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Structural Breaks and Stock Market Volatility in Emerging Countries

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Abstract Given the evidence of occasional discrete shifts in the conditional variance process, it is essential to test the volatility of financial markets when a reasonable suspicion exists for structural change. This paper examines the volatility changes of emerging stock markets over a period extending from April 2005 to March 2015. We apply the Bai and Perron technique to test multiple structural breaks in the volatility. We find evidence of structural breaks in the volatility series for the majority of markets, where most of coefficients of the structural dummy variables in the mean and volatility equations are significant. This suggests that the structural breaks have significant effects on the volatility behavior of the stock markets. We observe sharp drops in a measure of volatility persistence after incorporating the structural change. The results also show a performance improvement in our modeling by including structural break dummy variables into the variance equation. Overall, the findings are important in understanding the role of regime shifts on stock market stability and are of great significance to investors and market regulators.

Keywords: *volatility, structural breaks, emerging stock markets, GARCH models*

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1. Introduction

In light of the calm and turbulence of the global and emerging stock markets during the recent years due to domestic, macroeconomic, political events and financial crisis, models that take into consideration structural breaks may prove to be a more appropriate characterization of stock return volatility than models ignoring it.

In recent years, an extensive literature has been developed on studying the volatility of financial markets. Volatility of the returns of financial assets may be affected substantially by infrequent structural breaks or regime shifts which usually correspond to political or economic events. Clearly, any finding on the impact of these sudden shifts on measured or estimated volatility persistence would be quite helpful information from a financial perspective, since correct specification of volatility evolution has important implications for investors' decisions and effective portfolio diversification. In other words, it is a key input for assets and derivative pricing, portfolio allocation and risk measurement.

Many reasons suggest that this subject is essential and relevant. First, according to the relatively long sample period of our study which includes various crisis events, it seems logical to investigate the structural stability of financial markets. Then, the researches made on emerging financial markets are minimal and do not receive much attention as that given to developed financial markets.

The importance of the Middle East and African stock markets is that, in recent years, many African markets offer very high returns for investors. There was at least an African stock market in the top 10 of the best performing markets in the world every year since 1995 [22].

The purpose of this study is to identify sudden changes in volatility of financial time series and to examine its impact on the volatility of our sample, over a period extending from April 2005 to March 2015. Using a technique similar to the one employed by Cappiello et al. [10] and Chau et al. [21], we carry out an extensive model selection procedure for the most appropriate GARCH specification for each return series. Then, after detecting break dates, we examine the impact of structural breaks on stock markets' volatility using the carefully selected GARCH models. We apply the multiple structural change tests by Bai and Perron [6] to identify the break dates in volatility and incorporate them into GARCH models. The structural break model of Bai and Perron [6] test is relatively a recent approach to test for volatility shifts. It has the advantage of locating several structural breaks in time series with no knowledge of the breakpoint a priori.

Our results show that the application of Bai and Perron's test was able to detect structural breaks in the stock markets for the majority markets of our sample. We can note that most of the dummy variables in the mean and variance equations are significant at the 5% level. Then, after adding dummy variables into our model results, we derive superior estimation results, and the measure of volatility persistence declines substantially for most of the countries.

The rest of our paper is organized as follows. In section 2, we present the literature review. Section 3 describes the data used in this study. Section 4 describes the econometric methodology. Section 5 discusses the main empirical results. Section 6 concludes.

2. Literature Review

Recently, though, beginning with Ewing and Malik [20], a strand of research has been developed, which is specifically concerned with the consequences of structural breaks in volatilities. Huang [25], for instance, employs the Iterated Cumulative Sums of Squares (ICSS) algorithm developed by Inclan and Tiao [26] within their GARCH model. They find measured volatility spillovers to be much weaker or even to disappear after controlling for structural change in volatilities. Sulistya and Nursilah [42] analyze multiple structural changes in sukuk markets using the Bai and Perron [6] model. They found that structural shift significantly alter the volatility behavior of sukuk.

A. Sensoy [37] examined the efficiency of the MENA stock markets. The results show that all stock markets have different long-term degrees of dependence that vary over time and that the political transition had a negative effect on the efficiency of the markets in the region. W. Abdmoulah [44] examined Arab stock markets, and concluded that all markets are highly sensitive to past shocks and are judged inefficient. Chau et al. [21] found that Arab Spring and the political turbulence have an impact on volatility of MENA stock markets, in particular for the Islamic indices. Nevertheless, there is little or no significant effect on their interaction and integration with the World market. Earlier studies on developed and developing financial markets used the Markov-switching models for controlling regime shifts [24].

As we can see, the literature in the regard of structural breaks is vast: Regime Switching model [24] iterated cumulative sum of squares (ICSS) algorithm [26]. In our study, we employ Bai-Perron test which has the advantage of estimating multiple structural shifts endogenously. It also enables us to generalize specifications, for instance, to select whether to allow for heterogeneity and autocorrelation in the residuals. This technique allows for detecting multiple breakpoints in variance and is extensively used for identifying changes in the volatility of financial time series, but they are more flexible and instrumental in case of multiple breaks.

3. The Data

The study period runs from April 2005 to March 2015 with daily data (closing prices) from datastream. This list is constructed by emerging stock markets (See Table 1).

Table 1. A list of countries and indexes included in the empirical research

Country	Stock Market Index
Bahrain	Bahrain All Share (BHSEASI)
Dubai	Dubai Financial Market (DFM)
Egypt	EGX 100 (EGX100°
Jordan	Amman Se Market (ASE)
Kuwait	Kuwait SE Market (KSE)
Oman	Oman Muscat Securities Mkt(MSM)
Saudi Arabia	Saudi Tadawul All Share (TASI)
South Africa	FTSE/JSE All Share
Turkey	Borsa Istanbul (BIST National 100)
Tunisia	Tunisia Stock Exchange (Tunindex)

4. Econometric Methodology

We begin our analysis by constructing the Autoregressive (AR) model to describe a time series r_t of stock returns. Based on the Bayesian Information Criterion (BIC), Schwarz and the log-likelihood value, the AR (1) process is adequate to capture return dynamics and produces white-noise residuals for Tunisia, Turkey, Saudi, Oman, Morocco, Jordan and Egypt and AR (2) for Kuwait and Bahrain. The general mean return series equation equals the following:

$$r_t = a_0 + \sum_{i=1}^{2} a_1 r_{(t-1)} + \varepsilon_t. \qquad (1)$$

As for the conditional variance of returns, we use the s-GARCH and three typical variants of this model which are E-GARCH, T-GARCH and A-P-ARCH. These models use a nonlinear function to model time-varying volatilities as well as leverage effects which cannot be captured by conventional GARCH models.

Many econometric models have been used to investigate volatility characteristics. However, there is no consensus on the superiority of a model to another [41].

Many researchers found that the GARCH (1, 1) specification has been demonstrated to be the most suitable, in particular when it comes to estimating and predicting volatility given the existence of ARCH effects in return series [9]. While some authors noticed that despite the performance of the GARCH model, it fails to capture the asymmetric volatility. This limitation has been overcome by the introduction of more flexible volatility modeling to consider the asymmetric response of volatility to positive and negative shocks [10-21].

4.1. The Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

The GARCH (1, 1) model can be written as follows:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{(t-1)}^2 + \beta_1 \sigma_{(t-1)}^2 \qquad (2)$$

4.2. The Exponential Generalized Autoregressive Conditional Heteroscedastic (E-GARCH) Model

This model was developed by Nelson [31]:

$$\begin{aligned} \ln(\sigma_t^2) &= \omega + \alpha_1 \left\{ \left| \varepsilon_{t-1} / \sigma_{t-1} \right| - \sqrt{2/\pi} \right\} \\ &\quad + \beta_1 log(\sigma_{t-1}^2) - \gamma(\varepsilon_{t-1} / \sigma_{t-1}) \end{aligned} \qquad (3)$$

where γ parameter measures the asymmetry or the leverage. The α_1 parameter represents a magnitude effect or the symmetric effect of the model, the GARCH effect measures the persistence in conditional volatility irrespective of anything happening in the market.

4.3. The Threshold Generalized Autoregressive Conditional Heteroscedastic (T-GARCH) Model

In the T-GARCH (1, 1) version of the model, the specification of the conditional variance is:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (4)$$

where d_{t-1} is a dummy variable, that is 1 if; bad news and o if $\varepsilon_{t-1} > 0$; good news. The coefficient γ is known as the asymmetry or leverage parameter.

4.4. The Asymmetric Power ARCH Model (A-P-ARCH) Model

This model was developed by Ding et el. [17].

$$\sigma_t^2 = \omega + \alpha_1 \left(|\varepsilon_{t-1}| - \gamma_1 \varepsilon_{t-1} \right)^{\delta} + \beta_1 \sigma_1^{\delta} \quad (5)$$

where γ_1 is the asymmetric effect and δ is the parameter of the power term.

4.5. Structural Breaks Tests: Bai and Perron's Tests [6]

We use Bai-Perron test [7,8] to detect both the change of mean and variance of emerging stock index returns. One of the main advantages of this technique is that it permits to estimate multiple structural shifts endogenously. It also enables us to generalize specifications, for instance, to select whether to allow for heterogeneity and autocorrelation in the residuals.

We employ a two-step procedure to identify structural break points in the mean and volatility of stock index returns.

First, we estimate equation (1), allowing for the possibility of structural breaks in its coefficients[1], without prior knowledge of when those breaks occur. After finding some breaks in the parameters of r_t , we obtain the residuals from this estimation process. Next, following Cecchetti et al. [12], we identify breaks in the variance through equation (6).

$$\sqrt{(\pi/2}\,|\hat{\varepsilon}| = c + \mu_t . \quad (6)$$

Each set of residuals is assumed to follow a normal distribution and the transformations are unbiased estimators of the standard deviation of ε_t .

A common procedure aiming to select the number of breaks is to consider the information criterion. However, the BIC always chooses a much higher value than the true one in the presence of a serial correlation case, as documented by Bai and Perron [6]. We use the "sequential" method, which is described by Bai and Perron [6], may be proven to be a more appropriate characterization for detecting breaks than the other methods, based on simulations they conducted. We start by estimating up to 5 breaks in the series for each country. Then, we apply the method advanced by Bai and Perron [6] based on the sequential application of the sup $F(k+1/k)$ test, which is performed to detect the presence of $(k+1)$ breaks conditional on having found k breaks$_s$. In the process, rejecting k breaks favors a model with $(k+1)$ breaks, if the overall minimal value of the sum of k squared residuals (over all the segments where an additional break is included) is sufficiently smaller than the sum of squared residuals from the model with k breaks. The dates of the breaks selected are the ones associated with this overall minimum.

[1] We have applied the Bai and Perron's test to both the constant term and the AR persistence parameters in the mean equation (1).

5. Empirical Results

We consider daily closing price, all stock indices are in US dollars. Throughout the study, the returns are calculated $r_t = \ln(P_t / P_{t-1})*100$ where P_t is the daily closing price and r_t is the daily log-returns.

Summary statistics for daily returns of different stock markets are presented in Table 2. This table shows clear evidence of deviations from normality as it can be seen by the high values of skewness and kurtosis.

The LB statistics for the returns is very significant at 5% for all markets, indicating the presence of serial correlation. We can also notice when the residuals were examined for heteroscedasticity, the ARCH-LM test provided strong evidence of Arch effects in the residual series for the most of the markets. To model this conditional heteroscedasticity, we proceed by AR (p) – GARCH (1, 1) models.

5.1. Estimation Results of GARCH Models

For nonlinear ARMA–GARCH modeling, AIC and BIC are extensively adopted to guide the choice of alternative models. The models with smaller AIC or BIC values are usually preferred. The best conditional variance equation (as selected by model specification tests) is estimated for market returns. Specification tests reported in Table 3 indicate that (according to Log L, BIC and AIC) asymmetric GARCH models fit the data better than symmetric model in all cases, we can note that the T-GARCH performs relatively better than the E-GARCH for Dubai, Kuwait, Jordan, Morocco and Tunisia stock markets, while the P- GARCH is the most suitable for the rest of markets.

A large volume of empirical works on modeling and forecasting stock market volatility in both developed and developing countries around the world exists. Many econometric models have been used to investigate volatility characteristics. However, there is no consensus on the superiority of a model over another [41].

Our results are consistent with previous research which showed that the asymmetrical models use a non linear function to model time-varying volatilities as well as leverage effects which conventional GARCH models cannot capture. Chau et al. [21] studied the impact of Arab spring on MENA stock markets by using the GARCH models, and documented that (according to Log-L, HMSE and AIC) asymmetric GARCH models are more suitable to fit the financial time series than symmetric model in 14 cases (out of 16), with GJR-GARCH performing relatively better than E-GARCH. As widespread as the evidence of asymmetric volatility is in the equity series, where the empirical results show that 18 of the 21 models selected for the equity returns include a significant asymmetric term [10].

Table 2. Summary statics for daily returns

Country	Mean	Min	Max	Median	Std	Kurtosis	Skewness	J-B	ADF	PP	Arch-Lm	Q(12)	Qs(12)
Bahrain	-0.007	-4.918	3.612	-0.002	0.592	9.3514	-0.4456	4579.57*	-44.941*	-46.455*	0.0892*	109.57*	347.30*
								(0.0000)	(0.001)	(0.001)	(0.0000)	(0.0000)	(0.0000)
Dubai	0.011	-12.157	12.203	0.002	1.904	8.5389	-0.0994	3420.079*	-49.7898*	-50.792*	0.0250	27.749*	1101.8*
								(0.0000)	(0.001)	(0.001)	(0.2011)	(0.006)	(0.000)
Egypt	-0.010	-16.521	7.288	0.040	1.601	14.9636	-1.5615	15358.21	-40.9242*	-41.3638*	0.0603*	106.83*	139.59*
								(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Jordan	-0.002	-20.541	19.964	1.4338e-04	1.238	59.2572	-0.2848	352391.8*	-51.6141*	-51.614*	0.0169	10.344*	638.77*
								(0.0000)	(0.0001)	(0.0001)	(0.3913)	(0.000)	(0.000)
Kuwait	-0.001	-9.115	5.036	0.037	0.826	13.7233	-1.2177	13462.51*	-44.91613	-49.51451	0.0829*	159.84*	347.05*
								(0.0000)	(0.0000)	(0.0000)	(0.000)	(0.000)	(0.000)
Morocco	0.023	-6.4808	6.126	0.017	0.984	7.6413	-0.2477	2425.578*	-41.8651*	-41.5759*	0.0723*	135.50*	906.43*
								(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.000)	(0.000)
Oman	0.023	-8.697	8.039	0.005	1.096	17.9103	-0.9064	25117.10*	-42.1282*	-41.8429*	0.0624*	126.34*	2408.6*
								(0.0000)	(0.0001)	(0.000)	(0.0014)	(0.000)	(0.000)
Saudia Arabia	0.002	-11.686	16.215	0.068	1.688	14.384	-0.632	14608.09*	-47.5661*	-47.5268*	0.0208	50.995*	1192.4*
								(0.0000)	(0.0001)	(0.0001)	(0.2909)	(0.000)	(0.000)
South Africa	0.024	-12.852	12.889	0.099	-0.251	8.3228	1.896	3182.390*	-50.64547	-50.83325	0.0965*	33.284*	2141.3*
								(0.0000)	(0.0001)	(0.0001)	(0.000)	(0.001)	(0.000)
Turkey	0.019	-14.761	15.852	0.116	2.293	7.478	-0.388	2300.534	-49.4539*	-49.4892*	0.0971*	23.052*	717.21*
								(0.0000)	(0.0001)	(0.0001)	(0.000)	(0.027)	(0.000)
Tunisia	0.033	-6.357	3.839	0.030	0.708	9.067	-0.263	4050,587	-45.044*	-45.234*	0.020585	89.955*	714.27*
								(0.0000)	(0.000)	(0.000)	(0.2977)	(0.000)	(0.000)

Table 3. Results of specification tests for typical variants of GARCH models

		sGARCH			E-GARCH			T-GARCH			APARCH		Selected Model
Country	Log-l	AIC	SIC	Log-l	AIC	SIC	Log-l	AIC	SIC	Log-l	AIC	SIC	
Bahrain	-2046.96	1,5756	1,5891	-2040.291	1.5712	**1.5870**	-2046,4430	1,5759	1,5917	**-2038,5570**	**1,5707**	1,5887	APARCH
Dubai	-4922.98	3,7798	3,7888	-4923,4000	3,7809	3,7921	-4917,6890	**3,7765**	**3,7878**	**-4917,2990**	3,7770	3,7905	T-GARCH
Egypt	-4234.82	3,5185	3,5305	-4219.637	3.506753	3.521161	-4197,9060	3,4887	**3,5031**	**-4194,8860**	**3,4870**	3,5039	APARCH
Jordan	-3482.03	2,6751	2,6885	-3495,2130	2,6860	2,6995	-3480,8140	**2,6750**	**2,6864**	**-3480,7220**	2,6757	2,6914	T-GARCH
Kuwait	-2735.21	2,1038	2,1173	-2707.240	2.083070	2.098825	-2696,3840	2,0747	2,0905	-2693,2380	2,0731	2,0911	T-GARCH
Morocco	-3351.75	**2,5752**	2,5924	-3355,6300	2,5789	2,5924	-3351,7040	2,5759	2,5894	**-3351,6580**	2,5766	**2,5864**	T-GARCH
Oman	-2919.94	2,2439	2,2552	-2935,9950	2,2570	2,2705	-2913,7970	2,2400	**2,2535**	**-2912,3880**	**2,2397**	2,2554	APARCH
Saudia Arabia	-4231.5	3,2501	3,2613	-4181,4290	3,2125	**3,2260**	-4192,2150	3,2207	3,2342	**-4178,3470**	**3,2109**	3,2266	APARCH
South Africa	-4955.86	3,8036	3,8126	-4924,1130	3,7800	**3,7912**	-4930,4800	3,7849	3,7961	**-4923,0100**	**3,7799**	3,7934	APARCH
Turkey	6430.868	-4,9297	**-4,9185**	6459,3880	-4,9508	-4,9373	6454,4770	-4,9470	-4,9335	**6462,2440**	**-4,9522**	-4,9365	APARCH
Tunisia	-2529.40	1,9443	**1,9556**	-2530,1420	1,9456	1,9591	**-2526,0860**	**1,9426**	1,9561	-2526,1200	1,9433	1,9590	T-GARCH

Note: This table summarizes the results from an extensive GARCH model specification test. The standard (sGARCH) model is compared with the asymmetric E-GARCH, T-GARCH and APARCH models.
The 'best-performing' model is chosen on the basis of several information criteria, including the log-likelihood function (log L), Akaike Information Criterion (AIC) and Schwarz information criterion (SIC).
The best model according to each criterion is highlighted in bold while the selected specifications used in our analysis are reported in the final column.

Table 3 presents the specifications of selected GARCH processes and estimated parameters. The first three coefficients; the constant (ω), ARCH term (α) and GARCH term (β) are statistically significant at the 5 % level in the case of all models and for all the countries, which indicate that, lagged conditional variance and lagged squared disturbance have an impact on the conditional variance. In other words this means that news about volatility from the previous periods have an explanatory power on current volatility. We can also note that for the T-Garch (1, 1) model, the coefficients for the leverage effect are positive (except for Jordan and Morocco) and significant (except for Morocco) for the studied markets. Our findings suggest that these stock markets are more sensitive to 'bad' than 'good' news. The other version of asymmetric ARCH specification is the APARCH model.

Moreover, in most cases, the sum of the ARCH and GARCH coefficients is close to one, which is required to have a mean reverting variance process, indicating that volatility shocks are quite persistent, and for the rest of return series, it exceeds one, implying that volatility is an explosive process.

For model checking, and as reported in the data description part, we can notice that there is no serial correlation or conditional heteroskedasticity in residuals. This shows that the variance equations are well specified for these markets.

5.2. Incorporating Structural Changes

First, we have identified at least one break in the mean equation for 4 of the 11 countries, with 2 breaks for Bahrain. Then, we have found at least 3 breaks in volatility in Egyptian and Tunisian markets, and 4 breaks for the rest of the markets. We have allowed for as many as 5 breaks, but in no country we have found more than 4. While for the dating of the breaks, we can note that for both mean and variance equations, dates are almost synchronized across countries. Of the total of 47 breaks in volatility that we have identified, only 3 were in 2006, 4 took place in each one of these years 2007, 2010 and 2012, 6 were in 2009, 8 occurred in both 2011 and 2013 , and 10 others were in 2008.

This is clearly consistent with some previous researches, confirming the existence of structural shifts in the financial markets of MENA countries that may be caused by global or regional effects. For instance, Ata [5] shows that the global financial crisis has affected all countries, the MENA's relatively low integration into global financial markets have minimized some of the downturn on MENA's economies. Moreover, Shawkat and Huimin [38] tested sudden changes in volatility for five Gulf area Arab stock markets, over the period 1994-2001 and found that most of these stock markets were more influenced by major international events than local and regional factors.

Since the structural break dates have been detected, the suitable selected AR(p)–GARCH(1,1) models are re-estimated, with the dummy variables in the mean and variance equations, which equals unity from the break date forward, zero otherwise:

$$r_t = a_0 + \sum_{i=1}^{2} a_1 r_{(t-1)} + d_{m1}\, D_{m1} + \ldots + d_{mi}\, D_{mi} + \varepsilon_t \qquad (7)$$

$$\sigma_X^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + d_{h1} D_{h1} + \ldots + d_{hi} D_{hi} \qquad (8)$$

where $D_{mi}, \ldots, D_{hi}$ are dummy variables which take the value 0 before the breakpoint and 1 after the breakpoint until the end of the period.

Table 6 indicates that the estimation results of the AR (p)–GARCH (1, 1) models with dummy in the mean and variance provide significant findings. First, The improvement of the values of the maximum log-likelihood and the decreasing of the AIC and BIC values (see Table 2 and Table 4) indicate that including dummy variables in the GARCH models provides a better performance. Moreover, For all countries, we can note that the measure of volatility persistence decreases substantially when incorporating the structural change into our model, which is consistent, for both the emerging and major stock markets, with the results found by Aggarwal et al. [3]; Shawkat and Humin [38]; Wenshwo et al. [46]; Go and Hamori [23]; etc. These results suggest that estimation of GARCH models without considering sudden changes in volatility may significantly over-estimate the persistence of volatility.

Table 6 also shows that most of the dummy variables in the mean and variance equations are significant at the 5 % level. The above analysis suggests that the structural breaks have significant effects on the volatility behavior of the stock markets.

Table 4. Results of specification tests for selected AR (p)-GARCH models

Country	Bahrain	Dubai	Egypt	Jordan	Kuwait	Morocco	Oman	Saudi Arabia	South Africa	Turkey	Tunisia
Selected Model	APARCH	T-GARCH	APARCH	T-GARCH	T-GARCH	T-GARCH	APARCH	APARCH	APARCH	APARCH	T-GARCH
Parameters estimation											
a_0	-0,0114 (0.3245)	0,0179 (0.5217)	0,0466 (0.1510)	-0,0186 (0.2228)	0,0232 (0.1740)	0,0235 (0.2046)	0,0234 (0.1544)	0,0968** (0.0039)	0,0099 (0.7200)	0,0009** (0.0267)	0,0313 (0.0224)
a_1	0,0882* (0.0000)	--	0,1981* (0.0000)	0,0394*** (0.0878)	0,1700* (0.0000)	0,1365* (0.0000)	0,2536* (0.0000)	0,1089* (0.0000)	--	0,0528* (0.0093)	0,1414* (0.0000)
a_2	0,0461** (0.0163)	--	--	--	0,0809* (0.0002)	--	--	--	--	--	--
ω	0,0412* (0.0000)	0,0734* (0.0000)	0,0446* (0.0000)	0,0284* (0.0000)	0,0239* (0.0000)	0,0093* (0.0002)	0,0108* (0.0000)	0,0324* (0.0000)	0,0311* (0.0000)	0,0013** (0.0321)	0,0308* (0.0000)
α_1	0,1555* (0.0000)	0,0908* (0.0000)	0,0638* (0.0000)	0,2244* (0.0000)	0,0400* (0.0000)	0,0594* (0.0000)	0,1565* (0.0000)	0,1227* (0.0000)	0,0701* (0.0000)	0,1057* (0.0000)	0,1140* (0.0000)
$\beta 1$	0,8080* (0.0000)	0,8662* (0.0000)	0,8837* (0.0000)	0,8015* (0.0000)	0,8333* (0.0000)	0,9335* (0.0000)	0,8303* (0.0000)	1,0714* (0.0000)	0,9269* (0.0000)	0,8667* (0.0000)	0,7935* (0.0000)
γ	0,0627*** (0.0854)	0,0501* (0.0000)	0,2621* (0.0000)	-0,0364** (0.0213)	0,1767* (0.0000)	-0,0130 (0.7206)	0,0937* (0.0000)	0,5507* (0.0000)	0,6417* (0.0000)	0,6091* (0.0000)	0,0617* (0.0007)
δ	1,1366* (0.0000)	--	2,6975* (0.0000)	--	--	1,9099 (0.0000)	2,3493* (0.0000)	0,8866* (0.0000)	1,0402* (0.0000)	0,9503* (0.0000)	--
$\alpha_1+\beta_1$	0,9636	0,9570	0,9475	1,0259	0,8733	0,9929	0,9867	1,1941	0,9971	0,9725	0,9075
Qs(12)	9,7205 (0.640)	8,6766 (0.730)	7,2026 (0.844)	15,1850 (0.231)	5,1828 (0.959)	26,93 (0.106)	3,3189 (0.993)	3,6392 (0.989)	11,916 (0.452)	5,7818 (0.927)	15,3080 0.225
ARCH-LM (12)	0,0187 (0.3420)	-0,0096 (0.6233)	-0,0164 (0.4203)	-0,0146 (0.4583)	-0,0036 (0.8548)	0,0155 (0.4337)	-0,0078 (0.6898)	0,0037 (0.8509)	0,0174 (0.3752)	0,0145 (0.4617)	-0,0112 (0.5740)

Notes: This table reports the parameter estimates for each of the selected 'best-performing' GARCH model based on BIC, SIC and the log-likelihood value. While the AR (1) process proves adequate to capture return dynamics and
produces white-noise residuals for Tunisian, Turkish, Saudi, Omani, Moroccan, Jordanian and Egyptian markets , AR(2) works for Kuwaiti and Bahraini markets Bahrain, and finally AR(0) is suitable for Dubai and south African markets.
*, **, *** indicate significant at 1 %, 5% and 10% respectively.

Table 5. Empirical results of Bai and Perron's (1998, 2003) test

Tests [a]	Bahrain	Dubai	Egypt	Jordan	Kuwait	Morocco	Oman	Saudi Arabia	South Africa	Turkey	Tunisia
Panel A: Structural break test in mean											
Number of breaks selected											
Sequential:	2	0	0	0	1	1	0	0	0	0	1
LWZ	0	0	0	0	0	0	0	0	0	0	0
BIC	0	0	0	0	0	1	0	0	0	0	1
Break dates	16/06/2008				25/06/2008	18/03/2008					04/10/2010
	21/12/2012										
Panel B:Structural break test in volatility											
Number of breaks selected											
Sequential:	4	4	3	4	4	4	4	4	4	4	3
LWZ	3	3	2	2	3	3	3	2	3	2	2
BIC	2	4	4	3	3	3	4	4	3	4	2
Break dates	03/10/2006	03/10/2006	13/08/2008	28/01/2008	01/01/2007	06/11/2007	28/11/2007	14/12/2006	17/01/2008	27/07/2007	01/04/2008
	11/09/2008	06/08//2008	29/07/2011	28/07/2009	09/09/2008	06/05/2009	28/05/2009	14/05/2009	17/07/2009	16/03/2009	03/06/2011
	16/07/2010	09/02/2010	26/04/2013	28/04/2011	12/07/2010	13/01/2011	12/04/2011	05/04/2011	08/02/2011	30/11/2011	15/08/2013
	13/01/2012	28/08/2013		26/07/2013	02/05/2013	14/08/2012	29/03/2013	28/08/2013	08/08/2012	30/05/2013	

Notes: We search for up to five breaks and use a trimming parameter of 0.15.
* Significant at the 5% level.
a: We have sequentially tested the hypothesis of *l* breaks vs. *l+1* breaks, employing the *Sup FT(l+1/l)* statics.

Table 6. Model estimation AR (p)-GARCH models with dummies in mean and variance

Country	Bahrain	Dubai	Egypt	Jordan	kuwait	Morocco	Oman	Saudia Arabia	South Africa	Turkey	Tunisia
a_0	0,0180 (0.4117)	0,0234 (0.4055)	0,0502 0.1211	-0,0264** (0.0924)	0,1150* (0.0001)	0,1601* (0.0000)	0,0105 (0.4976)	0,0982* (0.0000)	0,0089 (0.7444)	0,0009** (0.0241)	0,0884* (0.0000)
a_1	0,0796* (0.0002)	--	0,2057* (0.0000)	0,0655* (0.0096)	0,1625* (0.0000)	0,1299* (0.0000)	0,2564* (0.0000)	0,0938* (0.0000)	--	0,0518** (0.0126)	0,1293* (0.0000)
a_2	0,0328*** (0.0998)	--	--	--	0,0759* (0.0005)	--	--	--	--	--	--
d_{m1}	-0,0865* (0.0016)	--	--	--	-0,1287* (0.0002)	-0,1726* (0.0001)	--	--	--	--	-0,1253* (0.0000)
d_{m2}	0,1191* (0.0000)	--	--	--	--	--	--	--	--	--	--
ω	0,1204* (0.0000)	0,8857* (0.0000)	0,0811* (0.0000)	0,2570* (0.0000)	0,0534* (0.0000)	0,0304* (0.0000)	0,0783* (0.0000)	0,0935* (0.0000)	0,0526* (0.0000)	0,0016** (0.0553)	0,0445* (0.0000)
α_1	0,1575* (0.0000)	0,0805* (0.0000)	0,0950* (0.0000)	0,1692* (0.0000)	0,0225** (0.0180)	0,0585* (0.0000)	0,1485* (0.0000)	0,1141* (0.0000)	0,057* (0.0000)	0,1034* (0.0000)	0,1020* (0.0000)
β_1	0,6970* (0.0000)	0,7454 (0.0000)	0,7883* (0.0000)	0,6818* (0.0000)	0,7931* (0.0000)	0,9070* (0.0000)	0,7352* (0.0000)	0,8686* (0.0000)	0,9297* (0.0000)	0,8304* (0.0000)	0,7319* (0.0000)
d_{h1}	-0,0097*** (0.0524)	-0,6258* (0.0000)	0,3526* (0.0000)	0,2754* (0.0000)	-0,0209* (0.0001)	0,0108 (0.2001)	0,2781* (0.0000)	-0,0002 (0.9604)	0,0142*** (0.0986)	0,0006** (0.0249)	0,0481* (0.0000)
d_{h2}	0,0353* (0.0000)	0,5483* (0.0000)	-0,1674* (0.0002)	-0,4270* (0.0000)	0,0677* (0.0000)	-0,0131 0.1179	-0,3394* (0.0000)	-0,0353* (0.0000)	-0,0198** (0.0369)	-0,0006** (0.0231)	-0,0354* (0.0003)
d_{h3}	-0,0512* (0.0000)	-0,6189* (0.0000)	-0,17850* (0.0001)	-0,0544* (0.0000)	-0,0724* (0.0000)	0,0007 0.9822	-0,0054** (0.0378)	-0,0118* (0.0000)	0,0027 (0.5601)	-0,0004** (0.0252)	-0,0208* (0.0007)
d_{h4}	-0,0081** (0.0221)	0,0211 -0,2624	--	0,0159* (0.0021)	-0,0016 (0.5386)	-0,0148** (0.0217)	0,0006 (0.7212)	0,0078* (0.002)	-0,0157* (0.0003)	1,034* (0.0000)	--
γ	0.094*** (0.0664)	0.1272* (0.0000)	0.2410* (0.0000)	0.0242* (0.2846)	0.2167* (0.0000)	0.9039 (0.0000)	0.187* (0.0000)	0.9081* (0.0000)	0.998* (0.0000)	0.6963* (0.0000)	0.0777* (0.0003)
δ	0,9276* (0.0000)	--	2,6992* (0.0000)	--	--	2,2221 (0.0000)	2,6980 (0.0000)	0,7579* (0.0000)	0,8552* (0.0000)	1,0340 (0.0000)	--
α1+β1	0,8546	0,8259	0,8833	0,8510	0,8156	0,9655	0,8837	0,9827	0,9867	0,9337	0,8340
Log-likehood	-1997,4980	-4874,7880	-4166,4750	-3428,4410	-2650,5960	-2434,7010	-2840,5230	-4136,7210	-4900,5660	6478,5010	-2495,7070
AIC	1,5437	3,7467	3,4660	2,6379	2,0434	2,5665	2,1876	3,1820	3,7658	-4,9616	1,9223
SIC	1,5753	3,7669	3,4900	2,6604	2,0704	2,5890	2,2123	3,2067	3,7883	-4,9369	1,9448
Qs(12)	4,2360 (0.962)	12,6640 (0.394)	3,6379 (0.989)	15,2580 (0.228)	5,2762 (0.948)	22,324** (0.034)	4,2965 (0.977)	5,0755 (0.955)	8,7575 (0.723)	8,2812 (0.763)	10,4410 (0.577)
ARCH-LM (12)	0,0287 (0.144)	0,0051 (0.7961)	-0,0103 (0.6101)	-0,0129 (0.5105)	-0,0075 (0.7086)	0,0225 (0.2566)	0,0012 (0.9531)	0,0031 (0.8767)	0,0123 (0.5327)	0,0003 (0.9988)	-0,0048 (0.8127)

Thus, it can be said that not taking structural change into account, can lead to a significant overestimation of volatility transmission. This result is in line with Huang [25]; Ewing and Malik [20]; etc.

6. Conclusion

This paper investigates the volatility of a group of emerging stocks markets over a period extending from April 2005 to March 2015.We have applied the Bai and Perron [6] technique in order to test for multiple structural breaks in the mean and volatility of stock index returns. We have begun our analysis by modeling the mean and variance equations using an extensive model selection procedure for the most suitable GARCH specification for each return series. Then, for countries where structural breaks were detected, we have included the dummy variables to incorporate regime shifts. Our results indicate that from estimated parameters of dummy variables, most of them are statistically significant. We may conclude also that for most of the markets, volatility persistence declines after taking into account the sudden exchange variance. Moreover, our empirical results show evidence of performance improvement in our modeling by incorporating structural shifts dummies into the variance equation.

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