Impact Of Structural Shifts on Variance Persistence in Asymmetric Garch Models: Evidence From Emerging Asian and European Markets

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ABSTRACT

In this study we examined the effect of structural break points in conditional volatility on variance persistency of asymmetric GARCH models. We used Bai and Perron methodology to detect structural break points in conditional variance of daily stock returns of 7 emerging markets (4-European and 3-Asian) from 1997 to 2014. We implied Exponential GARCH or EGARCH and Threshold GARCH or T-GARCH models with and without sudden structural breaks and tried to evaluate persistency in variance and leverage effect while estimating conditional volatility. We concluded that persistence in variance reduces while considering regime shifts in conditional volatility of these models. The half-lives of shock to volatility significantly decline when we consider these sudden break points. Moreover by comparing these two models we concluded that T-GARCH model reduces persistency more gladly than EGARCH model when we account these sudden changes.

Key words: *Structural Break Points, Variance Persistency, Asymmetric GARCH, Leverage Effect, Shock life.*

Jell Classification: *C32, C58, G14, G15*

INTRODUCTION

Forecasting and predicting the sterilized factors in finance is now becoming a huge and most prominent field. This area is getting enriched day by day due to the involvement of modern computing software and advancement in complex mathematical and probabilistic or statistical theories. The traders and investors, policy makers and fund managers are always interested to search some reliable hedging and trading strategies. The advancement in volatility forecast has broad influence on managing risk as well. In this scenario GARCH models gained attention of financial researchers due to successful modeling and estimating coverage of all volatility features such as volatility clustering, leverage effect, persistence of shock, mean reverting and risk premium etc. Sudden structural shifts or sudden fluctuations due to national and international global financial and economic events considerably affected the volatility of stock returns. Managing risk, making trading strategies, pricing derivative securities and confining uncertain future events accurately, we cannot deny these sudden breaks in volatility.

Among some topical studies related to structural shifts (Aggarwal et al. 1999) applied ICSS algorithm to examine sudden changes in volatility of eleven emerging markets from 1985 to 1995, the stock market crash of 1987 was major factor that was sufficiently detected by ICSS algorithm in their sample. Similarly (Ewing & Malik 2005) used the same algorithm of ICSS to investigate the asymmetric property of GARCH model, they consider Bivariate GARCH model and conclude that when sudden shifts are considered then the spillover effects vanishes while estimating the conditional variance in the small and large US companies. Also (Wang 2006) used the same procedure of ICSS algorithm to detect the date wise sudden changes in the daily data of several stock returns and investigate the effect of financial liberalization on conditional variance, according to them several sudden shifts present in the daily returns of all markets considered. Similarly (Malik et al. 2005) sufficiently identified the sudden changes in variance of Canadian stock returns data, and they proved that persistence of shocks become low if we considered these sudden breaks while estimation conditional volatility.

In context of persistency in variance (Lamoureux & Lastrapes 1990) give logical discussion that ignoring sudden shifts in volatility can provoke persistence in conditional variance of stock returns. So by considering these shift points can spectacularly reduce the persistency in conditional variance by using GARCH type models. (Hammoudeh & Li 2008) Investigated the same and examined the significant reduction in volatility persistency, considering valid sudden breakpoints in variance while predicting volatility in Gulf countries stock markets i-e Bahrain, Kuwait, Oman, Muscat, Saudi-Arab and Abu Dhabi. Recently (Ewing & Malik 2013), (Kang et al. 2011), (Çağli et al. 2012) and (Kang et al. 2009) contributed in the same way.

In second section continuation of this article we described our methodology, in 3rd section we explored data and some basic results, in 4th section we applied our methodology and discussed empirical results and finally in 5th section we presented concluding remarks.

METHODOLOGY

Bai and Perron procedure for structural breaks

In context of multiple structure break points (Bai & Perron 1998) plays vital rule to enhance the existing literature and they proposed some tests to predict persistently several shifts in variance. Lot of researcher used these procedures to study the behavior of time series. Similarly another article by (Bai & Perron 2003) contributed and strengthened the power of these tests more efficiently. The structural breaks sufficiently addressed in this article to detect the multiple structural breaks for linear modeling based on least square estimation. They deal with rate of convergence sufficiently and successfully predict the multiple break points. They also provide logical reasons to test these multiple break points accordingly. These tests based on no change as null hypothesis and random number of changes as an alternative hypothesis i-e l fluctuations verses $l+1$ fluctuations. To detect the suitable number of breaks in the data it is specifically helpful as it permits a particular modeling approach. In the model they considered m breaks or $m+1$ regimes as a multiple linear model.

$$y = x_i^T \beta + \mu_i \tag{1}$$

$$y_i = x_i^T \beta_i + z_i^T \delta + \mu_i \tag{2}$$

$$u_i \sim iid(0, \sigma^2)$$

Where $i = 1, 2, 3, ..., n$ and y_i is the response variables at time i and $x_i = [1, x_{i2}, x_{i3}, ..., x_{ik}]^T$ is a vector of order $k \times 1$ of independent variables one as its initial value and β_i is also $k \times 1$ vector of coefficients. The Hypothesis for structural change is "there is no structural change" i-e $null : \beta_i = \beta_0 (i = 1, 2, 3, ..., n)$

Versus alternative that with the change in time the vector of coefficients also changes, also assuming that they have no stochastic behavior as a departure from null hypothesis. I-e $\|x_i\| = O(1)$ and that, $\frac{1}{n}\sum_{i=1}^{n} x_i x_i^T \to Z$

Where Z representing a finite matrix. This expression permits to detect number of multiple breakpoints in data. In this study we first applied the same procedure to detect break points in the given markets before moving towards.

EGARCH Model with and without Shifts in Variance

After getting logical date wise breaks in variance, we tried to estimate persistency in variance to sort out the impact of breaks. We take start from EGARCH model without considering dummy variable for volatility shifts. This EGARCH model first of all presented by (Nelson 1991), he typically designed this model to consider the asymmetric effects against the good and bad news and as well as put no restrains on the coefficient of volatility equation, since it is logarithm of conditional variance. EGARCH can be expressed as under:

$$\ln(h_t) = \mu + \sum_{i=1}^{p} \beta \ln(h_{t-1}) + \sum_{j=1}^{q} \alpha_j \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} \right| \right] + \sum_{k=1}^{r} \lambda_k \left[\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \right] \quad (3)$$

Here λ representing the asymmetric coefficient in the model. In most cases if the association between variance and returns are negative than its value must be negative and significant. Also the difference between α_j and λ_k can be expressed as impact of shock on conditional volatility. Here β coefficient presenting the measure of persistency, mostly less than one but as its value approaches to unity the persistence of shock increases. To facilitate the sudden shifts in variance we can introduce dummy variable in the specification of above model as follows:

$$\ln(h_t) = \mu + \sum_{i=1}^{p} \beta \ln(h_{t-1}) + \sum_{j=1}^{q} \alpha_j \left[\left| \frac{\varepsilon_{t-j}}{\sqrt{h_{t-j}}} \right| \right] + \sum_{k=1}^{r} \lambda_k \left[\frac{\varepsilon_{t-k}}{\sqrt{h_{t-k}}} \right] + \sum_{l=1}^{n_c} \phi_{c,l} DUM_{c,l,t} \quad (4)$$

Here in this model n_c are total numbers of date wise shift in market c, DUM indicating dummy variable considering value 1 as the sudden shift appears in conditional volatility onwards and otherwise it takes value 0. We applied EGARCH model with and without sudden breaks in table-3 and table-4 respectively.

T-GARCH model with and without shifts in variance

Once the date wise break point have been detected, we applied another asymmetric GARCH model, known as TGARCH or threshold GARCH to confine negative and positive effects of good and bad news on volatility. The model was contributed by (Glosten L R 1993) and (Zakoian 1994). The model without dummy variable for structural break points is given bellow.

$$h_t = \mu + \sum_{i}^{p} \alpha_i (R_{t-i} - \varepsilon)^2 + \sum_{j}^{q} \beta_j h_{t-j} + \sum_{k}^{r} \delta_{t-k} \gamma_k (R_{t-k} - \varepsilon)^2 \quad (5)$$

Here δ_{t-k} takes value 1 when at time $t-k$ the residual is negative but 0 otherwise. We applied TARCH (1,1,1) model as given in table-3 and table-4.

Now we introduce dummy variable to the specification of the above model as follows.

$$h_t = \mu + \sum_i^p \alpha_i (R_{t-i} - \varepsilon)^2 + \sum_j^q \beta_j h_{t-j} + \sum_k^r \delta_{t-k} \gamma_k (R_{t-k} - \varepsilon)^2 + \sum_l^{n_c} \phi_c DUM_{c,j,t} \quad (6)$$

Whereas n_c are total numbers of date wise changes, DUM indicating dummy variable considering value 1 as the sudden shift come out in conditional volatility onwards and elsewhere it takes value 0.

Innovation Density

The distribution of Error has significant role in assessment of essential parameters in GARCH-type models. For innovation (Robert F. Engle 1982) and (Bollerslev 1986) contributed the normal distribution in ARCH and GARCH model respectively. Gaussian distribution is not sufficient to capture the high leptokurtic sample data, to overcome this problem we used Student-t distribution in this study to overcome this problem. As Gaussian distribution has great contribution but due to high kurtosis it is unsuccessful to incarcerate the heavy tails of stock returns, for this reason student-t distribution was anticipated by (Bollerslev 1987)

$$f(\eta_t) = \frac{\Gamma((v+1)/2)}{\Gamma(v/2)\sqrt{\pi(v-2)}(1+\frac{\eta_t^2}{v-2})^{v+1/2}}$$

Here $\Gamma(.)$ is the gamma function. The value of v (d.f) shows the number of parameter to be estimated. If $v > 4$ the conditional kurtosis equals $3(v-2)(v-4)^{-1}$ which is quite different from normal value 3, but if $v \to \infty$ it congregate to the standardized normal distribution also see (Pasha et al. 2007). Also the Germanized Error Distribution GED introduced by (Nelson 1991), where the parameter is degree of freedom model the heavy tails of return data.

$$f(\eta_t) = \frac{ve^{-0.5|x/\lambda|^v}}{\lambda 2^{(v+1/2)}\Gamma(1/v)}$$

Where as $\lambda = \left[\frac{2^{-2/v}\Gamma(1/v)}{\Gamma(3/v)} \right]^{0.5}$

Also here v is the fat tail parameter if v=2, h_t follows standard normal distribution, but if v<2 h_t has thicker tails and if v>2 it has thinner tails. Many researchers introduced several other densities for innovation. But in this study we focused on student-t distribution due to its heavy tails capturing ability and better estimation results.

Moreover at the end we used ARCH and GARCH parameters i-e a_1 and b_1 to estimate half-lives of shocks to volatility with and without considering these frequent shifts in conditional variance in table-5 by using the formula given bellow.

$$HLS = Ln(0.50) / Ln(b)$$

Where HLS stands for half life shock to volatility. Different researchers used different approaches in this regard. See (Suleman 2012) and (Hammoudeh & Li 2008).

DATA AND INTEGRATION

We downloaded the required data from yahoo finance website www.finance.yahoo.com, we downloaded daily stock return data from 1997 to 2014 for the given emerging 3-Asian and 4-European markets; we used closing prices to find continuously compounded returns as follows

$$C_r = [lnP_t - \ln P_{t-1}]*100$$

We calculated descriptive statistics i-e mean, standard deviation, skeewness, Kurtosis and some prerequisite tests like ARCH (LM) test, Augmented Dickey Fuller (ADF) unit root test and Jarque-Bera normality test to build some initial understanding before its application for structural changes and asymmetric GARCH models. Descriptive statistics results are presented in table-1, also some prerequisite test like Lagrange Multiplier of auto regressive conditionally Heteroscedastic proposed by (Robert F. Engle 1982) in the table ARCH-LM test in significantly indicating ARCH effect in data which is one of the important required assumptions, before application of ARCH type models.

Moreover to investigate that the considered data is stationary or not we applied Augmented Dickey Fuller (ADF) test presented by (Dickey

& Fuller 1979), the result shows that in all cases the daily returns data is significantly stationary, means no unit root at level. High values of Jarque Bera test also indicating that the data is non-normal. Also high values of kurtosis strengthening the same decision of non-normality and the value departure from 0 under skewness reconfirm non-normality in all cases.

Descriptive Statistics

Table 1

Country	**Mean**	**Max**	**Min**	**S.D**	**Sk**	**Kt**	**ARCH (LM)**	**J.Bera**	**ADF**	**Obs**
Belgium	0.000	0.0405	-0.036	0.0055	0.01759	8.489	349*	5560.7*	-40.1*	4430
Finland	0.000	0.0433	-0.038	0.0068	-0.0572	6.149	84.27*	1554*	-59.4	3757
France	0.000	0.0448	-0.040	0.0061	-0.0578	7.646	156.03*	4056*	-42.0*	4507
Greece	-0.000	0.0583	-0.044	0.0077	-0.0214	7.006	62.52*	1979*	-50.7*	2958
India	0.0002	0.0694	-0.051	0.0071	-0.0926	8.656	153.09*	5569*	-60.2*	4173
Pakistan	0.0000	0.0554	-0.057	0.0070	-0.3938	8.883	186.49*	6018*	-58.3*	4100
Seri Lank	0.0002	0.0794	-0.060	0.0052	0.1747	31.08	111.26*	132630*	-51.8*	4034

MODEL APPLICATION AND EMPIRICAL RESULTS

After application of Bai and Perron methodology we get different break points for different countries, we detect maximum 5 break points for Belgium and minimum 2 break points for Greece. The date wise time periods for these breaks are listed in Table: 2 as follows.

The logical reasons for these sudden break points in most cases are currency crisis in Asia 1997-98, terrorist attacks on 9/11 and the major one is financial global crisis of 2007-08 are particularly. Whereas in 1998 there were two major factors i-e crisis in Russia and the prices of oil problems, also in 1999 the economic recovery in Asia commonly affect these markets. The other breaks detected are due to local or domestic individual political and economic crisis within a country, these structural changes varies from country to country due to individual factors affecting domestically on these markets.

Structural Break Points in volatility with Time Periods

Table 2

Country	Break Points	Time Periods
Belgium	5	3rd January 1997-27th March 2000 28th March 2000- 6th December 2002 7th December-7th January 2003 8th January 2003-17th December 2007 18th December 2007-8 December 2011 9th December 2011-26th May 2014
Finland	3	23rd September 1999-10th March 2003 11th March 2003-1st June 2007 2nd June 2007-19th August 2009 20th August 2009-19th May 2014
France	4	1st January 1997-17th July 2000 18th July 2000-12th March 2003 13th March 2003-1st June 2007 2nd June 2007-22nd September 2009 23rd September 2009-19th May 2014
Greece	2	3rd December 2002-2nd January 2008 3rd January 2008-5th June 2012 6th June 2012-19th May 2014
India	3	1997-28th October 2002 29th October 2002-8th January 2008 9th January 2008-5th October 2011 6th October 2011-2014
Pakistan	3	3rd July 1997-2nd October 2001 3rd October 2001-15th March 2005 16th March 2005-26th January 2009 27th January 2009-18th April 2014
Seri Lank	4	2nd July 1997-17th August 2001 20th August 2001-4th October 2005 5th October 2005-22nd July 2008 23rd July 2008-14th February 2011 15th February 2011-28th April 2014

Note: Possible date-wise break points in the structure of return series of emerging 3-Asian and 4-European markets

After getting reasonable sudden structural break points in variance first we applied asymmetric EGARCH and TGARCH without dummy variable for these sudden changes and the results are presented in Table-A3. According to these results highly significant values of ARCH and GARCH parameters are observed, in literature this has been considered due to high frequency data, but recently it is sufficiently clarified that these highly significant parameters are due to ignoring structural breaks, In our sample almost all countries have highly significant persistence parameter b_1 = 0.9 in both EGARCH and TARCH models while not considering these sudden shifts, except one result of TGARCH in case of Belgium the persistence parameter b_1 = 0.88.

Also the sum of ARCH and GARCH parameters are 1 or more than 1, indicating that shocks have everlasting effect on conditional variance of return, reflecting persistence in variance. These models have significantly detain the leverage effect in almost all countries, the leverage parameter in negative and significant except in case of Belgium, shows that bad news have strong effect on increasing future volatility as compare to good news. Also these models detain the heavy tails while using student-t distribution for innovation.

In table-A4 we include the detected structural breaks by considering dummy variables in the variance equations of the models. Results indicating significant decline in persistence parameter b_1 due to incorporate these sudden changes. Only in just few cases it decline for minimum. At the end in table-A5 we calculated the half-lives of persistence in volatility or the number of days over which a shock to volatility decline to 0.5 to its size.

CONCLUDING REMARKS

This article incorporate with implication of Bai and Perron methodology to detect reasonable structural break points in conditional variance of daily stock returns of 4-European markets (Belgium, Finland, France and Greece) and 3-Asian emerging markets (India, Pakistan and Seri-Lanka) from 1997 to 2014. These sudden shifts in volatility are due to some major global financial crisis, terrorist attacks of 9/11 and also local or domestic political and economical events. After getting logical date wise structural breaks we employed two asymmetric GARCH models, i-e Exponential GARCH or EGARCH and Threshold GARCH or TGARCH models with and without considering dummy variables for these structural changes while estimating conditional volatility. From results we can conclude that, if these models are applied without structural changes, the persistence parameter b_1 is almost 0.9 shows over estimation of persistence in variance observed in almost all countries, but if we consider dummy variable for these sudden shocks we detect less persistence in variance means more accurate estimation in this regard. Moreover half lives of shocks to volatility decline significantly while accounting these sudden break points. Finally according to our study estimating volatility by using asymmetric GARCH-type models the incorporation of structural shifts are significantly essential to avoid the overestimation of persistence in variance.

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REFERENCES

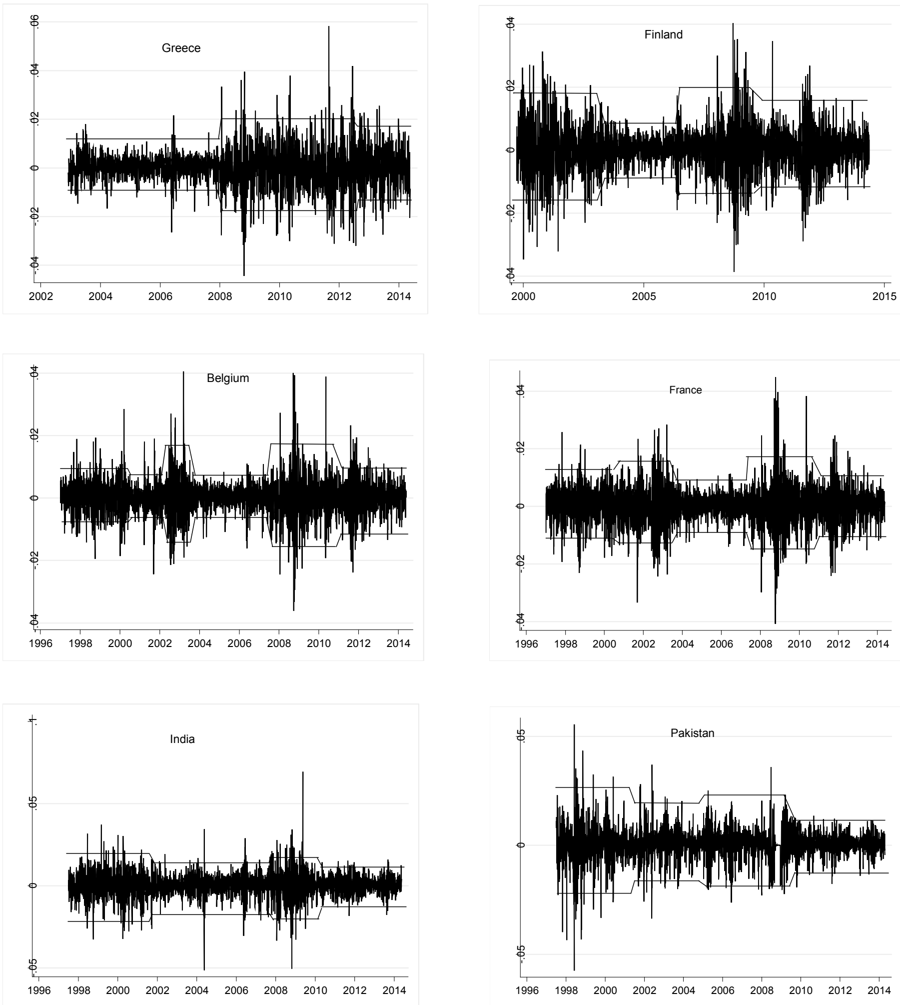
1. Aggarwal, R., Inclan, C. & Leal, R., 1999. Volatility in emerging stock markets. Journal of Financial and Quantitative Analysis, 34, pp.33–55.
2. Andersen, T.G. & Lund, J., 1943. Stochastic Volatility and Mean Drift in the Short Rate Diffusion : Sources of Steepness , Level and Curvature in the Yield Curve by Stochastic Volatility and Mean Drift in the Short Rate Diffusion : Sources of Steepness , Level and Curvature in the Yield. , (May 1996).
3. Bai, J. & Perron, P., 2003. Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), pp.1–22.
4. Bai, J. & Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica, 66(1), pp.47–78.
5. Bollerslev, T., 1987. A Conditionally Heteroskedastic Time Series Model for Speculative Prices and Rates of Return. The Review of Economics and Statistics, 69(3), pp.542–547.
6. Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of econometrics, 31, pp.307–327.
7. Çağli, E., Mandaci, P. & Kahyaoğlu, H., 2012. Volatility shifts and persistence in variance: evidence from the sector indices of Istanbul Stock Exchange. International Journal of …, 4(3), pp.119–140.
8. Dickey, D. & Fuller, W., 1979. Distribution of the estimators for autoregressive time series with a unit root. … the American statistical association.
9. Ewing, B.T. & Malik, F., 2005. Re-examining the asymmetric predictability of conditional variances: The role of sudden changes in variance. Journal of Banking & Finance, 29(10), pp.2655–2673.
10. Ewing, B.T. & Malik, F., 2013. Volatility transmission between gold and oil futures under structural breaks. International Review of Economics & Finance, 25, pp.113–121.
11. Glosten L R, J.R. and R.D.E., 1993. On the relation between the expected value and the volatility of the nominal excess returns on stocks. Journal of Finance, 48, pp.1779– 801.
12. Hammoudeh, S. & Li, H., 2008. Sudden changes in volatility in emerging

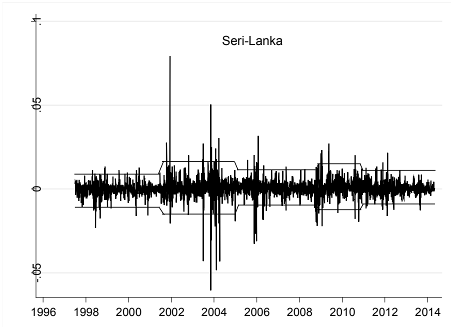
markets: The case of Gulf Arab stock markets. International Review of Financial Analysis, 17(1), pp.47–63.
13. Kang, S.H., Cheong, C. & Yoon, S.-M., 2011. Structural changes and volatility transmission in crude oil markets. Physica A: Statistical Mechanics and its Applications, 390(23-24), pp.4317–4324.
14. Kang, S.H., Cho, H.-G. & Yoon, S.-M., 2009. Modeling sudden volatility changes: Evidence from Japanese and Korean stock markets. Physica A: Statistical Mechanics and its Applications, 388(17), pp.3543–3550.
15. Lamoureux, C. & Lastrapes, W., 1990. Persistence in variance, structural change, and the GARCH model. Journal of Business & Economic Statistics, 8(2), pp.225–234.
16. Malik, F., Ewing, B.T. & Payne, J.E., 2005. Measuring volatility persistence in the presence of sudden changes in the variance of Canadian stock returns. Canadian Journal of Economics, 38(3), pp.1037–1056.
17. Nelson, D., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica: Journal of the Econometric Society, 59(2), pp.347–370.
18. Pasha, G.R., Qasim, T. & Aslam, M., 2007. Estimating and Forecasting Volatility of Financial Time Series in Pakistan with GARCH-type Models. The Lahore Journal of Economics, 2(Winter), pp.115–149.
19. Robert F. Engle, 1982. autoregressive conditional heteroskedasicity with estimates of the variance of U.K.inflation.pdf. Econometrica, 50(4), p.23.
20. Suleman, M.T., 2012. Stock Market Reaction to Good and Bad Political News. Asian Journal of Finance & Accounting, 4(1), pp.299–312.
21. Wang, K., 2006. The Impact of Financial Liberalization Announcement on the Volatility of Emerging Stock Markets in the Short Run. International Journal of the Information Systems for Logistics and Management (IJISLM), 1(2), pp.117–126.
22. Zakoian, J.-M., 1994. Threshold heteroskedastic models. Journal of Economic Dynamics and Control, 18(5), pp.931–55.

ANNEX FIGURE AND TABLES

Reseduals returns with structural break points

Figure A.1.





Note: In all figures the straight horizontal line with sudden drifts indicate possible breaks in the residuals data for all emerging 3-Asian and 4-European markets.

Model estimation results without Structural Breaks

Table-A3

EGARCH or Exponantial GARCH model results								
Countries	μ_0	μ_1	α_1	β_1	$\alpha_1+\beta_1$	γ	v	ARCH
Belgium	0.0038*	-0.3717*	0.18036*	0.97*	1.1591	-0.1051*	11.001*	1.88
Finland	0.00024*	-0.1899*	0.12439*	0.99*	1.1153	-0.0602*	9.2201*	1.32
France	0.000017*	-0.297*	0.1302*	0.99*	1.1211	-0.1117*	9.8109*	0.88
Greece	0.00032*	-0.2501*	0.1680*	0.98*	1.1495	-0.3844*	7.057*	2.10
India	0.00031	-0.4838*	0.2153*	0.97*	1.1842	-0.0888*	8.3070*	0.56
Pakistan	0.0004*	-0.61738*	0.3607*	0.97*	1.3265	-0.0539*	4.91*	0.73
Seri lank	0.00014*	-1.3744*	0.4997*	0.91*	1.4076	-0.03445*	4.4070*	1.10
TGARCH or Threshold GARCH model results								
Belgium	0.000*	0.000*	0.03*	0.88*	0.91	0.136*	10.5*	0.375
Finland	0.000*	-0.189*	0.124*	0.990*	1.12	-0.060*	9.22*	0.858
France	0.000*	-0.297*	0.130*	0.980*	1.11	-0.111*	9.811*	1.36
Greece	0.000*	-0.250*	0.168*	0.987*	1.15	-0.038*	7.057*	0.397
India	0.000*	-0.483*	0.215*	0.968*	1.18	-0.088*	9.00*	0.056
Pakistan	0.000*	-0.617*	0.360*	0.966*	1.27	-0.054*	4.966*	0.182
Seri lanka	0.000*	-0.374*	0.499*	0.907*	1.40	-0.034*	4.407*	1.445

Source: Yahoo Finance web site www.finance.yahoo.com, to get historical data of daily closing prices for each mention country from 1997 to 2014 and converted into continually compounded returns for GARCH model application.

Note: * represents the statistical significant result at 5%.

Model Estimation with Structural Breaks

Table-A4

EGARCH or Exponantial GARCH									
Countries	μ_0	μ_1	α_1	β_1	$\alpha_1+\beta_1$	γ	ν	ϕ	**ARCH(LM)**
Belgium	0.000*	-0.409*	0.184*	0.86*	1.148	-0.109*	11.27*	-0.024*	1.617
Finland	0.000*	-0.24*	0.122*	0.90*	1.106	-0.063*	9.35*	-0.0158	0.141
France	0.000*	-0.319*	0.131*	0.86*	1.110	-0.111	9.744*	0.258	1.31
Greece	0.000*	-0.335*	0.170*	0.95*	1.14	-0.037*	6.99*	-0.022*	0.828
India	0.000*	-0.542*	0.217*	0.92*	1.137	-0.089*	8.38*	-0.015*	0.119
Pakistan	0.000*	-0.363*	0.36*	0.84*	1.22	-0.054*	4.96*	-0.011*	0.219
Seri lank	0.000*	-1.68*	0.51*	0.88*	1.388	-0.052*	4.48*	0.092*	1.159
TGARCH or Threshold GARCH model									
Belgium	0.000*	0.000*	0.013*	0.85*	0.884	0.137	10.78*	-0.00	1.10
Finland	0.000*	0.000*	0.021*	0.82*	0.841	0.077*	9.218*	-0.00*	0.37
France	0.000*	0.000*	0.002	0.86*	0.862	0.137*	9.81*	0.000	4.6*
Greece	0.000*	0.000*	0.016*	0.88*	0.907	0.046*	7.316*	-0.00*	2.897
India	0.000*	0.000*	0.040*	0.87*	0.915	0.139*	8.47*	-6.3*	1.15
Pakistan	0.000*	0.000*	0.161*	0.78*	0.953	0.109*	4.859*	-0.00	0.96
Seri lank	0.000*	0.000*	0.291*	0.58*	0.857	0.149*	4.511*	0.00*	0.354

Source: Yahoo Finance web site www.finance.yahoo.com, to get historical data of daily closing prices for each country from 1997 to 2014 are and converted into continually compounded returns for GARCH model application.

Note: * represents the statistical significant result at 5%.

Half-Lives shocks to volatility with and without breaks

Table-A5

Country	EGARCH		TGARCH	
	Without dummy	With dummy	Without dummy	With dummy
Belgium	22.75	4.59	5.42	4.26
Finland	68.96	6.57	68.96	3.49
France	68.96	4.59	34.30	4.59
Greece	34.30	13.51	52.97	5.42
India	22.75	8.31	21.31	4.97
Pakistan	22.75	3.97	20.03	2.78
Seri lank	7.34	5.42	7.10	1.27

Note: Half-Live is calculated by using the formula $1-\left\{\frac{\log(2)}{\log(a_1+b_1)}\right\}$