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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 our 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.

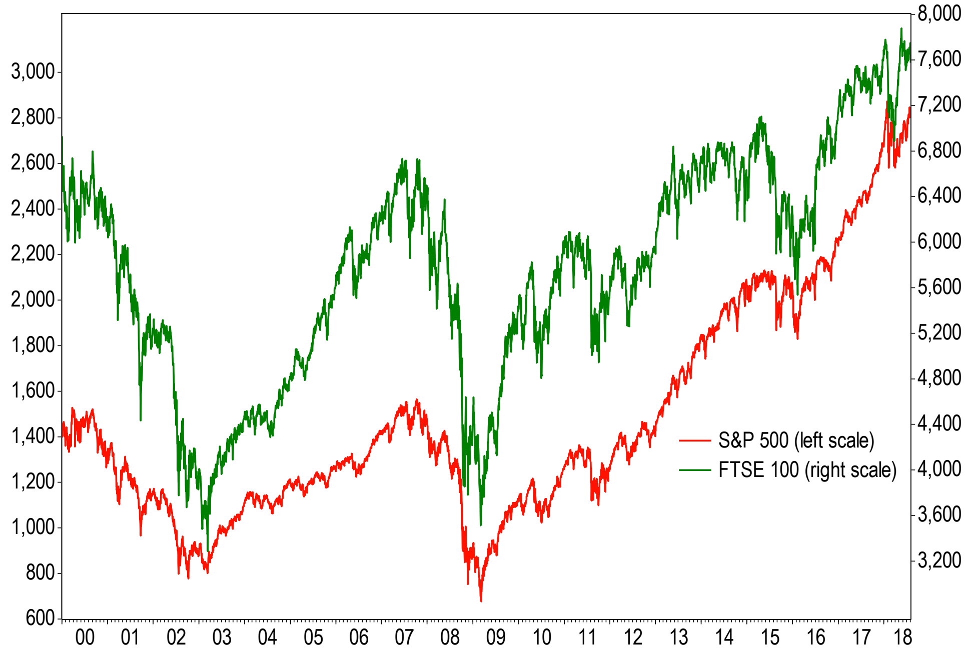

Figure 1. Evolution of S&P 500 and FTSE 100: From January 3, 2000 to August 2, 2018

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

	LRUS	LRUK
Mean	0.0137	0.0018
Median	0.0234	0.0023
Maximum	10.9572	9.3843
Minimum	−9.4695	−9.2656
Standard deviation	1.1855	1.1630
Skewness	−0.2242	−0.1644
Excess kurtosis	9.0723	6.6439

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 LRUK, 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.

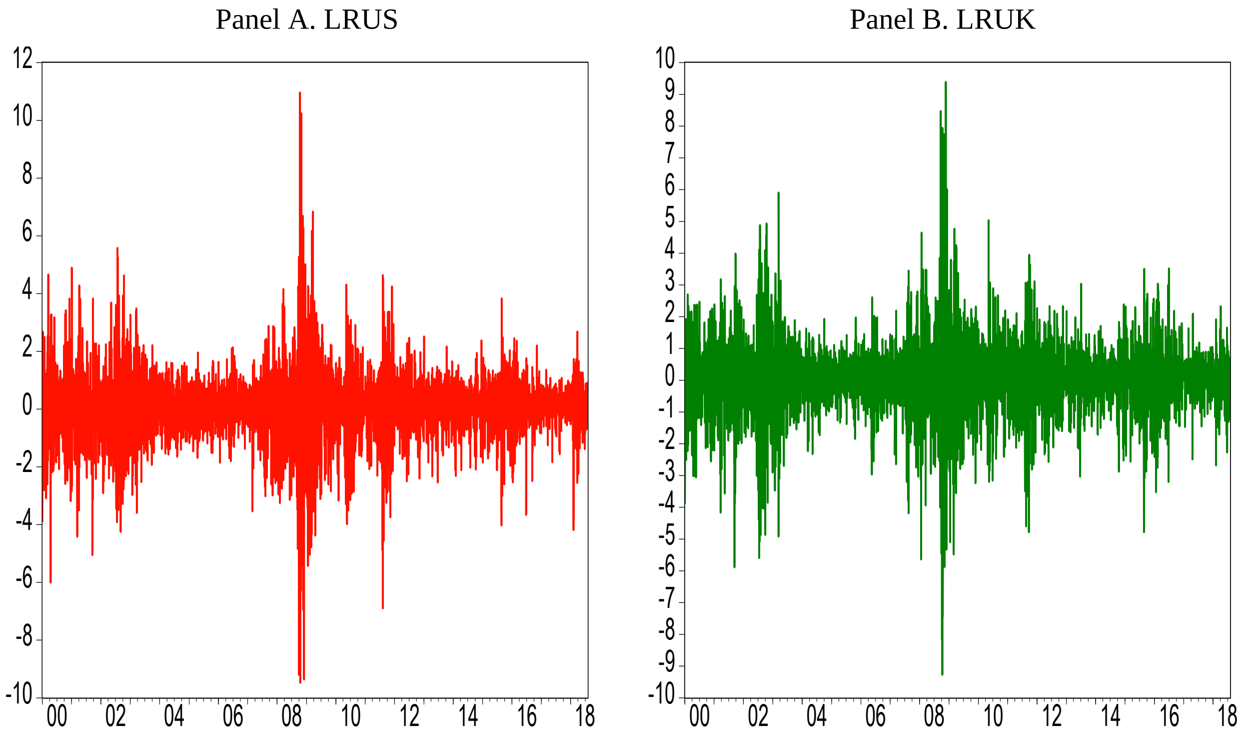

Figure 2. Evolution of percentage log returns of S&P 500 and FTSE 100: From January 4, 2000 to August 2, 2018

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

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

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				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUS)	0.0513***	0.0120	4.2779	0.0000
Constant term	0.0154***	0.0041	3.7304	0.0002
ARCH parameter	0.0957***	0.0126	7.5866	0.0000
GARCH parameter	0.8918***	0.0133	67.2395	0.0000
Log Likelihood	−6540.9084			
A−2. GARCH model with dummies				

Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUS)	0.0539***	0.0128	4.2038	0.0000
Constant term	0.0329***	0.0079	4.1774	0.0000
ARCH parameter	0.0901***	0.0120	7.5086	0.0000
GARCH parameter	0.8035***	0.0232	34.6679	0.0000
USSHIFT (1)	0.1489***	0.0336	4.4324	0.0000
USSHIFT (2)	0.5286***	0.1449	3.6479	0.0003
USSHIFT (3)	0.1885***	0.0488	3.8656	0.0001
USSHIFT (4)	0.0392***	0.0124	3.1628	0.0016
USSHIFT (5)	0.0164*	0.0087	1.8786	0.0603
USSHIFT (6)	0.1755***	0.0388	4.5233	0.0000
USSHIFT (7)	3.1042***	0.8617	3.6026	0.0003
USSHIFT (8)	0.5821***	0.1634	3.5613	0.0004
USSHIFT (9)	0.1068***	0.0284	3.7646	0.0002
USSHIFT (10)	0.0421**	0.0182	2.3208	0.0203
USSHIFT (11)	0.4432***	0.1423	3.1139	0.0018
USSHIFT (12)	0.0294***	0.0084	3.4800	0.0005
Log Likelihood	−6464.9087			
Panel B. UK				
B−1. GARCH model with no dummy				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUK)	0.0356***	0.0117	3.0387	0.0024
Constant term	0.0166***	0.0043	3.8400	0.0001
ARCH parameter	0.1062***	0.0143	7.4493	0.0000
GARCH parameter	0.8813***	0.0154	57.0479	0.0000
Log Likelihood	−6600.0922			
B−2. GARCH model with dummies				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUK)	0.0370***	0.0119	3.1198	0.0018
Constant term	0.1177***	0.0285	4.1350	0.0000
ARCH parameter	0.0995***	0.0109	9.1293	0.0000
GARCH parameter	0.7278***	0.0314	23.2075	0.0000
UKSHIFT (1)	0.1299***	0.0407	3.1945	0.0014
UKSHIFT (2)	0.0120	0.0305	0.3928	0.6945
UKSHIFT (3)	1.0013***	0.2495	4.0130	0.0001
UKSHIFT (4)	0.2706***	0.0762	3.5528	0.0004
UKSHIFT (5)	−0.0228	0.0247	−0.9229	0.3561
UKSHIFT (6)	−0.0625***	0.0239	−2.6211	0.0088
UKSHIFT (7)	0.1237**	0.0601	2.0589	0.0395
UKSHIFT (8)	−0.0422*	0.0255	−1.6513	0.0987
UKSHIFT (9)	0.2338***	0.0641	3.6502	0.0003
UKSHIFT (10)	2.6273***	0.6663	3.9434	0.0001
UKSHIFT (11)	0.4876***	0.1403	3.4761	0.0005
UKSHIFT (12)	0.1046***	0.0382	2.7398	0.0061
UKSHIFT (13)	0.0252	0.0272	0.9236	0.3557
UKSHIFT (14)	0.5625***	0.1683	3.3428	0.0008
UKSHIFT (15)	0.0500	0.0308	1.6232	0.1045
UKSHIFT (16)	−0.0240	0.0233	−1.0286	0.3037
UKSHIFT (17)	0.1306***	0.0498	2.6200	0.0088
UKSHIFT (18)	−0.0574**	0.0248	−2.3201	0.0203

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				
A−1. EGARCH model with no dummy				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUS)	0.0239**	0.0109	2.1952	0.0282
Constant term	−0.1022***	0.0125	−8.1866	0.0000
ARCH parameter	0.1272***	0.0165	7.7111	0.0000
GARCH parameter	0.9762***	0.0044	223.6279	0.0000
Asymmetry parameter	−0.1463***	0.0149	−9.8248	0.0000
Log Likelihood	−6430.1502			
A−2. EGARCH model with dummies				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUS)	0.0203**	0.0082	2.4665	0.0136
Constant term	−0.1422***	0.0245	−5.8098	0.0000
ARCH parameter	0.0753***	0.0174	4.3358	0.0000
GARCH parameter	0.9178***	0.0109	84.2371	0.0000
Asymmetry parameter	−0.2032***	0.0159	−12.7832	0.0000
USSHIFT (1)	0.1035***	0.0240	4.3195	0.0000
USSHIFT (2)	0.1864***	0.0384	4.8528	0.0000
USSHIFT (3)	0.1446***	0.0318	4.5405	0.0000
USSHIFT (4)	0.0555***	0.0197	2.8243	0.0047
USSHIFT (5)	0.0132	0.0153	0.8643	0.3874
USSHIFT (6)	0.1152***	0.0277	4.1617	0.0000
USSHIFT (7)	0.3161***	0.0548	5.7639	0.0000
USSHIFT (8)	0.2163***	0.0424	5.0984	0.0000
USSHIFT (9)	0.1032***	0.0241	4.2757	0.0000
USSHIFT (10)	0.0594***	0.0206	2.8804	0.0040
USSHIFT (11)	0.1730***	0.0370	4.6711	0.0000
USSHIFT (12)	0.0336**	0.0160	2.0966	0.0360
Log Likelihood	−6326.4628			
Panel B. UK				
B−1. EGARCH model with no dummy				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUK)	−0.0103	0.0091	−1.1392	0.2546
Constant term	−0.0872***	0.0128	−6.7921	0.0000
ARCH parameter	0.1105***	0.0164	6.7565	0.0000
GARCH parameter	0.9818***	0.0039	251.9283	0.0000
Asymmetry parameter	−0.1222***	0.0124	−9.8578	0.0000
Log Likelihood	−6491.6429			
B−2. EGARCH model with dummies				
Variable	Coefficient	Standard error	*t*-statistic	*p*-value
Mean (LRUK)	0.0038	0.0108	0.3506	0.7259
Constant term	−0.1059***	0.0283	−3.7495	0.0002
ARCH parameter	0.0787***	0.0172	4.5809	0.0000

GARCH parameter	0.9010***	0.0166	54.3707	0.0000
Asymmetry parameter	−0.1778***	0.0168	−10.5722	0.0000
UKSHIFT (1)	0.0674**	0.0294	2.2906	0.0220
UKSHIFT (2)	−0.0040	0.0331	−0.1197	0.9047
UKSHIFT (3)	0.2050***	0.0563	3.6439	0.0003
UKSHIFT (4)	0.1138***	0.0430	2.6441	0.0082
UKSHIFT (5)	−0.0219	0.0231	−0.9478	0.3432
UKSHIFT (6)	−0.0563**	0.0252	−2.2326	0.0256
UKSHIFT (7)	0.0515	0.0411	1.2542	0.2098
UKSHIFT (8)	−0.0307	0.0317	−0.9666	0.3337
UKSHIFT (9)	0.0917***	0.0347	2.6409	0.0083
UKSHIFT (10)	0.2823***	0.0634	4.4535	0.0000
UKSHIFT (11)	0.1613***	0.0487	3.3104	0.0009
UKSHIFT (12)	0.0646**	0.0274	2.3549	0.0185
UKSHIFT (13)	0.0131	0.0298	0.4394	0.6603
UKSHIFT (14)	0.1547***	0.0461	3.3529	0.0008
UKSHIFT (15)	0.0285	0.0338	0.8443	0.3985
UKSHIFT (16)	−0.0187	0.0247	−0.7567	0.4492
UKSHIFT (17)	0.0666*	0.0359	1.8586	0.0631
UKSHIFT (18)	−0.0582**	0.0279	−2.0884	0.0368
Log Likelihood	−6398.1993			

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.

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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