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# Stock market and GDP growth volatility spillovers

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**Keywords**

market, stock, gdp, spillovers, volatility, growth

**Disciplines**

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# Stock Market and GDP Growth Volatility Spillovers

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## Abstract

This paper examines the interplay between stock market returns and GDP growth rates in four Anglo-Saxon economies located in three separate continents (namely, the US, the UK, Canada and Australia). We analyse the dynamics of cross-country volatility transmission across these countries by using quarterly data from 1959 to 2010 and a multivariate GARCH model. Country specific cross-mean spillovers from GDP growth to stock market returns exist only from the US growth towards its stock market, while country specific cross-mean spillovers from stock market returns towards GDP growth exist in both the US and Australia. The US economy influences all three countries with the strongest impact exerted on the Canadian economy. In addition, own-volatility and co-volatility spillovers within and across all eight series are found to be positive and statistically significant, thereby confirming the close association between co-volatility of both stock returns and GDP growth series shared by these four countries.

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# I. Introduction

There has been a growing interest in recent years in relation to the impact of globalisation on the integration of national economies through international trade, capital flows, foreign direct investment, and the spread of technology. Understanding and quantifying these cross-country interactions is of increasing importance from the perspectives of investor and policy maker alike. For example, In (2007) and Shamsuddin and Kim (2003) argue that information regarding market interdependency is extremely important in determining diversification of international investment portfolios. In addition, policy makers need to understand the influences on both economic growth and financial market performance, and the nature of the relationship between the two, in order to effectively manage their economies.

According to Fama (1990), Liua and Sinclairb (2008), Oskooe (2010), *inter alia*, economic growth influences the profitability of firms by affecting the expected earnings, dividends of shares and stock prices fluctuations. Furthermore, Schwert (1989, 1990) relates stock return volatility to the level of economic activity through financial and operating leverages. When stock prices fall relative to bond prices or when firms increase financial leverage by issuing debt to buy back their stocks, the volatility of firms' stock return increases. With an unexpected decline in economic activity, the profits of firms with large fixed costs falls more than the profits of firms that avoid large capital investment or long-term supply contracts.

In addition, features of the financial system can amplify and propagate business cycle fluctuations (Ferreira da Silva, 2002) and macroeconomic stability can be achieved through the financial sector, especially from interest-rate induced shocks or liquidity shocks (Scharler, 2008). Another important aspect of the relationship between financial markets and GDP growth is that the development of the financial sector can be driven from the increases in the demand for financial services resulting from economic growth (Rousseau & Vuthipadadorn, 2005). This may arise with the availability of credits to domestic producers from financial systems. More recently, Antonios (2010) suggests that risk diversification through stock market integration can improve resource allocation and influence banking operations, hence affecting real GDP growth.

In addition, Wu *et al.* (2010) found that the short-run effect from stock market development on real output was opposite to its long-run influence. According to their findings, liquidity of the stock market has a negative short-run effect on economic growth while stock market capitalisation and liquidity have positive long-run consequences on economic development.[1] In the short-run financial institutions without full insurance would experience credit volatility and low output growth to cover risk during financial crises. However, in the long-run, financial institutions would be free from crises and would experience stable growth.

With regard to volatility, Diebold and Yilmaz (2008) find a unidirectional influence from GDP volatility to stock market volatility. Caporale and Spagnolo (2003) captured a positive influence on output growth volatility from the stock market volatility. In contrast, others have reported empirical evidence of a bidirectional relationship between stock market volatility and the volatility of GDP growth. For example, Leon and Filis (2008) posit that GDP shocks offset stock market volatilities, however, stock market volatility may give a rise to GDP volatilities.[2]

[1] Wu *et al.* (2010) used the ratio of value of domestic shares listed on domestic exchanges to GDP to represent stock market capitalisation and the value of the trade of domestic shares on domestic exchanges divided by the value of listed domestic shares as liquidity of stock market.

[2] Leon and Filis (2008) used spectral analysis using GDP, investments and the stock market quarterly data from Greece. The sample period was from 1989:Q1 – 2005:Q2.

Ahn and Lee (2006), on the other hand, argue that high volatility in the stock market is always followed by the increased volatility in the output sector and *vice versa*.[3]

It should be noted that these studies are methodologically different from each other. In the first group, Caporale and Spagnolo (2003) employed a bivariate version of the BEKK model, while Diebold and Yilmaz (2008) used the standard deviation of stock return and GDP growth and residuals from an AR(3) model to measure the volatility.[4] In the second group, Ahn and Lee (2006) applied a bivariate extension of the univariate GARCH model, whereas Leon and Filis (2008) adopted a VAR analysis. A major issue for all these studies was that although they use data from multiple countries in their sample, they focused only on one country at a time. In other words, these studies did not provide a systematic cross-country analysis of the mutual-interaction effects of volatilities across various stock market returns and GDP growth rates.

Although these empirical studies highlight the imporance of studying the interaction between economic growth and financial markets, Trew (2006) argues that many issues surrounding the interaction between financial market performance and economic growth have still not been fully investigated. In particular, research surrounding the cross country interaction between financial markets and economic performance is lacking. Therefore, in this paper we contribute to the literature by providing some insight into a noteworthy aspect of volatility transmission across stock markets and GDP growth in a number of integrated economies. This enables us to identify and quantify possible influences of shocks either arising from a particular real sector or stock market on the volatility and co-volatility on other stock markets and

[3] Ahn and Lee (2006) employed stock indices and seasonally adjusted industrial production from Canada, Italy, Japan, the UK, and the US for the univariate and bivariate GARCH models. Their sample period was from 1975 to 2000 for Italy, Japan, the UK, and the US, and 1977 to 2000 for Canada.

[4] The acronym, BEKK comes from the synthesis work done by Baba, Engle, Kraft, and Kroner for the earlier version of Engle and Kroner's (1995) paper.

economies. To evaluate the volatility and co-volatility dynamics across different international stock markets and GDP growth rates this paper employs a MGARCH model. Unlike the previous studies, the MGARCH model used in this study simultaneously takes into account the first and the second order moments of eight series in the sample. Our approach can also be extended allowing dummy variables to capture the abnormal observations mainly due to economic and financial crises during the sample period. The present study is the first to conduct a simultaneous analysis of the nature of volatility transmission across stock market and GDP growth rates in a multi-country context.

The remainder of this paper is organized as follows. Section II presents the empirical methodology, followed by the descriptive statistics of the data employed in Section III. The empirical econometric results are presented in Section IV with some concluding remarks in the last section.

## II. Methodology

This study uses the diagonal version of Engle and Kroner's (1995) BEKK model (DBEKK) to study the volatility spillovers within and across stock market returns and GDP growth rates and the vector autoregressive stochastic process for the mean equations to examine the nature of stock returns and GDP growth rate interdependencies. The DBEKK model is used specifically for this purpose as it reduces the number of parameters while also guaranteeing positive definite of variance and covariance matrix. The BEKK model has also widely been used in similar contexts in the literature for analysing second order moments across financial markets. For example, Henry *et al.* (2010) used the asymmetric version of bivariate BEKK model to evaluate the sign and phase asymmetry between equity returns and real activity using US data.

For the present study we use the DBEKK model to study the interaction effect of our eight series within equations (1) and (2).

First, the vector autoregressive stochastic process of stock returns and GDP growth rates is given in equation (1), which represents the mean equation for each of the eight series:

$$r_{it} = \mu_{0i} + \sum_{k=1}^{8}\sum_{j=1}^{4} \mu_{kj} r_{kt-j} + \theta_i W_i + \varepsilon_{it} \tag{1}$$

where $i$=1 for US stock returns, $i$=2 for UK stock returns, $i$=3 for Canadian stock returns, $i$=4 for Australian stock returns, $i$=5 for the US GDP growth rate, $i$=6 for the UK GDP growth rate, $i$=7 for Canadian GDP growth rate, and $i$=8 for Australian GDP growth rate; $\mu_{0i}$ is the intercept for series $i$; $\mu_{kj}$ indicates the conditional mean of stock returns/GDP growth such that when $k=i$ for all $k = 1, .. , 8$ and $j = 1, .. , 4$) represents the influence from own past returns/growth rates of series $k$ up to four lags (i.e. own-mean spillovers) and when $k \neq i$ for all $k = 1, .. , 8$ and $j = 1, .. , 4$) represents the influence from past returns/growth rates of series $k$ towards series $i$ up to four lags (i.e. cross-mean spillovers); $W_i$ is a dummy variable to capture the abnormal observations mainly due to economic and financial crises in series $i$ during the sample period; $\theta_i$ denotes the estimated coefficients of the dummy variables; and $\varepsilon_{it}$ represents own innovations.

Second, the variance and covariance matrix of our BEKK model can be written as follows:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

where $A$ and $B$ are $N \times N$ parameter matrices and $C$ is an upper triangular $N \times N$ matrix. $N$ is the number of series considered in the model. In order to make estimation relatively simple, further restrictions on the $A$ and $B$ matrices are considered to obtain a diagonal version of the BEKK model, which contains less parameters and guarantees a positive definite conditional variance and covariance matrix ($H_t$). Engle and Kroner (1995) find that the DBEKK model can be formulated from the BEKK parameterisation if and only if each of the *A* and *B* matrices in equation (2) are diagonal. Therefore, we use a similar diagonal version of the BEKK model for volatility (equation 3) and co-volatility (equation 4);

$$h_{iit} = c_{ii} + a_{ii}^2 \varepsilon_{it-1}^2 + b_{ii}^2 h_{iit-1} \tag{3}$$

$$h_{ijt} = c_{ij} + a_{ii} a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ii} b_{jj} h_{ijt-1} \tag{4}$$

where, $h_{iit}$ is the own-volatility of series *i*; $h_{ijt}$ is the co-volatility between series *i* and series *j*;

$a_{ii} \times a_{ii}$ is the coefficient of lagged own-volatility shocks of series *i*;

$b_{ii} \times b_{ii}$ is the coefficient of lagged own-volatility of series *i*;

$a_{ii} \times a_{jj}$ is the coefficient of cross products of lagged-volatility shocks between series *i* and *j*; and

$b_{ii} \times b_{jj}$ is the coefficient of lagged co-volatility between series *i* and *j*.

This implies that the volatility spillovers within one series can be determined by the sum of squares of the diagonal elements of matrix *A* and square of the diagonal elements of matrix *B*. In other words, volatility spillovers depend on the squared sum of own-volatility shocks representing the impacts arising from past squared innovations (shocks) and own-volatility spillovers representing the impact arising from past volatility. The co-volatility spillovers between two series can be estimated by the sum of cross-products of diagonal elements of *A* and cross-products of diagonal elements of *B*. That is, the sum of cross- products of past innovations and past co-volatility between two series.

## III. The Data and Preliminary Findings

In this paper we use quarterly stock market price indexes and GDP data on four countries namely the US, the UK, Canada, and Australia. Previous research has shown that the selected countries are highly integrated with regard to real GDP co-movements (Valadkhani *et al.*, 2013). Based on their findings, the present study used data from the four countries to further evaluate volatility spillovers across both GDP growth and stock return series. The data were obtained from the OECD main economic indicators included in the DX for Windows database (EconData, 2011) for the period spanning from 1959:Q3 to 2010:Q4 (n=206 observations).

Based on the stock market price index, the stock returns ($r_t$) at time *t* is calculated as $r_t = \ln\left(p_t / p_{t-1}\right)$ where $p_t$ is the stock market price index at time *t*. The GDP growth rate series is calculated in an analogous fashion. Table 1A presents the descriptive statistics for stock market return series while Table 1B shows the GDP growth series. During the sample period the quarterly mean of all four stock return series were positive, ranging from a minimum of 0.0149 (the US) to a maximum of 0.0176 (the UK). The mean GDP growth rates of all four countries were also positive during the sample period varying from a minimum of 0.0057 (the UK) to a maximum of 0.0090 (Australia). Based on the standard deviations (SD), the US (SD = 0.0648) and the Australian (SD = 0.0835) stock return series were the least and most volatile series, respectively. Similarly, the sample standard deviations for GDP growth rate series indicate that the US (SD = 0.0087) was the least volatile economy while the Australian output growth rate (SD = 0.0117) exhibited the highest volatility. A cursory look at Figures 1 and 2 confirms the above findings. It should be noted that large spikes in Figure 1 during 1987 and 2008-09 indicate high volatilities during the stock market crash in October 1987 and more recent global financial crisis (GFC). Similarly, Figure 2 indicates relatively large spikes in GDP growth during both the 1980s recession and GFC.

As expected, all stock return series are negatively skewed. However, only the Canadian and the US GDP growth series are negatively skewed. Thus, one can hypothesise that financial and economic crises during the sample period exerted a greater negative influence on the return series than GDP growth rates. However, this hypothesis will be formally tested in Section IV. In addition, our series show a typical leptokurtic distribution as the value of kurtosis is greater than 3.0 for all of the series, with the only exception being the Canadian GDP growth rate. Finally, the conventional ADF unit root test results are also given in Table 1A and Table 1B, suggesting that that all eight series are stationary.

**[Tables 1A, 1B and Figures 1 and 2]**

## IV. Empirical Results

Our empirical analysis in this section is focused on three main aspects: (1) the mean spillovers across stock returns and GDP growth rates; (2) the overall impact of major financial and economic crises during the sample period on each of the four countries' stock market and real output; and (3) the interdependent nature of volatility spillovers across the economies. First, this study uses the general-to-specific methodology to omit insignificant variables from each series in equation (1). Then, to analyse volatility and co-volatility dynamics, the DBEKK(1,1) specification is adopted, as shown in equations (3) and (4).

Table 2 reports the estimated results from the mean equation. Based on the estimated mean spillovers across eight series, our major findings can be highlighted as follows: First, the own-mean spillovers for all each of the eight series are statistically significant at the 5 per cent level or better, providing strong evidence for the influence of own-lagged effects on the current stock returns and GDP growth rates. The magnitudes of these lagged effects for the US are very similar (i.e. 0.246 for stock return and 0.240 for GDP growth). Second, country specific cross-mean spillovers from GDP growth to stock market returns exist only from the US growth to its stock market (-0.687). Third, country specific cross-mean spillovers from stock market returns to GDP growth exist in both the US and Australia. Fourth, cross-country mean spillovers across stock markets are present only from the US stock market to the Australian stock market (0.114). Fifth, in terms of cross-country mean spillovers across GDP growth rates, it is found that the US economy affects all three countries with the strongest impact exerted on the Canadian economy (0.321). Sixth, and the most important finding, is that cross-country mean spillovers arising from stock market towards GDP growth or GDP growth towards stock return series are not statistically significant across any country. Fry *et al.* (2008) also found similar results in an Australian context using a structural vector autoregressive model. They confirmed that real output growth in Australia was unaffected by international equity shocks.

On the whole, these findings can be interpreted to suggest that events in the US economy and its stock market can predominantly exert greater influence on the smallest economy and the smallest stock market (Australia). In addition, the above findings indicate that there is significant spillover interplay between the US economic growth and the US stock market. This is consistent with the in-sample observations in the past that the US economy enters into a recession phase after most financial and stock market crashes. The above results also provide evidence on regional economic integration within the North American region. However, it appears that the direction of this regional influence is always from the US towards smaller economies.

Finally, we have also captured the abnormal spikes in our series which are associated with financial and economic crises during the sample period using dummy variables. These abnormal spikes are as follows: the 1973-1974 oil shock, the 1979 energy crisis, and the 1980s recession, Black Monday in 1987, the Asian financial crisis in 1997 and 1998, and the recent GFC. Although these crises have impacted on our series, the magnitude of the impact is different for each country. In this paper we have tested for the statistical significance of these abnormal spikes via the use of aggregate dummy variables ($W_i$ for all $i=1..8$) for each series: $W_i$ equals $1$ when series $i$ has abnormal spikes during these major events outlined above and zero otherwise. It should be noted that the results from an analysis of individual crises/shocks would be interesting and more case-specific. However, this has not been undertaken in the present study because this involves the estimation of a large number of additional parameters in the model.

Based on the absolute values of the estimated coefficients, it appears that the overall impact arising from these abnormal observations is higher on stock returns than the growth rates. For instance, the absolute impact on the US stock market is -0.170 while for the US GDP growth the dummy variable coefficient is only -0.020. Overall, the estimated coefficient of the dummy variable is the largest for the Australian stock market ($W_1$ = -0.224). Although these crises were originated outside Australia, the effect of these external events affected the Australian stock market and its GDP growth rate more than the other three countries in the sample. This suggests how vulnerable the smaller countries are to the adverse effects of external financial and economic crises. In addition, one can argue that most of these events are related to the collapse of financial markets, thereby it is not counter-intuitive to observe the strongest impacts are exerted on stock markets rather than GDP growth rates.

**[Table 2 about here]**

Table 3 presents the estimated ARCH and GARCH coefficients of the variance and covariance equations of the DBEKK(1,1) model. First, the diagonal elements of *A* and *B* matrixes are estimated and because of the quadratic form of the parameters, the Wald test is then performed to obtain the ARCH and GARCH effects on each of the variance and covariance equations (3) and (4). The estimated results reveal that the significant squared own-volatility shocks exist for all eight series except for the Canadian and Australian GDP growth series. The results indicate that these past-squared volatility shocks are generally higher in the case of stock markets than those of GDP growth series. This means that unanticipated own shocks are more persistent in the equations for stock markets than for economic growth. The estimated co-volatility shocks (i.e. the cross-product of innovations) across stock markets are all positive and statistically significant. Based on these results, one can assert that similar to past-squared shocks in individual stock markets, lagged cross-product of innovations between each of the two stock markets pairwise can contribute to a rise in the corresponding future co-volatility. Furthermore, the co-volatility shocks between stock markets and GDP growth rates are also positive and mostly significant. Similarly, the co-volatility across GDP growth rates is also positive and significant except for the co-volatility shocks between the Canadian GDP growth and GDP growth rates of other countries. These positive and significant co-volatility shocks across series suggests that unanticipated shocks in any of our four countries can adversely impact on the stability of the remaining countries by increasing the volatility spillovers across stock markets as well as economic growth. Compared to the output growth series, the magnitude of the ARCH effects in Table 3 shows that the lagged shocks leading to rising volatilities is much stronger when they run from one stock market to the others. This further confirms that these four countries have highly interdependent and integrated economies, particularly in the context of stock market co-volatilities.

Unlike the squared own-volatility shocks (ARCH effects), the past own-volatility spillovers (GARCH effects) in the conditional variance equations for all eight series are positive and statistically significant at the 1 per cent level. Own-volatility spillovers corresponding to both return and growth series are the strongest for Canada (0.99 for both series) showing the persistent effect of the shocks on their own future volatility. Overall, the estimated GARCH coefficients for co-volatility spillovers are also positive and significant at the 1 per cent level, providing further evidence for high volatility spillover persistence across all of the eight series. It should be noted that the co-volatility between stock market and GDP growth varies in a narrow range between 0.99 for Canada and 0.97 for Australia.

According to the second order moment estimates, lagged co-volatilities between the return and growth series have a strong relationship with each other. There are at least three plausible explanations for such a relationship in the literature: First Kose *et al.* (2003) states that consumers with substantial amount of stocks from different countries could induce a decline in the demand for consumer and capital goods when stock markets are subject to a downturn. Second, Schwert (1989, 1990) on the other hand argues that financial leveraging can increase the volatility of leveraged stocks during economic recession and operating leverages can make the value of firms more sensitive to economic conditions of a country. Therefore, as Karolyi (2001) argued, if there are a substantial amount of stocks that are cross-listed across major stock markets in a country, their volatility can influence the economy and the stock market of other countries. Third, according to Schwert (1990), technological advancement can increase the information flow across different countries providing investors to access and respond quickly to that new information, hence both GDP and stock markets can be affected.

Finally, to validate our findings using the DBEKK(1,1) model, we have performed diagnostic tests on standardized residuals of each series and the results are presented in Table 4A and Table 4B. The estimated results from the Ljung-Box Q-statistics for the standardized residuals of eight series generated from the DBEKK(1,1) model support the null hypothesis of no autocorrelations at any conventional level. According to the ADF test results, all four standardized residual series are stationary. The Wald test for $\boldsymbol{a_i^2} + \boldsymbol{b_i^2} < 1$ for all *i=1..8* confirmed that our model satisfied the necessary and sufficient condition for covarianve stationarity of the MGARCH process. [5]

**[Tables 3, 4A and 4B about here]**

## V. Summary and Conclusion

This paper has used quarterly data on stock market returns and GDP growth rates for the US, the UK, Canada and Australia for the period 1959:Q3-2010:Q4 to quantify the extent and strength of the volatility spillover dynamics across both stock returns and GDP growth rates of these four highly integrated countries. We employed the DBEKK(1,1) specification and the estimated model passes the standard diagnostic tests. According to our empirical results, there exist significant own-mean spillovers effects in all eight series, indicating the past path dependencies in our series. More importantly, it is found that the lagged US stock returns directly impacted on the Australian stock returns. The US stock returns are in turn affected by

[5] These results have not been reported here but they are available from the authors upon request.

both lagged US stock returns and GDP growth rates. On the other hand, the Australian GDP growth is directly impacted by the own-lagged stock returns and growth rates as well as the lagged US growth rates. One can thus conclude that any slowdown in the US economy is initially expected to exert greater influence on its own stock market before engulfing the prospect of other countries' GDP growth and stock returns.

We also found the magnitudes of co-volatility spillovers across stock markets are generally higher than those of GDP growth series and there is a high degree of volatility persistence. Own-volatility and co-volatility spillovers within and across all eight series are positive and statistically significant, providing evidence for the existing interplay between co-volatility across both stock returns and GDP growth series among these four countries. We have provided three justifications in the literature for such interdependencies. The identification of the extent and strength of co-volatility across various stock markets and GDP growth series have important implications for both individual investors and policy makers. Investors are highly unlikely to benefit from investing their funds across only these four stock markets because we found that there exists a high-degree of time-varying co-volatility across these four markets. It also follows that policy makers' stimulus or austerity measures will have an impact outside of that country's borders and furthermore that coordinated monetary and fiscal policies should be considered if the objective is to curb or avoid future GFC and global recessions.

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TABLE 1A

Descriptive statistics for the stock market return series

| | US | UK | Canada | Australia |
|---|---|---|---|---|
| Mean | 0.0149 | 0.0176 | 0.0153 | 0.0157 |
| Median | 0.0187 | 0.0221 | 0.0235 | 0.0265 |
| Maximum | 0.1841 | 0.3567 | 0.1856 | 0.1962 |
| Minimum | -0.3622 | -0.2666 | -0.3337 | -0.4888 |
| Std. Dev. | 0.0648 | 0.0812 | 0.0734 | 0.0835 |
| Skewness | -1.3443 | -0.2124 | -1.0228 | -1.5555 |
| Kurtosis | 8.7778 | 5.9167 | 6.0990 | 10.0202 |
| Jarque-Bera | 346.8775 | 74.2065 | 117.7807 | 503.6213 |
| | *(0.0000)* | *(0.0000)* | *(0.0000)* | *(0.0000)* |
| ADF t statistics | | | | |
| Based on min. AIC | -9.44 | -9.73 | -11.31 | -11.98 |
| | *(0.0000)* | *(0.0000)* | *(0.0000)* | *(0.0000)* |
| Based on min. SIC | -10.11 | -10.93 | -11.31 | -11.97 |
| | *(0.0000)* | *(0.0000)* | *(0.0000)* | *(0.0000)* |

*Sources:* Quarterly stock market indexes of the US, the UK, Canada, and Australia for the period 1959:Q3- 2010:Q4 (n = 206 observations) are obtained from EconData (2011). The corresponding *p*-values are given in parenthesis.

TABLE 1B

Descriptive statistics for the GDP growth series

| | US | UK | Canada | Australia |
|---|---|---|---|---|
| Mean | 0.0077 | 0.0057 | 0.0082 | 0.0090 |
| Median | 0.0077 | 0.0061 | 0.0079 | 0.0078 |
| Maximum | 0.0385 | 0.0520 | 0.0331 | 0.0563 |
| Minimum | -0.0216 | -0.0248 | -0.0195 | -0.0281 |
| Std. Dev. | 0.0087 | 0.0098 | 0.0090 | 0.0117 |
| Skewness | -0.2795 | 0.3625 | -0.0082 | 0.5172 |
| Kurtosis | 4.2461 | 6.8858 | 3.4640 | 4.6817 |
| Jarque-Bera | 15.9307 | 133.4615 | 1.8409 | 33.2947 |
| | *(0.0003)* | *(0.0000)* | *(0.3983)* | *(0.0000)* |
| ADF t statistics | | | | |
| Based on min. AIC | -6.84 | -6.20 | -3.26 | -4.45 |
| | *(0.0000)* | *(0.0000)* | *(0.0181)* | *(0.0003)* |
| Based on min. SIC | -6.84 | -6.20 | -10.49 | -15.80 |
| | *(0.0000)* | *(0.0000)* | *(0.0000)* | *(0.0000)* |

*Sources*: Quarterly GDP data of the US, the UK, Canada, and Australia for the period 1959:Q3- 2010:Q4 (n = 206 observations) are obtained from EconData (2011). The corresponding *p*-values are given in parenthesis.

FIGURE 1

Quarterly stock returns from 1959:Q3 to 2010:Q4.

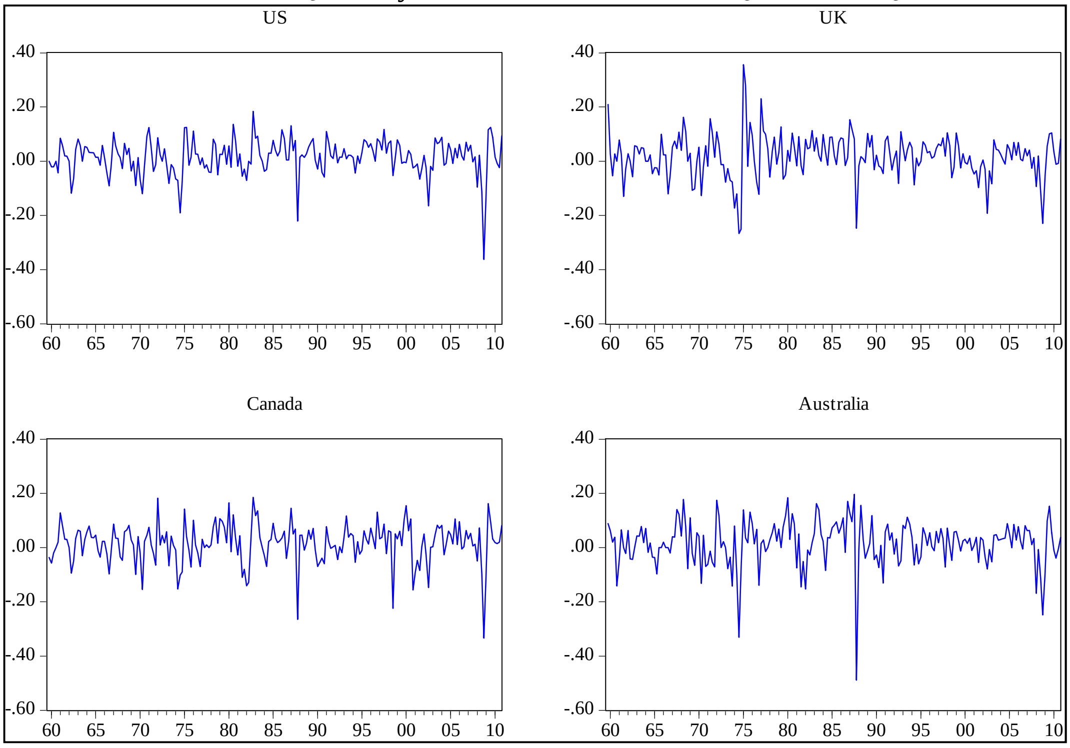


FIGURE 2

Quarterly GDP growth rates from 1959:Q3 to 2010:Q4.

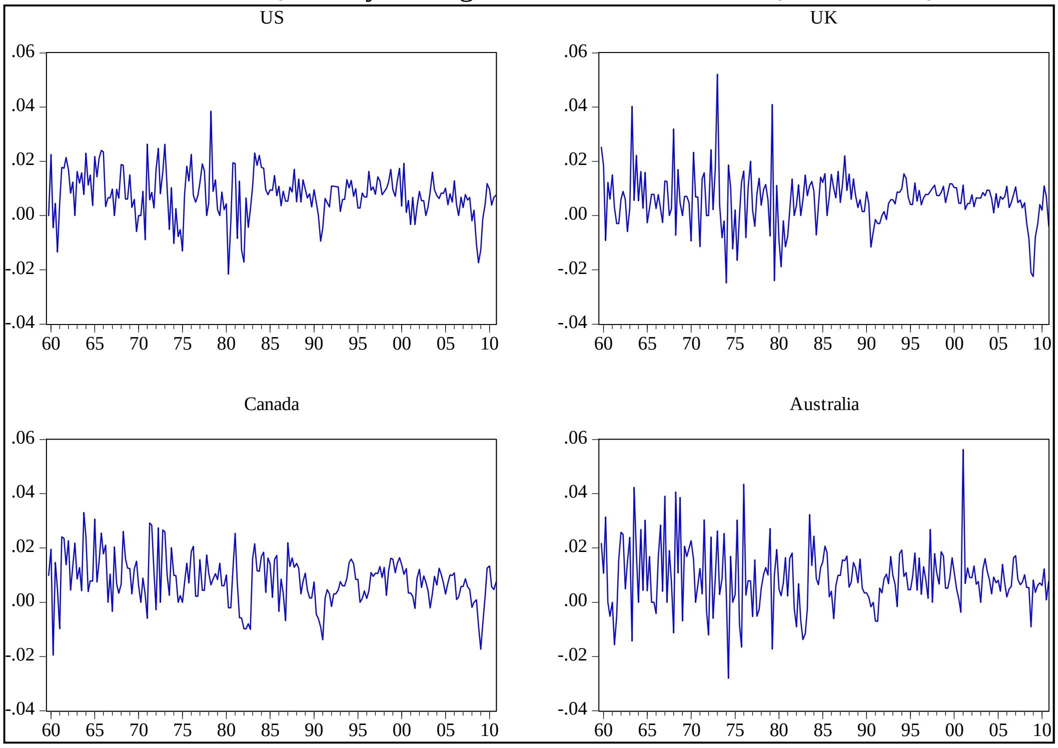

TABLE 2

Parameter estimation for mean equations

$$r_{it} = \mu_{0i} + \sum_{k=1}^{8}\sum_{j=1}^{4}\mu_{kj}r_{kt-j} + \theta_i W_i + \varepsilon_{it}$$

---

$$r_{1t} = \underset{(5.06)}{0.020^{***}} + \underset{(4.61)}{0.246 r_{1t-1}^{***}} - \underset{(-2.39)}{0.687 r_{5t-1}^{**}} - \underset{(-10.35)}{0.170 W_1^{***}}$$

$$r_{2t} = \underset{(4.08)}{0.017^{***}} + \underset{(4.35)}{0.190 r_{2t-1}^{***}} - \underset{(-4.08)}{0.149 W_1^{***}}$$

$$r_{3t} = \underset{(4.11)}{0.018^{***}} + \underset{(2.84)}{0.136 r_{3t-1}^{**}} - \underset{(-3.20)}{0.191 W_3^{***}}$$

$$r_{4t} = \underset{(4.32)}{0.019^{***}} + \underset{(1.55)}{0.081 r_{4t-3}^{*}} + \underset{(1.78)}{0.114 r_{1t-2}^{*}} - \underset{(-9.13)}{0.224 W_4^{***}}$$

$$r_{5t} = \underset{(8.37)}{0.005^{***}} + \underset{(4.52)}{0.034 r_{1t-1}^{***}} + \underset{(5.07)}{0.240 r_{5t-2}^{***}} - \underset{(-7.50)}{0.020 W_5^{***}}$$

$$r_{6t} = \underset{(5.26)}{0.004^{***}} + \underset{(1.82)}{0.099 r_{6t-2}^{*}} + \underset{(1.93)}{0.141 r_{5t-1}^{**}} - \underset{(-6.98)}{0.024 W_6^{***}}$$

$$r_{7t} = \underset{(6.62)}{0.004^{***}} + \underset{(3.19)}{0.156 r_{7t-1}^{***}} + \underset{(6.19)}{0.321 r_{5t-1}^{***}} - \underset{(-2.04)}{0.005 W_7^{**}}$$

$$r_{8t} = \underset{(9.63)}{0.009^{***}} + \underset{(-1.74)}{0.010 r_{4t-4}^{*}} - \underset{(-2.33)}{0.130 r_{8t-4}^{**}} + \underset{(-1.89)}{0.144 r_{5t-3}^{*}} - \underset{(-9.73)}{0.031 W_8^{***}}$$

---

*Note:* (a) $r_1$ for the US stock returns, $r_2$ for the UK stock returns, $r_3$ for Canadian stock returns, $r_4$ for Australian stock returns, $r_5$ for the US GDP growth, $r_6$ for the UK GDP growth, $r_7$ for Canadian GDP growth, and $r_8$ for Australian GDP growth. (b) The *t*-ratios are given in parenthesis. (c)***, ** and * indicate that the corresponding null hypotheses are rejected at 1, 5 and 10 per cent significance levels, respectively.

TABLE 3

Wald Test results for parameters of the variance and covariance equations

$$h_{iit} = c_{ii} + a_{ii}^2 \varepsilon_{it-1}^2 + b_{ii}^2 h_{iit-1}$$

$$h_{ijt} = c_{ij} + a_{ii} a_{ij} \varepsilon_{it-1} \varepsilon_{jt-1} + b_{ii} b_{jj} h_{ijt-1}$$

$$h_{11t} = a_{11} a_{11} \varepsilon_{1t-1}^2 + b_{11} b_{11} h_{11t-1} = \underset{(5.80)}{0.0210}\, \varepsilon_{1t-1}^{2\,**} + \underset{(15756.99)}{0.9763}\, h_{11}^{***}$$

$$h_{12_4 t} = a_{11} a_{22} \varepsilon_{1t-1} \varepsilon_{2t-1} + b_{11} b_{22} h_{12t-1} = \underset{(10.87)}{0.0221}\, \varepsilon_{1t-1} \varepsilon_{2t-1}^{***} + \underset{(25023.39)}{0.9732}\, h_{11}^{***}$$

$$h_{22t} = a_{22} a_{22} \varepsilon_{2t-1}^2 + b_{22} b_{22} h_{22t-1} = \underset{(10.26)}{0.0232}\, \varepsilon_{2t-1}^{2\,***} + \underset{(17384.83)}{0.9700}\, h_{22}^{***}$$

$$h_{13t} = a_{11} a_{33} \varepsilon_{1t-1} \varepsilon_{3t-1} + b_{11} b_{33} h_{13t-1} = \underset{(5.06)}{0.0144}\, \varepsilon_{1t-1} \varepsilon_{3t-1}^{**} + \underset{(26596.43)}{0.9821}\, h_{13}^{***}$$

$$h_{23t} = a_{22} a_{33} \varepsilon_{2t-1} \varepsilon_{3t-1} + b_{22} b_{33} h_{23t-1} = \underset{(8.31)}{0.0152}\, \varepsilon_{2t-1} \varepsilon_{3t-1}^{**} + \underset{(39011.66)}{0.9789}\, h_{23}^{***}$$

$$h_{33t} = a_{33} a_{33} \varepsilon_{3t-1}^2 + b_{33} b_{33} h_{33t-1} = \underset{(3.61)}{0.0099}\, \varepsilon_{3t-1}^{2\,*} + \underset{(41201.21)}{0.9879}\, h_{33}^{***}$$

$$h_{14t} = a_{11} a_{44} \varepsilon_{1t-1} \varepsilon_{4t-1} + b_{11} b_{44} h_{14t-1} = \underset{(12.46)}{0.0315}\, \varepsilon_{1t-1} \varepsilon_{4t-1}^{***} + \underset{(17144.34)}{0.9625}\, h_{14}^{***}$$

$$h_{24t} = a_{22} a_{44} \varepsilon_{2t-1} \varepsilon_{4t-1} + b_{22} b_{44} h_{24t-1} = \underset{(17.54)}{0.0331}\, \varepsilon_{2t-1} \varepsilon_{4t-1}^{***} + \underset{(18367.51)}{0.9593}\, h_{24}^{***}$$

$$h_{34t} = a_{33} a_{44} \varepsilon_{3t-1} \varepsilon_{4t-1} + b_{33} b_{44} h_{34t-1} = \underset{(9.35)}{0.0216}\, \varepsilon_{3t-1} \varepsilon_{4t-1}^{**} + \underset{(22796.97)}{0.9682}\, h_{34}^{***}$$

$$h_{44t} = a_{44} a_{44} \varepsilon_{4t-1}^2 + b_{44} b_{44} h_{44t-1} = \underset{(12.10)}{0.0472}\, \varepsilon_{4t-1}^{2\,***} + \underset{(7541.92)}{0.9488}\, h_{44}^{***}$$

$$h_{15t} = a_{11} a_{55} \varepsilon_{1t-1} \varepsilon_{5t-1} + b_{11} b_{55} h_{15t-1} = \underset{(6.58)}{0.0164}\, \varepsilon_{1t-1} \varepsilon_{5t-1}^{**} + \underset{(26562.17)}{0.9788}\, h_{15}^{***}$$

$$h_{25t} = a_{22} a_{55} \varepsilon_{2t-1} \varepsilon_{5t-1} + b_{22} b_{55} h_{25t-1} = \underset{(7.62)}{0.0172}\, \varepsilon_{2t-1} \varepsilon_{5t-1}^{**} + \underset{(27946.72)}{0.9756}\, h_{25}^{***}$$

$$h_{35t} = a_{33} a_{55} \varepsilon_{3t-1} \varepsilon_{5t-1} + b_{33} b_{55} h_{35t-1} = \underset{(5.65)}{0.0113}\, \varepsilon_{3t-1} \varepsilon_{5t-1}^{**} + \underset{(38521.02)}{0.9846}\, h_{35}^{***}$$

$$h_{45t} = a_{44} a_{55} \varepsilon_{4t-1} \varepsilon_{5t-1} + b_{44} b_{55} h_{45t-1} = \underset{(7.55)}{0.0246}\, \varepsilon_{4t-1} \varepsilon_{5t-1}^{**} + \underset{(17393.45)}{0.9649}\, h_{45}^{***}$$

$$h_{55t} = a_{55} a_{55} \varepsilon_{5t-1}^2 + b_{55} b_{55} h_{55t-1} = \underset{(2.76)}{0.0128}\, \varepsilon_{5t-1}^{2\,*} + \underset{(13932.46)}{0.9813}\, h_{55}^{***}$$

$$h_{16t} = a_{11} a_{66} \varepsilon_{1t-1} \varepsilon_{6t-1} + b_{11} b_{66} h_{16t-1} = \underset{(5.88)}{0.101}\, \varepsilon_{1t-1} \varepsilon_{6t-1}^{**} + \underset{(46054.25)}{0.9813}\, h_{16}^{***}$$

$$h_{26t} = a_{22} a_{66} \varepsilon_{2t-1} \varepsilon_{6t-1} + b_{22} b_{66} h_{26t-1} = \underset{(7.28)}{0.0106}\, \varepsilon_{2t-1} \varepsilon_{6t-1}^{**} + \underset{(49506.17)}{0.9782}\, h_{26}^{***}$$

$$h_{36t} = a_{33} a_{66} \varepsilon_{3t-1} \varepsilon_{6t-1} + b_{33} b_{66} h_{36t-1} = \underset{(5.19)}{0.0069}\, \varepsilon_{3t-1} \varepsilon_{6t-1}^{**} + \underset{(86834.30)}{0.9872}\, h_{36}^{***}$$

$$h_{46t} = a_{44} a_{66} \varepsilon_{4t-1} \varepsilon_{6t-1} + b_{44} b_{66} h_{46t-1} = \underset{(7.88)}{0.0150}\, \varepsilon_{4t-1} \varepsilon_{6t-1}^{**} + \underset{(26056.99)}{0.9674}\, h_{46}^{***}$$

$$h_{56t} = a_{55} a_{66} \varepsilon_{5t-1} \varepsilon_{6t-1} + b_{55} b_{66} h_{56t-1} = \underset{(4.31)}{0.0079}\, \varepsilon_{5t-1} \varepsilon_{6t-1}^{**} + \underset{(38656.35)}{0.9839}\, h_{56}^{***}$$

$$h_{66t} = a_{66} a_{66} \varepsilon_{6t-1}^2 + b_{66} b_{66} h_{66t-1} = \underset{(2.62)}{0.0048}\, \varepsilon_{6t-1}^2 + \underset{(60979.10)}{0.9864}\, h_{66}^{***}$$

TABLE 3 *(continued)*

$$h_{17t} = a_{11}a_{77}\varepsilon_{1t-1}\varepsilon_{7t-1} + b_{11}b_{77}h_{17t-1} = \underset{(1.04)}{0.0046}\,\varepsilon_{1t-1}\varepsilon_{7t-1} + \underset{(50787.08)}{0.9843}\,h_{17}^{***}$$

$$h_{27t} = a_{22}a_{77}\varepsilon_{2t-1}\varepsilon_{7t-1} + b_{22}b_{77}h_{27t-1} = \underset{(1.08)}{0.0048}\,\varepsilon_{2t-1}\varepsilon_{7t-1} + \underset{(54534.53)}{0.9812}\,h_{27}^{***}$$

$$h_{37t} = a_{33}a_{77}\varepsilon_{3t-1}\varepsilon_{7t-1} + b_{33}b_{77}h_{37t-1} = \underset{(0.99)}{0.0032}\,\varepsilon_{3t-1}\varepsilon_{7t-1} + \underset{(102586.10)}{0.9902}\,h_{37}^{***}$$

$$h_{47t} = a_{44}a_{77}\varepsilon_{4t-1}\varepsilon_{7t-1} + b_{44}b_{77}h_{47t-1} = \underset{(1.07)}{0.0069}\,\varepsilon_{4t-1}\varepsilon_{7t-1} + \underset{(26226.95)}{0.9704}\,h_{47}^{***}$$

$$h_{57t} = a_{55}a_{77}\varepsilon_{5t-1}\varepsilon_{7t-1} + b_{55}b_{77}h_{57t-1} = \underset{(0.85)}{0.0036}\,\varepsilon_{5t-1}\varepsilon_{7t-1}^{*} + \underset{(37534.03)}{0.9869}\,h_{57}^{***}$$

$$h_{67t} = a_{66}a_{77}\varepsilon_{6t-1}\varepsilon_{7t-1} + b_{66}b_{77}h_{67t-1} = \underset{(0.96)}{0.0022}\,\varepsilon_{6t-1}\varepsilon_{7t-1} + \underset{(134562.30)}{0.9894}\,h_{67}^{***}$$

$$h_{77t} = a_{77}a_{77}\varepsilon_{7t-1}^{2} + b_{77}b_{77}h_{77t-1} = \underset{(0.29)}{0.0010}\,\varepsilon_{7t-1}^{2} + \underset{(108197.5)}{0.9924}\,h_{77}^{***}$$

$$h_{18t} = a_{11}a_{88}\varepsilon_{1t-1}\varepsilon_{8t-1} + b_{11}b_{88}h_{18t-1} = \underset{(4.44)}{0.0120}\,\varepsilon_{1t-1}\varepsilon_{8t-1}^{**} + \underset{(29676.35)}{0.9802}\,h_{18}^{***}$$

$$h_{28t} = a_{22}a_{88}\varepsilon_{2t-1}\varepsilon_{8t-1} + b_{22}b_{88}h_{28t-1} = \underset{(5.29)}{0.0126}\,\varepsilon_{2t-1}\varepsilon_{8t-1}^{**} + \underset{(33250.34)}{0.9771}\,h_{28}^{***}$$

$$h_{38t} = a_{33}a_{88}\varepsilon_{3t-1}\varepsilon_{8t-1} + b_{33}b_{88}h_{38t-1} = \underset{(3.85)}{0.0082}\,\varepsilon_{3t-1}\varepsilon_{8t-1}^{**} + \underset{(43574.84)}{0.9861}\,h_{38}^{***}$$

$$h_{48t} = a_{44}a_{88}\varepsilon_{4t-1}\varepsilon_{8t-1} + b_{44}b_{88}h_{48t-1} = \underset{(6.04)}{0.0180}\,\varepsilon_{4t-1}\varepsilon_{8t-1}^{**} + \underset{(24716.10)}{0.9663}\,h_{48}^{***}$$

$$h_{58t} = a_{55}a_{88}\varepsilon_{5t-1}\varepsilon_{8t-1} + b_{55}b_{88}h_{58t-1} = \underset{(3.92)}{0.0094}\,\varepsilon_{5t-1}\varepsilon_{8t-1}^{**} + \underset{(31020.88)}{0.9827}\,h_{58}^{***}$$

$$h_{68t} = a_{66}a_{88}\varepsilon_{6t-1}\varepsilon_{8t-1} + b_{66}b_{88}h_{68t-1} = \underset{(3.54)}{0.0057}\,\varepsilon_{6t-1}\varepsilon_{8t-1}^{**} + \underset{(53801.80)}{0.9853}\,h_{68}^{***}$$

$$h_{78t} = a_{77}a_{88}\varepsilon_{7t-1}\varepsilon_{8t-1} + b_{66}b_{88}h_{68t-1} = \underset{(0.90)}{0.0026}\,\varepsilon_{7t-1}\varepsilon_{8t-1} + \underset{(56200.72)}{0.9883}\,h_{78}^{***}$$

$$h_{88t} = a_{88}a_{88}\varepsilon_{8t-1}^{2} + b_{88}b_{88}h_{88t-1} = \underset{(1.66)}{0.0068}\,\varepsilon_{8t-1}^{2} + \underset{(18427.50)}{0.9842}\,h_{88}^{***}$$

*Note:* (a) Chi-square values are given in parenthesis. (b) ***, ** and * indicate that the corresponding null hypotheses are rejected at 1, 5 and 10 per cent significance levels, respectively.

TABLE 4A

Diagnostic tests on the standardized residuals of stock market return series

| | US | | UK | | Canada | | Australia | |
|---|---|---|---|---|---|---|---|---|
| ADF *t* statistics | | | | | | | | |
| Based on min. AIC | -12.28 | | -12.62 | | -12.38 | | -12.55 | |
| Based on min. SIC | -12.28 | | -12.62 | | -12.38 | | -12.55 | |
| Ljung-Box test statistics for standardized residuals | | | | | | | | |
| | Statistic | *p*-value | Statistic | *p*-value | Statistic | *p*-value | Statistic | *p*-value |
| Q(1) | 3.43 | 0.06 | 2.28 | 0.13 | 3.16 | 0.08 | 3.24 | 0.07 |
| Q(2) | 3.44 | 0.18 | 2.49 | 0.29 | 3.49 | 0.18 | 4.99 | 0.08 |
| Q(3) | 3.93 | 0.27 | 3.58 | 0.31 | 5.40 | 0.15 | 4.99 | 0.17 |
| Q(4) | 4.31 | 0.37 | 4.28 | 0.37 | 6.38 | 0.17 | 5.67 | 0.23 |
| Q(5) | 4.35 | 0.50 | 4.82 | 0.44 | 7.53 | 0.18 | 7.45 | 0.19 |
| Q(6) | 4.37 | 0.63 | 5.07 | 0.53 | 7.53 | 0.27 | 7.93 | 0.24 |
| Q(7) | 6.20 | 0.52 | 7.24 | 0.40 | 11.66 | 0.11 | 12.10 | 0.10 |
| Q(8) | 7.36 | 0.50 | 7.36 | 0.50 | 11.87 | 0.16 | 12.18 | 0.14 |
| Q(9) | 8.51 | 0.48 | 7.44 | 0.59 | 12.11 | 0.21 | 12.51 | 0.19 |
| Q(10) | 9.63 | 0.47 | 9.75 | 0.46 | 13.70 | 0.19 | 13.30 | 0.21 |
| Q(11) | 9.65 | 0.56 | 9.98 | 0.53 | 15.97 | 0.14 | 14.04 | 0.23 |
| Q(12) | 10.16 | 0.60 | 10.16 | 0.60 | 16.11 | 0.19 | 14.41 | 0.28 |

*Note:* Q(n) is the $n^{th}$ lag Ljung-Box test statistics.

TABLE 4B

Diagnostic tests on the standardized residuals of GDP growth series

| | US | | UK | | Canada | | Australia | |
|---|---|---|---|---|---|---|---|---|
| ADF *t* statistics | | | | | | | | |
| Based on min. AIC | -12.11 | | -6.95 | | -14.43 | | -15.86 | |
| Based on min. SIC | -12.11 | | -13.95 | | -14.43 | | -15.86 | |
| Ljung-Box test statistics for standardized residuals | | | | | | | | |
| | Statistic | *p*-value | Statistic | *p*-value | Statistic | *p*-value | Statistic | *p*-value |
| Q(1) | 5.64 | 0.02 | 0.01 | 0.94 | 0.13 | 0.72 | 2.66 | 0.10 |
| Q(2) | 5.83 | 0.05 | 0.45 | 0.80 | 0.52 | 0.77 | 3.17 | 0.21 |
| Q(3) | 6.45 | 0.09 | 6.53 | 0.09 | 3.00 | 0.39 | 4.68 | 0.20 |
| Q(4) | 7.10 | 0.13 | 6.62 | 0.16 | 4.22 | 0.38 | 7.15 | 0.13 |
| Q(5) | 7.15 | 0.21 | 6.63 | 0.25 | 4.31 | 0.51 | 9.96 | 0.08 |
| Q(6) | 7.67 | 0.26 | 10.01 | 0.12 | 5.10 | 0.53 | 10.17 | 0.12 |
| Q(7) | 9.43 | 0.22 | 11.39 | 0.12 | 6.37 | 0.50 | 10.81 | 0.15 |
| Q(8) | 10.33 | 0.24 | 15.99 | 0.04 | 8.81 | 0.36 | 15.43 | 0.05 |
| Q(9) | 10.44 | 0.32 | 18.12 | 0.03 | 12.11 | 0.21 | 16.90 | 0.05 |
| Q(10) | 10.78 | 0.38 | 18.98 | 0.04 | 17.11 | 0.07 | 18.83 | 0.04 |
| Q(11) | 10.78 | 0.46 | 19.69 | 0.05 | 18.50 | 0.07 | 18.92 | 0.06 |
| Q(12) | 15.12 | 0.24 | 20.08 | 0.07 | 18.64 | 0.10 | 19.42 | 0.08 |

Note: Q(n) is the $n^{th}$ lag Ljung-Box test statistics.