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Volatility experience of major world stock markets

M. MALLIKARJUNA
Sri Sathya Sai Institute of Higher Learning,
Andhra Pradesh, India
mejarimallik@gmail.com
R. Prabhakara RAO
Sri Sathya Sai Institute of Higher Learning,
Andhra Pradesh, India
rprabhkararao@gmail.com

Abstract. *The stock markets are characterized with relatively higher returns and higher risk & uncertainty, which reflect in the volatility that has been increasing day by day, especially, after the globalization and integration of capital markets. Volatility is an important input to many investment decisions and portfolio selection. A reliable technique for modelling stock market volatility is crucial for effective hedging of stock market risk. There are several studies about the volatility in individual stock markets. However, there are very few studies about the volatility in a group of stock markets as developed, emerging and frontier markets. This paper aims at examining the volatility experiences, informational asymmetries and leverage effects in the major developed, emerging and frontier markets. The daily returns of stock indices of twenty-four markets have been considered from 2000 to 2018. This study observes that all the markets confirm the stylized facts of the financial time series. The volatility is highly persistent in all the markets, informational asymmetries and leverage effects exist in the developed and emerging markets, whereas the frontier markets do not exhibit any tendencies of informational asymmetries and leverage effects except the stock market of Argentina.*

Keywords: stock market, risk, volatility, asymmetries, leverage effect, impact curves.

JEL Classification: C22, C58, G11, G15.

1. Introduction

The Stock market yields relatively higher returns for our investments, however, they are ever dynamic with rapid dissemination of information into the markets leading to fluctuations in stock prices that cause volatility. The volatility of the stock market is closely related to the risk of assets. Higher volatility leads to higher risk with large variations in the prices. In finance, volatility is a crucial input to many investment decisions such as portfolio selection as well as risk management. As volatility is not directly observable in financial markets, it has to be estimated from directly observable quantities such as asset prices or returns. The common properties observed in most financial time series are classified as stylized facts. Employing quantitative models that capture these properties of asset returns would be helpful to estimate volatility (Cont, 2010). Rising levels of volatility across different asset classes, markets, and industries have increased the importance of volatility models. Proper modelling of asset price volatility is of paramount importance in assessing investment risk because the investors, portfolio managers and other stakeholders of the market make decisions based on the level of volatility and their risk appetite. Volatility has received substantial attention from investors, academicians, and regulators because of its role in the asset allocation, hedging, risk management and policy-making (Moreira and Muir, 2017).

The investors are more concerned about this stock market volatility because it affects the returns on their investments, whereas the policy makers attempt to curb excessive volatility to ensure financial and macroeconomic stability posed by the stock market phenomenon. It is observed that this volatility has been increasing ever since integration and globalization of capital markets. Due to this integration, price variations in one market affect the asset prices in other interlinked markets. These co-movements of stock market prices have major implications on investors' diversification strategies and decision-making (Li, 2009). It is necessary in the global financial markets to be informed about the volatility patterns of various assets and the relative volatility of the stock market. In this regard, there has been a lot of research to find the best volatility model that can capture various stylized facts associated with market volatilities. Stock market volatility, as witnessed during the recent "Global Financial Crisis of 2008", as well as earlier, can have wide repercussions on the economy as a whole. Hence, reliable models for stock market volatility is crucial for effective hedging of stock market risk.

Various methods have been developed to model the stock market volatility. There are two major approaches to estimate volatility. The first approach is implied volatility, which indicates the future volatility of an asset is determined by today's price of the asset. The second approach is the historical volatility, which is categorised into two methods, range based volatility and conditional heteroscedasticity. First, the range-based volatility can be estimated from the historical prices and uses a variety of information about stock prices during the trading day, such as the open, close, low, and high (Yang and Zhang, 2000). Second, conditional heteroscedasticity approaches, i.e., Autoregressive Conditional Heteroscedasticity (ARCH) proposed by Engle (1982) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) by Bollerslev (1986). The GARCH classes of models are now the standard tools for volatility modelling. Two of the widely used extensions are the EGARCH developed by Nelson (1991), and GJR GARCH developed by Glosten et al. (1993).

There are several studies about volatility modelling in stock markets. Siourounis (2002) used GARCH models to estimate the volatility in Athens stock exchange, and discovered that negative shocks affect asymmetrically on the daily return series. Najand (2003) estimated the volatility for S&P 500 returns and found that EGARCH and TGARCH models are more fit compared to symmetric GARCH. When the market is stable, the GARCH model performs better and during the times of wide fluctuations, and under the circumstances of asymmetric information, EGARCH and TGARCH can describe the volatility more accurately compared to GARCH model (Awartani and Corradi, 2005).

Banerjee and Sarkar (2006) observed that the asymmetric GARCH models are more suitable than the symmetric GARCH models in the Indian stock market. Girard and Biswas (2007) and Hung (2009) found that asymmetric GARCH models perform better in the estimation of stock market volatility. Whereas, Magnus and Fosu (2006) were in favour of the view that GARCH (1, 1) with an assumption of normal error distribution is superior to other conditional volatility models in modelling the daily data in the stock exchange of Ghana. A study conducted by Pagan and Schwert (2007) revealed that the predictive abilities of both GARCH and EGARCH models are preferable. Guidi (2009) applied some of the GARCH type models to the German, UK, and Swiss stock market indices and found that the EGARCH model is considered to be optimal in conditional variance modelling and forecasting. Sabiruzzaman et al. (2010) compared the accuracy of volatility estimation of GARCH and TGARCH models on the Hong Kong stock market and showed that between these two models, the TGARCH model could estimate the leverage effect in the stock better than the GARCH model. Liu and Huang (2010) verified that in case of asymmetric information and different distributions, the asymmetric GARCH models are of greater accuracy in modelling and predicting volatility in stock market returns, in their study on S&P 100 Index.

A plethora of studies on volatility in stock markets seem to have focused majorly on individual stock markets, small group of markets and African markets (see for ex. Gabriel, 2012; Lim and Sek, 2013; Guptha and Rao, 2014; King and Botha, 2015; Ismail et al., 2016; Herwarth, 2017). However, there are hardly any studies on different groups of markets, such as developed, emerging and frontier markets. The objective of this study is to see the volatility experiences, asymmetries and leverage effects in the world stock markets.

Hence, this study contributes to the existing literature through the expansion of the research concerning the estimation of volatility in major stock markets of the world consists of developed, emerging and frontier stock markets.

The rest of the paper is organized as: Section 2 describes the data and methodology. Section 3 presents the empirical results, and finally, the conclusions are given in Section 4.

2. Data and methodology

This section describes the data and methodology of various models. Here we considered representative markets of three groups viz. developed, emerging and frontier markets as classified by Morgan Stanley Capital International classification (MSCI, 2018). Based on the availability of data in open sources and for uniformity, we considered the following markets for the study. The markets in the developed category are Australia (ASX 200), Canada (TSX), France (CAC 40), Germany (DAX), Japan (NIKKEI 225) South Korea (KOSPI), Switzerland (SMI), United Kingdom (FTSE 100), and the United States of America (S&P 500). The markets in the emerging group are Brazil (BOVESPA), China (SSEC), Egypt (EGX 30), India (SENSEX), Indonesia (IDX), Mexico (BMV IPC), Russia (MOEX), South Africa (JSE 40), Thailand (SET), and Turkey (BIST 100). The markets in the frontier category are Argentina (S&P MERVAL), Estonia (TSEG), Kenya (NSE 20), Sri Lanka (CSE AS), and Tunisia (TUNINDEX). The daily closing prices of the selected indices data ranging from 1st January 2000 to 31st December 2018 have been obtained from the website www.investing.com.

The asset returns (R_t) are calculated as:

$$R_t = \frac{(P_t - P_{t-1})}{P_{t-1}} * 100 \tag{1}$$

Where, P_t is the price of the asset in the current time period and P_{t-1} is the price of an asset in the previous time period.

2.1. GARCH models

Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engel (1982) is the basis for GARCH model. This model was introduced to overcome one of the major limitations of the traditional volatility modelling techniques, i.e., the assumption of homoscedasticity in the returns series as these models were not able to capture the varying variance, i.e. heteroscedasticity observed in the series. Therefore, in order to model the varying variance, more sophisticated models needed to be developed to accommodate the heteroscedasticity. Thus, models under GARCH framework were developed to model volatility in the financial time series.

2.1.2. GARCH Model

The GARCH model has its root in the ARCH model. Under the Autoregressive Conditional Heteroskedasticity (ARCH) model, proposed by Engel (1982) the autocorrelation in volatility is modelled by allowing the conditional variance of the error term to be related to the immediately preceding value of the squared error term. Therefore, variance of the error term ε_t, which signifies the amount of volatility, and ARCH (P) model represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_p \varepsilon_{t-p}^2 \tag{2}$$

Later on, Tim Bollerslev (1986) introduced the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Although the ARCH model has the basic form, one of its characteristics is that it requires many parameters to describe appropriately the volatility process of an asset return. Thus the GARCH model has been introduced. GARCH model is more parsimonious than the ARCH model. The GARCH (p, q) model can be written as:

$$\sigma_t^2 = a + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (3)$$

A GARCH (1, 1) model incorporates the assumption that today's volatility depends upon three factors such as a constant, yesterday's "news" about volatility, and yesterday's variance.

The sum of the ARCH and GARCH $(\alpha + \beta)$ terms gives an idea of the level of persistence of volatility in the series measured. If the sum is close to one (unity), then volatility is said to be persistent. Furthermore, the GARCH specification incorporates and handles well the frequently observed financial time series behaviour called "volatility clustering" as well as the other stylized facts associated with the stock market.

2.1.3. EGARCH Model

The asymmetric effects of a shock upon volatility i.e. the impact of good news and the bad news will not have the same magnitude and are different. In order to model such asymmetric effects. Nelson (1991) proposed Exponential GARCH model. EGARCH model with a specification for the conditional variance:

$$\text{Log}(\sigma_t^2) = \omega + \beta.\log(\sigma_{t-1}^2) + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma(\varepsilon_{t-1}/\sigma_{t-1}) \quad (4)$$

Where γ will indicate whether there are asymmetries in the financial data. The model has several advantages over the pure GARCH model: Since log σ_t^2 is modeled, then conditional variance will be positive even if the parameters are negative. Hence, it is not necessary to enforce non-negative constraints. Asymmetries are taken care of under this specification if γ is negative it implies that the relationship between volatility and returns is negative.

2.1.4. TGARCH Model

This is an extension of the GARCH model given by Zakoian (1990) and Glosten, Jagannathan and Runkle (1993) independently and it was proposed with an additional term added to the conditional variance equation (3) to account for the asymmetric property of the stock returns. In TGARCH or GJR- GARCH, the conditional variance is thus given by:

$$\sigma_t^2 = a + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \quad (5)$$

Where, $I_{t-1} = 1$ if $\varepsilon_{t-1} < 1$

$= 0$ otherwise

In the case of leverage effect, we would expect $\gamma > 0$, i.e., the sign of γ should be positive. It should be noted that if the effect is positive, then the volatility measure would equal that of GARCH. But, if the effect is negative, then the volatility measure would rise by $\gamma\varepsilon_{t-1}^2$ Thus, good news and bad news have differential effects on the volatility. While the good news has the impact of α, bad news have an impact of $\alpha + \gamma$. Thus, the leverage effect is taken care off.

3. Empirical results

In this section, we present the empirical results including descriptive statistics, and the estimates of GARCH, EGARCH and TGARCH models for the stock returns of developed, emerging and frontier markets.

3.1. Descriptive statistics of the stock returns

The summary statistics such as mean, standard deviation, skewness, kurtosis and JB test statistic of developed, emerging and frontier stock markets returns are presented in Table 1. We can see that the mean returns in all the markets are positive, indicating overall positive returns on investments during the period of this study. The kurtosis values of the returns series of all the markets are observed to be greater than three indicating that all the series are leptokurtic, i.e. thick tails, which is a common phenomenon of stock returns. The Jarque-Bera test shows that the series are non-normally distributed. All these statistics confirm the stylized facts of financial time series observed in globally (Cont, 2010; Humala, 2013; Mallikarjuna et al., 2017).

Table 1. *Descriptive Statistics of Developed, Emerging and Frontier Markets*

	Stock Market	Mean	Standard Deviation	Skew-ness	Kurtosis	Jarque Bera Test	ARCH - LM Test
Developed Markets	**Australia**	0.0169	0.9813	-0.3661	8.457	5732.6 (0.000)	1064.3 (0.000)
	Canada	0.0167	1.0431	-0.4667	13.589	21277.9 (0.000)	1419.3 (0.000)
	France	0.0057	1.4296	0.1414	8.712	6275.9 (0.000)	828.34 (0.000)
	Germany	0.0217	1.4753	0.0970	8.111	4987.2 (0.000)	873.68 (0.000)
	Japan	0.0195	1.5011	-0.2113	9.413	7642.1 (0.000)	1081.2 (0.000)
	South Korea	0.0403	1.3845	-0.3503	9.724	8473.8 (0.000)	720.95 (0.000)
	Switzer-land	0.0077	1.1747	-0.0122	10.188	9766.6 (0.000)	1034.6 (0.000)
	UK	0.0092	1.1718	-0.0043	9.918	9061.4 (0.000)	1081.7 (0.000)
	US	0.0206	1.1479	-0.0890	12.102	15630.0 (0.000)	1309.3 (0.000)
Emerging Markets	**Brazil**	0.0555	1.7690	0.0750	7.347	3439.1 (0.000)	1064.8 (0.000)
	China	0.0164	1.5850	-0.2187	7.684	4025.9 (0.000)	422.28 (0.000)
	Egypt	0.0796	1.6588	-0.1214	13.150	18891.5 (0.000)	506.16 (0.000)
	India	0.0597	1.4143	0.1206	12.839	17795.2 (0.000)	515.88 (0.000)
	Indonesia	0.0706	1.3261	-0.5015	9.570	8083.9 (0.000)	597.36 (0.000)
	Mexico	0.0518	1.2132	0.1537	9.3565	7644.2 (0.000)	785.27 (0.000)
	Russia	0.0827	1.9653	0.3700	24.338	85492.6 (0.000)	738.93 (0.000)
	South Africa	0.0476	1.2987	0.0368	6.299	2044.6 (0.000)	901.03 (0.000)
	Thailand	0.0477	1.2639	-0.5200	13.237	19417.1 (0.000)	633.39 (0.000)

	Stock Market	Mean	Standard Deviation	Skew-ness	Kurtosis	Jarque Bera Test	ARCH - LM Test
	Turkey	0.0696	1.9733	-0.0374	9.689	8426.7 (0.000)	761.13 (0.000)
Frontier Markets	**Argentina**	0.1209	2.1628	0.0184	7.2029	3230.9 (0.000)	716.33 (0.000)
	Estonia	0.0526	1.0368	0.3168	14.296	24406.2 (0.000)	413.54 (0.000)
	Kenya	0.0127	0.8313	0.5557	15.160	28057.5 (0.000)	1115.2 (0.000)
	Tunisia	0.0351	1.2924	0.6036	20.461	59408.8 (0.000)	223.91 (0.000)
	Sri Lanka	0.0664	1.1288	0.9933	43.750	30019.2 (0.000)	1151.6 (0.000)

Figure 1. *Returns of developed markets*

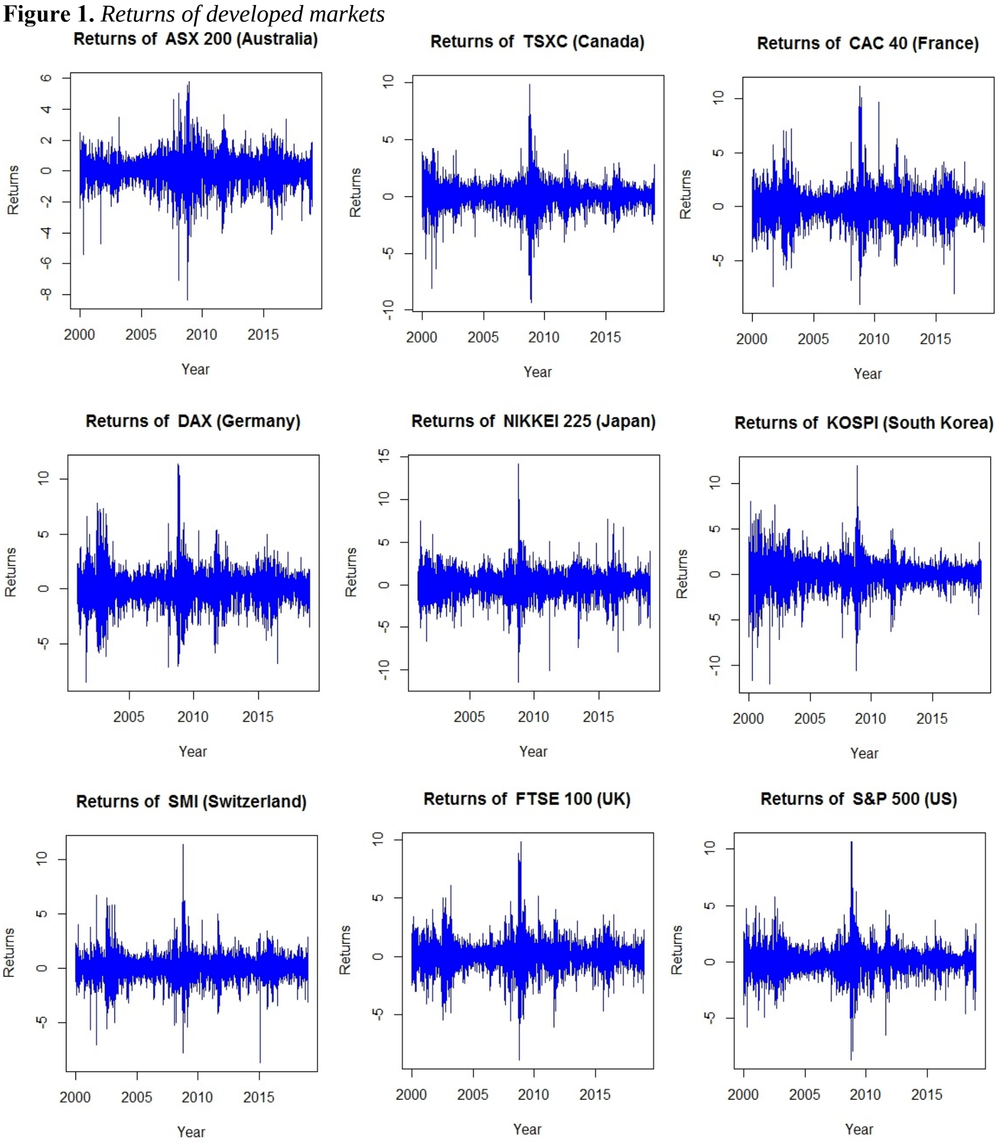


Figure 2. *Returns of emerging markets*

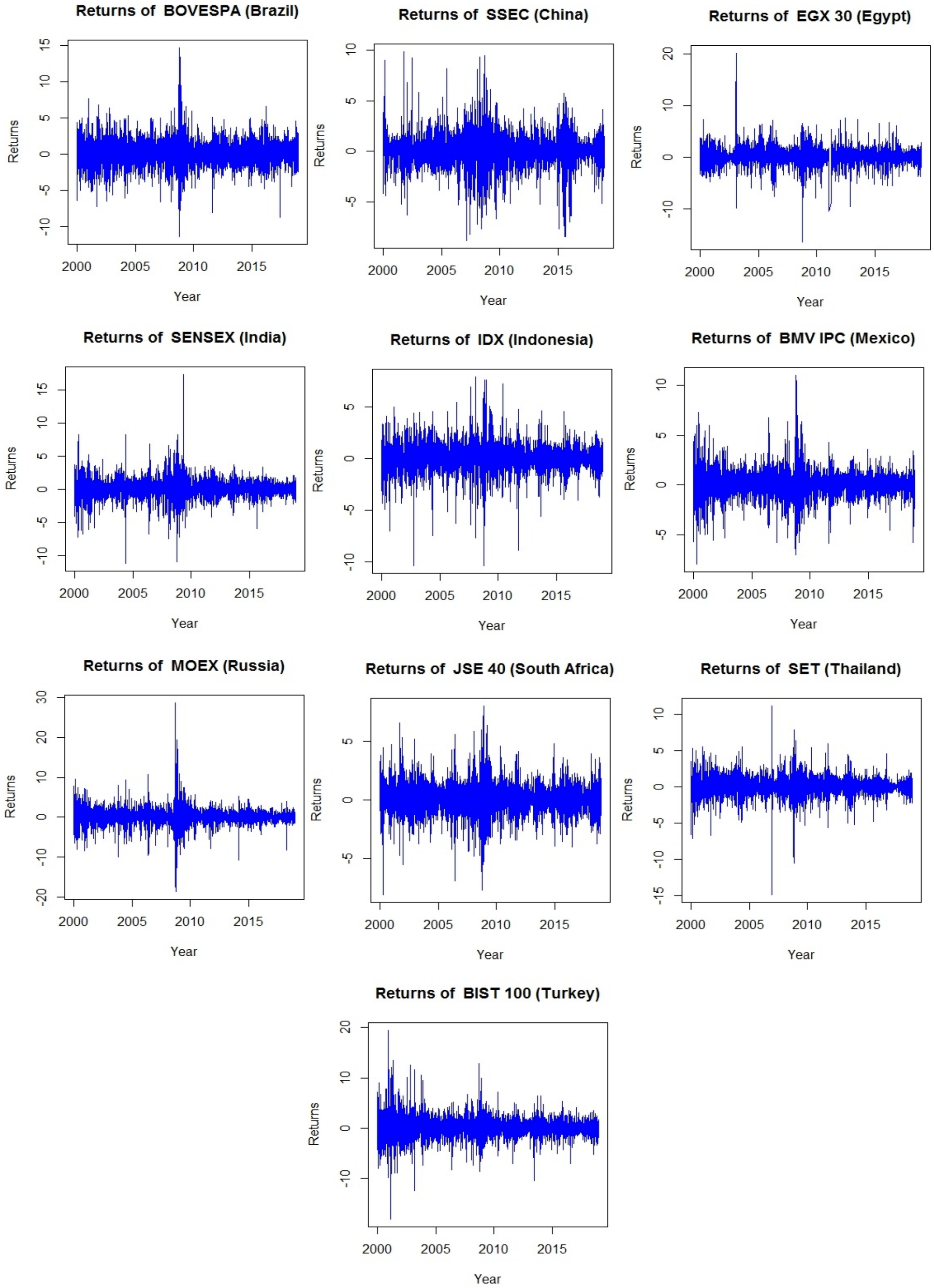
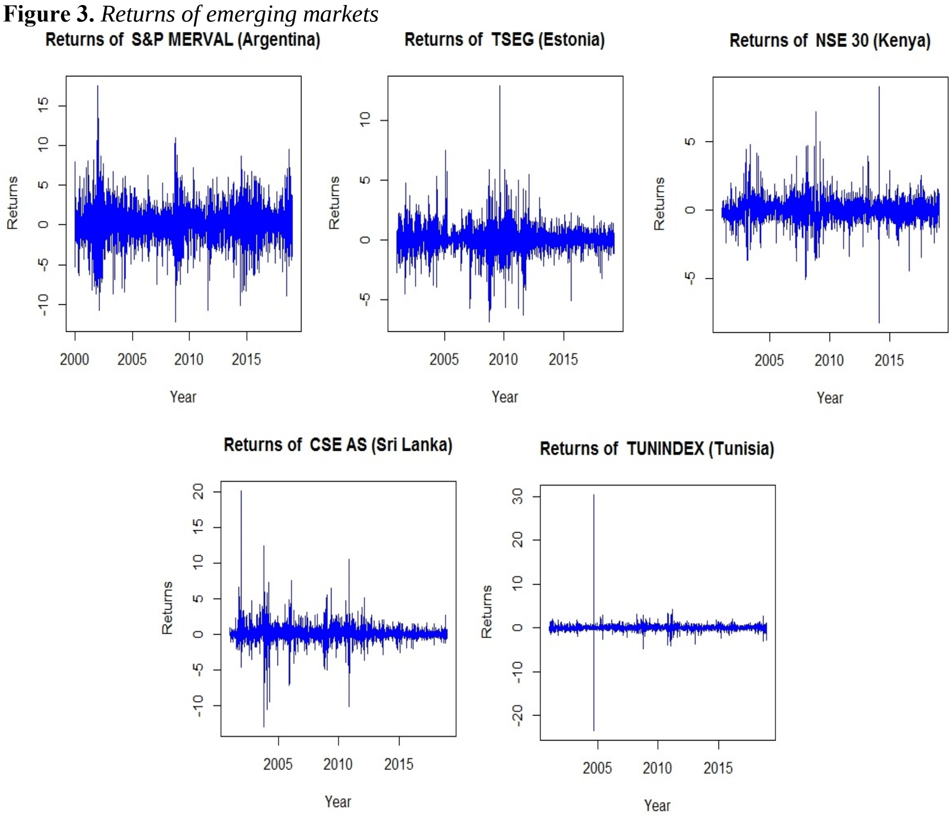


Figure 3. *Returns of emerging markets*



3.2. Results of GARCH Models

The returns of all the markets have been tested for Autoregressive Conditional heteroscedasticity (ARCH) effect in the data by employing Engle's ARCH test and found that all the market returns exhibit the ARCH effect. We employed the GARCH (1, 1) model the volatility persistence, EGARCH (1, 1) model to check the informational asymmetries, and to know the leverage effect we used TGARCH (1, 1) model. The estimates of GARCH (1, 1), EGARCH (1, 1), and TGARCH (1, 1) models for all the markets are given in Tables 2, 3 and 4 respectively.

3.2.1. Estimation of GARCH (1, 1)

It is evident from the Table 2 that the sum of ARCH (α) and GARCH (β) terms in all the indices is very high and close to one, which indicates the volatility persistence is very high in all the selected markets. Also, we can see that in developed markets, South Korea is relatively high volatile and Switzerland is relatively less volatile. In emerging markets, Indian stock market is relatively high and Egypt is relatively less volatile. Among frontier markets, Estonia and Sri Lanka are highly volatile and Tunisia is relatively low among all the twenty-four markets considered for this study. High volatility persistence is observed in all the markets. This phenomenon can be observed from the Figures 1, 2 and 3.

Table 2. *Estimates of GARCH (1, 1) model for developed, emerging and frontier markets*

	Stock Market	ARCH Term(α)	GARCH Term(β)	(α+ β)
Developed Markets	Australia	0.087448 (10.3352)	0.903005 (97.9755)	0.990453
	Canada	0.081584 (10.1410)	0.912677 (109.5037)	0.994261
	France	0.095482 (10.7096)	0.896320 (96.9243)	0.991802
	Germany	0.090369 (10.8664)	0.898893 (101.3136)	0.989262
	Japan	0.113641 (11.4915)	0.876162 (84.4562)	0.989803
	South Korea	0.073957 (8.8871)	0.922764 (110.6626)	0.996721
	Switzerland	0.126558 (11.8869)	0.853876 (73.6445)	0.980434
	UK	0.110249 (10.4685)	0.877237 (77.0517)	0.987486
	US	0.106848 (7.0175)	0.883275 (58.5636)	0.990123
Emerging Markets	Brazil	0.064213 (8.4084)	0.917087 (8.4084)	0.981300
	China	0.073446 (9.8876)	0.923887 (68.6512)	0.973330
	Egypt	0.16579 (11.9619)	0.80520 (21.4074)	0.970990
	India	0.099491 (7.1814)	0.893863 (61.9600)	0.993354
	Indonesia	0.115532 (10.0344)	0.869836 (67.0351)	0.985368
	Mexico	0.082577 (10.1843)	0.909424 (105.9648)	0.992001
	Russia	0.093930 (10.4857)	0.893251 (93.2743)	0.987181
	South Africa	0.09242 (10.8217)	0.894103 (94.3941)	0.986524
	Thailand	0.123447 (6.6988)	0.860446 (25.7845)	0.983893
	Turkey	0.088759 (4.2327)	0.901247 (38.1484)	0.990006
Frontier Markets	Argentina	0.10529 (7.2471)	0.86627 (46.2711)	0.971560
	Estonia	0.129805 (11.5247)	0.869195 (84.4573)	0.999000
	Kenya	0.246703 (12.9633)	0.708852 (35.4662)	0.955550
	Sri Lanka	0.31539 (15.7176)	0.68361 (30.6311)	0.999000
	Tunisia	0.342619 (12.3678)	0.440387 (10.3040)	0.783006

3.2.2. Estimation of EGARCH (1, 1)

From the Table 3, we can observe that the signs of asymmetry term in all the indices are negative, which indicates that there exists an inverse relationship between returns and volatility and it is in consistent with theoretical considerations. Among the developed markets, the US has relatively higher informational asymmetry, and Canada has relatively lower asymmetry. In case of emerging markets, South Africa has relatively higher informational asymmetry, and China has relatively lower asymmetry. In the frontier markets, the asymmetry term of Argentina is significant, the rest of the markets are observed to be statistically insignificant, which means that there are no asymmetric effects on the volatility of these markets. Overall, all the markets in developed and emerging groups have informational asymmetries. However, there is no informational asymmetry in frontier markets group, except Argentina.

Table 3. *Estimates of EGARCH (1, 1) model for developed, emerging and frontier markets*

	Country	EARCH Term	Asymmetry Term
Developed Markets	Australia	0.979363 (909.0633)	-0.105923 (-14.5342)
	Canada	0.987478 (1135.3223)	-0.082517 (-12.1054)
	France	0.981131 (1139.08438)	-0.142102 (-17.65517)
	Germany	0.979707 (1121.4799)	-0.116034 (-15.4356)
	Japan	0.966730 (213.6108)	-0.096694 (-9.9270)
	South Korea	0.988378 (1078.1696)	-0.067469 (-9.5875)
	Switzerland	0.971914 (262.83202)	-0.143354 (-11.64258)
	UK	0.981834 (1041.561502)	-0.125133 (-17.541989)
	US	0.974597 (904.5760)	-0.148677 (-18.4064)
Emerging Markets	Brazil	0.978998 (1016.0517)	-0.066900 (-9.2837)
	China	0.989359 (1075.5473)	-0.023933 (-3.9457)
	Egypt	0.943380 (36.2628)	-0.038982 (-4.0771)
	India	0.979667 (1119.9390)	-0.074531 (-9.4856)
	Indonesia	0.969499 (184.3736)	-0.060089 (-6.8800)
	Mexico	0.985194 (1159.5506)	-0.082389 (-11.4020)
	Russia	0.980620 (1135.5401)	-0.041319 (-5.8110)
	South Africa	0.982389 (1145.9315)	-0.092504 (-13.1189)
	Thailand	0.961514 (49.7916)	-0.078864 (-2.6438)
	Turkey	0.982841 (1694.6875)	-0.047544 (-4.0164)
Frontier Markets	Argentina	0.960604 (48.741)	-0.049973 (-5.8395)
	Estonia	0.981625 (173.7795)	-0.000105 (-0.016459)
	Kenya	0.921242 (37.85145)	-0.002684 (-0.27559)
	Sri Lanka	0.947095 (66.7727)	-0.016937 (-1.3924)
	Tunisia	0.772143 (33.70463)	0.003298 (0.24201)

3.2.3. Estimation of TGARCH (1, 1)

The leverage effect term in Table 4, reveals the presence of leverage effect in all the markets in developed markets, the US has a relatively higher leverage effect and South Korea being the relatively lower. Thailand has relatively higher leverage effect, and China has relatively lower in emerging markets. Among the frontier markets, there exists leverage effect in Argentina, but the rest of the markets are observed to be statistically insignificant, which means that there are no leverage effects on the volatility of these markets. Overall, the all the markets in developed and emerging group are have informational asymmetries and leverage effects.

Table 4. *Estimates of TGARCH (1, 1) model for developed, emerging and frontier markets*

	Stock Market	ARCH Term(α)	GARCH Term(β)	Leverage Effect(γ)
Developed Markets	Australia	0.006557 (1.0272)	0.909456 (107.9523)	0.133830 (9.8585)
	Canada	0.015504 (2.1820)	0.921839 (109.7080)	0.100044 (8.0599)
	France	0.004000 (0.000003)	0.905384 (102.294699)	0.168479 (11.006784)
	Germany	0.006030 (0.000007)	0.910565 (101.100687)	0.150442 (10.396660)
	Japan	0.045512 (5.6155)	0.874473 (85.7492)	0.123949 (8.1058)
	South Korea	0.029405 (4.2799)	0.919794 (100.1141)	0.086918 (6.9904)
	Switzerland	0.010054 (1.3876)	0.873521 (87.8389)	0.189487 (11.3118)
	UK	0.004512 (0.08745)	0.896009 (86.434830)	0.174758 (11.070792)
	US	0.000670 (0.000004)	0.889269 (90.902010)	0.189973 (11.482873)
Emerging Markets	Brazil	0.016757 (2.5704)	0.916838 (82.5600)	0.089274 (6.6702)
	China	0.059477 (8.1496)	0.923303 (69.55386)	0.027909 (3.2791)
	Egypt	0.132176 (10.1165)	0.796885 (20.5615)	0.073326 (4.2605)
	India	0.048024 (6.2358)	0.890208 (63.4005)	0.101698 (7.2559)
	Indonesia	0.073292 (6.8492)	0.865653 (60.8294)	0.076653 (5.2264)
	Mexico	0.018488 (2.9291)	0.918639 (99.2788)	0.106243 (8.5341)
	Russia	0.065986 (7.5800)	0.892412 (89.6307)	0.054222 (4.7325)
	South Africa	0.019974 (3.3316)	0.904279 (101.4396)	0.124233 (9.4904)
	Thailand	0.073900 (5.3482)	0.844869 (18.4998)	0.124757 (7.0532)
	Turkey	0.057254 (3.6798)	0.897725 (39.2394)	0.066849 (3.1310)

	Stock Market	ARCH Term(α)	GARCH Term(β)	Leverage Effect(γ)
Frontier Markets	Argentina	0.069520 (5.2301)	0.859759 (43.3162)	0.074825 (5.2769)
	Estonia	0.134295 (10.32631)	0.868914 (32.71373)	-0.008428 (-0.40467)
	Kenya	0.241861 (11.77118)	0.707655 (13.16432)	0.011788 (0.54881)
	Sri Lanka	0.312783 (13.74514)	0.683200 (30.52333)	0.006033 (0.23434)
	Tunisia	0.304917 (9.8682)	0.438640 (10.2324)	0.071390 (1.9748)

The informational asymmetry and the leverage effects can by observed from the news impact curves as well, which are given in Figures 4, 5 and 6. The news impact curves for developed markets are more or less L- Shaped, which indicate, the effect of bad news is more compared to same amount of good news on volatility. The news impact curves for frontier markets are U-shaped, indicating stock prices show symmetric effects to both good news as well as bad news. In case of emerging markets, the impact curves are neither L-shaped, nor U-Shaped, indicating that the stock prices in these markets are relatively more sensitive to information compared to frontier markets and are less sensitive compared to developed markets.

The findings of this study are consistent with the studies of Christensen et al. (2015), who confirmed the presence of the asymmetric volatility effect across fifteen stock markets. Guptha and Rao (2017) on BRICS markets, Baur and Dimpfl, (2017) and Herwarth (2017) with respect to asymmetries and leverage effects in stock returns. However, these results are in contrast with the results of Baig et al. (2015), where the authors found less volatility persistence in Sri Lankan Stock Market, this might be due to different time period (2005 – 2015) considered for the study.

Figure 4. *News impact curves for developed markets*

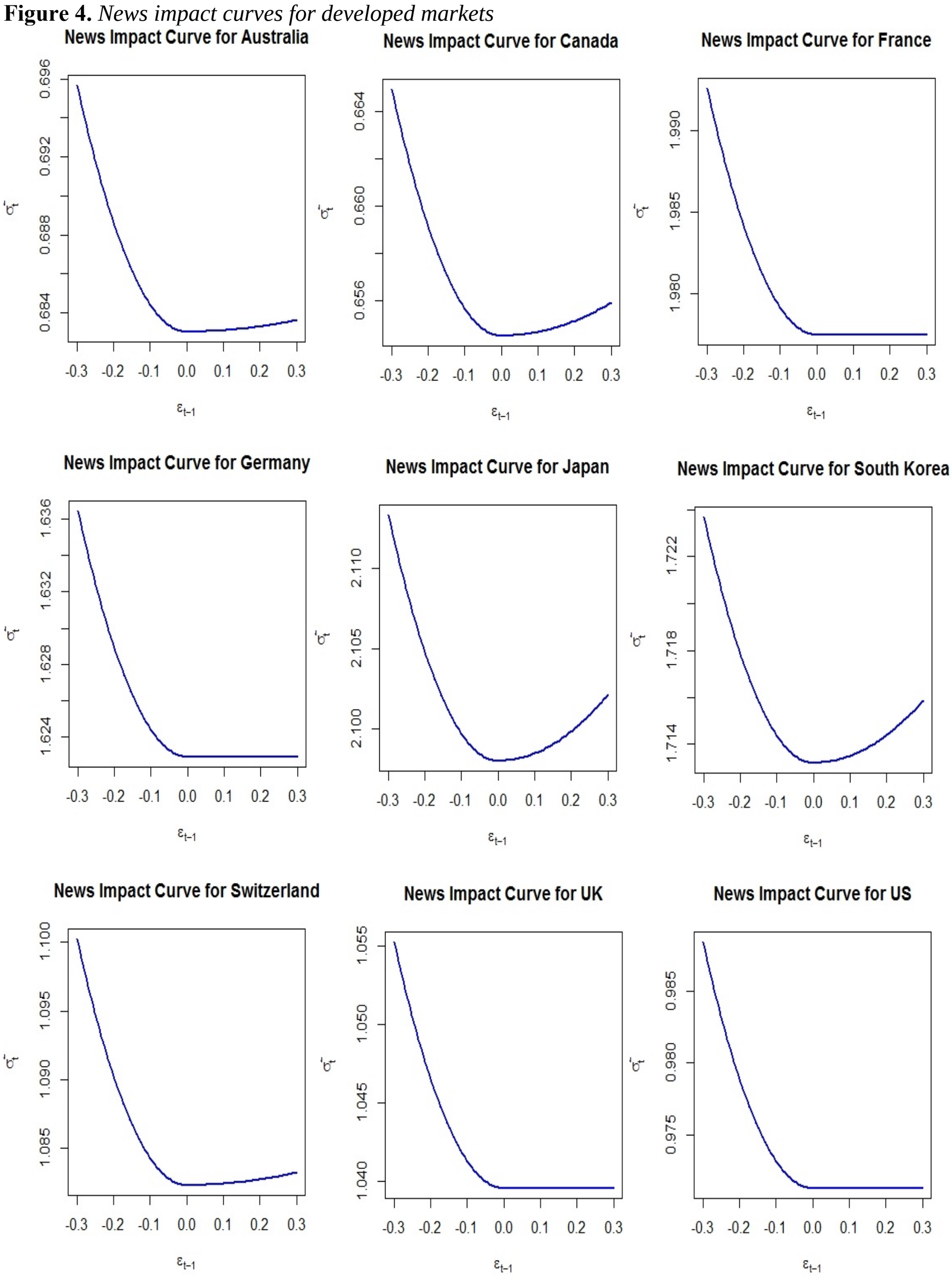


Figure 5. *News impact curves for emerging markets*

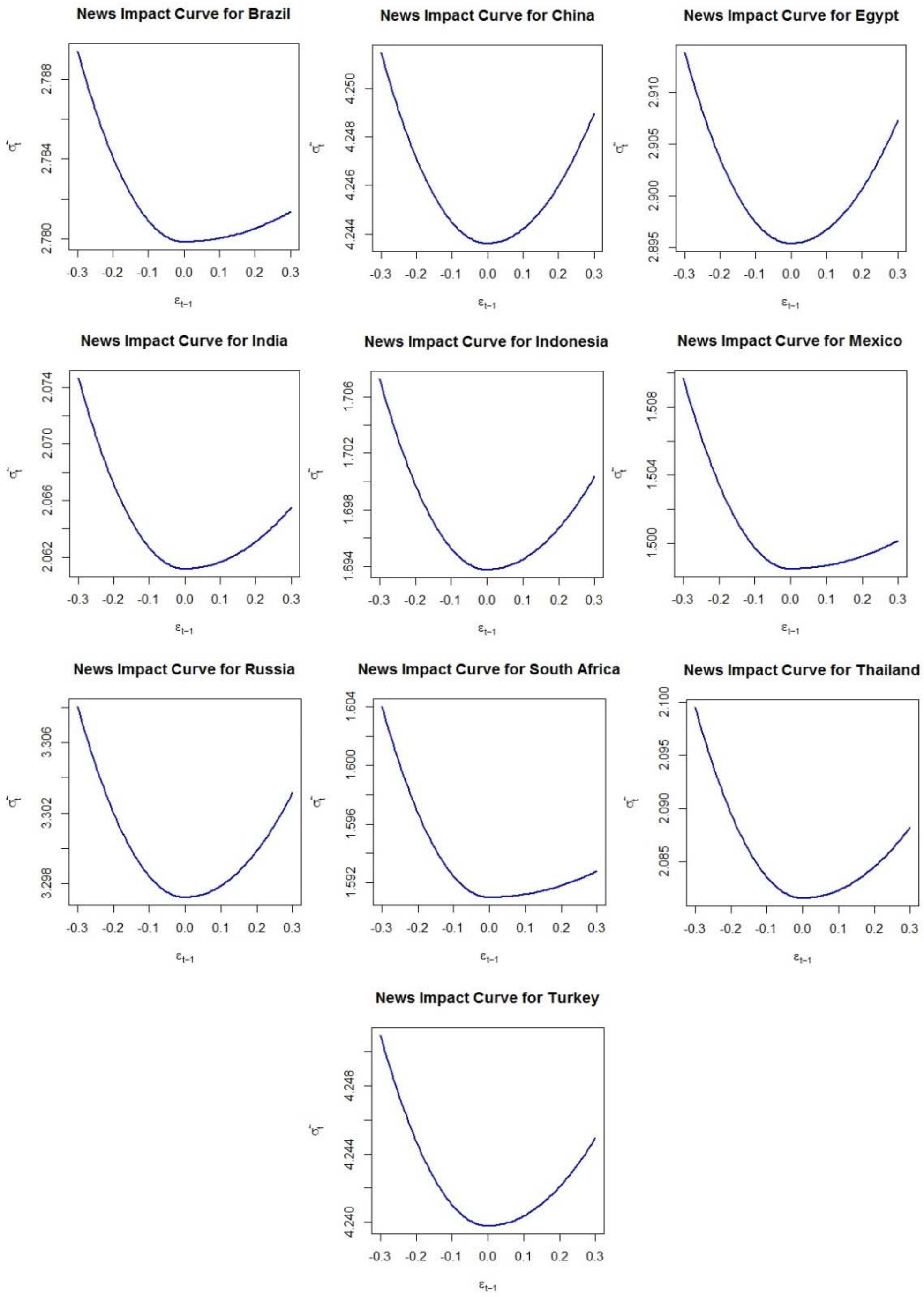
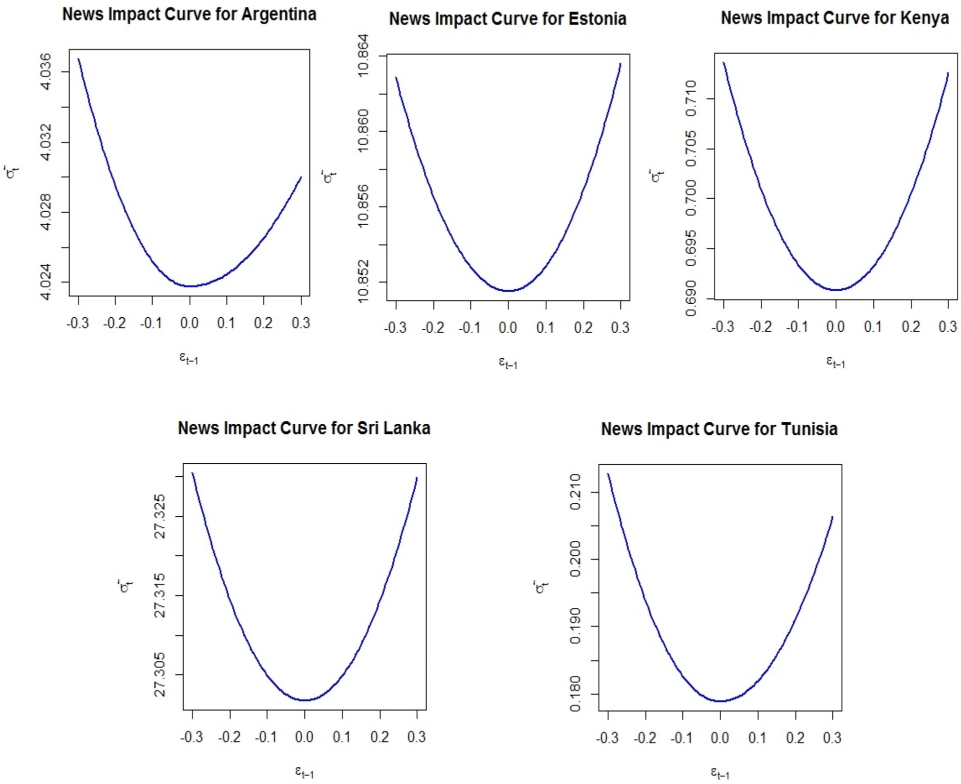


Figure 6. *News impact curves for frontier markets*



4. Summary and conclusions

Volatility in the stock markets has numerous implications on the real economy. Volatility affects investors' investment decisions and confidence to hold risky assets. Modelling volatility in the stock market is therefore crucial in order to hedge against risk, select portfolio and investment decision making. This paper examines the volatility in major global stock markets under three groups, i.e., developed, emerging and frontier markets according to MSCI classification of markets. The daily returns of selected stock indices were taken from 01st January 2000 to 31st December 2018. This study observes that the average returns of all the indices are positive, implying that these indices have appreciated during the period of the study and all the markets exhibit the stylized facts of financial time series. Further, the inferences from the estimated results of the GARCH, EGARCH and TGARCH models revealed that the volatility is found to be highly persistent in all the markets. Also, this study found that the developed markets exhibit relatively higher leverage effect and informational asymmetries compared to emerging and frontier markets. There exist leverage effect and information asymmetries in emerging markets as well. However, these tendencies are relatively lower compared to developed markets. Whereas the frontier markets do not exhibit any asymmetries and leverage effects at all, except the stock market of Argentina.

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