Moon Phases, Mood and Stock Market Returns: International Evidence

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Abstract

We employ recent data from 59 international emerging and mature stock markets to provide new evidence of a lunar cycle (full and new moon) effect on their stock market returns. Using a TGARCH model, we further examine the linkages between efficient-market theory, calendar-related effects and investors' mood resulted from moon phases. The empirical results show significant full moon effects in 6 markets, and significant new moon effects in 8 markets. In line with the theory, we report significant positive effect of new moon on stock market returns in 5 cases (UK, Switzerland, Bangladesh, Chile and Cyprus), while a negative effect of full moon is reported for the case of Jordan only. In addition, we find that lunar effects are strongly influenced by the calendar anomalies (Monday effect and January effect); several markets -mostly emerging markets- show evidence of full/new moon effects as well as Monday/January effects (Bangladesh, Brazil, Chile, Tunisia, Belgium, Cyprus). Further, we prove that the lunar phases are stronger outside America. These findings are recommended to investors, financial managers and analysts dealing with international stock indices.

Keywords: Moon; Mood; Emerging & Mature Markets; TGARCH; Stock Returns

JEL: G02, G14, G15

1. Introduction

Psychological factors (e.g. overconfidence and optimism) always play a role in economics and financial markets (Akerlof and Shiller, 2009; Krugman, 2009; Kahneman, 2003a, 2003b; Laibson and Zeckhauser, 1998; Ciccone, 2011). Further, theories from behavioural finance such as the efficient-market theory (stock prices reflect all available information) and calendar-market anomalies, i.e. Monday (low returns) and January (high returns) effects, may be explained by psychological principles of decision making[1] (Garling et al., 2009; Alt et al., 2011).

Numerous studies suggest that mood significantly affects human's behaviour and psychology[2] (Frijda, 1998; Loewenstein et al., 2001; Slovic et al., 2002), while recent studies on behavioural finance show significant effects of investors' mood[3] on asset returns (Hirshleifer and Shumway, 2003; Cao and Wei, 2005; Yuan et al., 2006). Further, there is much research which shows the importance of weather and other geophysical phenomena (see Saporoschenko, 2011; Chang et al., 2008; Pardo and Valor, 2003), including the lunar cycles (moon phases), on the pricing of assets. Evidence suggests that investors are subject to various behavioural biases when making financial decisions, such as cognitive errors, loss aversion, overconfidence and mood fluctuation (Harlow and Brown, 1990).

Moon has a natural power which plays a significant role in phenomena of nature and also on human behaviour; in particular, moon tends to affect decision makers (Levy and Yagil, 2011). The phases of the moon show when people are generally more optimist or pessimistic. There are two phases of the moon: the new moon, and the full moon. The full moon period is the day of the full moon and the seven days before it and after it, when people are more pessimistic. By contrast, the new moon is when the moon is 'hidden' and people have positive energy. This period marks the beginning of new life, development and the conception of hope. According to Dichev and Janes

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[1] Nofsinger (2003) argues that "*the recent trend of behavioural finance is developing by attributing psychological biases, emotions, and moods to economic participants*"; he further adds that "*the optimism (and overconfidence) causes the decision-maker to overestimate the probability of success and underestimate the risk of the decision outcomes*", see Nofsinger (2003, p. 2).

[2] A large body of papers in psychology show a link between depression and anxiety and a low risk-taking behaviour (Krivelyova and Robotti, 2003). Garling et al. (2009, pp. 5-6) argue that "*overconfidence and optimism are other psychological factors that make people take financial risks possibly disastrous consequences for the financial situation*".

[3] According to Garling et al. (2009, pp. 16-17), financial decision making is influenced by predecisional affective states (e.g. current mood), anticipatory affect (e.g. optimism-pessimism) and anticipated affect (e.g. disappointment).

(2003), phenomena of nature such as lunar cycles or even the energy of ocean can be used to explain and possible predict the pattern of stock market prices and their returns. On a general level, if lunar phases affect investors' mood, these phases may affect asset prices, and therefore, asset returns during full moon phases may be different from those during new moon phases (see Yuan et al., 2006; Keef and Khaled, 2011). In particular, a full moon reflects the trading behavior of investors; in other words, it increases their tendency to feel depressed or sad. Hence, they may feel to stay out of the stock market (at or near that day of full moon) and wait, or to sell out their positions due to the lunar effect, i.e. a full moon brings stress to the investors. The opposite happens with the new moon, i.e. it brings calmness. The lunar effect theory is that "*the lunar cycle affects human emotions and that financial markets, as reflections of the wisdom or madness of the crowd, are not immune to its effects*" (Stevenson, 2010). Empirical evidence shows that stock returns are lower on days around a full moon than on days around a new moon. This negative relationship around full-moon periods is firstly reported by Dichev and Jones (2003) and then by Yuan et al. (2006). Dichev and Jones (2003) show a significant lunar effect on the US returns; they report that moon cycles affect human behaviour especially abnormal behaviour around full moons. Yuan et al. (2006) employ a pooled regression to investigate the lunar phases-stock market returns relationship using data from 48 countries. They show that stock returns are lower on the days around a full moon than on the days around a new moon. Dowling and Lucey (2008) use weather and biorhythm (including lunar phases) to study the relationship between mood and UK equity pricing (UK Main index and UK Small capitalisation index) for the period 12 December 1994 to 10 November 2004. They employ an ARMA(1,1) Leveraged-GARCH(1,1) model with a GED error distribution assumption (UK Main index) and ARMA(1,1)-EGARCH(1,1) ARCH-in-mean with a student's t-error distribution assumption (UK Small capitalisation index). Dowling and Lucey (2008, p. 239) report "*problems with interpreting the lunar phases findings because the findings are stronger for the Main index compared to the Small capitalisation index*". Recently, Lucey (2010) shows the existence of a lunar cycle on silver and platinum returns (precious metals) for the period January 1998 to September 2007. They also report that full moons are bad news for precious metal returns. Finally, Keef and Khaled (2011) use a simple OLS to confirm that full moon is absent when daily returns of 62 international stock indices is considered; they find that lunar effects are weakly influenced by the calendar anomalies (Monday effect and turn-of-the-month effect).

In this paper, we empirically examine the effect of mood on asset returns, by investigating the empirical relation between moon phases (new moon and full moon) and stock returns from major international markets. We extend previous related studies by employing a Threshold Generalised Autoregressive Conditional Heteroskedasticity (TGARCH) model which captures volatility clustering as well as asymmetric behaviour of returns (most previous papers use a simple OLS model).

We focus on two sets of results. The main objective of our study is to test the effect of moon on stock market returns using recent daily data from fifty-nine markets (mature and emerging)[4], and see if our results obtained from TGARCH are consistent with the recent studies by Keef and Khaled (2011) for 62 international stock indices, Dowling and Lucey (2008) for UK and Yuan et al. (2006) for 48 international countries.

Furthermore, empirical evidence shows that the psychology and behavioural finance theories are strongly linked together; previous studies report that optimism[5] associated with the calendar effects may have implications for the stock markets (Ciccone, 2011). Hence, another goal of our paper is to investigate whether there is evidence of the potentially confounding effects, efficient-market hypothesis or calendar-related anomalies (Monday and January effects), on the stock market returns using the above methodology; Yuan et al. (2006) use a simple linear regression and report that the lunar effect is independent of calendar-related anomalies[6], while Keef and Khaled (2011, p. 62) argue that "*it would appear to be a nigh impossible to advance a market inefficiency explanation for the full moon effects and new moon effects*". Hence, we give further explanations beyond investors' mood, which in behavioral finance is the most common explanation of market anomalies (see Zaleskiewicz, 2008; DeBondt, 2008).

The remainder of the paper is organised as follows. Section 2 describes the data, while Section 3 outlines the methodology and presents the empirical results. Section 4 discusses the main findings and concludes the study.

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[4] We consider data from several stock markets to further examine if the lunar phases are stronger outside America (see Dichev and Janes, 2003).

[5] Optimism is associated with a feeling of personal control, and the stock market is indeed a place where confident people can attempt to exert their influence (Ciccone, 2011; p. 166).

[6] Garling et al. (2009, p. 11) states that "*market anomalies (deviations from efficient-market theory) may possibly be accounted for by psychological factors governing individual investor behavior*".

2. Data description

Most of our data covers a long-dated period (from January 1990 to December 2010). We consider daily data from the major indices of fifty-nine stock markets (emerging and mature) from all parts of the world (as given in Table 1). The stock market data were collected from *Datastream* and the data on moon phases were collected from the website of the *Munich Astronomical Archive* (www.maa.mhn.de). Descriptive statistics results (not reported here) confirm that all of the returns[7] series follow the stylised facts of financial time series such as leptokurtosis, volatility clustering and leverage effects (see Bollerslev, Engle and Nelson, 1994); in addition, the log levels of prices are found to be I(1), i.e. the series are non-stationary[8]. Hence, we are able to use time series models to capture volatility clustering and test the effect of investors' mood on stock market returns.

<< Table 1 - about here >>

3. Methodology

In formulating the hypotheses, we consider the relationships between (a) new/full moon and good/bad news (mood), (b) new/full moon and calendar-related effects (Monday/January), (c) mood and stock market returns. We re-examine the empirical linkages between moon phases and stock market returns using a TGARCH model which captures an effect where negative shocks have a greater volatility impact than positive shocks (this study is the first investigation of the possibility of moon-calendar anomalies using a TGARCH time-series approach which is able to capture the seasonal dependency, or the annual cycle of moon, as well as the fluctuation of returns or volatility response from market shocks)[9].

We not only test whether the phases of moon affect stock returns, but also we investigate whether the returns are higher in winter (January effect - see Floros, 2008a; Yuan *et al*., 2006; Floros, 2011; Khaled and Keef, 2011[10]; Ciccone, 2011) and

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[7] Daily returns are computed as logarithmic price relatives: $R_t = \ln\left(P_t / P_{t-1}\right)$, where P_t is the daily price at time *t*.

[8] These results are not reported to save space but they are available upon request.

[9] This study, in line with previous studies on the same area (Floros, 2011), ignores the impact of electronic trading on stock market returns.

[10] Khaled and Keef (2011) report that the January effect is explained by the tax-loss selling and window-dressing theories; the essence of the January hypothesis is that investment managers sell shares close to the end of the financial/calendar year and then reinvest early in the

lower during the first day of the week (Monday effect - see Levy and Yagil, 2011; Bohl et al., 2010; Alt et al., 2011). These calendar effects are heavily related with the behavioural finance theories (i.e. investors' mood) in the way that (1) the January effect shows that financial returns are large comparing to the returns of the other months (Floros, 2011), and (2) the Monday effect[11] is where the returns are significantly lower over the first trading day of the week (see Levy and Yagil, 2011; Yuan et al., 2006); explanations include the settlement procedure hypothesis, measurement errors, the timing of earnings announcements and the influence of institutional versus individual investor trading (Bohl et al., 2010), spill-over effect from other large markets, risk-return tradeoff, speculative short sales (Charles, 2010).

Most previous papers on the same area (Keef and Khaled, 2011; Lucey, 2010; Yuan et al., 2006) employ a simple OLS model to test the effect of moon on stock market returns; however, simple OLS fails to capture the stylised facts of financial returns, i.e. (i) returns have very little autocorrelation, (ii) distribution has fatter tails compared to the normal, (iii) distribution has negative skewness, and (iv) variance has positive autocorrelation. In this study, we follow the recent works of Floros (2008b), Floros (2011) and Charles (2010) on modeling behavioural finance; hence, we employ several TGARCH volatility models with Normal, Student's-t and GED distributional assumptions for the standardized residuals. Both AIC and SIC information criteria select the parsimonious AR(1)-TGARCH(1,1) model which accounts for temporal dependence in variance and excess kurtosis, while it controls the effect of good/bad news (mood) on conditional variance (see Zakoian, 1994; Glosten et al., 1993); further, we model returns using an AR(1) mean equation, consistently with the non-synchronous trading effect (see Floros, 2011; Charles, 2010).

The AR(1)-TGARCH(1,1) model for returns R is given by:

$$R_t = c_1 R_{t-1} + c_2 MON_t + c_3 JAN_t + c_4 D_{FULLt} + c_5 D_{NEWt} + \varepsilon_t \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} a_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \tag{2}$$

The specification for the conditional mean is given by equation (1) where JAN is a dummy variable for testing for the January effect (JAN =1 for January, and 0

New Year.

[11] Explanations include (i) the timing of corporate releases after Friday's close, (ii) short sellers closing positions over non-trading periods such as weekends as well as the comparative advantage of informed traders when markets first open after a period of no trading (see Alt et al., 2011).

otherwise) and MON is a dummy variable for testing for the Monday effect (MON =1 for Monday, and 0 otherwise). D_{FULLt} and D_{NEWt} test for the full moon and new moon effects, respectively.

The specification for the conditional variance is given by equation (2) where $d_t = 1$ if $\varepsilon_t < 0$ and $d_t = 0$ otherwise. In TGARCH model, good news ($\varepsilon_t > 0$) and bad news ($\varepsilon_t < 0$) - or good mood and bad mood - have differential effects on the conditional variance. In particular, good news/mood has an impact of a, while bad news/mood has an impact of $a + \gamma$. If $\gamma > 0$ and significant, then the leverage effect exists and bad news increases volatility, while if $\gamma \neq 0$ the news impact is asymmetric; if $\gamma = 0$, then the news impact curve is symmetric, i.e. past positive shocks have the same impact on today's volatility as past negative shocks (see Zakoian, 1994; Glosten et al., 1993; Floros, 2011).

4. Empirical Results

The results[12] from the equation (2) of the AR(1)-TGARCH(1,1) volatility model (not reported here) confirm the empirical finance literature: (1) the sum of ARCH and GARCH coefficients is very close to one, indicating that volatility shocks are quite persistent, (2) the coefficients of the lagged squared returns (ARCH) and the lagged variances (GARCH) are positive and statistically significant for almost all cases (i.e. strong GARCH effects are apparent for the selected sample, and news has a greater impact on stock market returns), (3) the magnitude of the GARCH coefficient, β, is especially high, indicating a long memory in the variance, and (4) positive and significant γ parameter shows that the leverage effect exists and bad news increases volatility[13].

Table 2 reports mean parameter estimates of the selected AR(1)-TGARCH(1,1) model[14], defined in the equation (1), for all countries. Firstly, we report evidence of

[12] The results from several ARMA(p,q)-TGARCH(p,q) models under different distributional assumptions for the standardized residuals are available upon request.

[13] The results from the variance equation of the AR(1)-TGARCH(1,1) model are not reported to save space but they are available upon request.

[14] We report the results from the AR(1)-TGARCH(1,1) model with Normal distributional assumption for the standardized residuals. Heteroskedasticity Consistent Covariance (HCC) option is used to compute quasi-maximum likelihood (QML) covariances and standard errors using the methods described by Bollerslev and Wooldridge (1992).

January effect in 15 stock market returns (Austria, Denmark, Greece, Brazil, Ireland, Pakistan, Philippines, Hungary, Kuwait, Peru, Portugal, Tunisia, Venezuela, Belgium and Cyprus). Hence, for these markets (most of them are emerging markets) the stock market returns are higher in January (winter) than in any other month of the year (empirical results indicate that investors' confidence peaks in January). In other words, many investors choose to sell some of their stock before the end of the year in order to claim a capital loss for tax purposes (Floros, 2011); according to Ciccone (2011, p. 160), "*stock susceptible to having optimism impounded into their prices should earn superior returns in January*". Further, our results show significant Monday effects (low returns) in 15 cases (Greece, Bangladesh, Brazil, Chile, Ireland, Jakarta, Malaysia, Mexico, Pakistan, Turkey, Luxembourg, India – S&P Nifty, Poland, Norway, Cyprus); hence, these returns are lower in the first trading day of the week due to the fact that firms announce their profits during that period (Floros, 2008a)[15].

Our results show significant effect of new moon in eight cases (UK, Switzerland, Australia, Bangladesh, Chile, Cyprus, Argentina and Tunisia), while there is evidence of full moon effect in six cases (Brazil, Jordan, Canada, Bulgaria, Russia and Belgium). In particular, we find a negative effect of Moon (New and Full) on four international stock market returns, as follows: Australia, Argentina and Tunisia (New Moon) and Jordan (Full moon); the rest of the markets show significant positive effects. This finding is partially in line with Yuan et al. (2006) who report that stock returns are lower on the days around a full moon than on the days around a new moon.

<< Table 2 – about here >>

5. Conclusion

It is widely believed that the phases of the moon affect behaviour (Owen and McGowan, 2006). Moon is considered as an influential source of energy, hence it is linked with elements in a life's cycle. In particular, new moon marks the beginning of new life, development and the conception of hope. On the other hand, full moon marks the beginning of growth and production, while financial decision making may

[15] Half of the markets considered in this study support the theories of January and/or Monday effects. Only the US indices show significant but positive effect with regards to the Monday effect.

be explained by psychological factors (Garling et al., 2009; Keef and Khaled, 2011). It is widely accepted that the relationship between moon phases and mood may have implications to investors' behaviour (Levy and Yagil, 2011). Yuan et al. (2006) argue that lunar cycles have a mood related economic impact. According to Economist (2001, p. 1021), "*there is a growing, heavenly body of evidence that share prices are influenced by forces from outer space – well, the sun and the moon, anyway*". Past empirical evidence is mixed; it shows that stock returns are lower on days around a full moon than on days around a new moon or that there are strong lunar cycle effects in stock returns (Dichev and Janes, 2001). This paper provides new evidence of a lunar cycle effect on stock market returns of emerging and mature markets around the world. Although we have some evidence about the effect of moon phases on stock market returns, we know little about the linkages between efficient-market theory, calendar-related effects and investors' mood resulted from moon phases. Therefore, we investigate the effects of moon phases (new moon and full moon) on International stock returns of fifty-nine international markets using an AR(1)-TGARCH model; we extend the work of previous authors, primarily by considering calendar-related dummy variables for Monday and January effects. For instance, given the fact that January (Monday) is hypothesized to be a month (day) of renewed optimism (pessimism), investors may feel a sense of optimism (pessimism) related to the overall market performance at the beginning of the year (week), see Ciccone (2011).

The empirical results show significant full moon effects in 6 markets, and significant new moon effects in 8 markets. We find significant positive effect of New moon on stock market returns in 5 cases (UK, Switzerland, Bangladesh, Chile and Cyprus), while a negative effect of full moon is reported for the case of Jordan only. This is partially consistent with Yuan et al. (2006) and Lucey (2010); Lucey (2010) argues that asset returns should peak at the new moon and reach a trough at the full moon (i.e. full moons are bad news for the returns). In our study, we find that full moon is mainly good news (positive effect) for the stock market returns.

In addition, seven markets show evidence of full/new moon effects as well as Monday/January effects. In particular, Bangladesh and Chile have a positive effect of new moon and Monday effects, while Tunisia shows a negative effect[16] of new moon and a January effect; so, this is supported by emerging markets. Belgium also

[16] These results are consistent with changes in risk-taking behavior caused by depressive disorders.

provides evidence of positive full moon effect along with a January effect on stock market returns. Further, Brazil shows evidence of a positive full moon effect on stock market returns as well as Monday and January effects. In addition, the stock market returns of the Cypriot stock exchange are influenced positively by the New Moon as well as there is a strong evidence of Monday and January effects on the returns. In other words, we find that lunar effects are strongly influenced by the calendar anomalies (Monday effect and January effect); this is not in line with Keef and Khaled (2011) for 62 international stock indices. Hence, we prove that: (1) investors dealing with the Cypriot and Brazilian emerging stock markets are influenced by calendar anomalies and, (2) lunar effects are strongly affected by Monday and January effects. In addition, we find that the lunar phases are stronger outside America (this is in line with Dichev and Janes, 2003).

Finally, our study shows that half of the international stock markets support the theories of behavioural finance (i.e. investors' decisions are influenced by many factors including their current mood). Therefore, we find that the January (Monday) effects are driven by investors' optimism (pessimism).

Further research should examine the impact of lunar days (moon day 1 - 30) using other quantitative approaches and methods (e.g. event study methodology, APARCH model, Monte Carlo simulations).

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Table 1: Data Information

Countries (Indices*/sample period)	
Netherlands (AEX/ 1.01.1990 - 31.12.2010)	Japan (NIKKEI225/ 1.01.1990 - 31.12.2010)
Austria (ATX/ 1.01.1990 - 31.12.2010)	Pakistan (Karachi SE 100/ 1.01.1990 - 31.12.2010)
Belgium (BEL-20/ 1.01.1990 - 31.12.2010)	Philippines (PSEi/ 1.01.1990 - 31.12.2010)
France (CAC-40/ 1.01.1990 - 31.12.2010)	U.S. (S&P500 Composite/ 1.01.1990 - 31.12.2010)
Germany (DAX-30/ 1.01.1990 - 31.12.2010)	Canada (S&P/TSX Composite/ 1.01.1990 - 31.12.2010)
U.S. (DOW JONES/ 1.01.1990 - 31.12.2010)	Taiwan (SE Weighted/ 1.01.1990 - 31.12.2010)
U.K. (FTSE-100/ 1.01.1990 - 31.12.2010)	Turkey (Istanbul SE National 100/ 1.01.1990 - 31.12.2010)
Spain (Ibex35/ 1.01.1990 - 31.12.2010)	Italy (FTSEMIB/ 31.12.1997 - 31.12.2010)
U.S. (NASDAQ-100/ 1.01.1990 - 31.12.2010)	Iceland (OMX ICE/ 31.12.1992 - 31.12.2010)
Denmark (OMXC20/ 1.01.1990 - 31.12.2010)	Bulgaria (SE SOFIX/ 20.10.2000 - 31.12.2010)
Finland (OMXH/ 1.01.1990 - 31.12.2010)	Hungary (Budapest BUX/ 1.02.1991 - 31.12.2010)
Sweden (OMXS30/ 1.01.1990 - 31.12.2010)	Kenya (NAIROBI SE/ 1.01.1990 - 31.12.2010)
Norway (OSLO All Share/ 1.01.1990 - 31.12.2010)	Kuwait (KIC General/ 28.12.1994 - 31.12.2010)
U.S. (S&P100/ 1.01.1990 - 31.12.2010)	Luxembourg (SE GENERAL/ 1.04.1999 - 31.12.2010)
Switzerland (SWISS/ 1.01.1990 - 31.12.2010)	Malta (SE MSE/ 27.12.1995 - 31.12.2010)
Greece (ATHEX/ 1.01.1990 - 31.12.2010)	Argentina (MERVAL/ 8.02.1993 - 31.12.2010)
Australia (MSCI / 1.01.1990 - 31.12.2010)	Morocco (ALL SHARE MASI/ 1.02.2002 - 31.12.2010)
Bangladesh SE All Share/ 1.01.1990 - 31.12.2010)	India (S&P CNX NIFTY 50/ 23.04.1996 - 31.12.2010)
Brazil (Bovespa/ 1.01.1990 - 31.12.2010)	New Zealand (NZX50/ 29.12.2000 - 31.12.2010)
Chile (GENERAL IGPA/ 1.01.1990 - 31.12.2010)	Oman (MUSCAT SEC MKT/ 22.10.1996 - 31.12.2010)
Hong Kong (Hang Seng/ 1.01.1990 - 31.12.2010)	Peru (LIMA SE GENERAL IGBL/ 1.02.1991 - 31.12.2010)
India (BSE Sensex 30/ 1.01.1990 - 31.12.2010)	Poland (Warsaw General/ 16.04.1991 - 31.12.2010)
Ireland (SE Overall ISEQ/ 1.01.1990 - 31.12.2010)	Portugal (PSI-20/ 31.12.1992 - 31.12.2010)
Israel (TA-100/ 1.01.1990 - 31.12.2010)	Czech Rep. (SE PX/ 4.06.1994 - 31.12.2010)

Jakarta (IDX Composite/ 1.01.1990 - 31.12.2010)	Russia (RTS/ 9.01.1995 - 31.12.2010)
Jordan (Amman SE Fin/ 1.01.1990 - 31.12.2010)	Slovakia (SAX-16/ 14.09.1993 - 31.12.2010)
Korea (SE COMPOSITE KOSPI/ 1.01.1990 - 31.12.2010)	South Africa (FTSE/JSE ALL SHARE/ 30.06.1995 - 31.12.2010)
Malaysia (FTSE BURSA MALAYSIA KLCI/ 1.01.1990 - 31.12.2010)	Tunisia (TUNINDEX/ 31.12.1997 - 31.12.2010)
Mexico (IPC BOLSA/ 1.01.1990 - 31.12.2010)	Venezuela (SE General/ 4.01.1993 - 31.12.2010)
Cyprus (Cyprus General Price Index/ 3.09.2004 - 31.12.2010)	

Notes: * Name of indices as provided by *Datastream.*

Table 2: AR(1)-TGARCH(1,1) Results (Mean Equation)

Coefficient/Country	AUSTRIA	US (DOW JONES)	UK
AR(1)	0.112736*** (0.0000)	0.002668 (0.8450)	-0.001897 (0.8918)
MON	-7.33E-05 (0.8396)	0.000873*** (0.0018)	-0.000201 (0.4634)
JAN	0.001022** (0.0270)	0.000212 (0.5447)	-0.000315 (0.4256)
D_{NEW}	0.000637 (0.3308)	0.000180 (0.7008)	0.000882* (0.0873)
D_{FULL}	2.40E-05 (0.9696)	-0.000175 (0.7223)	0.000460 (0.3599)
Coefficient/Country	**DENMARK**	**SWEDEN**	**CZECH REP.**
AR(1)	0.085807*** (0.0000)	0.034928* (0.0135)	0.133155* (0.0000)
MON	-0.000336 (0.3226)	0.000594 (0.1292)	0.000139 (0.7227)
JAN	0.001027** (0.0244)	0.000180 (0.7275)	-0.00034 (0.5031)
D_{NEW}	-0.000386 (0.5263)	0.000532 (0.4380)	-0.000672 (0.3269)
D_{FULL}	0.000355 (0.5866)	0.000621 (0.3736)	-0.000632 (0.3731)
Coefficient/Country	**GREECE**	**AUSTRALIA**	**BANGLADESH**
AR(1)	0.144444*** (0.0000)	0.020157 (0.1690)	0.072600 (0.2282)
MON	-0.001142** (0.0176)	0.000122 (0.6583)	-0.002650** (0.0183)
JAN	0.002231*** (0.0010)	-0.000173 (0.6229)	-0.000306 (0.5873)
D_{NEW}	0.000386 (0.5943)	-0.000941* (0.0604)	0.003053** (0.0455)
D_{FULL}	-0.000595 (0.4803)	-0.000257 (0.6110)	-0.002065 (0.1201)
Coefficient/Country	**BRAZIL**	**CHILE**	**INDIA (BSE Sensex)**
AR(1)	0.015612 (0.4620)	0.320007*** (0.0000)	0.096326*** (0.0000)
MON	-0.001694** (0.0280)	-0.001858*** (0.0000)	0.000208 (0.6966)
JAN	0.029375** (0.0422)	0.000154 (0.5810)	-0.000993 (0.1267)
D_{NEW}	0.000672 (0.6251)	0.000649* (0.0782)	0.000512 (0.5417)
D_{FULL}	0.002495* (0.0796)	0.000541 (0.1226)	2.65E-05 (0.9756)
Coefficient/Country	**IRELAND**	**ISRAEL**	**JAKARTA**
AR(1)	0.114410*** (0.0000)	0.057212*** (0.0002)	0.199664*** (0.0000)
MON	-0.000864*** (0.0048)	0.000569 (0.1224)	-0.001405*** (0.0003)
JAN	0.001338*** (0.0047)	-0.000561 (0.4371)	0.000614 (0.2149)
D_{NEW}	0.000336 (0.5189)	-0.000478 (0.5373)	-0.000846 (0.1330)
D_{FULL}	-4.23E-05 (0.9334)	-0.000352 (0.6168)	-0.000965 (0.1936)
Coefficient/Country	**JORDAN**	**MALAYSIA**	**MEXICO**
AR(1)	0.076587*** (0.0041)	0.187768*** (0.0000)	0.141711*** (0.0000)
MON	0.000359 (0.3534)	-0.000999*** (0.0009)	-0.000809* (0.0685)
JAN	0.001113 (0.1742)	0.000283 (0.5553)	4.11E-05 (0.9464)
D_{NEW}	-0.001024 (0.2588)	3.37E-05 (0.9471)	-0.000315 (0.6811)
D_{FULL}	-0.001402** (0.0370)	-0.000157 (0.7781)	-0.000270 (0.7290)
Coefficient/Country	**PAKISTAN**	**PHILIPINNES**	**US (S&P500)**
AR(1)	0.123361*** (0.0000)	0.175389*** (0.0000)	-0.000820 (0.9509)
MON	-0.001242*** (0.0050)	-0.000679 (0.1490)	0.000579** (0.0461)
JAN	0.001150* (0.0583)	0.001212* (0.0781)	0.000340 (0.3130)
D_{NEW}	-0.000212 (0.7768)	-0.000142 (0.8578)	0.000159 (0.7242)
D_{FULL}	6.03E-05 (0.9435)	4.58E-05 (0.9543)	9.31E-05 (0.8482)
Coefficient/Country	**CANADA**	**TURKEY**	**ICELAND**
AR(1)	0.120064*** (0.0000)	0.083721*** (0.0000)	0.098165* (0.0428)
MON	7.80E-05 (0.7657)	-0.001426* (0.0835)	0.000316 (0.1466)
JAN	-6.09E-05 (0.8486)	0.000958 (0.3886)	-0.000257 (0.5316)
D_{NEW}	0.000185 (0.6566)	-0.001098 (0.4760)	0.000289 (0.5680)
D_{FULL}	0.000900** (0.0366)	-0.000824 (0.6288)	2.99E-05 (0.9520)

Coefficient/Country	BULGARIA	HUNGARY	KENYA
AR(1)	0.1254* (0.0000)	0.107994* (0.0000)	0.3740* (0.0000)
MON	0.000652 (0.1660)	-8.05E-05 (0.8524)	2.26E-05 (0.9407)
JAN	-0.001221 (0.1508)	0.001277** (0.0778)	0.000296 (0.2006)
D_{NEW}	-0.000161 (0.8276)	-0.000363 (0.7272)	-0.000494 (0.3215)
D_{FULL}	0.001705** (0.0816)	0.000134 (0.8758)	0.000555 (0.2530)
Coefficient/Country	**KUWAIT**	**LUXEMBOURG**	**ARGENTINA**
AR(1)	0.087394* (0.0011)	0.025578 (0.2965)	0.063566* (0.0001)
MON	-0.000174 (0.7093)	0.000820* (0.00723)	-0.000599 (0.3815)
JAN	0.029875* (0.0204)	0.000106 (0.8715)	-0.000837 (0.2801)
D_{NEW}	-0.000781 (0.3939)	0.001309 (0.1338)	-0.003652* (0.0156)
D_{FULL}	0.000238 (0.7060)	0.000414 (0.6354)	6.46E-05 (0.9579)
Coefficient/Country	**INDIA (S&P NIFTY)**	**PERU**	**POLAND**
AR(1)	0.068589* (0.0003)	0.283191* (0.0000)	0.119260* (0.0000)
MON	-0.001266* (0.0219)	-7.28E-05 (0.9837)	-0.001558* (0.0104)
JAN	-0.000852 (0.3906)	0.001024** (0.0631)	-0.000571 (0.3691)
D_{NEW}	0.000171 (0.8547)	0.000236 (0.6952)	0.000255 (0.8377)
D_{FULL}	-9.41E-05 (0.9250)	-0.00043 (0.5086)	-0.00108 (0.2152)
Coefficient/Country	**PORTUGAL**	**RUSSIA**	**SLOVAKIA**
AR(1)	0.135552* (0.0000)	0.118053* (0.0000)	-0.006757 (0.7304)
MON	-0.000259 (0.3765)	0.000567 (0.4212)	-0.000469 (0.4089)
JAN	0.002094* (0.0000)	-0.000891 (0.2964)	0.000892 (0.1019)
D_{NEW}	0.000593 (0.2494)	-0.000193 (0.8840)	-0.000189 (0.8032)
D_{FULL}	0.000386 (0.4301)	0.002728** (0.0705)	-0.000262 (0.731)
Coefficient/Country	**TUNISIA**	**VENEZUELA**	**NETHERLANDS**
AR(1)	0.228916* (0.0000)	0.196687* (0.0000)	0.011384 (0.4273)
MON	4.64E-05 (0.8109)	0.000306 (0.5506)	0.000321 (0.3075)
JAN	0.000606* (0.02691)	-0.001847* (0.0238)	0.000136 (0.7674)
D_{NEW}	-0.001018* (0.0013)	-0.000113 (0.9050)	0.000500 (0.4460)
D_{FULL}	5.00E-05 (0.8840)	0.000838 (0.4084)	0.000122 (0.8148)
Coefficient/Country	**BELGIUM**	**FRANCE**	**GERMANY**
AR(1)	0.083877*** (0.0000)	0.000611 (0.9646)	-0.001692 (0.9020)
MON	-0.000101 (0.7048)	-0.000490 (0.1960)	-6.21E-05 (0.8783)
JAN	0.000694* (0.0580)	0.000135 (0.7782)	0.000335 (0.5355)
D_{NEW}	0.000225 (0.7768)	0.000775 (0.2760)	0.000560 (0.4803)
D_{FULL}	0.000841*(0.0900)	0.000883 (0.2023)	0.000463 (0.5147)
Coefficient/Country	**SPAIN**	**U.S (NASDAQ)**	**SOUTH AFRICA**
AR(1)	0.058013*** (0.0001)	-0.000356 (0.9796)	0.091202* (0.0000)
MON	-0.000581 (0.1829)	0.000265 (0.5472)	-0.000324 (0.4219)
JAN	0.000312 (0.5396)	-0.000193 (0.7399)	-0.000295 (0.4793)
D_{NEW}	0.000916 (0.1567)	0.000511 (0.5030)	0.000492 (0.4547)
D_{FULL}	0.000241 (0.7048)	0.000574 (0.4561)	0.000301 (0.7073)
Coefficient/Country	**FINLAND**	**NORWAY**	**U.S (S&P100)**
AR(1)	0.105233*** (0.0000)	0.087432*** (0.0000)	-0.030579** (0.0222)
MON	-0.000376 (0.3564)	-0.000685* (0.0614)	0.000692** (0.0152)
JAN	0.001024 (0.1320)	0.000121 (0.8017)	0.000339 (0.3384)
D_{NEW}	0.000985 (0.1785)	0.000582 (0.4257)	0.000285 (0.5372)
D_{FULL}	-0.000328 (0.6573)	3.91E-05 (0.9498)	-6.29E-05 (0.9002)

Coefficient/Country	SWITZERLAND	ITALY	HONGKONG
AR(1)	0.028918* (0.0592)	-0.022071 (0.2074)	0.068200*** (0.0000)
MON	-2.10E-05 (0.9485)	0.000539 (0.2136)	-0.000377 (0.4372)
JAN	-0.000132 (0.7562)	0.000319 (0.5830)	-0.000203 (0.7347)
D_{NEW}	0.001417** (0.0340)	-9.34E-05 (0.8925)	-0.000407 (0.5942)
D_{FULL}	0.000359 (0.5427)	0.000691 (0.3396)	0.000142 (0.8611)
Coefficient/Country	**KOREA**	**JAPAN**	**CYPRUS**
AR(1)	0.035606** (0.0149)	-0.013452 (0.3317)	0.082151* (0.0018)
MON	-0.000564 (0.2900)	-0.000432 (0.3680)	-0.002693* (0.0040)
JAN	-0.000850 (0.2308)	-0.000256 (0.6846)	0.004663* (0.0127)
D_{NEW}	0.000276 (0.7597)	-0.000684 (0.3742)	0.004024* (0.0350)
D_{FULL}	0.000282 (0.7487)	-0.001088 (0.1427)	-0.000633 (0.7256)
Coefficient/Country	**TAIWAN**	**MALTA**	**MOROCCO**
AR(1)	0.037385*** (0.0087)	0.233525* (0.0000)	0.253613* (0.0000)
MON	0.000369 (0.4912)	-0.000232 (0.3983)	0.000137 (0.6787)
JAN	0.000410 (0.5011)	0.000421 (0.1128)	0.000535 (0.2801)
D_{NEW}	-0.000732 (0.4196)	-0.000238 (0.5389)	-0.000502 (0.3924)
D_{FULL}	-0.000209 (0.8488)	0.000429 (0.3395)	0.000507 (0.4523)
Coefficient/Country	**NEW ZEALAND**	**OMAN**	
AR(1)	0.046756* (0.0318)	0.21512* (0.0000)	
MON	-0.000126 (0.6780)	-0.000676 (0.1223)	
JAN	6.44E-05 (0.8644)	-0.000512 (0.4423)	
D_{NEW}	-0.000952 (0.1667)	-0.000881 (0.1661)	
D_{FULL}	-0.000314 (0.5548)	0.000507 (0.4395)	

Notes:

- Probability values of t-statistics in the parentheses.
- *, **, *** Significant at 10%, 5%, 1% levels, respectively.