outSample.^2)...

./(BRIC_GARCH_ICSS_Fore_Vector_T(1:numel(Return_outSample),j).^2)...
        -log((Return_outSample.^2)...
        ./(BRIC_GARCH_ICSS_Fore_Vector_T(1:numel(Return_outSample),j).^2))-
1);

end

% 6.1.6 with Moving Average 0.5 Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.5 rolling window
    startpoint      = round(0.5*NuminSample)+1;
    endpoint        = NuminSample;

    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);
        MA05_Forecast  = mean(Return_rolling.^2);

        BRIC_MA05_Fore_Vector_Norm(i,j) = MA05_Forecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint   = endpoint + 1;

    end

    BRIC_MA05_RMSE(1,j)  = sqrt(mean((Return_outSample.^2 ...
        - BRIC_MA05_Fore_Vector_Norm(1:numel(Return_outSample),j)).^2));
```

```
    BRIC_MA05_QLIKE(1,j) = mean((Return_outSample.^2)...
        ./(BRIC_MA05_Fore_Vector_Norm(1:numel(Return_outSample),j))...
        -log((Return_outSample.^2)...
        ./(BRIC_MA05_Fore_Vector_Norm(1:numel(Return_outSample),j)))-1);

end

% 6.1.7 with Moving Average 0.75 Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.5 rolling window
    startpoint       = round(0.25*NuminSample)+1;
    endpoint         = NuminSample;

    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);
        MA75_Forecast  = mean(Return_rolling.^2);

        BRIC_MA75_Fore_Vector_Norm(i,j) = MA75_Forecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint   = endpoint + 1;

    end

    BRIC_MA75_RMSE(1,j)   = sqrt(mean((Return_outSample.^2 ...
        - BRIC_MA75_Fore_Vector_Norm(1:numel(Return_outSample),j)).^2));

    BRIC_MA75_QLIKE(1,j) = mean((Return_outSample.^2)...
        ./(BRIC_MA75_Fore_Vector_Norm(1:numel(Return_outSample),j))...
        -log((Return_outSample.^2)...
        ./(BRIC_MA75_Fore_Vector_Norm(1:numel(Return_outSample),j)))-1);

end

% 6.1.8 with Moving Average 0.25 Rolling Window

for j = 1:c

    BRIC_return       = price2ret(BRIC_data(2:BRIC_data(1,j)+1,j));
    NuminSample       = round(0.7*numel(BRIC_return));
    NumoutSample      = numel(BRIC_return)-NuminSample;
    Return_outSample = BRIC_return(NuminSample+1:end);

    % specify the 0.5 rolling window
    startpoint       = round(0.75*NuminSample)+1;
    endpoint         = NuminSample;
```

```
    for i = 1:NumoutSample

        Return_rolling = BRIC_return(startpoint:endpoint);
        MA25_Forecast  = mean(Return_rolling.^2);

        BRIC_MA25_Fore_Vector_Norm(i,j) = MA25_Forecast;

        % Rolling the window forward by 1 period
        startpoint = startpoint + 1;
        endpoint   = endpoint + 1;

    end

    BRIC_MA25_RMSE(1,j)  = sqrt(mean((Return_outSample.^2 ...
        - BRIC_MA25_Fore_Vector_Norm(1:numel(Return_outSample),j)).^2));

    BRIC_MA25_QLIKE(1,j) = mean((Return_outSample.^2)...
        ./(BRIC_MA25_Fore_Vector_Norm(1:numel(Return_outSample),j))...
        -log((Return_outSample.^2)...
        ./(BRIC_MA25_Fore_Vector_Norm(1:numel(Return_outSample),j)))-1);

end
```

Appendix 13 – Matlab Code – ICSS Algorithm

```
function [break_positions] = ICSS(Input,CV_1_2_3)
% ICSS performs the 'Iterated Cumulative Sums of Squares' algorithm
% to detect breaks in volatility of return series
% according to the paper by Inclan and Tiao (1994)

% Input: data series and critical value identifier
% Output: positions of break points

    % Find the potential breaks recursively
    possible_breaks = Procedure_One_and_Two(Input,CV_1_2_3);
    % Rearrange all the breaks in a row vector
    possible_breaks = unique([0,sort(possible_breaks),numel(Input)]);

    % Step 3: check each potential change point
    converge = false;

    while ~converge

        new_breaks = [];

        % test every possible breaks
        for i=2:(numel(possible_breaks)-1)
            Start = possible_breaks(i-1)+1;
            End   = possible_breaks(i+1);

            % compute the Dk and maximum
            Dk = Cum_Sum_Squares(Input(Start:End));
            [beyond,position] = Is_Beyond_CV(Dk,CV_1_2_3);

            if beyond
                % add the new break
                new_breaks(end+1) = Start + position;
            end
        end

        new_breaks = [0,sort(new_breaks),numel(Input)];
        converge   = Converge_Or_Not(possible_breaks,new_breaks,1000);

        if ~converge
            possible_breaks = new_breaks;
        end
    end

    % exclude 0 and end points
    break_positions = possible_breaks(2:end-1);

end


function converge = Converge_Or_Not(previous,current,diff)
% Converge_Or_Not check if two arrays of breaks are converged
% Convergence occurs if: 1. they have equal length;
% 2. the difference of each element in both arrays is less than diff
```

```
% It is recommended that the diff should not be too small, e.g. >50 is ok.

    converge = true;

    if numel(previous) == numel(current)
        for i=1:numel(current)
            maximum = max(previous(i),current(i));
            minimum = min(previous(i),current(i));
            if maximum - minimum >= diff
                converge = false;
                return;
            end
        end

    else
        converge = false;
    end

end

function [breaks] = Procedure_One_and_Two(Input,CV_1_2_3)
% Procedure_One_and_Two recursively executes the first two steps of the
ICSS
% The function attempts spot all the possible breaks.

    breaks = [];

    % 1.
    Dk = Cum_Sum_Squares(Input);
    [beyond,position1] = Is_Beyond_CV(Dk,CV_1_2_3);
    if beyond
    % Indicate a break

    % 2.1
        position = position1;

        while beyond
            % check first part
            S_1 = position;
            Dk_21 = Cum_Sum_Squares(Input(1:S_1));
            [beyond,position] = Is_Beyond_CV(Dk_21,CV_1_2_3);
        end

        break_start = S_1;

     % 2.2
        position = position1 + 1;
        beyond = true;

        while beyond
            % check last part
            S_2 = position;
            Dk_22 = Cum_Sum_Squares(Input(S_2:end));
            [beyond,position2] = Is_Beyond_CV(Dk_22,CV_1_2_3);
            position = position2 + position;
        end

        break_end = S_2 - 1;
```

```
    % 2.3
        if break_start == break_end
            breaks = break_start; % only one break in this case
        else
            % more than one break: apply the algorithm recursively
            recursive_Breakcheck =
ICSS(Input(break_start:break_end),CV_1_2_3);
            % Add the first position to all the returned change points of
            % the recursive, to get the correct offset
            breaks = [break_start,recursive_Breakcheck +
break_start,break_end];
        end
    end

end

function [beyond,position] = Is_Beyond_CV(Dk,CV_One_Two_Three)
% Is_Beyond_CV check if the max value of a range goes beyond the
% critcal value provided by Inclan and Tiao (1994)

% check if Test_stats is larger than the critical value
% according to Inclan and Tiao (1994): 10% 1.224;5% 1.358;1% 1.628
% the corresponding position will be recorded as well

    switch CV_One_Two_Three
        case 1
            Critical_Value = 1.628; % 1% significance level
        case 2
            Critical_Value = 1.358; % 5% significance level
        case 3
            Critical_Value = 1.224; % 10% significance level
    end

    [maximum, position] = max(abs(Dk));
    Test_stats = (sqrt(numel(Dk)/2) * maximum);
    beyond = Test_stats > Critical_Value;

end

function [Dk,Ck] = Cum_Sum_Squares(Input)
% Cum_Sum_Squares compute normalized cumulative sum of squared
% according to the paper Inclan and Tiao (1994)

    squared = Input.^2;
    Ck = cumsum(squared);
    CT = Ck(end);
    N = numel(Input);
    k_vector = (1:N)';

    Dk = Ck./CT - (k_vector/N); % compute normalized cumulative sum of
squared

end
```