Structural Breaks and Volatility Persistence of Stock Returns: Evidence from the US and UK Equity Markets

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Abstract

This paper quantitatively investigates the effects of structural breaks on stock return volatility persistence by using the US and UK stock market index return data. Applying two kinds of representative univariate GARCH models of standard GARCH and EGARCH models, we derive the following interesting findings. (1) First, we find that for both the US and UK stock market returns, the volatility persistence parameter values of standard GARCH models decrease when structural breaks are taken into account. (2) Second, we further reveal that for both the US and UK stock market returns, the volatility persistence parameter values of EGARCH models again decline when structural breaks are taken into consideration.

Keywords: GARCH model, EGARCH model, international stock markets, structural break, volatility persistence

1. Introduction

In recent economics and finance literature, structural breaks are being highly important, while well-known volatility persistence of stock returns is also traditionally important in financial modeling (e.g., Jung and Maderitsch, 2014; Tsuji, 2016a; Adesina, 2017; Ahmed, 2018; Tsuji, 2018a). Then what is the effect of structural breaks of stock returns on volatility persistence of stock returns? In addition, how are structural breaks as to stock returns related to volatility persistence of stock returns? In order to answer these research questions, this paper investigates the effects of structural breaks on stock return volatility persistence by using the US and UK stock market index return data. Applying two kinds of univariate GARCH models of standard GARCH and EGARCH models, we derive the following interesting findings. First, we find that for both the US and UK stock market returns, the volatility persistence parameter values of standard GARCH models decrease when structural breaks are taken into account. Second, we further reveal that for both the US and UK stock market returns, the volatility persistence parameter values of EGARCH models again decrease when structural breaks are taken into consideration.

As described later, these interesting findings are very robust. Thus, the evidence from our study is valuable for economic and financial modeling of many kinds of time-series variables in the fields of economics and finance. Therefore, these results demonstrated in this paper shall make important contributions to the existing and future research in economics and finance. As for the rest of this article, in Section 2, we review recent related studies; in Section 3, the data and variables for our study are explained; and in Section 4, we document our analyzing methodology. After these, in Section 5, we explain our main results, and Section 6 concludes the paper.

2. Literature Review

This section briefly conducts a recent literature review focusing on structural breaks. Salisu and Fasanya (2013) investigated West Texas Intermediate (WTI) and Brent crude oil prices, and found two structural breaks that corresponded to the Iraqi/Kuwait conflict around 1990 and the global financial crisis around 2008. Jung and Maderitsch (2014) examined volatility transmission between Hong Kong, European, and the US stock markets over the period from 2000 to 2011, and they identified the time-variations and structural breaks in volatility transmission. Further, Gil-Alana et al. (2015) investigated the statistical properties of major precious metal prices of gold, silver, platinum, rhodium, and palladium, and they found evidence of structural breaks in all the cases except for palladium. Block et al. (2015) investigated WTI and multiple energy return series, and they suggested the presence of at least one structural break in both their conditional volatilities and the correlations between WTI and each energy series. Recently, Adesina (2017)
explored volatility dynamics and volatility persistence under a supposed structural break by the Brexit-vote. As a result, this study suggested that in modeling volatility dynamics, a Brexit-vote structural break may be irrelevant. Furthermore, after controlling for structural breaks in conditional volatilities, the analyses of Ahmed (2018) found the unidirectional mean and volatility spillovers from natural gas to the Qatar’s stock market.

As above, recent studies suggested the importance of taking into consideration structural breaks. Thus, in this paper, we quantitatively examine the US and UK stock returns by controlling structural breaks by using dummy variables in below sections.

![Figure 1. Evolution of S&P 500 and FTSE 100: From January 3, 2000 to August 2, 2018](image)

**Table 1. Summary statistics of the US and UK daily percentage log stock returns**

<table>
<thead>
<tr>
<th></th>
<th>LRUS</th>
<th>LUK</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0137</td>
<td>0.0018</td>
</tr>
<tr>
<td>Median</td>
<td>0.0234</td>
<td>0.0023</td>
</tr>
<tr>
<td>Maximum</td>
<td>10.9572</td>
<td>9.3843</td>
</tr>
<tr>
<td>Minimum</td>
<td>−9.4695</td>
<td>−9.2656</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.1855</td>
<td>1.1630</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.2242</td>
<td>−0.1644</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>9.0723</td>
<td>6.6439</td>
</tr>
</tbody>
</table>

Notes: The sample period of the US and UK stock returns is from January 4, 2000 to August 2, 2018. The number of the observations is 4,848.

**3. Data**

This section explains our data and variables used in this study. All data are from Thomson Reuters. Our first variable is LRUS, which is the daily log return of the US S&P 500; our second variable is LUK, which is the daily log return of the UK FTSE 100. Our sample period of these two returns is from January 4, 2000 to August 2, 2018.

Figure 1 exhibits the evolution of the S&P 500 and FTSE 100 prices from January 3, 2000 to August 2, 2018. In addition, Figure 2 shows the evolution of daily percentage log returns of S&P 500 and FTSE 100 from January 4, 2000 to August 2, 2018. Table 1 shows the summary statistics of the above US and UK stock returns. Table 1 shows that for both return series, their means are very slightly positive, their skewness values are negative, and their kurtosis values are much higher than that of normal distributions.
4. Methodology

We next explain our analyzing methodology. In this study, we use two GARCH models of standard GARCH (Bollerslev, 1986) and EGARCH (Nelson, 1991) models. For the US and UK stock returns, we estimate these two models with and without dummy variables of structural breaks.

We construct the structural break dummy variables after we identify structural break points using ICSS algorithm. The determined break point numbers and time periods are shown in Table 2. As Table 2 indicates, for LRUS, there are 12 break points and for LRUK, there are 18 break points for our sample period. We denote our structural break dummy variables for LRUS as \( USSHIFT (k) \) and those for LRUK as \( UKSHIFT (j) \), where \( k = 1, \ldots, 12 \), and \( j = 1, \ldots, 18 \). More concretely, as for these dummy variables, \( USSHIFT (1) \) takes the value of one for January 4, 2000 to June 14, 2002, and zero elsewhere; and \( UKSHIFT (1) \) takes the value of one for January 4, 2000 to November 13, 2001, and zero elsewhere.

5. Results

This section documents our empirical results. First, Table 3 shows the estimation results of standard GARCH models with or without structural break dummies for the US and UK stock returns. As Panel A of Table 3 shows, for LRUS, the GARCH parameter values of standard GARCH models decrease from 0.8918 (A−1) to 0.8035 (A−2) when structural break dummies are included. Similarly, as Panel B of Table 3 shows, for LRUK, the GARCH parameter values of standard GARCH models largely decrease from 0.8813 (B−1) to 0.7278 (B−2) when structural break dummies are included.

Moreover, Table 4 shows the estimation results of EGARCH models with or without structural break dummies for the US and UK stock returns. As Panel A of Table 4 shows, for LRUS, the GARCH parameter values of EGARCH models decrease from 0.9762 (A−1) to 0.9178 (A−2) when structural break dummies are included. Similarly, as Panel B of Table 4 shows, for LRUK, the GARCH parameter values of EGARCH models decrease from 0.9818 (B−1) to 0.9010 (B−2) when structural break dummies are included.

We stress that our main concern of this study lies in the changes in volatility persistence parameter values of GARCH models, and as above, they always decrease when structural breaks are taken into account. These results are recognized for both the US and UK, and for both standard GARCH and EGARCH models; hence, it is noted that the above results are very robust. Therefore, from our above results, we generally understand that when structural breaks are not taken into consideration, volatility persistence of international stock returns is overestimated in GARCH models.
Table 2. Breakpoints and time periods identified by structural break tests for the US and UK stock returns: From January 4, 2000 to August 2, 2018

<table>
<thead>
<tr>
<th>Series</th>
<th>Break points</th>
<th>Time periods</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P 500</td>
<td>12</td>
<td>January 4, 2000 − June 14, 2002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>June 17, 2002 − October 17, 2002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>October 18, 2002 − April 28, 2003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>April 29, 2003 − May 11, 2004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May 12, 2004 − July 9, 2007</td>
</tr>
<tr>
<td></td>
<td></td>
<td>July 10, 2007 − September 12, 2008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>September 15, 2008 − December 2, 2008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>December 3, 2008 − May 18, 2009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May 19, 2009 − September 3, 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>September 6, 2010 − August 1, 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>August 2, 2011 − December 20, 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>December 21, 2011 − June 30, 2016</td>
</tr>
<tr>
<td></td>
<td></td>
<td>July 1, 2016 − August 2, 2018</td>
</tr>
<tr>
<td>FTSE 100</td>
<td>18</td>
<td>January 4, 2000 − November 13, 2001</td>
</tr>
<tr>
<td></td>
<td></td>
<td>November 14, 2001 − June 13, 2002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>June 14, 2002 − November 4, 2002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>November 5, 2002 − June 2, 2003</td>
</tr>
<tr>
<td></td>
<td></td>
<td>June 3, 2003 − August 16, 2004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>August 17, 2004 − May 1, 2006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May 2, 2006 − August 7, 2006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>August 8, 2006 − July 23, 2007</td>
</tr>
<tr>
<td></td>
<td></td>
<td>July 24, 2007 − September 2, 2008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>September 3, 2008 − December 8, 2008</td>
</tr>
<tr>
<td></td>
<td></td>
<td>December 9, 2008 − May 21, 2009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>May 22, 2009 − September 1, 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>September 2, 2010 − August 2, 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>August 3, 2011 − November 30, 2011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>December 1, 2011 − August 3, 2012</td>
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<tr>
<td></td>
<td></td>
<td>August 6, 2012 − August 18, 2015</td>
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<tr>
<td></td>
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<td>August 19, 2015 − July 11, 2016</td>
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<tr>
<td></td>
<td></td>
<td>July 12, 2016 − January 23, 2018</td>
</tr>
<tr>
<td></td>
<td></td>
<td>January 24, 2018 − August 2, 2018</td>
</tr>
</tbody>
</table>

Notes: The sample period for two return series is from January 4, 2000 to August 2, 2018. The number of our return series is 4,848.

Table 3. Estimation results of standard GARCH models without or with structural break dummies

Panel A. US

A−1. GARCH model with no dummy

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (LRUS)</td>
<td>0.0513***</td>
<td>0.0120</td>
<td>4.2779</td>
<td>0.0000</td>
</tr>
<tr>
<td>Constant term</td>
<td>0.0154***</td>
<td>0.0041</td>
<td>3.7304</td>
<td>0.0002</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.0957***</td>
<td>0.0126</td>
<td>7.5866</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.8918***</td>
<td>0.0133</td>
<td>67.2395</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Log Likelihood  $-6540.9084$

A−2. GARCH model with dummies
### Variable Coefficient Standard error t-statistic p-value

<table>
<thead>
<tr>
<th>Mean (LRUS)</th>
<th>0.0539***</th>
<th>0.0128</th>
<th>4.2038</th>
<th>0.0000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant term</td>
<td>0.0329***</td>
<td>0.0079</td>
<td>4.1774</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.0901***</td>
<td>0.0120</td>
<td>7.5086</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.8035***</td>
<td>0.0232</td>
<td>34.6679</td>
<td>0.0000</td>
</tr>
<tr>
<td>USSHIFT (1)</td>
<td>0.1489***</td>
<td>0.0336</td>
<td>4.4324</td>
<td>0.0000</td>
</tr>
<tr>
<td>USSHIFT (2)</td>
<td>0.5286***</td>
<td>0.1449</td>
<td>3.6479</td>
<td>0.0003</td>
</tr>
<tr>
<td>USSHIFT (3)</td>
<td>0.1885***</td>
<td>0.0488</td>
<td>3.8656</td>
<td>0.0001</td>
</tr>
<tr>
<td>USSHIFT (4)</td>
<td>0.0392***</td>
<td>0.0124</td>
<td>3.1628</td>
<td>0.0016</td>
</tr>
<tr>
<td>USSHIFT (5)</td>
<td>0.0164</td>
<td>0.0087</td>
<td>1.8786</td>
<td>0.0603</td>
</tr>
<tr>
<td>USSHIFT (6)</td>
<td>0.1755***</td>
<td>0.0388</td>
<td>4.5233</td>
<td>0.0000</td>
</tr>
<tr>
<td>USSHIFT (7)</td>
<td>3.1042***</td>
<td>0.8617</td>
<td>3.6026</td>
<td>0.0003</td>
</tr>
<tr>
<td>USSHIFT (8)</td>
<td>0.5821***</td>
<td>0.1634</td>
<td>3.5613</td>
<td>0.0004</td>
</tr>
<tr>
<td>USSHIFT (9)</td>
<td>0.1068***</td>
<td>0.0284</td>
<td>3.7646</td>
<td>0.0002</td>
</tr>
<tr>
<td>USSHIFT (10)</td>
<td>0.0421**</td>
<td>0.0182</td>
<td>2.3208</td>
<td>0.0203</td>
</tr>
<tr>
<td>USSHIFT (11)</td>
<td>0.4432***</td>
<td>0.1423</td>
<td>3.1139</td>
<td>0.0018</td>
</tr>
<tr>
<td>USSHIFT (12)</td>
<td>0.0294***</td>
<td>0.0084</td>
<td>3.4800</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

Log Likelihood: $-6464.9087$

#### Panel B. UK

### B–1. GARCH model with no dummy

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (LRUK)</td>
<td>0.0356***</td>
<td>0.0117</td>
<td>3.0387</td>
<td>0.0024</td>
</tr>
<tr>
<td>Constant term</td>
<td>0.0166***</td>
<td>0.0043</td>
<td>3.8400</td>
<td>0.0001</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.1062***</td>
<td>0.0143</td>
<td>7.4493</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.8813***</td>
<td>0.0154</td>
<td>57.0479</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

Log Likelihood: $-6600.0922$

### B–2. GARCH model with dummies

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (LRUK)</td>
<td>0.0370***</td>
<td>0.0119</td>
<td>3.1198</td>
<td>0.0018</td>
</tr>
<tr>
<td>Constant term</td>
<td>0.1177***</td>
<td>0.0285</td>
<td>4.1350</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.0995***</td>
<td>0.0109</td>
<td>9.1293</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.7278***</td>
<td>0.0314</td>
<td>23.2075</td>
<td>0.0000</td>
</tr>
<tr>
<td>USSHIFT (1)</td>
<td>0.1299***</td>
<td>0.0407</td>
<td>3.1945</td>
<td>0.0014</td>
</tr>
<tr>
<td>USSHIFT (2)</td>
<td>0.0120</td>
<td>0.0305</td>
<td>0.3928</td>
<td>0.6945</td>
</tr>
<tr>
<td>USSHIFT (3)</td>
<td>1.0013***</td>
<td>0.2495</td>
<td>4.0130</td>
<td>0.0001</td>
</tr>
<tr>
<td>USSHIFT (4)</td>
<td>0.2706***</td>
<td>0.0762</td>
<td>3.5528</td>
<td>0.0004</td>
</tr>
<tr>
<td>USSHIFT (5)</td>
<td>$-0.0228$</td>
<td>0.0247</td>
<td>$-0.9229$</td>
<td>0.3561</td>
</tr>
<tr>
<td>USSHIFT (6)</td>
<td>$-0.0625$*</td>
<td>0.0239</td>
<td>$-2.6211$*</td>
<td>0.0088</td>
</tr>
<tr>
<td>USSHIFT (7)</td>
<td>0.1237**</td>
<td>0.0601</td>
<td>2.0589</td>
<td>0.0395</td>
</tr>
<tr>
<td>USSHIFT (8)</td>
<td>$-0.0422$*</td>
<td>0.0255</td>
<td>$-1.6513$*</td>
<td>0.0987</td>
</tr>
<tr>
<td>USSHIFT (9)</td>
<td>0.2338***</td>
<td>0.0641</td>
<td>3.6502</td>
<td>0.0003</td>
</tr>
<tr>
<td>USSHIFT (10)</td>
<td>2.6273***</td>
<td>0.6663</td>
<td>3.9434</td>
<td>0.0001</td>
</tr>
<tr>
<td>USSHIFT (11)</td>
<td>0.4876***</td>
<td>0.1403</td>
<td>3.4761</td>
<td>0.0005</td>
</tr>
<tr>
<td>USSHIFT (12)</td>
<td>0.1046***</td>
<td>0.0382</td>
<td>2.7398</td>
<td>0.0061</td>
</tr>
<tr>
<td>USSHIFT (13)</td>
<td>0.0252</td>
<td>0.0272</td>
<td>0.9236</td>
<td>0.3557</td>
</tr>
<tr>
<td>USSHIFT (14)</td>
<td>0.5625***</td>
<td>0.1683</td>
<td>3.3428</td>
<td>0.0008</td>
</tr>
<tr>
<td>USSHIFT (15)</td>
<td>0.0500</td>
<td>0.0308</td>
<td>1.6232</td>
<td>0.1045</td>
</tr>
<tr>
<td>USSHIFT (16)</td>
<td>$-0.0240$</td>
<td>0.0233</td>
<td>$-1.0286$</td>
<td>0.3037</td>
</tr>
<tr>
<td>USSHIFT (17)</td>
<td>0.1306***</td>
<td>0.0498</td>
<td>2.6200</td>
<td>0.0088</td>
</tr>
<tr>
<td>USSHIFT (18)</td>
<td>$-0.0574$*</td>
<td>0.0248</td>
<td>$-2.3201$*</td>
<td>0.0203</td>
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</tbody>
</table>
Log Likelihood $-6512.7008$

Notes: The sample period for standard GARCH estimations without or with structural break dummies is from January 4, 2000 to August 2, 2018. The number of the US and UK return series is 4,848. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively. We constructed structural break dummy variables after we identified structural break points using ICSS algorithm.

Table 4. Estimation results of EGARCH models without or with structural break dummies

Panel A. US

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>$t$-statistic</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (LRUS)</td>
<td>0.0239**</td>
<td>0.0109</td>
<td>2.1952</td>
<td>0.0282</td>
</tr>
<tr>
<td>Constant term</td>
<td>$-0.1022^{***}$</td>
<td>0.0125</td>
<td>$-8.1866$</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.1272^{***}</td>
<td>0.0165</td>
<td>7.7111</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.9762^{***}</td>
<td>0.0044</td>
<td>223.6279</td>
<td>0.0000</td>
</tr>
<tr>
<td>Asymmetry parameter</td>
<td>$-0.1463^{***}$</td>
<td>0.0149</td>
<td>$-9.8248$</td>
<td>0.0000</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>$-6430.1502$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B. UK

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard error</th>
<th>$t$-statistic</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (LRUK)</td>
<td>$-0.0103$</td>
<td>0.0091</td>
<td>$-1.1392$</td>
<td>0.2546</td>
</tr>
<tr>
<td>Constant term</td>
<td>$-0.0872^{***}$</td>
<td>0.0128</td>
<td>$-6.7921$</td>
<td>0.0000</td>
</tr>
<tr>
<td>ARCH parameter</td>
<td>0.1105^{***}</td>
<td>0.0164</td>
<td>6.7565</td>
<td>0.0000</td>
</tr>
<tr>
<td>GARCH parameter</td>
<td>0.9818^{***}</td>
<td>0.0039</td>
<td>251.9283</td>
<td>0.0000</td>
</tr>
<tr>
<td>Asymmetry parameter</td>
<td>$-0.1222^{***}$</td>
<td>0.0124</td>
<td>$-9.8578$</td>
<td>0.0000</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>$-6491.6429$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The evidence from our study is valuable for economic and financial modeling of many kinds of stock returns shall be overestimated in GARCH models. We construct structural break dummy variables after we identified structural break points using ICSS algorithm.

### 6. Conclusions

This paper investigated the effects of structural breaks on stock return volatility persistence by using the US and UK stock market index return data. In economics and finance, GARCH models are highly useful and important as Guo (2017), Tsuji (2014, 2016b, 2016c, 2017a, 2017b, 2018b), and many other studies demonstrated. Based on this, applying two kinds of GARCH models of standard GARCH and EGARCH models, we derived the following interesting findings.

1. First, we found that for both the US and UK stock returns, the GARCH parameter values of standard GARCH models decreased when structural break dummies are included.

2. Second, we further revealed that for both the US and UK stock returns, the GARCH parameter values of EGARCH models again decreased when structural break dummies are included.

As above, according to all our empirical results, it is understood that when structural breaks are not taken into consideration, volatility persistence of international stock returns shall be overestimated in GARCH models. We note that this result is consistent with the results of Ewing and Malik (2016), for example.

Overall, the evidence from our study is valuable for economic and financial modeling of many kinds of related time-series variables since as noted, our results were very robust. In addition, it is noted that the time-series modeling presented in this paper can be widely applied to many other kinds of economic and financial time-series data. On the other hand, however, the structural break dummies used in this study may be somewhat difficult to directly apply to multivariate time-series modeling; hence, we further recognize the needs and importance of developing suitable structural break modeling methodology for multivariate time-series data in the fields of economics and finance. It is one of our important future tasks.

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<table>
<thead>
<tr>
<th>GARCH parameter</th>
<th>Asymmetry parameter</th>
<th>Log Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9010***</td>
<td>−0.1778***</td>
<td>−6398.1993</td>
</tr>
<tr>
<td>0.0166</td>
<td>0.0168</td>
<td></td>
</tr>
<tr>
<td>54.3707</td>
<td>−10.5722</td>
<td></td>
</tr>
<tr>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The sample period for EGARCH estimations without or with structural break dummies is from January 4, 2000 to August 2, 2018. The number of the US and UK return series is 4,848. ***, **, and * denote 1%, 5%, and 10% statistical significance levels, respectively. We constructed structural break dummy variables after we identified structural break points using ICSS algorithm.
References


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