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Transitory and Permanent Volatility Components: The Case of the Middle East Stock Markets

Bashar Abu Zarour and Costas P. Siriopoulos

Abstract

Recent research has suggested that returns volatility may contain both short-run and long-run components due to the existence of heterogeneous information flows or heterogeneous agents (Andersen and Bollerslev 1997a, 1997b; Müller et al., 1997). This paper investigates the existence of such volatility decomposition in daily index returns data for nine emerging markets in the Middle East region using the permanent-transitory component variance model of Engle and Lee (1993). The existence of a component structure to volatility is supported by the existence of a transitory component to volatility and a permanent volatility that decays over a much longer horizon in three markets in the Middle East, namely Jordan, Oman, and Saudi Arabia. The component model was able to capture all structure within the data for Saudi Arabia on the basis of residual tests. However, some structure in the residuals remains in the Oman and Jordan markets.

KEYWORDS: volatility decomposition, Middle East stock markets, GARCH

1. Introduction

There is a growing number of papers dealing with the decomposition of stock markets volatility to its components (Ghose and Kroner, 1996; Müller et al., 1997; Andersen and Bollerslev, 1997a, 1997b). The recent literature also studies the decomposition of stock return within the state space framework that allows for volatility transition between regimes for the return itself and for each of its components (Nelson and Plosser, 1982; Campbell and Mankiw, 1987).

Several explanations have been suggested that heterogeneous market volatility components may exist at high frequency data. For instance, Andersen and Bollerslev (1997b) suggest that market volatility may reflect the aggregation of numerous independent volatility components, each of which is endowed with a particular dependence structure due to the arrival of heterogeneous information. This ‘heterogeneous information’ extension of the information-flow approach to market volatility imparts both short-run and long-run volatility effects. If the decay of the short-run volatility component dominates over intra-day frequencies, and the long-run volatility component dominates over intra-day and lower frequencies, the aggregation of such component processes then gives rise to the (near-) integrated and long memory lower-frequency dependencies that have been shown to characterize many returns volatilities.

Using an alternative approach, Müller et al. (1997) argue that such volatility structure may arise due to heterogeneous traders rather than heterogeneous information flows. That is, different market-agent types possessing different time horizons, such that short-term traders evaluate the market at a higher frequency and has shorter memory than long-run traders, resulting in a component structure to volatility. Moreover, they divide not only the market agents but also volatility into components. A similar idea is presented in the model for conditional variance introduced by Engle and Lee (1993) where two components (‘permanent’ and ‘transitory’) are modeled without relating these to specific traders groups.

This paper applies the component model of Engle and Lee (1993) to nine new emerging markets in the Middle East region, in an effort to determine whether permanent and transitory components can be explicitly identified in such markets and, where present, whether the persistence of short-run volatility overwhelm the long-run component. Daily stock index market returns are used, which are the highest frequency data available for such markets.

The reminder of this paper is organized along the following lines. Section 2 presents the markets under consideration along with the description and some basic characteristics of the data set. Section 3 shows the structure and properties of the component model. The GARCH and the component models estimates are presented in section 4, while section 5 summarizes and concludes the paper.

2. Stock markets characteristics and data

By international standards, Middle Eastern emerging markets under examination here are considered relatively new. Most of them started operating over the last two decades, while others have been in existence for much longer, but until recently their level of activity was not significant. Table 1 presents some market indicators as it is at the end of 2005. For market capitalization as an indicator of market size, Saudi Arabia stands to be the largest market in the region followed by Abu Dhabi stock market, while Palestine stock exchange stands to be the smallest one.

Table 1

Some Market Indicators, 2005

Market	Market Capitalization, (Billion us$)	No. of Listed Companies	Turnover Ratio	Av. Daily Trading Value (million $)
Abu Dhabi	132.41	59	21.53%	95.02
Jordan	37.64	201	63.25%	97.57
Bahrain	17.63	47	4.10%	2.87
Saudi Arabia	646.12	77	170.80%	3690.91
Kuwait	123.89	156	78.53%	390.72
Dubai	111.99	30	98.49%	14.8
Oman	12.06	125	27.53%	13.02
Egypt	79.51	744	34.87%	111.78
Palestine	3.16	28	14.10%	6.11

Source: Arab Monetary Fund Database,AMDB

The number of listed companies by it self can provide an indication of the choices of firms available to an investor. In this sense, Egypt stands out among markets with the largest number of listed companies. However, if the number of listed companies is used in conjunction with market capitalization, it will indicate the average market value for listed companies. In this case, Saudi Arabia has by far the highest market value per listed company at about $ 8391 million followed by Dubai $ 3733 million, with Egypt having the lowest market value per listed company ($ 107 million). In the case of turnover ratio, as an indicator of market liquidity, the Saudi stock market stands to be the most active and liquid market in the region at the end of 2005. Its turnover ratio reached 171% with average daily trading value $ 3691 million.

The data used in this paper consist of daily closing prices of the general indices for each of the nine Middle Eastern emerging equity markets, namely the general stock market indices of Abu Dhabi, Jordan, Bahrain, Saudi Arabia, Kuwait, Dubai, Oman, Egypt, and Palestine, which are value weighted indices.

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The time periods vary from market to market, but usually run from about 1st January 1992 to 31 July 2005. The initial and final dates vary among markets due to the establishment date of the market and; in several cases, to the availability of the data. The data were collected directly from each stock market.

Table 2 provides some statistical properties of daily stock market returns for the nine exchanges. Palestine exhibits the highest standard deviation (1.8370) followed by Egypt (1.6658), Oman, Kuwait, Dubai, Saudi, Jordan, Bahrain, and Abu Dhabi (0.5388). This shows that Palestine and Egypt markets exhibit high fluctuations from the mean returns. All nine countries have distributions with positive excess kurtosis and are seen to have heavy tails, that is are leptokurtic relative to the normal. This implies that the distribution of stock returns in these stock exchanges tend to contain extreme values. According to the Jacque-Berra test, normality is rejected for all the returns series examined. It can be observed that Bahrain, Dubai and Saudi stock exchanges show the most extreme values for the daily returns compared to the other markets, which indicates that the volatility of these markets is much higher. Oman exhibits the lowest mean returns of 0.0251 followed by Bahrain, Jordan, Saudi, Egypt, Dubai, Palestine, Abu Dhabi, and Kuwait. The difference between the maximum and minimum returns is much higher for Palestine (52.59), which implies that the Palestine stock market undergoes large fluctuations compared to the other exchanges of the region. This is not surprising considering the relative smallness and openness of that stock market (see table 1) and, consequently, its vulnerability to global shocks.

Table 2

Descriptive Statistics for Daily Market Returns of the General Indices

$R_t = 100*log(p_t/p_{t-1})$

	Jordan	Egypt	Palestine	Kuwait	Saudi	Bahrain	AbuDhabi	Dubai	Oman
	4Jan.,91-1Dec.,05	1Jan.,98-24Jan.,05	8Jul.,97-28Apr.,05	17Jun.,01-26Sep.,04	26Jan.,94-15Mar.,05	1Jan.,91-3Jun.,04	1Jul.,01-31Dec.,03	26Mar.,00-31Dec.,03	2Jan.,97-13Oct.,04
Mean	0.0355	0.0425	0.0820	0.1876	0.0370	0.0257	0.0847	0.0435	0.0251
Median	-0.0090	-0.0289	0.0000	0.1618	0.0368	0.0104	0.0558	0.0206	-0.0043
Maximum	4.7465	18.3692	27.2330	4.0263	17.9204	20.6189	2.8665	21.6679	15.2225
Minimum	-4.3097	-10.9751	-25.3643	-5.6757	-17.5253	-19.8569	-2.4741	-8.4913	-13.5602
Std. Dev.	0.7341	1.6658	1.8370	1.0386	0.9342	0.7269	0.5388	1.0084	1.0842
Skewness	0.3075	0.7695	0.5314	-0.5134	0.1168	0.4033	0.1243	7.8917	0.7877
Kurtosis	7.7149	15.2906	73.4889	6.9037	93.8064	366.7102	7.8723	203.5124	50.9400
Jacque-Berra	2,940	10,651	244,349	466	1,058,905	18,321,581	640	1,850,786	182,045
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	3,121	1,666	1,180	687	3,082	3,324	645	1,098	1,899

The data for daily indices were collected directly from each stock market.

Table 3 shows the results of the unit root test, which examines stationarity for all time series both in levels and first differences. Three tests have been employed in this investigation: the augmented Dickey-Fuller, the Phillips-Perron, and the Kwaitkowski-Phillips-Schmidt-Shin (KPSS) tests (Dickey and Fuller 1979; Phillips and Perron 1988; Kwaitkowski et al. 1992).

Table 3

Unit Root Tests for Each Individual Series, Both in Levels and First Differences

	Levels						First Difference					
Variables	ADF	Lags	PP	Lags	KPSS	BW	ADF	Lags	PP	Lags	KPSS	BW
KSEI	-2.29^{IT}	1	-2.24^{IT}	9	0.32^{IT}	21	**-17.72^{I}**	1	**-22.14^{I}**	7	**0.16^{I}**	9
JSMI	-1.12^{IT}	12	2.43^{N}	1	0.56^{IT}	43	**-11.59^{I}**	16	**-43.63^{I}**	12	**0.29^{I}**	1
BSEI	-1.83^{I}	11	-1.61^{I}	24	0.42^{IT}	44	**-14.08^{I}**	10	**-65.95^{I}**	26	**0.16^{I}**	24
DFMI	-1.61^{IT}	1	-1.56^{IT}	7	0.81^{IT}	25	**-33.01^{IT}**	1	**-33.03^{IT}**	8	**0.03^{IT}**	8
EFMI	0.22^{IT}	2	0.21^{IT}	6	0.81^{IT}	32	**-27.38^{IT}**	1	**-32.95^{IT}**	13	**0.17^{IT}**	5
OSMI	-0.45^{IT}	6	0.74^{N}	15	0.98^{IT}	34	**-17.12^{N}**	4	**-41.83^{N}**	14	**0.39^{I}**	15
ABSMI	2.95^{N}	3	3.17^{N}	9	0.28^{IT}	21	**-12.18^{I}**	2	**-22.25^{I}**	7	**0.15^{I}**	9
PSEI	-2.55^{I}	4	-2.46^{I}	4	0.44^{IT}	26	**-13.82^{N}**	5	**-34.94^{I}**	4	**0.33^{I}**	3
SAUDI	-1.8^{IT}	6	-1.68^{IT}	8	0.83^{IT}	43	**-17.85^{IT}**	7	**-57.46^{IT}**	6	**0.07^{IT}**	17

Note: All variables are in natural logs. All unit root tests agree that all variables are ***I***(1). The lag selection is based on the lowest values for AIC criterion. Superscript *N* stands for no intercept and no trend. *I* for intercept only and no trend, and *IT* for both intercept and trend. Significant statistics are in bold, and the series are stationary. BW stands for bandwidth.

The results of these three tests show that all variables appear to be non-stationary in levels and stationary in the first differences or integrated of the first degree.

3. The component model

The conditional variance in the GARCH (1,1) model

$$h_t = \omega + \alpha(\varepsilon_{t-1}^2 - \omega) + \beta(h_{t-1} - \omega) \quad (1)$$

shows mean reversion to ω which is constant for all time. By contrast, the component model allows mean reversion to a varying level q_t, modeled as:

$$h_t - q_t = \omega + \alpha(\varepsilon_{t-1}^2 - \omega) + \beta(h_{t-1} - \omega) \quad (2)$$

$$q_t = \omega + \rho(q_{t-1} - \omega) + \phi(\varepsilon_{t-1}^2 - h_{t-1}) \quad (3)$$

here h_t is the volatility, while q_t takes the place of ω and is the time varying long run volatility. Equation (2) describes the transitory component h_t-q_t, which converges to zero with powers of ($\alpha+\beta$). Equation (3) describes the long run component q_t, which converges to ω with powers of ρ. Typically ρ is between

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0.99 and 1 so that q_t approaches ω very slowly. We can then combine the transitory and permanent equations and write the volatility as

$$h_t = (1-\alpha-\beta)(1-\rho)\omega + (\alpha+\phi)\varepsilon_{t-1}^2 - (\alpha\rho + (\alpha+\beta)\phi)\varepsilon_{t-1}^2 + (\beta-\phi)h_{t-1} - (\beta\rho - (\alpha+\beta)\phi)h_{t-2}$$

which shows that the component model is a (nonlinear) restricted GARCH(2,2) model

Following Engle and Lee (1993), let r_t denote the return on an asset, the expected return being m_t, and define the conditional variance of that return as $h_t \equiv Var(r_t \mid \Omega_{t-1}) = E[(r_t - m_t)^2 \mid \Omega_{t-1}]$ where Ω_{t-1} denotes the set of all information available at time t-1. The simple GARCH (1,1) process (Bollerslev, 1986) is then defined by:

$$r_t = m_t + \varepsilon_t \qquad (4)$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (5)$$

where (ω, α, β) are fixed parameters, ε_t is serially uncorrelated with zero mean and conditional variance h_t, and the standardized error $z_t = \varepsilon_t / \sqrt{h_t}$, is identically and independently distributed (*iid*) with zero mean and unit variance. To illustrate the extension of the component model over the GARCH model, consider the multi-step forecast of the conditional variance in the GARCH (1,1) model in eq. (5). Defining the multi-step variance forecast conditional on Ω_{t-1} as $h_{t+k} \equiv Var(r_{t+k} \mid \Omega_{t-1})$, and given the assumption that the returns process r_t is covariance stationary (i.e., $\alpha + \beta < 1$), the GARCH (1,1) multi-step conditional variance forecast is given by $h_{t+k} = \omega[1-(\alpha+\beta)^k]/(1-\alpha-\beta)$, which, as $k \to \infty$, converges to the unconditional variance $[\omega/(1-\alpha-\beta)] = Var(r_t) \equiv \sigma^2$, allowing the GARCH (1,1) model to be re-expressed as:

$$h_t = \sigma^2 + \alpha\left(\varepsilon_{t-1}^2 - \sigma^2\right) + \beta\left(h_{t-1} - \sigma^2\right) \qquad (6)$$

where the terms in parentheses have expected values of zero, reflecting the constancy of volatility in the long run. In contrast, the component model extends the expression in eq. (6) to allow the possibility that long-run volatility is not constant. That is, by allowing a time-varying permanent component, q_t, and its lagged value, to replace the constant long-run volatility, σ^2, above, where the lagged forecasting error ($\varepsilon_{t-1}^2 - h_{t-1}$) serves as the driving force for the time-dependent movement of that permanent component:

$$h_t = q_t + \alpha\left(\varepsilon_{t-1}^2 - q_{t-1}\right) + \beta\left(h_{t-1} - q_{t-1}\right) \qquad (7)$$

$$q_t = \omega + \rho q_{t-1} + \phi\left(\varepsilon_{t-1}^2 - h_{t-1}\right) \qquad (8)$$

and the autoregressive root, $0 < (\alpha+\beta) < \rho \leq 1$, accommodates the often empirically relevant case of (near-) integration in volatility for ρ values of (close to) unity. Thus, conditional variance is decomposed into a permanent or long-run component, and a transitory or short-run component defined simply as $(h_t\text{-}q_t)$.

The conditional variance is covariance stationary in this model if the permanent component and the transitory component are both covariance stationary, as satisfied by $\rho < 1$ and $(\alpha+\beta) < 1$, respectively. Those values also quantifying the persistence of shocks to these component processes. For $1 > \rho > (\alpha+\beta)$, the transitory component decays more quickly than the permanent component such that the latter dominates forecasts of the conditional variance as the forecasting horizon is extended, and eventually converges to a constant as long as the permanent component is stationary: $h_{t+k} = q_{t+k} = \omega/(1-\rho)$ as $k \to \infty$, for $0 < \rho < 1$. Further, by substitution using Eq (7) and (8), note that the component model may be expressed alternatively as either a GARCH (2,2) model, or a GARCH (1,1) model with time-varying intercept, the latter being:

$$h_t = [\omega + (\rho - \alpha - \beta)q_{t-1}] + (\alpha + \phi)\varepsilon_{t-1}^2 + (\beta - \phi)h_{t-1} \qquad (9)$$

such that for $\omega > 0$, $\alpha > 0$, $\beta > \varphi > 0$, $1 > \rho > (\alpha+\beta) > 0$, the conditional variance h_t is ensured to be non-negative as long as q_t is non-negative. Since substitution also allows the permanent component to be expressed as a GARCH (2,2) process, the results of Nelson and Cao (1992) may be used to verify constraints for the non-negativity of q_t , which in turn can be shown also to be satisfied under the restrictions already given.

Note that the component model reduces to the GARCH (1,1) model if either $\alpha = \beta = 0$, or $\rho = \varphi = 0$. Thus, the GARCH model is only capable of describing, at most, one element of the more general conditional variance component specification, and only represents the permanent component under the specific conditions $\alpha = \beta = 0$, $\rho = 1$.

4. Empirical results

Coefficient estimates for both GARCH and component models obtained by maximum likelihood, together with Bollerslev and Wooldridge (1992) non-normality robust standard errors, are reported in table 4 for each of the nine stock markets on a daily basis.

Residual diagnostics for both models are reported in table 5, and includes moment measures, Jacque-Berra tests for departures from normality, Engle ARCH-LM (Engle, 1982) tests, and BDS tests (Brock et al., 1996, 1987) of the null that the series in question are *iid* against an unspecified alternative. Moreover, the persistence of shocks is measured by $(\alpha+\beta)$ for both GARCH and transitory component, and by (ρ) for the permanent component. According to

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Engle and Bollerslev (1986), if $\alpha+\beta = 1$, a current shock persists indefinitely in conditioning the future variance. Since the sum of $\alpha+\beta$ (and ρ in the permanent component) represents the change in response function of shocks to volatility persistence, a value greater than unity implies that response function of volatility increases with time and a value less than unity implies that shocks decay with time (Chou, 1988). The closer to unity is the value of persistence measure, the slower is the decay rate.

The preliminary GARCH (1,1) results confirm the presence of persistence in volatility for six out of nine markets under examination, of 0.985, 0.997, 0.548, 1.059, 0.973, and 0.995 for Kuwait, Palestine, Dubai, Oman, Saudi Arabia, and Egypt, respectively, with corresponding half-lives of 46 days, 255 days, 1 day, 12 days, 25 days, and 152 days, respectively. While the results from GARCH model indicate that Abu Dhabi, Jordan, and Bahrain do not exhibit persistence in volatility. These results are confirmed by Wald tests of the null that persistence is integrated for GARCH models. Furthermore, the GARCH results indicate that Oman exhibits an increasing response function of volatility and shocks do not decay with time.

Table 4

Volatility Model Estimates

Market	Model	*Coefficient Estimates* ω	ρ	φ	α	β
Kuwait	GARCH	0.0000*	-	-	0.1903*	0.7947*
		(0.0000)	-	-	(0.0449)	(0.0449)
	Component	0.0002	0.9610*	0.2955	-0.1724	1.0410*
		(0.0001)	(0.0506)	(0.2529)	(0.2276)	(0.3370)
AbuDhabi	GARCH	0.0000*	-	-	0.1918*	0.6819*
		(0.0000)	-	-	(0.0274)	(0.0364)
	Component	0.0000*	0.8938*	0.1982*	0.0761	-0.5345
		(0.0000)	(0.0512)	(0.0878)	(0.0666)	(0.4895)
Palestine	GARCH	0.0000*	-	-	0.4431*	0.5536*
		(0.0000)	-	-	(0.0410)	(0.0278)
	Component	0.0086	0.9982*	0.3714*	0.1577*	0.3535
		(0.2672)	(0.0546)	(0.1250)	(0.0418)	(0.2261)
Dubai	GARCH	0.0001*	-	-	0.5995	-0.0518
		(0.0000)	-	-	(0.6012)	(0.0626)
	Component	0.0001*	0.5760	0.0142	0.1173	-0.0757
		(0.0000)	(0.4219)	(0.0224)	(0.0761)	(0.0754)
Jordan	GARCH	0.0000*	-	-	0.2196*	0.7196*
		(0.0000)	-	-	(0.0248)	(0.0287)
	Component	0.0001*	0.9960*	0.0329*	0.1993*	0.6803*
		(0.0000)	(0.0039)	(0.0174)	(0.0290)	(0.0472)
Oman	GARCH	0.0000*	-	-	0.2961*	0.7631*
		0.0000	-	-	-0.0666	-0.0350
	Component	0.0308*	0.9999*	0.2129*	-0.0455*	-0.8725*
		(0.0176)	(0.0000)	(0.0055)	(0.0055)	(0.0120)
Saudi Arabia	GARCH	0.0000*	-	-	0.3527*	0.6197*
		(0.0000)	-	-	(0.0151)	(0.0134)
	Component	0.0002	0.9885*	0.1439	0.2356*	0.6606*
		(0.0003)	(0.0181)	(0.1114)	(0.0763)	(0.0947)
Bahrain	GARCH	0.0000*	-	-	0.2003	-0.0448*
		(0.0000)	-	-	(0.1255)	(0.0143)
	Component	0.0001*	0.6177	-0.0039	0.1601	0.0426
		(0.0000)	(0.4636)	(0.0130)	(0.1317)	(0.0251)
Egypt	GARCH	0.0000*	-	-	0.1353*	0.8601*
		(0.0000)	-	-	(0.0098)	(0.0077)
	Component	0.0008	0.9943*	0.1230*	0.0771	0.2480
		(0.0014)	(0.0102)	(0.0200)	(0.0571)	(0.6400)

All standard errors, in parentheses, adjusted by the method of Bollerslev and Woolridge (1992)

* indicates significant at the 5% level.

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Table 5 presents residual diagnostics for these models and for the component models discussed below, and indicate that the degree of non-normality found to be statistically significant for both models and all markets, validating our use of robust standard errors throughout. For the GARCH models specifically, remaining diagnostics indicate the presence of residual ARCH structure in Egypt only. However, these results contradict BDS statistics, which broadly found to be significant for all GARCH (1,1) residuals for all markets other than Abu Dhabi. The component model implies the presence of a higher order GARCH structure, consistent with these residual diagnostics for GARCH (1,1) models.

The results of the component models for Jordan, Oman, and Saudi Arabia show that there exists a permanent-transitory component decomposition for these three markets with all parameters statistically significant. While for the other six markets, the transitory parameters ($\alpha+\beta$), or at least one of them, in the component model are found to be statistically not significant. For Jordan, Oman, and Saudi Arabia, the persistence of shocks to the permanent component is very high, in excess of 0.99 in Jordan and Oman. The persistence of shocks to the transitory component was found to be of values 0.88, -0.918, and 0.896 for Jordan, Oman, and Saudi Arabia, respectively. For these three markets the results imply transitory component half-lives of 5 days, 8 days, and 6 days, respectively, indicating full decay of a shock to the transitory component within few days.

Moreover, corresponding permanent component half-lives are 173 days, 6931 days, and 60 days for Jordan, Oman, and Saudi Arabia, respectively. Thus, the effect of a shock to the permanent component conditional volatility over several months, even years in the case of Oman, which indicates that the transitory component decays more quickly than the permanent component. Such that, the latter dominates forecasts of the conditional variance as the forecasting horizons is extended, and eventually converges to a constant as long as the permanent component is stationary, since the null hypothesis that $1 > \rho > (\alpha+\beta)$ cannot be rejected for each of the three markets (Jordan, Oman, and Saudi Arabia). Additionally, in comparison with these half-lives calculated using permanent component persistence measures for Jordan, Oman, and Saudi Arabia, the GARCH models reported above understate volatility shock half-lives by a factor of over ten in Oman and Jordan, and by more than two for Saudi Arabia.

Table 5

Residual Diagnostics

										BDS(2,d)		BDS(3,d)		BDS(4,d)	
Market	Model	Mean	S.D.	Sk.	Ku.	JB	A4	A8	A12	d = σ	d = σ/2	d = σ	d = σ/2	d = σ	d = σ/2
Kuwait	GARCH	-0.0595	0.9995	-0.3450	5.5123	194.015*	0.0667	0.6393	0.4592	0.4028	0.2444	0.1823	0.0667	0.2339	-0.0851
	Component	-0.0417	0.9989	-0.2992	5.0929	135.441*	0.1819	0.5791	0.4553	1.2147	1.0127	1.1915	0.9755	1.2269	0.8602
AbuDhabi	GARCH	0.0171	1.0000	0.1248	9.3944	1098.85*	0.0584	0.1161	0.3457	1.4545	1.8224	1.5335	1.3343	2.2050*	2.1195*
	Component	0.0170	0.9996	0.1108	9.3027	1067.261*	0.1004	0.1511	0.3409	0.7104	1.1696	1.3476	1.1861	2.0966	1.9995
Palestine	GARCH	0.0500	0.9990	-0.1358	8.1382	1300.592*	0.4417	0.7628	0.5470	2.1966*	4.5218*	2.5462*	6.0503*	2.1112*	6.4753*
	Component	0.0567	1.0023	-0.1180	7.8544	1160.355*	0.2829	0.6078	0.4157	1.2510	3.5692*	2.1894*	5.4640*	2.2342*	6.3785*
Dubai	GARCH	-0.1233	0.9115	8.4779	233.6142	2444044*	0.0162	0.0101	0.0098	2.3680*	5.1209*	4.8097*	7.3897*	6.9388*	9.4895*
	Component	-0.0306	1.0115	8.6341	231.9794	2410189*	0.0105	0.0078	0.0075	5.7346*	7.8101*	7.9056*	9.8723*	9.6160*	11.8582*
Jordan	GARCH	0.0238	1.0004	0.3213	5.5139	656.766*	1.1018	1.5451	1.0701	1.9627*	2.0056*	2.8863*	3.2412*	2.9312*	3.5840*
	Component	0.0284	0.9992	0.3391	5.0092	584.584*	1.1766	1.3114	0.9570	1.3190	1.5285	2.3656*	2.7598*	2.5045*	3.1489*
Oman	GARCH	-0.0385	0.9992	1.2263	24.6215	37446.39*	0.3714	0.3051	0.2981	2.6878*	3.6856*	3.5275*	5.3874*	3.2680*	5.8535*
	Component	-0.0488	1.0439	0.8980	20.4575	24356.85*	1.8324	1.0138	0.7629	5.0924*	5.7767*	5.6720*	7.2188*	5.6508*	7.9426*
Saudi Arabi	GARCH	-0.0017	1.0000	-0.1358	10.0894	6461.595*	0.1149	0.3330	0.5028	0.0959	0.2575	0.5649	1.0939	1.2924	2.2289*
	Component	0.0007	1.0002	-0.1592	10.0820	6451.574*	0.1683	0.4648	0.6064	-0.4407	-0.4888	-0.0336	0.2522	0.8120	1.5812
Bahrain	GARCH	0.0313	0.9730	11.5473	422.54	24444429*	0.0235	0.0134	0.0098	9.7512*	10.1152*	12.2773*	12.5321*	13.7225*	15.1557*
	Component	0.0198	0.9239	11.2534	408.8693	22878361*	0.0548	0.0286	0.0198	11.3507*	11.2306*	13.4195*	13.4007*	14.6856*	15.9834*
Egypt	GARCH	0.0312	0.9995	0.3472	9.0956	2611.182*	1.3879	1.2943	4.1227*	2.4040*	2.2751*	4.0770*	4.7262*	5.0402*	6.4120*
	Component	0.0313	0.9993	0.2891	9.0364	2551.098*	0.4597	0.7445	4.2087*	0.8136	0.8390	2.7315*	3.5519*	3.9775*	5.5082*

'Sk.' and 'Ku.' denote measures of the second and third moments of skewness and kurtosis, on the basis of which the Jacque-Berra test for normality is calculated; 'JB', 'Ai' denotes the *i-th* order Engle (1982) ARCH test, distributed as χ^2_i ; 'BDS' denotes the Brock et al. (1987) test for departures from iid defined over (*m, d*) where *m* denotes embedding dimension and *d* distance (determined with reference to the sample residual standard deviation, σ), asymptotically distributed as $N(0,1)$.

* indicates asymptotic test significance at the 5% level (with the exception of moment measures).

On the basis of Wald tests, the hypothesis of integration in variance (ρ=1) can be rejected for all markets other than Abu Dhabi at the 5% significance level. The results for Egypt imply complete dissipation of the transitory component and reversion to an integrated GARCH model. Reduction of the component model to the GARCH (1,1) form is confirmed by Wald tests of the null hypothesis parameter restrictions that $\alpha = \beta = 0$, $\rho = 1$. Furthermore, residual diagnostics for the component model in table 5 suggest that the component model is able to capture all structure within Saudi Arabia daily stock returns, while BDS statistics indicate some remaining residual structure for both Oman and Jordan. Thus, an alternative variance specifications to those employed here using higher frequency data (intra-day data) may prove fruitful in further modeling time series under examination here.

These results can have various explanations especially in the case of Oman and Saudi Arabia. One explanation could be due to existence of heterogeneous traders with different time horizon strategies in these markets. This could be corroborated by the sharp fluctuations of the Gulf stock markets recently that can be attributed partly to the existence of speculative activities.

Another explanation could be due to heterogeneous information flows and the processing mechanism of new information in these markets. Such information processes may affect the volatility structure given that previous studies put the information efficiency for these markets under question at least in the weak form of the efficient market hypothesis EMH (Haque et al. 2004; Abraham et al. 2002; Abu Zarour 2007).

5. Conclusion

Müller et al. (1997) have suggested that heterogeneous market agents characterized by different trading horizons, imparts both short-run and long-run volatility, such that the short-run effects dominate over highly-frequency intervals while the impact of a highly persistent process dominates over long horizons. Andersen and Bollerslev (1997b) have alternatively suggested that such structure results from the arrival of heterogeneous information to a financial market. However, the standard GARCH model implicitly assumes homogeneity of the price discovery process and is unable to capture these effects.

This paper examined explicit volatility decomposition using the variance component model of Engle and Lee (1993) using daily data for nine emerging markets in the Middle East region. We started the analysis by providing some market indicators for each market under examination. Descriptive statistics for daily market returns of the general indices have been provided, while the stationarity for all time series both in levels and first difference have been examined by the means of unit root test (ADF, PP, KPSS).

Several models have been used to decompose the volatility structure for each market: GARCH (1,1), the integrated GARCH and the component model. The existence of a component structure to volatility is supported by the existence of a transitory component to volatility and a permanent volatility that decays over a much longer horizon in three markets only: Jordan, Oman, and Saudi Arabia. Furthermore, the component model was able to capture all structure within the data on the basis of the residual tests for Saudi Arabia. However, this cannot be said for Oman and Jordan as some structure in the residuals remain in these two markets.

The extension of the analysis conducted here to high frequency return data, when available, for such new emerging markets, would provide interesting avenues for further research.

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